# Immigrants, educational systems and background.

## Cross-country evidence from PISA 2006

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**Abstract**. This paper uses data from PISA 2006 to analyze immigrant gaps in twenty-nine countries, considering school systems - tracking and comprehensive - and background. Results show that gaps are wider in continental Western Europe than in other areas; in European countries with tracking, both school type and background - and their interactions - tend to be highly significant, while in those with comprehensive schools, other segregation mechanisms seem to be at work. Gaps are small in English-speaking countries with comprehensive education. More than the distinction between tracking and comprehensive models, the existence of incentives for improving individual abilities seems to be crucial for the catching up of immigrants in education.

Keywords: International migration, educational systems, PISA.

***JEL:*** F22, I21

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## I. Introduction

While the existence of an immigrant gap in school performance (difference in scores compared to natives) is widely acknowledged, its causes are still unclear. Recent studies focus on the characteristics of immigrants and their backgrounds (Schneeweiss, 2009; Ammermueller, 2007b; Entorf, and Minoiu, 2005; Entorf and Tatsi, 2009; OECD, 2006) and seldom look at the structural features of educational systems in residence countries (Entorf and Lauk, 2006; Schnepf, 2006) or the interrelations between these two groups of factors. The economic implications of an immigrant gap in education are, however, clear: they consist of inequality of opportunity in labour markets (Dustmann, 2004)

Educational systems vary significantly across countries, but are based on two main models of education: tracking and comprehensive. In the former, students are channeled into schools with different programs, academic and vocational, with the vocational schools ranked below the academic ones in terms of quality, program content and students' prospects of pursuing further studies at the tertiary level. In the comprehensive model, all students follow the same programfor the entire cycle of compulsory schooling.

Several studies find a lower dispersion in the scores of students in countries with comprehensive schooling, which is interpreted in several cases as an indicator of higher equity (Schutz et al., 2008; Brunello and Checchi, 2007; Wömann, 2004; Ammermueller, 2007a; Hanushek and Wömann, 2006; Bauer and Riphahn, 2006; Raitano and Vona, 2010). This suggests that the school performance and potential social mobility of immigrant students may be affected by the educational models of their host countries and, in particular, that the performance of immigrant students in countries with comprehensive schools can be expected to be more similar to those of natives, once background and other factors have been controlled for.

This paper uses the PISA 2006 database to analyze the performance of immigrant students in different international environments by taking into account educational models, students' backgrounds and the interactions between these two groups of factors. School types are studied at the micro-level, in a novel approach not found in previous research.

We find that immigrant gaps are wider in continental Western Europe, where the two main systems of education – tracking and comprehensive – are both present, and are narrow in other world-areas. More precisely, in several central Western European countries, students' scores and immigrant gaps are strongly related to school types, to background and also to the interactions between the two groups of variables. In other European areas where schooling is comprehensive – especially Scandinavia – school factors and background matter less, but immigrant gaps remain high, suggesting other forms of segregation or discrimination.

Symmetrically, in other areas of the world gaps are narrower, both in countries with tracking and in those with comprehensive schools. However, outside continental Western Europe tracking is generally milder - there is a lower differentiation between school types. Also, the comprehensive model is implemented differently;  the subjects are taught at different levels of difficulty, which can be either chosen by students or accessed through examination.

This does not confirm prior expectations on the higher equity of the comprehensive system, but suggests that rather than the usual distinction between the two basic educational models, what really matters is their actual implementation. In sharp tracking systems immigrant students are often channeled to vocational schools, where their education is leveled down in all subjects, while in comprehensive systems with uniform courses the initial specific disadvantage is ignored, allowing the gap to persist or even widen across the years of education. The most rigid versions of both models are present in continental Western Europe. Outside this area, a higher flexibility in the choice of subjects or courses allows students to better overcome initial disadvantages in specific subjects. The paper is structured as follows: Section 2 presents some basic traits of the educational models; Section 3 presents the data and descriptive statistics; Section 4 illustrates the estimation strategy; Section 5 analyses the results and Section 6 offers our conclusions.

## 2. Educational systems

The implementation of tracking and comprehensive education differs across countries. The age at which the type of school is selected varies from ten years old in some countries to sixteen in others. We include in our definition of tracking those countries where school selection takes place at or before fifteen years old. Among these, the number of tracks may be two or more, and, more importantly, the differentiation between tracks may be mild or sharp. The latter happens especially in mainland Western European countries, where the quality and programs of academic and vocational schools differ substantially. Outside this area, the number of tracks and the differentiation between programs are in generally lower, while the age of choice is higher.

In turn, comprehensive systems differ in the degree of uniformity with which the common school programme is taught within schools. In some countries, especially European ones, courses are taught to all students at a uniform level, while in others, mostly English-speaking, core courses are taught at different levels of difficulty, which can be either chosen by students or accessed through examination. This type of schooling is often denominated comprehensive with “streaming”.

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One significant phenomenon is the proportion of grade repeaters - students below the average grade at their age -, which also varies significantly between countries. Grade repetition is related to educational customs rather than institutional rules, but may be of interest if considered together with tracking. Table 1 depicts the countries included in this study (selected as explained in Section 3). It shows that, with few exceptions, grade repetition is common in continental Europe, especially in countries where tracking is sharp. It is also present in some countries with comprehensive schools, such as Spain, Denmark, Estonia, Latvia, Macao and Hong Kong, while it is rare among English-speaking countries (which are all comprehensive except for Ireland, where selection takes place late).

### 3. Data and descriptive statistics

Promoted by the OECD, 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. Countries in this paper have been selected with the same criteria used in OECD (2006), referred to PISA 2003, immigrant students account for at least 3% of the student population.[1]

The PISA student questionnaire includes an indicator (*ISCEDO*) that distinguishes between general, pre-vocational and vocational schools, but figures are missing or unreliable for several countries. We have therefore used the UNESCO (2006) classification of educational systems to build a proxy of the "school type" variable. More precisely, we have split the schools of each country into three main categories, i.e., type 1: academic, type 2: intermediate, and type 3: vocational.[2] We have then linked this classification to the variable *(PROGN)* of the student database indicating the school attended by each student, and obtained, as a result, a proxy of school types at the micro level (details from the authors upon request). This differs from previous studies of educational systems, where school models are considered at the aggregate country level (Schutz et al., 2008; Brunello and Checchi, 2007; Wömann, 2004; Ammermueller, 2007a; Hanushek and Wömann, 2006; Bauer and Riphahn, 2006).

[1] The 3% condition holds only for the second-generation student population in Estonia, Latvia and Slovenia, and for first generation ones in Greece, Ireland, Montenegro, and Italy. First-generation students: born outside the country of assessment, with parents born in a different country; second-generation students: born in the country of assessment, with parents born in a different country.

[2] "Special schools" – schools for children with special needs – were included in type 3; within our sample, they are present only in countries with tracking.

Table 2 reports the values of an index of “specialization” of immigrants with respect 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 grade to the share of native students in that school type or grade. Values above unity denote the relative specialization of immigrant students. The last column indicates the average grade for fifteen-year-olds in each country. Numbers in bold print indicate the specialization of immigrants in vocational or technical schools or in the lower grades. Grade numbers are in bold type only where, as depicted in Table 1, repeating grades is frequent among the overall student population. Indexes for Switzerland are biased in favor of type-1 schools because large numbers of international students, who are not immigrants, move to the country for educational purposes and mainly attend schools of type 1.

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Several numbers in bold type in Table 2 concern countries - such as the Netherlands, Belgium, Austria, Germany, Luxembourg and Switzerland, Italy and France - where tracking is sharp and repeaters are frequent even among the overall student population. Among countries with comprehensive schools, there is a relative specialization of immigrants in the lower grades in Denmark, Spain, Hong Kong and Macao. It is also worth noting that index numbers are often, but not always, higher for first-generation immigrants.

Figure 1 depicts the gaps of first and second generation immigrants measured as variations with respect to the scores of native students. More precisely, they are the coefficients of the dummy variable “immigrant” in regressions – one for each country – where this variable is the sole regressor. Coefficient numbers and the adjusted $R^2$ are depicted in Model 1 of Table 3 below. Significance is always at the 1% level except for first-generation immigrants in Ireland and second-generation immigrants in Hong Kong, where it is at the 5% and 10% levels respectively. We found that the distribution of gaps across countries is not correlated to the presence of immigrant students in countries.

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The left-hand side of the Figure depicts countries with school tracking and the right-hand side those with comprehensive schools. It clearly emerges that the most negative gaps are clustered in continental Western Europe and occur in both educational models. More specifically, among countries with tracking, gaps are wide in Switzerland, Belgium, Luxembourg, Netherlands, Austria, Germany, France, Italy and Portugal, while, among countries with comprehensive schools, gaps are wide in Scandinavian countries - Denmark, Norway, Sweden - and in Spain.

Outside this area, negative gaps are smaller or non-significant; in particular, they are small in English-speaking countries, in Eastern European countries - Russia, Latvia, Estonia -, as well as in Israel and Hong Kong (despite the high index of repeaters of the latter, in Table 2). Conversely, immigrant scores are above those of natives in Montenegro, Qatar and Macao (despite index numbers concerning repeaters in the last two countries).[3]

A notion of the dimension of immigrant gaps is given by the PISA standardization of scores for OECD countries, with an average of 500 and a standard deviation of 100. On PISA data, a school year corresponds to about a third of an international standard deviation (Schuetz, Ursprung and Woessmann, 2008). From this it follows that immigrants lag behind natives by much more than a school year in Switzerland, Belgium, Austria, Germany, Netherlands, Luxembourg, France, Italy, Denmark, Sweden and Spain. In some cases the difference corresponds to more than two school

[3] We checked for the correlation between these gaps and the average scores in science of the overall student population as well as just those of native students in countries and found it to be non significant.

years, in others it is nearly three. These, however, are unconditional regressions. In the following sections the main factors related to immigrant gaps at school are measured.

## 4. Estimation strategy

We estimate a linear educational production function where the output is the score of each student and inputs are school type, grade and several factors concerning students' characteristics and socio-economic backgrounds. The measure of the immigrant gap is the coefficient of the respective dummy variable "immigrant" (Guiso et al. 2008, Fryer and Levitt 2010, adopt this procedure to measure gender gaps . We proceed by a sequence of steps: after the estimation depicted in Figure 1, where the dummy immigrant was the only regressor, students' scores were regressed on the immigrant status and on schooling factors regarding school types and grade:

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \beta_S S_{ij} + \beta_G G_{ij} + \varepsilon_{ij} \,. \qquad (1)$$

$Y$ are the scores of student $i$ in country $j$. $\beta_I$, is the coefficient of interest: the immigrant status – of first or second generation - of students. Type of school and grade are, respectively, $S_{ij}$ and $G_{ij}$, and $\beta_S$ and $\beta_G$ are their coefficients. This specification is useful for highlighting the impact of the inclusion of school factors in the regression on the coefficient of $\beta_I$, after the initial, unconditional regression of Figure 1. As an effect of the introduction of the school variables, it can be expected that coefficients $\beta_I$ will change more in countries with sharp tracking, with frequent repeaters and with a relative specialization of immigrants in schools of types 2 and 3 and in the lower grades.

As a further step, we consider students' characteristics and their families' socio-economic backgrounds; among these we include parents' educational level, their employment status, the number of books at home, an index of the family's socio-economic status and other variables such as country of birth and language spoken at home (a list is in Table A1). The specification of the regression equation is now:

$$Y_{ij} = \beta_0 + \beta_I I_{ij} + \beta_S S_{ij} + \beta_G G_{ij} + \boldsymbol{\beta}_X \boldsymbol{X}_{ij} + \varepsilon_{ij}, \qquad (2)$$

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

Some background variables, such as the country of birth of students and parents and the main language spoken at home, may be of especial interest for our investigation. Schnepf (2004), Fertig and Schmidt (2002), Entorf and Lauk (2006), find that a non-national language spoken at home tends to be negatively correlated with performance, especially in English-speaking countries.

Even controlling for background factors, the correlations of *school type* and *grade* with scores and their impact on the coefficient $\beta_I$, the immigrant gap can be only partial. Correlations may be affected by the education received by immigrant students before age fifteen and before entering the country (first-generation immigrants), which we cannot control for with cross-section regressions. However, the quality of education provided by the schools attended by immigrant students before entering the country is likely to be correlated with family background, especially as regards parents' level of education, and with the country of birth of students and or parents, all variables included in the regressions.

Furthermore, and perhaps more significantly, the student's socio-economic background or characteristics may influence both the school type attended and the grade the student is in. In this case, the coefficients of "school type" and "grade" will capture these factors' direct correlation with scores as well as the indirect effects of background. To control for such possible correlations, we add the interacted variables of background and type of school and background and grade to the regressions. The model specification then becomes:

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

where $S_{ij} \times \boldsymbol{X}_{ij}$ and $G_{ij} \times \boldsymbol{X}_i$ are the interactions of background factors with *school types* and *grade,* and $\boldsymbol{\beta}_{SX}$ and $\boldsymbol{\beta}_{GX}$ are the coefficient vectors. In all cases, we shall refer to correlations between variables, not to causal relations.

Despite the inclusion of a long list of regressors and interactions between variables, other problems related to sample bias may arise from differences in ability between immigrants and natives. For example, immigrants may be distributed non-randomly between countries if more able individuals systematically prefer some destinations to others. Up to now, however, theoretical predictions on the kinds of countries more able immigrants should prefer have found no empirical support (Fuchs and Wömann, 2007). We therefore suppose that there is no systematic relationship between immigrants' ability and country of residence. Ability cannot be measured, but the country of birth variable, included in the above specification, may help to control for this type of sample bias. Everything relating to parents' educational and other background factors should be captured by our control variables.

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 have a better knowledge of school practices than first-generation students (Schneeweiss, 2009; Schnepf, 2004). Therefore, once all relevant factors have been controlled for, the scores of second-generation immigrant students should be more similar to those of natives than those of their first-generation peers.

Regressions have been run by using weighted OLS after applying the Bayesian Information Criterion (BIC) to select relevant sets of variables from a large set of potential candidate factors. For each country, backward selection has been applied up to the point where removing another regressor from the model increases the BIC (e.g. see Burnham and Anderson, 1998). By studying the out-of-sample prediction performance on the PISA data, comparing BIC with the Akaike Information Criterion (AIC) and the Least Absolute Shrinkage and Selection Operator (LASSO), we found that BIC was to be preferred to the other methods. Generally, BIC selects more parsimonious models (fewer variables) with smaller prediction errors. Here, we applied the BIC selection five times, once for each student's plausible value, weighting the regression for the student final weights and choosing variables selected in all runs. Thus, except for the immigrant dummy variable, which is included in all regressions, the control variables actually selected may differ from country to country.

To be more specific, for computing model parameter estimates and their standard errors we used balanced repeated replications (BRRs) (e.g. see Särndal et al., 1992), based on the weights provided in the PISA dataset. BRR is a method of estimating the sampling variability of a statistic that takes the properties of the sampling design into account. Similarly to the 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). The confidence intervals for the inferences reported in Tables 3 are standard (1-$\alpha$)% confidence intervals ($\alpha$<0.05) based on the asymptotic normality assumption of the coefficient estimates. We performed diagnostic analysis on the BBR coefficient estimate replicates to confirm that this assumption is trustworthy for all the reported results.

## 5. Results

Tables 3a and 3b depict the immigrant gaps, i.e. the coefficients, $\beta_I$, of the dummy regarding *1^st gen* and *2^nd gen* immigrant students, and the adjusted $R^2$ of the different specifications. Countries are ordered as in Figure 1. Complete results, on school-type, grade and background coefficients, are available from the authors upon request.

Model 1, where the dummy "immigrant" variable is the only regressor (Figure 1), shows that not only immigrant gaps but also adjusted $R^2$ vary widely between countries. While immigrant status alone explains more than 10% of the total variation in Switzerland, about 10% in Luxembourg, Austria, Belgium and Germany and about 5% in the Netherlands, Denmark and Sweden – all countries where immigrant gaps are wide –, it has no explanatory power in the regressions concerning the English-speaking countries - Ireland, New Zealand, Australia, Great Britain and Canada- and in Hong Kong, Latvia and Macao.

As expected, the introduction of the school variables in Model II affects immigrant gaps. When compared to Model I, the $\beta_I$ coefficients tend to shrink. This happens especially for mainland Western European countries – the Netherlands, Belgium, Germany, France, Slovenia, Italy, Portugal and Spain – and is accompanied by a significant increase in the proportion of explained variation (Table 3a). Adjusted $R^2$ now rises to almost 0.6 for the Netherlands and is about 0.5 for Belgium and France and 0.3 for Luxembourg and Austria. In the regression for Spain, a country with comprehensive schools, the adjusted $R^2$ is around 0.3 (Model II of Table 3b). As Table 2 shows, in these countries immigrants are relatively concentrated in both non-academic schools and - or - in the lower grades. This suggests that much of the difference in scores between immigrants and natives in these countries is related to school tracking and grade repetition.

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.[4] The results, not reported in this paper but available from the authors upon request, show that differences are statistically significant at the 99% level for all the above countries.

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INSERT TABLES 3a & 3b HERE

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[4] The same procedure cannot be used for the difference between coefficients of Models II and III because the number of observations changes for some countries, but also, more significantly, because the introduction of the country of origin variable often captures many of the effects originally captured by the immigrant gap.

Complete regressions of Model III – not reported in this paper - show that the negative, significant coefficients of schools of type 2 and 3 can be above half, or three quarters, of an international standard deviation, especially in mainland Western European countries, which implies that students – natives and immigrants – attending vocational or technical schools may lag behind students attending academic schools by about two academic years or more. The coefficients of the variable concerning grade repetition can also be strongly negative and significant. Therefore, attending non academic schools, repeating grades, or both (more frequent for immigrants than for natives) may make the possibility of catching up with students in academic schools and not repeating grades extremely unlikely.

These findings can be only indicative without considering other students' characteristics and their backgrounds. Model III of Tables 3a and 3b depicts the immigrant variable coefficients once gender, family socio-economic background, a foreign language spoken at home and the countries of origin of immigrant students and their parents are included in the regressions. The results of Table 3b are that background seems to plays a proportionately more important role than schooling in countries with the comprehensive model (Table 3b), which is not surprising, as for most of these countries school factors explained little of the total variation. The adjusted $R^2$ increases substantially compared to Model II in the regressions for English-speaking and, to a smaller extent, Scandinavian countries. However, it can be observed that background in these countries tends to explain less than just schooling in those with tracking. The $R^2$ values of Table 3b – Model III – are in general below those of countries with school tracking, and in some cases even below those of the latter in Model II. With the increase in the variations, immigrant gaps in Denmark, Sweden, Norway, the US and Great Britain shrink substantially compared to Model II.

The inclusion of background factors in the regressions also causes a further reduction in gaps in countries with tracking – Model III of Table 3a –, especially Switzerland, Belgium, Germany, the Netherlands, Luxembourg and Slovenia. In this European area, therefore, both background and schooling turn out to be significantly correlated with scores.

The "country & language" column of Model III indicates that the coefficients of the "country of origin" and "language at home" variables are significant. The Table shows that both variables, country of origin and a foreign language spoken at home, are significant in Belgium, Austria and Germany. Only the origin country of students is significant in Switzerland, Italy, Spain, Slovenia, Estonia, and, outside Europe, in Qatar; while a foreign language spoken at home matters, as well as in the three former countries, in the Netherlands, Denmark, Spain, Russia, and, outside Europe, in Israel, Canada, New Zealand, Australia, Hong Kong and Qatar. The results on the "language at home" factor do not confirm the findings of previous studies (Schnepf, 2004; Fertig and Schmidt, 2002; Entorf and Lauk (2006), where it appears to be significant in English-speaking countries. In this papers, a foreign language spoken at home is correlated with test scores in several countries, both English-speaking and not. Besides, a closer look at the "country of origin" coefficients show that they are negative and significant especially for immigrant students residing in European countries and originating from Middle Eastern and African countries.

Conversely a direct comparison between the immigrant gaps of Models III and II is not possible. One reason is that they measure different things: with the inclusion of the country of origin and language variables in Model III the immigrant effect is split into separate components. Also, the number of observations may vary between Models II and III, with which the procedure used above, based on Allison (1995), cannot be utilized. However, the fact that in several Western European countries much of the correlation with scores is already captured in Model II, and gaps vary further in Model III, suggests that school choice, grade repetition, students' characteristics and family background may be related factors in this group of countries.

The results of the interactions between background factors and school variables (Model IV in Table 3) mostly confirm these predictions: the coefficients of interacted variables are significant in the regressions regarding Belgium, Austria, Netherlands, Luxembourg, Italy and Slovenia, all continental European countries where gaps were wide in Model I and where both school and background coefficients were high and significant in Models II and III. The background variables most often involved in these interactions are the levels of education and employment status of mother and father, the number of books at home, immigration status and country of origin, while the schooling variables are both school types and grades in Austria, school types in Italy, Belgium and Netherlands and grades in Luxembourg and Slovenia. One interesting finding is that the interactions between background and school factors are not necessarily more significant in countries where tracking starts earlier. For example, family characteristics and type of school appear to be strongly interrelated in Italy, where tracking starts at fourteen, while the coefficients of the interacted variables are not significant in Germany, where it starts at ten. These results may also arise from the mechanism of school selection, with choices made by students' families or school teachers (on Germany, see also Checchi and Flabbi, 2007; Dustmann, 2004).

The coefficients of the immigrant and country of origin variables in Models III and IV are the part of the immigrant school gap still not "explained" once students' characteristics, schooling, family background, and the interactions between these variables have been taken into account. Table 3 shows that gaps remain large in Scandinavian countries: in Sweden (the coefficient equals more than half an international standard deviation, which is more than a school year) as well as in Luxembourg and Spain, where coefficients are about a third of a standard deviation (one school year), and in the United States, where they are smaller. These "unexplained" correlations may depend on school inputs - class size, sources of funding, existence of external examinations - not considered in this paper, but which in previous studies proved to be only weakly related to immigrants' scores (Entorf and Lauk, 2006). Alternatively, gaps could be due to residential segregation or discrimination within schools and classes, a phenomenon that can develop especially in countries where the separation between immigrants and natives, or more generally between students with different backgrounds, does not take place through school types and courses, i.e., in countries with the comprehensive-uniform model of education: in our sample, Scandinavia and Spain (Raitano and Vona, 2010). Some studies on education have interpreted the low $R^2$ of regressions in Scandinavian countries as evidence of a high correlation between innate ability –

randomly distributed – and scores (Ammermueller, 2007a) and, consequently, of high equality of opportunity. Our results do not confirm this interpretation: the lower performance of immigrants in Scandinavian countries reveals the existence of systematic factors correlated with the performance of immigrant minorities. The remaining gaps in Luxembourg and, to a lesser extent, in the USA, suggest, here again, the existence of still missing explanatory factors. It is well known, for example, that school quality in the USA varies widely between locations.

## 6. Conclusion

An intense debate has developed on the relative fairness of the tracking and comprehensive models of schooling. Although the results are not unequivocal, the comprehensive model is frequently indicated as the best means of increasing social mobility, i.e. for making students' performance as independent as possible of gender, ethnicity and other circumstances.

This paper shows that the distinction between the two main models of education is not sufficient for an understanding of the "educational mobility" of immigrants – their prospects of catching up with natives – in the broad sample of countries considered. On the one hand, immigrant students lag substantially and systematically behind natives in countries with the most uniform version of the comprehensive model, which, according to the literature, should be expected to ensure a greater equality of opportunity. On the other hand, gaps are found to be narrow in some countries with tracking.

The previous findings in the literature are instead confirmed for two sub-sets of countries. One includes continental Western European countries with sharp tracking. There, immigrant gaps are wide and are related to the school types, grades, background and the interactions between these factors. The other concerns countries with comprehensive schooling and streaming, especially English-speaking ones, where gaps are related to background but are generally narrow and smaller for second-generation immigrants.

An interpretation of these results is that, rather than the distinction between the two basic models of education, what matters is the way they are actually implemented and, in particular, the existence within each of instruments and incentives that enable students to make full use of their individual abilities. This is crucial for immigrants, who may have specific knowledge - related to culture, tradition, family, relations - that differs from that of natives, but who also possess general knowledge and abilities that should not be overlooked. With flexibility in education, the performance of immigrants can be more similar to that of natives in culture-free subjects, such as mathematics or science, than in other disciplines. In the latter, a gradual convergence to average levels can take place. This flexibility seems to be present especially in the comprehensive model with streaming, or in forms of mild tracking. Improvements in the performance of immigrant students, and in that of students with disadvantaged initial conditions in general, are of importance not only for reasons of fairness. Efficiency in the selection and promotion of talents also appears to be conducive to economic growth (Bertocchi and Spagat, 2004; Krueger and Kumar, 2004).

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***Figure 1. Performance gaps of immigrant students***
***Unconditional regression***

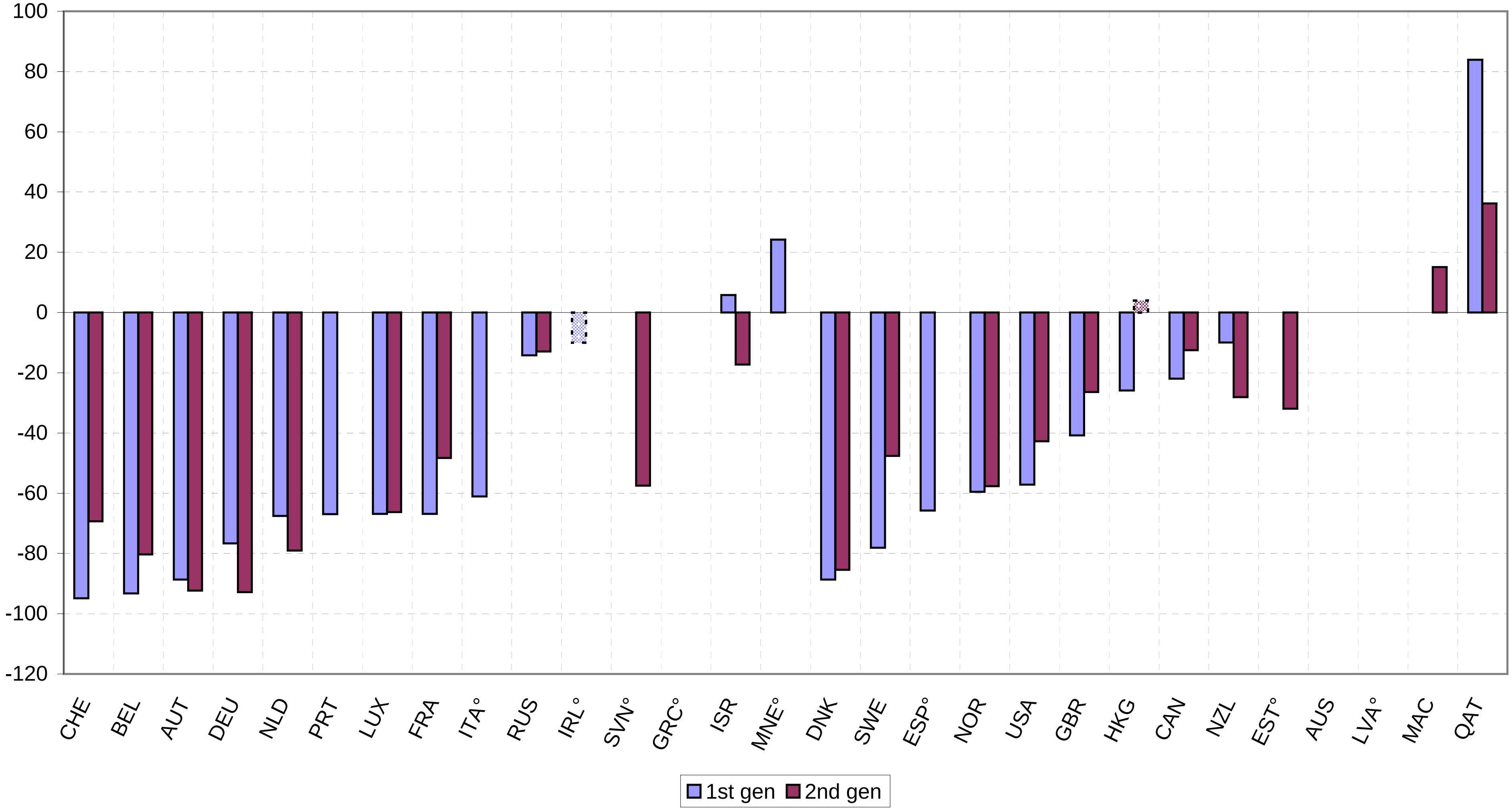

**Table 1. School systems.**

***First age of selection and proportion of repeaters***

| share of repeaters | tracking | | comprehensive | |
|---|---|---|---|---|
| | | | *streaming* | *homogenous* |
| | AUT | [10] | | |
| | DEU | [10] | | |
| | BEL | [12] | | |
| | CHE | [12] | | ESP |
| *high* | NDL | [12] | | DNK |
| | LUX | [13] | | EST |
| | FRA | [14] | | LVA |
| | ITA | [14] | HKG | |
| | RUS | [14.5] | MAC | |
| | PRT | [15] | QAT | |
| | | | CAN | |
| *medium* | IRL | [15] | USA | SWE |
| | ISR | [15] | AUS | |
| *low* | MNE | [14] | GBR | |
| | SVN | [14] | NZL | NOR |
| | GRC | [15] | | |

*Source: UNESCO (2006)*

*First age of selection in square brackets; source: PISA 2006.*

## *Table 2. Grades and School types.*

***Index: % immigrant students / %native students***

| Countries | School 1 | | School 2 | | School 3 | | Grade 9 | | Grade ≤ 8 | | grade at 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Tracking* | **2nd gen** | **1st gen** | **2nd gen** | **1st gen** | **2nd gen** | **1st gen** | **2nd gen** | **1st gen** | **2nd gen** | **1st gen** | |
| AUT | 0.92 | 0.78 | 0.82 | **1.08** | **1.31** | **1.05** | **1.17** | **1.22** | **1.84** | **3.09** | 10 |
| BEL | 0.98 | 0.7 | 0.93 | 1.02 | **2.52** | **6.03** | **1.78** | **1.86** | **3.38** | **7.85** | 10 |
| CHE | *1.11* | *1.09* | *1.02* | *1.01* | *0.78* | *0.84* | 0.95 | 0.81 | **1.33** | **1.9** | 9 |
| DEU | 0.5 | 0.52 | **1.21** | **1.17** | **1.27** | **1.26** | 0.99 | 1.05 | **1.91** | **2.34** | 9 |
| FRA | 0.91 | 0.63 | **1.09** | **1.4** | **1.46** | **1.48** | **1.15** | **1.32** | **1.58** | **4.09** | 10 |
| GRC | | 0.5 | | **3.35** | | | | 9.28 | | 7.66 | 10 |
| IRL | | 1.45 | | 0.94 | | | | 0.92 | | **3.39** | 9 |
| ISR | 0.94 | 0.69 | **1.16** | **1.77** | | | **1.45** | **2.63** | | | 10 |
| ITA | | 0.4 | | **1.58** | | **1.3** | | **4.09** | | **13.21** | 10 |
| LUX | 0.69 | 0.77 | 0.83 | 0.7 | **1.18** | **1.15** | **1.12** | **1.17** | **1.65** | **1.83** | 10 |
| MNE | | 1.08 | | 0.91 | | 0.87 | | 1.01 | | | 9 |
| NLD | 0.59 | 0.63 | 0.91 | 0.79 | **1.89** | **2.26** | **1.34** | **1.46** | **1.97** | **5.35** | 10 |
| PRT | 0.73 | 0.42 | **1.19** | **1.43** | 0.93 | | 0.84 | 0.99 | **1.99** | **2.77** | 10 |
| RUS | 0.85 | 0.91 | **1.11** | **1.16** | **1.55** | 0.43 | 1.08 | 1.09 | **1.63** | **1.98** | 10 |
| SVN | 0.69 | | **1.24** | | **1.32** | | | | | | 10 |
| *Comprehensive* | | | | | | | | | | | |
| AUS | | | | | | | 0.45 | 1.32 | | | 10 |
| CAN | | | | | | | 0.57 | 1.09 | 0.33 | 1.06 | 10 |
| DNK | | | | | | | 0.95 | 0.75 | **1.3** | **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 | | | | | | | 1.3 | 1.59 | 0.52 | 0.81 | 10 |

*Notes: School 1: academic; School 2: intermediate; School 3: vocational.*

*Switzerland (CHE): international students with immigrant students*

*Hong Kong and Macao: no significant share of students in schools of types 2 and 3*

***Table 3a: immigrant performance gaps, schooling, background and interacted variables. Tracking***

*Dependent variable: student scores in Science*

| Countries | **Model I** - *Dummy* | | | | **Model II** - *School type and grade* | | | | **Model III -** Background | | | | | **M. IV** *Interact. backg. - school* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2nd gen | 1st gen | *Ad. R2* | *N° observ.* | 2nd gen | 1st gen | *Ad. R2* | *N° observ.* | 2nd gen | 1st gen | *country lang* | *Ad. R2* | *N° observ.* | |
| CHE | -69.3 | -94.8 | *0.12* | 12021 | -67.33 | -87.6 | *0.28* | 12021 | 24.68 | *-21.7* | *c o* | *0.5* | 10736 | — |
| | *[10.36]* | *[7.93]* | | | *[10.54]* | *[4.92]* | | | *[11.77]* | *[10.3]* | | | | |
| BEL | -80.3 | -93.2 | *0.09* | 8743 | -55.8 | -36.6 | *0.49* | 8742 | -5.8 | -12.8 | *c o - l* | *0.57* | 7509 | *yes* |
| | *[2.53]* | *[1.41]* | | | *[2.42]* | *[4.82]* | | | *[5.6]* | *[1.86]* | | | | |
| AUT | -92.3 | -88.7 | *0.10* | 4891 | -75.9 | -68.0 | *0.37* | 4891 | -2.6 | -12.8 | *c o - l* | *0.54* | 4456 | *yes* |
| | *[13.40]* | *[6.66]* | | | *[5.05]* | *[2.43]* | | | *[4.8]* | *[10.3]* | | | | |
| DEU | -92.8 | -76.7 | *0.09* | 4063 | -67 | -46 | *0.45* | 4481 | -23.5 | -9.09 | *c o - l* | *0.53* | 3707 | — |
| | *[1.88]* | *[5.42]* | | | *[1.64]* | *[3.88]* | | | *[3.34]* | *12.25* | | | | |
| NLD | -79 | -67.5 | *0.06* | 4787 | -49.2 | -30.3 | *0.58* | 4786 | -36 | *-12* | *l* | *0.64* | 4186 | *yes* |
| | *[3.61]* | *[3.67]* | | | *[3.72]* | *[4.13]* | | | *[5.16]* | *[4.87]* | | | | |
| PRT | -37.2 | -66.9 | *0.02* | 5053 | -16.3 | -26.7 | *0.44* | 4960 | [-14.5] | -18.4 | — | *0.55* | 4701 | — |
| | *[22.0]* | *[6.53]* | | | *[12.1]* | *[3.57]* | | | *[9.0]* | *[4.86]* | | | | |
| LUX | -66.2 | -66.9 | *0.11* | 4490 | -55.2 | -57.9 | *0.32* | 4490 | -35.5 | -39 | — | *0.47* | 4212 | *yes* |
| | *[2.14]* | *[1.92]* | | | *[2.12]* | *[1.77]* | | | *[2.18]* | *[1.76]* | | | | |
| FRA | -48.3 | -66.8 | *0.03* | 4575 | -39.8 | -35.4 | *0.47* | 4575 | -29.7 | -7.8 | — | *0.58* | 4349 | — |
| | *[2.53]* | *[2.72]* | | | *[4.28]* | *[2.7]* | | | *[2.17]* | *[32.4]* | | | | |
| ITA° | | -61.1 | *0.01* | 21260 | | *-12.9* | *0.24* | 21260 | | 10.55 | *c o* | *0.38* | 20173 | *yes* |
| | | [1.75] | | | | *[4.84]* | | | | [2.64] | | | | |
| RUS | -13 | -14.2 | *0.00* | 5714 | -6.3 | -9.9 | *0.11* | 5714 | -1.0 | -4.1 | *l* | *0.32* | 5377 | — |
| | *[1.55]* | *[2.80]* | | | *[1.54]* | *[3.01]* | | | *[1.4]* | *[2.2]* | | | | |
| IRL° | | *-10.1* | *0.00* | 4442 | | -4.6 | *0.05* | 4442 | | -1.3 | — | *0.33* | 4232 | — |
| | | *[3.74]* | | | | *[2.7]* | | | | *[3.1]* | | | | |
| SVN° | -57.4 | | *0.03* | 6486 | -40.8 | | *0.47* | 6486 | -28.7 | | *c o* | *0.55* | 5915 | *yes* |
| | *[2.34]* | | | | *[2.74]* | | | | *[2.24]* | | | | | |
| GRC° | | -49.5 | *0.02* | 4795 | | 10.9 | *0.28* | 4794 | | 26.1 | — | *0.42* | 4397 | — |
| | | *[26.9]* | | | | *[6.9]* | | | | *[3.09]* | | | | |
| ISR | -17.3 | 5.8 | *0.00* | 4201 | -14.9 | 17 | *0.04* | 4201 | -1.8 | 31.5 | *l* | *0.25* | 3427 | — |
| | *[2.20]* | *[1.58]* | | | *[1.88]* | *[1.36]* | | | *[1.2]* | *[4.18]* | | | | |
| MNE° | | 24.2 | *0.00* | 4302 | | 21.5 | *0.21* | 4302 | | 13 | — | *0.37* | 3880 | — |
| | | *[2.15]* | | | | *[2.5]* | | | | *[3.82]* | | | | |

*Notes: robust standard errors in brackets. '°': ony one immigrant generation above 3%. c o: country of origin, l: language. Grey: significance below 1%.*

**Table 3b: immigrant performance gaps, schooling, background and interacted variables. Comprehensive**

*Dependent variable: student scores in Science*

| Countries | **Model I** - *Dummy* | | | | **Model II** - *School type and grade* | | | | **Model III -** Background | | | | | **M. IV** *Interact. backg. - school* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2nd gen | 1st gen | *Ad. R2* | *N° observ.* | 2nd gen | 1st gen | *Ad. R2* | *N° observ.* | 2nd gen | 1st gen | *country lang* | *Ad. R2* | *N° observ.* | |
| DNK | -85.4 | -88.6 | 0.06 | 4493 | -84.1 | -75.8 | 0.11 | 4493 | -23.1 | -39.8 | *l* | 0.37 | 3861 | — |
| | *[7.3]* | *[5.8]* | | | *[7.8]* | *[8.1]* | | | *[19.7]* | *[10.8]* | | | | |
| SWE | -47.6 | -78.1 | 0.04 | 4362 | -49 | -74.3 | 0.06 | 4362 | -35.3 | -55 | — | 0.36 | 4107 | — |
| | *[5.2]* | *[3.3]* | | | *[4.8]* | *[3.2]* | | | *[4.7]* | *[3.1]* | | | | |
| ESP° | | -65.7 | 0.03 | 19367 | | -37.74 | 0.31 | 19367 | | -36 | *c o +* | 0.46 | 17679 | — |
| | | *[10.0]* | | | | *[9.8]* | | | | *[4.6]* | | | | |
| NOR | -57.6 | -59.6 | 0.02 | 4585 | -57.4 | -57.6 | 0.02 | 4585 | -32.9 | -35.2 | — | 0.25 | 4264 | — |
| | *[3.9]* | *[6.1]* | | | *[4.0]* | *[5.8]* | | | *[4.5]* | *[5.25]* | | | | |
| USA | -42.8 | -57.1 | 0.03 | 5422 | -41.5 | -52.9 | 0.12 | 5420 | *-22.3* | -29.3 | — | 0.38 | 5055 | — |
| | *[5.43]* | *[9.97]* | | | *[5.50]* | *[11.21]* | | | *[10.85]* | *[4.05]* | | | | |
| GBR | -26.4 | -40.8 | 0.01 | 12751 | -26.4 | -40.7 | 0.01 | 12751 | -9.4 | *-22* | *c o* | 0.39 | 11449 | — |
| | *[4.59]* | *[11.32]* | | | *[4.59]* | *[11.39]* | | | *[3.16]* | *[9.95]* | | | | |
| HKG | *4* | -25.9 | 0.01 | 4584 | *3.5* | 20.9 | 0.12 | 4584 | 16.4 | 2.1 | *l* | 0.39 | 4458 | — |
| | *[1.67]* | *[2.27]* | | | *[1.70]* | *[2.99]* | | | *[2.41]* | *[1.9]* | | | | |
| CAN | -12.5 | -21.9 | 0.01 | 21743 | -17 | -21.2 | 0.07 | 21743 | -9.1 | -19.3 | *l* | 0.29 | 19911 | — |
| | *[1.53]* | *[1.42]* | | | *[2.28]* | *[2.82]* | | | *[2.18]* | *[1.98]* | | | | |
| NZL | -28.1 | -10 | 0 | 4711 | -28.1 | -9.8 | 0 | 4711 | -7.3 | -9.8 | *l* | 0.4 | 4399 | — |
| | *[3.04]* | *[1.93]* | | | *[3.16]* | *[1.46]* | | | *[1.08]* | *[2.73]* | | | | |
| EST° | -31.9 | | 0.02 | 4756 | -38.3 | | 0.09 | 4756 | *10.97* | | *c o* | 0.35 | 4517 | — |
| | *[1.73]* | | | | *[1.55]* | | | | *[4.15]* | | | | | |
| AUS | -1.7 | -2.5 | 0 | 13844 | -4.3 | -0.2 | 0.02 | 13844 | -3.8 | -1.0 | *l* | 0.34 | 12786 | — |
| | [1.6] | [4.5] | | | [1.52] | [3.5] | | | *[3.3]* | *[5.2]* | | | | |
| LVA° | -3.2 | | 0 | 4596 | -4.6 | | 0.11 | 4571 | -9.1 | | — | 0.33 | 4413 | — |
| | *[3.45]* | | | | *[3.13]* | | | | *[2.94]* | | | | | |
| MAC | 15 | -3.6 | 0.01 | 4672 | 11.2 | 21.2 | 0.25 | 4672 | 8.7 | 14.9 | — | 0.37 | 4618 | — |
| | *[1.44]* | *[2.10]* | | | *[0.88]* | *[2.42]* | | | *[1.32]* | *[2.34]* | | | | |
| QAT | 36.2 | 83.9 | 0.15 | 5718 | 34.6 | 80.7 | 0.19 | 5718 | 29.1 | 45.3 | | 0.35 | 5128 | — |
| | *[1.32]* | *[1.95]* | | | *[1.48]* | *[1.94]* | | | *[1.25]* | *[1.89]* | *c o + l +* | | | |

*Notes: robust standard errors in brackets. '°': ony one immigrant generation above 3%. c o: country of origin, l: language. Grey: significance below 1%.*

**_Table A: Variables' notation_**

| | |
|---|---|
| *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)<br>[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] |

*Note: Table A2 can be seen in [http://www.recent.unimore.it/wp/recent-wp54.pdf](http://www.recent.unimore.it/wp/recent-wp54.pdf)*