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How should we organize schooling to further children with migration background?

by

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Abstract

Educational integration of children with migration background is an important issue in the social sciences. Few studies exist that quantify the disadvantage of immigrant children in education and there has not been any attempt to identify institutional conditions of the education system that contribute to educational integration. Using data from five international student assessments, this study tries to fill that gap. First, Blinder-Oaxaca decompositions are used to allow for a comparison of (dis)integration of students with migration background across countries and time. In a second step, (dis)integration is related to institutional characteristics of the schooling system. The study shows that early education, time in school and central exams further integration, while social segregation of students among schools is detrimental to educational integration.

Keywords: Institution, Integration, Immigrant, Pisa, Timss, Education

JEL Classification: I21, I28, J15

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1 Introduction

Educational integration is an important precondition for the economic assimilation of immigrants in the host societies. Analyses of international student assessment studies cause concern about the integration of immigrant children in schools. In the OECD-countries, two international student assessments (Pisa and Timss) show that students who were born abroad perform significantly worse in the achievement tests, compared to native students. The mean achievement gap amounts to about 25 test scores in mathematics and even 28 in science (25% and 28% of the standard deviation in test scores).

There are several studies investigating the achievement gaps in more detail. For example, Entorf and Minoiu (2005) have shown that not only the Pisa achievement gaps between migrants and non-migrants vary substantially across some OECD-countries, but also the socio-economic background of the immigrants and its influence on achievement. Furthermore, Ammermüller (2005a) has raised the question, why immigrants in Germany performed so poorly in Pisa. The answer is twofold: immigrants in Germany come from less favorable social backgrounds and they get lower returns to their characteristics than German natives.

Why is there such a wide gap in cognitive skills between students with foreign background and native students? Can this gap be explained by differences in student characteristics? *What is the role of the educational system, how should schooling be organized to further the integration of children with foreign background?*

This essay is aimed at quantifying the disadvantage of immigrant children in education and relating it to institutional conditions of the education system. In the first step, educational (dis)integration of immigrants and second-generation immigrants is measured and made comparable across countries and time. In the second step, I estimate the effects of certain characteristics of the education system, such as pre-primary education, segregation of students among schools or the length of the school year on the integration of foreign students based on a cross-country time-series analysis.

2 The disadvantage of immigrants

The raw data of various achievement tests give a substantial drawback for students with migration background. These achievement gaps cannot be directly compared across countries. Educational success is largely determined by the social background of the students, like the education of parents and the learning climate at home (cf. Hanushek and Luque, 2003, Wößmann, 2005a). Moreover, different countries have different immigrant populations. Depending on the income situation, the geographic region, the immigration policy and many other characteristics, they attract migrants with different abilities and social backgrounds.

To obtain a reliable indicator for the disadvantage of students with foreign background, the raw achievement gaps have to be made comparable across countries and time. I use the Blinder-Oaxaca decomposition to construct such a measure of disintegration (cf. Blinder, 1973, Oaxaca, 1973). The achievement gaps between native and immigrant students are decomposed into a part that is explained by differences in productivity characteristics and a part that remains unexplained. Educational production functions are estimated separately for natives, immigrants and second-generation immigrants.[2] The average native, immigrant and second-generation immigrant test scores ($\overline{Y}_n, \overline{Y}_i, \overline{Y}_s$) can then be written as products of the estimated coefficients ($\hat{\beta}_{\mathbf{n}}, \hat{\beta}_{\mathbf{i}}, \hat{\beta}_{\mathbf{s}}$) and the average endowments ($\overline{\mathbf{X}}_{\mathbf{n}}, \overline{\mathbf{X}}_{\mathbf{i}}, \overline{\mathbf{X}}_{\mathbf{s}}$) of the three groups:

$$\overline{Y}_n = \hat{\beta}_{\mathbf{n}}\overline{\mathbf{X}}_{\mathbf{n}}, \quad \overline{Y}_i = \hat{\beta}_{\mathbf{i}}\overline{\mathbf{X}}_{\mathbf{i}} \text{ and } \overline{Y}_s = \hat{\beta}_{\mathbf{s}}\overline{\mathbf{X}}_{\mathbf{s}}. \tag{1}$$

The average achievement differentials between native students and students with foreign background can be formulated as

$$\Delta\overline{Y}_{n-i} = \hat{\beta}_{\mathbf{n}}\overline{\mathbf{X}}_{\mathbf{n}} - \hat{\beta}_{\mathbf{i}}\overline{\mathbf{X}}_{\mathbf{i}} = \underbrace{\hat{\beta}_{\mathbf{n}}(\overline{\mathbf{X}}_{\mathbf{n}} - \overline{\mathbf{X}}_{\mathbf{i}})}_{explained} + \underbrace{\overline{\mathbf{X}}_{\mathbf{i}}(\hat{\beta}_{\mathbf{n}} - \hat{\beta}_{\mathbf{i}})}_{unexplained}. \tag{2}$$

$$\Delta\overline{Y}_{n-s} = \hat{\beta}_{\mathbf{n}}\overline{\mathbf{X}}_{\mathbf{n}} - \hat{\beta}_{\mathbf{s}}\overline{\mathbf{X}}_{\mathbf{s}} = \underbrace{\hat{\beta}_{\mathbf{n}}(\overline{\mathbf{X}}_{\mathbf{n}} - \overline{\mathbf{X}}_{\mathbf{s}})}_{explained} + \underbrace{\overline{\mathbf{X}}_{\mathbf{s}}(\hat{\beta}_{\mathbf{n}} - \hat{\beta}_{\mathbf{s}})}_{unexplained}. \tag{3}$$

The explained part of the test score gap considers that students with foreign background may be endowed with less favorable socio-economic characteristics, compared to native students, and therefore less successful in education. The unexplained part of the achievement gap can be interpreted as a measure of disintegration. It shows, by how much students with a migration background would perform better, given their own endowments, if they had the same returns as native students.

The separate estimation of the educational production function for the three groups allows the returns to individual characteristics to differ for natives and students with migration background. It is plausible to assume that natives and foreign students are different populations and obtain different returns to their endowments. A high educa-

[2] The analysis is done separately for immigrants (born abroad) and second-generation immigrants (one or both parents born abroad). I do not distinguish between second-generation immigrants whose both parents were born abroad and those who live in interethnic families. In this context, Meng and Gregory (2005) have shown that a marriage with a native spouse is a vehicle for immigrants to assimilate economically.

tional attainment of parents, for example, might not have the same positive impact for migrated students as for natives.[3]

The unexplained differential is interesting to analyze and compare across countries, nevertheless problematic for the purpose of this paper. The identification of institutional effects needs a measure of integration that is comparable across countries and does not depend on the average characteristics of immigrant students in a certain country. The question, the measure should be able to answer, is the following: *How much better would a representative student with foreign background perform in a given institutional regime if he or she had the same returns as the native students in that regime?*

The unexplained differentials of the above equations are, therefore, standardized to obtain a comparable measure of disintegration:

$$D_i = \overline{\mathbf{X}}_{\mathbf{i}}^{\mathbf{st}}(\hat{\beta}_{\mathbf{n}} - \hat{\beta}_{\mathbf{i}}) \quad \text{and} \quad D_s = \overline{\mathbf{X}}_{\mathbf{s}}^{\mathbf{st}}(\hat{\beta}_{\mathbf{n}} - \hat{\beta}_{\mathbf{s}}), \tag{4}$$

where $\overline{\mathbf{X}}_{\mathbf{i}}^{\mathbf{st}}$ and $\overline{\mathbf{X}}_{\mathbf{s}}^{\mathbf{st}}$ are vectors of mean characteristics of immigrants and second-generation immigrants in the whole sample.

Note that the measure of disintegration is a relative one. It gives the drawback of students with migration background, relative to the native students in that country. This is exactly the measure I need to represent the situation of immigrants. It is not important, whether immigrants in the USA are better than German natives or the average native in the sample. The only important question is the relative position of immigrant students in the host society, the place where they are going to live and work.

A typical educational production function includes the students' family background characteristics, school resources and institutional features of the education system as explanatory variables, whereat the family background is seen to insert the most important influence (e.g. Hanushek and Luque, 2003, Wößmann, 2005a). I do not include school and institutional features in the achievement regressions. School resources are not randomly allocated across schools, just as little as students with migration background are. The allocation of school resources is seen as a potential source of integration policy and controlling for school characteristics in the educational production functions would underestimate the true level of disintegration. Institutional features are excluded because these factors are of main policy interest and their influence will be explored in the second part of this paper.

[3]Similarly, studies on the returns to education on the labor market show that individuals with migration background get a significantly smaller payoff to their education (cf. Chiswick and Miller, 2005, Hartog and Zorlu, 2005).

2.1 Data from Pisa and Timss

I use data from several waves of two different international student assessment studies. The Trends in International Mathematics and Science Study (Timss) has been conducted by the IEA (International Association for the Evaluation of Educational Achievement) in 1995, 1999 and 2003 in about 50 different countries and the Program for International Student Assessment (Pisa) has been organized by the OECD in 2000 and 2003. In both surveys about 4,000 students from about 170 schools were assessed in each participating country in each wave. Among other things, the surveys provide estimates of student proficiencies in mathematics and science, as well as detailed background information of students and schools.

After excluding some country-years due to a lack of observations and background information, the sample consists of 167 country-years which span a time period of 9 years (from 1994 to 2003). See table 1 for a list of the countries. For each of these 167 country-years, I estimate the disintegration of immigrants and second-generation immigrants (D_i, D_s). The dependent variable in the underlying educational production function is the student test score in Pisa and Timss, respectively and individual student characteristics are *age, grade, sex, the highest obtained education level of parents, the number of books at home, whether students have a computer, a calculator, an own desk to study at home and whether they speak the national language at home.* Table 2 gives summary statistics and a description of the student-level variables.[4]

This rich list of explanatory variables represents the individual characteristics of the students and their family background. Some more variables concerning the immigration status, like the reasons why the families migrated, the number of years since immigration and the home countries of the immigrants can, unfortunately, not be observed in all data-sets. A variable that is seen to play an important role for the economic assimilation of immigrants is, whether the students speak the national language at home. This variable is available in the data and included in the achievement regressions.

Some unobserved ability differences between natives and immigrants may exist, leading to an up- or downward bias in the measure of disintegration. However, the used variables should proxy the ability of the students well. In particular, the education of parents, the number of books and the language spoken at home are seen as powerful proxies for student abilities.

The achievement functions are estimated with survey regression techniques, taking into account that the students are not a random sample but the result of the stratified

[4] For some students not all explanatory variables are available. Due to the possibility of non-random missing values, these observations are not ignored but missing dummies are included in the educational production functions.

survey designs of Pisa and Timss. Students are weighted according to the inverse of their probabilities of being sampled and the possible dependence of standard errors within clusters (schools) is taken into account. Part of the difference in the study designs between Pisa and Timss can thereby be eliminated.

Overall, Pisa and Timss are of similar type. Both are aimed at obtaining an internationally comparable measure of the proficiency level of secondary education students and both incorporate a comparable quality standard with respect to the design and implementation of the assessment (e.g. sampling procedure, response rates, elaboration of background and test questions, marking of student answers and the generation of reliable achievement estimates).[5] The similarity of the Pisa and Timss survey designs allows the use of both studies together.[6]

Moreover, for the identification of institutional effects in the second step, it is important that each data point provides equally precise information. Following Silber and Weber (1999), standard errors of the decompositions are computed and their inverse are used as weights in the second step of the analysis. The standard errors of the decompositions are obtained by bootstrapping, with 200 bootstrap replications employed. Country-years in which disintegration is estimated with a lower degree of accuracy are weighted less in the second step.

2.2 Disintegration in various countries

This section summarizes the actual (non-standardized) results of the Blinder-Oaxaca decompositions in mathematics and science. Figure 1 shows the total achievement gaps between natives and foreign students, decomposed into an explained and an unexplained part. Due to the wide range of different countries, these are arranged into seven country groups, wherefrom mean values are reported.

On average, students with foreign background achieve lower scores than native students and a positive part of the test score gap can be explained with differences in student characteristics in each country group. The total mean gaps range from about 35 science test points in Africa to about 1 science test point in the Near East. Remember, the test scores are normally distributed with a (weighted) mean of 500 and a (weighted) standard deviation of 100 in math and science.

Most country groups exhibit similar gaps in math and science. The European countries show on average a large achievement gap, 22 points in math and 23 points in science, with

[5] See OECD (2001, 2002, 2003, 2004) and IEA (*http://timss.bc.edu/isc/publications.html*) for detailed information on the Pisa and Timss surveys.

[6] Although the surveys are very similar, some aspects that differ between Pisa and Timss are described in appendix A. Appendix B deals with the student achievement scores in Pisa and Timss and describes the applied transformation strategy to reach comparability.

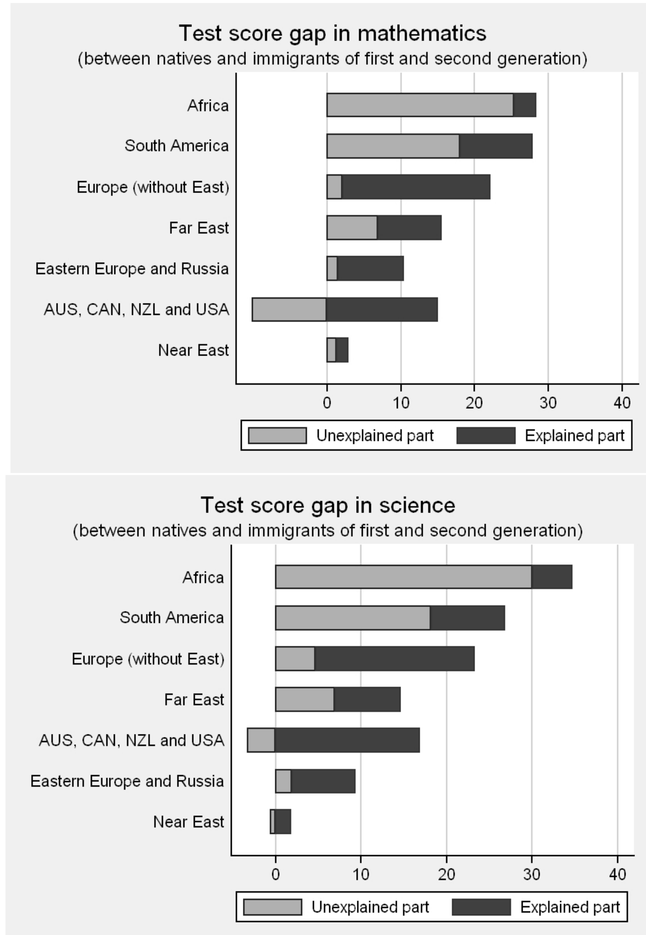

Figure 1: **Achievement gaps in math and science by country groups**

about 9% and 20% remaining unexplained. In the country group consisting of Australia, Canada, New Zealand and the United States the mean gaps are much lower and amount to about 5 math points and 14 science points. In these countries, the mean unexplained differential is even negative, which means that foreign students receive higher returns to their characteristics than natives.

An interesting pattern arises if one compares the disintegration measures with and without controlling for the national language proficiency of students in the achievement regressions. In the latter case, the unexplained differentials are substantially larger. In the European countries 35% and 42% of the gaps remain unexplained if language at home is not deducted. In Australia, Canada, New Zealand and the USA the mean unexplained differentials turn positive and add up to 12% and 75% of the whole gap. Hence, the proficiency of the national language is a major vehicle for migrated students to catch up in education. This result is an important finding, since language proficiency can be influenced by public policy in different ways, like the provision of special language courses in schools or language trainings for adult migrants.

Most countries in the sample are members of the OECD. Since these countries have comparable characteristics regarding the economic and social environment, the decomposition results from these countries are shown separately in figure 2.

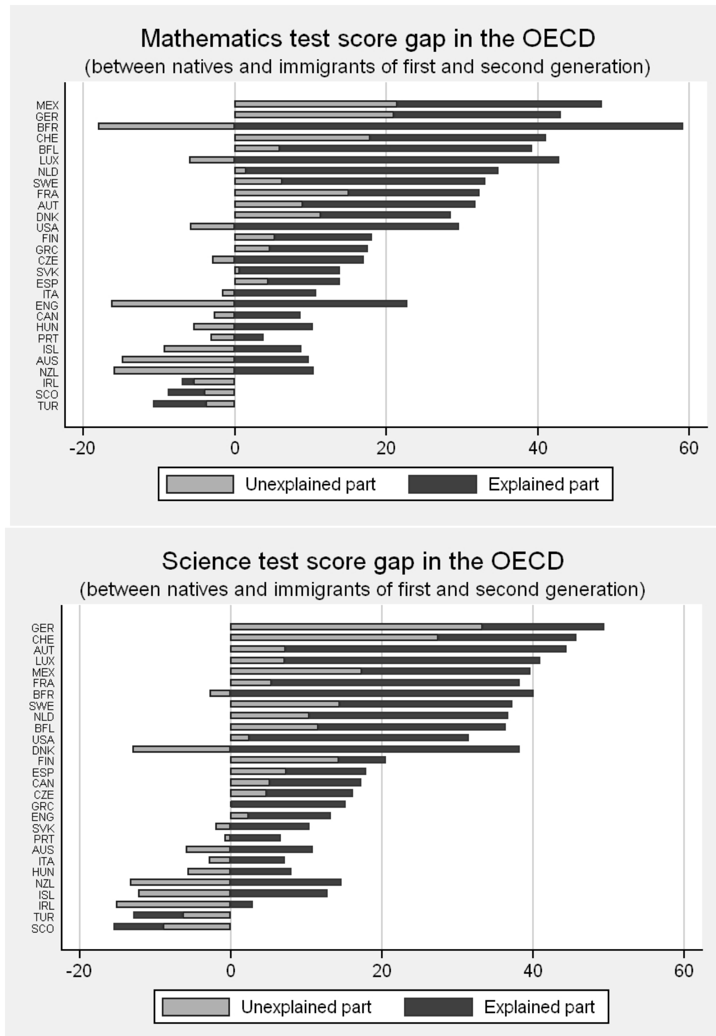

Figure 2: **Achievement gaps in math and science in the OECD**

In addition to the large variation of achievement gaps and unexplained differentials, the graphs tell us two important stories:

- *Australia, Canada, New Zealand and the United States*, frequently characterized as traditional countries of immigration, are found in the middle and lower tail of the gap distribution, whereat in some countries children with migration background outperform native students. Most of these countries follow a selected immigration policy, targeted at individuals with high education, professional skills and good language proficiency (cf. Miller, 1999, Entorf and Minoiu, 2005). The United States are located in the middle of the gap distribution and have a somewhat different migration population due to its border to Mexico and its large fraction of family reunions (cf. Entorf and Minoiu, 2005). The total gaps between migrated students and native Americans amount to 24 math points and 32 science points. Students with migration background come from families with less favorable characteristics and they get on average higher returns in math and lower returns in science compared to native Americans.

- *Within Europe*, the German-speaking countries, the Benelux-countries, France and the Scandinavian countries can be found in the upper part of the distribution. The Southern and Eastern European countries as well as England, Ireland and Scotland are ranked in the lower tail.

As mentioned above, a standardized version of the unexplained differential is used as measure of disintegration in the regression analysis of the second part. Table 4 gives summary statistics of the actual and the standardized unexplained differentials in mathematics and science. In all cases, immigrants face a higher level of disintegration than second-generation immigrants. This result was expected, as the assimilation of immigrants is associated with their length of stay in the host country. Furthermore, for immigrants, disintegration is larger in science than in math.

The unexplained part of the test score gap can be interpreted as a measure of disintegration, since it tells us how much better students with migration background would perform if they had the same returns than native students. This measure is not reliable if unobserved ability differences between natives and immigrants exist, which are not covered by the rich list of individual and family background characteristics.

2.3 Unobserved ability differences?

The immigrants of a given country are a highly selected group of people. Certain factors motivated their decision to migrate, while others decided to stay in the country. Economic models have been developed that investigate the selectivity of *economic migrants* with respect to their ability. The most important is the Roy model, applied by Borjas (1987, 1999) and extended by Chiswick (1999). This human-capital migration model assumes that the rate of return from migration is different for high-ability and low-ability individuals and determines whether an individual decides to migrate. Positive fixed costs of migration lead to a positive selection of migrants, which is intensified if high-ability individuals are more efficient in the migration process. Furthermore, economic immigrants are negatively selected if the wages in the destination, relative to the home country, are higher for low-ability individuals. This result implies that, for a constant ability distribution across countries, a lower relative income inequality in the destination country negatively selects migrants. In total, due to the costs of migration and the likelihood that such costs are lower for high-ability individuals, economic migrants are positively self-selected. The positive selectivity is diminished if the relative income inequality is higher in the home county.

Economic reasons are not the only ones, why people migrate. Refugees have to move because their safety or freedom is at risk and other people move to accompany family members in other countries. Such migrants are mostly not favorably selected, as studies on unemployment and earnings show (Chiswick, 1999). Furthermore, not only the supply of immigrants determines the foreign population of a country, but demand side effects are relevant, too. Some countries follow an immigration policy that is restricted to well-educated immigrants with good language skills.

Overall, as long as ability and motivation cannot be observed entirely, the estimated disintegration is likely to be over- or underestimated depending on unobserved ability differences. Economic theories predict that in countries with a relatively low level of income inequality and a big part of immigration due to non-economic reasons, immigrants are likely to be negatively self-selected with respect to their ability. On the contrary, a selective immigration policy leads to a positive selection of immigrants. Thus, the high level of disintegration in the European countries, may be overestimated, whereat the low or even negative level of disintegration in traditional immigration countries may be underestimated.

3 The role of institutions

Why does educational integration vary so dramatically between different countries? What is the influence of the education system and what can policy do to further the integration of students with migration background?

To find answers to these questions, I relate the unexplained part of the test score gap to institutional characteristics of the education system, such as ethnic and social segregation of students among schools, pre-primary education, starting age of schooling, class size, full-time schooling, external student assessment, costs of education and promotion activities.

Segregation School systems differ with respect to the segregation of migrants and poor students among schools. A high degree of ethnic or social segregation is caused either by selectivity mechanisms of the education system, like general tracking, or by a high degree of residential segregation in comprehensive education systems. On the one hand, immigrants may profit from segregated schools because teachers may be more able to target the needs of the students in more homogenous classes. On the other hand, a higher degree of segregation can harm immigrant children because they have a higher probability of being allocated to low grade school types and schools (e.g. Rees et al., 1996, Epple et al., 2002). Attending a lower grade school type or a school in a poor neighborhood can have negative effects for mainly two reasons: school resources might not be equally allocated to the different schools and the absence of clever classmates and students from supporting homes may have negative effects on the learning climate. Some empirical studies on peer effects show that low-ability students and students from less favorable family backgrounds could profit from being placed with high-ability peers (Winston and Zimmerman, 2003, Sacerdote, 2001, Schneeweis and Winter-Ebmer, 2006). Whether the negative effects of segregation overwhelm the positive ones will be seen.

Pre-primary education Carneiro et al. (2005) have studied labor market discrimination of ethnic minorities in the United States and argue that deficits in cognitive skills of minorities emerge early and widen with schooling. The authors recommend that policy measures to increase the labor market success of minority groups should be applied as early as possible. Early-childhood programs, like kindergartens, day care centers and pre-schools are aimed at preparing children for primary education and providing an equal starting point for all children. Currie (2001) investigated pre-school programs in the United States and found significant benefits for educational attainment and earnings, especially for disadvantaged children. In another study, Currie and Thomas (1999) focused on the impacts of Head Start, a subsidized pre-school program in the US. The authors show that all children benefit from Head Start, compared to their siblings, who did not attend the program and Head Start closes one quarter of the test score gap between Hispanic and white children. Head Start has also shown to have significant long-term effects: white children are more likely to complete high school and attend college and African-Americans are less likely to be involved in criminal activity (Garces et al., 2002). In total, the evidence on pre-primary education suggests that a country should be more effective in decreasing inequality between ethnic groups, the more children of immigrants and second-generation immigrants attend pre-primary education.

Starting age of schooling Whether to enroll children in school at an earlier or later time has been discussed frequently. Most economic studies in this regard rely on within-country variation in entry age due to month or quarter of birth (e.g. Angrist and Krueger, 1992). In this cross-country study a wider range of variation in school starting age is investigated. It is hypothesized that enrollment at age 7 is detrimental for immigrant students, since the integration process in school starts later and the effect of parental background gets stronger. Attendance at age 5 should operate the other way around and reduce the drawback of migration.

Pupil-teacher ratio The question, whether class size affects student achievement, has been studied extensively. In general, only little solid evidence has been found to support class size reduction policies. Krueger (1998) has found significant negative effects of the pupil-teacher ratio, with higher magnitudes in mathematics than in science. The investigation of the Tennessee Student-Teacher Achievement Ratio experiment (STAR) shows that smaller classes in primary education help students, especially low-income and minority students. The pupil-teacher ratio in primary education, thus, is assumed to have a negative impact on the integration of foreign students.

Time in school If foreign students spend more time in school, pedagogically supported, together with kids of other ethnic groups, they should communicate more, learn the national language and other national habits and integration can take place. Additionally, the influence of the parents on the learning of their children is limited. A full-time school system should, therefore, lead to a higher degree of integration. On the other hand, especially for students with learning or language problems, top much time in school might be too demanding. Aksoy and Link (2000) investigated US panel data and found mathematics achievement to be positively affected by the number of minutes per math class. The number of legal days in school and hours of school week show no consistent effects. Lewis and Seidman (1994) found large positive effects of the length of school year in a cross-section analysis. In total, it is expected that up to a certain level, time in school should have positive effects on the integration of children with migration background.

External student assessment Central examinations restrict the latitude of teachers' grading practices, provide information on the relative standing of students and schools and induce parental and public pressure on students, teachers and schools. It is not surprising that central student assessments are positively related to academic achievement. Wößmann (2005b) has shown that central exams exert heterogenous performance effects and reduce the achievement drawback of children with migration background. Thus, external student assessment should increase educational integration.

Costs of schooling Educational costs influence the decision of accumulating human capital (Becker, 1964). Higher costs of schooling should reduce educational attainment and, thus, learning motivation and effort of teenage students, in particular those from less favorable home environments. Direct costs as well as opportunity costs of schooling should decrease the success of integrating ethnic minorities. Following Bauer and Riphahn (2007), I use the population density as a proxy for direct and the unemployment rate as an indicator for indirect education costs. It is assumed that a lower population density increases the mean distance to school and in turn raises the costs of schooling. Furthermore, the opportunity costs of education are higher, the more jobs available, thus, the lower unemployment.

Promotion of students Immigrant children should profit from school systems which offer special courses in academic subjects for low achieving students. Enrichment activities for gifted students, on the other hand, may increase the achievement gap. If students with migration background are less frequently promoted in enrichment courses, such programs are detrimental to the integration of these children.

3.1 Identification of institutional effects

I use pooled weighted least squares and fixed-effects methods to identify institutional effects on disintegration. The model can be written as

$$D_{ct} = \alpha_0 + \alpha_1 \mathbf{I_{ct}} + \alpha_2 \mathbf{Y_{ct}} + \alpha_3 \mathbf{C_{ct}} + v_c + u_{ct}, \tag{5}$$

where c and t index countries and time. The dependent variable D_{ct} is the standardized unexplained differential of immigrants and second-generation immigrants, respectively. The vector $\mathbf{I_{ct}}$ represents educational institutions, $\mathbf{Y_{ct}}$ stands for the income situation of the country and $\mathbf{C_{ct}}$ is a vector of control variables. The error term of the model is split up in a part that is constant within each country v_c and an idiosyncratic part u_{ct}.

A country fixed-effects estimation is a perfect way to eliminate the country specific unobservables v_c, like the ability composition of the immigrant population which is not entirely observed. The main identifying assumption is then reduced to the condition that foreign students observed in 1994 should not differ from those in 2003 in their unobserved characteristics within each country.

The problem of a country fixed-effects estimation is that only the variation over time within the countries is used to estimate the coefficients. With a time span of not even 10 years, it is difficult to rely on time variation only. Institutional characteristics show little time-variability and the effects of explanatory variables that do not change over time cannot be estimated. Furthermore, differencing out country effects may cause attenuation bias because of measurement errors. Measurement errors might arise in this study from an imprecise measurement of disintegration, the fact that it is calculated from different student assessment studies and the aggregation of institutional characteristics to the country-level.

Due to these reasons, three methods are used to estimate the model, pooled WLS, WLS with country group dummies as listed in table 1 and WLS with country fixed-effects. Furthermore, to account for major changes in the unobserved characteristics of the immigrants over time, I control for changes in the home countries (migration regions) of the foreign population. For a small number of countries, I have aggregate data on the home regions of the migrant population stock. Moreover, the model is estimated for the whole sample and for the subsample of OECD-countries. Though the OECD-sample is rather small, it includes countries that show comparable characteristics and the identifying assumptions are more likely satisfied.

3.2 Explanatory variables

The empirical analysis of institutions is based on data from different sources. First, the Pisa and Timss databases include useful information on schools, whereat the relevant school variables are aggregated to the country-level.[7] One might ask, why school data are aggregated to the country-level and their effects on immigrant performance are not estimated directly. Exploiting the variation among schools entails the problem of student self-selection. If high-ability immigrants are more likely to choose better schools with clever peers and adequate equipment, the effects of school resources cannot be identified. Aggregation helps to overcome this identification problem to the cost of measurement errors in focusing only on the mean level of resources, regardless of their distribution.

Further data sources are the World Banks' World Development Indicators 2005, the UNESCO Institute for Statistics and the Trends in International Migration published by the OECD. Table 5 gives summary statistics of the country-level variables. Unfortunately, the used data is incomplete. As is explained in detail in appendix C, some missing values are imputed from other years. Further unavailable data that cannot be imputed from other years are not dropped from the sample but missing dummies are included in the regressions.

Segregation of students among schools is measured by the Duncan and Duncan (1955) dissimilarity index, recently applied by Burgess and Wilson (2003) and Jenkins et al. (2006). The dissimilarity index of ethnic segregation is based on a binary variable that splits the population into two groups:

$$\text{Ethnic segregation} = \frac{1}{2}\sum_{s=1}^{S}\left|\frac{f_s}{F} - \frac{n_s}{N}\right|, \tag{6}$$

where f_s and n_s are the numbers of foreign and native students in school s and F and N are the total numbers of foreign and native students in the country. The index

[7]Because Pisa and Timss do not provide representative samples of schools in a country, the aggregation is based on weighted schools, whereat the weight for a school is simply the sum of all student weights within this school. Since the student sample is representative for the total student population, weighted school aggregates are good proxies for the school population.

ranges from 0 to 1 and gives the fraction of students with migration background that has to be moved to other schools to ensure an equal representation of foreign students in each school. Analogously, a social segregation index is calculated, where the two groups represent students with more and less than 25 books at home.[8]

A measure of pre-primary education is the percentage of students enrolled in pre-primary education (from all eligible students). Enrollment rates by immigration status are not available, thus, it is assumed that higher total enrollment rates can be associated with higher enrollment rates of minorities, too. Chiswick and DebBurman (2005) have shown that immigration status, next to socio-economic background, education and family size positively affects pre-primary enrollment. The variable is used in a lagged form and matches the years where the children were 4 to 5 years old.

The starting age of schooling ranges from 5 to 7, whereat in most countries the students enter primary education at age 6. The pupil-teacher ratio in primary education refers to the years 1988 to 1996, the period when the children of the sample were 7 to 8 years old. Time in school is represented by the instructional hours per school year. This information is available for each school that participated in Pisa and Timss and was aggregated to the country-level. External student assessment is given by the fraction of schools that does not have the primary responsibility for student assessment policies. The costs of schooling are measured by the population density and the unemployment rate of youth. Promotion of students is given by the fraction of schools that offers, on the one hand, enrichment courses in mathematics and science for gifted students and, on the other hand, remedial courses for low achieving pupils.

Furthermore, GDP per capita and the Gini coefficient represent the income situation of the country. GDP per capita is an indicator for the general availability of resources and the Gini coefficient gives a picture of inequality in the labor market. Moreover, high-income countries with a lower degree of income inequality may suffer from negatively self-selected economic migrants. Unfortunately, there is no time variation in the Gini coefficient in the available data. It is assumed that income inequality has not changed substantially within the analyzed time period and the Gini coefficient is taken as fixed for each country.

The Trends in International Migration provides information on migration regions for a small number of country-years. Thus, I have the information on where the foreign population comes from. This information is used to account for the possibility that unobserved characteristics of the foreign population change over time.

[8]The segregation indices differ between Pisa and Timss. While Pisa sampled single students from schools, Timss assessed whole classes. Thus, the Pisa data refer to school segregation, whereas the Timss data measure segregation among classes.

4 Results

Table 6 gives the estimation results in math and science for all countries. The first two columns of figures contain the results of the pooled WLS estimations, followed by the country group fixed-effects and country fixed-effects methods. The regressions are weighted with the inverse standard error of the underlying decomposition. The dependent variable is disintegration in math and science of immigrants and second-generation immigrants, respectively. The effects of income inequality as well as starting age of schooling cannot be estimated with country fixed-effects because these variables do not change over time.

4.1 Baseline specification

Income situation Pooled WLS as well as country group fixed-effects show that the income situation of the country has a significant influence on the level of disintegration, at least in mathematics. This may be due to a resource effect, but also to non-random economic migration. The results indicate that high income countries show a higher level of disintegration. Furthermore, a higher level of income inequality increases disintegration of foreign students. This result was expected, since migrants often belong to the poor part of the society and unequally spent resources should affect them negatively. Interestingly, the interactions of GDP and Gini show that foreign students are better integrated in high-income countries with a higher level of income inequality. The effect may represent the selectivity of economic migrants. This is exactly what economic theory about migration predicts. Remember, economic migrants with high abilities are more likely to migrate to countries where they earn more. Thus, migrants are positively self-selected in high-income countries with a higher level of income inequality. Unfortunately, the results on the income situation cannot be checked with country fixed-effects. However, the aim is the revelation of a selection mechanism, not the inference of a causal relationship. Pooled WLS and WLS with country group effects should, therefore, be sufficient to support the human capital migration model.

Institutions Ethnic segregation of students among schools shows significant effects in some regressions. It seems that the predicted negative effects of segregation (peers and resources) overwhelm the predicted positive ones (homogenous classes). Students with migration background profit from schooling systems that do not separate them in different schools or classes, wether by tracking or by residential segregation in comprehensive systems. However, the statistical significance is rather small and the effect totally breaks down when differencing out country effects. The degree of social segregation in the school system shows the expected positive sign in all regressions, but the statistical significance is too low to draw any conclusion.[9]

Enrollment in pre-primary education reduces disintegration in the pooled WLS science estimation. Most of the other coefficients on pre-primary enrollment show the expected sign but are not statistically significant.

Starting age of schooling is important for educational integration. The pooled WLS estimations in mathematics and science show that education systems where students enter at an age of five can be associated with significantly lower levels of disintegration. Including country group effects reduces the statistical significance. On the other hand, a late entry age of seven is correlated with a higher level of disintegration. However, the effect is only statistically significant in science when differencing out country group effects. Countries where children enter primary education at an age of seven, compared to six, show remarkably higher levels of disintegration in science. The effect amounts to 40% of the standard deviation of the dependent variable and is statistically significant at the 1%-level. This result may be due to unobserved country heterogeneity and, unfortunately, cannot be approved with country fixed-effects.

Time in school is represented by the number of instructional hours per school year (divided by 100). The variable is also included in a quadratic form to allow for non-linear returns to school hours. The coefficients are statistically significant in almost all regressions and show the expected effects. According to the country fixed-effects results, more time in school reduces disintegration up to 1,049 hours in mathematics and up to 1,006 hours in science. Given a mean value of 932 hours per year in the whole sample, an increase in schooling time would further integration in a number of countries.

Direct schooling costs are important for children with migration background in math, while the coefficients for science are not statistically significant. A higher population density can be associated with lower direct costs of education and reduces disintegration.

Promotion activities for weak students show some negative effects on disintegration, but these are only statistically significant in the first and second specification. When introducing country dummies the statistical significance is reduced to 12%. Promotion of gifted students is detrimental for educational integration if students with migration background are less likely to be accepted in such courses. This seems to be true in mathematics, as the country fixed-effects specification shows.

Mixed and mostly insignificant results are obtained for the pupil-teacher ratio, external student assessment and youth unemployment.

[9] As mentioned above, the Timss observations measure segregation across classes and Pisa refers to schools. To account for this circumstance, both segregation measures were interacted with a Timss and a Pisa dummy, but no systematic differences have been found.

Control variables The control variable for the Pisa study is mostly statistically significant and a quadratic time trend was found in some specifications.[10] As was expected, second generation immigrants do better than immigrants, both in mathematics and in science. The gaps between immigrants of the first and second generation are of equal magnitudes in all regressions, about 6 test scores in mathematics and 10 test scores in science. The coefficients are economically and statistically more significant in science. One reason for this result may be the students' language proficiency. One may assume that knowledge in science is more influenced by reading habits compared to knowledge in mathematics. The reading habits, in turn, should be impaired by insufficient language skills, from which immigrants do suffer more than second-generation immigrants.

4.2 Sensitivity checks

Two kinds of sensitivity checks are implemented. First, the model is estimated for the subsample of OECD-countries and second, the regions wherefrom the foreign populations have been migrated are controlled for.

Results for OECD-countries As mentioned above, the identifying assumptions of the model are more likely satisfied if one compares similar countries, only. This is particularly important for the pooled and country group fixed-effects specifications. The subset of OECD-countries meets this requirement, since these countries share a number of economic and social characteristics. Table 7 gives the estimation results.

The income situation gives the same picture as above and shows significant effects in science, too. This result can be interpreted as a selection mechanism. Immigrants and second-generation immigrants in high-income countries with a higher degreee of income inequality are better off. This is consistent with the predictions of economic theory on the selectivity of economic migrants.

The effect of ethnic segregation on disintegration cannot be approved with the OECD-sample, but social segregation is statistically more significant. All coefficients have the expected positive sign and the statistical significance in science is 10% for the first two estimations and 11% when differencing out country effects.

The effects of pre-primary education are also statistically and economically more significant within the OECD and show an important magnitude even in the country fixed-effects specification. According to this specification, an increase in the total enrollment rate by 25%-points (one standard deviation within the OECD) reduces disintegration by about 30 math points. That is approximately one standard deviation of the dependent variable within the OECD.

[10] The inclusion of dummy variables for the different study-waves instead of Pisa and time does not change the results

Moreover, the results on school starting age of primary education can be approved. Migrants perform considerably better if they enter school at an age of 5, compared to 6.

Total hours per school year influence mathematics proficiency. According to the country fixed-effects specification, schooling time reduces disintegration up to 1,174 instructional hours per year. Given a mean of 954 within the OECD, this is an important message. The magnitude of the effect is sizeable: starting from the mean, an increase of 100 hours (one standard deviation within the OECD) can be associated with a decrease in disintegration by 6.5 math scores.

While most of the other variables show mixed and insignificant results, external student assessment seems important within the OECD. Disintegration in science is much smaller if schools are not responsible for assessment policies. The country fixed-effects specification gives a large coefficient which is statistically significant at the 5% level.

Overall, when estimating the model with OECD-countries only most effects on institutions that have been obtained for all countries are corroborated and additional insights for the OECD-countries are won.

Results with migration regions The second sensitivity check is based on a model that controls for the regions where the immigrants of a given country come from. This strategy should remove the remaining problem that unobserved country characteristics, like the composition of the immigrant population, change over time. The information on migration regions is only available for 65 country-years. As mentioned above, the other observations are not dropped but a missing dummy is included in the regressions. The results are given in table 8 and are very similar to those of table 6, where migration regions are not included.

4.3 How much do institutions explain?

Do institutional characteristics of the education system explain differences in educational integration? To answer this question, I ran the pooled weighted least squares regressions once only with institutional characteristics of the education system and once only with income variables. The resulting R^2 are given in table 9. As one can see, institutions matter. 21.8% and 18.4% of the overall variation in disintegration can be explained by institutions in the whole sample and 14.3% and 11.9% can be explained within the OECD.

5 Summary and policy recommendations

This essay was aimed at quantifying disintegration of immigrants of the first and second generation in secondary schools. Blinder-Oaxaca decompositions show that, on average, the test score gaps between students with foreign background and native students cannot be entirely explained with differences in the students' productivity characteristics. In most countries a positive part of the test score gap remains unexplained. As shown in figure 2, educational gaps between native and foreign students and the parts that remain unexplained vary substantially among the OECD-countries.

Australia, Canada, New Zealand and the United States, frequently characterized as traditional countries of immigration, are found in the middle and lower tail of the gap distribution. The mean achievement gaps amount to 5 points in math and 14 points in science. In this country group disintegration is negative, which means that students with foreign background get higher returns to their characteristics than natives. The achievement gaps in Europe are larger and average out to 22 math scores and 23 science scores, with 9% and 20% remaining unexplained.

The proficiency of the the national language turned out to have significant effects on integration. Disintegration is substantially larger if national language is not included in the achievement regressions. In the traditional countries of immigration, the unexplained gaps turn positive and amount to 12% and 75% of the whole gap. In Europe the unexplained gaps increase to 35% in math and 42% in science. These findings strongly argue for public policies that encourage immigrants to learn the national language.

In the second part, I related disintegration of students with migration background to institutional characteristics of the education system, the income situation of the country and some control variables. The estimations show significant statistical evidence on the influence of some institutional characteristics and other variables.

Interestingly, the estimated effects of the income situation show exactly the results predicted by economic theory of migration: high income countries with a high level of income inequality should attract immigrants with higher abilities. In fact, educational integration is higher in high income countries with higher levels of income inequality.

The design of the education system explains a significant part of the variation in disintegration, 21.8% in math and 18.4% in science. The study indicates that early education is very important for children with migration background. While immigrant students profit from a school starting age of 5, a late entry in primary education is detrimental to their integration. Moreover, enrollment in pre-primary education decreases disintegration. According to the country fixed-effects estimation, an increase in the total enrollment rate by 25%-points in the OECD-countries reduces disintegration by about

30 math points. This result is in line with the studies on Head Start and indicates that promotion of students with migration background should start as early as possible.

Social segregation of students among schools is detrimental to the integration of immigrants in the OECD-countries. A higher degree of social segregation, either due to general tracking or residential segregation in comprehensive education systems, can be associated with a higher unexplained test score gap in science.

Furthermore, I strongly recommend an increase in schooling time for a number of countries. According to the country fixed-effects results, more time in school reduces disintegration in the OECD-countries up to 1,174 hours. Given a mean value of about 920 hours in Germany and 955 hours in the United States and Canada, an increase in schooling time would be beneficial for children with migration background.

Central examinations increase the academic achievement of immigrant students. This is consistent with other studies and may be due to the involved restriction in the latitude of teachers' grading practices and information-induced pressure on students, teachers and schools. In the OECD-countries, the implementation of external student assessments would decrease educational disintegration substantially. An increase in the fraction of schools without main responsibility for student assessment by 0.20 can be associated with a decline in disintegration by about 11 science points.

Overall, the study has shown that the design of the education system is important for children with migration background. Recent demographic trends in many industrialized countries indicate that the integration of migrants will be a major challenge in future. To meet this challenge, policy makers have to regard educational integration as important precondition and education policy as a main instrument to further the economic assimilation of immigrants.

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A Appendix: Comparability of Pisa and Timss

Although the surveys are very similar, some aspects that differ between Pisa and Timss should be mentioned. Timss measures the mastery of an internationally agreed curriculum while Pisa focuses on challenges of every-day life. Thus, the test questions span the same topics, but differ in their reference to reality. Furthermore, the target population consists of teenagers in secondary education. Timss covers children in the grade(s) with the highest proportion of 13-year-olds (typically grade 7 or 8) and Pisa covers 15-year-old students, independent of grade. It is possible that immigrants of the first generation are more likely placed in lower grades, given their age, for two reasons: they might have started later with schooling and, in countries where grade-repetition is common practice, they are more likely to repeat a grade than native students. This problem is taken into account and the student variables age and grade are included in the educational production functions. In other words, foreign and native students are only compared on the grade level, anyway.

From the target population, schools were randomly sampled, but whereas in Pisa all eligible students from that schools (up to a maximal number of 35 students) were assessed, in Timss one class per grade was randomly chosen and all students from this class were assessed. In addition, the form of test questions is slightly different. While about two thirds of all Timss questions show a multiple choice character, Pisa uses only 50% of multiple choice questions.

Finally, the item response model differs. As the assessment consists of a set of test questions with different levels of difficulty and the students answered different questions, the actual scores are not directly observed, but must be inferred from the observed item responses. For this aggregation, Pisa used a one-parameter item response model and Timss relied on a three-parameter model. Brown et al. (2005) present a discussion on the influence of the item-response model and conclude that the item response model influences the test score distribution. Nevertheless, the authors have shown that the Pisa 2000 one-parameter model results match the results of the Timss 1995 three-parameter model better than the Timss 1995 one-parameter model. The proficiency scores of Timss 1995 have been generated with a one-parameter and a three-parameter response model and are available to compare.

B Appendix: Student achievement scores

Timss achievement scores in mathematics and science are directly comparable across the three different waves. In 1995, the Timss team standardized the achievement scores on an international level, based on weighted student data of nearly all participating countries. The distribution of all assessed 8^{th} grade students was set to a mean of 500 and a standard deviation of 100. This was done only for students in grade 8 (not for those in grade 7) because in the repeated Timss studies in 1999 and 2003 the target population consisted of 8^{th} grade students, only.

The achievement scores in Pisa have been also standardized to a weighted mean of 500 and a standard deviation of 100 on the basis of the participating OECD-countries. Because of the alternate major subject assessment in each wave, the Pisa achievement scores are directly comparable across waves in science, but not in mathematics.

The different scales (Timss, Pisa 2000 and Pisa 2003) have been standardized by the survey teams to a weighted mean of 500 and a standard deviation of 100, but on the basis of a different group of countries. Pisa focused on OECD-countries primarily, while Timss included a more heterogeneous country set. A typical OECD-country is likely to perform above average in Timss, but not in Pisa and the test scores cannot be compared without transformation.

To my advantage, 15 countries participated in both, the Timss wave 2003 and the Pisa wave 2003. Given the very similar design of the surveys, it is assumed that the test score distribution in Timss should be equal to that in Pisa in these 15 countries. Thus, the Pisa scores of the common subsample were transformed to the same weighted mean and standard deviation as the Timss subsample and in science all other Pisa science scores were then just added to the scale. In mathematics, a second step was necessary. I calculated the score distribution of the Pisa 2003 data for the subsample of countries participating in 2000 and 2003 and applied this distribution to the Pisa 2000 subsample.

After this transformation procedure, the math and science scales were transformed to a weighted mean and standard deviation of 500 and 100. Note that the transformation has no influence on the ranking of the students and does not change the distance in terms of standard deviations between any two students. Very similar approaches were used by Hanushek and Wößmann (2005), Schütz et al. (2005) and Ammermüller (2005b). Table 3 shows the correlation coefficients of the weighted country means of the achievement scores in math and science among the different waves of Pisa and Timss. On average, country means correlate with about 85% in mathematics and 84% in science. The correlations of medians give a similar picture. Interestingly, the correlations among the different Timss waves are higher than those of Pisa and those between the studies.

C Appendix: Treatment of missing explanatory variables

As mentioned above, the country-level variables show a number of missing values, whereat some have been imputed from information of other years:

- Enrollment in pre-primary education is needed for the years where the students of the sample were 4 to 5 years old: 1985/86, 1988/89, 1991, 1992 and 1993. The information is available for 1985, 1990, 1991, 1992 and 1993 for all countries, thus, the missings values for the years between 1985 and 1990 are imputed with the information on these years. For example, the information on 1989 is calculated with the weighted mean of 1985 and 1990. Furthermore, a few countries show some missing values for single years. These observations have been imputed with the values of the previous or following year, if available.
- The pupil-teacher ratio and the unemployment rate are not available for a few relevant years. Therefore, the information is used from the previous or following year, if available.
- Hours per year is not included in the Pisa 2003 data, thus, the Pisa 2000 indicators are used for those countries that participated in both waves.
- The Timss 1995 (2003) data do not include school information for the Philippines and South Africa (Netherlands), thus, the information on time in school, external student assessment and promotion activities for these three countries was taken from Timss 1999.
- The data on migration regions are not available for the years 2002 and 2003 and the years 2000 or 2001 are used instead. Furthermore, some countries show missing values in some years and, again, the information from the previous or following year is taken.

D Appendix: Tables

Table 1: **List of countries used in the analysis**

Country	ISO-Code	Study-Years
Europe (without Eastern European countries)		
Austria	AUT	t1995, p2000, p2003
Belgium flemish	BFL	t1995, t1999, p2000, t2003, p2003
Belgium french	BFR	t1995, p2000, p2003
Switzerland	CHE	t1995, p2000, p2003
Germany	GER	t1995, p2000, p2003
Denmark	DNK	t1995, p2000, p2003
England	ENG	p2000, t2003, p2003
Spain	ESP	t1995, p2000, p2003
Finland	FIN	p2000, p2003
France	FRA	p2000, p2003
Greece	GRC	t1995, p2000, p2003
Ireland	IRL	t1995, p2000, p2003
Iceland	ISL	t1995, p2000, p2003
Italy	ITA	t1995, t1999, p2000, t2003, p2003
Luxembourg	LUX	p2000, p2003
Netherlands	NLD	t1995, t1999, p2000, t2003, p2003
Portugal	PRT	t1995, p2000, p2003
Scotland	SCO	t1995, t2003, p2003
Sweden	SWE	t1995, p2000, t2003, p2003
Eastern Europe and Russia		
Bulgaria	BGR	t1999, t2003
Czech Republic	CZE	t1995, t1999, p2003
Estonia	EST	t2003
Hungary	HUN	t1995, t1999, t2003, p2003
Lithuania	LTU	t1995, t2003
Latvia	LVA	t1995, t1999, p2000, t2003, p2003
Macedonia	MKD	t1999, t2003
Moldova	MDA	t1999, t2003
Romania	ROM	t1995
Russian Federation	RUS	t1995, t1999, p2000, t2003, p2003
Slovak Republic	SVK	t1995, t1999, t2003, p2003
Slovenia	SVN	t1995, t1999, t2003
Serbia	YUG	t2003, p2003
Australia, Canada, New Zealand and the USA		
Australia	AUS	t1994, t1998, p2000, t2002, p2003
Canada	CAN	t1995, t1999, p2000, p2003
New Zealand	NZL	t1994, t1998, p2000, t2002, p2003
United States	USA	t1995, t1999, p2000, t2003, p2003

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Country	ISO-Code	Study-Years
South America and Mexico		
Chile	CHL	t1998, t2002
Colombia	COL	t1995
Mexico	MEX	p2000, p2003
Uruguay	URY	p2003
Near East		
Armenia	ARM	t2003
Bahrain	BHR	t2003
Cyprus	CYP	t1995, t1999, t2003
Iran	IRN	t1995, t2003
Israel	ISR	t1995, t1999, p2002, t2003
Jordan	JOR	t1999, t2003
Kuwait	KWT	t1995
Lebanon	LBN	t2003
Saudi Arabia	SAU	t2003
Turkey	TUR	t1999, p2003
Far East		
Hong Kong	HKG	t1995, t1999, p2002, t2003, p2003
Indonesia	IDN	t2003
Macao, China	MAC	p2003
Malaysia	MYS	t1998, t2002
Philippines	PHL	t1995, t1999, t2003
Singapore	SGP	t1994, t1998, t2002
Thailand	THA	t1995, t1999
Africa		
Egypt	EGY	t2003
Ghana	GHA	t2003
Morocco	MAR	t1999, t2003
South Africa	ZAF	t1995, t1998, t2002
Tunisia	TUN	t1999, p2003
# Countries = 62		
# Country-years = 167		

Notes: Due to differences in their education systems, Flemish and French Belgium as well as England and Scotland participated separately in Timss and are treated as different countries. Furthermore, the Timss waves 1995, 1999 and 2003 were implemented in the years 1994, 1998 and 2002 in some countries and some countries carried out the Pisa 2000 assessment in 2002.

Table 2: **Student-level variables**

Variable	Description	Mean	Stdev
Test score			
Math score	Transformed plausible value of math proficiency	500	100
Science score	Transformed plausible value of science proficiency (science sample)	500	100
Ethnicity			
Immigrant	Student was born in a foreign country	0.082	
Second-Generation Immigrant	Student's father, mother or both were born in a foreign country and student was born in the country	0.132	
Native	Student and his/her parents were born in the country	0.786	
Individual characteristics			
Age	Age of student in years	14.779	1.050
Grade	Grade at school	8.480	1.046
Female	Student is female	0.509	
Number of books at home			
Books1	None - 10 books	0.123	
Books2	11 - 25 books	0.201	
Books3	26 - 100 books	0.276	
Books4	101 - 200 books	0.177	
Books5	More than 200 books	0.222	
Highest education level reached by a parent			
Hisced01	No schooling or primary education (Isced 0, 1)	0.122	
Hisced2	Lower secondary education (Isced 2)	0.099	
Hisced34	Upper secondary education (Isced 3, 4)	0.491	
Hisced56	Tertiary education (Isced 5, 6)	0.287	
Computer	Student has a computer at home	0.608	
Calculator	Student has a calculator at home	0.935	
Study desk	Student has an own desk to study at home	0.876	
National language	Student speaks the national language, another national language or a national dialect at home, most of the time	0.853	
# Students in the mathematics sample = 753,282			
# Students in the science sample = 753,445			
# Country-years = 167			

NOTES: The means and standard deviations are based on the mathematics sample and weighted according to the students' sampling probabilities. The weights are adjusted to ensure an equal contribution of each country-year.

Table 3: **Correlations among Pisa and Timss achievement scores**

	Timss 1995	**Timss 1999**	**Timss 2003**	**Pisa 2000**	**Pisa 2003**
Timss 1995	1 (1) 37 obs				
Timss 1999	0.97*** (0.96***) 20 obs	1 (1) 29 obs			
Timss 2003	0.97*** (0.93***) 21 obs	0.97*** (0.96***) 24 obs	1 (1) 38 obs		
Pisa 2000	0.65*** (0.57***) 22 obs	0.84*** (0.83***) 12 obs	0.82*** (0.88***) 13 obs	1 (1) 28 obs	
Pisa 2003	0.71*** (0.69***) 25 obs	0.85*** (0.89***) 15 obs	0.75*** (0.80***) 15 obs	0.94*** (0.87***) 26 obs	1 (1) 35 obs

NOTES: Correlation coefficients of weighted country means of math scores (science scores). ***, ** and * indicate a statistical significance at 1%, 5% and 10%.

Table 4: **Actual and standardized unexplained test score differentials**

	Mathematics		Science		
Variable	Mean	Stdev	Mean	Stdev	Obs
Total:					
Disintegration (actual)	2.71	21.82	4.67	22.64	334
Disintegration (standardized)	5.84	32.29	5.45	36.19	334
By ethnicity:					
Immigrants (actual)	2.84	26.88	6.34	27.39	167
Second-generation (actual)	2.59	15.24	3.00	16.50	167
Immigrants (standardized)	6.65	36.74	8.97	44.28	167
Second-generation (standardized)	5.02	27.21	1.92	25.34	167

Table 5: **Country-level variables**

Variable	Description	Mean	Stdev	Obs
Pisa and Timss data				
Ethnic segregation	Dissimilarity index of foreign students in schools (immigrants and second-generation immigrants)	0.386	0.103	167
Social segregation	Dissimilarity index of students with less than 25 books at home in schools	0.339	0.074	167
Hours per year	Mean instructional hours per school year divided by 100	9.318	1.707	155
External student assessment	Fraction of schools that does not have the primary responsibility for student assessment policies	0.143	0.212	151
Promotion weak (math)	Fraction of schools that provides remedial courses in mathematics (academic subjects) for weak students	0.766	0.185	167
Promotion weak (science)	Fraction of schools that provides remedial courses in science (academic subjects) for weak students	0.518	0.263	104
Promotion gifted (math)	Fraction of schools that provides enrichment courses in mathematics (academic subjects) for gifted students	0.512	0.281	167
Promotion gifted (science)	Fraction of schools that provides enrichment courses in science (academic subjects) for gifted students	0.465	0.275	104
World development indicators 2005				
GDP	GDP per capita (ppp, in constant 2000 international $) divided by 100	180.630	101.593	162
Gini	Gini coefficient	0.355	0.081	154
Preprimary enrollment	Gross percentage of students who are enrolled in pre-primary education (lagged: time when students were 4/5 years old)	63.712	29.810	157
Pupil-teacher ratio	Number of pupils per teacher in primary education (lagged: time when students were 7/8 years old)	16.738	6.946	141
Population density	People per sq km	537.604	2062.43	167
Youth unemployment	Unemployed youth as percentage of total labor force ages 15-24	15.948	8.670	132
UNESCO Institute for statistics				
Age primary 5	Starting age of primary education is 5	0.067		165
Age primary 6	Starting age of primary education is 6	0.679		165
Age primary 7	Starting age of primary education is 7	0.254		165
OECD Trends in international migration				
Migration regions: Fraction of foreign population coming from . . .				
Western Europe	. . . Western European countries	19.046		65
Southern Europe	. . . Southern European countries	3.456		65
Eastern Europe	. . . Eastern European countries	14.481		65
North America	. . . North America	8.375		65
South America	. . . South America	1.553		65
Africa	. . . Africa	7.274		65
Asia	. . . Asia	13.500		65
Oceania	. . . Oceania	2.986		65
Other	. . . other countries	29.330		65

Table 6: **Results for all countries**

Dependent variable:	*Pooled*		*Country-group-effects*		*Country-effects*	
Disintegration	Mathematics	Science	Mathematics	Science	Mathematics	Science
Control variables						
Pisa	-7.311	-19.006	-6.953	-14.348	-4.695	-12.803
	(4.068)*	(5.665)***	(3.849)*	(5.638)**	(5.303)	(8.114)
Time	-5.699	-3.873	-4.606	-2.521	1.785	1.100
	(1.991)***	(2.307)*	(1.908)**	(2.049)	(3.354)	(3.785)
Time sq	0.600	0.431	0.493	0.320	-0.054	0.029
	(0.189)***	(0.233)*	(0.184)***	(0.209)	(0.293)	(0.324)
Second generation	-6.407	-10.411	-5.523	-9.547	-5.239	-9.337
	(3.212)*	(3.561)***	(3.189)*	(3.494)***	(2.546)**	(2.875)***
Income situation						
GDP	0.250	0.185	0.144	0.072	0.013	-0.126
	(0.060)***	(0.084)**	(0.043)***	(0.069)	(0.156)	(0.181)
Gini	96.847	54.155	39.072	-4.974		
	(34.322)***	(47.980)	(30.002)	(37.734)		
GDP*Gini	-0.651	-0.355	-0.344	-0.073		
	(0.154)***	(0.224)	(0.114)***	(0.174)		
Institutions						
Ethnic segregation	18.180	25.035	20.925	17.912	-26.231	-18.916
	(10.868)*	(13.654)*	(10.942)*	(12.080)	(31.584)	(35.636)
Social segregation	6.406	27.488	20.129	45.108	41.094	16.806
	(19.030)	(20.077)	(17.932)	(19.313)**	(43.299)	(48.074)
Preprimary enrollment	-0.071	-0.171	-0.015	-0.070	-0.373	0.026
	(0.090)	(0.088)*	(0.076)	(0.079)	(0.226)	(0.257)
Age primary 5	-11.280	-11.256	-7.563	-10.086		
	(5.528)**	(3.493)***	(6.239)	(6.115)		
Age primary 7	2.487	6.281	8.288	14.490		
	(4.335)	(3.964)	(5.180)	(4.928)***		
Pupil-teacher ratio	0.644	1.124	-0.033	0.492	-1.160	-0.825
	(0.330)*	(0.483)**	(0.293)	(0.394)	(0.603)*	(0.681)
Hours per year	-19.372	-17.255	-21.564	-19.552	-20.374	-15.928
	(6.015)***	(6.436)***	(5.515)***	(4.859)***	(8.115)**	(9.439)*
Hours per year sq	0.997	0.964	1.068	1.056	0.971	0.792
	(0.292)***	(0.345)***	(0.283)***	(0.273)***	(0.431)**	(0.507)
External studass	-2.756	-8.529	4.141	-0.107	-2.217	-21.115
	(7.299)	(8.935)	(5.181)	(7.633)	(16.830)	(18.640)
Population density	-0.001	-0.001	-0.002	-0.002	-0.037	-0.008
	(0.001)*	(0.001)	(0.001)**	(0.001)	(0.019)*	(0.022)
Youth unemployment	0.026	0.030	0.041	0.052	0.895	0.612
	(0.258)	(0.295)	(0.212)	(0.229)	(0.473)*	(0.549)
Prom weak math/scie	-32.899	-10.516	-28.597	-0.337	-22.181	-3.762
	(8.352)***	(7.849)	(8.386)***	(7.383)	(14.278)	(16.744)
Prom gifted math/scie	8.776	-4.401	12.420	-5.869	31.424	-8.767
	(5.782)	(7.515)	(5.214)**	(5.988)	(11.484)***	(14.711)
Constant	79.415	45.456	107.630	73.260	153.458	127.801
	(35.675)**	(35.000)	(35.191)***	(27.979)**	(49.963)***	(59.277)**
R^2	0.282	0.258	0.345	0.315	0.477	0.457
Adj R^2	0.219	0.192	0.287	0.255	0.301	0.274
N	334	334	334	334	334	334

NOTES: Weighted least squares, cluster robust standard errors in parentheses (countries), missing dummies included, ***, ** and * indicate a statistical significance at 1%, 5% and 10%.

Table 7: **Results for OECD-countries**

Dependent variable:	*Pooled*		*Country-group-effects*		*Country-effects*	
Disintegration	Mathematics	Science	Mathematics	Science	Mathematics	Science
Control variables						
Pisa	-5.943	-19.897	-7.766	-20.700	0.446	-16.037
	(7.959)	(7.945)**	(8.192)	(8.143)**	(7.177)	(10.829)
Time	-3.895	-4.272	-3.183	-5.225	-3.534	-3.330
	(2.794)	(3.531)	(2.947)	(3.670)	(4.469)	(4.948)
Time sq	0.362	0.424	0.307	0.457	0.238	0.469
	(0.270)	(0.314)	(0.271)	(0.328)	(0.388)	(0.421)
Second generation	2.315	-3.100	2.370	-3.431	2.245	-3.234
	(3.021)	(3.632)	(3.036)	(3.623)	(3.346)	(3.744)
Income situation						
GDP	0.307	0.382	0.280	0.474	-0.139	-0.123
	(0.111)**	(0.136)***	(0.220)	(0.196)**	(0.182)	(0.212)
Gini	138.612	144.209	93.598	165.546		
	(71.275)*	(74.814)*	(190.591)	(158.818)		
GDP*Gini	-0.788	-0.764	-0.677	-1.024		
	(0.311)**	(0.352)**	(0.639)	(0.580)*		
Institutions						
Ethnic segregation	20.416	-3.101	21.594	-17.872	15.921	-29.853
	(17.251)	(15.541)	(19.022)	(16.613)	(43.827)	(49.330)
Social segregation	27.473	69.887	12.955	65.452	67.592	93.712
	(27.480)	(35.207)*	(26.519)	(35.204)*	(50.698)	(57.539)
Preprimary enrollment	-0.134	-0.263	-0.225	-0.401	-1.193	-0.303
	(0.130)	(0.135)*	(0.129)*	(0.120)***	(0.413)***	(0.466)
Age primary 5	-10.895	-11.446	-9.963	-12.401		
	(5.731)*	(5.386)**	(7.199)	(7.135)*		
Age primary 7	9.523	0.246	6.124	2.204		
	(7.103)	(7.332)	(7.997)	(7.083)		
Pupil-teacher ratio	-0.002	0.098	-0.065	0.180	0.270	-0.679
	(0.386)	(0.631)	(0.458)	(0.681)	(1.005)	(1.098)
Hours per year	-34.060	-6.807	-28.553	-10.770	-34.612	11.785
	(12.691)**	(13.234)	(13.271)**	(13.240)	(19.721)*	(23.916)
Hours per year sq	1.735	0.252	1.434	0.412	1.474	-0.840
	(0.677)**	(0.721)	(0.705)*	(0.703)	(1.057)	(1.314)
External studass	2.420	-17.736	0.220	-16.776	-1.654	-52.709
	(9.625)	(8.435)**	(10.582)	(5.951)***	(21.087)	(23.284)**
Population density	0.020	0.014	0.016	0.053	0.923	-0.212
	(0.017)	(0.016)	(0.026)	(0.027)*	(1.090)	(1.220)
Youth unemployment	-0.161	-0.273	-0.213	-0.085	-0.689	-0.750
	(0.213)	(0.321)	(0.200)	(0.290)	(0.875)	(1.048)
Prom weak math/scie	-19.383	6.245	-21.727	-4.992	-30.659	30.528
	(14.574)	(18.131)	(14.815)	(18.405)	(19.961)	(29.603)
Prom gifted math/scie	9.033	-24.305	8.570	-25.323	65.131	-42.971
	(8.305)	(21.837)	(12.393)	(21.513)	(20.769)***	(29.035)
Constant	123.118	-11.764	125.850	19.625	189.819	66.656
	(61.857)*	(66.456)	(101.463)	(89.155)	(151.297)	(178.525)
R^2	0.186	0.222	0.212	0.243	0.368	0.337
Adj R^2	0.067	0.109	0.097	0.133	0.153	0.111
N	190	190	190	190	190	190

Notes: Weighted least squares, cluster robust standard errors in parentheses (countries), missing dummies included, ***, ** and * indicate a statistical significance at 1%, 5% and 10%.

Table 8: **Results with migration regions**

Dependent variable:	*Pooled*		*Country-group-effects*		*Country-effects*	
Disintegration	Mathematics	Science	Mathematics	Science	Mathematics	Science
Control variables						
Pisa	-6.469	-16.603	-5.396	-11.074	-4.958	-15.478
	(4.325)	(5.941)***	(4.129)	(5.650)*	(5.469)	(9.315)*
Time	-5.549	-4.153	-4.441	-2.231	2.745	3.113
	(2.350)**	(2.507)	(2.287)*	(2.101)	(4.069)	(4.738)
Time sq	0.581	0.445	0.469	0.290	-0.101	-0.080
	(0.212)***	(0.246)*	(0.201)**	(0.208)	(0.331)	(0.376)
Second generation	-6.390	-10.518	-5.489	-9.529	-5.262	-9.281
	(3.258)*	(3.604)***	(3.251)*	(3.558)***	(2.567)**	(2.910)***
Income situation						
GDP	0.234	0.131	0.160	0.043	0.023	-0.271
	(0.071)***	(0.076)*	(0.054)***	(0.064)	(0.198)	(0.229)
Gini	106.511	54.064	42.443	-1.480		
	(33.292)***	(45.286)	(29.574)	(37.165)		
GDP*Gini	-0.660	-0.343	-0.454	-0.171		
	(0.183)***	(0.214)	(0.132)***	(0.181)		
Institutions						
Ethnic segregation	21.171	35.415	14.839	13.876	-28.898	-7.532
	(12.053)*	(14.551)**	(14.164)	(13.426)	(33.067)	(37.480)
Social segregation	-5.890	16.366	14.943	34.064	34.940	1.579
	(19.901)	(19.330)	(17.921)	(19.126)*	(47.314)	(52.994)
Preprimary enrollment	-0.067	-0.166	0.041	-0.020	-0.272	0.096
	(0.107)	(0.092)*	(0.091)	(0.090)	(0.243)	(0.276)
Age primary 5	-8.323	-17.130	-12.279	-24.169		
	(7.040)	(7.017)**	(7.781)	(7.562)***		
Age primary 7	1.463	3.223	10.386	13.134		
	(5.349)	(4.722)	(5.968)*	(5.366)**		
Pupil-teacher ratio	0.604	1.001	-0.088	0.340	-1.197	-0.948
	(0.376)	(0.492)**	(0.329)	(0.412)	(0.676)*	(0.776)
Hours per year	-19.383	-17.087	-22.130	-19.865	-21.112	-17.123
	(6.294)***	(6.997)**	(5.548)***	(5.266)***	(8.290)**	(9.703)*
Hours per year sq	0.964	0.904	1.067	1.021	1.013	0.863
	(0.309)***	(0.389)**	(0.286)***	(0.298)***	(0.442)**	(0.525)
External studass	-7.134	-17.641	2.533	-7.675	-3.469	-18.633
	(9.031)	(9.159)*	(6.428)	(7.456)	(18.345)	(20.397)
Population density	-0.001	-0.001	-0.002	-0.002	-0.041	-0.010
	(0.001)	(0.001)	(0.001)***	(0.001)*	(0.020)**	(0.024)
Youth unemployment	0.109	0.051	0.149	0.095	0.803	0.499
	(0.280)	(0.315)	(0.245)	(0.256)	(0.493)	(0.573)
Prom weak math/scie	-31.564	-14.193	-25.931	-1.142	-27.241	-7.357
	(8.979)***	(7.994)*	(9.342)***	(7.527)	(14.982)*	(17.883)
Prom gifted math/scie	12.379	1.825	12.615	-2.143	32.883	-11.393
	(6.365)*	(7.647)	(5.247)**	(6.260)	(11.767)***	(16.183)
Constant	80.569	59.255	112.651	92.650	161.271	178.694
	(38.541)**	(38.394)	(35.536)***	(29.957)***	(59.906)***	(71.044)**
F-Statistics						
(migration regions)	1.84	3.50	1.18	3.92	0.58	0.39
R^2	0.295	0.275	0.356	0.334	0.485	0.460
Adj R^2	0.209	0.187	0.277	0.253	0.292	0.257
N	334	334	334	334	334	334

NOTES: Weighted least squares, cluster robust standard errors in parentheses (countries), missing dummies and migration regions included, ***, ** and * indicate a statistical significance at 1%, 5% and 10%.

Table 9: **How much do institutions explain?**

	Pooled WLS	
	Mathematics	Science
All countries:		
Contribution of Institutions		
R^2	0.218	0.184
Adjusted R^2	0.173	0.137
Contribution of Income situation		
R^2	0.092	0.064
Adjusted R^2	0.078	0.050
N = 334		
OECD countries:		
Contribution of Institutions		
R^2	0.143	0.119
Adjusted R^2	0.064	0.038
Contribution of Income situation		
R^2	0.031	0.073
Adjusted R^2	0.010	0.053
N = 190		

NOTES: Pooled weighted least squares estimations, once with institutions and once with the income situation as explanatory variables only.