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Equity in Student Achievement Across OECD Countries: An Investigation of the Role of Policies

by
Orsetta Causa *and* Catherine Chapuis*

This paper focuses on inequalities in learning opportunities for individuals coming from different socio-economic backgrounds as a measure of (in)equality of opportunity in OECD countries and provides insights on the potential role played by policies and institutions in shaping countries' relative positions. Based on harmonised 15-year old students' achievement data collected at the individual level, the empirical analysis shows that while Nordic European countries exhibit relatively low levels of inequality, continental Europe is characterised by high levels of inequality – in particular of schooling segregation along socio-economic lines – while Anglo-Saxon countries occupy a somewhat intermediate position. Despite the difficulty of properly identifying causal relationship, cross-country regression analysis provides insights on the potential for policies to explain observed differences in equity in education. Policies allowing increasing social mix are associated with lower school socio-economic segregation without affecting overall performance. Countries that emphasise childcare and pre-school institutions exhibit lower levels of inequality of opportunity, suggesting the effectiveness of early intervention policies in reducing persistence of education outcomes across generations. There is also a positive association between inequality of opportunities and income inequality. As a consequence, cross-country regressions would suggest that redistributive policies can help to reduce inequalities of educational opportunities associated with socio-economic background and, hence, persistence of education outcomes across generations.

JEL classification: I20, I21, I28, I38, H23

Keywords: education, equality of opportunity, equity in student achievement, school socio-economic segregation, public policies

* Causa (orsetta.causa@oecd.org) and Chapuis (catherine.chapuis@oecd.org), OECD Economics Department. The authors would like to thank Anna d'Addio, Sveinbjörn Blöndal, Jørgen Elmeskov, Miyako Ikeda, Åsa Johansson, Stephen Machin, Fabrice Murtin, Giuseppe Nicoletti and Jean-Luc Schneider for their valuable comments as well as Irene Sinha for excellent editorial support. The views expressed in this paper are those of the authors and do not necessarily reflect those of the OECD or its member countries.

This paper focuses on inequalities in learning opportunities for individuals coming from different socio-economic backgrounds as one of the major drivers of intergenerational social mobility. It analyses cross-country differences in the extent of equality of opportunity (Romer, 1998) – the idea that individual achievement should not reflect circumstances that are beyond an individual's control, such as family socio-economic background – among OECD countries and looks at the role played by policies and institutions in shaping countries' relative positions. While there is little scope for attenuating inequalities arising from the transmission of inheritable factors, inequalities in the distribution of learning opportunities might signal economic inefficiencies that are potentially amenable to policy intervention.

The study is based on harmonised 15-year old students' achievement data available for all OECD countries through the Program for International Student Assessment (PISA). Equality in educational achievement is measured with respect to the students' socio-economic background and is used as a proxy for equality of opportunity within OECD countries.

The empirical analysis shows that OECD countries are extremely heterogeneous with respect to inequality of educational opportunities associated with family background. In particular, while Nordic European countries exhibit relatively low levels of inequality, continental Europe is characterised by high levels of inequality – in particular of schooling segregation along socio-economic lines – while Anglo-Saxon countries occupy a somewhat intermediate position. By looking at non-linearities and asymmetries arising in the effect of socio-economic background on learning opportunities, the empirical analysis also sheds light on contextual effects and the impact of school socio-economic mix.

Cross-country regression analysis can give insights on the potential for policies to explain observed differences in equity in education. Keeping in mind that estimated correlations should not be interpreted in a causal sense, empirical results suggest that a number of policies and institutions have the potential to impact upon inequality in learning opportunities. Policies allowing increasing social mix are associated with lower school socio-economic segregation without affecting overall performance, at least in countries where such segregation is relatively high, as in continental Europe. Schooling differentiation and early tracking policies are found, as in earlier studies, to increase socio-economic inequality in learning opportunities. There is mixed evidence on the impact of public education spending on equality of learning opportunities, but empirical results suggest that financial incentives to teachers and effective mechanisms for allocating public resources to schools might help increase equality of opportunities in educational achievement. Countries that emphasise childcare and pre-school institutions exhibit lower levels of inequality of opportunity, suggesting the effectiveness of early intervention policies in reducing persistence of education outcomes across generations. There is also a positive association between inequality of opportunities and income inequality. As a consequence, cross-country regressions suggest that redistributive policies can help to reduce inequalities of educational

opportunities associated with socio-economic background and, hence, persistence of education outcomes across generations. Finally, there is some empirical evidence suggesting a role for labour and social policies in shaping cross-country differences in the impact of socio-economic background on student achievement.

The document is organised as follows. Section 1 provides the motivation and background underlying the analysis, by illustrating the link between educational equality of opportunity and intergenerational social mobility. Section 2 presents and discusses the estimated impact of parental background on secondary educational achievement on a country-by-country basis, focusing on different dimensions of equality of learning opportunities. Section 3 relates the patterns observed across OECD countries to differences in their institutional settings, by focusing on educational and early intervention policies, as well as welfare, redistribution, and labour market policies. Before presenting the empirical results, the section provides a brief overview of the comparable studies that have focused on the relationship between institutions and equality of opportunity.

1. Motivation and background

The idea that education is one of the main drivers of intergenerational social mobility has been formally modelled under various assumptions. The theoretical framework is based on models of intergenerational transmission of inequality and allocation of resources within the family, which have led to a close focus on the role of human capital and education policy (Becker and Tomes, 1979, 1986). These models were further developed by Solon (2004), who integrated public and private investment in education into a single framework. Restuccia and Urrita (2004) studied intergenerational human capital transmission focusing on innate ability, early education, and college education, and the implications for early and college education policies. In addition, Heckman (2007) emphasised the importance of human capital investment at the right time in the lifecycle in order to correct for disadvantageous individual conditions inherited from parents.

There is ample empirical evidence that education is one of the major drivers of intergenerational social mobility, particularly income mobility. Among others, Machin (2004) and Blanden *et al.,* (2004) argue that the recorded fall in intergenerational mobility in the United Kingdom between the cohorts born at the end of the 1950s and those born in the 1970s was, to a large extent, due to the fact that increased educational opportunities in the reference period disproportionately benefited individuals from better-off backgrounds.

The estimation of economic returns to education has been the object of numerous empirical contributions.[1] Topical studies (Card, 1999, Ashenfelter *et al.,* 1999) have documented substantial earnings returns to quantitative measures of education, such as years of schooling. The earnings returns to qualitative measures of education, like test scores on cognitive achievement, seem to be even higher (Bishop, 1992, Riviera-Batiz, 1992), and, contrary to quantitative measures, increasing with an individual's time on the labour market (Altonji and Pierret, 2001). The results of these studies suggest that qualitative measures of education are relevant for assessing individual future economic success.

The development of cognitive skills tends to be stronger early on in life. Therefore, intergenerational mobility studies have devoted attention to the relationship between children's cognitive skills and parental background as an important early indicator of (dis)advantage. In this respect, empirical research that relates ability test scores of children to the socio-economic background of parents (see Heckman, 1995) suggests that the link

emerges at a young age.[2] Against this background, the present empirical study focuses on the impact of parental background on adolescents' test scores as an indicator of equity in education and, in this respect, a measure of intergenerational social mobility.[3]

The OECD has adopted a consistent approach for measuring equality of educational opportunities (OECD, 2001a, 2004, 2007a). It also produced a specific publication on factors related to quality and equity through the use of the 2000 PISA database (OECD, 2005a). PISA results highlight substantial differences across OECD countries. In particular, while Nordic European countries, as well as Canada and Australia, appear to display relatively high levels of educational equity, other countries, notably in continental (Germany, Austria, Belgium, France) and southern Europe (Italy in particular), are characterised by relatively low levels of educational equity.[4] This cross-country picture appears to have been stable over the period covered by PISA surveys, with no deterioration of measured equity in student achievement in OECD countries between 2000 and 2006.

2. Equity in student achievement across OECD countries

2.1. The PISA dataset[5]

This study uses cross-country comparable microeconomic data on student achievement, collected consistently across and within OECD countries through the Programme for International Student Assessment (PISA), which assesses the skills of students approaching the end of compulsory education. It targets the 15-year-old student population in each country and independently of how many years of schooling are foreseen for 15-year-olds by the structure of the national school systems. It was conducted in a total of 67 countries, including all OECD countries. The PISA 2006 survey assesses the mathematical, scientific, and reading literacy as well as the problem-solving skills of the student population in each participating country.

The PISA sampling procedure ensures that a representative sample of the target population is tested in each country. Most countries employ a two-stage sampling procedure. The first stage draws a random sample of schools in which 15-year-old students are enrolled. In most countries, the probability of each school being selected is proportional to its size, as measured by the estimated numbers of 15-year-old students enrolled in the school. The second stage randomly samples 35 of the 15-year-old students in each of these schools, with each 15-year-old student in a school having equal selection probability. The empirical analysis undertaken in what follows explicitly takes into account the complex survey design of the data, as well as its probabilistic structure.

The main focus of the PISA 2006 study is on scientific literacy, with about 70% of the testing time devoted to this item. Given the very high correlation among science, mathematics, and reading scores, the following analysis focuses on science scores. OECD (2007a) points to the robustness of country-specific and cross-country empirical assessments to the use of either score. PISA uses item response theory scaling and calculates five plausible values for proficiency in each of the tested domains for each participating student. The performance in each domain is mapped on a scale with an international mean of 500 and a standard deviation of 100 test-score points across OECD countries.[6] To simplify the empirical analysis, in this paper it was decided to focus on one – specifically, the first – of the five individual's plausible values. This procedure is superior to the *ex ante* averaging of all values (OECD, 2005c). Not surprisingly, results are robust to the use of either of them as a dependent variable.

The PISA dataset provides a rich array of background information on each student, as well as on his/her school. In separate background questionnaires, students are asked to provide information on their personal characteristics and family background, and school principals provide information on their schools, resource endowments and institutional settings.

2.2. Measuring equity in student achievement: definitions and methodology

Equity in student achievement is defined consistently with the concept of equality of opportunity. The empirical counterpart to the concept is constructed by estimating how strongly educational achievement, as measured by PISA test scores, depends on the socio-economic background of the students' families in each country. Specifically, the analysis uses the Index of Economic, Social, and Cultural Status (ESCS) provided by PISA as the measure of family background. The size of the achievement difference between students with high and low values of the ESCS index provides a measure of how fair and inclusive each school system is: the smaller the difference, the more equally distributed is education. This methodology is standard in the empirical literature using cross-country educational datasets (OECD PISA reports 2001a, 2004, 2007a; Schutz *et al.,* 2005, Schutz *et al.,* 2007, Woessmann, 2004, d'Addio, 2007).

The PISA ESCS index is intended to capture a range of aspects of a student's family and home background. It is explicitly created in a comparative perspective by PISA experts with the goal of minimising potential biases arising as a result of cross-country heterogeneity (OECD, 2005b). It is derived from a Principal Component Analysis applied to the following variables: *i)* the international socio-economic index of occupational status of the father or mother, whichever is higher; *ii)* the level of education of the father or mother, whichever is higher, converted into years of schooling; *iii)* the PISA index of home possessions obtained by asking students whether they had at their home a number of items allowing and facilitating learning (*inter alia*, a desk at which to study, a computer, books ...).[7] The student scores on the index are standardised to have an OECD mean of zero and a standard deviation of one.[8]

2.3. Equity in student achievement across OECD countries: the results

Regression estimates suggest that there are substantial differences among OECD countries in terms of equality of learning opportunities. Causa and Chapuis (2009) present detailed findings on a country-by-country basis. Part of the results confirm and reflect previous OECD findings (OECD, 2007a). In this paper, previous OECD work is extended with further empirical results on country-specific patterns of equity in the distribution of learning opportunities among students and schools.

2.3.1. Socio-economic segregation and equity in student achievement in OECD countries

We investigate how student performance is separately affected by student's own family background and the average socio-economic background of families of other students in the same school, *i.e.* the school socio-economic environment. Separating these two effects allows a better understanding of how learning opportunities are distributed both within and across schools. In turn, this facilitates exploration of how equality of learning opportunities is related to differences in policies and institutions across OECD countries.

2.3.1.1. Individual background and school environment effects: definition and empirical approach. The baseline empirical model focuses on the estimation of the so-called "socio-economic gradient", β that is the influence of parental background on achievement. Hence, the student-level score is regressed upon his/her family socio-economic background:

$$Y_{isc} = \alpha_{1c} + \beta_{1c} \cdot F_{isc} + \varepsilon_{isc} \quad (1)$$

where index *i* refers to individual, *s* to school, and *c* to country. Y_{isc} denotes the student's science test score, F_{isc} denotes family background as measured by the ESCS index, and ε_{isc} is an error term.

The overall socio-economic gradient can be decomposed in two parts, a "within-school" gradient – or individual background effect – and a "between-school" gradient – or school environment effect. The former can be defined as the relationship between student socio-economic background and student performance within a given school, while the latter can be defined as the relationship between the average socio-economic status of the school and student performance, controlling for his/her background. As explained in OECD, (2004, 2007a), the decomposition of the overall gradient is a function of the between-school gradient, the average within school gradient, and a "segregation" parameter that measures the proportion of variation in socio-economic background that is between schools (OECD, 2007a).[9]

The empirical approach for estimating the influence of individual background and school environment on students' test scores is an extension of equation (1):

$$Y_{isc} = \alpha_{1c} + \beta_{wc} \cdot F_{isc} + \beta_{bc} \cdot \overline{F_{sc}} + \varepsilon_{isc} \quad (2)$$

where $\overline{F_{sc}}$ is defined as the weighted average (by student sampling weights) of student socio-economic background in the school attended by individual *i* (which is computed excluding the student himself).[10] The baseline empirical model focuses on the estimation of the so-called "socio-economic gradient", β that is the influence of parental background on achievement. Hence, while β_{wc} refers to the within-school gradient, β_{bc} refers to the between-school gradient. Equation (2) can be extended to control for student and school-level characteristics.

2.3.1.2. Interpreting school environment effects. Estimation of the school environment effect, or parameter β_{bc}, is a topical question in educational research. Box 1 provides a brief summary of the underlying conceptual framework. Broadly speaking, this parameter captures two interrelated effects: *i*) contextual effects, arising when student achievement depends on the socio-economic composition of his/her reference group (which is exogenous to this group's behaviour); *ii*) peer effects, arising when student achievement depends on that of his/her reference group (*i.e.* on the behaviour of other members of the group).

In this study, the between-school socio-economic gradient estimated in equation (2) can be considered as a proxy for the contextual effect arising in the school. It is not possible to apportion the contribution of peer effects to this estimate. Indeed, as recalled in Box 1, contextual and peer effects are difficult to identify separately. Moreover, a number of caveats apply to this analysis, among which the most important is self-selectivity, whereby wealthier and more skilled students choose a better school and peer group, causing an over-estimation of contextual effects. This bias does not appear to be important in the present context, given that the estimated contextual effects are robust to the introduction of school level controls – such as various measures of school characteristics, resources, and

Box 1. **School environment effects: methodological issues and policy implications**

The literature on social interactions at school is abundant and results are controversial.* Manski (1995, 2000) provides a framework for a systematic analysis of social interactions. He states three possible reasons why individuals belonging to the same group might tend to behave alike: *i)* endogenous effects, also called peer effects: the probability that an individual behaves in some way is increasing with the presence of this behaviour in the group; that is, student achievement depends positively on the average achievement in the reference group; *ii)* contextual effects: the probability that an individual behaves in some way depends on the distribution of exogenous background characteristics in the group; that is, student achievement depends on the socio-economic composition of the reference group; *iii)* correlated effects: individuals behave in the same way because they have similar background characteristics and face similar environments.

Peer and contextual effects refer to externalities and are driven by social interactions; correlated effects are a non-social phenomenon. Contextual and peer effects cannot be separated empirically due to identification problems, first of all multicollinearity. Moreover, the investigation of peer effects faces a classical simultaneity problem because a student both affects his/her peers and is in turn affected by them. One of the solutions advocated by scholars to overcome this issue is that of estimating contextual effects – that is, the effect of group's socio-economic composition on student achievement. Endogeneity bias is reduced by excluding the student from the average socio-economic background of the group.

Peer and contextual effects are of policy relevance because they can serve as a basis for reallocating students into different schools or environments. The argument is that weak students would benefit if they were in the same class as high-performing students. However, increasing equity in this way potentially threatens overall efficiency in terms of average cognitive achievement at the class, school or even country level. In order to be efficiency-enhancing, in the sense of increasing average cognitive development of students, two conditions have to be met. First, peer effects should be higher for low-skilled students than for high-skilled ones, and second, higher mix in schools should not have detrimental effects on average learning in the group. These topics have been analysed in the educational and economic literature on peer effects, whose main results can be summarised as follows:

- Peer effects are sizeable, both at the primary and secondary levels (Amermuller and Pischke, 2003, Hanushek *et al.,* 2003, Vidgor and Nechyba, 2004, Schneeweis and Winter-Ebmer, 2005), as well as at the tertiary level (Sacerdote, 2000, Winston and Zimmerman, 2003).
- Peer effects are asymmetric, and favour weaker students. This result is slightly more controversial, although most studies find that peer effects are stronger – more positive – for low-ability students (Schindler, 2003, Levin, 2001, Sacerdote, 2000, Winston and Zimmerman, 2003, Schneeweis and Winter-Ebmer, 2005).
- Asymmetries in favour of weaker students have to be weighted against the potential negative effects of within-class mix. The literature is controversial in that respect, although a number of studies have found no impact of mix on student performance (Hanushek *et al.,* 2003, Schindler, 2003, Vidgor and Nechyba, 2004, Schneeweis and Winter-Ebmer, 2005).

* See Brock and Durlauf (2001), Moffitt (2001), Hanushek *et al.,* (2003).

funding,[11] as well as school selection of students on the basis of past achievement.[12, 13] Regressions also control for a number of family characteristics that are likely to downplay this effect, first of all, own socio-economic background. Furthermore, the potential upward bias induced by self-selectivity might be somewhat compensated by the potential downward bias arising because of the impossibility of estimating contextual effects at the class level. Indeed, PISA data do not contain information on students' classes. The educational literature stresses that contextual and peer effects are higher at the class than at the school level (see Vidgor and Nechyba, 2004), a finding that would suggest a potential under-estimation of social interactions effects in the PISA data.

Although properly measuring, quantifying, and characterising peer and contextual effects is beyond the scope of the present study (not least because of data unavailability at the class level), comparing estimates of these effects across countries can provide interesting insights. There need not be *a priori* systematic differences across countries in terms of social interaction effects; and similarly there need not be *a priori* systematic differences across countries in terms of estimation biases. Therefore, the observed *ex post* distribution of estimated school environment effects across OECD countries might, to a large extent, reflect differences in policies and institutions. For instance, higher estimated school environment effects can be interpreted as resulting from policies and institutions that induce higher segregation along socio-economic lines and, therefore, lower levels of social mix. Cross-country studies are rare on this subject. One exception is Entorf and Lauk (2006), who use a comparative approach based on PISA 2000 data, and estimate peer effects for different groups of countries, depending on schooling systems and immigration patterns. They find sizeable differences across groups of countries, and conclude that non-comprehensive and ability-differentiated school systems exhibit the highest levels of peer effects.[14]

2.3.1.3. Individual background and school environment effects in OECD countries: the results. Based on the regression results reported in Table 1, Figure 1 compares the estimated individual background and school environment effects across countries. Box 2 provides details on the methodology used for this comparison and on the differences with the approach used in the 2007 PISA report. The figure illustrates *i*) the estimated between-school effect, or school environment effect, defined as the gap in predicted scores of two students with identical socio-economic backgrounds attending different schools (where the average background of students is separated by an amount equal to the inter-quartile range of the country-specific school socio-economic distribution); *ii*) the estimated within-school effect, or individual background effect, defined as the gap in predicted scores of two students within the same school coming from different family backgrounds (where the family backgrounds are separated by an amount equal the inter-quartile range of the country-specific average within school socio-economic distribution). While the first effect refers to the increase in a student's score obtained from moving the student from a school where the average socio-economic intake is relatively low to one where the average socio-economic intake is relatively high, the second refers to the increase in student's score obtained from moving the student from a relatively low socio-economic status family to a relatively high socio-economic status family, while he/she stays in the same school. The numbers presented in Figure 1 should not be taken at face value and are only indicative of the ranking of OECD countries in terms of individual and school environment effects.

Table 1. **Estimates of the socio-economic gradient in OECD countries: school environment and individual background effects**

Impact of parental background on PISA science scores of teenagers

	Australia	Austria	Belgium	Canada	Czech Republic	Denmark	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Italy	Japan
Individual background	30.424***	16.279***	20.645***	25.679***	24.097***	33.675***	30.330***	23.415***	19.535***	19.268***	11.205***	28.341***	30.177***	10.885***	8.987***
	[1.405]	[1.661]	[1.032]	[1.297]	[1.570]	[1.523]	[1.498]	[1.774]	[1.179]	[1.471]	[1.434]	[1.857]	[1.722]	[1.012]	[1.965]
School environment	53.140***	103.910***	101.220***	39.427***	110.141***	36.766***	11.972**	98.903***	107.591***	59.354***	82.570***	–6.836	43.813***	75.631***	125.737***
	[4.244]	[6.053]	[5.052]	[4.464]	[6.855]	[6.943]	[5.716]	[4.683]	[5.297]	[4.981]	[4.884]	[4.142]	[5.253]	[5.158]	[8.698]
Constant	510.484***	487.508***	490.381***	512.577***	509.669***	475.406***	553.324***	508.298***	480.865***	485.832***	512.492***	474.953***	510.543***	526.669***	534.546***
	[1.512]	[3.285]	[2.594]	[2.427]	[3.335]	[3.110]	[1.946]	[3.164]	[2.887]	[2.528]	[2.660]	[3.451]	[2.114]	[4.650]	[3.090]
Number of observations	13 995	4 908	8 777	22 132	5 902	4 496	4 697	4 606	4 686	4 861	4 462	3 733	4 501	21 678	5 862
R-squared	0.147	0.348	0.387	0.107	0.314	0.160	0.085	0.388	0.421	0.249	0.410	0.063	0.158	0.316	0.236

	Korea	Luxembourg	Mexico	Netherlands	New Zealand	Norway	Poland	Portugal	Slovak Republic	Spain	Sweden	Switzerland	Turkey	United Kingdom	United States
Individual background	11.492***	24.889***	7.947***	14.972***	42.907***	30.925***	36.362***	18.534***	23.251***	24.636***	34.299***	29.721***	10.755***	34.645***	35.111***
	[1.694]	[1.089]	[0.749]	[1.175]	[1.768]	[1.798]	[1.483]	[1.187]	[1.689]	[1.187]	[2.335]	[1.401]	[1.121]	[1.983]	[1.726]
School environment	80.049***	70.134***	35.939***	120.000***	50.897***	29.559***	15.842***	30.693***	64.124***	21.949***	33.414***	75.539***	65.692***	65.766***	51.149***
	[7.950]	[2.281]	[2.183]	[5.317]	[5.452]	[8.123]	[5.289]	[3.233]	[7.216]	[2.638]	[7.546]	[5.971]	[4.937]	[4.704]	[7.092]
Constant	522.712***	478.659***	453.385***	491.176***	522.973***	463.253***	513.414***	504.485***	501.467***	503.282***	489.080***	502.251***	521.766***	498.342***	477.770***
	[2.573]	[1.126]	[2.207]	[2.819]	[2.311]	[4.967]	[2.473]	[2.292]	[2.172]	[1.862]	[2.858]	[2.022]	[7.599]	[2.028]	[3.102]
Number of observations	5 168	4 488	30 869	4 838	4 727	4 601	5 502	5 091	4 723	19 499	4 386	12 136	4 934	12 806	5 568
R-squared	0.193	0.336	0.262	0.439	0.194	0.084	0.151	0.214	0.288	0.152	0.119	0.249	0.344	0.189	0.218

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), and school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run). Regressions for Italy include regional fixed effects. Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level.

Example: In Australia, for each improvement of one international standard deviation in the individual socio-economic background, student performance on the OECD PISA science scale improves by 30 points, within a given school socio-economic environment. In Australia, for each improvement of one international standard deviation in the school socio-economic environment, student performance on the OECD PISA science scale improves by 53 points, for a given level of individual socio-economic background.

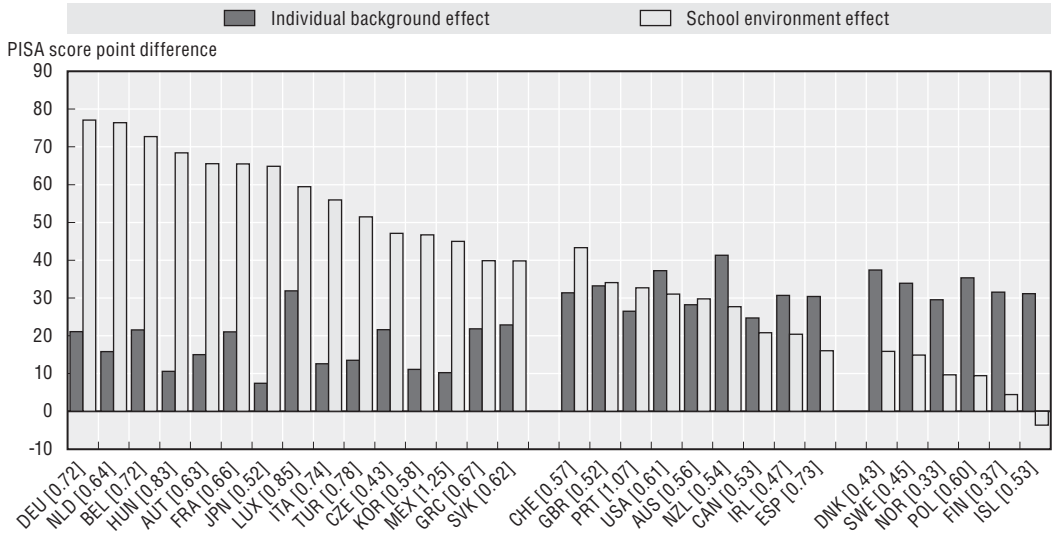
Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

Figure 1. **Effects of individual background and school socio-economic environment on students' secondary achievement**[1]

Socio-economic gradient taking cross-country distributional differences into account

Differences in performance on the science scale associated with the difference between the highest and the lowest quartiles of the country-specific distribution of the PISA index of economic, social and cultural status



Notes: The individual background effect is defined as the difference in performance on the PISA science scale associated with the difference between the highest and the lowest quartiles of the average individual background effects distribution of the PISA index of economic, social and cultural status, calculated at the student level. The school environment effect is defined as the difference in performance on the PISA science scale associated with the difference between the highest and the lowest quartiles of the country-specific school level average distribution of the PISA index of economic, social and cultural status, calculated at the student level.

Data in parentheses are values of the difference between the highest and the lowest quartiles of the country-specific school-level average distribution of the PISA index of economic, social and cultural status, calculated at the student level.

The negative school environment effect for Iceland is not statistically significant.

1. Regression of student science performance on student family socio-economic background (as measured by PISA ESCS), and school-level socio-economic background (average PISA ESCS across students in the same school, excluding the individual student for whom the regression is run). Country-by-country least-square regressions are weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. Regressions for Italy include regional fixed effects.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

In all OECD countries, there is a clear advantage in attending a school where students are, on average, from more advantaged socio-economic backgrounds. Some countries exhibit substantial inequalities associated with school attendance: this is, for instance, the case of Germany or France, where moving a student from a low socio-economic environment school to a high socio-economic environment school would produce a 73 and 65 points difference respectively, compared with 14 in Sweden and 15 in Denmark.[15] These cross-country patterns confirm earlier findings, in particular when comparing comprehensive school systems – such as in Nordic European countries – and non-comprehensive systems – such as in Austria and Germany (see in particular OECD PISA reports, but also Fuchs and Woessmann, 2004, Entorf and Lauk, 2006).

Box 2. **Individual's background and school environment effects in OECD countries**

The regression results presented in Table 1 suggest that, on average across OECD countries, for each improvement of one standard deviation in student socio-economic background within a given school environment, the student performance on the science scale improves by 24 points, with cross-country differences ranging from 9 advantage points (Italy) to 43 (New Zealand). The impact of the school socio-economic background is estimated to be substantially higher: on average across OECD countries, for each improvement of a student-level standard deviation in the average school socio-economic background, the student performance on the science scale improves by 62 points, independent of his/her own socio-economic background, with cross-country differences ranging from 11 advantage points (Finland) to 126 (Japan).[1]

Based on these raw estimates, the effects of an individual's background and a school's environment can be adjusted for more meaningful cross-country comparisons using the same approach as in the PISA 2007 report (OECD, 2007a), which accounts for the impact of the within-country distribution of students' socio-economic status. However, the approach in this study departs from OECD (2007a) in one respect: cross-country differences in the distribution of students' socio-economic status are taken into account using country-specific within and between distributions in the computations. Hence, the comparison is made both within and across countries. This requires calculating, for each country, the school-level distribution of socio-economic background, as well as the average within-school distribution of socio-economic background, based on student-level data. Such concepts allow measuring consistently the effects associated with relevant moves along both the within and between-school distributions.[2]

1. In Iceland, the estimated negative within effect is not statistically significant (see Table 1).
2. Intuitively, the overall distribution of socio-economic status can be decomposed into the between and within school components. Given that each school is mixed in terms of its socio-economic intake, differences in the average of schools' socio-economic backgrounds are naturally smaller than comparable differences between individual students.

2.3.1.4. School environment effect along the school socio-economic distribution. The effect of the school socio-economic environment on educational achievement is not always uniform within the school socio-economic distribution. Table 2 presents results from a regression specification that accounts for possible non-linearities in the effect of socio-economic background by simply introducing square terms of individual and school socio-economic variables (equation 3):

$$Y_{isc} = \alpha_{1c} + \beta_{1wc} \cdot F_{isc} + \beta_{1bc} \cdot \overline{F_{sc}} + \beta_{2wc} \cdot F_{isc}^{\ 2} + \beta_{2bc} \cdot \overline{F_{sc}}^{2} + \varepsilon_{isc} \quad (3)$$

In some countries, there are large differences in the between-school gradient for students attending schools at the top and those attending schools at the bottom deciles of the school distribution of socio-economic background. For example, in the United Kingdom it is the very "rich" schools that make a difference, providing a relatively high pay-off to students attending schools where the average student is socially advantaged, independent of their individual background. Conversely, in France and Germany it is the very "poor" schools that make a difference and provide a relative high penalty to students attending schools where the average student is socially disadvantaged, independent of their own individual background.[16]

Table 2. **Estimates of the socio-economic gradient in OECD countries: non-linearities in the impact of socio-economic background**

Impact of parental background on PISA science scores of teenagers

	Australia	Austria	Belgium	Canada	Czech Republic	Denmark	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Italy	Japan
Individual background	30.455***	12.712***	18.767***	26.892***	23.687***	28.609***	27.516***	23.148***	16.501***	19.756***	9.764***	28.717***	30.740***	9.681***	8.866***
	[1.429]	[2.002]	[1.075]	[1.556]	[1.559]	[1.694]	[1.552]	[1.852]	[1.632]	[1.518]	[1.471]	[3.088]	[1.658]	[1.151]	[2.078]
Individual background squared	–3.324***	–3.497***	–0.139	–3.091**	–4.097***	1.472	2.002	2.023	–0.850	–3.055**	–2.023**	–1.180	0.059	–2.492***	–5.991***
	[1.218]	[1.243]	[0.753]	[1.189]	[1.547]	[1.164]	[1.396]	[1.503]	[0.990]	[1.191]	[0.945]	[1.555]	[1.280]	[0.750]	[1.974]
School environment	48.585***	108.204***	95.736***	45.289***	108.844***	39.820***	–2.942	93.726***	111.147***	53.877***	84.888***	–18.107	46.470***	73.651***	123.128***
	[6.288]	[9.085]	[5.827]	[8.242]	[7.528]	[8.039]	[9.541]	[4.798]	[6.999]	[4.234]	[5.479]	[12.146]	[4.477]	[5.222]	[8.995]
School environment squared	7.383	–15.011	–8.552	–6.842	8.375	–5.234	29.462**	–27.038***	–16.974**	–19.242***	–6.401	9.468	–24.051***	–13.090**	–18.216
	[8.373]	[11.481]	[8.107]	[7.657]	[10.087]	[11.369]	[11.966]	[8.579]	[8.102]	[4.312]	[6.384]	[9.030]	[6.620]	[6.126]	[20.363]
Female student	–1.403	–14.573***	–6.368**	–7.409***	–11.935**	–7.462**	0.694	–7.634**	–10.913***	7.614**	–19.596***	5.438*	–1.121	–11.888***	–5.050
	[2.351]	[4.101]	[2.670]	[1.831]	[4.654]	[2.851]	[2.819]	[3.042]	[2.303]	[3.795]	[3.029]	[3.113]	[3.035]	[2.704]	[5.162]
Migration background: first generation	1.950	–28.747***	–14.402***	–9.271**	–54.888***	–30.276***	–60.102**	–17.741**	–26.164***	–16.677	–45.038***	–19.355	–11.445	–47.480***	3.550
	[3.819]	[8.642]	[5.270]	[4.299]	[17.018]	[11.049]	[26.607]	[7.884]	[7.168]	[12.852]	[14.137]	[22.670]	[13.954]	[16.834]	[36.562]
Migration background: second generation	–1.199	–32.774***	–39.543***	–22.227***	–26.632**	–23.683**	–72.923***	–35.993***	–19.135***	–4.006	–3.561	–35.513*	20.781**	–55.573***	38.963
	[4.020]	[7.256]	[7.709]	[5.107]	[12.490]	[9.957]	[16.538]	[9.665]	[6.109]	[8.780]	[9.748]	[20.424]	[9.298]	[10.123]	[30.478]
Foreign language spoken at home	–13.967**	–25.553***	–22.782***	–1.995	–4.881	–37.087***	–16.383	4.734	–29.044***	–25.012**	–25.799**	–36.258**	–74.552***	–5.563	–119.733***
	[5.629]	[7.868]	[5.122]	[5.311]	[14.679]	[9.219]	[13.905]	[7.717]	[5.380]	[9.667]	[11.551]	[15.142]	[13.177]	[11.257]	[20.796]
Number of observations	13 573	4 760	8 026	21 285	5 787	4 268	4 624	4 453	4 187	4 581	4 408	3 658	4 404	18 640	5 638
R-squared	0.148	0.385	0.395	0.115	0.316	0.173	0.099	0.397	0.439	0.276	0.423	0.071	0.173	0.328	0.239

Table 2. **Estimates of the socio-economic gradient in OECD countries: non-linearities in the impact of socio-economic background** *(cont.)*

Impact of parental background on PISA science scores of teenagers

	Korea	Luxembourg	Mexico	Netherlands	New Zealand	Norway	Poland	Portugal	Slovak Republic	Spain	Sweden	Switzerland	Turkey	United Kingdom	United States
Individual background	11.485***	16.703***	10.479***	11.656***	41.821***	30.286***	36.394***	19.184***	23.129***	22.520***	31.233***	22.038***	17.258***	34.560***	33.355***
	[1.725]	[1.496]	[0.913]	[1.213]	[2.015]	[2.177]	[1.492]	[1.295]	[1.561]	[1.106]	[1.949]	[1.457]	[2.665]	[2.009]	[1.765]
Individual background squared	1.684	–0.656	1.519***	0.818	2.731	–2.964**	–0.042	0.666	–5.143***	–3.403***	–0.106	0.926	3.069***	–2.397*	2.909**
	[1.379]	[0.770]	[0.390]	[1.200]	[1.663]	[1.402]	[1.040]	[0.679]	[1.472]	[0.870]	[1.443]	[0.897]	[0.952]	[1.347]	[1.219]
School environment	80.094***	65.910***	37.046***	121.846***	51.600***	10.323	26.150***	25.056***	73.009***	22.855***	41.060***	75.236***	85.129***	48.701***	47.129***
	[8.433]	[2.899]	[3.180]	[7.444]	[6.130]	[19.271]	[5.679]	[2.417]	[4.910]	[2.508]	[12.527]	[5.663]	[9.625]	[5.900]	[9.080]
School environment squared	–10.571	2.296	1.672	–8.365	–2.840	23.063	27.676***	–6.928***	19.106***	3.330	–17.003	–0.674	8.794**	30.976***	–3.018
	[13.341]	[4.205]	[1.300]	[10.049]	[9.326]	[15.964]	[6.700]	[2.349]	[5.821]	[3.638]	[17.573]	[8.467]	[3.689]	[9.907]	[10.742]
Female student	2.761	–6.505**	–10.398***	–11.217***	–0.011	2.649	–1.000	–2.871	–9.096**	–5.218***	–0.393	–11.244***	4.097	–8.739***	–2.929
	[4.033]	[2.583]	[1.772]	[2.584]	[3.602]	[3.281]	[2.323]	[2.368]	[3.477]	[1.889]	[2.760]	[1.959]	[3.540]	[2.212]	[2.865]
Migration background: first generation	38.128***	–21.944***	–35.831***	–21.920***	–9.063	–29.104**	37.656	–52.736***	–30.009	–2.889	–15.634*	–39.658***	–19.343	–3.700	1.303
	[3.367]	[4.272]	[8.825]	[7.793]	[5.537]	[11.708]	[62.558]	[9.919]	[19.767]	[11.371]	[8.437]	[3.974]	[16.232]	[6.308]	[7.148]
Migration background: second generation	0.000	–21.579***	–74.390***	–25.141***	–8.761	–19.686	–99.875**	–61.677***	–29.207	–49.289***	–33.838***	–54.872***	11.176	–13.699	–3.287
	[0.000]	[4.783]	[6.485]	[8.795]	[5.451]	[13.661]	[49.676]	[8.341]	[33.640]	[6.354]	[9.835]	[5.582]	[11.586]	[9.258]	[8.698]
Foreign language spoken at home	–14.001	–22.048***	25.977	–14.347**	–31.190***	–16.938	–0.254	–0.246	–16.937	–2.035	–26.548***	–25.287***	5.085	–11.795	–19.874***
	[25.738]	[4.379]	[23.447]	[6.695]	[6.196]	[10.569]	[16.061]	[8.358]	[22.092]	[12.300]	[6.775]	[4.757]	[10.543]	[9.210]	[5.985]
Number of observations	5 059	3 981	29 715	4 690	4 524	4 488	5 354	4 880	4 621	18 861	4 256	11 347	4 784	12 430	5 311
R-squared	0.195	0.356	0.280	0.446	0.203	0.092	0.160	0.243	0.303	0.175	0.142	0.320	0.364	0.194	0.212

Notes: Regression of student science performance on student ESCS, student ESCS squared, individual control variables (gender, migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), and school-level ESCS squared. Regressions for Italy include regional fixed effects. Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level.
Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: OECD calculations based on the 2006 *OECD PISA Database*.

2.3.1.5. Educational inequality and socio-economic differences in rural an urban areas.

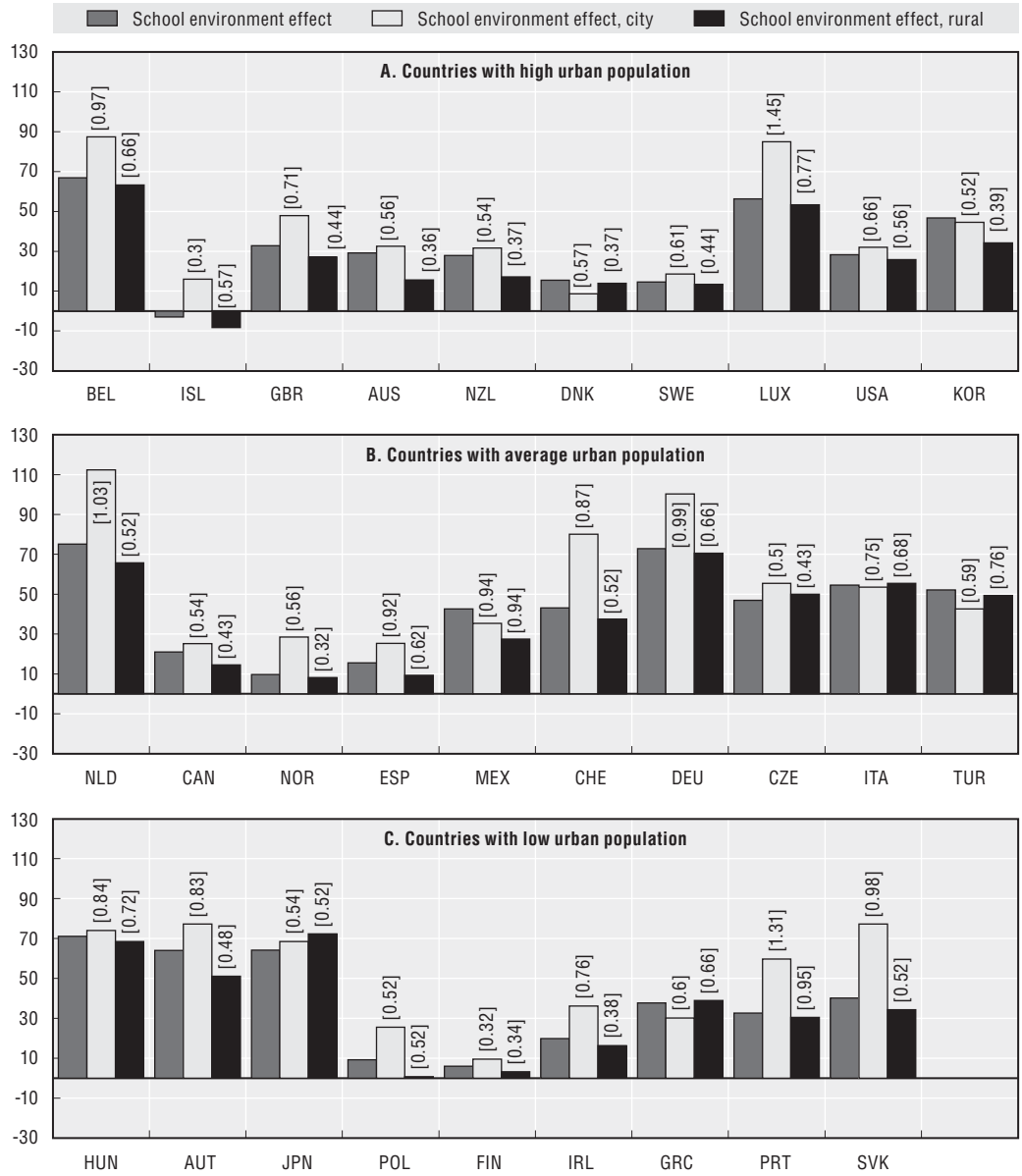
Taking distributional differences into account, Figure 2 compares the effect of school environment on student performance in rural and urban areas. It shows the differences in performance on the PISA science scale associated with the difference between the highest and the lowest quartiles of the country-specific distribution of the school average PISA ESCS index. One limitation of this analysis is that, due to data limitations, the threshold between urban and rural has been arbitrarily fixed at 100 000 inhabitants for all countries, ignoring possible country specificities in this respect. However, the figure distinguishes groups of countries, based on their proportion of urban population (where the definition of "urban" is country-specific). The values of the inter-quartile range of the distribution of the school-average PISA ESCS index, for rural and urban areas are reported in parentheses.

The corresponding regressions, run separately for urban and rural areas, are presented in Tables 3a and 3b.[17] The analysis suggests that in many countries school socio-economic segregation might, to a large extent, be concentrated in cities. However, for most of the countries covered by the analysis, this finding is not the result of (statistically) significant differences in the estimated school environment effects across urban and rural areas, but rather of the substantial differences in the distribution of schools by socio-economic background across urban and rural areas.[18] Indeed, the school socio-economic distribution is much wider in cities than in rural areas: it is, for example, around twice as wide in Luxembourg, the Netherlands, Germany and Belgium.[19] These countries also have some of the highest estimated levels of overall school environment effects (adjusted or unadjusted for distributional cross-country differences).

2.3.1.6. Asymmetries and the impact of social heterogeneity. Empirical results indicate that contextual and peer effects are stronger for low-skilled students in a number of OECD countries, pointing to the potential effectiveness of policies aimed at increasing schools' social mix in those countries. Table 4 shows rough measures of the so-called "peer effects", *i.e.* the impact of school-average science scores (excluding the student for whom the regression is run) on individual science scores.[20] Estimates are run separately for low, average, and high achievers, where the thresholds are defined according to the country-specific distribution of PISA science scores. The regressions control for student and school-level characteristics (location, resources, size, status and funding).[21] For almost all OECD countries included in the estimation, projected effects are asymmetric: they are relatively weak around the median score of the achievement distribution and stronger at the extremes, with the strongest impact often found on low ability students (exceptions include Italy, Mexico, Poland, Switzerland and the United States). For example, in Belgium, for each improvement of one international standard deviation in the average-school science score, the student performance improves by 39 points at the low end of the skill distribution, while it improves by 12 points around the median, and by 18 points at the high end.[22] Thus, particularly in countries where school socio-economic inequalities are higher, low-skilled/disadvantaged students would benefit more from interacting with high-skilled/socio-economically advantaged students, than the latter would lose from interacting with low-skilled/socio-economically-disadvantaged students. This result has to be taken with care, given the methodological difficulties attached to the estimation of contextual and peer effects, as highlighted above.

Figure 2. **The influence of school environment on students' secondary educational achievement:[1] cities *versus* rural areas**

Differences in performance on the PISA science scale associated with the difference between the highest and the lowest quartiles of the country-specific distribution of the school average PISA index of economic, social and cultural status over the entire territory or in rural and urban areas



Notes: Regressions run over rural and urban areas separately where urban areas are defined as communities with more than 100 000 inhabitants. Countries are classified following urban population proportion (urban population over total population where urban population is defined as the mid-year population of areas defined as urban in each country and reported to the United Nations).

Data in parentheses are values of the inter-quartile range of distribution of the school-level average ESCS calculated at the student level for rural and urban areas separately.

France is not included in the analysis because data are not available at the school level.

1. Regression of student science performance on student family socio-economic background (as measured by PISA ESCS), individual control variables (gender, migration status and language spoken at home) and school-level socio-economic background (average PISA ESCS across students in the same school, excluding the individual student for whom the regression is run). Country-by-country least-square regressions are weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. Regressions for Italy include regional fixed effects.

Source: OECD calculations based on the 2006 *OECD PISA Database*, urban population as a proportion of total population is taken from the *World Development Indicators Database*.

Table 3a. **Estimates of the socio-economic gradient in OECD countries: urban areas**

Impact of parental background on PISA science scores of teenagers

	Australia	Austria	Belgium	Canada	Czech Republic	Denmark	Finland	Germany	Greece	Hungary	Iceland	Ireland	Italy	Japan	Korea
Individual background	28.441***	12.119***	17.042***	24.228***	21.754***	23.131***	32.360***	17.561***	20.025***	8.833***	31.558***	28.670***	9.551***	7.066***	11.088***
	[1.665]	[2.890]	[2.782]	[2.097]	[2.908]	[6.764]	[2.999]	[2.561]	[2.958]	[2.595]	[3.649]	[2.954]	[2.109]	[1.933]	[1.862]
School environment	57.521***	93.391***	90.512***	46.451***	111.080***	15.184	29.522***	100.900***	50.122***	88.498***	53.964***	47.397***	71.247***	127.281***	85.654***
	[5.513]	[8.592]	[7.160]	[5.012]	[12.968]	[22.473]	[10.161]	[10.731]	[8.884]	[8.726]	[13.291]	[6.480]	[6.153]	[12.284]	[9.600]
Female student	–4.422	–7.431	–2.872	–8.017***	–11.948	–9.567	6.319	–6.036	–3.238	–23.717***	2.564	9.343	–12.637***	–1.791	–0.672
	[3.038]	[5.959]	[7.081]	[2.960]	[9.216]	[12.750]	[6.838]	[3.767]	[5.530]	[5.374]	[4.805]	[6.936]	[3.972]	[6.040]	[4.146]
Migration background: first generation	8.063*	–31.385**	4.480	–7.576	–67.319***	–35.577	–48.477	–26.629*	–0.893	–54.978**	–9.393	–27.092	–50.736*	4.801	0.000
	[4.656]	[12.872]	[8.366]	[5.008]	[14.176]	[28.966]	[42.498]	[13.466]	[20.325]	[22.524]	[32.137]	[27.403]	[27.476]	[45.441]	[0.000]
Migration background: second generation	4.144	–38.678***	–41.512***	–25.362***	–32.462	–32.039	–72.964***	–29.951**	–3.442	0.727	9.486	–30.771	–52.812***	54.809*	0.000
	[4.700]	[9.704]	[13.079]	[6.659]	[20.207]	[27.231]	[22.357]	[13.895]	[14.014]	[13.022]	[28.804]	[19.939]	[14.541]	[29.176]	[0.000]
Foreign language spoken at home	–11.106*	–23.846**	–21.288***	7.541	24.251	–79.925***	–16.873	–33.014***	–23.816	–5.845	–43.532**	–13.641	10.946	–112.741***	–9.640
	[6.274]	[11.105]	[5.996]	[6.217]	[35.777]	[27.649]	[19.478]	[9.947]	[16.693]	[19.851]	[21.387]	[20.994]	[16.096]	[20.683]	[24.887]
Number of observations	8 156	1 503	1 360	6 769	914	435	928	937	1 585	1 846	1 168	1 187	4 673	3 701	4 259
R-squared	0.162	0.495	0.488	0.136	0.368	0.250	0.169	0.526	0.256	0.414	0.110	0.241	0.328	0.238	0.193

	Luxembourg	Mexico	Netherlands	New Zealand	Norway	Poland	Portugal	Slovak Republic	Spain	Sweden	Switzerland	Turkey	United Kingdom	United States
Individual background	20.580***	8.533***	10.211***	45.132***	30.172***	37.851***	17.788***	18.863***	21.354***	34.396***	19.609***	11.682***	31.581***	37.688***
	[4.958]	[0.849]	[2.468]	[3.079]	[4.848]	[3.476]	[2.389]	[3.651]	[1.259]	[3.618]	[3.830]	[1.745]	[3.777]	[3.087]
School environment	58.561***	37.590***	108.987***	58.494***	51.235***	49.583***	45.401***	78.862***	27.604***	30.507**	92.375***	72.617***	67.677***	48.251***
	[8.870]	[3.244]	[6.455]	[6.948]	[15.894]	[13.226]	[6.035]	[8.418]	[4.412]	[11.800]	[15.916]	[6.564]	[6.938]	[13.272]
Female student	–2.236	–12.206***	–15.427***	–4.719	7.010	–4.951	–9.372*	–20.595*	–7.107**	–7.902	–8.217	–0.944	–7.070	4.030
	[8.778]	[2.609]	[5.170]	[3.797]	[10.912]	[3.015]	[5.491]	[11.245]	[3.338]	[5.735]	[5.692]	[4.756]	[5.722]	[6.156]
Migration background: first generation	–13.619	–20.133**	–21.527**	–9.797	–17.844	–114.272***	–9.599	–65.725	–17.058*	–0.109	–29.622***	–22.729	–0.571	7.202
	[13.969]	[9.425]	[9.597]	[5.906]	[24.091]	[9.303]	[17.172]	[50.238]	[9.724]	[11.014]	[10.274]	[22.513]	[9.059]	[10.345]
Migration background: second generation	–19.334	–73.430***	–18.627	–13.340**	–5.182	–145.079***	–39.669***	0.000	–53.655***	–44.184**	–46.983***	14.042	–12.270	11.499
	[17.582]	[13.136]	[12.715]	[6.490]	[26.710]	[16.722]	[8.114]	[0.000]	[9.255]	[17.405]	[9.674]	[16.002]	[13.038]	[10.818]
Foreign language spoken at home	–14.699	12.701	–0.322	–24.824***	–14.878	3.771	5.791	–20.471	8.350	–30.721***	–14.443	15.384	–17.339	–13.227
	[14.171]	[31.443]	[13.477]	[7.405]	[19.232]	[18.617]	[9.854]	[22.763]	[21.591]	[11.028]	[10.007]	[16.323]	[13.551]	[8.033]
Number of observations	374	14 739	1 096	2 588	533	1 335	1 021	628	7 563	888	943	2 588	3 165	1 733
R–squared	0.437	0.208	0.566	0.244	0.164	0.240	0.363	0.377	0.205	0.214	0.434	0.386	0.230	0.252

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (migration status and language spoken at home), and school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run). Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. Regressions for Italy include regional fixed effects. Regressions run over rural and urban areas separately where urban areas are defined as communities with more than 100 000 inhabitants.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

Table 3b. **Estimates of the socio–economic gradient in OECD countries: rural areas**

Impact of parental background on PISA science scores of teenagers

	Australia	Austria	Belgium	Canada	Czech Republic	Denmark	Finland	Germany	Greece	Hungary	Iceland	Ireland	Italy	Japan	Korea
Individual background	32.228***	9.096***	19.320***	26.070***	24.448***	30.112***	27.359***	16.192***	20.957***	10.624***	25.164***	31.011***	8.904***	12.326***	13.566***
	[2.430]	[2.464]	[1.034]	[2.043]	[1.671]	[1.606]	[1.735]	[1.456]	[1.540]	[2.102]	[2.489]	[1.980]	[1.270]	[4.127]	[4.728]
School environment	43.009***	106.672***	95.346***	33.488***	116.818***	37.221***	9.645	106.580***	59.190***	94.587***	–14.563***	42.903***	81.195***	139.349***	88.648***
	[8.897]	[6.815]	[6.431]	[6.644]	[9.575]	[7.143]	[6.624]	[6.192]	[7.376]	[5.204]	[5.008]	[7.834]	[7.190]	[13.428]	[19.535]
Female student	3.171	–19.668***	–8.102***	–6.695***	–12.223**	–8.547**	–0.513	–12.689***	13.831**	–18.975***	7.904**	–4.259	–12.281***	–14.330*	21.979*
	[3.634]	[4.885]	[2.902]	[2.361]	[5.509]	[3.400]	[2.897]	[2.859]	[5.473]	[3.208]	[3.712]	[3.478]	[3.343]	[7.793]	[11.861]
Migration background: first generation	–16.482**	–46.643***	–21.844***	–11.262	–54.771***	–22.917**	–73.639***	–30.441***	–29.902	–28.299***	–33.470	–4.276	–45.048***	–2.094	15.552*
	[7.013]	[8.248]	[6.459]	[7.475]	[18.278]	[11.106]	[20.176]	[6.166]	[19.391]	[7.208]	[33.879]	[15.605]	[16.845]	[7.562]	[8.708]
Migration background: second generation	–16.785**	–28.359**	–37.933***	–4.679	–25.038	–22.662*	–66.530***	–12.078*	–10.959	3.349	–68.078**	27.743***	–53.381***	–162.198	0.000
	[7.975]	[11.262]	[9.040]	[8.726]	[16.526]	[12.850]	[23.265]	[6.969]	[10.116]	[15.625]	[27.604]	[9.012]	[13.980]	[102.923]	[0.000]
Foreign language spoken at home	–40.405***	–41.874***	–18.488**	–39.314***	–14.180	–32.490***	–5.839	–29.441***	–34.202***	–39.685**	–22.584	–101.134***	–18.997	0.000	0.000
	[12.747]	[10.161]	[7.378]	[8.217]	[17.096]	[12.186]	[22.414]	[6.821]	[11.958]	[15.174]	[23.088]	[17.390]	[14.279]	[0.000]	[0.000]
Number of observations	5 417	3 257	6 571	13 666	4 656	3 128	3 696	3 081	2 929	2 469	2 367	3 165	13 583	1 937	800
R-squared	0.103	0.313	0.369	0.094	0.290	0.157	0.075	0.423	0.253	0.441	0.066	0.140	0.318	0.253	0.139

	Luxembourg	Mexico	Netherlands	New Zealand	Norway	Poland	Portugal	Slovak Republic	Spain	Sweden	Switzerland	Turkey	United Kingdom	United States
Individual background	16.332***	7.306***	12.360***	37.810***	27.867***	36.056***	18.883***	22.942***	25.441***	29.865***	22.391***	10.175***	36.276***	32.018***
	[1.533]	[0.990]	[1.458]	[2.885]	[2.166]	[1.586]	[1.299]	[1.882]	[1.502]	[2.434]	[1.456]	[1.558]	[2.207]	[2.522]
School environment	68.880***	29.156***	127.463***	46.447***	25.702**	1.458	32.005***	66.365***	15.134***	30.507***	71.781***	64.630***	61.676***	45.915***
	[2.795]	[2.802]	[7.822]	[7.761]	[9.979]	[6.918]	[4.200]	[9.098]	[4.024]	[7.921]	[5.437]	[8.571]	[6.958]	[6.219]
Female student	–7.001***	–8.933***	–9.692***	5.761	2.864	0.039	0.010	–7.922**	–4.197**	1.583	–11.439***	5.742	–11.144***	–6.612**
	[2.585]	[2.453]	[2.950]	[5.876]	[3.539]	[2.868]	[2.765]	[3.884]	[2.093]	[3.213]	[2.162]	[4.986]	[3.110]	[2.816]
Migration background: first generation	–23.511***	–57.839***	–26.399***	15.140	–28.409**	90.148*	–61.763***	–11.668	4.020	–27.282**	–40.938***	–15.746	–8.356	8.087
	[4.282]	[11.854]	[9.296]	[12.853]	[14.178]	[51.542]	[9.873]	[14.506]	[16.691]	[11.407]	[4.619]	[27.432]	[10.559]	[9.033]
Migration background: second generation	–22.284***	–76.097***	–32.887***	13.660	–30.344*	76.407***	–63.028***	–30.632	–45.145***	–27.516**	–55.086***	–0.117	–8.052	–10.422
	[4.646]	[7.342]	[8.402]	[11.657]	[15.321]	[2.814]	[12.632]	[32.575]	[9.768]	[12.503]	[6.818]	[12.396]	[13.873]	[13.660]
Foreign language spoken at home	–22.924***	69.331**	–22.114***	–49.295***	–15.870	–0.944	–2.498	–16.796	–8.495	–26.382**	–27.225***	4.995	–1.071	–18.519**
	[4.479]	[30.838]	[7.573]	[17.980]	[12.045]	[17.463]	[10.542]	[26.585]	[15.733]	[10.050]	[5.973]	[12.413]	[13.130]	[8.173]
Number of observations	3 607	14 447	3 582	1 936	3 868	4 019	3 827	3 979	11 276	3 292	10 312	2 196	8 384	3 428
R-squared	0.346	0.184	0.400	0.149	0.076	0.117	0.202	0.271	0.141	0.118	0.295	0.288	0.179	0.182

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (migration status and language spoken at home), and school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run). Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. Regressions for Italy include regional fixed effects. Regressions run over rural and urban areas separately where urban areas are defined as communities with more than 100 000 inhabitants.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

Table 4. **Estimates of the socio-economic gradient in OECD countries: asymmetric contextual effects, by science score**

	Austria			Belgium			Canada			Czech Republic			Finland		
Achievement level	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High
Parental background	6.797***	0.303	0.233	6.462***	1.381	5.143***	6.496***	2.449***	5.262***	4.376*	3.106***	7.889***	7.316***	2.277***	7.159***
	[1.686]	[1.040]	[1.442]	[1.404]	[0.938]	[0.981]	[1.757]	[0.709]	[1.242]	[2.306]	[0.998]	[1.555]	[1.835]	[0.645]	[1.896]
School science score	0.347***	0.114***	0.244***	0.393***	0.120***	0.183***	0.201***	0.066***	0.127***	0.233***	0.128***	0.284***	0.180***	0.014	0.097
	[0.028]	[0.019]	[0.034]	[0.053]	[0.016]	[0.031]	[0.030]	[0.020]	[0.035]	[0.036]	[0.014]	[0.024]	[0.052]	[0.022]	[0.059]
Index of quality of educational resources	0.334	–1.275	0.068	–1.664	1.175**	–0.215	0.744	0.187	0.765	–3.113*	0.867	2.463	–3.887*	0.215	–3.241*
	[1.480]	[0.909]	[1.617]	[1.785]	[0.574]	[1.066]	[1.160]	[0.512]	[1.182]	[1.832]	[0.881]	[1.581]	[1.962]	[0.955]	[1.857]
Private government dependent school	–6.700	8.685*	17.673	19.323***	–6.893**	5.038	–4.124	0.480	–1.081	3.384	–26.246***	–6.315	–10.909	0.000	13.892
	[11.183]	[4.518]	[11.419]	[5.422]	[2.623]	[4.494]	[10.446]	[3.282]	[4.538]	[25.743]	[4.023]	[8.091]	[12.391]	[4.301]	[13.261]
Public school	–10.446	11.191***	11.688	18.909***	–8.631***	5.647	–10.391	2.382	–3.153	7.670	–26.656***	0.000	0.000	3.574	0.000
	[10.400]	[4.173]	[11.227]	[6.603]	[2.490]	[4.407]	[9.860]	[2.853]	[3.819]	[22.975]	[3.871]	[6.769]	[11.815]	[3.459]	[13.339]
Proportion of certified teachers	–8.199	–1.947	–3.534	–5.183	3.733**	–1.531	–0.894	–6.334*	–0.879	–6.837	–16.684***	–5.268	–0.626	3.282	–2.548
	[5.672]	[4.668]	[4.896]	[4.995]	[1.854]	[4.111]	[3.142]	[3.689]	[7.543]	[6.201]	[4.940]	[6.225]	[6.350]	[3.152]	[3.965]
Ratio of computers for instruction to school size	–0.393	–7.395	5.126	16.211	–2.630	–6.873	–5.233	–1.210	7.708	32.920	–2.359	–16.913**	38.582*	–1.394	27.621
	[8.746]	[6.844]	[12.859]	[13.212]	[4.006]	[8.000]	[6.973]	[4.066]	[9.137]	[20.814]	[3.715]	[8.165]	[20.230]	[11.089]	[20.965]
Average student learning time at school	0.144	–0.531	1.489**	–0.914	0.314	0.912	1.318**	–0.129	0.644	0.969	0.519	1.594*	–0.217	0.095	0.021
	[0.884]	[0.557]	[0.744]	[1.012]	[0.310]	[0.666]	[0.541]	[0.269]	[0.470]	[0.754]	[0.445]	[0.824]	[0.840]	[0.477]	[0.988]
Average class size	0.467*	0.126	–0.640***	0.106	–0.024	–0.067	0.259	–0.051	0.232	0.938***	–0.070	–0.402	0.368**	–0.096	–0.060
	[0.272]	[0.162]	[0.221]	[0.245]	[0.156]	[0.265]	[0.251]	[0.127]	[0.196]	[0.289]	[0.142]	[0.261]	[0.157]	[0.089]	[0.191]
Teacher shortage	–0.659	–0.186	3.717**	–3.673**	1.026**	0.770	1.663	–0.075	1.365	–2.971	–0.764	–2.612	2.482	3.548***	–1.381
	[2.020]	[0.980]	[1.736]	[1.594]	[0.497]	[1.155]	[1.323]	[0.579]	[1.007]	[2.133]	[0.943]	[1.702]	[1.856]	[0.979]	[1.977]
Female student	–7.003***	0.519	–7.857***	0.564	–1.944	–9.934***	4.054*	–1.625	–6.785***	–7.140**	–0.069	–8.681***	8.771***	0.288	–6.442***
	[2.640]	[1.356]	[2.228]	[2.904]	[1.174]	[2.014]	[2.363]	[1.084]	[2.275]	[2.877]	[1.553]	[2.170]	[2.325]	[1.032]	[2.327]
Migration background: first generation	–23.737***	–6.844	4.445	6.338	–0.680	–9.145	–5.671	–1.528	–0.873	–21.885*	13.954**	5.128	–22.531	–4.123	–14.426***
	[8.498]	[5.295]	[8.338]	[5.226]	[3.138]	[5.522]	[4.310]	[2.012]	[4.225]	[13.016]	[5.414]	[11.233]	[18.339]	[9.024]	[3.418]
Migration background: second generation	–32.753***	–2.817	–9.855	–11.128**	–1.403	2.657	–11.820**	2.210	–3.463	–14.196	–13.683	–30.691***	–24.372	–4.900	28.322
	[6.786]	[4.382]	[6.068]	[5.557]	[3.125]	[5.983]	[5.190]	[2.773]	[8.059]	[15.929]	[9.069]	[8.473]	[14.999]	[10.672]	[20.204]
Foreign language spoken at home	–2.558	–4.951	–15.219*	–22.243***	–2.862	–12.800**	–2.576	–0.429	7.446	–15.441	10.564	14.657	–13.015	5.047	–25.878**
	[6.456]	[4.126]	[8.131]	[5.360]	[3.110]	[6.374]	[4.584]	[2.766]	[6.218]	[17.577]	[7.553]	[8.938]	[17.492]	[11.022]	[9.895]
Number of observations	1 237	1 466	1 479	1 792	2 158	2 296	5 291	4 807	4 440	1 357	1 492	2 263	1 413	1 439	1 432
R-squared	0.356	0.095	0.096	0.269	0.098	0.101	0.076	0.024	0.036	0.182	0.085	0.208	0.079	0.017	0.038

Table 4. **Estimates of the socio-economic gradient in OECD countries: asymmetric contextual effects, by science score** *(cont.)*

	Germany			Greece			Hungary			Iceland			Ireland		
Achievement level	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High
Parental background	4.060*	2.846***	6.756***	5.711***	1.810*	7.886***	3.657**	–0.740	2.042	4.612***	1.267	6.600***	8.661***	1.457	7.802***
	[2.110]	[0.886]	[1.597]	[2.056]	[0.952]	[1.327]	[1.633]	[0.733]	[1.579]	[1.567]	[0.873]	[1.590]	[2.149]	[0.994]	[1.573]
School science score	0.332***	0.080***	0.270***	0.375***	0.084***	0.255***	0.346***	0.100***	0.287***	0.162***	0.038	0.093*	0.172***	0.062**	0.023
	[0.040]	[0.018]	[0.029]	[0.056]	[0.024]	[0.042]	[0.034]	[0.021]	[0.039]	[0.061]	[0.030]	[0.053]	[0.050]	[0.029]	[0.047]
Index of quality of educational resources	1.459	0.996	–1.998	–4.048	–0.621	–1.696	1.652	–0.852	2.566*	1.134	–2.395**	0.489	1.478	1.291*	1.688
	[1.948]	[0.888]	[1.299]	[2.525]	[0.971]	[1.423]	[1.657]	[1.087]	[1.500]	[1.949]	[1.124]	[1.850]	[2.155]	[0.719]	[1.629]
Private government dependent school	–13.448	8.956**	6.318	0.000	0.000	0.000	–9.879	0.285	14.741**	1.755	0.000	–14.044	8.061	1.222	–6.869
	[9.932]	[4.390]	[11.276]	[0.000]	[0.000]	[0.000]	[13.221]	[5.318]	[5.740]	[53.114]	[14.984]	[19.826]	[11.874]	[4.499]	[15.328]
Public school	–12.035*	0.118	1.193	11.128	5.078	6.214	–11.906	0.915	10.943*	10.444	13.174	0.000	4.564	–2.758	–12.407
	[6.846]	[3.299]	[7.693]	[8.609]	[3.169]	[5.002]	[13.517]	[5.335]	[6.292]	[49.170]	[13.142]	[12.954]	[12.193]	[4.451]	[15.890]
Proportion of certified teachers	2.580	–1.858	–5.069	–8.726	–10.898	–8.497	4.375	–3.311	11.302	–7.620	–8.957	–5.706	–8.941	5.689	1.874
	[6.615]	[3.177]	[6.751]	[15.819]	[7.059]	[5.253]	[6.325]	[6.842]	[7.821]	[15.636]	[9.072]	[21.884]	[7.057]	[4.911]	[25.664]
Ratio of computers for instruction to school size	–13.319	6.038	31.747	9.798	5.233	53.709*	–2.691	–3.421	–25.971***	–36.024	–7.117	11.212	–30.468	7.570	9.564
	[25.500]	[12.255]	[27.528]	[22.932]	[14.106]	[27.214]	[8.332]	[6.144]	[6.538]	[29.603]	[12.768]	[21.409]	[26.246]	[12.366]	[26.778]
Average student learning time at school	1.165	0.686	1.619*	0.351	0.084	0.890	0.937	1.503**	0.526	3.945***	–0.107	0.346	–0.070	–1.451**	–0.556
	[0.807]	[0.446]	[0.968]	[1.363]	[0.611]	[1.304]	[0.906]	[0.678]	[0.995]	[1.251]	[0.728]	[1.419]	[1.350]	[0.556]	[1.066]
Average class size	0.735*	0.049	–0.388	0.019	–0.038	0.003	0.587**	–0.109	0.069	–0.396*	0.037	–0.121	0.233	0.305	0.026
	[0.442]	[0.195]	[0.424]	[0.106]	[0.055]	[0.083]	[0.225]	[0.098]	[0.157]	[0.226]	[0.105]	[0.170]	[0.467]	[0.218]	[0.378]
Teacher shortage	–0.144	0.855	–0.659	–3.848**	–1.715**	1.511	4.738**	–0.782	–6.013***	–1.910	–1.767*	3.251*	–1.871	0.734	–1.494
	[1.937]	[0.807]	[1.301]	[1.864]	[0.684]	[1.070]	[1.965]	[1.212]	[2.105]	[2.052]	[1.001]	[1.756]	[2.293]	[0.831]	[1.720]
Female student	–4.596*	–0.439	–8.452***	–0.383	1.264	–9.159***	–6.570**	–2.470**	–13.472***	9.083***	0.888	–5.359**	3.538	–2.102	–5.831**
	[2.330]	[1.438]	[2.143]	[3.260]	[1.405]	[3.063]	[2.741]	[1.158]	[2.272]	[3.354]	[1.377]	[2.562]	[2.475]	[1.425]	[2.534]
Migration background: first generation	–4.493	–8.156*	–13.854	–4.276	–7.627	15.794	–9.637	–19.484***	–39.364***	–29.433	9.875	–21.106*	–11.081	–11.808**	–7.753
	[5.582]	[4.849]	[8.787]	[13.601]	[7.883]	[15.170]	[24.192]	[4.055]	[7.322]	[23.877]	[10.517]	[11.593]	[10.604]	[5.391]	[9.064]
Migration background: second generation	–10.926	–5.480	–2.836	5.628	0.689	17.374*	–11.635	2.596	3.252	–0.278	–11.261	14.218	4.383	6.789*	7.903
	[7.137]	[3.512]	[9.684]	[7.766]	[3.139]	[9.126]	[19.652]	[6.144]	[10.884]	[16.809]	[8.458]	[33.367]	[7.316]	[3.990]	[7.667]
Foreign language spoken at home	–8.660*	0.320	–3.685	–16.836	0.964	–9.456	–12.780	9.865	19.475	–25.645*	–5.727	–8.959	–41.472***	–11.683*	–29.448**
	[5.195]	[2.884]	[7.758]	[10.652]	[5.755]	[10.886]	[12.634]	[8.208]	[12.575]	[13.655]	[7.102]	[16.114]	[12.250]	[6.866]	[11.187]
Number of observations	933	1 131	1 206	1 142	1 131	1 194	1 169	1 390	1 455	1 045	1 119	1 130	1 122	1 183	1 187
R-squared	0.313	0.101	0.132	0.283	0.040	0.108	0.246	0.084	0.205	0.072	0.020	0.029	0.097	0.036	0.040

Table 4. **Estimates of the socio-economic gradient in OECD countries: asymmetric contextual effects, by science score** *(cont.)*

	Italy			Japan			Korea			Luxembourg			Mexico		
Achievement level	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High
Parental background	2.404**	0.047	4.422***	1.179	0.274	3.846**	–1.124	–0.094	4.365***	4.254***	1.665**	4.765***	–0.048	1.192**	3.267***
	[1.180]	[0.588]	[1.129]	[2.338]	[0.908]	[1.792]	[1.803]	[0.889]	[1.198]	[1.589]	[0.686]	[1.206]	[1.310]	[0.530]	[0.810]
School science score	0.288***	0.106***	0.321***	0.365***	0.098***	0.295***	0.369***	0.097***	0.243***	0.290***	0.038	0.274***	0.212***	0.089***	0.382***
	[0.025]	[0.012]	[0.016]	[0.037]	[0.013]	[0.031]	[0.048]	[0.018]	[0.033]	[0.051]	[0.026]	[0.045]	[0.037]	[0.019]	[0.033]
Index of quality of educational resources	–0.931	1.038**	–0.279	0.745	–0.501	–0.712	–2.576	0.122	1.289	0.420	2.867***	0.186	0.904	1.018**	0.350
	[1.137]	[0.433]	[0.908]	[1.671]	[0.643]	[1.114]	[1.813]	[0.746]	[1.151]	[2.021]	[0.957]	[1.594]	[0.892]	[0.493]	[0.977]
Private government dependent school	24.891**	–6.122	11.068**	–1.159	9.126***	–8.422	6.306	–2.210	–3.054	–4.497	3.367	17.602	0.000	0.000	0.000
	[10.426]	[3.792]	[5.144]	[6.431]	[2.269]	[5.860]	[4.342]	[2.131]	[3.517]	[6.048]	[3.757]	[16.999]	[0.000]	[0.000]	[0.000]
Public school	12.379	–5.103	0.650	3.630	2.934*	–0.332	3.667	0.160	–2.120	0.000	0.000	0.000	4.976	2.693*	4.187
	[9.308]	[3.871]	[4.440]	[4.368]	[1.597]	[2.511]	[3.759]	[1.940]	[3.106]	[5.454]	[3.006]	[17.901]	[5.788]	[1.532]	[3.182]
Proportion of certified teachers	–3.065	–1.360	–10.999***	–21.116	–9.716**	3.685	–15.367***	–2.445	0.492	–6.998	6.680	–14.209	0.828	–0.644	1.448
	[3.446]	[2.256]	[2.878]	[19.013]	[4.541]	[7.525]	[4.724]	[1.893]	[6.330]	[14.451]	[6.152]	[12.155]	[1.973]	[1.229]	[2.141]
Ratio of computers for instruction to school size	–14.358	–5.496	–12.334*	5.468	0.423	–5.992	15.953*	–2.813	1.847	–2.086	–7.290	–18.744**	3.019	1.526	–11.668
	[9.294]	[5.147]	[6.282]	[6.247]	[3.775]	[11.063]	[9.212]	[4.392]	[13.484]	[10.792]	[7.031]	[9.337]	[8.909]	[6.937]	[7.500]
Average student learning time at school	0.389	0.297	0.526	0.310	0.239	–0.886	1.111	–0.174	–1.342*	–0.427	2.598**	–2.677	0.135	–0.026	–0.177
	[0.621]	[0.264]	[0.490]	[0.903]	[0.328]	[0.846]	[1.099]	[0.422]	[0.766]	[2.704]	[1.139]	[1.937]	[0.465]	[0.424]	[0.711]
Average class size	–0.040	–0.168***	0.028	0.535***	0.022	–0.074	–0.151	–0.267	0.259	–2.907***	0.175	0.877	0.038	–0.037	–0.111
	[0.135]	[0.042]	[0.101]	[0.183]	[0.110]	[0.207]	[0.473]	[0.216]	[0.297]	[0.825]	[0.341]	[0.606]	[0.068]	[0.046]	[0.121]
Teacher shortage	–0.116	0.288	–2.127**	1.477	1.090	–1.383	–0.799	0.313	0.360	–5.883*	4.797***	2.213	–1.158	–0.052	0.449
	[1.096]	[0.519]	[0.892]	[1.503]	[0.892]	[1.665]	[2.029]	[0.676]	[1.125]	[3.165]	[1.556]	[3.328]	[0.921]	[0.526]	[1.065]
Female student	3.347*	–3.136***	–9.934***	0.410	–1.231	–5.780***	6.539**	–0.467	0.021	5.191*	1.914	–8.867***	–2.515	–0.314	–6.950**
	[2.000]	[0.873]	[1.568]	[2.742]	[1.143]	[1.678]	[2.850]	[1.158]	[1.801]	[2.986]	[1.447]	[2.146]	[1.921]	[1.222]	[2.833]
Migration background: first generation	–42.970**	8.673*	–3.231	–53.645**	3.550	68.830***	0.000	19.585***	0.000	–6.551	–2.794	–8.039*	–4.622	–9.482**	–11.845**
	[18.051]	[5.134]	[21.825]	[20.542]	[3.270]	[3.549]	[0.000]	[2.104]	[0.000]	[4.805]	[2.061]	[4.114]	[6.956]	[4.281]	[5.302]
Migration background: second generation	–23.389**	–3.063	–37.823***	–12.910	5.591	–27.066***	0.000	0.000	0.000	–17.189***	–6.163**	0.940	–26.899***	–17.793**	–24.379***
	[10.812]	[3.887]	[12.679]	[51.704]	[16.753]	[3.457]	[0.000]	[0.000]	[0.000]	[5.369]	[2.691]	[5.326]	[7.278]	[7.035]	[6.001]
Foreign language spoken at home	4.147	–5.328	30.426*	–56.487***	–4.637	20.615	51.008***	0.000	–50.012***	–3.694	–1.988	1.776	14.392**	7.022	62.916***
	[12.191]	[4.329]	[16.399]	[11.619]	[2.881]	[14.979]	[10.476]	[0.000]	[2.162]	[5.058]	[2.450]	[5.405]	[6.244]	[5.577]	[21.174]
Number of observations	3 560	4 664	6 196	1 685	1 856	1 944	1 615	1 636	1 670	1 162	1 348	1 447	3 364	4 804	4 873
R-squared	0.161	0.066	0.145	0.169	0.062	0.133	0.184	0.040	0.089	0.123	0.064	0.097	0.099	0.073	0.218

Table 4. **Estimates of the socio-economic gradient in OECD countries: asymmetric contextual effects, by science score** *(cont.)*

	Netherlands			New Zealand			Norway			Poland			Portugal		
Achievement level	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High
Parental background	3.613**	0.549	6.786***	12.147***	4.175***	15.374***	5.621***	2.146**	8.976***	11.696***	2.920***	9.725***	2.829**	2.030***	6.420***
	[1.577]	[0.855]	[1.229]	[2.576]	[1.117]	[1.868]	[1.725]	[0.898]	[1.953]	[1.352]	[0.755]	[1.283]	[1.345]	[0.592]	[0.975]
School science score	0.291***	0.177***	0.278***	0.130**	–0.010	0.117**	0.238***	0.108***	0.095*	0.175***	0.074***	0.215***	0.258***	0.087***	0.075
	[0.042]	[0.018]	[0.024]	[0.055]	[0.025]	[0.046]	[0.045]	[0.021]	[0.053]	[0.047]	[0.021]	[0.033]	[0.032]	[0.020]	[0.048]
Index of quality of educational resources	2.192	0.750	–2.064**	–2.653	0.844	0.424	6.242**	1.002	–1.385	1.608	–1.121	0.801	–2.347	–0.015	0.495
	[1.711]	[0.924]	[0.852]	[1.894]	[0.991]	[1.569]	[2.502]	[1.063]	[2.693]	[1.270]	[0.688]	[1.197]	[2.292]	[0.783]	[1.518]
Private government dependent school	–4.263	0.193	0.000	0.000	0.000	0.000	–6.050	–2.524	0.000	–37.449***	2.668	–1.332	–14.063	2.402	–10.130
	[4.233]	[1.312]	[1.871]	[0.000]	[0.000]	[0.000]	[8.520]	[3.810]	[6.086]	[12.735]	[6.594]	[9.745]	[17.261]	[8.451]	[6.250]
Public school	0.000	0.000	–0.374	–0.085	–3.045	–1.708	0.000	0.000	–2.403	–17.177***	0.298	0.519	–19.379	–0.671	–4.981
	[3.597]	[0.534]	[1.310]	[13.679]	[3.579]	[5.289]	[6.838]	[3.085]	[5.404]	[5.857]	[4.831]	[9.969]	[17.464]	[8.031]	[5.714]
Proportion of certified teachers	4.396	4.933	–7.334	–13.378	–2.630	–8.772	–18.928***	2.702	6.578*	–2.504	6.469	15.713***	7.419	3.248	–14.820
	[7.647]	[4.631]	[5.297]	[8.350]	[5.400]	[7.780]	[6.796]	[2.547]	[3.586]	[6.996]	[4.603]	[4.976]	[7.190]	[2.641]	[9.568]
Ratio of computers for instruction to school size	–18.114	9.995	–4.136	6.971	13.922	–0.178	–1.951	–2.920	2.819	10.217	–0.958	22.220	12.725	17.325	–11.133
	[17.396]	[9.673]	[18.108]	[26.876]	[10.386]	[17.725]	[19.849]	[7.979]	[18.354]	[22.513]	[9.980]	[22.127]	[65.991]	[14.911]	[32.648]
Average student learning time at school	3.760***	0.715	–0.309	2.906**	0.234	–0.832	1.754	0.271	–1.489	0.341	0.494	–1.205	0.214	0.656	2.669***
	[0.976]	[0.610]	[0.732]	[1.191]	[0.874]	[1.436]	[1.199]	[0.500]	[1.088]	[1.058]	[0.505]	[0.880]	[1.222]	[0.665]	[0.941]
Average class size	0.206	–0.381**	0.382	0.733*	–0.157	0.299	–0.216	0.031	–0.238	–0.026	–0.219	–0.078	0.527*	–0.008	0.240
	[0.188]	[0.168]	[0.274]	[0.415]	[0.267]	[0.521]	[0.196]	[0.084]	[0.187]	[0.370]	[0.210]	[0.362]	[0.315]	[0.150]	[0.249]
Teacher shortage	0.646	0.008	–1.294	2.249	1.320	–2.143	4.489**	1.829**	–0.270	0.875	1.165	–3.656*	2.351	0.597	–1.551
	[1.640]	[0.818]	[1.235]	[2.343]	[0.952]	[1.360]	[2.253]	[0.906]	[1.962]	[2.241]	[0.894]	[1.888]	[2.417]	[1.511]	[2.613]
Female student	–4.324	–3.981***	–9.180***	5.933*	–1.042	–6.490**	11.832***	–0.486	–2.851	3.907*	–0.777	–7.849***	3.088	0.001	–2.353
	[3.233]	[1.472]	[2.273]	[3.138]	[1.921]	[3.056]	[3.923]	[1.460]	[3.052]	[2.003]	[1.037]	[2.100]	[2.580]	[1.397]	[2.124]
Migration background: first generation	–4.446	–10.578***	–10.845***	0.812	4.222	–6.775	–21.142**	4.013	–17.134	62.593***	–30.396***	42.775	–14.009	–3.434	–3.180
	[5.476]	[3.215]	[3.578]	[5.566]	[3.726]	[5.534]	[8.785]	[6.347]	[10.550]	[3.514]	[2.353]	[32.332]	[9.230]	[4.905]	[7.008]
Migration background: second generation	–9.644	–9.016*	–1.801	–5.477	–2.146	–3.157	–9.843	–0.904	2.779	–44.766**	0.000	–19.950***	–13.848**	2.072	1.266
	[10.584]	[4.837]	[6.197]	[7.605]	[3.227]	[4.818]	[12.980]	[6.138]	[15.232]	[19.136]	[0.000]	[2.235]	[6.572]	[4.052]	[14.346]
Foreign language spoken at home	–14.035	–4.704	–8.663*	–21.984**	–4.920	11.839	–3.649	–1.791	0.603	32.218***	–1.760	11.379	5.111	–6.524	–2.383
	[10.055]	[4.810]	[5.195]	[9.410]	[3.700]	[8.392]	[11.706]	[5.586]	[13.223]	[6.524]	[9.327]	[17.659]	[7.216]	[4.871]	[12.853]
Number of observations	1 074	1 362	1 576	1 090	1 254	1 315	1 220	1 328	1 320	1 585	1 703	1 838	1 267	1 426	1 489
R-squared	0.291	0.165	0.119	0.125	0.025	0.087	0.102	0.029	0.036	0.075	0.031	0.095	0.139	0.074	0.094

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), school-level (weighted) average performance (average across students in the same school, excluding the individual student for whom the regression is run), plus individual control variables (gender, migration status and language spoken at home) and school-level control variables (school location, school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type: private independent, private government dependent or public). Regressions are run separately for each tertile of the student science score distribution, where the distribution is country specific. Tertiles are ordered as low, average and high where low refers to the first tertile and high to the last. Regressions for Italy include regional fixed effects.

Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. All regressions include a constant. Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

Table 4. **Estimates of the socio-economic gradient in OECD countries: asymmetric contextual effects, by science score** *(cont.)*

	Slovak Republic			Sweden			Switzerland			United Kingdom			United States		
Achievement level	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High	Low	Average	High
Parental background	6.090***	1.668*	4.301***	5.506**	3.948***	7.925***	6.039***	2.207***	5.902***	3.974**	3.920***	7.452***	3.647	3.699***	8.069***
	[2.178]	[0.887]	[1.432]	[2.111]	[1.076]	[1.675]	[1.583]	[0.695]	[1.176]	[1.900]	[0.953]	[1.966]	[2.245]	[1.296]	[1.778]
School science score	0.374***	0.089***	0.229***	0.246***	0.033	0.089**	0.240***	0.107***	0.265***	0.280***	0.053***	0.205***	0.085**	0.039	0.241***
	[0.041]	[0.016]	[0.026]	[0.054]	[0.028]	[0.043]	[0.053]	[0.014]	[0.029]	[0.075]	[0.019]	[0.024]	[0.042]	[0.027]	[0.041]
Index of quality of educational resources	1.090	0.903	0.610	3.052**	0.145	1.360	0.101	0.379	1.678	–0.038	0.553	–1.197	–0.666	–0.374	0.046
	[1.504]	[0.801]	[1.477]	[1.518]	[0.847]	[1.816]	[1.430]	[0.481]	[1.025]	[1.856]	[0.797]	[1.029]	[1.526]	[0.852]	[1.648]
Private government dependent school	–27.500***	3.772	7.799	0.000	–3.804	6.307	–33.845*	2.339	35.490***	34.154***	–3.156	–0.351	–33.411***	7.623	17.933**
	[5.721]	[3.954]	[5.595]	[6.131]	[4.467]	[7.484]	[20.297]	[5.415]	[4.578]	[8.336]	[5.347]	[5.914]	[8.077]	[4.890]	[8.673]
Public school	–9.767***	2.007	4.958	5.406	0.000	0.000	9.561	5.730	10.053**	17.244**	–1.086	–1.535	–12.123*	1.170	8.818
	[2.571]	[1.988]	[3.095]	[5.603]	[4.039]	[6.547]	[9.372]	[4.489]	[4.387]	[8.496]	[3.882]	[3.935]	[6.982]	[4.408]	[6.583]
Proportion of certified teachers	–6.087	–0.258	11.425	39.482***	–13.651*	–0.112	11.313*	–2.748	3.022	2.028	–5.022	8.465	–6.884	7.170	–20.731**
	[8.511]	[4.149]	[7.449]	[14.776]	[8.129]	[13.103]	[5.858]	[1.957]	[3.886]	[14.766]	[3.694]	[9.036]	[7.408]	[6.426]	[9.659]
Ratio of computers for instruction to school size	41.492	0.634	–40.386	11.167	10.880	–6.613	6.695	4.605	–12.825	–7.361	3.886	–5.591	–9.036	–0.668	1.718
	[49.036]	[19.475]	[32.276]	[17.251]	[12.872]	[13.206]	[7.004]	[4.035]	[8.612]	[12.932]	[7.089]	[11.093]	[12.423]	[5.816]	[9.280]
Average student learning time at school	–0.658	–0.189	–0.723	4.764***	0.642	0.536	1.272	0.152	–0.987	2.228**	0.410	–0.373	2.193*	0.967*	–2.108**
	[0.828]	[0.364]	[0.584]	[1.745]	[0.882]	[1.384]	[0.965]	[0.334]	[0.764]	[1.117]	[0.574]	[0.948]	[1.147]	[0.576]	[1.014]
Average class size	0.119	0.179*	0.086	–0.060	0.151	0.027	0.558	0.273	–0.170	–0.183	–0.250	–0.571	–0.522*	–0.026	–0.132
	[0.270]	[0.095]	[0.239]	[0.346]	[0.184]	[0.294]	[0.368]	[0.184]	[0.318]	[0.436]	[0.223]	[0.461]	[0.271]	[0.167]	[0.379]
Teacher shortage	–1.184	–0.690	–1.987	2.566	–0.315	–0.430	1.107	–0.627	0.404	–4.292***	–0.926	–0.726	0.648	–1.447	–0.021
	[1.581]	[0.562]	[1.605]	[2.202]	[1.226]	[1.877]	[1.377]	[0.572]	[1.093]	[1.556]	[0.743]	[1.292]	[1.874]	[0.871]	[1.336]
Female student	–0.225	–1.786	–11.951***	4.930	1.164	–2.034	–1.735	–1.705	–6.790***	2.955	–0.877	–6.577**	10.416***	–0.282	–8.040**
	[2.641]	[1.275]	[1.909]	[3.545]	[2.037]	[2.733]	[2.367]	[1.299]	[1.883]	[2.865]	[1.330]	[2.545]	[2.955]	[1.632]	[3.257]
Migration background: first generation	5.584	–8.152	–17.183***	–6.437	–2.163	6.167	–10.708**	–4.253**	–8.705**	21.510***	–7.164**	–10.954*	2.078	–0.718	6.252
	[20.620]	[7.762]	[5.529]	[8.043]	[3.972]	[7.437]	[4.331]	[1.699]	[3.821]	[5.086]	[3.564]	[6.119]	[5.718]	[3.653]	[6.271]
Migration background: second generation	–61.197***	22.126**	–20.927	–20.631***	–9.787*	13.061	–24.075***	–3.962	–7.005*	–7.291	–7.734	–1.565	–11.620	2.484	8.127
	[11.797]	[8.739]	[21.632]	[7.474]	[5.340]	[12.177]	[5.561]	[2.673]	[3.782]	[8.798]	[6.643]	[7.717]	[7.219]	[4.131]	[11.276]
Foreign language spoken at home	–11.633	–2.628	13.226	–7.030	3.375	–17.542**	–13.089**	–0.509	–2.326	1.904	8.340	–13.022	0.165	–5.429	–17.666**
	[27.742]	[9.627]	[49.677]	[7.350]	[4.089]	[6.726]	[5.442]	[2.322]	[5.519]	[7.879]	[5.918]	[8.252]	[6.976]	[3.720]	[8.508]
Number of observations	1 401	1 503	1 544	1 135	1 202	1 232	2 912	3 142	2 899	3 028	3 380	3 410	1 244	1 397	1 389
R-squared	0.208	0.049	0.138	0.132	0.034	0.038	0.200	0.067	0.158	0.108	0.039	0.091	0.079	0.041	0.089

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), school-level (weighted) average performance (average across students in the same school, excluding the individual student for whom the regression is run), plus individual control variables (gender, migration status and language spoken at home) and school-level control variables (school location, school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type: private independent, private government dependent or public). Regressions are run separately for each tertile of the student science score distribution, where the distribution is country specific. Tertiles are ordered as low, average, high where low refers to the first tertile and high to the last. Regressions for Italy include regional fixed effects.

Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. All regressions include a constant. Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: OECD calculations based on the 2006 *OECD PISA Database*.

Social gains from reallocating students across schools and/or classes are realised if there is no adverse effect of social heterogeneity *per se* on educational achievement. Students may be influenced, not only by the mean level of peer quality, but also by the diversity of their peers. Regression results presented in Table 5 suggest that in most OECD countries there is no adverse effect of social heterogeneity on student performance. The effect of social heterogeneity on educational achievement is tested by including the standard deviation of the student socio-economic background in each school. The regressions also control for student and school-level characteristics (socio-economic intake, location, resources, size, ownership and funding). The impact of social heterogeneity is statistically insignificant for 26 out of 29 countries, the exceptions being Italy, the Czech Republic, and Finland, where a negative impact is found. These results are only suggestive, given that, due to data limitations, the data used is school-level as opposed to class-level, which would be needed to properly analyse peer effects. Taken at face value, the results reported in Tables 4 and 5 suggest that in some countries increasing school mix could achieve equity and efficiency goals, particularly in highly socially-segregated countries.

3. The impact of policies on equity in education achievement across OECD countries

3.1. Motivation

As one of the major mechanisms through which economic advantages and disadvantages are transmitted, education plays a central role in intergenerational social mobility. This makes it, by the same token, an accessible policy instrument to increase intergenerational social mobility. Indeed, while there is little scope nor rationale for attenuating inequalities arising from the transmission of inheritable factors, inequalities in the distribution of learning opportunities might signal economic inefficiencies potentially amenable to policy intervention. Cross-country empirical analysis allows examining to what extent different institutions would moderate or reinforce the relationship between socio-economic background and student performance.

Research in this field has generally focused on the role of educational policies and institutions. Institutional features such as early intervention, education, welfare and redistribution policies are likely to have an impact on equity in student achievement in OECD countries. This section describes the empirical approach undertaken in trying to identify the effects of policies at the cross-country level, and presents and discusses the relevant results, in the light of those already provided in the literature.

3.2. Empirical approach

3.2.1. The model

The baseline empirical approach for analysing the impact of policies on equity in educational achievement in this study is based on two cross-country variants of equation (2):

$$Y_{isc} = \alpha_1 + \beta_w \cdot F_{isc} + \beta_b \cdot \overline{F_{sc}} + \gamma_c \cdot X_{isc} + \chi_c \cdot Z_{sc} + \psi \cdot W_{c\cdot} + \varepsilon_{isc} \quad (4a)$$

$$Y_{isc} = \alpha_1 + \beta_w \cdot F_{isc} + \beta_b \cdot \overline{F_{sc}} + \gamma_c \cdot X_{isc} + \chi_c \cdot Z_{sc} + \theta \cdot C_{c\cdot} + \varepsilon_{isc} \quad (4b)$$

where X_{isc} denotes student characteristics, Z_{sc} denotes school characteristics, W_c denotes country-level variables, and C_c denotes country fixed effects. In these equations, all school and student-level characteristics display country-specific coefficients. Equations (4a) and (4b) describe country-specific models, in which only the impact of the variables F_{isc}, $\overline{F_{sc}}$

Table 5. **Estimates of the socio-economic gradient in OECD countries: the impact of heterogeneity in the school environment**

	Austria	Belgium	Canada	Czech Republic	Finland	Germany	Greece	Hungary	Iceland	Ireland	Italy	Japan	Korea
Individual background	7.696***	17.404***	25.581***	22.923***	28.520***	15.333***	18.139***	8.202***	27.739***	30.226***	9.354***	7.097***	10.383***
	[1.884]	[1.080]	[1.740]	[1.620]	[1.684]	[1.371]	[1.646]	[1.589]	[1.989]	[1.854]	[1.327]	[1.983]	[1.774]
School environment	68.751***	58.553***	29.425***	75.675***	4.067	70.916***	31.300***	73.048***	12.700*	37.553***	79.572***	98.088***	59.508***
	[8.465]	[7.040]	[5.988]	[9.200]	[6.783]	[7.929]	[7.120]	[5.002]	[6.509]	[6.532]	[4.751]	[11.711]	[9.440]
School-level ESCS standard deviation	11.512	30.520	–13.239	–70.335**	–44.579**	–5.041	8.996	14.363	–5.512	6.143	–94.208***	–39.736	6.505
	[26.674]	[19.396]	[18.871]	[29.087]	[18.374]	[16.025]	[22.138]	[15.348]	[17.724]	[21.362]	[19.720]	[34.285]	[30.606]
Index of quality of educational resources	1.555	1.501	–0.095	–2.207	–3.150	2.922	0.361	–0.522	–1.776	4.137	5.229**	1.120	4.061
	[3.412]	[3.264]	[2.088]	[4.059]	[2.413]	[2.742]	[3.781]	[2.564]	[2.035]	[3.051]	[2.399]	[2.760]	[3.379]
Private government dependent school	–78.602***	–5.493	6.017	96.429**	0.715	45.064**	0.000	16.142	123.954***	30.314***	50.575**	–70.706***	0.760
	[21.680]	[9.507]	[11.610]	[46.218]	[10.901]	[20.661]	[0.000]	[17.194]	[39.970]	[8.882]	[19.639]	[8.531]	[8.241]
Public school	–78.954***	–17.113*	–12.864	126.164***	0.000	40.745***	27.990**	16.100	167.977***	18.520*	46.852***	51.266***	5.199
	[22.173]	[9.168]	[9.135]	[47.755]	[6.931]	[14.130]	[11.433]	[16.419]	[33.815]	[9.472]	[12.265]	[6.649]	[6.711]
Proportion of certified teachers	–0.956	12.971	–5.842	–1.980	2.292	3.747	–21.975	38.816**	47.234**	26.410*	11.876	–46.650***	–34.358***
	[16.197]	[11.912]	[8.917]	[20.162]	[7.869]	[13.100]	[25.667]	[16.148]	[22.472]	[14.293]	[12.802]	[16.177]	[10.034]
Ratio of computers for instruction to school size	27.469	42.375**	20.087	71.926*	12.004	–13.518	47.780	41.407**	–13.012	29.473	22.236	21.478	17.023
	[19.052]	[18.628]	[13.261]	[42.964]	[20.975]	[55.118]	[36.276]	[19.693]	[27.670]	[51.566]	[21.593]	[17.190]	[24.061]
Average student learning time at school	6.960***	7.181***	1.782*	5.380***	4.757***	7.229***	16.665***	10.367***	4.556***	4.434**	7.563***	8.645***	11.889***
	[2.129]	[1.143]	[0.949]	[1.478]	[1.493]	[1.443]	[1.744]	[1.485]	[1.481]	[1.763]	[1.091]	[1.775]	[1.448]
Average class size	2.256***	0.870	1.477***	1.791***	0.203	1.701**	0.570**	0.625*	–0.359*	0.858	–0.707**	1.329***	–1.155
	[0.636]	[0.566]	[0.380]	[0.601]	[0.277]	[0.783]	[0.241]	[0.333]	[0.206]	[0.665]	[0.298]	[0.449]	[1.012]
Teacher shortage	–2.281	–10.630***	1.215	–12.070**	–4.233	–3.733	0.123	–0.336	–4.319**	2.381	9.039***	1.280	0.446
	[4.609]	[2.283]	[1.664]	[5.324]	[2.963]	[3.194]	[3.004]	[4.264]	[1.685]	[2.551]	[2.761]	[5.183]	[2.944]
Female student	–11.769***	–9.326***	–7.009***	–9.874**	1.268	–11.796***	–3.965	–23.765***	5.321*	–0.188	–10.303***	–3.577	0.828
	[3.997]	[3.064]	[2.305]	[3.870]	[3.003]	[2.722]	[3.066]	[2.579]	[3.139]	[3.703]	[2.844]	[3.204]	[3.456]
Migration background: first generation	–35.519***	–9.686**	–6.086	–49.082***	–58.706**	–32.195***	–23.003	–43.112***	–21.747	–22.897	–47.386**	–16.846	14.649*
	[8.474]	[4.788]	[4.629]	[14.601]	[27.260]	[6.927]	[15.703]	[15.813]	[20.300]	[14.903]	[21.192]	[43.729]	[7.871]
Migration background: second generation	–36.636***	–31.825***	–12.124	–34.450***	–79.701***	–19.481***	1.782	4.967	–30.929	14.358	–38.395***	34.462	0.000
	[6.897]	[9.808]	[7.357]	[12.642]	[16.283]	[6.635]	[10.613]	[8.013]	[20.233]	[9.048]	[8.897]	[28.111]	[0.000]
Foreign language spoken at home	–30.334***	–25.596***	–3.411	–1.757	–6.008	–26.417***	–28.464***	–18.845	–35.992**	–84.296***	–5.474	–104.619***	5.045
	[8.343]	[6.040]	[7.356]	[13.795]	[12.892]	[6.144]	[8.909]	[12.120]	[15.737]	[13.616]	[11.163]	[21.964]	[29.504]
Number of observations	4 182	6 246	14 538	5 112	4 284	3 270	3 467	4 014	3 294	3 492	14 420	5 485	4 921
R-squared	0.432	0.448	0.109	0.377	0.106	0.479	0.389	0.496	0.094	0.184	0.334	0.351	0.255

Table 5. **Estimates of the socio-economic gradient in OECD countries: the impact of heterogeneity in the school environment** *(cont.)*

	Luxembourg	Mexico	Netherlands	New Zealand	Norway	Poland	Portugal	Slovak Republic	Sweden	Switzerland	United Kingdom	United States
Individual background	16.690***	7.714***	9.979***	39.934***	29.216***	36.234***	18.034***	20.520***	30.535***	20.641***	34.881***	31.795***
	[1.502]	[0.869]	[1.105]	[2.146]	[1.977]	[1.509]	[1.281]	[1.526]	[2.294]	[1.628]	[2.274]	[1.967]
School environment	48.895***	24.484***	87.607***	33.240***	28.955**	13.518*	18.983***	55.758***	22.454***	52.701***	50.186***	22.614***
	[5.438]	[3.732]	[7.352]	[8.518]	[11.056]	[7.972]	[4.297]	[9.304]	[7.537]	[5.429]	[7.520]	[7.098]
School-level ESCS standard deviation	–10.823	–17.459	80.293***	–5.557	2.026	16.978	15.020	–18.543	4.322	4.948	0.728	42.986*
	[13.609]	[11.290]	[23.794]	[14.815]	[15.819]	[19.486]	[13.651]	[23.838]	[16.544]	[14.554]	[16.240]	[24.957]
Index of quality of educational resources	5.250***	3.419*	8.154***	–3.495	–5.695	–1.447	–0.974	–3.042	3.891	4.325**	–0.679	1.921
	[1.503]	[2.051]	[2.918]	[2.519]	[4.115]	[2.172]	[2.733]	[3.959]	[2.446]	[1.936]	[2.582]	[2.864]
Private government dependent school	4.233	0.000	5.693	0.000	0.000	–17.653	12.387	10.220	22.638	–12.964	0.882	–12.359
	[5.379]	[0.000]	[7.364]	[0.000]	[40.915]	[23.190]	[20.492]	[14.451]	[22.399]	[54.348]	[19.352]	[15.293]
Public school	0.000	18.702	0.000	–9.579	–40.368	–22.567	4.788	19.239***	0.000	45.330***	–0.753	–6.968
	[4.483]	[11.761]	[5.046]	[9.238]	[37.834]	[21.400]	[21.365]	[6.950]	[22.697]	[13.381]	[12.922]	[11.416]
Proportion of certified teachers	35.842***	–11.285*	–4.277	–4.596	–22.403***	25.941	3.826	14.437	75.488***	–8.360	5.820	–5.656
	[12.045]	[6.200]	[13.970]	[6.577]	[7.426]	[20.398]	[13.528]	[16.856]	[26.149]	[6.962]	[18.116]	[23.679]
Ratio of computers for instruction to school size	3.915	40.392	–180.837***	17.250	18.044	0.145	119.194	272.316***	25.779	19.889	–14.671	–17.979
	[9.691]	[36.156]	[39.716]	[23.920]	[39.939]	[37.200]	[72.419]	[80.312]	[30.638]	[16.739]	[23.610]	[18.318]
Average student learning time at school	10.420***	5.864***	6.985***	10.645***	5.353***	5.310**	12.504***	3.629***	7.819***	8.336***	7.374***	9.494***
	[1.885]	[1.145]	[1.711]	[2.048]	[1.779]	[2.215]	[1.571]	[1.301]	[2.628]	[1.518]	[2.256]	[2.005]
Average class size	–0.172	0.402**	0.996	0.592	–0.177	0.721	0.651	0.823	0.301	1.515**	–0.541	0.191
	[0.568]	[0.166]	[0.607]	[0.692]	[0.265]	[0.712]	[0.505]	[0.654]	[0.537]	[0.613]	[0.764]	[0.825]
Teacher shortage	12.253***	0.698	1.122	–5.533**	1.303	0.470	–6.897	–11.738***	3.079	–1.521	–3.880*	1.186
	[2.546]	[2.013]	[3.146]	[2.530]	[3.567]	[4.860]	[4.277]	[3.641]	[3.067]	[2.276]	[2.313]	[2.836]
Female student	–7.069**	–8.643***	–12.520***	–6.796*	3.856	–1.673	–2.193	–10.207***	–0.360	–13.930***	–10.512***	–5.117*
	[2.707]	[2.745]	[2.424]	[3.921]	[3.787]	[2.339]	[2.385]	[3.191]	[2.848]	[2.316]	[2.888]	[2.597]
Migration background: first generation	–22.716***	–37.027***	–30.342***	–5.829	–37.079***	40.818	–32.554***	–22.822	–9.683	–34.738***	–4.316	–3.265
	[4.431]	[10.721]	[5.848]	[5.986]	[10.793]	[57.433]	[9.225]	[18.419]	[8.431]	[4.048]	[6.885]	[7.413]
Migration background: second generation	–22.392***	–65.729***	–27.326***	–7.546	–17.753	–86.461**	–49.162***	–44.724	–27.641**	–55.692***	–12.986	–8.402
	[5.135]	[11.224]	[9.490]	[6.424]	[14.385]	[42.389]	[9.623]	[30.291]	[10.776]	[5.809]	[10.839]	[9.815]
Foreign language spoken at home	–22.493***	44.471	–13.254*	–28.072***	–9.937	1.888	8.012	–13.251	–27.341***	–24.212***	–9.808	–15.404**
	[4.358]	[27.115]	[7.333]	[6.940]	[10.769]	[15.796]	[8.750]	[22.660]	[8.432]	[4.528]	[11.191]	[6.797]
Number of observations	3 957	13 041	4 012	3 659	3 868	5 126	4 182	4 448	3 569	8 953	9 818	4 030
R-squared	0.369	0.319	0.535	0.232	0.099	0.164	0.307	0.306	0.150	0.362	0.204	0.209

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), school–level standard deviation in student socio-economic background (calculated using student-level weights), and school-level controls (school location, school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type: private independent, private government dependent, public), regressions for Italy include regional fixed effects (not reported). Country-by-country least-square regressions weighted by student sampling probability. Robust standard errors adjusted for clustering at the school level. Regressions for Italy include regional fixed effects.
Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.
Source: OECD calculations based on the 2006 *OECD PISA Database*.

and country-level variables is restricted to be equal across countries. The difference between equations (4a) and (4b) is that equation (4b) allows country-specific intercepts whereas equation (4a) allows estimating the direct impact of country-specific variables. Because of the presence of country fixed effects, equation (4b) is to be considered as less restrictive in terms of cross-country homogeneity assumptions.

The choice of the control variables included in models (4a) and (4b) is based on the "education production function" approach (see *e.g.* Hanushek, 1994). The variables included are: individual characteristics (gender, migration status and language spoken at home), school location (small town or village, city), school size and school size squared, school resources (index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size), average class size, average student learning time at school, and school type (private independent, private government dependent, public). These variables are allowed to have a heterogeneous impact across countries. Therefore, the findings on the impact of country-level features on equity in student achievement do not depend on the country-level effect of student and schools characteristics on student performance.[23] Baseline estimates of equation (4a) also include GDP per capita as a control variable, as usually done in comparable empirical studies.

3.2.2. How policies and institutions are modelled

Policies and institutions are introduced in the model by assuming that the influence of student and school socio-economic background varies across institutional regimes. In this specification, it is no longer required that parameters β_w and β_b and are equal across countries. These parameters are made regime-specific, by introducing policy interaction terms:

$$Y_{isc} = \alpha_1 + \beta_w \cdot F_{isc} + \beta_b \cdot \overline{F_{sc}} + \delta_w \cdot P_c \cdot F_{isc} + \delta_b \cdot P_c \cdot \overline{F_{sc}} + \gamma_c \cdot X_{isc} + \chi_c \cdot Z_{sc} + \phi \cdot P_{c\cdot} + \psi \cdot W_{c\cdot} + \varepsilon_{isc} \quad (5a)$$

$$Y_{isc} = \alpha_1 + \beta_w \cdot F_{isc} + \beta_b \cdot \overline{F_{sc}} + \delta_w \cdot P_c \cdot F_{isc} + \delta_b \cdot P_c \cdot \overline{F_{sc}} + \gamma_c \cdot X_{isc} + \chi_c \cdot Z_{sc} + \theta \cdot C_{c\cdot} + \varepsilon_{isc} \quad (5b)$$

where P_c denotes policies or system-level features. Specifications (5a) and (5b) identify whether institutional features affect the impact of student and school background on achievement. In specification (5b), which includes country fixed effects, it is not possible to estimate the direct effect of institutional features on student performance, given that those do not vary within countries.

Variants of models (5a) and (5b) are estimated, depending on the nature of the policy under consideration. While both policy interaction terms may be relevant for education policies, it can be argued that welfare, redistributive and labour market policies are generally targeted towards households or individuals and should, therefore, have no direct impact on school environment effects. Thus, for these policies, only the interactions with the individual background, within-school effect are considered. In this case, the model is further relaxed by assuming that the impact of schools' socio-economic background is country-specific. In terms of the above equations, only parameter δ_w does not vary across countries (but varies across institutional regimes).[24]

As already mentioned, specification (5b) is more restrictive in terms of model assumptions than specification (5a) but it provides estimates of the direct impact of policies on student achievement. Hence, in theory it might allow investigating whether

there is a trade-off between efficiency – increasing students' overall performance – and equity – reducing the dependence of performance on socio-economic background. However, caution is needed in this respect. Due to the very limited degrees of freedom under which the corresponding parameter is estimated, the specification cannot provide a consistent estimate of the causal impact of system-level features on student performance. As will appear clear below, given the very unrestricted nature of the model in terms of country heterogeneity, the direct impact of policies on performance is weakly identified. Moreover, the main purpose of this analysis is to assess the influence of policies on equity in education, rather than gauging the average impact of institutions on student and school performance, which is extensively discussed in PISA reports (see, for instance, OECD, 2007a). Hence, discussion of regression results will focus on interaction effects, rather than the direct impact of policies.

The institutional features are all measured at the country level. While most of them are systemic by definition and, therefore, do not vary within countries, others have a within-country dimension, such as school level policy settings – class sizes, proportion of qualified teachers, school selectivity, or ability grouping.[25] These variables are, however, averaged at the country level (using school weights), and the analysis only uses between-country variation in policies and institutions. Indeed, the extent of within-country variation in school-level features is very low and selection bias, whereby students with the same parental background would be found in schools applying certain policies,[26] would make the identification of causal effects difficult. For example, rich families are likely to opt to send their children to schools with high resource levels or highly-qualified teachers. Also, in systems where countries provide disadvantaged areas with additional resources, it is possible to observe an opposite selection bias, whereby disadvantaged students self-select into targeted schools that display specific features – such as lower class sizes. Relying only on between-country variation in policies also makes it easier to interpret results from a policy perspective.[27] However, one drawback of this approach is that the degrees of freedom at the country level are limited, which prevents from investigating potential interactions among policies themselves, and in their relationship with equity in student performance. It is also impossible to introduce various policies simultaneously in the equation, with the associated risk that one policy-specific effect might capture the effect of another, omitted and correlated policy.[28]

The cross-country regressions include a maximum of 27 OECD countries. Due to the heterogeneity of Turkey and Mexico in terms of overall socio-economic background, these OECD countries are excluded from the sample. Indeed, the average ESCS level for students in these countries is a full standard deviation below the international mean, suggesting that the comparisons between these countries and the rest of the OECD countries in terms of equity in educational achievement may be misleading. Also, France is excluded from the regressions since school principals did not respond to the PISA school questionnaire.[29]

3.2.2.1. Interpretation of the interaction effects. As already mentioned, specifications (5a) and (5b) make it is possible to measure how within- and between-school socio-economic effects vary across institutional regimes. Indeed, the impact of school and family background varies across systems as follows:

$$\frac{\partial Y_{isc}}{\partial F_{isc}} = \beta_w + \delta_w \cdot P_c \text{ and } \frac{\partial Y_{isc}}{\partial \overline{F}_{sc}} = \beta_b + \delta_b \cdot P_c \qquad (6)$$

A positive δ means that equity in education achievement decreases ($\beta + \delta > \beta$) while a negative δ means that it increases ($\beta + \delta < \beta$) with the relevant policy.

Alternatively, specification (5a) also allows calculating the influence of policies at different levels of the school and/or students' socio-economic background, as follows:

$$\frac{\partial Y_{isc}}{\partial P_c} = \phi + \delta_w \cdot F_{isc} + \delta_b \cdot \overline{F_{sc}} \qquad (7)$$

In order to ease the interpretation, the policy variables are mean-centred so that coefficient ϕ is to be interpreted as the impact of policy P at the cross-country average of the schools' and students' socio-economic background distribution.[30]

Difficulties in identifying proper causal relationships between policies and equity in educational achievement are enormous with the data at hand. As already mentioned, it is not possible to disentangle nature from nurture effects in the (overall or within-school) gradient estimation, nor is it possible to disentangle contextual from endogenous effects in the between-school gradient estimation. Indeed, estimated within- and between-school gradients are descriptive of the distribution in school performance, and should not be interpreted in a causal sense. Yet, cross-country differences in the distribution of within- and between-school gradients are likely to reflect to a large extent differences in policies and institutions. Therefore, cross-country regression results concerning the role of policies should not be influenced by the empirical limitations attached to the interpretation of the estimated gradients. However, in order to properly identify the causal impact of policies, one would need to be in a natural experiment setting, arising when specific reforms are put in place within countries, and implemented differentially across "treated" and "control" groups (such as the Pekkarinen *et al.,* 2006 study on Finnish education reform in the 1970s). Nonetheless, the cross-country analysis can still identify a number of policies and institutions that are associated with higher levels of equity in educational achievement, and, as such, potentially playing some role in influencing intergenerational social mobility.

3.3. Results on policies and equity in education achievement[31]

3.3.1. Education policies

Results of cross-country regressions in this section confirm that increasing education spending has an ambiguous link with equity in educational opportunities, but other aspects of the education system, such as differentiation policies and financial incentives embedded in teachers' remuneration, have a significant association with equality of learning opportunities.

3.3.1.1. Education policies and school practices. One robust and common finding is that early differentiation of students' curricula tends to be associated with larger socio-economic inequalities, with no corresponding gains in average performance. Both cross-country and country-specific studies have highlighted the negative impact of ability tracking on educational socio-economic inequalities (for cross-country evidence, see OECD, 2004, 2007a, Schutz *et al,* 2005, Hanushek and Woessmann, 2005, Sutherland and Price, 2007, Duru-Bellat and Suchaut, 2005, Amermuller, 2005; for country-specific evidence, see *e.g.* Bauer and Riphahn, 2006, Pekkarinen *et al.,* 2006, Holmlund, 2006, and Bratberg *et al.,* 2005).[32]

Regression results confirm earlier findings according to which educational early tracking increases socio-economic segregation between schools. Interpreting results causally, when educational tracking is brought forward by one year, the impact of a school's

environment on student performance would increase by 8.2 PISA science-score points. Bringing forward tracking is associated with a much lower decrease in the within-school relationship between students' socio-economic background and science performance, by 2.9 PISA science-score points. Implied changes in the school environment effect are quantitatively high, as they would range between 27.7 (PISA score points) in systems with no tracking before age 16 to 77.1 (PISA score points) in systems with early tracking.[33, 34] A similar negative link with equity in educational achievement is found for the number of school types programmes available to 15-year olds. This system-level variable indeed captures the existence of early differentiation and, in this setting, polarisation of the schooling system along socio-economic lines. Comparable results emerge also for selection policy and ability grouping within schools.

Enrolment in vocational education is also associated with a higher impact of schools' socio-economic background on student performance and a lower impact of an individual's background on student performance (Table 6a). Because disadvantaged students are overrepresented in vocational training, it is found to exacerbate school socio-economic inequalities, without increasing overall performance. This result is consistent with empirical evidence on the German case. Buchel (2002) shows that lower-educated school leavers are selected into apprenticeships with less favourable employment prospects and, over time, they also find it increasingly difficult to transfer successfully from apprenticeship to work.

However, the long-term effects of apprenticeship on individuals' economic outcomes are controversial.[35] Moreover, there are substantial differences across OECD countries in the way vocational education is designed, which could lead to different implications for equity in education achievement. Some studies found positive effects of vocational education on equity; in the French case, Bonnal *et al.,* (2002) show that disadvantaged students who tend to opt for apprenticeships gain by being more likely to find a job than those who obtained a mere school-based vocational education. Therefore, it is difficult to draw any clear-cut policy conclusion from cross-country empirical results.

3.3.1.2. Education policies and resources. The cross-country evidence available suggests insignificant effects of aggregate spending variables (Schutz *et al.,* 2005, for example). Some country studies show that increasing educational spending on disadvantaged students or schools does not help increase equity (for the Netherlands, Leuven and Oosterbeek, 2007; for France, Benabou *et al.,* 2004; for the United States, Hanushek, 2007). Other studies suggest that targeted spending can reduce educational inequalities. Using highly disaggregated school data at the territorial level, Bratti *et al.,* (2007) suggest that differences in specific resources can explain geographical differences across Italian regions. Piketty and Valdenaire (2006) show that in France class size reductions at the primary and secondary levels would be particularly beneficial to disadvantaged students. A similar result on class size is suggested by Krueger (1999).

The regression results in Table 6b confirm that educational spending *per se* is not significantly associated with student performance (Schutz *et al.,* 2005, for example), even though it is weakly correlated with higher equity in educational achievement within schools (as suggested by the negative sign of the student socio-economic background interaction in the regression with country fixed effects). Some studies show that increasing educational spending on disadvantaged students or schools does not help increase equity (for the Netherlands, Leuven and Oosterbeek, 2007; for France, Benabou *et al.,* 2004; for the

United States, Hanushek, 2007). Other studies suggest that targeted spending can reduce educational inequalities (Bratti *et al.*, 2007). Table 6b indeed suggests that while the level of spending is not found to be very relevant, the quality of allocation mechanisms, as measured by OECD indicators of "spending decentralisation" and "mechanisms to match resources to needs" appears to be positively related to equity in educational achievement.[36] Indeed, the ability to prioritise and allocate resources efficiently has a very significant negative impact on educational inequalities associated with school environment, while being associated with a smaller negative impact on equity within schools. Decentralisation between central government and sub-national public authorities can improve efficiency in the allocation of public spending resources to the extent that it allows adapting to differing local circumstances; in the same vein, spending mechanisms aimed at supporting the disadvantaged can reduce educational inequalities associated with school environment.

Regression results suggest that lower class sizes at the secondary and primary levels are associated with lower school environment effects: namely, reducing class size is found to increase disadvantaged schools' performance, relative to that of advantaged schools (Table 8b). This is consistent with Piketty and Valdenaire (2006), who show that in France class-size reductions at the primary and secondary levels would be particularly beneficial to disadvantaged students. A similar result on class size is suggested by Krueger (1999). This result can be interpreted along two main lines. First, it can be argued that reducing class size is a useful tool for increasing performance in poor areas, where relatively more resources might be needed to cope with educational disadvantages. Second, insofar as the impact of school socio-economic background captures the contextual and peer effects arising within classes, one alternative interpretation is that these effects are lower in small classes because there is less scope for pupil interaction. This idea, which emerges from recent educational studies on contextual effects (Levin, 2001), points to the difficulties associated with the interpretation of contextual effects from a policy perspective.[37] Indeed, if class size reduction is associated with lower impact of school socio-economic background merely because it reduces student interaction and peer effects, then it might not be the most effective tool for promoting educational equity.

Higher ratios of students to teaching staff are found to be negatively related with equity in educational achievement both between and within schools (Table 6b). Student-teacher ratios measure the total teaching staff relative to students within schools. Thus, it is not only class size *per se* that matters, but also the number of teachers relative to a school's population. Countries displaying relatively high ratios of teachers per student would, therefore, seem to be able to attenuate the influence of school socio-economic disparities on performance while at the same time coping better with disadvantaged students within schools.[38]

There is no empirical evidence on the impact of teacher quality on educational equity. This may be due to the methodological difficulties of measuring teacher quality (see discussion by Vignoles *et al.,* 2000), as well as the endogeneity in the distribution of teachers across schools, in that better teachers may choose to teach in relatively advantaged schools. However, there is some US evidence on the positive relationship between teacher quality, as measured by salaries and experience, and student outcomes (Hanushek. *et al.,* 1998, Dewey *et al.,* 2000, Goldhaber, 2002). Recent cross-country evidence has supported this view (Dolton and Marcenaro-Gutierrez, 2009). If teacher quality matters for student performance, it is arguable that it should matter all the more for that of

disadvantaged students. The effect of measures providing financial incentives to teachers is less controversial (Lazear, 2003). Studies in the United Kingdom (Atkinson *et al.,* 2004) and Israel (Lavy, 2004) have shown that monetary incentives to teachers can have powerful effects on student performance. However, in practice, designing and implementing performance-related schemes has not always proved successful, as discussed in OECD (2005d). From an equity perspective, such policies incur a real risk of exacerbating inequalities across schools by giving teachers incentives to move into advantaged schools. To promote equity, financial incentives for teachers can be targeted at disadvantaged schools or students (Lavy, 2002).

Table 6b shows that the individual background effect is relatively lower in countries where teachers' wage progression is higher. The variable used in this setting does not cover performance-based pay but rather proxies for cross-country differences in teachers' social status, as measured by their expected earnings growth. Experienced teachers might be more motivated to work with disadvantaged students if appropriately remunerated. Since there is evidence that experience is a key dimension of teachers' qualifications,[39] this might signal that financial incentives for attracting qualified or experienced teachers are an effective tool for promoting equity in educational achievement. Studies in the United Kingdom (Atkinson *et al.,* 2004) and Israel (Lavy, 2004) have also shown that monetary incentives to teachers can have powerful effects on student performance. However, in practice, designing and implementing performance-related schemes has not always proved successful, as discussed in OECD (2005d). From an equity perspective, such policies incur a real risk of exacerbating inequalities across schools by giving teachers incentives to move into advantaged schools. To promote equity, financial incentives for teachers can be targeted at disadvantaged schools or students (Lavy, 2002).

There is sparse empirical evidence on the impact of teacher quality on educational equity. This may be due to the methodological difficulties of measuring teacher quality (see discussion by Vignoles *et al.,* 2000), as well as the endogeneity in the distribution of teachers across schools, in that better teachers may choose to teach in relatively advantaged schools. However, there is some US evidence on the positive relationship between teacher quality, as measured by salaries and experience, and student outcomes (Hanushek *et al.,* 1998, Dewey *et al.,* 2000, Goldhaber, 2002). Recent cross-country evidence has supported this view (Dolton and Marcenaro-Gutierrez, 2009). Similar conclusions are reached when estimating the impact of cross-country differences in the proportion of qualified teachers, as measured through the corresponding PISA synthetic indicator. Indeed, a higher proportion of qualified teachers is associated with a lower impact of socio-economic background within schools, suggesting that raising teachers' skills might help in promoting educational equity.[40]

3.3.2. Early schooling and childcare policies

While there is a consensus on the importance of early intervention for intergenerational social mobility,[41] cross-country quantitative evidence on the relationship between childhood policies and equity in education is scarce. This is due to lack of data on a cross-country comparable basis and, hence, the difficulty of identifying the impact of pre-school institutions. One exception is Schutz *et al.,* (2005), who provide empirical cross-country evidence that early enrolment and duration of pre-school are positively related to student achievement.[42] Countries' experience suggests that policy measures to increase equality of learning opportunities through interventions in early childhood have the

potential to yield very high returns. Evidence for the United States – mostly based on scientific evaluations of experimental set-ups, such as the Perry pre-school – is abundant (Carneiro and Heckman, 2003; Blau and Currie, 2006; Cunha *et al.,* 2006).[43] European evidence is more scattered. Some specific examples of the economic benefits of early education on disadvantaged individuals include Leuven *et al.,* (2004) for the Netherlands, as well as Kamerman *et al.,* (2003) for France, Sweden, and the United Kingdom.

Against this background, the present study provides an important contribution to the literature on childcare policy. Cross-country regression results presented in Table 6c show that higher enrolment in childcare is associated with higher equity in student achievement, consistent with earlier – mostly country-specific – studies. More precisely, relatively high levels of childcare enrolment appear to be associated with relatively low levels of school environment effects, even though they appear to be associated with relatively high levels of individual background effects. However, this equity-decreasing impact within schools is much lower quantitatively than the equity-increasing impact between schools. This result holds both for measures of enrolment in childcare and early education services, as well as enrolment in day-care and pre-school. In terms of quantitative impact, a tentative calculation assuming causality would suggest that increasing enrolment in childcare and early education services from the lowest OECD level (2%), to the highest (62%) would bring the between-school gradient from a level of 61 (PISA score points) to a level of 12. A similar impact would be found for public expenditure on childcare and early education services, as shown in the last column of Table 6c, delivering comparable results in terms of the magnitude of estimated causal effects.

A number of caveats apply to this analysis. First, the childcare variables should be measured at a time when the relevant PISA cohort was in age of childcare. This is not possible, however, because the series are not available for the period before 2003. Thus, the implicit assumption is that countries' relative positions in terms of those policies have remained unchanged over time. Second, one would ideally want to measure if individual achievement depends on past childcare enrolment. This variable is not available at the individual level in PISA 2006. However, even if it were, endogeneity and selection bias with respect to childcare enrolment would possibly bias its estimated impact.[44]

3.3.3. Social and labour market policies

Empirical evidence suggests the existence of a positive link between cross-sectional income inequality and intergenerational income persistence.[45] As one of the key drivers of income persistence, equality of opportunity could also be influenced by cross-sectional inequality. Yet, the relationship between income inequality and equity in educational achievement has not been studied in the literature. A number of studies have suggested that the countries with the most equal distribution of income at a point in time exhibit the highest earnings mobility across generations. Explanations of this relationship include differences in the returns to education, but also, more broadly, as suggested in D'Addio (2007), the idea that a number of institutional characteristics – redistributive policies, but also labour market institutions – are potentially important for understanding both intergenerational mobility and the level of cross-section inequality.

This section therefore focuses on the relationship between equality of learning opportunities and taxation and social policies across OECD countries. It uses both direct *policy indicators* (for example tax policy measures), but also *outcome indicators* (for example, relative poverty rates) that (at least partly) reflect cross-country differences in institutional

Table 6a. **Individual background and school environment effects:[1] the impact of education policy/school practices, regression results**

	Baseline		Number of years since first tracking		School selection policy		Ability grouping within schools		System-level number of school types programmes		Enrolment rate in vocational education	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Individual background effect of the PISA index of economic, social, and cultural status on performance												
Individual background	21.488***	21.484***	22.879***	22.874***	22.530***	22.527***	21.378***	21.381***	23.147***	23.147***	22.210***	22.201***
	[0.791]	[0.373]	[0.723]	[0.390]	[0.834]	[0.384]	[0.707]	[0.375]	[0.673]	[0.396]	[1.027]	[0.432]
Interaction Individual background x policy			–2.932***	–2.941***	–0.236***	–0.236***	–0.245***	–0.245***	–4.056***	–4.074***	–0.396***	–0.397***
			[0.299]	[0.171]	[0.022]	[0.013]	[0.043]	[0.028]	[0.525]	[0.271]	[0.052]	[0.025]
School environment effect of the PISA index of economic, social, and cultural status on performance												
School environment	46.717***	46.445***	40.738***	40.496***	42.261***	41.985***	46.853***	46.687***	40.839***	40.664***	41.233***	41.059***
	[3.595]	[1.664]	[3.332]	[1.698]	[3.490]	[1.625]	[3.145]	[1.678]	[3.097]	[1.745]	[4.098]	[1.854]
Interaction school environment x policy			8.279***	8.234***	0.719***	0.719***	0.623***	0.633***	10.863***	10.696***	0.986***	0.977***
			[1.353]	[0.777]	[0.110]	[0.061]	[0.211]	[0.123]	[2.222]	[1.277]	[0.241]	[0.122]
Policy			–0.010		0.064		0.589		–0.716		–0.352	
			[2.271]		[0.202]		[0.370]		[3.790]		[0.287]	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	132 347	132 347	132 347	132 347	132 347	132 347	132 347	132 347	132 347	132 347	114 133	114 133
R-squared	0.316	0.316	0.320	0.320	0.320	0.321	0.317	0.317	0.319	0.319	0.325	0.326
Number of countries			27	27	27	27	27	27	27	27	24	24

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (gender, migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), school location (small town or village, city), school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type (private independent, private government dependent, public). Country–level controls include GDP per capita (in PPP terms) and the direct effect of the considered policy variable (Model 1), or country fixed effects (Model 2). Student science performance on student PISA index of economic, social and cultural status (ESCS) and school-level ESCS are interacted with policy variables, entered one at a time. Country-specific parameters are used for all variables except student science performance on student PISA index of economic, social and cultural status (ESCS), school-level ESCS, and policy interactions.

Cross-country least-square regressions weighted by student sampling probability, rescaled so that each country receives an equal weight, while taking country-specific sample representativeness into account. Robust standard errors adjusted for clustering at the school level. All variables are mean-centred. All regressions exclude Mexico and Turkey.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.

1. All education policy variables are drawn from the *PISA 2006 Database*.

Sources: PISA 2006 database and *OECD ADB Database*.

Table 6b. **Individual background and school environment effects:[1] the impact of education policy/resources, regression results**

	Baseline		Spending per student in secondary education[2]		Decentralisation[3]		Matching resources to specific needs[3]		Class size[1]		Class size in primary[2]		Class size in lower secondary[2]		Student-teacher ratio[1]		Student-teacher ratio lower-secondary[2]		Ratio of teacher's salary at top of scale to starting salary[2]		Proportion of qualified teachers[1]	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Individual background effect of the PISA index of economic, social, and cultural status on performanc																						
Individual background	21.488***	21.484***	21.311***	21.306***	21.785***	21.786***	21.084***	21.077***	21.416***	21.413***	18.585***	18.581***	19.421***	19.427***	21.659***	21.658***	21.593***	21.590***	19.727***	19.711***	21.434***	21.434***
	[0.791]	[0.373]	[0.758]	[0.383]	[0.935]	[0.414]	[0.806]	[0.401]	[0.844]	[0.372]	[0.847]	[0.415]	[0.949]	[0.447]	[0.634]	[0.376]	[0.760]	[0.416]	[0.600]	[0.422]	[0.738]	[0.380]
Interaction individual background x policy			–0.356	–0.351**	1.626***	1.634***	1.408***	1.407***	–0.740***	–0.740***	–0.364***	–0.365***	–0.590***	–0.592***	0.491**	0.493***	0.511***	0.512***	–5.939***	–5.972***	–4.601	–4.599***
			[0.411]	[0.151]	[0.220]	[0.160]	[0.286]	[0.164]	[0.131]	[0.091]	[0.126]	[0.117]	[0.121]	[0.104]	[0.187]	[0.135]	[0.160]	[0.128]	[1.050]	[0.904]	[2.834]	[1.625]
School environment effect of the PISA index of economic, social, and cultural status on performance																						
School environment	46.717***	46.445***	47.170***	46.848***	45.505***	45.256***	46.624***	46.491***	46.592***	46.388***	52.057***	51.884***	48.974***	48.903***	47.470***	47.208***	46.720***	46.538***	51.818***	51.334***	46.751***	46.582***
	[3.595]	[1.664]	[3.308]	[1.673]	[4.105]	[1.776]	[3.526]	[1.760]	[3.644]	[1.647]	[3.761]	[1.881]	[4.035]	[1.993]	[3.042]	[1.656]	[3.397]	[1.842]	[2.987]	[1.884]	[3.343]	[1.711]
Interaction school environment x policy			0.325	0.206	–3.100**	–3.167***	–3.974***	–3.904***	1.415*	1.479***	1.894**	1.900***	1.324*	1.341***	2.466***	2.465***	1.886**	1.902***	–4.315	–3.898	0.807	0.913
			[1.656]	[0.619]	[1.333]	[0.746]	[1.451]	[0.723]	[0.748]	[0.430]	[0.735]	[0.527]	[0.677]	[0.508]	[0.888]	[0.583]	[0.729]	[0.533]	[6.523]	[4.286]	[11.278]	[7.540]
Policy			7.338		–0.547		1.229		–1.902		–1.819		–4.206**		–0.304		–0.763		–2.500		–9.589	
			[4.933]		[2.544]		[2.395]		[1.381]		[2.005]		[2.019]		[1.592]		[1.469]		[17.197]		[29.618]	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	132 347	132 347	117 809	117 809	118 808	118 808	118 808	118 808	132 347	132 347	98 937	98 937	88 679	88 679	132 347	132 347	102 480	102 480	90 818	90 818	125 015	125 015
R-squared	0.316	0.316	0.319	0.320	0.333	0.334	0.333	0.334	0.316	0.317	0.348	0.348	0.329	0.329	0.316	0.317	0.321	0.322	0.350	0.351	0.317	0.318
Number of countries			26	26	24	24	24	24	27	27	21	21	19	19	27	27	21	21	21	21	26	26

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (gender, migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), school location (small town or village, city), school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type (private independent, private government dependent, public). Country-level controls include GDP per capita (in PPP terms) and the direct effect of the considered policy variable (Model 1), or country-fixed effects (Model 2). Student science performance on student PISA index of economic, social and cultural status (ESCS) and school-level ESCS are interacted with policy variables, entered one at a time. Country-specific parameters are used for all variables except student science performance on student PISA index of economic, social and cultural status (ESCS), school-level ESCS, and policy interactions.

Cross-country least-square regressions weighted by student sampling probability, rescaled so that each country receives an equal weight, while taking country–specific sample representativeness into account. Robust standard errors adjusted for clustering at the school level. All variables are mean-centred. All regressions exclude Mexico and Turkey.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.

1. *PISA 2006 Database.*
2. *OECD Education at a Glance Database.*
3. Index from Sutherland and Price (2006).

Sources: *PISA 2006 Database*, *OECD Education at a Glance Database*, Sutherland and Price (2007), *OECD ADB Database.*

Table 6c. **Individual background and school environment effects: the impact of early intervention policies, regression results**

	Baseline		Enrolment rate in childcare and early education services[1]		Enrolment rate in daycare and pre-school[1]		Public expenditure on childcare and early education services/GDP[2]	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Individual background effect of the PISA index of economic, social, and cultural status on performance								
Individual background	21.488***	21.484***	21.496***	21.497***	21.478***	21.478***	21.021***	21.014***
	[0.791]	[0.373]	[0.818]	[0.384]	[0.725]	[0.385]	[0.906]	[0.383]
Interaction individual background x policy			0.230***	0.231***	0.243***	0.244***	4.910**	4.983***
			[0.068]	[0.026]	[0.065]	[0.027]	[2.318]	[0.991]
School environment effect of the PISA index of economic, social, and cultural status on performance								
School environment	46.717***	46.445***	45.370***	45.163***	45.399***	45.189***	48.121***	47.869***
	[3.595]	[1.664]	[3.536]	[1.721]	[3.167]	[1.717]	[3.936]	[1.687]
Interaction school environment x policy			–0.773***	–0.762***	–0.822***	–0.810***	–32.206***	–31.265***
			[0.261]	[0.125]	[0.247]	[0.126]	[11.107]	[4.775]
Policy			0.192		0.202		13.236	
			[0.502]		[0.550]		[19.436]	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	132 347	132 347	123 394	123 394	123 394	123 394	117 809	117 809
R-squared	0.316	0.316	0.315	0.316	0.315	0.316	0.321	0.321
Number of countries			26	26	26	26	26	26

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (gender, migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), school location (small town or village, city), school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size, average class size, average student learning time at school, school type (private independent, private government dependent, public). Country-level controls include GDP per capita (in PPP terms) and the direct effect of the considered policy variable (Model 1), or country-fixed effects (Model 2). Student science performance on student PISA index of economic, social and cultural status (ESCS) and school-level ESCS are interacted with policy variables, entered one at a time. Country-specific parameters are used for all variables except student science performance on student PISA index of economic, social and cultural status (ESCS), school-level ESCS, and policy interactions.

Cross-country least-square regressions weighted by student sampling probability, rescaled so that each country receives an equal weight, while taking country–specific sample representativeness into account. Robust standard errors adjusted for clustering at the school level. All variables are mean-centred. All regressions exclude Mexico and Turkey.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.

1. *OECD Family Database* and *OECD Education at a Glance Database*.
2. *OECD Social Expenditure Database*.

Sources: *PISA 2006 Database*, *OECD Education at a Glance Database*, *OECD Family Database*, *OECD ADB Database*.

Table 6d. **Individual background effect: the impact of social and labour market policies,[1] regression results**

	Baseline		Child poverty after taxes and transfers		Gini coefficient		Material deprivation		Tax progressivity rate		Short-term net unemployment replacement rate		Long-term net unemployment replacement rate	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Individual background effect of the PISA index of economic, social, and cultural status on performance														
Parental background	21.451***	21.437***	22.325***	22.341***	21.512***	21.507***	20.285***	20.274***	21.599***	21.586***	21.504***	21.504***	20.903***	20.896***
	[0.781]	[0.371]	[0.579]	[0.471]	[0.504]	[0.371]	[0.874]	[0.423]	[0.501]	[0.375]	[0.692]	[0.372]	[0.663]	[0.377]
Interaction parental background x policy			0.229*	0.232***	38.603**	38.972***	0.145*	0.145**	–33.923***	–33.980***	–0.079	–0.078**	0.104***	0.104***
			[0.132]	[0.076]	[17.927]	[8.880]	[0.080]	[0.057]	[7.445]	[3.826]	[0.061]	[0.035]	[0.031]	[0.016]
Policy			–0.610		–86.825		1.282		–34.502		0.866		0.166	
			[0.886]		[119.522]		[1.244]		[50.409]		[0.588]		[0.228]	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	132 347	132 347	98 708	98 708	132 347	132 347	107 652	107 652	132 347	132 347	132 347	132 347	132 347	132 347
R-squared	0.320	0.320	0.326	0.326	0.320	0.320	0.346	0.347	0.320	0.321	0.320	0.320	0.320	0.321
Number of countries			20	20	27	27	22	22	27	27	27	27	27	27

Notes: Regression of student science performance on student PISA index of economic, social and cultural status (ESCS), individual control variables (gender, migration status and language spoken at home), school-level ESCS (average across students in the same school, excluding the individual student for whom the regression is run), school location (small town or village, city), school size and school size squared, index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size), average class size, average student learning time at school, school type (private independent, private government dependent, public). Country-level controls include GDP per capita (in PPP terms) and the direct effect of the considered policy variable (Model 3), or country-fixed effects (Model 4). Student science performance on student PISA index of economic, social and cultural status (ESCS) is interacted with policy variables, entered one at a time. Country-specific parameters are used for all variables except student science performance on student PISA index of economic, social and cultural status (ESCS) and policy interactions.

Cross-country least-square regressions weighted by student sampling probability, rescaled so that each country receives an equal weight, while taking country-specific sample representativeness into account. Robust standard errors adjusted for clustering at the school level. All variables are mean-centred. All regressions exclude Mexico and Turkey.

Balanced repeated replicate variance estimation, standard errors clustered by school in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include a constant.

1. See data appendix for policy variables definitions and sources.

Sources: *PISA 2006 Database*, *OECD Education at a Glance Database*, Boarini and Mira d'Ercole, 2006, *Going for Growth Database*, *Taxing Wages Database*, *OECD ADB Database*, OECD (2001c), OECD(2008).

settings. Indeed, in previous studies, cross-sectional inequality has been shown to be related to low intergenerational inequality. Moreover, welfare policies, by targeting disadvantaged family situations – either due to permanent factors or to temporary loss of income (*e.g.* loss of employment) – reduce cross-sectional inequality, thereby potentially helping to mitigate intergenerational persistence. At the same time, ill-designed taxation and social policies would also perpetuate welfare dependency, with potentially negative effects on social mobility. The net effect of these policies on educational opportunities is, therefore, an important empirical issue, even though causal relationships are particularly difficult to establish in this area

Cross-country regression results suggest that countries displaying high levels of child poverty are also characterised by a high level of inequality in educational achievement, as indicated by the positive interaction between child poverty rates and the individual background effect (Table 6d). Whichever school environment students face, the penalty associated with coming from a disadvantaged background is stronger in countries where child poverty rates are relatively high.[46] This result, while not interpretable in a causal way, confirms the importance of early child development for educational outcomes. In a social policy context, it points to a strong case in favour of investing in early childhood education as an efficient tool to promote intergenerational equity.[47]

Results also suggest that cross-sectional income inequality and educational opportunities are positively correlated. While this has long been a conjecture in the intergenerational social mobility literature (Andrews and Leigh, 2007; Aaronson and Mazunder, 2005; Blanden, 2008), empirical evidence has been much less conclusive. Table 6d suggests that income inequality, as measured by the Gini coefficient calculated on disposable household income, is associated with higher educational inequalities, as suggested by the higher impact of individual socio-economic background on student achievement. Similar results are found when using indicators of material deprivation, consistent with findings on the role played by child development in the context of intergenerational social mobility. Results linking inequality and poverty to lack of social mobility may underpin some of the further findings on the impact of welfare and redistributive policies on equity in education. Indeed, regression results suggest that tax progressivity is positively associated with learning opportunities. Interpreting these results in a causal way would suggest that the estimated impact of increasing tax progressivity is relatively important: indeed, the variation in the impact of individual family background on teenagers' cognitive skills from minimum to maximum tax progressivity would range from 25.4 (PISA score points) to 12.4. These calculations are only illustrative, but, nevertheless, point to the potential for redistributive policies to help reduce inequality of learning opportunities.

Unemployment benefits might help to alleviate liquidity constraints on the parents of disadvantaged children. At the same time, relatively high levels of such benefits might discourage unemployed parents to take up employment (*e.g.* Bassanini and Duval, 2006). While it is not possible to identify the nature of the indirect mechanisms at work, the empirical results in Table 6d show a negative link between the level of short-term net unemployment benefits and the impact of individual socio-economic background on student performance, while the level of long-term net unemployment benefits has an opposite link. This pattern is consistent with the interpretation that while short-term unemployment benefits help to ensure the transition from job to job and consequently alleviate transitory liquidity constraints, long-term unemployment benefits, might – if

fixed at too high a level – discourage job transition and result in unemployment or welfare-dependency traps. Long-term unemployment benefit dependency may also be associated with social stigma, in turn harming children's cognitive development. This result is consistent with the findings of child development studies relating parent welfare dependency to children's outcomes (Corak and Heisz, 1999; Corak *et al.,* 2004).

4. Concluding remarks

This work has provided measures of equality of educational opportunities across OECD countries. It suggests that the majority of OECD countries exhibit ample scope for increasing educational opportunities for disadvantaged individuals, allowing for coping with both equity as well as efficiency concerns. However, the empirical analysis shows that OECD countries are extremely heterogeneous with respect to educational socio-economic inequalities. In particular, while Nordic countries exhibit relatively low levels of inequality, continental Europe is characterised by relatively high levels of inequality in educational achievement – in particular related to schooling segregation along socio-economic lines – while Anglo-Saxon countries occupy a somewhat intermediate position. Broadly speaking, these results confirm literature findings on intergenerational social mobility (d'Addio, 2007). Causa *et al.,* (2010) discusses the relative positions of OECD countries, comparing income and educational mobility, and discussing methodological limitations of the comparative approach. The analysis also uncovers non-linearities and asymmetries in the impact of school environment on student performance – or the so-called contextual effects: since contextual effects appear to favour disproportionately weak students in a number of OECD countries, increasing schools' social mix is likely to increase equality in educational opportunities without being detrimental to average performance.

Cross-country regressions should not be interpreted as causal relationships. Despite this important limitation, this paper provides a number of relevant findings on the association between equality of educational opportunities and public policies in OECD countries. First, this work confirms earlier findings on the negative impact of early differentiation and tracking policies on educational equality of opportunity. Second, it confirms also the relative weakness and ambiguity attached to the empirical identification of the relationship between educational spending and educational equity. However, the empirical results suggest that an equity-increasing use of educational resources may be obtained through policies that provide the relevant signals to schools and teachers: for instance, providing financial incentives to qualified teachers may prove to be an effective tool for targeting disadvantaged students or areas. Thirdly, this work fills a gap in empirical research by providing cross-country (as opposed to country-specific) evidence on the importance of early intervention policy for attenuating intergenerational socio-economic inequalities in educational opportunities. It suggests that childcare and early intervention policies could be effective to reach this objective. Finally, the cross-country analysis attempts to uncover the role played by social and labour-market policies in influencing equality of educational opportunities, given the positive relationship between intergenerational and cross-sectional (income) inequality. Empirical results suggest that some redistributive and income support policies are associated with lower inequality of educational opportunities.

Once again, given the empirical limitations of the analysis, results on policies and educational outcomes of teenagers do not imply causality. More needs to be done in order to provide empirical estimates of the causal impact of policies on equality of educational

opportunities, either through specific case studies looking at the effects of policy changes, or through the development of more refined cross-country time-series data on individuals and the policies that affected their cognitive skills.

Notes

1. Boarini and Strauss (2008) provide recent cross-country estimates for OECD countries.
2. For example, in the United States, ability test scores of children as young as five have been found to be closely related to family background (income levels, education of parents, family situation, etc.).
3. Throughout this document, the expressions "equality of opportunity", "equity in learning opportunities", or "educational equity" are used interchangeably.
4. PISA data have also been used extensively outside the OECD both in a cross-country perspective (Esping-Andersen, 2004, Fuchs and Woessmann, 2004, Entorf and Lauk, 2007) and in country-specific studies (among others: for Germany, Fertig, 2003a, 2003b; for Italy, in a cross-regional perspective, Foresti e Pennisi, 2007, and Bratti *et al.*, 2007; for Austria, Schneeweis and Winter-Ebner, 2005).
5. For a presentation of PISA, see the latest OECD report (OECD, 2007a) as well as the PISA website (*www.pisa.oecd.org*). For technical documentation on survey design and data analysis, see OECD (2005b, 2005c).
6. This mean refers to the OECD aggregate, using appropriate students' weights.
7. A word of caution is needed here. Indeed, this index contains information on a number of items which can be considered as educational expenditures; those expenditures may vary by country depending on the school system (*e.g.* in some countries students do not have to buy books because they are provided by the school) and not on families' socio-economic status.
8. This mean refers to the OECD aggregate, using appropriate students' weights.
9. OECD (2004, 2007a) presents this index as a measure of "segregation by socio-economic background": intuitively, for a given level of overall variation in students' socio-economic background, systems can be either highly segregated, where students within schools come from identical backgrounds, but average socio-economic background varies across schools, or highly desegregated, where each school is identically mixed in terms of socio-economic background, and there are no differences across schools.
10. The results do not change when this correction is not made. See, for instance, the PISA study which does not exclude the student from the calculation of this average.
11. These are: school location (small town or village, city), school size and school size squared, school resources (index of quality of educational resources, index of teacher shortage, proportion of certified teachers, ratio of computers for instruction to school size), average class size, average student learning time at school, and school type (private independent, private government dependent, public).
12. School selection policy is measured through the PISA school questionnaire. A school is defined as academically selective if principals report that students' academic records and/or students' recommendation of feeder schools are a prerequisite or a high priority for students' admission.
13. Estimates including these controls are not shown for space concerns, but are available upon request.
14. Comprehensive school systems refer to school systems that do not systematically separate students according to ability; students follow generally unified *curricula* across secondary schools.
15. As seen above, this difference does not arise because of distributional differences, given the already high cross-country differences in "uncorrected" gradients.
16. These results on non-linearities in educational opportunities echo some of the findings of intergenerational earnings mobility studies. In particular, both Jannti *et al.*, (2006) and Grawe (2004) show that low mobility in the United Kingdom is the result of very high persistence in the upper tails of the distribution, a finding which is confirmed here.
17. The regressions control for individual characteristics. Due to data unavailability at the school level, France is not included in these estimations.

18. The countries for which the estimated school environment effects are statistically different between urban and rural areas are: Iceland and Poland (at 1% confidence level); Spain and Mexico (at 5% confidence level); and Portugal and the Netherlands (at 10% confidence level). For the Netherlands, which in a comparative perspective exhibits one of the highest levels of socio-economic inequality between schools in both rural and urban areas, the estimated effect is slightly stronger in rural areas than in cities; the opposite pattern is observed in other countries.

19. The Slovak Republic and Ireland also exhibit large differences in school's socio-economic distribution across rural and urban areas. However, the school environment effect is relatively low in those countries.

20. This analysis does not have to be interpreted as a proper estimate of peer effects, given the empirical difficulties of identifying them. Moreover, it has to be kept in mind that the analysis would have to rely on class as opposed to school scores for estimating peer effects. Class level data are not available in PISA.

21. It is not possible to introduce simultaneously achievement scores and socio-economic variables at the school level because of collinearity issues, as extensively discussed in the literature. Some countries are omitted from the regressions because of missing data on some or all school variables.

22. These tentative calculations are simply obtained by multiplying the corresponding estimated coefficients by 100, which is the international standard deviation of PISA science scores.

23. Moreover, contrary to expectations, country-level estimates of the "net" within- and between-schools gradients are not much affected by the introduction of student and school controls. This is the reason why country estimates including school controls are not presented in previous sections, where only estimates accounting for student-level characteristics were discussed.

24. In theory, it could also be possible to estimate variants of the above model where only interactions between the school socio-economic background and policies are considered, controlling for country-specific effects of own socio-economic background. For example, housing policies might be associated with higher or lower contextual effects across schools. Unfortunately, institutional cross-country data on housing or urban policies are currently not available. Moreover, the difficulty of properly identifying and understanding the nature of contextual and peer effects would make interpretation of the results difficult. Hence, this strategy is not followed in the present approach.

25. These variables are directly available in the PISA dataset through the school questionnaire.

26. Schutz *et al.*, (2007) use the same approach for evaluating the impact of school autonomy, accountability and choice on equity in student achievement.

27. An attempt was made to estimate country-by-country regressions on the impact of school policies that display some variation within countries. It revealed the presence of important endogeneity and selection bias issues that made it very difficult to understand the results.

28. Indeed, a preliminary pair-wise correlation analysis reveals very high correlation between policies belonging to the same institutional area. For example, among education policies, the cross-country correlation between number of years since first tracking and system-level number of school types available to 15-year olds is 0.88. Among social and labour market policies, the cross-country correlation between the Gini coefficient on household's disposable income and tax progressivity is 0.90.

29. As discussed above, the estimation controls for the complex survey design of the PISA dataset. Also, student weights are rescaled so that each country receives an equal weight, while maintaining student and school sample representativeness within countries.

30. This average is not regression-specific and includes all OECD countries except Turkey and Mexico.

31. The sources and definitions of policy and institutional variables are provided in the data appendix.

32. Checchi and Flabbi (2007) have a slightly different approach, in that they focus on differences *within* tracking systems. The authors compare Germany and Italy and find that Italy, where parents have more latitude to interfere with the schooling careers of their children, exhibits less equality of opportunity than Germany.

33. This effect refers to the minimum age of first tracking, which is 10 years old across the countries under consideration.

34. These tentative calculations are based on cross-country average estimates and should be interpreted cautiously. The associated effects might be stronger or weaker, depending on countries' specificities.

35. See Machin and Vignoles, 2005, Buchel, 2002.

36. For details on the definition and computation of these educational institutional indicators, see Sutherland and Price (2007).

37. Also, this interpretation is indeed suggestive since this study makes use of *country-level* average class size (either from the school questionnaire averaged through school weights or from the Education at a Glance database), as opposed to *student-level* class size. As explained above, using the PISA class size variable (defined at the school level, and not at the student level, as required in theory for identifying peer effects) is not possible because of endogeneity bias. Moreover, class size at the school level is one of the (country-specific) control variables included in the regressions.

38. One interpretation of this finding could be that the positive association with equity occurs because in some countries students are exposed to different teachers for different topics, while in others the same teachers cover different topics. In this case, the results would not identify the impact of higher resources devoted to each student, but rather the impact of teachers' variety and diversity on equity. Disadvantaged schools and children could benefit disproportionately from being exposed to a diversity of teachers and teaching methods.

39. Greenwald *et al.,* (1996), Hanushek *et al.,* (1998).

40. These results do not take into account the potential endogenous impact of teacher quality on the housing market. Indeed, educational policies aimed at raising school quality in disadvantaged areas can be ineffective if they are internalised in housing markets. For instance, research on France found school quality effects on the Paris area housing markets (Fack and Grenet, 2007). Simulations suggest that a standard-deviation increase in average school quality would raise prices by about 2%, which would imply that the fraction of housing price differentials across school zones that can be explained by school quality differential amounts to about 7% in Paris.

41. See, for example OECD (2007b).

42. More precisely, the authors suggest that only after a certain threshold level is reached enrolment in pre-school has a positive impact on equity, which they interpret as an effect of non-random sorting of well-off children into pre-school at low levels of enrolment.

43. For the United States, a recent study on the effects of pre-kindergarten on children's school readiness shows larger and longer lasting associations with academic gains for disadvantaged children (Magnuson *et al.,* 2007).

44. Another limitation of this analysis is the absence of France, where there are both high levels of childcare enrolment and high estimated school environment effects, potentially contradicting this result. Unfortunately, as mentioned above, French data at the school level are not available in the PISA 2006 survey.

45. Bjorklund and Jsannti (1997); Gottschalk and Smeeding (1997); Aaberg *et al.,* (2002); Andrews and Leigh (2007); Blanden (2008).

46. This model is highly unrestricted and allows for heterogeneity, given that contextual effects are country-specific.

47. See d'Addio, (2007), for a review of the child development literature in the context of intergenerational social mobility, as well as Duncan *et al.,* 1994; Carneiro and Heckman, (2003); and OECD (2001b).

Data Appendix
Policy Variables: Sources and Definitions

This section provides data definitions and sources on policy variables used in the cross-country regressions. The PISA dataset is presented in the main text. Policy variables from the *PISA Database* refer to 2006.

Early intervention and childcare policies: *i)* Enrolment rates of children under the age of six in childcare and early education services (2003 or 2004); and *ii)* enrolment in day-care for children under the age of three and pre-school from three to six years old (2003 or 2004): the sources of these variables are the *OECD Family Database* and the *OECD Education at a Glance Database*. *iii)* Public expenditure on childcare and early education services as a percentage of GDP (2003): the source of this variable is the *OECD Social Expenditure Database*.

Education spending is defined as annual expenditure on educational institutions per student for all services (all secondary) in 2004. The source is *OECD Education at a Glance Database*.

Indicators of spending efficiency ("decentralisation", "matching resources to specific needs") are from Sutherland and Price (2007).

Variables measuring class size and student teacher ratio come from two sources: *i)* the PISA questionnaire, in which case they are averaged at the country level using school weights; *ii) OECD Education at a Glance Database*, where this study makes use of average class size in lower secondary and primary education for public and private institutions and the ratio of students to teaching staff in lower secondary education (2005 data).

The variable measuring **the ratio of the teachers' salary at top of scale** as a proportion of teachers' salary at the minimum training in lower secondary education is drawn from OECD's *Education at a Glance database* (2005 data). The index of **proportion of qualified teachers** is computed in the PISA project. It is based on the school questionnaire and averaged at the country level using school weights.

The variable measuring **ability tracking** within schools is based on the PISA school questionnaire and is constructed as follows. First, a school-level binary variable is created, where a value of one is given when principals report that schools regroup students according to ability in all subjects. Aggregated at the country level, this variable measures the proportion of schools that are estimated to regroup students according to ability. The variable on **school selection policy** is constructed in a similar way, following the school questionnaire; a school is defined as academically selective if principals report that students' academic records, students' recommendation of feeder schools are a prerequisite, or a high priority for student admission. Aggregated at the country level, this variable measures the proportion of academically selective schools.

System-level educational variables on **tracking and vocational education** are available in the *PISA Database*: *i)* age of first tracking, on the basis of which this work constructs the variable "number of years since first tracking", measured as 15 minus the age of first tracking; *ii)* the number of school types of programmes available to 15-year olds; *iii)* the percentage of 15-year olds enrolled in vocational education. The latter variable is computed from the student-level PISA dataset.

Relative **child poverty rate** is defined after taxes and transfers and refers to the 1990s; it is taken from OECD (2001b). The **Gini coefficient** on income inequality is based on OECD (2008) and refers to the mid-2000s. Data refer to the distribution of household disposable income in cash across people, with each person being attributed the income of the household where they live adjusted for household size. **Material deprivation** is measured through household data and defined as the share of household reporting material deprivation in terms of six dimensions (this work uses the synthetic indicator defined as the average of the six dimensions). The data refer to the beginning or mid-2000s and come from Boarini and Mira d'Ercole (2006). The measure of **tax progressivity** is the difference between the marginal and average personal income tax rate, divided by one minus the average personal income tax rate, for an average single production worker. The data are averaged across the years 1995-2004. The source is the *OECD Taxing Wages Database*. Short- and long-term net **unemployment benefits** refer to the year 2002 and are drawn from the *OECD Going for Growth Database*.

Glossary

- **Equality of opportunity:** The concept of equality of opportunity was originally introduced by Roemer (1998) and states that individual achievement should not reflect circumstances that are beyond an individual's control, such as family background.
  - ❖ Throughout this work, the expressions *equality of opportunity, equity in learning opportunities, educational equity, inequalities associated with socio-economic background, or socio-economic inequalities,* are used interchangeably to cover the differences in achievement between students coming from socio-economically advantaged and disadvantaged family backgrounds, or between students attending socio-economically advantaged and disadvantaged schools (identified by the average socio-economic status of the students enrolled in their school).
- **PISA 2006 science score:** This study uses cross-country comparable microeconomic data on student achievement, collected consistently across and within OECD countries through the Programme for International Student Assessment (PISA). PISA aims to assess the skills of students approaching the end of compulsory education. The main focus of the PISA 2006 study is on science literacy, with about 70% of the testing time devoted to this item. Given the very high correlation among science, mathematics, and reading scores, the following analysis focuses on science scores. *The performance in science is mapped on a scale with an international mean of 500 and a standard deviation of 100 test-score points across OECD countries* (aggregate OECD mean, using appropriate student weights).
- **PISA index of economic, social, and cultural status (ESCS):** The PISA ESCS index is intended to capture a range of aspects of a student's family and home background. It is explicitly created by PISA experts in a comparative perspective and hence with the goal of minimising potential biases arising as a result of cross-country heterogeneity. It is derived from the following variables: *i)* the international socio-economic index of occupational status of the father or mother whichever is higher; *ii)* the level of education of the father or mother, whichever is higher, converted into years of schooling; *iii)* the index of home possessions obtained by asking students whether they had at their home: a desk at which to study, a room of their own, a quiet place to study, an educational software, a link to the Internet, their own calculator, classic literature, books of poetry, works of art (*e.g.* paintings), books to help with their school work, a dictionary, a dishwasher, a DVD player or VCR, three other country-specific items, as well as the number of cellular phones, televisions, computers, cars and books at home. *The student scores on the index are factor scores derived from a Principal Component Analysis which are standardised to have an OECD mean of zero and a standard deviation of one* (aggregate OECD mean, using appropriate student weights).

- **(Socio-economic) gradient:** The (socio-economic) gradient measures the relationship between student performance, as measured by PISA 2006 science scores, and student socio-economic background, as measured by the PISA ESCS index.
  - ❖ The (socio-economic) gradient is called "(socio-economic) gradient taking cross-country distribution differences into account" when the estimated gradient is used to predict country-specific differences in student performance associated with the difference between the highest and the lowest quartiles of the country-specific distribution of the PISA ESCS index.
  - ❖ The (socio-economic) gradient can be called "gross (socio-economic) gradient" when the estimated relationship between student performance and student socio-economic background does not include control variables.
  - ❖ The (socio-economic) gradient can be called "net (socio-economic) gradient" when the estimated relationship between student performance and student socio-economic background includes control variables (individual control variables: gender, migration status, language spoken at home).
- **The individual background effect, or within-school effect:** The individual background effect or within-school effect measures the relationship between student performance, as measured by PISA 2006 science scores, and student socio-economic background, as measured by the student-level PISA ESCS index, controlling for school socio-economic background, as measured by the average ESCS level across students within the school.
  - ❖ The individual background effect can be used to predict country-specific differences in student performance associated with the difference between the highest and the lowest quartiles of the country-specific within-school average distribution of the PISA ESCS index, calculated at the student level.
- **The school environment effect, or between-school effect:** The school environment effect or between-school effect measures the relationship between student performance, as measured by PISA 2006 science scores, and school socio-economic background, as measured by the average ESCS index, across students within the school, controlling for student socio-economic background as measured by the student-level PISA ESCS index.
  - ❖ The school environment effect can be used to predict country-specific differences in student performance associated with the difference between the highest and the lowest quartiles of the country-specific school-level average distribution of the PISA ESCS, calculated at the student level.
- **Contextual effects:** Contextual effects arise when the probability that an individual behaves in some way depends on the distribution of exogenous background characteristics in the group: in the present work, student achievement depends on the socio-economic composition of the reference group, measured at the school level.
- **Peer effects:** Peer effects arise when the probability that an individual behaves in some way is increasing with the presence of this behaviour in the group: in the present work, student achievement depends positively on the average achievement in the reference group, measured at the school level. Peer effects are also referred to as endogenous effects.

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