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Ethnic Discrimination in Education: The Swiss Case

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Abstract

This paper investigates the role that discrimination plays in the educational marginalization of foreign youth commonly observed in European countries with a long guest-worker tradition. Economic theory offers two basic explanations for discrimination of this form: taste-based discrimination arising from personal prejudices and statistical discrimination stemming from ability uncertainty. Which theory applies in reality has important policy implications. If taste-based discrimination is the source of ethnic segregation, then measures to eliminate prejudice are required to promote integration; whereas if statistical discrimination is the cause, then better measures of ability are needed. Using Switzerland as a case study, we provide evidence that statistical discrimination is the source of ethnic segregation in schooling. Further we find that teachers generally do not grade foreign youth differently than native students. This result runs counter to previous research which suggests that disadvantaged pupils are graded more leniently.

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Keywords: education, discrimination, migration, PISA

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1. Introduction

It is a well-documented fact (cf. OECD, 2007a) that a disproportionate share of young foreigners in Europe are concentrated in low-level academic paths of study offering little opportunity for educational and economic advancement. This form of ethnic segregation appears to be particularly pronounced in European countries with a long tradition of recruiting low-skilled foreign guest workers such as Germany or Switzerland.

A variety of explanations have appeared in the literature to explain the educational marginalization of foreign youth. One group of accounts emphasizes individual background characteristics. FASE (1994), for example, stresses parents' socio-economic status and level of education, which tend to be lower among immigrant families. Other authors (e.g., FULGINI, 1997) focus on cultural factors such as immigrants' general attitudes towards education or motivation problems, which can hinder educational integration as well. Still others (e.g., CHISWICK/MILLER, 2003) emphasize the role of language skills, arguing that the lack of proficiency in the native language of the host country poses a hurdle to educational assimilation.

Another set of explanations emphasizes the importance of the host country's education system. On the basis of this work, it appears that sorting students into different levels of schooling at a young age based on previous academic performance, also known as "early tracking", exacerbates the initial educational inequality between foreign and native youth [cf. HANUSHEK/WÖSSMANN (2006), ENTORF/LAUK (2007)]. In addition, it raises the probability of foreign youth replicating the low educational attainment of their parents (cf. BAUER/RIPHAHN, 2005).

Recently, the OECD (2007a, b) has listed discrimination as an additional cause of the lower educational attainment of foreign youth. They base their assessment in part on findings from Switzerland [cf. AMOS ET AL. (2003) and HAEBERLIN ET AL. (2004)] which show that a youth's nationality lowers his or her chances of entering a higher level of schooling even after controlling for differences in PISA (Programme for International Student Achievement) scores, grade point average, language skills, and socio-economic background. The OECD (2007b) also points to work by LANFRANCHI (2005), who finds that pupils with foreign-sounding names are more likely to be assigned to remedial classes than otherwise identical youth.

Taken at face value, these results suggest that foreign youth are not treated equitably in the education system. This need not be the case, however. Whether foreign youth are treated impartially depends on the cause of discrimination. Economic literature offers two basic explanations.[1] The one approach, developed by BECKER (1957) and known as taste-based discrimination, posits that gatekeepers in the education system hold prejudices against foreign youth, even if they know they are equally able. According to this theory, it is bigoted gatekeepers that are partly to blame for the low educational attainment of foreign youth. The other approach, known as statistical discrimination, assumes instead that gatekeepers harbor no animus towards foreigners but cannot predict their ability perfectly given the limited information at their disposal. In this case, gatekeepers in assessing a candidate's ability assign some weight to personal attributes such as nationality that are known to correlate with ability, instead of basing their judgments solely on the individual's grades. In contrast to taste-based discrimination, statistical discrimination arises from imperfect information.

Statistical discrimination is widespread in the business world where it is more commonly termed profiling. Insurance companies employ it regularly to assess the risk of insurance takers. In the United States, for example, car insurance companies often charge students with high grade point averages lower premiums because statistics

[1] See CAIN (1986) for a broader overview of the various theoretical approaches.

have shown that good students cause fewer accidents on average. Employers, too, often make use of profiling when assessing a candidate's employment potential. For example, Google uses over 300 correlates, even including whether a jobseeker owns a pet, to estimate a candidate's unknown capabilities -- again because correlation analysis has shown that successful employees typically carry certain traits.[2] Basing placement decisions on seemingly unrelated characteristics may seem arbitrary, but it is fairer and more meritocratic than if one were to ignore such information altogether since including it yields more accurate assessments of an individual's true abilities than discarding it. Hence, the finding that factors other than grades affect the placement of students does not necessarily mean that foreign youth are treated inequitably. In fact, if profiling were perfect it would eliminate placement injustices altogether.

Determining the source of ethnic discrimination in education is an important policy issue as different causes demand different remedies. If the low educational attainment of foreign youth results from prejudice then measures are needed to eliminate bias. If, on the other hand, ethnic segregation arises from statistical discrimination then better measures of ability are required so that school authorities can make more informed placement decisions.

The following paper explores the causes of educational marginalization of foreign youth in Switzerland. There are a number reasons for choosing Switzerland as the focus of our study. For one, educational segregation by ethnicity is particularly pronounced in Switzerland. Foreign youth are roughly twice as likely to be in a low-level course of study than their Swiss compatriots.[3] For another, a large share of the foreign workforce is unskilled, which -- as mentioned above-- tends to serve as a barrier to educational integration. Furthermore, sorting pupils into different level schools occurs at an early age, viz., after 4 to 6 years of primary school, which -- as previously noted

2 See HANSELL (2007).

3 *Statistisches Jahrbuch der Schweiz* (Statistical Yearbook of Switzerland), various issues.

-- further exacerbates segregation. In addition, the Swiss education system is quite opaque. Essentially it consists of 26 separate and heterogeneous school systems, one for each canton. Despite this heterogeneity, Switzerland lacks a uniform measure of scholastic ability such as standardized test scores. As a result, school authorities must depend on school grades in making their placement decisions. Finally, as noted by the OECD (2007b), the under-achievement of foreign students on the PISA test is more pronounced in Switzerland than in most other OECD countries. Taken together, all of these factors suggests that foreign youth are at a particular disadvantage in Switzerland.

Our investigation of the sources of ethnic segregation proceeds in three steps. To start, we show that school grades, which according to HAEBERLIN ET AL. (2004) are the principal criterion for school placement in Switzerland, are a poor predictor of scholastic ability as measured by PISA test scores. Then we demonstrate that the predictive ability of grades improves significantly when the nationality of a student is also taken into account. Together, these results imply that discriminating according to ethnicity in school placement decisions is statistically justified on average. Finally we demonstrate that teachers do not as a rule discriminate against foreigners in setting grades, indicating that at least in this respect ethnic prejudices do not play a role in placement.

The work in this paper relates to two current strands of literature. The one pertains to grade discrimination. LAVY (2004) investigates whether teachers in Israel favor a certain sex when setting grades. EMANUALSSON and FISCHBEIN (1986) along with LINDAHL (2007) have performed similar work in Sweden. Lindahl considers ethnicity as well. All three studies use a differences-in-differences (DiD) methodology which investigates whether the difference between a pupil's school grade and an objective measure of his or her academic ability varies systematically across sex or nationality. The results of these studies indicate that girls and the foreign-born are more generously graded on average. The DiD approach does not lend itself to our data, however, as the two grades we compare -- PISA scores and marks -- are scaled differently so that any measured differences may simply reflect scale heterogeneity.[4] Instead we apply the decomposition method introduced by BLINDER (1973) and OAXACA (1973) to measure wage discrimination. Unlike the DiD method, the BLINDER/ OAXACA approach has the advantage of not assuming that grade discrimination has a uniform impact on all affected individuals. It has the disadvantage, however, of not controlling for unobserved heterogeneity.

The other strand of literature that relates to our paper pertains to the identification of statistical discrimination. In general, there is no set way to test for the presence of this form of discrimination. It depends on the particular market setting and the available data. YINGER (1998) reports on approaches applied in consumer markets, LADD, H. (1998) on those employed in credit markets, and DARITY/MASON (1998) on those used in labor markets. Unlike that work, our approach does not provide a direct test of statistical discrimination as we lack the required data. Instead we provide evidence that strongly suggests the presence of statistical discrimination in school placement decisions. To our knowledge, ours is the first study to examine the sources of discrimination in education.

Our paper unfolds as follows. In the next section we present the theoretical model of statistical discrimination that underlies our empirical approach. Section 3 describes our data. Section 4 explains our empirical methodology. Section 5 presents our results. And Section 6 summarizes our findings, draws policy conclusions, and suggests paths for future research.

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4 The centigrade and Fahrenheit temperature scales illustrate our point. Although both scales measure the temperature equally accurately, the difference in the number of degrees the two scales report nevertheless increases with the distance that the temperature departs from the point where the two scales intersect at minus 39. In our case, we compare PISA scores, ranging from 200 to 800, with school grades, varying from 1 to 6.

2. Theoretical Background

Our model of statistical discrimination is based on the work of PHELPS (1972) and AIGNER and CAIN (1977). In line with their approach, we assume that the gatekeepers in the education system must base their placement decisions on an inaccurate measure y of a candidate's true scholastic ability q, which we equate with a youth's grade point average (GPA). We model the measurement inaccuracy of y as a linear function of true ability q and a measurement error u

$$y = \alpha + \beta \cdot q + u \,. \tag{1}$$

Further, we assume that u and q are normally and independently distributed random variables. The independence assumption implies that average measurement error does not vary with ability. In other words, ability is measured equally poorly by grades whether ability be high or low. The measurement error u is taken to have mean 0 and variance σ_u^2, and the ability variable q to have mean $\overline{q}$ and variance σ_q^2. The parameters α and β correct for scale differences between ability y and grades q.

Based on these assumptions, y and q have the following bivariate normal distribution[5]

$$(q, y) \sim N_2\left[\overline{q},\ \alpha + \beta\overline{q},\ \sigma_q^2,\ \beta^2\sigma_q^2 + \sigma_u^2,\ \rho\right], \tag{2}$$

where ρ is the correlation coefficient between q and y. If grades y were a perfect predictor of ability q, the correlation coefficient ρ would equal 1, and the variance σ_u^2 of the measurement error would be 0.

[5] See e.g. GREENE (2008, p. 1010).

Given the above assumptions, the question then arises as to the level of ability q that a gatekeeper should expect on average from a youth with a given GPA of y. According to (2) the answer is

$$E\left[q|y\right]=a+by \ , \tag{3}$$

where

$$a=\left[\left(1-\rho^2\right)\overline{q}-\frac{\alpha\rho^2}{\beta}\right] \text{ and } b=\frac{\rho^2}{\beta}.$$

Equation (3) shows that the conditional expectation of ability q given a GPA of y is equivalent to a linear regression of ability on GPA. Furthermore, it indicates that the expected value depends critically on the value of ρ, i.e., on the ability of school grades to predict scholastic ability. If grades are a perfect predictor ($\rho = 1$) then no measurement error occurs and (3) is simply the inverse of (1), that is

$$a=-\frac{\alpha}{\beta} \quad \text{and} \quad b=\frac{1}{\beta}.$$

If, on the other hand, grades have no predictive power whatsoever ($\rho = 0$) then the expected value of q is equal to the population mean $\overline{q}$ no matter what one's grades are.

Now assume that grades are an equally reliable predictor of ability for immigrants (I) and natives (N), implying $\rho_N = \rho_I$, and that the scaling parameters α and β apply equally to immigrants and natives. Suppose too that immigrants are less capable scholastically than natives on average, i.e., $\overline{q}_I < \overline{q}_N$. These assumptions, combined with the ones before, imply that the expected capabilities of native and immigrant youth with identical GPAs are equal to

$$E\left[q_N\left|y\right.\right]=a_N+by \quad \text{and} \quad E\left[q_I\left|y\right.\right]=a_I+by \tag{4}$$

and hence that

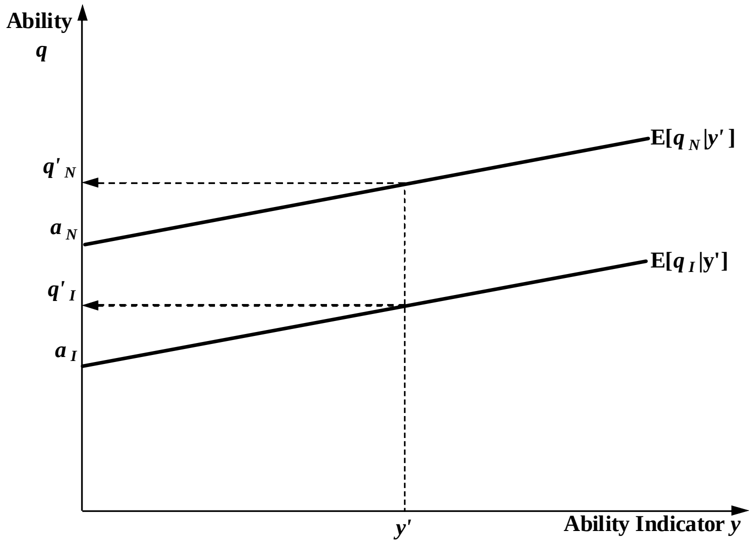
$$E\left[q_N\left|y\right.\right]-E\left[q_I\left|y\right.\right]=a_N-a_I=\left(1-\rho^2\right)\left(\overline{q}_N-\overline{q}_I\right) . \tag{5}$$

In other words, under these circumstances an unbiased estimate of the difference in abilities between a native and an immigrant with the same GPA, is equal to the difference in average abilities of natives and immigrants in the population, weighted with the inaccuracy (1 - ρ^2) with which grades predict ability. If grades were perfect predictors ($\rho = 1$), equal grades would imply equal abilities and no discrimination would occur. If, on the other hand, no correspondence existed between grades and ability then the best unbiased estimate of the difference in abilities between a native and an immigrant with identical GPAs would be the average difference of abilities between natives and immigrants in the population. Seen in this way, statistical discrimination is a form of stereotyping in which individuals' capabilities are judged by group averages up to a degree that depends on the inaccuracy of the capability measure y.

Note in (5) that the difference between the regression constants a_N and a_I is simply a linear transformation of the difference between the mean abilities of natives and immigrants. Hence whether gatekeepers base their assessments of the relative abilities of natives and immigrants on a linear regression as in (4) or on unbiased estimates of the mean abilities of natives and immigrants drawn from personal experience has no effect on the results. Experienced gatekeepers and statisticians would end up making the same choices on average.

Figure 1 illustrates the basics of our model. It views a gatekeeper's decision-making process under the assumption that grades are equally accurate measures of scholastic ability for native and foreign youth, i.e., that $\rho_N = \rho_I$, and that the scale parameters apply equally to foreigners and natives. These assumptions imply the two curves appearing in *Figure 1*. They correspond to the equations in (4). The curves show what abilities a gatekeeper should expect from natives and immigrants for given GPAs. Based on these curves, a gatekeeper faced with natives and immigrants with a common GPA of y' will expect an average ability of q'_N for natives and of q'_I for immigrants and make his or her placement decision accordingly.

Figure 1: Statistical Discrimination with $\rho_N = \rho_I$



It is important from the background *Figure 1* to note that a regression of the gatekeepers' placement decisions on youths' GPA and ethnicity would find that ethnicity has an effect on individual placement even after controlling for grades, although placement decisions rest here solely on statistical regularities and not on prejudices. Hence, the observation that factors other than grades affect school placement is not necessarily a sign of inequitable treatment.

Figure 1 should not be construed as implying that gatekeepers make uniform placement decisions for given GPA and nationality. To the contrary, placement decisions will vary across gatekeepers as a result of sampling error. To see why, consider the following estimates of the mean abilities of native and immigrant youth

$$\hat{\hat{q}}_{Ni} = \overline{q}_N + \varepsilon_{Ni} \quad \text{and} \quad \hat{\hat{q}}_{Ii} = \overline{q}_I + \varepsilon_{Ii}$$

by a given gatekeeper *i*, where a caret denotes an estimate and the error terms ε_N and ε_I, constituting sampling error, are independent and normally distributed with expected values 0 and covariance matrix Ω. Given the sampling error, one can only say with a certain probability whether the gatekeeper *i* will judge a native student to be more able than a foreign student with the same GPA and thus favor the former over the latter. This probability is equal to

$$P\left(\hat{\hat{q}}_{Ni} > \hat{\hat{q}}_{Ii}\right) = \Phi\left[\frac{\overline{q}_N - \overline{q}_I}{\sigma_\varepsilon}\right], \tag{6}$$

where Φ signifies the standard normal c.d.f. and σ_ε is the standard error of the difference of the two error terms ε_N and ε_I. Equation (6) indicates that, the probability of a given gatekeeper favoring natives over immigrants with the same GPA depends not only on the mean ability differential between natives and immigrants, but also on the accuracy σ_ε of gatekeepers' estimates of this differential. If $\hat{\hat{q}}_{Ni} >> \hat{\hat{q}}_{Ii}$ and/or the sampling error varies little then the probability in (6) will approach 100%, indicating that most gatekeepers will make the same placement decision for given GPAs, i.e., that they will generally favor natives. If, on the other hand, $\overline{q}_N = \overline{q}_I$ and/or the sampling error varies a lot then the probability in (6) will approach 50%, meaning that gatekeepers' placement decisions will differ greatly and that on average neither natives nor immigrants will be strongly favored.

Observe that statistical discrimination, by stereotyping individuals for lack of better information, does not impose a disadvantage on all the affected. Below-average achievers actually profit from statistical discrimination in school placement, be they natives or foreigners, since they are treated as being average. Nonetheless, statistical discrimination will still lead to ethnic segregation.

The above discussion assumes that school grades measure the academic ability of natives and immigrants equally well. Were this not the case, the difference in expected abilities given in (5) would vary by GPA (i.e., y). If, for example, school grades measure immigrants' scholastic abilities less accurately ($\rho_I < \rho_N$) and all else is held equal, then according to the definition of a and b, the curves in *Figure 1* will intersect. Moreover, the curve for foreigners will be flatter. That means that gatekeepers will pay less heed to grade differences among foreigners since grades reflect differences in ability less accurately among foreigners. Under these conditions, gatekeepers will thus judge foreigners with low (high) grades as being more (less) capable than natives with the same grade. However, as we show below, school grades are equally good measures of ability for natives and immigrants. Thus we need not pursue this matter further.

3. Data

We apply our theoretical model to data drawn from the 2000 PISA sample for Switzerland. As is well known, PISA is a standardized achievement test in reading, mathematics and science, administered to 15 year olds and/or ninth graders in over 30 OECD-member countries at three-year intervals. Our study concentrates on ninth graders, regardless of age, in order to compare students with equal amounts of schooling.

Besides testing the students, PISA also collects data on the background of the tested pupils and on the quality of their schools. Particularly germane in this study is information on the tested students' GPA, their participation in class, and their nationality. Nationality in this study is defined principally by country of birth. Natives are individuals born in Switzerland to parents also born in Switzerland, and immigrants or foreigners are persons either born abroad themselves or to a parent born outside Switzerland.

We use 6,492 or roughly 80 % of the original sample of 7,997 students. Observations were dropped due to missing values or inappropriate school levels.

Table 1 presents descriptive statistics of our sample. As the figures indicate, natives display higher means both with regard to GPA and PISA scores. Furthermore, the figures show that immigrants are heavily concentrated in low-level schools. They also tend to turn in homework later, to have problems concentrating, and to be absent from class more. In our regression analysis, we assume that high PISA scores, turning in homework on time, attention in class, and high attendance all contribute to receiving high grades in school.

4. Empirical Methodology

Our empirical approach consists of three steps. First we subdivide the ninth-graders that participated in the PISA study into three groups according to their schooling level (advanced, intermediate or low) and regress their PISA scores respectively in reading, mathematics and science on their corresponding GPAs in order to determine how well school grades predict scholastic ability. In other words, we estimate equation (3) for each sub-group, defined by school level and subject, yielding nine sets of estimates. As previously stated, school grades are the principal criterion used by the school authorities in Switzerland to place students. If school grades do a good job of reflecting scholastic ability, regressing PISA scores on them should yield high R^2 statistics, which correspond to ρ^2 in *Section 2*. Our approach assumes that PISA scores measure academic ability perfectly.[6]

The second step in our approach consists of estimating the same equations and including ethnic background as both a shift factor as well as a slope factor in order (i) to see whether ethnic background can aid in predicting cognitive ability and (ii) to explore whether the data support the assumptions (equal values for ρ^2, α and β for natives and immigrants) upon which equation (4) rests.

Finally we investigate whether teachers discriminate against foreigners in setting grades by regressing school grades respectively in reading, mathematics and science on (i) a constant, (ii) the corresponding PISA scores, (iii) other variables in the PISA sample that could contribute to grades, and (iv) interactions of these regressors with an individual's ethnic background. We also include school dummies to control for school-specific differences in grading. We then test whether the regression coefficients vary by ethnicity, i.e., whether the coefficients of the interaction terms are statistically significantly different from zero. This procedure is equivalent to the decomposition approach developed by BLINDER (1973) and OAXACA (1973) to measure wage discrimination. Our procedure assumes that teachers can accurately assess the scholastic ability of a pupil, that they base their grading at least in part on scholastic ability, and that the PISA scores accurately measure scholastic ability. If teachers are impartial in grading then the interaction terms should have no statistically significant effect on grades. The identifying restriction in our approach is that the error terms in

6 Our assumption that standardized test scores measure cognitive ability accurately has appeared in the literature before. For example, the test of statistical discrimination conducted by ALTONJI and PIERRET (2001) rests on this assumption. Moreover, a number of researchers (see the overview in DARITY and MASON, 1998) have shown that including standardized test scores from the Armed Forces Qualification Test (AFQT) in an earnings equation virtually eliminates racial differences in wages, implying that standardized tests can even capture unobserved differences in ability. To what extent PISA scores perform as well is to our knowledge unknown. But given that the purpose of PISA is to measure cognitive ability accurately and that scholastic testing is an advanced science, we find assuming that PISA scores give an accurate appraisal of an individual's ability to be reasonable.

the PISA and GPA regression equations are independent. Otherwise an endogeneity problem arises.

5. Results

Tables 2 to *10* present the results from regressing PISA scores on GPA and ethnicity. The values of R^2 in *column 1* of the tables show that GPA is a poor predictor of PISA scores, explaining between 3 and 12 % of the variation across students depending on the level of schooling and subject. Predictive ability generally increases with the level of schooling and is higher with respect to reading and math. This implies that grades are less informative in low-level schools and in reading.

The values of R^2 in *column 2* of the tables indicate that including ethnicity in the regression equation increases predictive ability to between 5 and 14 %. The largest increases occur among students from low-level schools where R^2 increases by roughly 3 percentage points or by as much as 75 % in relative terms. The values of R^2 in *column 4* of the tables show that distinguishing among foreigners from Western Europe, Southern Europe, the Balkans and Turkey further improves predictive ability to between 7.8 and 14.6 %, the greatest increases of 3 percentage points again occurring among students from low-level schools. Including nationality roughly doubles our ability to predict the academic ability of students on the basis of grades.

The standard errors of the coefficient estimates in *column 3* of the tables generally suggest that ethnic background has no statistically significant effect on the slope coefficient. This supports the assumptions underlying (4), i.e., that the predictive ability of grades and the scaling coefficient β do not vary by nationality.

Furthermore, the coefficient estimates show that the PISA scores of immigrants lie between 15 and 31 points below those of natives with the same GPA on average. These values correspond to $a_n - a_I$ in equation (5). Since the correlation between PISA scores and school grades is so low, ethnicity -- as a proxy for the difference between the average scholastic abilities of foreign and native youth -- should play a large role in school placement according to the theory of statistical discrimination.

Tables 11 to *13* address the question as to whether foreign students are graded differently than natives. We assume that high scholastic ability (as measured by the PISA score), completing homework on time, attention in class, and high attendance all contribute to high grades. The coefficient estimates indicate that this is indeed the case, although only PISA scores consistently have a statistically significant effect. This suggests that scholastic ability is the main determinant of grades. Getting homework in on time seems to be somewhat less important, while attention and high attendance appear to be decidedly less germane. This ranking would seem to correspond to what one would generally expect.

More importantly, the *F* tests presented in *Tables 11* to *13* provide no evidence that immigrants and natives with similar ability and class participation are graded differently. We also obtain the same results (not presented here to conserve space) when we break down the immigrants according to their geographical affiliation, as in *Tables 2 to 10*, with albeit two exceptions: Balkan pupils in intermediate-level schools with respect to reading and Turkish students in low-level schools in regard to mathematics. Yet if one considers the number of Type I errors to be expected in 36 tests (3 levels of schooling times 3 subjects times 4 geographical affiliations) of the null (impartial grading) then 2 rejections out of a possible 36 or 5.6% seem to provide scant support for biased grading.

6. Conclusions

Our results indicate that school grades, upon which school placement is principally based in Switzerland, are a poor predictor of scholastic ability as measured by PISA test scores. This is particularly true at low-level schools. These results show that the school authorities are indeed subject to quality uncertainty when making their placement decisions on the basis of marks. Secondly, our findings reveal that the predictive power of grades improves significantly when the nationality of a student is also taken into account. Hence it is statistically fairer and more meritocratic to consider a student's nationality when trying to assess his or her scholastic abilities on the basis of grades than to ignore ethnicity altogether. And finally we discover that teachers do not generally discriminate against foreigners in setting grades. Taken together, these results provide greater support for the statistical-discrimination explanation for the educational marginalization of foreign youth than for the taste-based theory.

With regard to policy, our results call into question efforts to reduce ethnic segregation by campaigning to reduce prejudice. Our findings suggest instead that measures should be adopted to improve the capability of the placement authorities to assess individual scholastic ability. In the case of Switzerland, an obvious choice would be the introduction of standardized achievement tests nationwide. The results of such tests would not only increase transparency and thus support more meritocratic placement. They would also at long last provide an output-based measure for comparing the relative effectiveness and efficiency of the wide variety of local school systems in Switzerland.

Our study of course represents just a first step in the investigation of the sources of discrimination in school placement. Further work is needed. For one, it is necessary to investigate to what extent our findings hold up in other countries and to examine the factors underlying any observed variation in results. Unfortunately, the PISA data available to us lacked the necessary detail to repeat our study for other countries. Secondly, we need to develop a test to discriminate more conclusively between the taste-based and statistical-discrimination explanations of educational marginalization. Only then will we be in a position to draw more definitive conclusions.

References

AIGNER, D., G. CAIN (1977), "Statistical Theories of Discrimination in Labor Markets," *Industrial and Labor Relations Review* 30(2), pp. 175-187.

ALTONJI, J., C. PIERRET (2001), "Employer Learning and Statistical Discrimination," *Quarterly Journal of Economics*, 116(1), pp. 313-350.

AMOS, J., E. BÖNI, M. DONATI, S. HUPKA, T. MEYER, B. STALDER (2003), *Wege in die nachobligatorische Ausbildung. Die ersten zwei Jahre nach Austritt aus der obligatorische Schule. Zwischenergebnisse des Jugendlängsschnitts TREE*. Neuchâtel: Bundesamt für Statistik.

BAUER, P., R. RIPHAHN (2005), "Timing of School Tracking As a Determinant of Intergenerational Transmission of Education," *Economics Letters*, Vol. 91, pp. 90-97.

BECKER, G. (1957), *The Economics of Discrimination*, Chicago: University of Chicago Press.

BLINDER, A. (1973), "Wage Discrimination: Reduced Form and Structural Variables," *Journal of Human Resources*, 8, pp. 436-455.

CAIN, G. (1986), "The Economic Analysis of Labor Market Discrimination: A Survey," in: O. Ashenfelter, R. Layard (eds.), *Handbook of Labor Economics*, Vol. 1, Chapter 13, pp. 693-785, Amsterdam: Elsevier Science/North-Holland.

CHISWICK, B., P. MILLER (2003), "The Complementarity of Language and Other Human Capital: Immigrant Earnings in Canada," *Economics of Education Review*, Vol. 22, pp. 469-480.

DARITY, W., P.MASON (1998), "Evidence on Discrimination in Employment: Codes of Color, Codes of Gender," *Journal of Economic Perspectives*, 12(2), pp. 63-90.

EMANUELSSON I., S. FISCHBEIN (1986), "Vive la Difference? A Study on Sex and Schooling," *Scandinavian Journal of Educational Research*, 30(2), pp. 71-84.

ENTORF, H., M. LAUK (2007), “Peer Effects, Social Multipliers and Migrants at School: An International Comparison,” CEGE Discussion Paper No. 57, Georg-August-Universität Göttingen, March.

FASE, W. (1994), *Ethnic Divisions in Western European Education*, Münster: Waxmann.

FULIGNI, A. (1997), “The Academic Achievement of Adolescents from Immigrant Families: The Roles of Family Background, Attitudes, and Behaviour,” *Child Development*, Vol. 68(2), pp. 351-363.

GREENE, W. (2008), *Econometric Analysis*, 6th edition, Upper Saddle River: Prentice Hall.

HAEBERLIN, U., C. IMDORF, W. KRONIG (2004). *Von der Schule in die Berufslehre. Untersuchungen zur Benachteiligung von ausländischen und von weiblichen Jugendlichen bei der Lehrstellensuche*. Bern: Haupt

HANSELL, S. (2007), “Google Answer to Filling Jobs Is an Algorithm,“ *New York Times*, January 3.

HANUSHEK, E., L. WÖSSMANN (2006), “Does Educational Tracking Affect Performance and Inequality? Differences-in-Differences Evidence across Countries,” *Economic Journal*, 116 (March), pp. C63–C76.

LADD, H. (1998), “Evidence on Discrimination in Mortgage Lending,” *Journal of Economic Perspectives*, 12(2), pp. 41-62.

LANFRANCHI, A. (2005), “Nomen est omen: Diskriminierung bei sonderpädagogischen Zuweisungen,“ *Schweizerische Zeitschrift für Heilpädagogik*, Nr. 7-8, pp. 45-48.

LAVY, V. (2004), “Do Gender Stereotypes Reduce Girls’ Human Capital Outcomes? Evidence from a Natural Experiment,” NBER Working Paper 10678, NBER, Cambridge, August.

LINDAHL, E. (2007), "Comparing Teachers' Assessments and National Test Results – Evidence from Sweden," Working Paper 2007:24, Institute for Labour Market Policy Evaluation (IFAU), Uppsala.

OAXACA, R. (1973), "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14 (October), pp. 693-709.

OECD (2007a), *Trends in International Migration*: SOPEMI 2007, Paris: OECD.

OECD (2007b), *Switzerland*, OECD Economic Surveys, Volume 2007/19 (November), Supplement No. 1, Paris: OECD.

PHELPS, E. (1972), "The Statistical Theory of Racism and Sexism,“ *American Economic Review* 62, pp. 659-661.

YINGER, J. (1998), "Evidence on Discrimination in Consumer Markets," *Journal of Economic Perspective*s, 12(2), pp. 23-40.

Table 1: Sample Summary Statistics

	Natives					Immigrants				
	Mean	Variance	Minimum	Maximum	Cases	Mean	Variance	Minimum	Maximum	Cases
GPA										
Reading	4.92	0.60	1	6	4116	4.78	0.65	1	6	2346
Math	4.87	0.75	2	6	2293	4.72	0.83	1	6	1292
Science	5.10	0.62	2	6	1590	4.89	0.68	1	6	873
PISA score										
Reading	521	84.5	197	884	4116	479	95.9	192	813	2346
Math	551	85.8	205	812	2293	505	97.6	202	816	1292
Science	518	86.2	169	830	1590	472	92.3	170	739	873
School Level										
Low	0.24	0.43	0	1	1011	0.41	0.49	0	1	966
Itermediate	0.47	0.50	0	1	1950	0.37	0.48	0	1	866
Advanced	0.28	0.45	0	1	1172	0.22	0.42	0	1	527
Homework late	1.98	0.74	1	4	4079	2.05	0.81	1	4	2328
Inability to concentrate	1.75	0.95	1	4	4098	1.90	0.98	1	4	2331
Truant	1.11	0.43	1	4	4085	1.20	0.58	1	4	2322

Notes: GPA (grade point average; 1 = lowest possible grade, 6 = highest possible grade), homework late (1 = never, 2 = sometimes, 3 = usually, 4 = always), inability to concentrate (1 = untrue, 2 = less true, 3 = truer, 4 = true), truant (1= never, 2 = 1-2 times per fortnight, 3= 3-4 times per fortnight, 4 = 5 times or more per fortnight)

Table 2: Least Squares Estimates of PISA Scores in Reading: Advanced-Level Schooling

	(1)	(2)	(3)	(4)
Reading GPA	0.366 ***	0.358 ***	0.336 ***	0.353 ***
	(0.028)	(0.027)	(0.033)	(0.026)
Immigrant		-0.152 ***	-0.456	
		(0.033)	(0.289)	
Western Europe				-0.046
				(0.058)
Southern Europe				-0.285 ***
				(0.063)
Balkans				-0.247 ***
				(0.078)
Turkey				-0.121 *
				(0.049)
Immigrant * reading GPA			0.063	
			(0.059)	
Intercept	3.968 ***	4.057 ***	4.163 ***	4.080 ***
	(0.13)	(0.134)	(0.159)	(0.131)
R^2	0.102	0.113	0.114	0.119
Adj R^2	0.102	0.112	0.112	0.116
No. obs.	1692	1692	1692	1692

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in reading and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 3: Least Squares Estimates of PISA Scores in Math: Advanced-Level Schooling

	(1)	(2)	(3)	(4)
Math GPA	0.321 ***	0.314 ***	0.318 ***	0.311 ***
	(0.029)	(0.029)	(0.033)	(0.028)
Immigrant		-0.237 ***	-0.187	
		(0.054)	(0.309)	
Western Europe				-0.086
				(0.087)
Southern Europe				-0.303 ***
				(0.1)
Balkans				-0.345 ***
				(0.122)
Turkey				-0.290 ***
				(0.073)
Immigrant * math GPA			-0.011	
			(0.063)	
Intercept	4.448 ***	4.556 ***	4.538 ***	4.574 ***
	(0.138)	(0.141)	(0.162)	(0.138)
R^2	0.120	0.140	0.140	0.145
Adj R^2	0.119	0.138	0.137	0.141
No. obs.	951	951	951	951

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in math and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 4: Least Squares Estimates of PISA Scores in Science: Advanced-Level Schooling

	(1)	(2)	(3)	(4)
Science GPA	0.284 ***	0.276 ***	0.304 ***	0.271 ***
	(0.06)	(0.062)	(0.074)	(0.058)
Immigrant		-0.203 **	0.261	
		(0.088)	(0.631)	
Western Europe				0.042
				(0.144)
Southern Europe				-0.697 ***
				(0.162)
Balkans				-0.341 *
				(0.174)
Turkey				-0.062
				(0.116)
Immigrant * science GPA			-0.092	
			(0.125)	
Intercept	4.295 ***	4.390 ***	4.248 ***	4.416 ***
	(0.299)	(0.314)	(0.375)	(0.297)
R^2	0.055	0.070	0.071	0.105
Adj R^2	0.053	0.065	0.064	0.094
No. obs.	401	401	401	401

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in science and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 5: Least Squares Estimates of PISA Scores in Reading: Intermediate-Level Schooling

	(1)	(2)	(3)	(4)
Reading GPA	0.342 ***	0.335 ***	0.306 ***	0.331 ***
	(0.024)	(0.024)	(0.029)	(0.021)
Immigrant		-0.185 ***	-0.649 **	
		(0.027)	(0.26)	
Western Europe				-0.053
				(0.05)
Southern Europe				-0.151 ***
				(0.039)
Balkans				-0.399 ***
				(0.052)
Turkey				-0.156 ***
				(0.045)
Immigrant * reading GPA			0.094 *	
			(0.052)	
Intercept	3.519 ***	3.608 ***	3.752 ***	3.626 ***
	(0.106)	(0.12)	(0.143)	(0.105)
R^2	0.084	0.101	0.102	0.108
Adj R^2	0.084	0.100	0.101	0.107
No. obs.	2805	2805	2805	2805

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in reading and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 6: Least Squares Estimates of PISA Scores in Math: Intermediate-Level Schooling

	(1)	(2)	(3)	(4)
Math GPA	0.281 ***	0.266 ***	0.276 ***	0.270 ***
	(0.023)	(0.023)	(0.028)	(0.024)
Immigrant		-0.245 ***	-0.101	
		(0.039)	(0.244)	
Western Europe				-0.105
				(0.072)
Southern Europe				-0.268 ***
				(0.057)
Balkans				-0.480 ***
				(0.074)
Turkey				-0.123 ***
				(0.068)
Immigrant * math GPA			-0.030	
			(0.051)	
Intercept	4.102 ***	4.252 ***	4.203 ***	4.228 ***
	(0.117)	(0.116)	(0.138)	(0.117)
R^2	0.083	0.107	0.108	0.117
Adj R^2	0.082	0.106	0.106	0.114
No. obs.	1538	1538	1538	1538

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in math and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 7: Least Squares Estimates of PISA Scores in Science: Intermediate-Level Schooling

	(1)	(2)	(3)	(4)
Science GPA	0.277 ***	0.239 ***	0.270 ***	0.234 ***
	(0.037)	(0.037)	(0.043)	(0.035)
Immigrant		-0.313 ***	0.172	
		(0.047)	(0.405)	
Western Europe				-0.207 **
				(0.085)
Southern Europe				-0.293 ***
				(0.069)
Balkans				-0.621 ***
				(0.098)
Turkey				-0.238 ***
				(0.076)
Immigrant * science GPA			-0.097	
			(0.081)	
Intercept	3.759 ***	4.042 ***	3.882 ***	4.068 ***
	(0.179)	(0.189)	(0.22)	(0.18)
R^2	0.047	0.080	0.081	0.089
Adj R^2	0.046	0.079	0.079	0.086
No. obs.	1292	1292	1292	1292

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in science and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 8: Least Squares Estimates of PISA Scores in Reading: Low-Level Schooling

	(1)	(2)	(3)	(4)
Reading GPA	0.226 ***	0.197 ***	0.218 ***	0.186 ***
	(0.024)	(0.024)	(0.033)	(0.023)
Immigrant		-0.278 ***	-0.082	
		(0.033)	(0.228)	
Western Europe				-0.041
				(0.079)
Southern Europe				-0.103 ***
				(0.045)
Balkans				-0.558 ***
				(0.044)
Turkey				-0.133 **
				(0.063)
Immigrant * reading GPA			-0.041	
			(0.048)	
Intercept	3.168 ***	3.441 ***	3.340 ***	3.492 ***
	(0.114)	(0.118)	(0.16)	(0.115)
R^2	0.044	0.077	0.077	0.119
Adj R^2	0.043	0.076	0.076	0.117
No. obs.	1965	1965	1965	1965

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in reading and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 9: Least Squares Estimates of PISA Scores in Math: Low-Level Schooling

	(1)	(2)	(3)	(4)
Math GPA	0.285 ***	0.266 ***	0.336 ***	0.274 ***
	(0.032)	(0.032)	(0.046)	(0.028)
Immigrant		-0.303 ***	0.296	
		(0.046)	(0.317)	
Western Europe				-0.083
				(0.11)
Southern Europe				-0.162 ***
				(0.062)
Balkans				-0.551 ***
				(0.06)
Turkey				-0.142 *
				(0.084)
Immigrant * math GPA			-0.125 *	
			(0.064)	
Intercept	3.245 ***	3.480 ***	3.139 ***	3.441 ***
	(0.141)	(0.162)	(0.232)	(0.14)
R^2	0.081	0.117	0.121	0.146
Adj R^2	0.080	0.115	0.118	0.142
No. obs.	1096	1096	1096	1096

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in math and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 10: Least Squares Estimates of PISA Scores in Science: Low-Level Schooling

	(1)	(2)	(3)	(4)
Science GPA	0.196 ***	0.178 ***	0.253 ***	0.162 ***
	(0.042)	(0.042)	(0.056)	(0.04)
Immigrant		-0.210 ***	0.500	
		(0.057)	(0.412)	
Western Europe				0.220
				(0.143)
Southern Europe				-0.121
				(0.077)
Balkans				-0.443 ***
				(0.076)
Turkey				-0.137
				(0.114)
Immigrant * science GPA			-0.146 *	
			(0.084)	
Intercept	3.428 ***	3.621 ***	3.247 ***	3.700 ***
	(0.198)	(0.211)	(0.28)	(0.202)
R^2	0.030	0.047	0.051	0.078
Adj R^2	0.029	0.044	0.047	0.072
No. obs.	770	770	770	770

Note: Dependent variable is students' PISA test scores divided by 100. Independent variables are the students' GPA in science and ethnicity. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses. Western Europe consists of Germany, Austria, France, and Belgium; Southern Europe of Italy, Spain, and Portugal; and the Balkans of Serbia, Croatia, Kosovo, and Albania.

Table 11: Least Squares Estimates of GPA: Advanced-Level Schooling

	Reading		Mathematics		Science	
Intercept	4.222	***	3.608	***	3.839	***
	(0.187)		(0.351)		(0.413)	
Immigrant	-0.155		0.485		0.436	
	(0.325)		(0.523)		(0.665)	
PISA score	0.268	***	0.414	***	0.255	***
	(0.025)		(0.041)		(0.056)	
Immigrant * PISA score	0.001		-0.101		-0.074	
	(0.049)		(0.074)		(0.095)	
Homework late	-0.074	***	-0.142	***	-0.038	
	(0.024)		(0.048)		(0.063)	
Homework * Immigrant	0.020		0.037		-0.050	
	(0.042)		(0.090)		(0.107)	
Homework value missing	0.037		-0.452		0.304	
	(0.221)		(0.313)		(0.291)	
(Homework value missing) * Immigrant	-0.218		-0.235		-0.410	
	(0.285)		(0.520)		(0.422)	
Concentration problems (CP)	-0.025		-0.024		0.019	
	(0.021)		(0.038)		(0.045)	
CP * Immigrant	-0.042		-0.042		0.039	
	(0.036)		(0.087)		(0.079)	
CP value missing	-0.469		-0.792		0.176	
	(0.561)		(1.041)		(0.402)	
(CP value missing) * Immigrant	0.087		0.622		-	
	(0.594)		(1.097)		-	
Truancy	-0.059		-0.162	**	-0.072	
	(0.053)		(0.073)		(0.104)	
Truancy * Immigrant	0.131	*	0.134		0.048	
	(0.070)		(0.149)		(0.201)	
Truancy value missing	0.050		0.251		-0.454	
	(0.197)		(0.273)		(0.325)	
(Truancy value missing) * Immigrant	0.287		0.122		0.167	
	(0.366)		(0.358)		(0.463)	
Schools: 52 fixed effects	yes		yes		yes	
No. obs.	1692		951		401	
F statistic	13.01	***	10.16	***	2.61	***
R squared	0.245		0.292		0.300	
Adj R squared	0.204		0.221		0.120	
F-tests of joint significance						
Immigrant-Interactions, F(5)	1.31		0.79		0.35	
School fixed effects, F(52)	4.97	***	3.27	***	413.68	***

Note: Dependent variable is students' GPAs in the given subject. Independent variables are PISA scores (divided by 100), homework late, concentration problems, truancy, immigrant, and immigrant interactions. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses.

Table 12: Least Squares Estimates of GPA: Intermediate-Level Schooling

	Reading		Mathematics		Science	
Intercept	4.396	***	4.279	***	4.367	***
	(0.144)		(0.240)		(0.188)	
Immigrant	-0.122		0.253		0.493	
	(0.217)		(0.358)		(0.326)	
PISA score	0.240	***	0.325	***	0.189	***
	(0.022)		(0.033)		(0.028)	
Immigrant * PISA score	0.014		-0.061		-0.096	*
	(0.034)		(0.057)		(0.050)	
Homework late	-0.067	***	-0.117	***	-0.071	**
	(0.018)		(0.031)		(0.030)	
Homework * Immigrant	0.040		-0.033		-0.015	
	(0.03)		(0.056)		(0.052)	
Homework value missing	-0.345	**	-0.290		-0.170	
	(0.171)		(0.293)		(0.140)	
(Homework value missing) * Immigrant	0.333		-0.383		0.307	
	(0.256)		(0.394)		(0.253)	
Concentration problems (CP)	-0.049	***	0.003		-0.040	*
	(0.013)		(0.023)		(0.023)	
CP * Immigrant	-0.007		0.023		0.018	
	(0.025)		(0.046)		(0.043)	
CP value missing	0.245	**	0.407	***	-0.134	
	(0.113)		(0.140)		(0.220)	
(CP value missing) * Immigrant	-0.108		-0.648	**	0.020	
	(0.171)		(0.327)		(0.302)	
Truancy	-0.018		-0.065		0.075	
	(0.041)		(0.071)		(0.050)	
Truancy * Immigrant	-0.011		0.077		-0.123	
	(0.06)		(0.090)		(0.095)	
Truancy value missing	0.058		-0.229		0.101	
	(0.125)		(0.215)		(0.233)	
(Truancy value missing) * Immigrant	-0.290		0.123		-0.270	
	(0.201)		(0.302)		(0.348)	
Schools: 97 fixed effects	yes		yes		yes	
No. obs.	2805		1538		1292	
F statistic	20.36	***	12.07	***	6.61	***
R squared	0.228		0.239		0.254	
Adj R squared	0.179		0.147		0.147	
F-tests of joint significance						
All ethnic groups, F(5)	0.52		0.58		1.25	
School fixed effects, F(97)	18.7	***	2.5	***	3.26	***

Note: Dependent variable is students' GPAs in the given subject. Independent variables are PISA scores (divided by 100), homework late, concentration problems, truancy, immigrant, and immigrant interactions. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses.

Table 13: Least Squares Estimates of GPA: Low-Level Schooling

	Reading	Mathematics	Science
Intercept	3.838 ***	3.819 ***	4.615 ***
	(0.182)	(0.304)	(0.277)
Immigrant	-0.128	0.610 *	0.252
	(0.226)	(0.327)	(0.368)
PISA score	0.242 ***	0.354 ***	0.192 ***
	(0.030)	(0.043)	(0.049)
Immigrant * PISA score	-0.007	-0.101 *	-0.060
	(0.042)	(0.058)	(0.069)
Homework late	-0.080 ***	-0.061	-0.065
	(0.025)	(0.042)	(0.046)
Homework * Immigrant	0.049	-0.053	-0.016
	(0.037)	(0.065)	(0.066)
Homework value missing	0.048	0.033	-0.268
	(0.177)	(0.212)	(0.538)
(Homework value missing) * Immigrant	0.100	-0.380	0.424
	(0.251)	(0.329)	(0.571)
Concentration problems (CP)	-0.044 **	0.014	-0.032
	(0.022)	(0.032)	(0.037)
CP * Immigrant	0.005	0.044	0.065
	(0.03)	(0.046)	(0.052)
CP value missing	-0.002	0.253	0.427 *
	(0.137)	(0.210)	(0.220)
(CP value missing) * Immigrant	0.234	0.489	0.017
	(0.232)	(0.348)	(0.492)
Truancy	0.005	0.043	0.085
	(0.055)	(0.06)	(0.069)
Truancy * Immigrant	0.021	-0.080	-0.083
	(0.069)	(0.078)	(0.107)
Truancy value missing	0.051	-0.033	-0.265
	(0.191)	(0.186)	(0.470)
(Truancy value missing) * Immigrant	-0.393	0.240	-0.205
	(0.247)	(0.208)	(0.564)
Schools: 76 fixed effects	yes	yes	yes
No. obs.	1965	1096	770
F statistic	11.3 ***	8.9 ***	2.99 ***
R squared	0.277	0.321	0.401
Adj R squared	0.207	0.196	0.237
F-tests of joint significance			
All ethnic groups, F(5)	0.58	1.06	0.60
School fixed effects, F(76)	22.62 ***	12.57 ***	353.61 ***

Note: Dependent variable is students' GPAs in the given subject. Independent variables are PISA scores (divided by 100), homework late, concentration problems, truancy, immigrant, and immigrant interactions. ***, **, and * represent statistical significance at the 1, 5, and 10 percent level, respectively. White standard errors in parentheses.