[PRELIMARY VERSION]

Immigrant students and school systems.

Cross-country evidence from PISA 2006

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Abstract. This paper uses the PISA 2006 dataset to analyse the performance of immigrant students and the structural features of schooling – stratified or comprehensive - in 29 countries. Controlling for background variables, we find that gaps can be high in both school systems. In particular, they are higher where educational systems are less flexible in terms of students' mobility between tracks or courses.

Keywords: International migration, school education systems, PISA.

JEL: F22, I21

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I. Introduction

The existence of an immigrant gap in school performance (difference in scores with respect to natives) is highly debated, especially since the decisive evidence provided by cross-country surveys as the Trends in Mathematics and Science Study (TIMSS) and the Program for International Student Assessment (PISA) has become available. Its causes may be related to host countries' features, to immigrants' characteristics, or to both; its more likely and direct economic consequences are unequal opportunities in the labour market (Dustmann, 2004).

Searching for the causes, most of the recent literature has focused on immigrants' characteristics and socio-economic background; some papers have controlled also for school inputs (Schneeweiss, 2009; Ammermueller, 2007; Entorf, and Minoiu, 2005; Entorf and Tatsi, 2009; OECD, 2006), but only a very restricted number of them have considered a central feature of host countries' institutions, which is their educational system of (among these Entorf and Lauk, 2006; Schnepf, 2006).

Educational institutions may matter for social mobility. Recent studies find that opportunities can be less equal in stratified systems of schooling, where students attend either academic or vocational secondary schools, than in systems of general education, where schools are comprehensive (Schutz et al., 2008; Brunello and Checchi, 2007; Wömann, 2004; Ammermueller, 2005; Hanushek and Wömann, 2006; Bauer and Riphahn, 2006). Even the economic growth and innovation capacity of countries appears to be related to their systems of education, and the relation is positive, also in this case, with the comprehensive model (Hanushek and Wömann, 2009; Bertocchi and Spagat, 2004; Krueger and Kumar, 2004)

Focusing more directly on education, some articles find that the dispersion of tests' scores is lower, and equity is higher, in countries with the comprehensive system, while average scores and efficiency are not clearly related to any of the two models (Meghir, 2005; Meier and Schutz, 2007). Several reasons, therefore, seem to suggest that the school performance of immigrants may be, in some way, related to the educational models of receiving countries.

This paper analyses this performance twenty-nine countries. It uses the PISA 2006 database, controls for student’s characteristics and family background and focuses on educational systems. The wide number of countries taken into account, the inclusion of several control variables, among which the country of origin of immigrants, and the use of a proxy of the type of school attended by each student, provides a new perspective with respect to previous work.

Despite the expectation of a superior fairness of the comprehensive model, we find that the scores of immigrant students can be significantly and substantially different to that of natives in both education systems. More precisely, negative gaps with respect to natives are higher in countries of continental Western Europe, an area where both models are implemented. Elsewhere, in particular in English-speaking countries, gaps tend to be lower.

School models tend to differ radically between countries of Western Europe, where the stratified system can imply sharp differences between school types, or tracks, and the comprehensive system consists into largely homogenous programs. In both cases, the mobility of students between school types or courses is very low. Outside this area, both forms of schooling have been implemented in 'intermediate' versions. In the US and in other English-speaking countries, comprehensive schools coexist with the 'streaming' of courses, which are taught at different levels of difficulty. In Ireland, Greece and other countries, there are milder differences between the programs of academic and technical schools, and the channelling of students into tracks occurs at later ages than in the central area of continental Western Europe. The higher chances of educational mobility and improvement of these intermediate versions of both systems may help to interpret our results, of lower gaps not just where schools are comprehensive, but where students have more than one possibility to discover their own abilities and to develop them by choosing the right program of studies.

The paper is structured as follows: Section 2 presents some basic traits of educational models, Section 3 concerns the data and descriptive statistics, Section 4 regards the estimation strategy, Section 5 comments results an Section 6 concludes.

2. Educational systems

Several states of Western Europe made schooling compulsory by integrating and centrally regulating existing forms of instruction. These were provided, on the one hand, by craftsmanship workshops and guilds, which supplied rudimental and practical training, and, on the other, by religious institutions, which taught theoretical and classical subjects. This lead to stratified system of schooling, where, after elementary school, children were channelled into either vocational schools, which supplied the practical instruction and were mainly attended by the working classes, or academic schools, which provided the theoretical teaching and were attended by the higher classes and the aristocracy (Bertocchi and Spagat, 2004).

Differently, the USA and later other English speaking countries of immigration, aimed to provide all students with general and multi-purpose knowledge. A rapid and effective cultural integration of populations originating from different countries, rather than the conservation of the pre-existing stratification of the society, was a central goal. This implied a unique study program at the national level for the secondary school. Students could acquire the specific skilled needed by the progressive industrialization of the economy at later stages of education or in practical elective courses taught together with the more theoretical subjects within the 'comprehensive' school.

After World War II, the UK, the Scandinavian countries of Northern Europe and, later, Spain, modified their educational systems in favour of the comprehensive model. In the process, the more classical subjects of the curricula were gradually substituted by more general topics, concerning scientific and modern knowledge (Leschinsky and Mayer, 1999). Programs in these countries are generally homogenous in content and in level of difficulty (some exceptions are foreign languages in Norway or mathematics in Sweden). This differs from the US model of comprehensive schools, where core subjects are taught at different levels of difficulty among which students can choose.

The implementation of the stratified school system also differs between countries. Differences concern especially the age of selection of school type and in the number and degree of differentiation between tracks. School types are chosen at the age of ten years in Austria and Germany, at twelve in Netherlands, Belgium and Switzerland, later elsewhere (Table 1). During the last decades, some countries have lessened the degree of differentiation between tracks by delaying the first age of selection and by making programs more similar. They have also lifted the restrictions that impeded students of technical schools to access university studies.

The proportion of students in grades below those corresponding to their age, or repeaters, depends on the educational customs of countries rather than on institutions and norms, but it can reinforce the central features of each education system and, above all, can especially concern immigrant students. It presents a wide variability between countries.

Table 1 groups countries according to their education models, comprehensive (streaming or homogeneous) and tracking, as well as according to the frequency of repeaters on the students' population. It shows that tracking is present especially in continental Western Europe, with some countries having an early age of selection (Wömann, 2009); repeaters are also more frequent in this area than elsewhere (data on repeaters from PISA 2006).

Table 1

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3. Data and descriptive statistics.

The Programme for International Student Assessment (PISA) is an every-three-year internationally standardised assessment promoted by OCSE since 2000. Its main purpose is to collect data on the 15-year-old students' competencies in reading, mathematics and science to be used to compare results both within and between countries. This paper is based on the third wave of PISA, which includes 57 jurisdictions, refers to data collected in 2006 and focuses on science. In the cross-country OECD dataset, PISA scores have been standardized with an international mean of 500 and a standard deviation of 100.

We consider only countries where the presence of immigrant students for each generation is at least 3% of the students' population.[1] The twenty-nine countries of Table 1 above satisfy these conditions. Table A1 in the Appendix depicts the shares of immigrant students of first and second generation in each country.

The PISA student's questionnaire includes an indicator (*ISCEDO*) of our main variables of interest that splits schools into general, pre-vocational and vocational, but figures are missing or are unreliable for some countries of our sample, as Belgium, Germany, Italy, Switzerland. We therefore use the UNESCO (2006) classification of education to split countries according to their schooling systems and, for those with tracking, to divide schools into three main types: 1 leading to university studies, 2 leading to the labour market or to further studies, 3 leading to the labour market.[2] We link this classification to the variable *(PROGN)* that indicates the kind of school attended by each student and, in this way, obtain a proxy of school types at the student level (details in Table A2).

Table 2 depicts the values of an index of "specialization" of immigrants relatively to natives in each school type and grade. Index numbers are the share of immigrant students in a given school type or in a grade on the share of native students in the same school type or grade. Values above unity denote a higher relative presence, or specialization, of immigrant students. The last column indicates the average grade for fifteen years old in each country. Indexes in Switzerland are biased in favour of schools of type 1 because large numbers of international students, not belonging to the category of immigrants, move each year to the country to attend schools of type 1.[3] Numbers at or above 1.05 are in bold, indicating a relatively higher presence of immigrants in the lower grades or in non academic schools.

[1] Similar conditions were adopted in OECD (2006) based on PISA 2003, where 17 countries were selected. The 3% condition hold only for the second generation in Estonia, Latvia and Slovenia and the first generation in Greece, Ireland, Montenegro, Italy. First generation students are those who were born outside the country of assessment and whose parents were also born in a different country, while second generation ones are those who were born in the country of assessment but whose parents were born in a different country

[2] Several of these countries have also 'special schools' for children with special needs, which we include in type 3, while our dataset contains no data on students attending special schools in countries of the comprehensive model.

[3] Data from the *Statistique Swisse* show that foreign students that have not completed elementary school in Switzerland show significantly lower rates of participation in vocational schools, and higher rates in general high schools or gymnasiums than foreign students that have attended elementary school in Switzerland (higher also than those of the general students' population):
http://www.bfs.admin.ch/bfs/portal/fr/index/themen/15/04/ind4.indicator.40101.401.html?open=412#412.

Table 2

Table 2 shows that several numbers in bold concern countries of continental Western Europe. The same area has also a relatively higher proportion of immigrants in the lower grades. Considering both the relative specialization of immigrants in grades and school types, the age of selection and the share of repeaters on the students' population (Tables 2 and 1), it turns out that the countries where there is a relative specialization of immigrants among repeaters and in vocational schools are also those having a sharper stratification of the educational system: Netherlands, Italy, France, Belgium, Austria, Germany, Luxembourg, Switzerland. On the other hand, among countries with the comprehensive systems, a high proportion of repeaters and a relative specialization of immigrants among repeaters is present in Denmark and Spain, as well as in Honk Kong and Macao In the other countries of our sample with comprehensive schools the proportion of repeaters is low or there isn't a relative specialization of immigrants among them. How are these distributions related to the performance gaps of immigrant students? A first, raw indicator is provided by simple regressions of the students' test scores on the dummy regarding immigrant-native status:

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the response variable representing the science score obtained by student i in country j, I_{ij} is the student's immigrant status (immigrants of first and second generation), β_I denotes the coefficient and ε_{ij} is the error term, with $\varepsilon_i \sim N(0\,;\sigma^2)$.

Figure 1 depicts these gaps, which are variations with respect to the mean scores of native students, captured by the intercept. Coefficient numbers are in Model 1 of Table 3 below. They are significant at the 99% level, except for first generation immigrants in Ireland and second generation in Honk Kong, which are significant at the 95% and 90% level, respectively. The distribution of gaps across countries is independent from the relative presence of immigrant students (Table A1).

Figure 1

The left hand side of the Figure depicts countries with school tracking and the right hand side those with the comprehensive model. It is worth noticing that, with the exception of Greece, the more negative gaps are in countries of continental Western Europe. Interestingly, both systems of education are involved. More specifically, among countries of the stratified system negative gaps are high in Switzerland, Belgium, Austria, Germany, Netherlands, France, Italy, Portugal and Luxembourg. in all these countries there is a relative specialization of immigrants in the lower grades or schools. Among countries with comprehensive schools, gaps are high in Denmark, Norway, Sweden and Spain. Results can be related to the phenomenon of repeaters in Denmark and Spain.

Outside this area, gaps are lower. They are lower or non significant in English-speaking countries, in Russia, Latvia, Estonia, Israel, Honk Kong (despite in this country immigrants repeat grades more frequently than natives, in Table 2). Immigrants perform above natives in Montenegro, Qatar and Macao (despite repeaters in Table)

4. Estimation strategy.

4.1 Models.

Gaps in performance between groups of individuals are often measured by using decomposition techniques, the more popular of which are those proposed by Oaxaca (1973) and Blinder (1973) or, also, by utilizing the coefficients of the dummy variable denoting the group of interest in OLS regressions. Recently, Elder et al. (2010) have shown that the value of the OLS gap generally lies between the boundaries represented by the two Oxaca-Blinder gaps that follow from alternative applications of the base formulae. The distance between the latter tends to increase as the shares of the two groups on the total population are more uneven, as typically are those of immigrant and native students. In these cases, the dummy variable calculation of the gap should be preferred.

Also, there is a risk of country-specific missing variables in using separate regressions, one for each country. However, by turning to regressions on the whole dataset, and by adding fixed effects to control for country-specific factors, we would loose the information on countries that interests us more. Hence, we use the dummy measure of the gap, keep regressions separate, and add, in subsequent specifications of the model, control variables and interactions that help to mitigate the above problems. In all cases, we will refer to correlations between variables, not to causal relations.

Problems of sample bias may in turn be related to differences in ability. For example, immigrants can be distributed non-randomly between countries: more able individuals may systematically prefer some countries with respect to others, and this can affect students' scores. Theoretical predictions on the kind of countries that should attract more able immigrants, however, have not found empirical support (Fuchs and Wömann). Hence, we suppose that in terms of innate ability immigrants are randomly distributed across our countries of interest and, similarly, that they do not systematically differ from natives. All what regards skills, parents' education and other background factors should be captured by our control variables.

We estimate a linear educational production function, where the output is the science test score of each student and the inputs are the school type they attend, the grade they are in, and a number of regressors regarding their characteristics and socio-economic background (see Table A3). To check for the direct impact of school factors, we add the variables regarding school types and grades to the initial regression on the immigrant condition (equation 1):

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \beta_G G_{ij} + \beta_S S_{ij} + \varepsilon_{ij} \qquad (2)$$

where G_{ij} and S_{ij} are dummies representing, respectively, grade and type of school type of student i in country j and β_G and β_S are their coefficients. In all models, β_I is our coefficient of interest. In general, we expect this coefficient to be affected by the inclusion of the school and grades variables. Following the empirical results of papers that find a higher dispersion in scores associated to stratified systems of education, (Hanushek and Wömann, 2010) we expect this inequality to affect especially immigrants and, consequently, the value of the gap to change more, with respect to equation (1), in the countries of the tracks system. Among these countries, gaps should change more in those with an earlier age of selection, which generally implies a higher differentiation between tracks. More generally, gaps should be affected by the inclusion of school factors in countries where tracks are sharply differenced, the proportions of repeaters are high and the index values of Table 2 are significantly above unity, denoting a relative specialization of immigrants in lower grades and non-academic schools.

Of course, scores will also be related to the students' characteristics and to their family socio-economic backgrounds, which we add in the following specification of the regression equation (a list of variables is in Table A3):

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \beta_G G_{ij} + \beta_S S_{ij} + \boldsymbol{\beta}_X \boldsymbol{X}_{ij} + \varepsilon_{ij} \qquad (3)$$

where $\boldsymbol{X}_{ij}$ is a vector of control variables and $\boldsymbol{\beta}_X$ is the vector of their coefficients.

Some of the background variables are of particular interest because they especially concern immigrant students, they are the country of birth of the student and of their parents and the main language spoken at home (if different from the national language). The country-of-birth variable can help to control for the sample bias mentioned above. Some studies, as Schnepf (2004), Fertig and Schmidt (2002), Entorf (2006), find that a non-national language spoken at home tends to be negatively correlated with performance. They especially consider OECD countries and find that the coefficient tends to be more negative in English-speaking countries.

Even controlling for background, the correlations with the dependent variable of our variables of interest, *school type* and *grade*, could be only partial. The coefficients of *school type* and of *grade* can be affected by the education received by immigrant students before age fifteen, which we cannot control in our cross-section regressions and can especially affect results for first generation immigrants, the more likely to have attended school outside the host country. This missing variable can be supposed to affect scores directly in countries with comprehensive schools and where repetition of grades is less frequent. However, the quality of education provided by the schools attended by immigrant students before entering the country is likely to be correlated with the level of education of parents and with the country of birth of the student and of her parents, all variables we control for.

Furthermore, and perhaps more significantly, the coefficients of *school type* and of *grades* can be influenced by the student socio-economic background, which can be correlated to test scores directly, but also through the school attended by the student and the grade she is in. These the indirect effects working through the *school type* variable and through *grades* can be captured by the interactions between background and school variables. Hence, we add the interacted variables. The model specification now is:

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \beta_G G_{ij} + \beta_S S_{ij} + \boldsymbol{\beta_X} \boldsymbol{X}_{ij} + \boldsymbol{\beta_{IS}} (S_{ij} \times \boldsymbol{Z}_{ij}) + \boldsymbol{\beta_{IG}} (G_{ij} \times \boldsymbol{Z}_{ij}) + \varepsilon_{ij} \qquad (4)$$

where $\boldsymbol{Z}_{ij}$ is a subset of background variables, $S_{ij} \times \boldsymbol{Z}_{ij}$ and $G_{ij} \times \boldsymbol{Z}_i$ represent the interactions with our variables of interest, *school types and grade*, and $\boldsymbol{\beta_{IS}}$ and $\boldsymbol{\beta_{IG}}$ are the vectors of their coefficients.

Finally, in all specifications we distinguish between first and second generation immigrant students. Once all relevant factors have been controlled for, the scores of the second generation can be expected to more similar to those of natives than those of the first generation. Since second generation immigrants attend the entire school cycle in the residence country and their families have been living in it for a longer time, they should be more integrated and know school practices better than first generation ones (Schneeweiss, 2009; Schnepf, 2004).

4.2 Methods: BRRs and BIC selection.

For a given set of candidate regressors, we select the relevant background variables to be included in the regression for each country by using the Bayesian Information Criterion (BIC) and, as mode of stepwise search, we apply the backward selection up to the point where taking away another regressor from the model increases the BIC (e.g. see Burnham and Anderson, 1988). We a apply automatic selection based on BIC to select relevant sets of candidate background variables from a large set of potential candidate variables A study on the out-of-sample prediction performance on the PISA data comparing BIC with the Akaike Information Criterion (AIC) and the recently popular Least Absolute Shrinkage and Selection Operator (LASSO) showed that BIC should be preferred to the other methods. Generally, BIC has selected more parsimonious models (fewer variables) with smaller prediction errors. Here, we apply the BIC selection five times, one for each plausible value, weighting the regression for the student final weights and choosing variables selected in all runs. This implies that the regressors effectively selected differ between regressions and countries. We then run the regressions with the OLS method using BRR.

For computing model parameter estimates and their standard errors, we employed the balanced repeated replications (BRRs) (e.g., see Särndal l et al., 1992) based on the weights provided in the PISA dataset. BRR is a method to estimate the sampling variability of a statistic that takes into account the properties of the sample design. Similarly to Jacknife and Bootstrap methods, uses re-sampling principles and provides unbiased estimates of the sampling error arising from complex sample selection procedures. For our data, BBR accounts for the two-stage sample design for selection of schools and students within schools (see OECD, 2009). In particular, PISA provides a set of 80 alternative weights that have to be assigned to each student to form alternative samples at country level. We employed the BBR weights to estimate regression coefficient standard errors as in OECD (2009). Analogously, we used the same re-sampling weights to compute standard errors of other statistics of interests. In particular, we computed the standard errors for the differences between regression coefficients.

The confidence intervals for the inferences reported in Tables 3 and A3a-b are standard (1-α)% confidence intervals (α<0.05) based on the asymptotic normality assumption of the coefficient estimates: (i.e., $\hat{\beta} \pm z_{\alpha}.\mathrm{if}(\hat{\beta})$).

We performed diagnostic analysis on the BBR coefficient estimates replicates to confirm that such an assumption is trustworthy for all the reported results.

5. Results

Table 3 depicts the coefficients of our variable of interest, the immigrant gap, distinguishing between 2nd and 1st generation immigrants. More complete results, including the coefficients of the school and grades variables, background variables and significant interactions are in Tables A3a and A3b in the Appendix.[4]

Table 3

There is a wide variability between countries of immigrant gaps (Figure 1 above) and of the part of total variation explained by the immigrant status (Model I). The values of the adjusted R2 of Model 1 vary from around 0.1, in Switzerland, Luxembourg, Austria, Germany, to about 0.5, in Denmark and Sweden, to zero in other countries. Table A1 shows that the R2 do not depend on the relative presence of immigrant students in countries.

Introducing the school variables into the regression affects the immigrant gap and the R2 of some countries (Model II of Table 3). The explained part of the total variation grows to around 0.5 in Netherlands, Belgium, Germany, France, Slovenia and to about 0.3 in Luxembourg, Austria and Spain (only grades in this country), indicating that the scores of students are strongly correlated with the stratification of schools and the repetition of grades. Of particular interest for us are immigrant coefficients: Table 3 shows that they shrink substantially with respect to Model I in the above countries plus Italy. This suggests that much of the original immigrant gap was due to school factors, which matter for the whole students' population and especially for immigrants. We checked for the significance of the difference in *1st gen* and *2nd gen* coefficients between Models II and I by applying the BRR method to the procedure indicated by Allison (1995), based on Clogg et al.(1995).[5] Results, in Table A5, are that differences between coefficients are statistically significant at the 99% confidence level in all countries cited above, except Austria, where the significance is at the 90% level.

Being in Schools of type 2 or 3 can imply, with respect to students in schools of type 1, a negative difference in scores corresponding to a standard variation (as said above, equal to 100 in for OECD countries); similar results are associated to coefficients of grades 8 and 9 (Model 2, Table A3). In several of the above countries the age of first selection is low and the number of

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[4] The more complete regressions, including all the coefficients of the background and interacted variables are available from the authors upon request.

[5] The same procedure cannot be used for the distance between coefficients of Models II and III, because the number of observations change in some countries but also, more significantly, because the introduction of the country of origin variable can capture much of the effects originally included into the immigrant gap.

repeaters is high and (Table 2) there is also a relative specialization of immigrants in the lower grades and in non-academic schools. This can explain the substantial impact of school factors on the initial immigrant gaps.

Among the countries of the comprehensive system, where the only regressor related to school is grades, the more marked differences between gaps in Models 2 and 1 and the higher increases in the adjusted R2 concern Spain and in Macao, two countries where the number of repeaters is high and there is a relative specialization of immigrants in the lower grades. In Macao, however, the immigrant gap is non negative, indicating that, on average, immigrants perform better than natives. Also in this case, differences between coefficients are significant (Table A5).

The introduction of background factors (Model III of Table 3) concerning socio economic-factors, the foreign language spoken at home and the countries of origin of immigrants and their parents (coefficients in Table A4) gives some interesting results. On the one hand, there is a further contraction of the negative immigrant gap in Switzerland, Belgium, Germany, Netherlands, Luxembourg and Slovenia, showing that both background and school are important in these countries and that not all the correlation between background and scores was captured by the school variables. It will be seen below that background matters a lot also in countries as Italy or Austria, but its relation with scores is significantly channelled through school types and grades.

On the other hand, background appears to play a *relatively* more important role than schooling in most countries of the comprehensive system. For example, the adjusted R2 of the regressions increases substantially in English-speaking and Scandinavian countries in Model III. In some of them, there is also a contraction of the original immigrant gap from Model II. However, it is worth noting that the explained part of the total variation of these countries is generally lower than that of the above, ‘core’, countries of the tracking system, in some cases it is even below the one explained only by school factors in the latter (R2 of Model II). This suggests that if background matters in English-speaking and Scandinavian countries, it matters less than in the core countries of the tracking system, and of course less than schooling *and* background in them.

The results of introducing the interactions between background factors and school variables confirm most of what was becoming evident with the previous findings: all countries where these interactions are significant belong to the core group of continental Western Europe. They are (Model IV of Table 3) Belgium, Austria, Netherlands, Luxembourg, Italy and Slovenia. Tables A3a-b show that the background variables more frequently involved are education level and occupation of mother and father, books at home, gender, and, in Luxembourg and Slovenia, immigrant status and country of origin, while the education variables involved are, in Italy, Belgium and Netherlands, school types, in Austria, school types and grades, in Luxembourg and Slovenia, grades. Some of the significant background variables confirm what could be expected given the results of several previous empirical investigations: books at home, parents' education and occupation. Our findings are that also gender, immigrant status, country of origin, can matter in the channelling of students in one type of school or the other, or on their repeating of grades. What also interests us here is that these interactions are not necessarily more important in countries where tracking starts earlier; for example, family background and school choice are strongly intertwined in Italy, where tracking starts at fourteen and are show no significance in Germany, where it starts at ten. This is consistent with the findings of Checchi and Flabbi (2007), based on PISA 2003 but less with those of Dustmann (2004), based on the German Socio-Economic Panel dataset.

Speaking a foreign language at home shows to have a negative correlation with scores in several countries, but, differently from expected (Schpneff, 2007), they are not especially the English speaking ones (indicated with 'l' in the column Immi. backg. of Table 3, coefficients in Tables A3a-b). They are Belgium, Austria, Germany, Netherlands, Denmark, Russia, Israel, Honk Kong, as well as Canada, New Zealand and Australia. On the other hand, speaking a foreign language at home is *positively* correlated with scores in Qatar, where it is also positive the correlation of the variable 'student from another country' (Table A3b).

A background variable specifically related to the immigrant condition is the country of origin of the immigrant student or of her parents. Coefficients are more negative in Western European countries, specifically in Switzerland, Austria, Belgium, Estonia, Great Britain and concern especially immigrants from the Middle East or, in some cases, from Africa (indicated by ‘c-o’ in column Immi. backg. of Table 3; see also Tables A3a-b).

As said above, sample bias is a potential problem with these regressions: more able individuals may systematically migrate to certain countries. This can influence the immigrant students’ scores and explain the higher gaps in the ‘core’ countries of continental Western Europe. However, as different skills and abilities may be related to the country of origin of immigrants, by controlling for background factors *and* country of origin, at least partially, we control for this potential sample bias.

Columns IV and III of Table 3 depict the immigrant gaps in countries once schooling, background and the interactions between the two have been taken into account. What remains, or the ‘unexplained’ part of the immigrant gap, can presumably be related to other factors. For example, school inputs, concerning class size, source of funding, existence of external examinations, have not been considered in this paper, but in previous work have shown to be only weakly related to the immigrant students’ performance (Entorf and Lauk, 2006). The reasons explaining the remaining part of the gap are maybe only indirectly related to family characteristics, but can nonetheless result in efficacious forms of segmentation of the students' population: they are, for example, residential segregation or discrimination within schools. The countries where coefficients remain high and significant are Sweden, where the gap is more than half of a standard variation, Denmark, Norway, Luxembourg and Spain, where they are about a third of a standard variation, and the United States.

The Scandinavian countries have been found to be positive examples in previous work on equality in education (Ammermueller, 2007): the low explanatory power of family background coefficients has been interpreted as a signal of a higher relation between scores and innate ability here than in other countries. Our results do not confirm this interpretation: the systematic lower performance of immigrants, once all other factors have been controlled for, suggest forms of discrimination and segregation which are not channelled through the school system, as in other countries of central Western Europe, but are not even related to background. Immigrants, appear to be discriminated as such, at least partly independently from the socio-economic characteristics of their families. This applies also to Luxembourg, Spain and the USA. Luxembourg is the only country of the tracking system where much of the variation is not explained by school and background factors.

Conclusion

[To be done]

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Table 1. School systems.

First age of selection and proportion of repeaters

<table>
<tr><th rowspan="2">share of repeaters</th><th rowspan="2">tracking</th><th colspan="2">comprehensive</th></tr>
<tr><th>streaming</th><th>homogenous</th></tr>
<tr><td rowspan="10">high</td><td>AUT [10]</td><td></td><td></td></tr>
<tr><td>DEU [10]</td><td></td><td></td></tr>
<tr><td>BEL [12]</td><td></td><td></td></tr>
<tr><td>CHE [12]</td><td></td><td>ESP</td></tr>
<tr><td>NDL [12]</td><td></td><td>DNK</td></tr>
<tr><td>LUX [13]</td><td></td><td>EST</td></tr>
<tr><td>FRA [14]</td><td></td><td>LVA</td></tr>
<tr><td>ITA [14]</td><td colspan="2">HKG</td></tr>
<tr><td>RUS [14.5]</td><td colspan="2">MAC</td></tr>
<tr><td>PRT [15]</td><td colspan="2">QAT</td></tr>
<tr><td rowspan="3">medium</td><td></td><td>CAN</td><td>SWE</td></tr>
<tr><td>IRL [15]</td><td>USA</td><td></td></tr>
<tr><td>ISR [15]</td><td>AUS</td><td></td></tr>
<tr><td rowspan="3">low</td><td>MNE [14]</td><td>GBR</td><td>NOR</td></tr>
<tr><td>SVN [14]</td><td>NZL</td><td></td></tr>
<tr><td>GRC [15]</td><td></td><td></td></tr>
</table>

Source: UNESCO (2006)
First age of selection in square brackets; source: PISA 2006.

Table 2. Grades and School types.
Index: % immigrant students / %native students

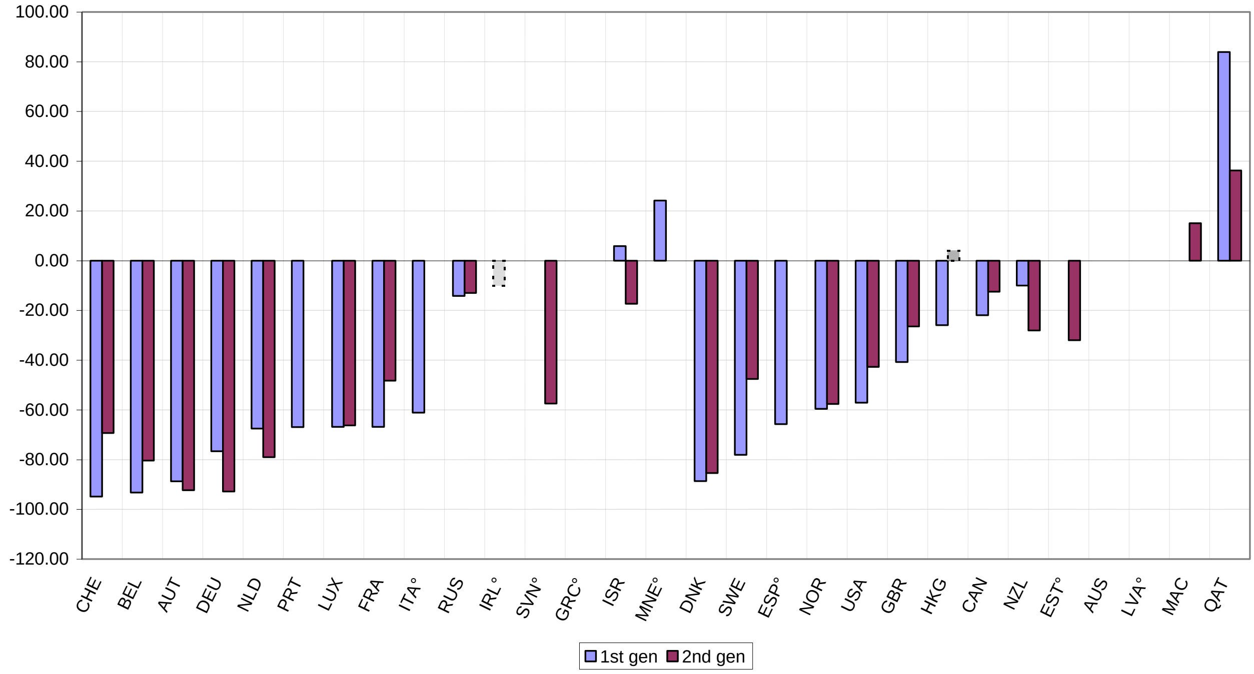
	Grade 9		Grade ≤ 8		School 1		School 2		School 3		
	2nd gen	1st gen	2nd gen	1st gen	2nd gen	1st gen	2nd gen	1st gen	2nd gen	1st gen	grade at 15
AUT	**1.17**	**1.22**	**1.84**	**3.09**	0.92	0.78	0.82	**1.08**	**1.31**	**1.05**	10
BEL	**1.78**	**1.86**	**3.38**	**7.85**	0.98	0.70	0.93	1.02	**2.52**	**6.03**	10
CHE	0.95	0.81	**1.33**	**1.90**	*1.11*	*1.09*	*1.02*	*1.01*	*0.78*	*0.84*	9
DEU	0.99	1.05	**1.91**	**2.34**	0.50	0.52	**1.21**	**1.17**	**1.27**	**1.26**	9
FRA	**1.15**	**1.32**	**1.58**	**4.09**	0.91	0.63	**1.09**	**1.40**	**1.46**	**1.48**	10
GRC		**9.28**		**7.66**		0.50		**3.35**			10
IRL		0.92		**3.39**		**1.45**		0.94			9
ISR	**1.45**	**2.63**			0.94	0.69	**1.16**	**1.77**			10
ITA		**4.09**		**13.21**		0.40		**1.58**		**1.30**	10
LUX	**1.12**	**1.17**	**1.65**	**1.83**	0.69	0.77	0.83	0.70	**1.18**	**1.15**	10
MNE		1.01				**1.08**		0.91		0.87	9
NLD	**1.34**	**1.46**	**1.97**	**5.35**	0.59	0.63	0.91	0.79	**1.89**	**2.26**	10
PRT	0.84	0.99	**1.99**	**2.77**	0.73	0.42	**1.19**	**1.43**	0.93		10
RUS	**1.08**	**1.09**	**1.63**	**1.98**	0.85	0.91	**1.11**	**1.16**	**1.55**	0.43	10
SVN					0.69		**1.24**		**1.32**		10
AUS	0.45	**1.32**									10
CAN	0.57	**1.09**	0.33	**1.06**							10
DNK	0.95	0.75	**1.30**	**2.91**							9
ESP	**1.17**	**1.76**	**1.08**	**1.83**							10
EST			0.56								9
GBR											11
HKG	**1.02**	**1.62**	0.86	**9.99**							10
LVA			0.92								9
MAC	0.97	1.01	0.87	**1.97**							10
NOR											10
NZL											11
QAT	**1.37**	0.92	0.51	0.48							10
SWE			**1.98**	**5.57**							9
USA	**1.30**	**1.59**	0.52	0.81							10

Notes: School 1: academic studies; School 2: mixed; School 3: labour market.

Switzerland (CHE): international students with immigrant students
Hong Kong and Macao: no significant share of students in schools of types 2 and 3
All statistics are weighted by using the student final weights provided by the dataset.

Note. "°': only one generation of immigrant student above 3% of students' populations.

Figure 1: performance gaps of immigrant students
immigrant dummy



"°" only one generation of immigrant students above 3% of students' population.

Table 3: immigrant students performance gaps, schooling, background and interacted variables.

	M1 - Dummy		***ad. R2***	**M2** -School & Grades		***adj. R2***	**M3** Background		Immi back	***adj. R2***	**M4** Inter. M2-M3
	2nd gen	1st gen		2nd gen	1st gen		2nd gen	1st gen			
tracking											
CHE	-69.3	-94.8	*0.12*	-67.3	-87.6	***0.28***	*-24.7*	*-21.7*	*c o*	***0.50***	
BEL	-80.3	-93.2	*0.09*	-55.8	-36.6	***0.49***		-12.8	*c o - l*	*0.57*	yes
AUT	-92.3	-88.7	*0.10*	-75.9	-68.0	***0.37***			*c o -* ***l***	***0.54***	yes
DEU	-92.8	-76.7	*0.09*	-67.0	-46.0	***0.45***	-23.5	.	*c o -* ***l***	*0.53*	
NLD	-79.0	-67.5	*0.06*	-49.2	-30.3	***0.58***	-36.0	*-12.0*	*l*	*0.64*	yes
PRT		-66.9	*0.02*		-26.7	***0.44***		-18.4		*0.55*	
LUX	-66.2	-66.9	*0.11*	-55.2	-57.9	***0.32***	-35.5	-39.0		*0.47*	yes*
FRA	-48.3	-66.8	*0.03*	-39.8	-35.4	***0.47***	-29.7			*0.58*	
ITA°		-61.1	*0.01*		*-12.9*	***0.24***			*c o*	***0.38***	yes
RUS	-13.0	-14.2	*0.00*	-6.3	-9.9	*0.11*			***l***	***0.32***	
IRL°		*-10.1*	*0.00*			*0.05*				*0.33*	
SVN°	-57.4		*0.03*	-40.8		***0.47***	-28.7			*0.55*	yes
GRC°			*0.02*			*0.28*	26.1			*0.42*	
ISR	-17.3	5.8	*0.00*	-14.9	17.0	*0.04*		31.5	*l*	***0.25***	
MNE°		24.2	*0.00*		21.5	*0.21*		13.0		*0.37*	
comprehensive											
DNK	-85.4	-88.6	*0.06*	-84.1	-75.8	*0.11*		-39.8	***l***	***0.37***	
SWE	-47.6	-78.1	*0.04*	-49.0	-74.3	*0.06*	-35.3	-55.0		***0.36***	
ESP°		-65.7	*0.03*		-21.2	***0.31***		-36.0	*c o +*	*0.46*	
NOR	-57.6	-59.6	*0.02*	-57.4	-57.6	*0.02*	-32.9	-35.2		***0.25***	
USA	-42.8	-57.1	*0.03*	-41.5	-52.9	*0.12*	*-22.3*	-29.3		***0.38***	
GBR	-26.4	-40.8	*0.01*	-26.4	-40.7	*0.01*	-9.4	*-22.0*	*c o*	***0.39***	
HKG	*4.0*	-25.9	*0.01*	*3.5*	20.9	*0.12*	16.4		***l***	***0.39***	
CAN	-12.5	-21.9	*0.01*	-17.0	-21.2	*0.07*	-9.1	-19.3	*l*	***0.29***	
NZL	-28.1	-10.0	*0.00*	-28.1	-9.8	*0.00*	-7.3	-9.8	***l***	***0.40***	
EST°	-31.9		*0.02*	-38.3		*0.09*	.		*c o*	***0.35***	
AUS			*0.00*	-4.3		*0.02*			*l*	***0.34***	
LVA°			*0.00*			*0.11*	-9.1			***0.33***	
MAC	15.0		*0.01*	11.2	21.2	***0.25***	8.7	14.9		*0.37*	
QAT	36.2	83.9	*0.15*	34.6	80.7	*0.19*	29.1	45.3	*c o +, l +*	*0.35*	

Note

Table 4. Main factors affecting immigrant gaps in countries.					
	School	Background	School* Background	Country of origin	Language
tracking					
CHE		*		*	
BEL	*	*	*	*	*
AUT	*	*	*	*	*
DEU	*	*		*	*
NLD	*	*	*		*
PRT	*	*			_
LUX		*	*		
FRA	*	*			_
ITA°	*	*	*	*	_
RUS		*			*
IRL°		*			
SVN°	*	*	*	_	
GRC°		*			
ISR		*			
MNE°		*			
comprehensive					
DNK		*			*
SWE		*			
ESP°	*	*		*	_
NOR		*			
USA		*			
GBR		*		*	
HKG		*			*
CAN		*			*
NZL		*			*
EST°		*		*	
AUS		*			*
LVA°		*			
MAC	*	*			_
QAT	*	*		*	*

Note. In Italics countries where unconditional gaps are zero or positive.

Appendix

Table A1.	*Share of immigrant students*		*Share of immigrants speaking a foreign language at home*	
	Second generation	**First generation**	**Second generation**	**First generation**
AUS	12.85	9.02	25.84	44.92
AUT	5.31	7.86	68.41	68.74
BEL	7	6.27	31.23	32.77
CAN	11.22	9.93	29.19	66.23
CHE	11.83	10.57	39.42	60.78
DEU	7.68	6.56	42.84	51.3
DNK	4.17	3.4	38.23	62.23
ESP	(0.82)	6.1	20.05	31.87
EST	10.5	(1.06)	2.16	15.42
FRA	9.6	3.4	25.62	51.89
GBR	4.98	3.66	22.97	57.8
GRC	(1.17)	6.38	9.66	38.48
HKG	24.6	19.19	2.81	4.4
IRL	(1.06)	4.5	6.38	37.67
ISR	11.48	11.54	13.86	65.06
ITA	(0.67)	3.13	18.8	67.51
LUX	19.47	16.59	51.34	58.14
LVA	6.58	(0.48)	0.29	2.63
MAC	57.85	15.8	2.22	14.92
MNE	(1.83)	5.39	4.71	3.06
NLD	7.77	3.48	34.96	63.16
NOR	(2.99)	3.14	49.08	69.43
NZL	6.95	14.34	21.77	46.48
PRT	(2.41)	3.52	13.14	33.22
QAT	21.97	18.5	4.51	11.34
RUS	3.96	4.79	10.33	20.23
SVN	8.53	(1.75)	46.56	54.72
SWE	6.16	4.68	48.31	74.05
USA	9.39	5.84	52.29	71.91

Note: share of immigrant students under 3% in parentheses.

Table A2. List of school types by country

AUT	BEL	CHE	DEU	FRA
0400002 = 2	0560101 = 2	7560001 = 2	2760001 = 2	2500001 = 2
0400003 = 2	0560103 = 2	7560002 = 3	2760002 = 3	2500002 = 3
0400004 = 3	0560104 = 1	7560003 = 1	2760003 = 3	2500003 = 1
0400005 = 3	0560105 = 1	7560004 = 3	2760004 = 1	2500004 = 2
0400006 = 2	0560106 = 2	7560005 = 3	2760005 = 1	
0400007 = 1	0560107 = 1	7560006 = 2	2760006 = 2	
0400008 = 2	0560108 = 2	7560007 = 3	2760008 = 3	
0400009 = 1	0560109 = 3		2760009 = 2	
0400010 = 3	0560110 = 3		2760010 = 2	
0400011 = 3	0560111 = 3		2760012 = 3	
0400012 = 3	0569612 = 1		2760013 = 3	
0400013 = 3	0569613 = 3		2760014 = 3	
0400014 = 2	0569614 = 2		2760015 = 3	
0400015 = 2	0569615 = 3		2760016 = 2	
	0569616 = 1		2760017 = 1	
	0569617 = 2		2760018 = 2	
	0569618 = 2		2760019 = 2	
	0569619 = 2		2760020 = 2	
	0569620 = 3			
	0569622 = 3			
	0569623 = 3			
	0569624 = 3			

GRC	IRL	ISR	ITA	LUX
3000001 = 2	3720001 = 2	3760001 = 2	3800001 = 1	4420001 = 3
3000002 = 1	3720002 = 2	3760002 = 2	3800002 = 2	4420002 = 3
3000003 = 2	3720003 = 2	3760003 = 1	3800003 = 3	4420003 = 3
3000004 = 1	3720004 = 1	3760004 = 1	3800004 = 2	4420004 = 3
3000097 = NA	3720005 = 2	3760005 = 1	3800005 = 3	4420005 = 2
		3760006 = 2		4420006 = 1
		3760007 = 2		4420007 = 1
		3760008 = 2		4420008 = 2
		3760009 = 1		4420009 = 1
		3760010 = 2		
		3760011 = 1		

MNE	NLD	PRT	RUS	SVN
4990001 = 2	5280001 = 3	6200001 = 2	6430001 = 2	7050001 = 2
4990002 = 1	5280002 = 3	6200002 = 2	6430002 = 1	7050002 = 3
4990003 = 2	5280003 = 3	6200003 = 1	6430003 = 3	7050003 = 3
4990004 = 2	5280004 = 3	6200004 = 2	6430004 = 2	7050004 = 2
4990005 = 1	5280005 = 3	6200005 = 3		7050005 = 1
4990006 = 1	5280006 = 2	6200006 = 3		7050006 = 1
4990008 = 1	5280007 = 3	6200007 = 3		
4990009 = 1	5280008 = 2	6200008 = 3		
4990010 = 3	5280009 = 2			
4990011 = 3	5280010 = 2			
	5280011 = 1			
	5280012 = 1			
	5280097 = NA			

Table A3.a. Tracking system. Dependent variable: student scores in Science

	CHE**			**DEU****			**FRA***		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	530.86 [11.02]	625.54 [2.25]	591.19 [3.03]	531.77 [0.95]	631.76 [2.03]	627.30 [3.46]	504.5 [0.37]	565.61 [0.75]	582.75 [1.93]
2nd gen.	-69.32 [10.36]	-67.33 [10.54]	*-24.68 [11.77]*	-92.82 [1.88]	-67.02 [1.64]	-23.54 [3.34]	-48.25 [2.53]	-39.84 [4.28]	-29.70 [2.17]
1st gen.	-94.84 [7.93]	-87.61 [4.92]	*-21.71 [10.3]*	-76.66 [5.42]	-46.03 [3.88]		-66.82 [2.72]	-35.44 [2.7]	
mother.east.europe			-19.42 [4.36]						
student.east.europe			*-17.14 [7.21]*						
student.other.country			-30.82 [7.46]						
other language						*-27.20 [9.7]*			
grade 9		-41.70 [7.51]			-45.23 [3.62]	-31.32 [4.63]		*-10.78 [4.95]*	-17.52 [3]
grade 8		-101.93 [6.41]	-51.05 [6.55]		-98.47 [4.61]	-66.18 [5.37]		-55.54 [6.93]	-47.85 [4.75]
school 2		-53.67 [7.96]	-29.98 [5.95]		-117.28 [4.16]	-71.24 [5.25]		-110.77 [3.3]	
school 3		-95.39 [2.15]	-44.09 [2.51]		-89.49 [3.24]	-65.45 [2.58]		-202.24 [8.5]	
background			yes			yes			yes
n. obs.	12021	12021	10736	4603	4481	3707	4575	4575	4349
adj. R^2	0.12	0.28	0.49	0.09	0.45	0.53	0.03	0.47	0.58

	GRC*°			**IRL°**			**ISR**		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	477.64 [0.97]	498.31 [1.05]	517.95 [3.05]	510.42 [3.63]	531.39 [3.46]	517.95 [2.23]	461.85 [2.06]	474.42 [1.50]	545.82 [3.51]
2nd gen.							-17.29 [2.20]	-14.86 [1.88]	
1st gen.			26.15 [3.09]	*-10.06 [3.74]*			5.83 [1.58]	17.04 [1.36]	31.52 [4.18]
other language									-12.30 [4.17]
grade 9		*-21.02 [8.81]*			-29.23 [1.46]	-28.63 [1.41]			
grade 8		-95.63 [8.48]	-47.36 [12.63]		-118.70 [12.51]	-88.28 [2.9]		-51.79 [13.99]	
school 2		-102.37 [1.69]	-76.49 [1.64]					-41.38 [3.74]	-26.63 [2.12]
school 3									
background			yes			yes			yes
n. obs.	4795	4794	4397	4442	4442	4232	4201	4201	3427
adj. R^2	0.02	0.28	0.42	0.00	0.05	0.33	0.00	0.04	0.25

Table A3.a. Continued.									
	MNE*°			**PRT**			**RUS***		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	411.39 [0.78]	460.08 [3.02]	495.15 [1.37]	478.54 [2.16]	536.2 [7.61]	525.5 [3.56]	481.38 [0.45]	506.92 [0.76]	526.79 [3.10]
2nd gen.							-12.98 [1.55]	-6.25 [1.54]	
1st gen.	24.19 [2.15]	21.48 [2.5]	12.99 [3.82]	-66.92 [6.53]	-26.68 [3.57]	-18.38 [4.86]	-14.18 [2.80]	-9.94 [3.01]	
other language									-34.73 [1.77]
grade 9		-19.39 [1.75]	-15.57 [1.44]		-52.49 [3.13]	-41.16 [3.79]		-30.62 [3]	-13.89 [2.24]
grade 8		-91.35 [12.84]	-76.94 [16.71]		-118.36 [2.2]	-91.85 [1.79]		-68.09 [3.92]	-36.85 [3.09]
school 2		-73.82 [1.61]	-51.37 [2.52]		-30.77 [8.46]	-14.42 [4.85]		-16.91 [2.82]	-13.05 [1.51]
school 3		-63.4 [5.78]	-46.39 [5.11]		-48.72 [15.36]	-35.93 [11.03]		-84.93 [1.98]	-56.76 [1.85]
background			yes			yes			yes
n. obs.	4302	4302	3880	5053	4960	4701	5714	5714	5377
adj. R^2	0.00	0.21	0.37	0.02	0.44	0.55	0.00	0.11	0.32

Notes: standard errors in square brackets

° Only aggregate coefficient for the immigrant variable

** Countries where first year of selection at school is between 10 and 12 years old

* Countries where first selection at school is between 13 and 15 years old

Table A3.a. Continued.								
	AUT**							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	523.42	[1.99]	607.56	[1.92]	585.86	[2.94]	586.13	[6.07]
2nd gen.	-92.29	[13.40]	-75.94	[5.05]				
1st gen.	-88.69	[6.66]	-67.98	[2.43]				
father.middle.east					-59.86	[4.96]	-59.74	[4.80]
father.other.country					-16.9	[4.60]	-15.5	[4.71]
other language					*-25.61*	*[9.69]*	-25.88	[7.98]
grade 9			-42.56	[1.92]	-25.8	[1.22]	-21.3	[1.42]
grade 8			-116.13	[21.71]	-82.59	[8.56]	*-53.59*	*[21.18]*
school 2			-47.7	[1.76]	-24.39	[2.06]	-43.18	[4.79]
school 3			-120.48	[2.48]	-71.11	[2.37]	-65.84	[4.96]
books<100							-20.67	[1.62]
*grade 9*books<100*							-8.52	[1.09]
*school 2*occupHP*							0.34	[0.06]
*school 3*occupHP*							*-0.22*	*[0.08]*
background					yes		yes	
n. obs.	4891		4891		4456		4452	
adj. R^2	0.10		0.37		0.54		0.54	
	BEL**							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	523.16	[1.24]	585.68	[0.66]	578.86	[1.85]	581.9	[1.86]
2nd gen.	-80.34	[2.53]	-55.76	[2.42]				
1st gen.	-93.25	[1.41]	-36.62	[4.82]	-12.85	[1.86]	-12.48	[1.92]
father.east.europe					-21.87	[7.11]	-22.22	[7.77]
father.africa.north					-37.12	[7.23]	-38.39	[6.9]
father.africa.south					-20.35	[4.66]	-20.26	[4.8]
father.middle.east					-52.88	[6.20]	-53.11	[6.45]
father.other.country					-30.42	[2.19]	-30.89	[2.45]
other language					-16.21	[3.65]	-14.88	[3.45]
grade 9			-63.95	[2.96]	-48.59	[2.09]	-48.04	[2.24]
grade 8			-128.7	[3.35]	-101.19	[19.14]	-98.55	[18.45]
school 2			-81.66	[1.35]	-53.23	[2.33]	-58.2	[2.53]
school 3			-109.72	[9.37]				
female							-11.86	[2.28]
*school 2*female*							11.87	[0.77]
background					yes		Yes	
n. obs.	8743		8742		7509		7477	
adj. R^2	0.09		0.49		0.57		0.57	

Table A3.a. Continued.								
	ITA*°							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	479.3	[1.35]	520.97	[0.43]	529.99	[7.62]	547.29	[7.36]
2nd gen.								
1st gen.	-61.08	[1.75]	*-12.88*	*[4.84]*	10.55	[2.64]	9.36	[2.65]
student.other.country					-20.34	[5]	-18.99	[4.93]
other language								
grade 9			-39.9	[1.48]	-29.28	[1.18]	-28.32	[1.22]
grade 8			-131.7	[2.61]	-87.5	[12.11]	-88.38	[12.85]
school 2			-36.9	[1.15]	-27.89	[0.81]	-56.65	[2.65]
school 3			-94.29	[21.02]	-58.15	[2.2]	-91.33	[3.85]
female							-21.61	[0.91]
books<100							-31.99	[0.62]
hisced(Primary education)							-17.23	[5.95]
*school 2*female*							10.36	[1.8]
*school 3*female*							23.6	[1.97]
*school 2*books<100*							12.8	[3.39]
*school 2*books<100*							12.25	[3.47]
*school 2*hisced(Secondary education)*							19.01	[2.31]
*school 3*hisced(Secondary education)*							8.72	[2.25]
*school 2*hisced(Primary education)*							25.12	[2.40]
*school 3*hisced(Primary education)*							28.36	[4.27]
background					yes		yes	
n. obs.	21260		21260		20173		20173	
adj. R^2	0.01		0.24		0.38		0.38	
	LUX**							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	511.5	[0.95]	574.02	[2.82]	585.65	[3.04]	568.08	[7.65]
2nd gen.	-66.22	[2.14]	-55.17	[2.12]	-35.47	[2.18]	-18.15	[5.72]
1st gen.	-66.87	[1.92]	-57.88	[1.77]	-38.99	[1.76]		
other language							*-20.49*	*[8.20]*
grade 9					-10.75	[3.27]		
grade 8			-14.23	[2.98]	-25.51	[2.62]	-29.09	[6.22]
school 2			-61.74	[5.43]	-44.57	[6.32]	-41.26	[5.88]
school 3			-97.98	[3.09]	-58.02	[3.08]	-52.54	[2.90]
*grade 9*1st gen.*							-33.99	[5.10]
*grade 9*escs*							8.34	[1.77]
background					yes		yes	
n. obs.	4490		4490		4212		3765	
adj. R^2	0.11		0.32		0.47		0.49	

Table A3.a. Continued.								
	NLD**							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	534.42	[2.20]	638.27	[2.09]	631.61	[5.60]	648.64	[7.65]
2nd gen.	-79	[3.61]	-49.17	[3.72]	-35.99	[5.16]	-35.63	[5.23]
1st gen.	-67.52	[3.67]	-30.31	[4.13]	*-11.96*	*[4.87]*	-11.5	[5.07]
other language					-22.49	[3.42]	-22.76	[3.46]
grade 9			-29.39	[3.13]	-28.34	[1.85]	-28.39	[1.9]
grade 8					*-7.42*	*[3.01]*	*-7.46*	[3.02]
school 2			-93.86	[1.28]	-69.05	[1.28]	-95.12	[5.18]
school 3			-205.95	[1.19]	-152.18	[1.32]	-160.91	[6.77]
*school 2*occupHP*							0.46	[0.08]
background					yes		yes	
n. obs.	4787		4786		4186		4186	
adj. R^2	0.06		0.58		0.64		0.64	
	SVN°							
variables	Model 1		Model 2		Model 3		Model 4	
(Intercept)	525.48	[1.11]	589.41	[1.97]	603.43	[3.63]	603.5674	[2.83]
2nd gen.	-57.44	[2.34]	-40.8	[2.74]	-28.74	[2.24]	-21.39	[4.07]
1st gen.								
other language								
grade 9			-72.3	[5.76]	-67.4	[6.08]		
grade 8								
school 2			-89.47	[1.25]	-67.06	[1.43]	-69.38	[1.39]
school 3			-166.32	[1.99]	-130.05	[1.59]	-131.65	[1.39]
*grade9*father.east.europe*							*75.87*	*[28.36]*
*grade9*mother.east.europe*							*-80.97*	*[28.86]*
*grade9*hisced(Secondary education)*							-84.94	[24.28]
background					yes		yes	
n. obs.	6486		6486		5915		5850	
adj. R^2	0.03		0.47		0.55		0.56	

Notes: coefficients and standard errors (square brackets) of weighted survey regressions.

° Only one generation above 3% of students' population

** Countries where first year of selection at school is between 10 and 12 years old

* Countries where first selection at school is between 13 and 15 years old

Table A3.b. Comprehensive system. Dependent variable: student scores in Science

	AUS			CAN		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	529.18 [0.42]	534.16 [0.45]	546.89 [2.06]	540.9 [1.71]	549.96 [1.33]	539.78 [2.69]
2nd gen.		-4.28 [1.52]		-12.48 [1.53]	-16.95 [2.28]	-9.14 [2.18]
1st gen.				-21.94 [1.42]	-21.19 [2.82]	-19.31 [1.98]
other language			-18.12 [4.94]			-9.93 [3.34]
grade 9		-51.32 [1.66]	-36.55 [2.29]		-47.88 [3.04]	-25.44 [3.83]
grade 8					-137.2 [4.95]	-88.66 [5.75]
background			yes			yes
n. obs.	13844	13844	12786	21743	21743	19911
adj. R^2	0	0.02	0.34	0.01	0.07	0.29

	DNK			ESP°		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	502.98 [5.26]	558.96 [5.26]	571.26 [7.01]	493.63 [4.16]	529.68 [3.13]	552.15 [5.54]
2nd gen.	-85.4 [7.32]	-84.06 [7.82]	-39.79 [10.76]			
1st gen.	-88.64 [5.81]	-75.83 [8.07]		-65.73 [9.98]	-37.74 [9.84]	-35.98 [4.6]
father.other.country						12.23 [3.13]
other language			*-29.67 [15.1]*			
grade 9		-50.52 [2.35]	-41.3 [4.38]		-85.76 [1.69]	-57.08 [2.27]
grade 8		-110.08 [6.74]	-75.27 [22.44]		-139.65 [2.65]	-99.08 [1.86]
background			yes			yes
n. obs.	4493	4493	3861	19367	19367	17679
adj. R^2	0.06	0.11	0.37	0.03	0.31	0.46

	EST°			GBR		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	536.79 [0.46]	597.46 [3.96]	572.83 [4.26]	519.48 [1.20]	519.48 1.20]	521.28 [3.08]
2nd gen.	-31.94 [1.73]	-38.26 [1.55]	*10.97 [4.15]*	-26.42 [4.59]	-26.42 [4.59]	-9.41 [3.16]
1st gen.	-41.72 [5.96]	-40.53 [6.84]	18.86 [6.55]	-40.79 [11.32]	-40.67 [11.39]	*-22.04* [9.95]
father.middle.east			-21.62 [2.83]			-30.03 [3.72]
father.other.country			-29.79 [4.42]			
mother.middle.east			-19.76 [2.52]			
mother.other.country			-43.26 [4.50]			
other language						
grade 9		-47.76 [3.63]	-26.2 [3.66]			
grade 8		-93.7 [4.44]	-49.07 [4.54]		-	-
background			yes			yes
n. obs.	4756	4756	4517	12751	12751	11449
adj. R^2	0.01	0.09	0.35	0.01	0.01	0.39

Table A3.b. Continued.

	HKG			LVA°		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	546.75 [1.40]	561.3 [1.01]	588.7 [1.53]	491.82 [3.08]	565.31 [3.33]	556.14 [6.51]
2nd gen.	*3.95 [1.67]*	*3.55 [1.70]*				-9.09 [2.94]
1st gen.	-25.89 [2.27]	20.86 [2.99]	16.36 [2.41]		*-15.6 [7.08]*	
other language			-58.56 [15.94]			
grade 9		-44.98 [1.53]	-37.3 [1.5]		-63.39 [3.05]	-35.51 [3.25]
grade 8		-104.23 [3.28]	-69.88 [2.83]		-128.38 [2.69]	-75.13 [3.44]
background			yes			yes
n. obs.	4584	4584	4458	4596	4571	4413
adj. R^2	0.01	0.12	0.39	-0.00	0.11	0.32

	MAC			NOR		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	503.95 [0.87]	546.19 [1.76]	560.6 [1.38]	493.01 [1.27]	493.24 [1.25]	475.47 [3.33]
2nd gen.	15.04 [1.44]	11.15 [0.88]	8.7 [1.32]	-57.63 [3.93]	-57.43 [3.96]	-32.93 [4.53]
1st gen.		21.2 [2.42]	14.89 [2.34]	-59.56 [6.1]	-57.57 [5.84]	-35.24 [5.25]
other language						
grade 9		-47.86 [2.36]	-37.45 [3.18]		-64.78 [8.79]	
grade 8		-97.89 [1.4]	-74.38 [1.36]		-	-
background			yes			yes
n. obs.	4672	4672	4618	4585	4585	4264
adj. R^2	0.01	0.25	0.37	0.02	0.02	0.25

	NZL			QAT		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	535.98 [0.51]	536 [0.46]	573.37 [3.45]	329.62 [0.87]	338.48 [0.67]	383.89 [3.59]
2nd gen.	-28.09 [3.04]	-28.12 [3.16]	-7.26 [1.08]	36.23 [1.32]	34.61 [1.48]	29.07 [1.25]
1st gen.	-9.96 [1.93]	-9.84 [1.46]	-9.84 [2.73]	83.92 [1.95]	80.71 [1.94]	45.35 [1.89]
student.other.country						18.46 [6.68]
other language			-29.06 [2.66]			*20.77 [10.3]*
grade 9					-23.47 [1.05]	-14.03 [1.18]
grade 8		-	-		-62.17 [3.51]	-49.6 [2.94]
background			yes			yes
n. obs.	4711	4711	4399	5718	5718	5128
adj. R^2	0.00	0.00	0.40	0.15	0.19	0.35

	SWE			USA		
variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
(Intercept)	512.05 [2.77]	563.27 [5.62]	520.08 [6.92]	498.86 [2.48]	509.76 [2.37]	538.39 [3.13]
2nd gen.	-47.6 [5.2]	-49.02 [4.82]	-35.33 [4.70]	-42.75 [5.43]	-41.48 [5.50]	*-22.3 [10.85]*
1st gen.	-78.11 [3.33]	-74.34 [3.21]	-54.95 [3.05]	-57.14 [9.97]	-52.94 [11.21]	-29.34 [4.05]
other language						
grade 9		-51.02 [6.16]	-34.38 [5.58]		-83.32 [1.64]	-50.6 [2.98]
grade 8		-129.23 [5.40]	-98.86 [7.64]		-161.26 [17.13]	-100.28 [11.56]
background			yes			yes
n. obs.	4362	4362	4107	5422	5420	5055
adj. R^2	0.04	0.06	0.36	0.03	0.12	0.37

Notes: significant coeff. at 1% level, in Italics at 5 and 10%. Standard errors in square brackets. * Only aggregate coeff. for immigrant.

Table A4: Variables

Variable	Meaning
immigr	Status of immigration of student (intercept=native, 1= second generation immigrant, 2= first generation immigrant) [from *IMMIG*. PISA codebook]
language	Language spoken at home (intercept= test language, 1= other national language, 2= other language) [from *st12q01*. PISA codebook]
Fcountry, Mcountry, Scountry	Country of birth of father, mother and student (1= Western Europe, 2= North America, 3= Asia-rich countries, 4= North Africa ,5= East Europe, 6= South America, 7= North Africa, 8= Sub-Saharan Africa, 9= Meddle East, 10= Asia-poor countries, 11= other countries) [from *COBN_F, COBN_M, COBN_S*. PISA codebook]
categHP	Highest socio-economics employment category of parents (intercept = white collar high skilled, 1 = white collar low skilled, 2 = blue collar high skilled, 3 = blue collar low skilled) [from *HsECATEG*. PISA codebook]
hisced	Highest educational level of parents (intercept = tertiary education, 1 = secondary, 2 = primary) [from *hisced*. PISA codebook]
occupHP	Index of highest parental occupational status (range 16- 90) [from *HISEI*. PISA codebook]
gender	Gender of student (intercept=male, 1= female) [from *st04q01*. PISA codebook]
books	How many books at home (intercept= >100, 1 = <100) [from *st15q01*. PISA codebook]
pc	Computer at home (intercept = yes, 1 = no) [from *st13q04*. PISA codebook]
escs	Index of economic, social and cultural. [from *escs*. PISA codebook]
regular lessons of science, mathematics, reading	Number of regular lessons (weekly) in science, mathematics and reading, respectively (intercept = more than 4 hours, 1= up to 4 hours) [from *st31q01, st31q04, st31q07*. PISA codebook]
grade	The grade student is in. (intercept = grade >9, 1= grade 9, 2= grade<9) [from *ST01Q01*. PISA codebook]
school	Type of school attended by the student. See Table A2.
envware	Index of students' awareness of environmental issues. [from *envaware*. PISA codebook]
sciefut	Index of future-oriented motivation to learn science. [from *sciefut*. PISA codebook]

Table A5: Comparison of coefficients between Models II and I

	AUT				**BEL**				**CHE**			
	model 1	model 2	distance		model 1	model 2	distance		model 1	model 2	distance	
(Intercept)	523.42 [1.99]	607.56 [1.92]	-84.14 [0.68]	***	523.16 [1.24]	585.68 [0.66]	-62.52 [0.90]	***	530.86 [11.02]	625.54 [2.25]	-94.68 [9.13]	***
2nd gen.	-92.29 [13.40]	-75.94 [5.05]	-16.36 [8.65]		-80.34 [2.53]	-55.76 [2.42]	**-24.58 [0.36]**	***	-69.32 [10.36]	-67.33 [10.54]	-1.99 [0.21]	***
1st gen.	-88.69 [6.66]	-67.98 [2.43]	-20.72 [8.42]	*	-93.25 [1.41]	-36.62 [4.82]	**-56.63 [4.85]**	***	-94.84 [7.93]	-87.61 [4.92]	-7.22 [3.18]	*

	DEU				**FRA**				**GRC**			
	model 1	model 2	distance		model 1	model 2	distance		model 1	model 2	distance	
(Intercept)	531.77 [0.95]	631.76 [2.03]	-99.99 [1.36]	***	504.5007 [0.37]	565.607 [0.75]	-61.11 [0.68]	***	477.6383 [0.97]	498.308 [1.05]	-20.67 [0.90]	***
2nd gen.	-92.82 [1.88]	-67.02 [1.64]	**-25.80 [0.58]**	***	-48.25 [2.53]	-39.84 [4.28]	-8.41 [2.20]	***				
1st gen.	-76.66 [5.42]	-46.03 [3.88]	**-30.63 [2.74]**	***	-66.82 [2.72]	-35.44 [2.7]	**-31.38 [3.21]**	***			**-60.34 [20.63]**	***

	IRL				**ISR**				**ITA**			
	model 1	model 2	distance		model 1	model 2	distance		model 1	model 2	distance	
(Intercept)	510.4228 [3.63]	531.386 [3.46]	-20.96 [1.84]	***	461.851 [2.06]	474.4199 [1.50]	-12.57 [0.95]	***	479.30 [1.35]	520.97 [0.43]	-41.67 [1.15]	***
2nd gen.	-12.46 [4.25]		-5.25 [0.34]	***	-17.29 [2.20]	-14.86 [1.88]	-2.43 [0.76]	***				
1st gen.	*-10.06 [3.74]*				5.83 [1.58]	17.04 [1.36]	-11.21 [0.66]	***	-61.08 [1.75]	*-12.88 [4.84]*	**-48.21 [6.09]**	***

	LUX				**MNE**				**NLD**			
	model 1	model 2	distance		model 1	model 2	distance		model 1	model 2	distance	
(Intercept)	511.50 [0.95]	574.02 [2.82]	-62.53 [2.49]	***	411.3859 [0.78]	460.0809 [3.02]	-48.69 [2.34]	***	534.42 [2.20]	638.27 [2.09]	-103.85 [1.10]	***
2nd gen.	-66.22 [2.14]	-55.17 [2.12]	-11.05 [1.52]	***					-79.00 [3.61]	-49.17 [3.72]	**-29.83 [0.21]**	***
1st gen.	-66.87 [1.92]	-57.88 [1.77]	-8.99 [0.31]	***	24.19 [2.15]	21.48 [2.5]	2.71 [0.69]	***	-67.52 [3.67]	-30.31 [4.13]	**-37.22 [5.03]**	***

	PRT				**RUS**				**SVN**			
	model 1	model 2	distance		model 1	model 2	distance		model 1	model 2	distance	
(Intercept)	478.5372 [2.16]	536.20 [7.61]	-57.66 [5.52]	***	481.3785 [0.45]	506.918 [0.76]	-25.54 [0.42]	***	525.48 [1.11]	589.41 [1.97]	-63.93 [1.03]	***
2nd gen.			-20.93 [10.29]	*	-12.98 [1.55]	-6.25 [1.54]	-6.73 [0.16]	***	-57.44 [2.34]	-40.80 [2.74]	-16.64 [1.60]	***
1st gen.	-66.92 [6.53]	-26.68 [3.57]	**-40.24 [6.32]**	***	-14.18 [2.80]	-9.94 [3.01]	-4.24 [0.36]	***				

Table A5 (cont.)

	AUS			**CAN**			**DNK**		
	model 1	model 2	distance	model 1	model 2	distance	model 1	model 2	distance
(Intercept)	529.1794 [0.42]	534.1581 [0.45]	-4.98 [0.21] ***	540.90 [1.71]	549.96 [1.33]	-9.06 [0.43] ***	502.98 [5.26]	558.96 [5.26]	-55.98 [2.36] ***
2nd gen.		-4.28 [1.52]	2.61 [0.08] ***	-12.48 [1.53]	-16.95 [2.28]	4.47 [0.99] ***	-85.40 [7.32]	-84.06 [7.82]	-1.34 [0.52] *
1st gen.			-2.32 [1.02] *	-21.94 [1.42]	-21.19 [2.82]	-0.75 [1.55]	-88.64 [5.81]	-75.83 [8.07]	-12.81 [2.41] ***
	ESP			**EST**			**GBR**		
	model 1	model 2	distance	model 1	model 2	distance	model 1	model 2	distance
(Intercept)	493.63 [4.16]	529.68 [3.13]	-36.05 [1.17] ***	536.79 [0.46]	597.46 [3.96]	-60.68 [3.81] ***	519.482 [1.20]	519.482 1.20]	0.00 [8.79]
2nd gen.			-5.24 [0.44] ***	-31.94 [1.73]	-38.26 [1.55]	6.32 [0.29] ***	-26.42 [4.59]	-26.42 [4.59]	0.00 [2.79]
1st gen.	-65.73 [9.98]	-37.74 [9.84]	**-27.99 [0.47]** ***				-40.79 [11.32]	-40.67 [11.39]	-0.12 [7.09]
	HKG			**LVA**			**MAC**		
	model 1	model 2	distance	model 1	model 2	distance	model 1	model 2	distance
(Intercept)	546.7533 [1.40]	561.30 [1.01]	-14.55 [0.50] ***	491.8216 [3.08]	565.3087 [3.33]	-73.49 [2.65] ***	503.9518 [0.87]	546.1927 [1.76]	-42.24 [1.96] ***
2nd gen.	*3.95 [1.67]*	*3.55 [1.70]*	0.40 [0.46]			1.41 [0.61] *	15.04 [1.44]	11.15 [0.88]	3.89 [1.57] *
1st gen.	-25.89 [2.27]	20.86 [2.99]	*-46.75 [1.17]* ***		*-15.60 [7.08]*	11.39 [0.39] ***		21.20 [2.42]	*-24.79 [0.43]* ***
	NOR			**NZL**			**QAT**		
	model 1	model 2	distance	model 1	model 2	distance	model 1	model 2	distance
(Intercept)	493.01 [1.27]	493.24 [1.25]	-0.23 [0.03] ***	535.98 [0.51]	536.00 [0.46]	-0.03 [0.12] .	329.6178 [0.87]	338.4801 [0.67]	-8.86 [0.36] ***
2nd gen.	-57.63 [3.93]	-57.43 [3.96]	-0.20 [0.11] .	-28.09 [3.04]	-28.12 [3.16]	0.03 [0.12] .	36.23 [1.32]	34.61 [1.48]	1.62 [0.47] ***
1st gen.	-59.56 [6.1]	-57.57 [5.84]	-1.99 [0.39] ***	-9.96 [1.93]	-9.84 [1.46]	-0.12 [0.70]	83.92 [1.95]	80.71 [1.94]	3.21 [0.36] ***
	SWE			**USA**					
	model 1	model 2	distance	model 1	model 2	distance			
(Intercept)	512.05 [2.77]	563.27 [5.62]	-51.22 [5.99] ***	498.86 [2.48]	509.76 [2.37]	-10.90 [0.25] ***			
2nd gen.	-47.60 [5.2]	-49.02 [4.82]	1.42 [0.61] *	-42.75 [5.43]	-41.48 [5.50]	-1.27 [0.15] ***			
1st gen.	-78.11 [3.33]	-74.34 [3.21]	-3.77 [0.57] ***	-57.14 [9.97]	-52.94 [11.21]	-4.19 [1.32] ***			