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Assessing students' equality of opportunity in OECD countries: the role of national and school-level policies

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Abstract

This paper analyses the relationship between equality of opportunities and characteristics of the educational systems, jointly considering country- and school-level features. Because the peer group composition represents a fundamental channel in shaping educational opportunities, we consider all policies, surveyed in the PISA 2006 dataset, that affect the sorting of students to schools. Our empirical analysis shows that the inclusion of sorting policies enhances the capacity of explaining the determinants of the socio-economic gradient with respect to previous studies including only country-level features. In particular, it casts doubts on the prominent role attributed to school tracking. However sorting policies do not fully account for the influence of school composition on the socio-economic gradient; the direct inclusion of peer variables allows to highlight the equalizing impact of mixing students from different backgrounds. Among the other policies, also pre-school enrolment, public expenditure in education and ability tracking display a significant equalizing effect.

JEL Codes: I21, I24, J62, H52

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1. Introduction

Inequality in students' performances still remains a persistent feature of modern societies in spite of the generalized expansion in educational attainments. Beyond differences in attained degrees, a large part of inequality pertains qualitative differences among attended schools and are related to the increased diversification of the educational offer (e.g. private vs. public, vocational vs. academic-oriented). From a normative standpoint, the fraction of educational inequality related to circumstances out of the individual responsibility, i.e. the family background[1], appears unacceptable.

Standardized measures of students' performances – collected by international assessment programs, e.g. PISA, PIRLS, TIMMS – offer a unique tool to analyze the issue of equality of opportunities looking at the effective skills of students from different family backgrounds, attending different schools in different countries. Additionally, international assessment programs contain information on policies both at the school level and, when merged with other datasets on education (e.g. UNESCO or OECD), at the country level. These desirable features make these datasets particularly suitable for analyzing the correlations between a given policy and the socio-economic gradient, which is identified through the family background effect (FBE), i.e. the estimated coefficient linking parental background to the student's achievement.

The purpose of this paper is to analyze the relationships between the socio-economic gradient and the features of the educational system using the PISA 2006 dataset. With respect to studies using comparable datasets for the same purpose (Ammermueller 2005; Hanushek and Wößmann 2006; Schuetz et al. 2008, Waldinger 2005), our main original contribution consists in broadening the set of policies that are believed to have a significant impact on educational inequality. In particular, following a large theoretical and empirical literature on peer effects (e.g. Nechyba 2006), we claim that policies affecting student sorting to schools are crucial determinants of the FBE, since they modify the peer group composition and the general learning environment.

Factors affecting the peer group composition and the learning environment at school include tracking, both between-schools (i.e. the choice between vocational or general programmes) and within-school (i.e. grouping students by ability in all or in some subjects), urban segregation, school admission policies, parents' and students' preferences, etc. All

1. Family background could influence offspring performances directly, affecting their values and preferences, and indirectly, affecting the student's sorting in the different types of schools.

these factors concur in sorting students to schools of different quality; however, the impact of each policy is often difficult to disentangle in a casual way by empirical analysis because either policies and/or initial student's abilities are not observed (Nechyba 2006). Even if one-to-one causal effects linking each educational policy to inequality through the peer group composition are difficult to disentangle, it is still possible to estimate an "ex-post" association between school composition variables and educational inequality.

These insights are incorporated in our empirical strategy, which consists in comparing the estimates derived from two main econometric specifications. In the first, we attempt to decompose the level of the FBE using a set of "exogenous" country- and school-level policies that are known to have a direct impact on students' sorting, namely tracking and school admission procedures. In the second, we directly estimate the relationship between peer level variables and the socio-economic gradient, also controlling for country-level features as in the first specification. The comparison of these two models allows to evaluate if sorting policies are sufficient for explaining the link between equality of opportunities and peer effects. Of particular interest, the estimated impact of school tracking – a variable considered crucial in previous studies on equality of opportunity in education (Brunello and Checchi 2007, Schuetz et el. 2008) – becomes statistically not significant when the peer variables are explicitly added.

More in general, the inclusion of peer variables substantially enhances the understanding of the determinants of the socio-economic gradient. Although the PISA dataset does not offer reliable identification strategy for the peer effects[2], we believe that including these variables consents to assess the interesting correlation between a "broad contextual effect" and the socio-economic gradient and, further, adds explanatory power to our regressions. Having in mind this caveat, we keep talking of "peer effects" rather than of "contextual effects" in order to simplify the exposition.

This paper departs from comparable studies such as works of Schuetz et el. (2008) and Brunello and Checchi (2007), in two respects. First, these studies focus only on the effect of country-level characteristics and policies on the socio-economic gradient, whereas we attempt to explain the FBE also considering policies and features affecting students sorting at the school level. Second, among these sorting policies we do not include only tracking among

2. In particular, it does not offer an identification strategy that consents to copy with the well-known endogeneity of the peer effects. The only possibility in the PISA dataset is to claim that this endogeneity problem can be substantially mitigated by adding variables related to the sorting of students to schools, such as school-level effects and admission policies at the school level. This claim has been used by Rangvid-Schindler (2007) and Schneeweiss and Winter-Ebmer (2007).

different school programs (i.e. general vs. vocational), but we consider a broader set of channels affecting the peer group composition (e.g. the school admission procedures and how students are tracked by ability inside the school).

The remaining of the paper is organized as follows. Section 2 briefly reviews the theoretical link between policies affecting peer group composition and educational inequality. Section 3 presents the dataset and introduces the main variables of interest. Section 4 offers a preliminary analysis of the relationship between sorting policies and peer variables. Section 5 describes the econometric strategy, whereas section 6 shows the results and section 7 concludes.

2. Policies affecting the peer group composition

In both theoretical and empirical literature on peer effects, the impact of peer composition has been mainly analyzed in relation to the issue of maximizing the stock of human capital. The key finding of this literature is that alternative ways of sorting heterogeneous students affect the aggregate level of human capital only if peer effects enter non-linearly in the schooling production function (Benabou 1996, Hoxby 2000). With respect to inequality, theoretical predictions are more straightforward since the equalizing effect of more heterogeneous classes does not hinge upon the shape of the educational production function (e.g. de Bartolome 1990, Durlauf 1994, Benabou 1996, Fernandez and Rogerson 1996)[3]. On one hand, if the transfer of knowledge depends upon personal interactions, a low ability student benefits from the interaction with a high ability student, which in turn would have been better off by interacting with peers at its level. On the other hand, teachers should adapt to a more heterogeneous class setting higher (resp. lower) targets than the ones prevailing in a class with only low (resp. high) ability students.

Since peer group composition is largely endogenous, the existing empirical literature has mainly analyzed the indirect impact of policies affecting it. Among these policies, vast empirical evidence shows that postponing the choice of school offering different programmes reduces the effect of parental background on students' choices and attainments (see Meghir and Palme 2005, Dustmann 2004, Checchi and Flabbi 2005 and works quoted in Brunello and Checchi 2007). In systems tracking students earlier, parental influence on students' choices is

3. From the empirical side, it is not clear whether the levelling of educational outcomes is stronger for low ability students, as it appeared in earlier works (Zimmer and Toma 2000; Vandenberghe 2002; Hanushek et al. 2003; Rangvid 2007; Schneeweiss and Winter-Ebmer 2007), or from high to average ability students, as more recent researches for the UK have shown (Gibbons and Telhaj 2008; Lavy et al. 2009).

larger and social stratification at school more likely to emerge[4]. As a result, schools might turn out being more homogeneous not necessarily along an ability dimension (which under certain assumptions on the human capital production function can enhance the aggregate level of human capital[5]) but along other dimensions with direct consequences for the allocation of talents[6]. Teacher quality and resource allocation represent other channels through which school tracking might reinforce the dependence between student achievement and the family background. Specifically, better teachers could be attracted by the academic schools while vocational ones are likely to be endowed with relatively less resources (Brunello and Checchi 2007)[7].

Ability tracking represents another important policy affecting the peer group composition. The impact of this policy on the socio-economic gradient is however less clear even when abilities are partially correlated with family background. In principle, more homogenous classes reinforce students' differences through peer effects and therefore increase the dispersion of students' achievements. On the other hand, ability tracking might favour the homogenization of programs and teaching styles, hence increasing the outcomes of both low- and high-ability students with no clear consequences on educational inequality. In addition, the interaction of students which are too heterogeneous might favour the emergence of disruptive behaviour, such as envy, conflict or polarized behaviour. These contrasting forces might explain the disagreement of studies attempting to assess the relationship between ability tracking and educational inequality (Argys et al. 1996, Figlio and Page 2002, Rees et al. 2000, Betts and Shkolnik 2000a, 2000b; Zimmer 2003).

It is worth noticing that tracking does not exhaust the set of policy features influencing students' sorting and the dispersion of students' achievements (Nechyba 2006, Waldinger 2006). The sorting process is in fact constrained by other structural factors shaping individual choices. Admission procedures at the school level and residential segregation (strongly related to income through housing prices) could constrain students choices and make them more

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4. However, educational systems with an early tracking age often puts vocational and specific training at the centre of their development strategy (Hall and Soskice 2001), hence vocational schools might attract also students with background above the average

5. In particular: i) complementarity among similar ability types or equivalently convexity of the peer effects (Benabou 1996); ii) positive learning externalities brought about by a more homogeneous class; for instance because greater homogeneity eases teaching (Lazear 2001).

6. On this point, the interesting paper of Checchi and Flabbi (2005) compares the criteria of admission to the academic track (preparatory to university education) in Italy and Germany. They found that in Germany the main criterion is ability, whereas in Italy unrestricted tracking renders parental background more important.

7. The number of slots in academic schools also matters (Brunello and Checchi 2007, Brunello et al. 2007). Consistently with the model of Betts (1998), they show that a smaller number of slots in academic schools, equivalent to a higher standard for entering these schools, might decrease inequality as some high ability students end up in vocational schools.

dependent on parental background (Durlauf 1994, Fernandez and Rogerson 1996). For instance, costs of mobility or limited number of slots in schools located in rich-neighbourhood could restrain the choice set of more motivated students from disadvantaged backgrounds. Finally, parental and students' idiosyncratic preferences are likely to generate a large amount of variability in the analysis of the determinants of peer group composition.

In light of these considerations, tracking policies alone are likely to be an imperfect predictor of school peers composition, i.e. they could not be considered the main policies influencing the dispersion in students achievements. This motivates our claim of considering the joint impact of a broader set of educational policies affecting the peer group composition.

3. Dataset and main variables

In this paper, we analyze the relationship between peer group composition and the socio-economic gradient using the 2006 release of the PISA survey, carried out by the OECD. This survey interviews 15 year-old students, using schools as principal sample units from which students are sampled at a second stage. Differently from other dataset such as TIMMS, the PISA survey focuses on cognitive problem solving skills and real world applications rather than on strictly curricular competences. PISA 2006 provides standardized scores on students' capacities in three broad domains: math, science and reading.

In this study, we focus on test scores in math for sake of comparability with the more closely related work (Schuetz et al. 2008, which, using TIMMS, analyze performances in math). For the same reason, we use the variable "number of books at home" as the proxy of the family background. Preliminary analyses available upon request show that, consistently with other studies using different datasets (Wößmann 2003, 2004), books outperform other possible family background variables, such as parental occupation or education, in explaining students' achievements. In the PISA dataset, books at home are recorded through six categories, not directly providing a synthetic index. However, Schuetz et al (2008) show that this multinomial variable can be linearized without losing the explanatory power of the regression, so we follow them in doing this linearization.

As measures of peer level variables at school-level[8], we use the average number of "books at home" among schoolmates, net of the individual one, and the standard deviation of the number of books at home among schoolmates, to capture possible non-linearities and the role

8. Pisa does not provide information about students at the class-level; hence peer composition can be inferred at the school-level.

of peer heterogeneity (Rangvid 2007, Raitano and Vona 2011). In order to partially account for cross-country differences in students' sorting, peer heterogeneity is measured as the ratio between the standard deviation at the school level and the one computed at the country level. This normalization is required since peer heterogeneity at the school level could be inflated by higher background dispersion at the country level.

Finally, the PISA dataset records several exogenous students' characteristics – i.e. age, grade, gender, first- or second-generation immigrant –, whose averages at the school level (net of the individual one) represent other peer group composition variables potentially affecting students' outcomes. In particular, the shares of first- and second-generation immigrants in the school encompass interesting characteristics of the school and the contextual environment, being probably higher in ghettoes or in less rich neighbourhoods.

Concerning policies affecting the peer group composition, the literature has emphasized the importance of national policies setting the age of the first tracking among schools offering different curricula, i.e. academic vs. vocational, and the number of tracks available. However, there is no widespread agreement in the literature on the best way of measuring tracking policies[9]. Here, we use two alternative measures: 1. the age of first tracking; 2. a dummy capturing the comprehensiveness of the educational systems, which is equal to one if the system tracks students before they are aged 13 and 0 otherwise (i.e. in more comprehensive systems)[10].

Moreover, additional information on school-level policies potentially related to the peer group composition are available in the PISA dataset. Specifically, admission procedures (i.e. if the area of residence and the previous student record is a priority for being admitted in the school) and ability tracking inside the school (available in the three modalities: none, in some subjects or in all subjects) determine the extent to which students with similar ability and background tend to be sorted in the same learning environment. Therefore, we build a set of what we call "sorting policies" potentially affecting peer level characteristics using dummies capturing partial and full ability tracking, admission through residence, admission through student record and, at the national level, school tracking policies.

Finally, the socio-economic gradient could depend on several country-level educational policies and systemic features (Schuetz et al. 2008, Brunello and Checchi 2007): the duration

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9. Hanushek and Woessmann (2006) and Schuetz et al. (2008) use the age at which students first choose between academic-oriented and vocational schools, Ammermueller (2005) the number of different types of schools experienced by the student before enrolling in upper secondary education, Waldinger (2006) the minimum school grade at which a significant share of students is allocated in different tracks.

10. Following this definition, early tracking countries are the following (see table 2): Austria, Belgium, Czech Republic, Germany, Switzerland, Hungary, Netherlands, Mexico, Slovakia and Turkey.

of the pre-primary school and the enrolment share in it, the share of public expenditures in education, the enrolment rate in private schools, the per capita GDP and the per-capita spending in education. Table 1 provides further details on the variables used in this paper.

4. Descriptive and preliminary analysis

Equality of educational opportunities widely differs across countries and this fact represents the main motivation of our study. Differences are evident by carrying on by-country OLS regressions of the math scores on "books at home" controlling for basic individual characteristics (grade, gender, age, first- and second-generation immigrants and considering interactions between the immigrant status and the background variable). Estimated coefficients of the "books at home variable" in single OECD countries are shown in figure 1. The estimated average FBE computed on PISA 2006 data appears slightly larger than the one found in the work of Schuetz et al. (2008) on TIMMS data by using the same control variables[11] – 21.2 versus 17.5 – but the country-ranking in term of FBE does not substantially differ between ours and their estimates. Interestingly, all countries having a FBE a full standard deviation above the average track students relatively earlier.

This preliminary analysis seems to partially justify the approach followed by previous studies, which gave a prominent importance to tracking policies. However, looking at other sorting policies potentially affecting the peer group composition, namely proxies of ability tracking and of admission procedures followed by schools, it has to be noticed that their diffusion is far from being uniform across countries (table 2). Ability tracking is confirmed to be widely diffused in Anglo-Saxon countries (Epple et al. 2002, Betts and Shkolnik 2000a). In turn, the share of students admitted by residential location is generally higher in comprehensive systems, with distinct exceptions of Germany, Switzerland, Luxembourg, Italy, Korea and Japan. Admission criteria based on student records are fairly prevalent in the early-tracking system and in Korea and Japan.

Next step is to show that sorting policies affect the peer group composition along both the unobservable ability and the family background dimensions. Concerning the first – absent information on individual ability before school enrolment –, we proxy heterogeneity in ability within the school as the ratio between the standard deviation in test scores within the school and the standard deviation in test scores at the national level. From the theoretical insights

11. This discrepancy could be due to the larger number of countries included in their dataset.

discussed in previous sections, the ability dispersion within the same school should be: 1) higher in the comprehensive system, as between schools selection is absent; 2) lower if students are selected according to previous marks, as students turn out being more homogeneous; 3) higher in presence of ability tracking within the school, as it leads to polarization in attainments among classes; 4) ambiguous with respect to residential admission[12]. Table 3 (column 2) shows regressions of our measure of ability heterogeneity on sorting policies, including country fixed effects. In spite of this limited number of controls, the explanatory power of the regression is above 40%. All sorting policies have the expected sign and are statistically significant. Interestingly, admission by residential location leads to a greater heterogeneity, probably because urban segregation is not particularly strong in the majority of countries considered.

A second check consists in analyzing how observable peer composition, based on family background of schoolmates, is affected by sorting policies. In table 3, column 3 and 4 show results obtained using the same specification as in column 2 considering, respectively, the school-level average and the normalized standard deviation of the book at home variable as dependent variables. The average peer level is significantly higher in comprehensive systems and lower when any other sorting policy is implemented, apart from the case of students chosen according to their previous records. Peer heterogeneity is significantly higher the later school tracking is and when admission depends on residence. Conversely, ability tracking seems to increase the heterogeneity in backgrounds when it regards some subjects. In general, sorting policies explain a decent fraction of the between school differences in peer group composition. However, especially for peer heterogeneity, still a large fraction is left unexplained including only these policies. The inadequacy of available sorting policies to deal with the issue of peer group endogeneity will be addressed in the next section.

5. Empirical strategy

Testing the effects of policies, both at the school- and country-level, on equality of opportunities can be carried out in two ways. A first possibility is to estimate the socio-economic gradient by country and, in a second step, regresses it on national-wide educational policies. Alternatively, the interaction between the policy of interest and the FBE can be inserted in the student-level cross-country regressions. As Schuetz et al. (2008) pointed out,

12. This depends on the complex interlocked relationships between ability, family background and residential segregation.

this strategy allows to relax the quite restrictive assumptions on the distributions of the residuals implicit in the two-stage regressions. For our purposes, an additional advantage of this method consists in the possibility to add school-level variables to explain the process of inequality transmission.

With respect to the work of Schuetz et al. (2008), we use a slightly modified version of the second approach considering school-level features together with country-level policies. In fact, within-country between-school differences contribute to explain large fractions of the dispersion in attainments and, being student's attainments strongly related with family background, also explain a large fraction of the FBE.

Moving from the claim that the peer group composition is the main factor affecting the dispersion of student achievements, we directly include school- and national-level policies and features related to the school composition. The preliminary analysis of the previous section suggests that sorting policies available in the PISA dataset partially predict peer level variables, both along an observable and an unobservable peer dimension. Likewise, the first step of our analysis consists in including interactions between these school-level policies S_{sc} and the family background proxy B_{isc} in a model where, following Schuetz et al. (2008), the achievement of student i in country c and school s also depend on a set of basic individual controls X_{isc} (age, gender, grade and immigrant status) and on country-level policies P_c:

$$(1)\ A_{isc} = \alpha + \beta X_{isc} + \gamma B_{isc} + \delta P_c + \lambda F_{sc} + \eta\left(P_c * B_{isc}\right) + \nu\left(S_{sc} * B_{isc}\right) + \vartheta\left(I_{isc} * B_{isc}\right) + m_{isc} + u_{isc}$$

where u_{isc} is an independent error term and m_{isc} is a dummy equal 1 for imputed values of the books at home variable, built following the standard procedure as in Fuchs and Woessman (2007). Among student characteristics, family background B_{isc} is then affected by school- and country-level policies through their respective interaction terms. Furthermore, we interact the FBE with first- and second-generation immigrant status I_{isc} in order to capture the possibility that the FBE varies between natives and immigrants. The inclusion of country-level policies P_c is required to disentangle their impacts on equity from the one on efficiency. For the same reason, we add broad school fixed effects (F_{sc}), built as the deciles of the average background level of the students in school s of country c. These school-level effects roughly capture the quality of the school-specific learning environment.

In estimating equation (1) and all following specifications presented in this paper, individual observations are weighted for their sample probability. Besides, the hierarchical structure of the data is considered taking countries as the primary sampling units and applying cluster-robust linear regressions, which impose independence of observations across sample units but any structure of the errors' variance-covariance matrix for observations belonging to each unit[13].

An important remark is in order here. Schuetz et al. (2008) excluded school-level characteristics from the empirical specification since, focusing only on cross-country comparison, they wanted to depurate the FBE from school-level features affecting the sorting of students to schools of different quality. Our empirical strategy is complementary to theirs as we attempt to quantify the importance of cross-country differences in school-level policies that are known to affect student sorting and the distribution of educational opportunities.

However, as pointed out by Schuetz et al. (2008), results obtained estimating equation (1) could be driven by unobservable country-level characteristics affecting students' sorting. Hence, following their suggestions, we run a second specification where country fixed effects F_c and their interactions with basic student characteristics X_{isc} are added. More precisely, we estimate:

$$\begin{aligned} (2) \qquad & A_{isc} = \alpha + \beta X_{isc} + \gamma B_{isc} + \lambda F_{sc} + \eta(P_c * B_{isc}) + \nu(S_{sc} * B_{isc}) + \vartheta(I_{isc} * B_{isc}) + \\ & \rho F_c + \phi(X_{isc} * F_c) + m_{isc} + u_{isc} \end{aligned}$$

As Schuetz et al. (2008) pointed out, this specification does not allow to identify the effect of country-level policies and features P_c, but it consents to assess how these policies affect the FBE under the assumption that unobservable cross-country heterogeneity is unrelated to the size of the FBE. This identification requirement appears more likely to be satisfied with our approach where, explicitly, within-country heterogeneity in school policies affecting sorting is controlled for. In a nutshell, since sorting policies are relevant determinants of FBE through peer group composition and substantially differ across countries (see table 2), there is still a fraction of unobservable cross-country heterogeneity that is not accounted for by policies and systemic features considered at the country-level. Therefore, adjusting for these school-level features reduces the bias associated to unobservable country features.

However, the sorting policies are only an imperfect predictor of peer group composition, which is recognized to be the key factor shaping the distribution of educational opportunities. A more direct way to assess the impact of the peer variables on the socio-economic gradient

13. In fact, in the PISA dataset, the primary sample units are schools. Since we use both school- and country-level variables, the choice of the hierarchical structure is less clear. However, results available upon request show that nothing changes by taking schools as basic sample units in the cluster-robust regression.

consists in interacting peer variables with the FBE. In this case, the econometric specifications of eq. 1 and 2 become respectively:

(1')
$$A_{isc} = \alpha + \beta X_{isc} + \gamma B_{isc} + \delta P_c + \lambda F_{sc} + \mu\left(\overline{B}_{sc-i} * B_{isc}\right) + \omega\left(\sigma\left(B_{sc}\right) * B_{isc}\right) + \eta\left(P_c * B_{isc}\right) + \vartheta\left(I_{isc} * B_{isc}\right) + m_{isc} + u_{isc}$$

(2')
$$A_{isc} = \alpha + \beta X_{isc} + \gamma B_{isc} + \lambda F_{sc} + \eta\left(P_c * B_{isc}\right) + \mu\left(\overline{B}_{sc-i} * B_{isc}\right) + \omega\left(\sigma\left(B_{sc}\right) * B_{isc}\right) + \vartheta\left(I_{isc} * B_{isc}\right) + \rho F_c + \phi\left(X_{isc} * F_c\right) + m_{isc} + u_{isc}$$

where the mean, net of the individual one, and the standard deviation of the number of books in the school are included. The difference in the explanatory power and in the results of these two (direct and indirect) estimation approaches captures the extent to which observable selection polices fully account for peer level variables. It is, however, worth to remark that peer effects are not precisely identified by our econometric strategy, so they are basically not distinguishable from broader contextual effects.

However, insofar as sorting policies and broad school fixed effects are correlated with peer effects, an extended empirical specification including both sorting policies and peer variables would consent to mitigate the endogeneity of peer effects, hence reaching a more accurate identification. This extended specification is also useful to investigate if sorting policies capture other mechanisms affecting the FBE. For instance, after controlling for family background, ability tracking might reduce inequality as it allows high-ability students from worse family background to interact more closely with high-ability well-off peers.

6. Results

Basic Specification

In table 4 model 1, following Schuetz et al. (2008), we present the benchmark specification with only country-level policies. Our results generally confirm theirs even if the effects of several policies appear now insignificant. Specifically, the effect of pre-school enrolment is inversely U-shaped, while the ones of duration of the pre-primary school, of GDP per capita and of the private enrolment share are all weakly negative. Only two country-level policies appear to significantly affect the size of the FBE: a higher share of public expenditures in education has an equalizing effect as it is for postponing the age of first tracking. It is worth noticing that, compared to the TIMMS dataset used by Schuetz et al.

(2008), the inequality-enhancing effect of early school tracking is here smaller and less significant[14]. In particular, a one year postponement of the age of tracking leads to a 4.7% decrease of the average FBE. However, this result might be simply driven by the larger number of countries included in Schuetz et al. (2008) analysis.

Model 2 of Table 4 reports results of the model with school selection policies and school fixed effects. A later track still reduces the FBE, but the effect is only weakly significant. Concerning school-level policies, ability tracking significantly reduces the FBE after controlling for family background, whereas admission policies based on students' abilities increases it and residential location does not encompass any particular effect. Finally, a large 27% increase in the explanatory power of the regressions occurs when moving from model 1 to model 2[15].

Another 8% improvement in the R^2 is obtained by including peer level variables, i.e. the average and the standard deviation of the number of books in the school, rather than sorting policies. Even more important, model 3 in table 4 shows that the inclusion of peer variables halves the size of the "autonomous" FBE (i.e. the coefficient of the individual books at home variable) whereas the mere inclusion of sorting policies leads to a much smaller 21% reduction in the FBE with respect to model 1. The linear peer effect appears stronger the higher the FBE, pointing to complementarity between good individual background and good school peers. In turn, peer heterogeneity has the theoretically expected equalizing effect at the 95% significance level. With regards to the size of this effect, an increase in one standard deviation in peer heterogeneity accounts for 5.3% of the FBE and corresponds to 5.5% in terms of grade-equivalent. Moreover (model 4), the effect of age track turns out completely insignificant while the one of the early-tracking dummy declines but remains statistically significant[16]. Finally, pre-school enrolment displays a plainly negative relationship with the FBE, consistent with studies showing the importance of pre-school education for worse-off students (Carneiro Heckman 2005; Garces et al. 2005; Currie 2001). When inserting pre-school enrolment linearly instead than in a quadratic form, its equalizing effect is larger and

14. The effect of tracking is significant at 95% if we use the early-tracking dummy partitioning the educational systems in early and non-early tracking and only at 90% if we use the age of first tracking, as in Schuetz et al. (2008).
15. The two models are not fully comparable as we do not have school information for France, which is missing in all models with sorting policies, namely models 2, 5 and 6 of table 4 and models 8, 11 and 12 of table 5.The same caveat holds in comparing the model with peer variables, e.g. model 3 of table 4, and the model with sorting policies, e.g. model 2 of table 4. However, dropping France in all models does not alter the main results as shown in additional material available upon request.
16. In spite of the strong correlation between our two ways of measuring school tracking, the early-tracking variable appears to capture additional features of the educational system positively correlated with the FBE.

significant with a 1% increase in pre-school enrolment leading to a 1.1 reduction in the FBE (see the third last row in table 4).

Results of fully-fledged models, when we enrich the model 4 with either school tracking or the full set of sorting policies, are shown in table 4, models 5-6, respectively. In both models 5 and 6, our main variables of interest remain of similar sizes and at same significance levels, with the exception of the admittance by residence that now exerts a significant impact on inequality of opportunity. Our results are also robust to the inclusion of other attributes of the peer group composition, such as the share of females and the ones of first and second-generation immigrants, which are not statistically significant (model 6).

Country Fixed Effect Specification

A tougher test of our results consists in replacing the linear country-level policies with a full set of country and country per student fixed effects and in re-estimating models 1-6 (table 5, models 7-12). This specification is our favourite one as it encompasses several unobservable features of the education system that might render indistinguishable the effect of targeted policies on equity and efficiency. As would be expected, the R^2 of country fixed effect models is substantially higher than the one of basic models (compare table 4 and table 5). Looking across table 5, the size of the autonomous FBE appears much smaller than in the basic models of table 4.

Concerning our main variables of interest, school tracking stops having any significant impact on the FBE already in the benchmark model 7 and independently on the way used to measure it. School sorting policies exert the same kind of impact shown in table 4 – apart from the admittance by residence which is not significant also when peer composition variables are added – whereas country-level policies are never significant. Even if slightly smaller with respect to the basic specification, a one-percent increase in pre-school enrolment brings about a decline in the FBE which ranges between 0.67 and 0.96. Another interesting result emerges looking at the model with peer variables, i.e. model 9. In the country fixed effect specification, peer heterogeneity increases its effect on students' scores: an increase in one standard deviation of peer heterogeneity leads to a larger 8.4% decrease in the average FBE. In turn, linear peer remains significant, but almost halves in size.

7. Concluding remarks

This paper extends previous analyses on the relationship between students' equality of opportunities and characteristics of the educational system, jointly considering country- and school-level features. With respect to previous studies, tracking policies appear much less important up to become statistically insignificant when either other sorting policies at the school level or peer variables are included in the analysis.

However, policies affecting students' sorting do not fully account for the peer group composition. This explains why the influence of peer group composition on the FBE, also if not perfectly identified, remains largely significant in spite of the inclusion of a full set of sorting policies and increases the explanatory power of the model. Consistent with the theoretical literature, peer heterogeneity reduces the FBE, especially in our favourite country fixed-effect specification. With regards to school sorting policies, ability tracking appears to reduce the FBE across different empirical specifications.

These results enable us to drawn two main insights for future works. First, the effect of school tracking is mainly captured by its indirect effect on the peer group composition. But the opposite is not true as determinants of the peer group composition and especially of its relationship with the FBE remains largely unexplained. Unfortunately, identifying the impact of each sorting policy on the FBE via the peer group composition cannot be carried out in absence of a comprehensive set of sorting policies, both at the national and at the neighbourhood-school-level. These considerations bring us directly to the second practical insight derived from our analysis. We claim that, being absent detailed information on policies affecting student sorting, an ex-post direct specification of the relationship between the socio-economic gradient and the peer variables is a useful policy instrument. Rather than general conclusions on how each policy affects educational opportunities, our analysis could be useful to policy-makers for setting a target level of peer variables and then searching locally the best solution to reach it.

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Tab. 1: Control variables used in regressions

School sorting policies	
Residence	Dummy variable showing if residence is a prerequisite or a high priority for being admitted to the school
Student record	Dummy variable showing if previous academic records (or a specific test) are a prerequisite or a high priority for being admitted to the school
Full sorting by ability	Dummy variable showing if students are grouped according to their abilities within schools for all subjects
Partial sorting by ability	Dummy variable showing if students are grouped according to their abilities within schools for some subjects
School composition	
Share of females	Share of females among schoolmates
Share of first generation immigrants	Share of first generation immigrants among schoolmates
Share of second generation immigrants	Share of second generation immigrants among schoolmates
Books average	Average level of the “books at home” variable among schoolmates
Books standard deviation	Standard deviation (corrected for the country “books at home” standard deviation) of the “books at home” variable at school
Country-level policies	
Gdp per capita	Average 2000-2005, source Oecd dataset
Spending in education per capita	Average 2000-2005, source UNESCO dataset
Age of first track	Source Brunello and Checchi (2007)
Early_track	Dummy variable: 1 if school track occurs before age 13, 0 otherwise
Duration of pre-primary schools	In years, source UNESCO dataset
Enrolment to pre-primary schools	Share of students enrolled to pre-primary, 1993-95 UNESCO dataset
Public expenditure share	Share of the spending on education coming from public sources, 2000-2005 average, source Oecd dataset
Private enrolment share	Share of students enrolled in private schools, average 2000-2005, source UNESCO dataset
Students’ characteristics	
Age	
Sex	
Grade	Students below grade 8 and beyond grade 11 are excluded from the sample; hence, grade is captured by 3 dummies
First generation immigrant	Dummy variable showing if the student is a first generation immigrant
Second generation immigrant	Dummy variable showing if the student is a second generation immigrant
Books at home	Multinomial variable with six categories recording the number of books at home: less than 11, 11-25, 26-100, 101-200, 201-500, more than 500

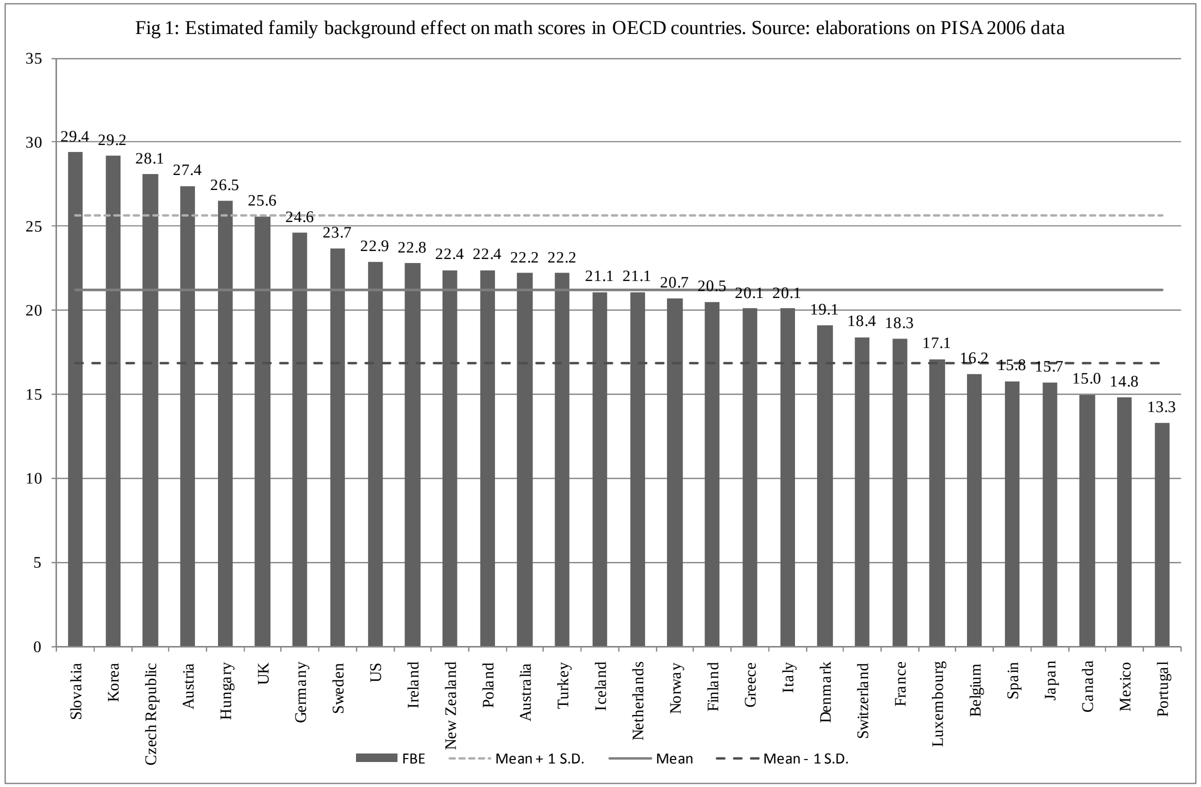

Table 2: Sorting policies at school-level in OECD countries and age of first track

	Share admitted by residence	Share admitted by students' records	Share of ability track in all subjects	Share of ability track in some subjects	Share of no ability track	Age of first track	Number of sample observations
Australia	41.9	9.4	4.7	89.9	5.4	16	14,666
Austria	21.5	68.9	3.4	36.9	59.8	10	4,807
Belgium	2.4	25.9	22.0	22.0	56.0	12	9,078
Canada	78.0	10.4	13.3	78.4	8.3	16	22,484

Switzerland	81.7	53.3	41.5	33.9	24.6	12	11,610
Czech Republic	19.7	44.8	12.3	53.1	34.6	11	5,732
Germany	65.2	39.6	10.8	30.5	58.7	10	4,762
Denmark	55.5	3.3	7.4	76.7	16.0	16	4,568
Spain	68.2	3.2	15.4	55.9	28.7	16	20,297
Finland	75.5	4.3	2.1	48.0	49.9	16	4,875
France	n.a.	n.a.	n.a.	n.a.	n.a.	15	4,767
UK	60.8	9.7	8.3	91.4	0.3	16	13,389
Greece	71.1	4.8	0.7	10.2	89.1	15	4,834
Hungary	1.4	70.2	1.7	67.5	30.9	11	4,401
Ireland	42.8	2.6	7.0	90.9	2.1	15	4,722
Iceland	94.5	1.0	6.6	78.3	15.2	16	3,496
Italy	11.1	6.6	21.4	24.9	53.7	14	22,098
Japan	20.4	86.5	9.9	46.0	44.1	15	6,123
Korea	22.1	60.2	7.1	81.1	11.7	14	5,323
Luxembourg	42.4	41.4	46.0	27.0	27.1	13	4,743
Mexico	11.3	41.9	27.9	43.4	28.8	12	29,219
Netherlands	10.3	65.7	48.2	33.2	18.6	12	5,053
Norway	79.0	0.0	2.7	39.2	58.1	16	4,747
New Zealand	49.8	9.7	5.9	91.1	3.0	16	4,677
Poland	82.8	13.2	3.3	43.7	53.1	16	5,613
Portugal	56.3	6.2	12.1	39.7	48.2	15	4,740
Slovakia	17.3	49.9	16.0	59.3	24.7	11	4,537
Sweden	58.8	0.6	5.0	70.3	24.7	16	4,486
Turkey	35.0	30.5	18.4	21.6	60.0	11	5,002
US	80.8	8.1	7.6	80.1	12.3	16	5,760
Mean values and total obs	46.8	26.6	13.4	53.9	32.7	14	250,609

Source: elaborations on PISA 2006 data

Table 3: Determinants of school composition and heterogeneity in scores in math in OECD countries

	Dependent variable		
	School standard deviation in scores in math	School average parental background	School standard deviation of parental background
age track	0.024***	0.062***	0.017***
residence	0.033***	-0.133***	0.018***
student records	-0.024***	0.260***	-0.015***
full sorting by ability	0.023***	-0.098***	-0.010
partial sorting by ability	0.021***	-0.027*	0.020***
Number of observations	7,425	7,425	7,425
R^2	0.412	0.439	0.293

[1] Country fixed effects are included. Regressions are weighting by students' sampling probabilities. Significance level: *** 99%; ** 95%; * 90%. Source: elaborations on PISA (2006)

Table 4: Students scores in maths in OECD countries: student-level interaction specification without country fixed effects[1].

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
books	83.79***	65.99***	41.37**	38.91*	37.25*	36.43*
books*schoolmates books average			10.41***	10.38***	10.19***	10.27***
books*schoolmates books st. dev.			-5.47*	-5.45*	-5.51*	-5.46*
books*share of female sc.mates						-0.19
books*share of first gen. immig. sc.mates						3.19
books*share of sec. gen. immig. sc.mates						4.50
books*full sorting by ability		-3.72***			-3.05***	-3.05***
books*partial sorting by ability		-2.14**			-2.33***	-2.34***
books*student records		5.40*			4.91***	4.97***
books*residence		1.43			1.99***	1.95***
books*age track	-1.02*	-1.33*		-0.45	-0.89	-0.88
books*enrol preprimary	16.58	45.20	-9.36	-0.86	17.76	17.94
books*enrol preprimary^2	-15.06	-41.18	1.04	-6.94	-25.20	-25.34
books*gdp per capita/1000	-0.10	0.67**	0.23	0.18	0.74**	0.72**
books*educ. spending per student/1000	-0.16	-2.61*	-1.71	-1.43	-3.10***	-3.08***
books*duration preprimary	-0.33	0.74	-0.96	-0.83	0.24	0.28
books*public expenditure share	-47.20***	-45.97**	-39.95**	-33.32*	-36.00*	-35.60*
books*private enrolment share	-0.49	1.65	-3.20	-1.51	0.57	0.62
age track	-1.00	4.50	-3.55	-1.98	1.32	1.38
enrol preprimary	121.90	-53.12	168.83**	140.02*	57.55	56.18
enrol preprimary^2	-91.37	77.64	-124.53	-97.54	-14.71	-13.18
gdp per capita/1000	-4.37*	-6.07***	-4.76**	-4.60**	-5.92***	-5.92**
educational spending per student/1000	17.68**	23.59***	19.63***	18.67***	22.34***	22.33***
duration preprimary	3.55	-3.45	3.61	3.13	-2.06	-2.14
public expenditure share	224.23	191.64	212.88	189.90	185.59	185.42
private enrolment share	64.71	53.95	74.70*	69.21	57.77	57.49
*books*early track*	*5.93***	*5.96**		*4.29**	*4.97**	*4.83**
*books*enrol preprimary*	*-4.72*	*-2.08*	*-11.23***	*-12.23***	*-12.53***	*-12.46***
Number of observations	245,036	227,670	245,036	245,036	227,670	227,670
R^2	0.266	0.337	0.364	0.364	0.362	0.362

[1] In all models the following control variables at the individual level are included: age, gender, attended grade, two dummies if first or second generation immigrants and two interactions between the immigrant dummies and the number of books at home. Apart from model 1, school level fixed effects are included (i.e. a dummy equal 1 for the decile of the country specific distribution of the average parental background at which the school belongs to). Regressions are run by clustering (by countries) robust standard errors and weighting by students' sampling probabilities. Significance level: *** 99%; ** 95%; * 90%. Source: elaborations on PISA (2006)

Table 5: Students scores in maths in OECD countries: student-level interaction specification with country fixed effects[1].

	Model 7	*Model 8*	*Model 9*	*Model 10*	*Model 11*	*Model 12*
books	48.76***	35.86*	31.48**	31.37**	31.17**	31.27**
books*schoolmates books average			4.26***	4.26***	4.02***	4.02***
books*schoolmates books st. dev.			-8.62**	-8.62**	-7.92**	-7.95**
books*share of female sc.mates						0.19
books*share of first gen. immig. sc.mates						2.52
books*share of sec. gen. immig. sc.mates						-1.51
books*full sorting by ability		-2.08***			-2.11***	-2.12***
books*partial sorting by ability		-1.84***			-1.58**	-1.58**
books*student records		4.13***			3.64***	3.64***
books*residence		-0.50			0.08	0.08
books*age track	-0.43	0.34		-0.02	0.18	0.17
books*enrol preprimary	-8.47	-18.18	-14.07	-13.68	-14.33	-14.29
books*enrol preprimary^2	1.20	8.80	4.17	3.81	3.44	3.32
books*gdp per capita/1000	0.04	0.28	0.23	0.22	0.39	0.39
books*educ. spending per student/1000	0.45	-0.16	-0.42	-0.41	-0.81	-0.81
books*duration preprimary	0.28	0.26	-0.26	-0.26	-0.03	-0.02
books*public expenditure share	-23.57	-28.30	-16.56	-16.26	-20.95	-21.08
books*private enrolment share	1.60	0.42	0.55	0.62	0.38	0.43
*books*early track*	*0.13*	*-2.42*		*-0.65*	*-1.32*	*-1.31*
*books*enrol preprimary*	*-6.41*	*-8.34***	*-9.20****	*-9.39****	*-10.49****	*-10.59****
Number of observations	245,036	227,670	245,036	245,036	227,670	227,670
R^2	0.351	0.414	0.427	0.427	0.419	0.419

[1] In all models the following control variables at the individual level are included: age, gender, attended grade, two dummies if first or second generation immigrants and two interactions between the immigrant dummies and the number of books at home. Further, country fixed effects and the interactions between country fixed effects and all the individual level variables are included. Apart from model 1, school level fixed effects are included (i.e. a dummy equal 1 for the decile of the country specific distribution of the average parental background at which the school belongs to). Regressions are run by clustering (by countries) robust standard errors and weighting by students' sampling probabilities. Significance level: *** 99%; ** 95%; * 90%. Source: elaborations on PISA (2006)