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Immigrants, schooling and background.

Cross-country evidence from PISA 2006

Marina Murat*, Davide Ferrari, Patrizio Frederic***, Giulia Pirani******

Abstract. Using data from PISA 2006, we examine the performance of immigrant students in different international educational environments. Our results show that immigrant gaps – differences in scores with respect to natives - are smaller where educational systems are more flexible and students' mobility between courses and school curricula is higher. Unlike previous studies, our analysis reveals no direct relation between these gaps and the schooling models, be they comprehensive or tracking, adopted by countries.

Keywords: International migration, educational 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 widely acknowledged. However, while its most likely economic consequences are unequal opportunities for immigrants and natives in the labour market (Dustmann, 2004), its causes are still unclear. Recent literature focuses on the characteristics of immigrants (Schneeweiss, 2009; Ammermueller, 2007; Entorf, and Minoiu, 2005; Entorf and Tatsi, 2009; OECD, 2006), and only rarely considers the structural features of educational systems (Entorf and Lauk, 2006; Schnepf, 2006).

Educational systems do vary significantly across countries and may have different implications in terms of fairness and equality of opportunities. While some countries track students in differing-ability schools by the age of ten, others keep their entire school system comprehensive. Several studies find that comprehensive schooling seems to be positively related to greater equality of opportunities in society (Schutz et al., 2008; Brunello and Checchi, 2007; Wömann, 2004; Ammermueller, 2005; Hanushek and Wömann, 2006; Bauer and Riphahn, 2006), and even that it boosts the economies' long-term development (Bertocchi and Spagat, 2004; Krueger and Kumar, 2004).

The data from the standardized cross-country surveys, Trends in Mathematics and Science Study (TIMSS) and the Program for International Student Assessment (PISA), provide some evidence of a lower dispersion of test scores, and hence higher equity, among groups of countries with comprehensive schools. All this suggests that the school performance and potential social mobility of immigrant students can be affected by the education models of their host countries and also that the scores of immigrants should be more similar to those of natives with comprehensive schooling.

This paper uses the PISA 2006 database to analyse the performance of immigrant students in different international educational environments. It takes into account a large number of countries, several background factors and the type of school attended by each student. To our knowledge, this micro-level approach to the study of education systems is new with respect to previous research. A first finding is that immigrant gaps are not directly related to the two main educational systems prevailing in these countries and, moreover, that these gaps are not necessarily smaller in countries characterized by the comprehensive education model.

More precisely, we find the scores of immigrants to be more similar to those of natives where there is more flexibility in education, i.e., where students can change the level of difficulty of the core courses of their study program more than once during their years of secondary education. This flexibility, however, is determined more by how each of the two main educational systems is actually implemented, rather than by being comprehensive or tracking alone.

Comprehensive, education in Continental Europe is generally based on a unique and uniform program, while in English-speaking countries it coexists with the streaming of courses. In the latter version, schools teach the same subjects at different levels of difficulty and students choose among them. School tracking, on the other hand, is based on a choice at an early age and a clear-cut differentiation between school types in some countries of Continental Western Europe, and on later ages of choice and more modest differences between tracks in other countries of the world. In our results, the larger gaps are found in Continental Western Europe, where the versions of both models are more rigid, while the narrower gaps concern English-speaking and other countries characterized by greater flexibility, again, in both models.

The possibility of choosing the level of difficulty of some main courses of secondary-school study programs is important for all students, in that it allows them to discover and develop their individual abilities, but it can be crucial for immigrants, especially if they are from culturally distant countries. Because of their background, the latter may find certain subjects to be harder. The the option to choose allows them to take these courses at more elementary levels, at least initially, and increase the level of difficulty later; other courses can be taken at normal levels of difficulty. This can explain the narrower gaps of comprehensive-streaming countries with respect to other systems. In comprehensive systems that do not allow streaming, the relative disadvantage of immigrants will simply be ignored, with the likely consequence of lowering their overall performance, while with tracking, immigrant students are most likely to attend vocational and technical schools, where all subjects are taught at levels below those of academic schools

These findings imply that no matter what type of educational system is in force, greater flexibility that increases the possibility of choice in education helps to close the immigrant gap. In turn, it can positively affect subsequent labour market opportunities and the social mobility of these immigrants. The paper is structured as follows: Section 2 presents some basic traits of the education models, Section 3 presents the data and descriptive statistics, Section 4 illustrates the estimation strategy, Section 5 analyzes the results and Section 6 offers our conclusions.

2. Educational systems

Before schooling was made compulsory, education in Western Europe was provided by the workshops and guilds of craftsmen. They trained the children of the working classes to master practical tasks. Religious institutions also offered education, providing theoretical learning to the children of the aristocracy and the upper classes. When school attendance was made compulsory, these pre-existing forms of instruction were integrated and regulated in the new systems. After elementary education, the children, of different social extraction, were channelled either into vocational schools, which provided practical instruction, or into academic schools, which supplied academic education. This reproduced the previous separation in education and preserved the hierarchical stratification of the society (Bertocchi and Spagat, 2004).

The goal of the United States and, later, of other English-speaking immigrant receiving countries was that of rapidly and effectively integrating populations originating from different areas of the world and of supporting the expansion of the economy through schooling. The choice in those cases fell on general education and on ‘comprehensive’ secondary schools that provided multi-purpose knowledge to all students. However, while there was only one curriculum, education was not entirely uniform: the ‘streaming’ of courses allowed schools to teach core subjects at different levels of difficulty, and students to choose the preferred level for each course. In this setting, the specific skills needed by the progressive industrialization of the economy were provided by technical courses either within comprehensive schools or during tertiary education.

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, such as Latin and Greek culture and languages, were gradually substituted by more general topics concerning scientific knowledge and by modern languages (Leschinsky and Mayer, 1999). The comprehensive model adopted in Continental Western Europe, however, differs from that of the US and other English-speaking countries in that not only is the curriculum unique, but the core courses are taught at a uniform level (some exceptions are foreign languages in Norway and mathematics in Sweden).

Tracking school systems also differ between countries. In this case, the differences lie especially in the age at which the type of school is selected, the number of school tracks, or types, and the degree of differentiation between them. Selection takes place at the age of ten in Austria and Germany, at twelve in the Netherlands, Belgium and Switzerland and later elsewhere (Table 1). During recent decades, some of these countries have delayed the first age for selection, reduced the degree of differentiation between tracks and lifted some of the restrictions that barred university access to students from technical schools.

The number of students in grades below their age, or 'repeaters', also varies widely between countries. This depends on educational customs rather than on the institutions, but it can significantly interact with the institutional characteristics of each education model. For example, a large proportion of repeaters can reinforce the segmentation of the student population in tracking systems if they are channelled into non-academic schools more than non-repeaters, or it can create an artificial stratification within comprehensive schools. Both cases are relevant to our analysis of immigrant students.

Table 1 groups the countries according to their education models, comprehensive - streaming or homogeneous - and tracking, as well as by the frequency of repeaters in the student population. It shows that the tracking system of education is especially present among the countries of Continental Western Europe, where selection can take place early (at 10 years of age in Austria and Germany, at 12 in Belgium, Switzerland and the Netherlands, at 13 in Luxembourg and at 14 in Italy and France; see also Wömann, 2009) and repeaters are more frequent than in other areas. There is less differentiation between tracks and there are less repeaters in Ireland, Greece, Montenegro, Slovenia and Israel. Among European countries, comprehensive schools are present in Scandinavia, Spain, Estonia and Latvia, with a high proportion of repeaters in Spain, Denmark and the two Baltic countries. Repeaters are instead less frequent in English-speaking countries, where schooling is mostly comprehensive: UK, Australia, Canada, New Zealand and the US (data on repeaters from PISA 2006).

3. Data and descriptive statistics

Promoted by OCSE since 2002, the Programme for International Student Assessment (PISA) is an internationally standardized evaluation conducted every three years. Its main purpose is to collect data on the competencies of 15-year-old students 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, referring to data collected in 2006, which included 57 jurisdictions and focused on science. For the OECD group of countries, students' scores were standardized with an international mean of 500 and a standard deviation of 100.

The twenty-nine countries in Table 1 are those where the presence of immigrant students is equal to at least 3% of the student population.[1] Table A1 illustrates the shares of first- and second-generation immigrant students in each of them.

The PISA student questionnaire includes an indicator (*ISCEDO*) of our main variables of interest, school types, listing them as general, pre-vocational and vocational, but figures are missing or are unreliable for Belgium, Germany, Italy, Switzerland and other countries making up our sample. Hence, we have built a proxy by using the UNESCO (2006) classification of education systems by first splitting the school types existing in each country into three main categories, i.e., type 1: general or academic, type 2: intermediate, and type 3: vocational.[2] We have linked this classification to the variable *(PROGN)* of the student database indicating the school attended by each student and, as a result, obtain a proxy of school types at the micro level (details in Table A2). This differs from previous studies on educational systems, where school types are considered at an aggregate country level (Schutz et al., 2008; Brunello and Checchi, 2007; Wömann, 2004; Ammermueller, 2005; Hanushek and Wömann, 2006; Bauer and Riphahn, 2006).

Table 2 reports the values of an index of "specialization" of immigrants compared to natives in each school type and grade. Index numbers are the ratio of the share of immigrant students in a given school type or in a grade, to 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-year olds in each country. Numbers in bold print (at or above 1.05) indicate a relative specialization of immigrants in non-academic schools or in the lower grades. Regarding repeaters, numbers are in bold print only for those countries where, as indicated in Table 1, repeating grades is a common phenomenon even among the overall student population. Indexes for Switzerland are biased in favour of type-1 schools because large numbers of international students, not belonging to the category of immigrants, move there every year to attend these schools.[3]

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[1] Similar conditions were adopted in OECD (2006) based on PISA 2003, where 17 countries were selected.
The 3% condition holds only for the second-generation student population in Estonia, Latvia and Slovenia, and the first generation in Greece, Ireland, Montenegro, and 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 students 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 have included in type 3, while our dataset contains no data on students attending special schools in countries with comprehensive education models.

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

Several numbers in bold print in Table 2 indicate a relatively higher proportion of immigrants attending non-academic schools and in the lower grades concern the following countries of Continental Western Europe: the Netherlands, Italy, France, Belgium, Austria, Germany, Luxembourg and Switzerland, which are characterized by marked stratification of the educational system and high proportions of repeaters. Immigrants repeat grades more than natives also in Denmark and Spain in Europe and Hong Kong and Macao in Asia. Index numbers are generally higher for first-generation immigrants.

In this context, what are the scores of immigrant students? A first, raw indicator of the immigrant gap in school performance is obtained from simple regressions of the students' test scores on the dummy variable regarding immigrant/native status. The regression equation, one for each country, is:

$$Y_{is} = \beta_0 + \beta I s_i + \varepsilon_{is} \qquad (1)$$

where Y_i is the response variable representing the science score obtained by student i in school s, I_{is} is the student's immigrant status (first- and second-generation), β_I denotes the coefficient and ε_{is} is the error term.

Gaps depicted in Figure 1 are variations with respect to the mean scores of native students, which are captured by the intercept. Coefficient numbers are in Model 1 of Table 3 below. Significance is at 1% level, except for first-generation immigrants in Ireland and second-generation immigrants in Hong Kong, where it is at the 5% and 10% level, respectively. It is worth noting that the distribution of gaps across countries is independent of the relative presence of immigrant students (Table A1).

The left-hand side of the figure depicts countries with school tracking and the right-hand side, those with the comprehensive model. It clearly shows that, with the exception of Greece, the more negative gaps are in Continental Western Europe, where both systems of education are present. More specifically, among countries that adopt the tracking system, negative gaps are high in Switzerland, Belgium, Austria, Germany, Netherlands, France, Italy, Portugal and Luxembourg, and among countries with comprehensive schools, negative gaps are high in Denmark, Norway, Sweden and Spain. This is consistent with the relative specialization of immigrants in the non-academic schools and in the lower grades of Table 2.

Outside this area, negative gaps are smaller or non-significant; in particular, they are small in English-speaking countries (smaller in the USA) and, in Eastern Europe, in Russia, Latvia, Estonia, as well as in Israel and Hong Kong (despite the fact that immigrants repeat grades more frequently than natives in Hong Kong, as shown in Table 2). Immigrant scores are above those of natives in Montenegro, Qatar and Macao. Finally, the underlying data show that gaps are unrelated to the average scores of the overall student population or of just native students.

4. Estimation strategy

4.1 Models

Our first concern is how to compare gaps across countries. Most of the recent literature measures differences in performance between groups of individuals by using either decomposition techniques - a well-known one has been proposed by Oaxaca (1973) and Blinder (1973) - or the coefficient of the dummy variable denoting the group of interest in pooled regressions. Recently, Elder et al. (2010) have shown that the value of the OLS gap of pooled regressions tends to lie between the boundaries represented by the two Oaxaca-Blinder alternative gaps resulting from the base formulae. Moreover, the distance between these bounds tends to be higher as the shares of the two groups in the total population are more uneven; in this case the dummy variable approach is preferable. As the shares of immigrant and native students differ greatly in all countries in our sample, we chose to use the latter.

We use separate regressions, one for each country, which implies that country-specific variables could be missing. On the other hand, by using the aggregate dataset, with country fixed effects added to the regressions, we would lose much of the information that interests us more. Hence, we shall keep regressions separate and add, in subsequent specifications of the model, control variables and interactions between them that help to mitigate the above problems.

Problems of sample bias may in turn be related to differences in ability between groups of students. For example, immigrants can be distributed non-randomly between countries if more able individuals systematically prefer some destinations with respect to others. In principle, the innate ability of parents could affect immigrant student scores. Up to now, however, theoretical predictions on the kind of countries more able immigrants prefer have found no empirical support (Fuchs and Wömann, 2007). Hence, we suppose that, in terms of innate ability, immigrants are randomly distributed across countries and, similarly, that immigrant students do not systematically differ from natives. All that regards skills, educational level of parents and other background factors should be captured by our control variables. In all cases, we shall refer to correlations between variables, not to causal relations.

We estimate a linear educational production function, where the output is the score of each student and inputs are the school type they attend, the grade they are in and a number of regressors regarding their characteristics and socio-economic background (Table A3). In all models, our coefficient of interest is β_I, the immigrant gap of equation (1). We first look at the sole impact of school factors on β_I by adding the variables regarding schools and grades to the regression (again, one for each country):

$$Y_{is} = \beta_0 + \beta_I I_{is} + \beta_G G_{is} + \beta_S S_{is} + \varepsilon_{is} . \tag{2}$$

G_{is} and S_{is} are dummies, respectively representing grade and type of school of student i and β_G and β_S are their coefficients. Empirical findings indicate a higher dispersion of scores in tracking systems of education (Hanushek and Wömann, 2010), while the negative gaps seen above imply that immigrant scores tend to lie at the lowest tail of the distribution of scores. Hence, relatively to equation (1), we expect gaps to change more as effect of the introduction of the school regressors in countries having the tracks system of education. In turn, gaps should change more where tracks are more dissimilar, the proportions of repeaters are high and the index values of Table 2 are significantly above unity, denoting a relative specialization of immigrants in the lower grades and in non-academic schools.

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

$$Y_{is} = \beta_0 + \beta_I I_{is} + \beta_G G_{is} + \beta_S S_{is} + \boldsymbol{\beta}_X \boldsymbol{X}_{is} + \varepsilon_{is} , \tag{3}$$

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

Some of the background variables such as the country of birth of students and their parents and the main language spoken at home (if different from the national language) are especially pertinent to immigrant students and are of particular interest. The country of birth variable can help to control for the sample bias mentioned above. Some studies such as those by Schnepf (2004), Fertig and Schmidt (2002), Entorf (2006), which give OECD countries special attention, find that a non-national language spoken at home tends to be negatively correlated with performance, and that coefficients tend to be more negative in English-speaking countries.

Even controlling for background factors, the correlations with the dependent variable of our variables of interest, *school type* and *grade*, could be only partial. Coefficients can be affected by the education received by immigrant students before age fifteen, which we cannot control for with our cross-section regressions, especially regarding first-generation students, who are 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 a low frequency of grade repetition, and indirectly in countries having a tracking system of education, as demonstrated by a higher presence of first-generation immigrants in lower grades or non-academic schools (Table 2). However, the quality of education provided by the schools attended by immigrant students before entering the country is likely to be correlated with the family background, especially as regards the level of education of parents and the country of birth, both variables we control for in our analysis.

Furthermore, and perhaps more significantly, the student's socio-economic background or her characteristics may influence her choice of school or the grade she is in. In this case, coefficients will capture the school factors' direct correlation with scores, but also the indirect effects of background. To control for such possible correlations, we add the interacted variables, regarding background and school or type of school, to our regressions. The model specification now becomes:

$$Y_i = \beta_0 + \beta_I I_{is} + \beta_G G_{is} + \beta_S S_{is} + \boldsymbol{\beta}_X \boldsymbol{X}_{is} + \boldsymbol{\beta}_{\boldsymbol{IS}} (S_{is} \times \boldsymbol{Xs}_i) + \boldsymbol{\beta}_{\boldsymbol{IG}} (G_i \times \boldsymbol{Xs}_i) + \varepsilon_i \qquad (4)$$

$S_{is} \times \boldsymbol{X}_{is}$ and $G_{is} \times \boldsymbol{X}_{is}$ represent the interactions between background and our variables of interest, *school types and grade*, and $\boldsymbol{\beta}_{\boldsymbol{IS}}$ and $\boldsymbol{\beta}_{\boldsymbol{IG}}$ are the vectors of their coefficients.

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

4.2 Methods: BRRs and BIC selection

We select the relevant background variables to be included in the regression for each country by using the Bayesian Information Criterion (BIC) and, as the mode of stepwise search, backward selection is applied up to the point where taking away another regressor from the model increases the BIC (e.g. see Burnham and Anderson, 1988). We 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 now popular Least Absolute Shrinkage and Selection Operator (LASSO) has shown that BIC should be preferred to the other methods. Generally, BIC selects 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. Thus, except for the variables *1^st^ gen* and *2^nd^ gen*., which are included in all regressions, the control variables effectively selected can differ among countries. We then run the regressions by the weighted OLS method using BRR.

For computing model parameter estimates and their standard errors, we employed the balanced repeated replications (BRRs) (e.g. see Särndal 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 sampling design. Similarly to Jacknife and Bootstrap methods, it 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 the 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 interest. 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 estimate replicates to confirm that such an assumption is trustworthy for all the reported results.

5. Results

Table 3 reports only the coefficients of the immigrant gap of 2nd- and 1st- generation students and the adjusted R^2. More complete results, including the significant coefficients of the school-type and grade variables, of selected background variables and of significant interactions are reported in Tables A3a and A3b of the Appendix.[4] To simplify matters, only significant coefficients are depicted in all Tables.

Model 1 shows that not only gaps (shown in Figure 1), but also the adjusted R^2 of the regressions differ widely between countries. The sole immigrant-native status condition explains more than 10% of the total variation in Switzerland, about 10% in Luxembourg, Austria, Belgium and Germany, about 5% in the Netherlands, Denmark and Sweden, and has no explicative power in Ireland, New Zealand, Australia, Great Britain, Canada, Hong Kong, Latvia, Macao and other countries. As shown by Table A1, these R^2 values are unrelated to the shares of immigrant students in the total student populations of countries.

As expected, the introduction of the school variables into the regressions affects immigrant gaps. In Model II of Table 3 they shrink substantially with respect to Model I in the regressions regarding the Netherlands, Belgium, Germany, France, Slovenia, Italy, Portugal and Spain. This suggests that much of the original immigrant gap in these countries of Continental Western Europe is related to school factors. Despite the fact that Model II does not include control variables and is still incomplete, we applied the BRR method to the procedure indicated by Allison (1995), based on Clogg et al. (1995), to check for the significance of the differences between the immigrant coefficients of Models II and I.[5] The results, in Table A5, show differences that are statistically significant at the 1% confidence level for all the above countries, except Austria, where significance reaches the level of 10%.

As may be noted from Table A3, the scores of students attending vocational or technical schools in these countries can be lower than those of students attending academic schools in measures equal or above an international standard deviation (as said: 100 for OECD countries). This is much more than a school year – on PISA tests, one grade-level equivalent equals roughly 35 percent of a standard deviation (Schuetz, Ursprung and Woessmann, 2008). Repeating grades while attending a non-academic school, a condition more frequent for immigrants than for natives, adds up to the already huge disadvantage.

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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 is not the same for some countries, but also, more significantly, because the introduction of the country of origin variable often captures much of the effects originally included in the immigrant gap.

Turning back to Table 3, school factors explain a large part of the total variation among countries in Continental Western Europe: the adjusted R^2 for the Netherlands almost reaches 0.6; it is about 0.5 for Belgium and France, and around 0.3 for Luxembourg, Austria and Spain (where only the grades regressor applies). With the exception of Spain, these countries have tracking systems of education and also a relative specialization of immigrants in lower grades and in non-academic schools (Table 2). Hence, school factors in this area matter substantially for the whole student population, and especially for immigrants

These results are merely indicative, however, without the inclusion of control variables into the regressions. Model III of Table 3 depicts the immigrant variable coefficients, once family background, a foreign language spoken at home and the countries of origin of immigrants and their parents have been included (coefficients in Table A3). The results show further contraction of gaps in the regressions regarding Switzerland, Belgium, Germany, the Netherlands, Luxembourg and Slovenia, with both background and schooling being significantly correlated with scores. Now gaps must be read by taking into account the immigrant variable coefficients and also the country of origin variable coefficients. The fact that in these countries, as well as in Italy and Austria, much of the correlation with scores was already captured by school variables in Model II, in turn, suggests that school choice, grade repetition and family background may be related factors. Their interactions will be considered below.

Background seems to plays a more important role than schooling in most countries that adopt the comprehensive education system. This is not surprising, as for most of them school factors in Model II did not explain much of the total variation. The adjusted R^2 of Model III in Table 3 increases substantially for English-speaking and Scandinavian countries; in the latter there are also significant contractions of the immigrant gaps with respect to Model II. It can be observed that even with this increase, the adjusted R^2 remains generally below those of countries with school tracking, and in some cases even below the R^2 of the latter in Model II. Hence, background and school factors together, in countries with comprehensive schools can explain less of the total variation than just schooling in Western European countries having the tracking system.

The results of the interactions between background factors and school variables (Model IV in Table 3) mostly confirm what could be expected from the above results: the coefficients of interacted variables are significant in Belgium, Austria, Netherlands, Luxembourg, Italy and Slovenia, all countries of Continental Europe where both school and background factors were highly significant in Models II and III. The background variables more frequently involved in these interactions (Tables A3a-b) are: levels of education and occupation of mother and father, books at home, gender, and, in Luxembourg and Slovenia, immigrant status and country of origin. On the other hand, the educational variables are: school types in Italy, Belgium and Netherlands, school types and grade in Austria, and grade in Luxembourg and Slovenia. Unexpectedly, however, the interactions between background and school factors are not necessarily more important in countries where tracking starts earlier. For example, family characteristics and type of school seem to be strongly interrelated in Italy, where tracking starts at fourteen, while the interacted variables have no significant coefficients in Germany, where it starts at ten (on Germany, see also Checchi and Flabbi, 2007; Dustmann, 2004).

Table 4 summarizes our main results. Speaking a foreign language at home (*Language* column in the Table, coefficients in Tables A3a-b) is negatively correlated with scores in several countries, but, unlike the results of a previous study (Schpneff, 2007), not especially in English-speaking countries. They are Belgium, Austria, Luxembourg, Germany, Netherlands, Denmark, Russia, Israel, Hong 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. Another background variable especially related to the immigrant condition is the country of origin of the immigrant student or of her parents (indicated by *Country of origin* in Table 4, coefficients in Tables A3a-b). Coefficients are negative especially in the regressions concerning Western European countries: Switzerland, Austria, Belgium, Germany, Italy, Spain, Great Britain, as well as Estonia. In Qatar, consistently with *Language*, originating from another country is correlated with higher scores with respect to natives. For most of the above host countries, coefficients are more negative for students originating from Middle Eastern and, in some cases, African countries.

The significant gaps remaining in Models III and IV in Table 3, given by the coefficients of the immigrant and country of origin variables, are what remains ‘unexplained’ once schooling, family background, students’ characteristics and the interactions between these variables have been taken into account. The gaps remain large in Sweden, where the coefficient equals more than half an international standard deviation, in Denmark, Norway, Luxembourg and Spain, where they are about a third of a standard deviation, and in the United States, where they are smaller. The gaps may depend on still other factors such as school inputs concerning class size, sources of funding, existence of external examinations. These factors are not been considered in this paper, but in a previous study they proved to be only weakly related to immigrant students’ scores (Entorf and Lauk, 2006). Alternatively, gaps could depend on residential segregation or discrimination within schools and classes. These factors would not be captured entirely by our control variables, but could be present especially in contexts where segregation cannot take place through school types and not even through the streaming of courses, i.e., in countries having the purely comprehensive model of education: in our sample, Scandinavia, Estonia and Spain. The remaining gaps in Luxembourg and, to a lesser extent, in the USA, indicate that in these countries, tracking and streaming, respectively, do not capture all factors dividing immigrant students from native students. It is well known, for example, that school quality in the USA varies widely between locations.

Several articles on education have interpreted the low R^2 of regressions regarding Scandinavian countries as a signal of a high correlation between scores and innate ability (Ammermueller, 2007) and, consequently, of more equal opportunities compared to other countries. Our results do not confirm this interpretation: the lower systematic performance of immigrants suggests the existence of factors that are not randomly distributed, as discussed above.

6. Conclusion

Our results show narrower immigrant gaps in school performance where there is more flexibility in education, i.e., where secondary-school students can choose their program of studies and the level of difficulty of core courses.

Flexibility, however, is not an inherent characteristic of any one of the two prevailing models of education, comprehensive and tracking, but rather, it depends on their actual implementation, which varies significantly across countries. Within the general education system, the streaming of courses makes choices possible, while a uniform curriculum for all students does not. Within the tracking system, students can modify their program of studies only in the case that the differences in the school types are limited.

Flexibility may be important for all students, but it can be crucial for those with disadvantaged initial conditions. In particular, a flexible choice of courses allows immigrants originating from culturally distant countries to take courses that are new and relatively harder for them at elementary levels, and other courses at higher levels of difficulty. With this, during secondary-school education, they can gradually catch up on those subjects with higher initial difficulties. This is allowed by the comprehensive system with streaming. On the other hand, neither under the entirely uniform version of the comprehensive model, nor under the more rigid implementation of the tracking system, do these possibilities exist. With the former, the 'hardest' subjects will be studied at the same level of the other students, with a real risk of falling behind . With the second system, of rigid track separation, a student initially disadvantaged in one area of knowledge will most likely be channelled into a vocational or technical school, where all disciplines are taught at a lower level of quality with respect to academic schools. Once again, the initial specific gap will be widened and generalized, rather than reduced. These problems are exacerbated if the quality of schools varies with location, and immigrants are segregated in areas with poor school facilities: their performance will be below average on all subjects, and not just on the initially difficult ones.

Greater flexibility in terms of choices implies a modification of the uniformly comprehensive systems towards greater heterogeneity in the teaching of core subjects, and a change in curricula where school tracking entails too deep a separation between school types. In these cases, the programs of academic schools that include the study of classical cultures and languages can be too burdensome for immigrants, while the programs of vocational schools with their excessive focus on applied studies may dwarf their potential abilities.

References

Allison P.D. (1995) "The impact of random predictors on comparisons of coefficients between models: comment on Clogg, Petkova, and Haritou", *The American Journal of Sociology*, 100:1294-1305

Ammermueller A. (2007) "PISA: What makes the difference? Explaining the gap in test scores between Finland and Germany", *Empirical Econ*omics 33:263–287

Ammermueller A. (2007) "Poor Background or Low Returns? Why Immigrant Students in Germany Perform so Poorly in the Programme for International Student Assessment", *Education Economics,* 15 (2): 215–230.

Bauer P, R.T. Riphahn (2006) "Timing of school tracking as a determinant of intergenerational transmission of education" *Economics Letters*, 91(1):90-97.

Blinder, A.S. (1973) "Wage discrimination: reduced form and structural estimates", Journal of Human resources 8(4), 436-455.

Burnham - Anderson (1998)

Brunello G., D. Checchi (2007) "School tracking and equality of opportunity", *Economic Policy*, pp. 782-862.

CloggClogg C.C., E. Petkova, A. Haritou (1995) "Statistical Methods for Comparing Regression Coefficients between Models", *American Journal of Sociology* 100:1261-93.

Dustmann C. (2004) "Parental background, secondary school, track choice and wages", *Oxford Economic Papers* 56: 209-230.

Elder, T.E., Godeeris J.H., Haider J.S. (2010) "Unexplained gaps and Oaxaca-Blinder decompositions", *Labour Economics*, 17: 284-90

Entorf, H., Lauk, M. (2006) "Peer effects, social multipliers and migrants at school: an international comparison", *IZA Discussion Paper*, No.2182.

Entorf, H., Minoiu N. (2005) "What a difference immigration policy makes: A comparison of PISA scores in Europe and traditional countries of immigration", German Economic Review, 6(3): 355-376.

Entorf H., Tatsi E. (2009) "Migrants at School: Educational Inequality and Social Interaction in the UK and Germany", *IZA* DP No. 4175

Fertig M., Shimdt, C.M. (2002) "The role of background factors for reading literacy: straight National scores in the PISA 2000 study", *IZA Discussion Paper*, No. 545.

Fuchs T., Wömann, L. (2007) "What accounts for international difference in student performance? A re-examination using PISA data", *Empirical Economics*, 32, 433-464.

Hanushek E.A., L. Wömann (2006) "Does educational tracking affect performance and inequality? Differences-in-differences evidence across countries" *The Economic Journal*, 116: 63–C76.

Krueger D., Kumar K.B. (2004) "US–Europe differences in technology-driven growth: quantifying the role of education", Journal of Monetary Economics, 51: 161-190.

Leschinsky A. and K.U.Mayer (1999) *The Comprehensive School Experiment Revisited: Evidence from Western Europe,* Peter Lang Pub Inc; 2 Upd Sub edition, pp. 216.

Meghir C., M. Palme (2005) "Educational reform, ability and family background", *American Economic Review, American Economic Association*, 95(1): 414-424.

OECD (2006) *Where immigrant student succeed- A comparative review of performance and engagement in PISA 2003*, Paris, OECD Publishing.

OECD (2009) *PISA Data Analysis Manual. SPSS, second edition*., Paris, OECD Publishing.

Oaxaca R. (1973) "Male-female wage differentials in urban labour markets, *International Economic Review* 14(3), 693-709.

Särndal C.E., B. Swensson, J.Wretman, (1992) *Model Assisted Survey Sampling*, Springer, Verlag.

Schnepf S.V. (2007) "Immigrants' educational disadvantage: an examination across ten countries and three surveys", *Journal of Population Economics*, 20:527–545.

Schneeweis N. (2009) "Educational institutions and the integration of migrants", Journal of Population Economics, DOI 10.1007/s00148-009-0271-6.

Schutz G., H.W Ursprung, L. Wömann (2008) "Education Policy and Equality of Opportunity", *Kyklos*, 61(2): 279–308

UNESCO (2006) "World data on education. Sixth edition, 2006/07", http://www.ibe.unesco.org/Countries/WDE/2006/index.html

Wömann L. (2009) "International evidence on school Tracking: A Review" CESifo DICE Reporrt 1: 26-34

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>HKG</td><td></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.

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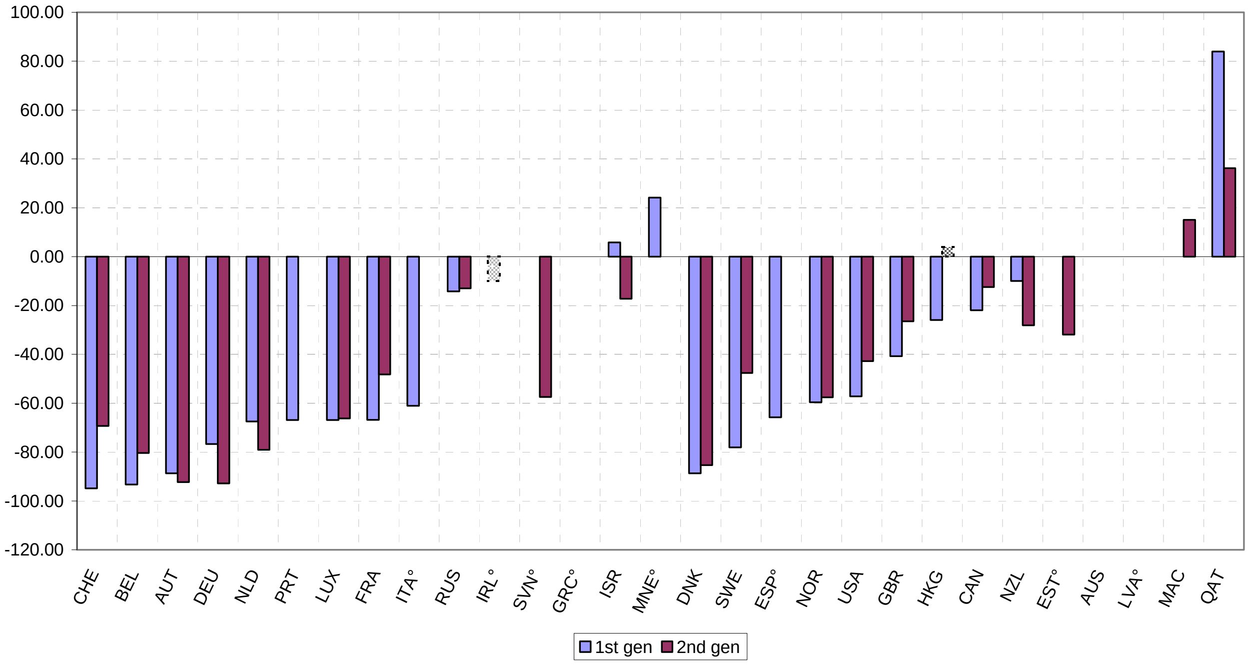
Figure 1: performance gaps of immigrant students immigrant dummy



Note. "°': only one generation of immigrant student above 3% of students' populations. Significance at 1%, except Ireland, Hong Kong.

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	

Notes. Italics: significance at 5 and 10%. 'co': country of origin.' l ': foreign language at home

Table 4. Main factors affecting immigrant gaps in countries.

	School	Background	School x 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			

Tables 3-5 →

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	0.1	0.37	0.54	0.54

Table A3.a. Continued.

	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

Table A3.a. Continued.								
	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.								
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: standard errors in square brackets

Table A3.b. Comprehensive systems. 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

Table A3.b. Continued

	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]			
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	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]
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

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	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]
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

Notes: standard errors in square brackets

° Only aggregate coefficient for the immigrant variable

Table A4: Variables from PISA Codebook

immigr	Status of immigration of student (categorical variable: intercept=native) [*IMMIG*]
language	Language spoken at home (categorical variable: intercept= test language) [*st12q01*]
Fcountry, Mcountry, Scountry	Country of birth of father, mother and student (categorical variable: Western Europe, North America, Asia-rich countries, North Africa , East Europe, South America, North Africa, Sub-Saharan Africa, Middle East, Asia-poor countries, non-Western European countries) [*COBN_F, COBN_M, COBN_S*]
hisced	Highest educational level of parents (categorical variable: intercept = tertiary education) [*hisced*.]
occupHP	Index of highest parental occupational status (categorical variable) [*HISEI*.]
gender	Gender of student (binary variable: intercept=male, 1= female) [*st04q01*]
books	How many books at home (binary variable: intercept= >100, 1 = <100) [*st15q01*]
pc	Computer at home (binary variable: intercept = yes, 1 = no) [*st13q04*]
escs	Index of economic, social and cultural. [*escs*]
regular lessons of science, mathematics, reading	Number of regular lessons (weekly) in science, mathematics and reading, respectively (binary variable: intercept = more than 4 hours, 1= up to 4 hours) [*st31q01, st31q04, st31q07*]
grade	The grade student is in (categorical variable: intercept = grade) [*ST01Q01*]
school	Type of school attended by the student. See Table A2.
envware	Index of students' awareness of environmental issues. [*envaware*]
sciefut	Index of future-oriented motivation to learn science. [*sciefut*]

Table A5: Difference in 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]	***				

Notes: standard errors in square brackets

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