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INDIVIDUAL AND SCHOOL VARIABLES EFFECTS ON SCIENCE LEARNING: A MULTILEVEL ANALYSIS OF PISA 2006 DATA IN ALTO-ADIGE

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1. INTRODUCTION

PISA (Programme for International Student Assessment) is a project promoted by OECD to verify the extent to which students completing compulsory education have acquired knowledge and skills that are necessary to a full participation in a developed economy and society. PISA surveys are administered every three years and focus on three key subjects: reading comprehension, mathematics and science. Starting from 2000, each PISA session measures 15-year-old students competencies in all three areas, but one of them is object of closer examination: in the first round the focus was on reading, in the second one on mathematics and in the third one on science.

Italy is since 2000 one of the participating countries. In 2006, 11 Italian regions and the two autonomous provinces of Trento and Bolzano chose to take part in the survey not only as a part of the national sample, but also individually to get data about their own schools and students performance. The present paper analyzes PISA 2006 science results[1] in Bolzano province (Alto-Adige). They are particularly interesting because the organization of the education system in Alto-Adige is the same for all students but schools are separated by language group: German, Ladin and Italian. If Alto-Adige overall results on PISA science test can be regarded as generally good (average = 526 score points)[2], there is however a gap between the performance of German/Ladin speaking students[3] on the one hand and Italian speaking students on the other hand, as table 1 shows. Mean scores of 2064 sampled students are reported by language group and type of school track: academic (*liceo*), technical (*istituto tecnico*), vocational (*istituto professionale*) and training school (*CFP*).

[1] The present study concentrates on science that was the focus of PISA 2006. However, because of high correlation between PISA test scores in all subject areas our outcomes would be very similar if we had analyzed performance in reading or mathematics.

[2] PISA test scores in all areas are standardized so that OECD average is equal to 500 and standard deviation to 100.

[3] Due to the low number, Ladin speaking students are gathered with German speaking students. Italian language group comprises 523 students and German/Ladin group 1541.

TABLE 1

Mean score in science - PISA 2006, Alto-Adige

	German/Ladin Group		Italian Group	
	Mean	Standard error	Mean	Standard error
Academic sc.	585	3.4	548	5.4
Technical sc.	555	3.7	496	7.1
Vocational sc.	514	5.3	424	8.4
Training sc.	483	5.4	404	7.4
All schools	535	2.3	493	3.6

As can be seen, the differences are relevant and concern the two groups as a whole as well the students of the same track in each group. To better understand these results, a multilevel regression analysis was undertaken.

2. ANALYSIS METHOD AND PROCEDURE

In recent years, education survey data have been increasingly analyzed with multilevel regression models. This because they are able to take into account the hierarchical structure of the data that simple linear regression models don't consider. Indeed, students are grouped in classes, which in turn are grouped in schools, and so on. Since students most often are not randomly assigned to schools or to classes within schools, the choice of a model not taking into account the potential correlation between observations pertaining to the same group leads to biased estimates of parameters, particularly standard-errors (Bryk and Raudenbush, 2002, Snjider and Bosker, 1999). Moreover, in many education surveys and even in PISA, sampling method reproduces the hierarchical structure of the target population[4].

A multilevel model can be formally described as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij} \tag{1}$$

where $j = 1, 2, ..., J$ is the second level units index and $i = 1, 2, ..., I$ is the first level units index.

In our case, equation (1) allows to express the performance Y_{ij} of *i*-th student belonging to j-th school in function of the mean school performance (β_{0j}) and the mean effect (β_{1j}) of a covariate (for instance, the student socio-economic background) on the performance within the *j*-th school, with an error term e_{ij}.

In turn, coefficients β_{0j} and β_{1j} may be expressed in function of a group mean, γ_{00} and γ_{10}, of some group feature Z_j (e.g., school mean background, or

[4] The sampling design used for PISA assessments is a two-stage stratified sample design: in the first stage, within each country, schools are selected with probabilities that are proportional to their sizes; in the second stage, 35 students are randomly selected among all 15-year-old students in each school.

its public/private status) plus an error term, u_{0j} and u_{1j}, associated to each school. In formulae:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j} \quad \text{with} \quad u_{0j} \sim N(0, \sigma^2_{uo}) \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} Z_j + u_{1j} \quad \text{with} \quad u_{1j} \sim N(0, \sigma^2_{u1}) \tag{3}$$

Replacing (2) and (3) in (1) gives the "complete" or "combined" model, easily extended to the case in which first and second level explanatory variables (predictors) are more than one.

In multilevel analysis, the first step consists in the estimation of a "null" or "empty" model[5], with no predictor either at level 1 or at level 2 assuming Y_{ij} depends only on the population mean γ_{00} and the error terms u_{0j} and e_{ij}. The variance of Y_{ij} is so decomposed into two components: variance "between" groups (σ^2) and variance "within" groups (σ^2). This allows to calculate the "intraclass correlation coefficient" (ICC) measuring the degree of similarity between observations of the same group. In formula:

$$ICC = \frac{\sigma^2_{uo}}{\sigma^2_{uo} + \sigma^2} \in [0; 1] \tag{4}$$

In the case of education surveys data, ICC is the percentage of the total variance that is accounted for by the school.

Our analysis of PISA science test scores in the province of Bolzano[6] was run in three steps after the preliminary computation of the level 1 and level 2 variance estimates for the dependent variable. As seen in tables 2, 3, and 4 (Random Components), level 2 variance, that is variance attributable to school, is about 41% of the total variance, a high percentage due to the tracked organization of Italian education system at upper secondary level. The remaining variance depends on the differences among students within schools.

In the first step of analysis, only level 1 predictors were introduced into multilevel models by grouping similar variables (for a description of all variables see Appendix) in order to evaluate the effects of individual characteristics on students performance within schools. Every group of variables was added in turn to one of four subsequent models and then variables of each group with a significant effect were entered in a fifth model to select those to be used at a later stage of analysis (see table 2).

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[5] That is the same as a one way ANOVA with random effects.

[6] The considered sample is composed by 2064 students from 77 upper secondary schools: 27 academic schools (*licei*), 20 technical schools (*istituti tecnici*), 11 vocational schools (*istituti professionali*), and 19 training schools (*CFP*).

A similar procedure was followed in the second step to estimate the effects of level 2 predictors. Each group of similar variables has been at first examined separately by means of a series of models containing only level 2 variables to test their impact on school performance (means as outcomes regression). Then, the variables with a significant effect have been added to a further model to identify those to be used in the next step (see table 3).

Finally, in the third step a set of final models has been estimated. At level 1 all the students' individual variables which survived the second stage were introduced together, while at level 2 significant schools' variables surviving the third stage were added one at a time in order to gradually reach a conclusive model with all the relevant level 1 and level 2 variables. However, because of their importance in all PISA studies, three variables (socio-economic-cultural status, gender and national origin) have been retained in the analysis regardless of the significance of their effects (see table 4).

Before concluding the description of the analysis procedure, it might be helpful to supply more details about the missing values issue and the specification of estimated models[7].

With regard to the first point, missing values of all continuous variables have been imputed with the school mean if first level variables, or with the general mean (that is the mean of Bolzano province) when they were second level indicators. In the case of dummy variables, missing data have been assigned to one of the two categories at stake (see Appendix). In order to control for possible distortions of the results, due to the imputation process, for every variable with missing values a new variable has been constructed (missing dummy) and codified with "0" if the associated variable value was present and with "1" if the value was missing. When the percentage of missing values reached or exceeded 5%, the corresponding missing dummy was introduced into models to test its effect on science performance[8].

With reference to the second and more relevant point, in all the estimated models the regression lines slopes were fixed to their mean and only intercepts were allowed to vary randomly. All continuous variables, moreover, were centered around the general mean ($\bar{X}_{..}$), while dummy variables were not centered at all (Paccagnella, 2006).

3. INDIVIDUAL EFFECTS

To calculate individual effects within schools, we used the following general equations:

[7] All the models were calculated using software HLM 6.06 (Raudenbush *et al.*, 2008).

[8] In the outcomes tables, nevertheless, *missing dummies* (taking the name of the corresponding variable preceded by M) appear only if their effect is significant. In practice, that is the case only for LANG (student speaks or doesn't speak at home the language of the test).

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{1ij} - \bar{X}_{..}) + ... + \beta_{kj}(X_{kij} - \bar{X}_{..}) + e_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

Table 2 reports the results of models with only level 1 variables.

TABLE 2

Net effects of level 1variables on science performance

	Mod. 0	Mod. 1	Mod. 2	Mod. 3	Mod. 4	Mod. 5
INTERCEPT	522.9	540.9	529.0	522.9	523.2	544.0
INDIVIDUAL VARIABLES						
Background variables						
ESCS		7.6**				1.0
ESCS2		-2.8				
FEMALE		-19.4***				-17.2***
IMMIG		-31.6***				-21.1***
LANG		-12.0**				-7.5*
MLANG		-23.2**				-16.1*
Scholastic variables						
GRADE			-40,2***			-39.8***
ANYSCIE1			-8.2			
ANYSCIE2			-12.6			
ANYSCIE3			29.1**			8.6
HOMSCIEH			-3.0*			-3.1**
Motivational variables						
SCIEEFF				23.8***		24.3***
SCSCIE				11.4***		11.2***
JOYSCIE				3.9		
INTSCIE				4.7		
INSTSCIE				-6.1***		-0.3
SCIEFUT				-0.5		
SCIEACT				-2.7		
SCIS5				5.0		
SCIEIMP				-0.0		
ICT variables						
HIGHCONF					13.8***	6.1*
PRGUSE					-8.1**	-10.4***
INTCONF					6.3***	8.3***
INTUSE					-6.4**	-6.3**
RANDOM COMPONENTS						
Level 1 Variance	4701.7	4529.7	4410.7	4094.7	4529.4	3622.2
Level 2 Variance	3244.0	2785.9	2799.9	2459.0	2988.6	1776.5
Level 2 Variance (%)	40.8					
Level 1 Variance explained (%)		3.7	5.9	12.9	3.7	23.0
Level 2 Variance explained (%)		14.1	12.3	24.2	7.9	45.2

* 0.05 < p ≤ 0.10 ; ** 0.01 < p ≤ 0.05 ; *** p ≤ 0.01 (p = p-value)

Researches on education have often found that social background has more or less a close relation to achievement. To capture the quality of the student's family environment PISA has created an indicator (ESCS) by combining three dimensions: the highest occupational status of the father or mother, the highest educational level of parents converted into years of schooling and the possession of items related to household wealth (e.g., a dictionary, a desk to study, a dish-washer, etc). In our case, ESCS index[9] has a significant linear effect[10] on performance when only students' background characteristics are taken into account, while the increase in science score is negligible when, in model 5, additional predictors are considered.

Gender regression coefficients are significant and negative both in model 1 and 5. Females in science, *ceteris paribus*, score nearly 20 points lower than males. The result is noteworthy because, unlike mathematics, where boys outperform girls in almost all countries taking part in PISA, in science this occurs only in some Italian regions and in some countries involved in the survey (Ricci, 2008).

An immigrant status is associated in model 1 with a significant negative effect that is reduced by 10 points when additional predictors are considered together with background variables in model 5.

Language spoken at home produces effects not easily interpretable, probably because of the complex situation in Bolzano province. At level 1, if students speak at home a language other than the language used in the assessment, their attainment in science is usually worse than the result obtained by a student speaking the language of the test, although the effect of this predictor is no more significant when school variables are introduced (see table 4). Moreover, the language spoken at home is the only level 1 variable whose associated missing dummy (MLANG) is significant in all models. In general, MLANG tends to mark out within each language group students not significantly different as for their socio-economic-cultural background, yet achieving poorer science performances. The results always rank German/Ladin students first if the comparison is made between language groups. The same occurs if the analysis is done crossing science performance and immigrant background. In this case too, students that do not respond validly to the question about the language spoken at home[11], achieve worse results, but anyway better when belonging to the German/Ladin group than to the Italian one.

Regarding the block of variables related to the educational career of students (model 2), as it could be expected, lagging behind in the course of studies turns into a net negative effect. Having studied a scientific subject in both years of the first two of upper secondary school (ANYSCIE3) shows a positive net effect, that becomes insignificant if this predictor is considered together with other individual variables (model 5).

Unlike what might be expected, the increase of one hour spent on science homework (HOMSCIEH) produces a negative effect, albeit weak, probably because that indicates the existence of learning difficulties more than a special interest for scientific subjects. It should be noted that this result is not new but is confirmed by other researches (Martin *et al.*, 2000; Martini and Ricci, 2007).

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[9] ESCS index and all other individual indicators used in PISA are standardized so that they have a mean equal to 0 and a standard deviation equal to 1.

[10] ESCS effect in the province of Bolzano can be considered linear because square ESCS is not statistically significant. This variable has been therefore eliminated from the analysis.

[11] It should be noted that *missing LANG* are represented more by "invalid" answers than by omissions.

Motivational variables (model 3) showing a net positive effect on the mean result in science are self-efficacy (SCIEEF) and self-concept (SCSCIE)[12], while instrumental motivation to learn science (INSTSCIE) has a negative effect, yet disappearing when additional predictors are considered in model 5. On the contrary, the contribution of self-efficacy and academic self-concept to the explanation of variance remains almost the same. As underlined by the International PISA report, these two variables do not simply reflect the student's performance but go beyond that. Students who are confident in their own ability to learn and believe that engagement in learning can make a difference are more likely to be successful at school. In our case, these two variables can even contribute to account for some differences between the two language groups, German/Ladin and Italian. As for self-efficacy, when considering both groups as a whole, there is a statistically significant difference (0.12) in favor of the Italian group, but when comparison is made across tracks, in academic and technical schools the opposite occurs so that significant differences (0.11 in the first case and 0.17 in the second) are observed to the advantage of the German/Ladin group. Likewise, despite of equal averages on self-concept indicator in the two language groups, the score by track highlights significant differences to the advantage of the German/Ladin group in academic and technical schools (0.21 and 0.22 respectively). The highest level of these two variables - one of the aspects distinguishing the so called "strong learners" - in German/Ladin students attending academic and technical schools may indicate they have different characteristics than their Italian counterparts, a point we will return on in the conclusions.

Variables related to ICT use (model 4) show significant effects on the mean performance in science but in opposite directions. While self-confidence in ICT high-level tasks (HIGHCONF) and in Internet tasks (INTCONF) are associated with higher science scores, using information and communication technologies for entertainment (INTUSE) is related to lower science scores. The negative effect of using computer to program and implement software seems to be counter-intuitive, but the result is plausibly explained by the indicator assuming a value inferior to the OECD mean (equal to zero) in academic schools (-0.09) and higher in technical (0.17), vocational (0.06), and training (0.05) schools, where, generally, science performance is lower than in academic schools.

In conclusion, the amount of variance accounted for by student variables taken into account in model 5 is 23% of the level 1 variance[13]. In turn level 2 variance is reduced by 45%: that proves the uneven distribution of students' characteristics across schools and does not represent a real contextual effect (Hox, 2002).

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[12] Self-efficacy is a measure of how much students believe in their own ability to handle tasks effectively and overcome difficulties, whereas self-concept is a measure of students' beliefs in their own academic abilities in science (PISA, 2006).

[13] The amount of level 1 and level 2 explained variance is obtained by difference with the initial variance.

5. SCHOOL EFFECTS

The second step of analysis was conducted by using the following equations:

Level 1:

$$Y_{ij} = \beta_{0j} + e_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_{1j} + \ldots + \gamma_{0h} Z_{hj} + u_{0j}$$

Table 3 reports the outputs of models with only school variables. As can be noticed, the residual level 1 variance (Random Components) remains constant from one model to the other, as it could be expected by considering first level equation.

TABLE 3

Net effects of level 2 variables on science performance

	Mod. 0	Mod. 6a	Mod. 6b	Mod. 6c	Mod. 7	Mod. 8	Mod. 9
INTERCEPT	522.9	518.7	587.4	567.6	515.5	525.4	551.4
SCHOOL VARIABLES							
Contextual variables							
a) *External context variables*							
LOC		3.8	-4.0	-2.6			
COMPET		-7.1	-3.1	-5.0			
PRESSGE		40.9**	15.6	12.2			
b) *Global variables*							
SCHLANG			-62.2***	-48.6***			-40.2***
TECH			-30.2***	-10.5			-13.5*
VOC			-78.5***	-33.4***			-19.6*
TRA (CFP)			-105.3***	-58.2***			-14.6
c) *Intake variables*							
SCHESCS				54.7***			71.6***
SCHSIZE				4.4			
SCHSIZE2				-0.7			
HPCTGIRLS				-13.2*			-1.4
HPCTIMMIG				-40.2***			-42.0***
Human and material resources							
STRATIO					7.6**		-1.7
TCSHORT					-2.9		
SCMATEDU					0.5		
IRATCOMP					21.1		
Science teaching							
SCHSCIEH						15.1***	14.8***
SCIPROM						9.2	
SCAPPLY						3.2	
SCHANDS						28.9***	6.0
SCINVEST						-80.6***	-14.4
RANDOM COMPONENTS							
Level 1 Variance	4701.7	4701.8	4701.8	4700.9	4701.6	4702.3	4700.5
Level 2 Variance	3244.0	3158.3	931.3	584.8	3132.9	1298.8	367.8
Level 2 Variance (%)	40.8						
Level 1 Variance explained (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Level 2 Variance explained (%)		2.6	71.3	82.0	3.4	60.0	88.7

* 0.05 < p ≤ 0.10 ; ** 0.01 < p ≤ 0.05 ; *** p ≤ 0.01 (p = p-value)

Of the four blocks of variables examined, the one which accounts for the greatest amount of between schools variance is the contextual indicators block, reducing level 2 variance by 82%. Having the highest number of variables, some of them particularly interesting in the case in exam, contextual variables have been divided into three sub-groups (models from 6a to 6c). Variables related to external context - school location (LOC), exposure to competition with other schools (COMPET) and parents' pressure (PRESSPA) – play a small explanatory role.

Parents' pressure, the only one showing a significant effect - evidently because connected to the kind of school[14] - stops being such as soon as language group and school track variables are introduced (model 6b). All variables of this sub-group have a strong and statistically significant effect on school science performance: belonging to the Italian language group (SCHLANG) involves a 62 points decrease of the mean score, but if the school is a technical (TECH), a vocational (VOC), or a training school (TRA), this implies a further reduction of the mean score, by 30, 79, and 105 points, respectively. When variables related to the composition of the school intake are added (model 6c), the difference between academic and technical schools stops being significant, while the gap of vocational and training schools is reduced by half. This indicates that the difference in performances highlighted in the previous model (6b) is completely or in part attributable to the different social background of students attending different tracks. The increase of a standard deviation unit of the school mean ESCS (SCHESCS) implies an increase in science performance of about 55 points. On the contrary, a significant negative effect comes from the presence of a high percentage of girls (HPCTGIRLS) and of immigrant students (HPCTIMMIG) in the school. The percentage of females, nevertheless, does not keep - unlike the percentage of immigrant students - a significant effect when considered together with the variable related to science curricular hours (model 9). The school size (SCHSIZE), finally, does not weigh in any way on its mean result.

If variables related to human and material resources are considered, only the number of students per teacher (STRATIO) exerts a significant effect of almost 8 points on schools performance. It's a result verified in other studies (Martini and Ricci, 2007), although it might appear counterintuitive. The significance of this effect, still, like the presence of a high percentage of girls, is nullified in model 9.

Among variables of the block pertaining to science teaching (model 8), only curricular hours of science per week (SCHSCIEH) show a significant effect substantially unvaried when the variable is placed together with the contextual ones in model 9, increasing the school mean score of almost 15 points by one hour in addition to the provincial mean. The presence of activities to promote science learning (SCIPROM) does not seem to be important, while the effects of two indicators related to science teaching (SCHANDS and SCINVEST) are spurious, so much that their significance disappears in model 9.

[14] Academic school parents usually are the ones to exert more pressure towards better scholastic results.

To sum up, school variables showing a significant net effect once the composition of the school intake is controlled are only the kind of school (language group and track) and the weekly hours of science.

6. THE MODELS WITH FIRST AND SECOND LEVEL EXPLANATORY VARIABLES

Table 4 reports the results of models estimation with both first and second level predictors. The general equations used in this final step are:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{1ij} - \bar{X}_{..}) + ... + \beta_{kj}(X_{kij} - \bar{X}_{..}) + e_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_{1j} + \ldots + \gamma_{0h}Z_{hj} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

In order to better evaluate their effects on students science performance second level variables have been introduced one at a time into the models.

TABLE 4

Net effects of level 1and level 2 variables on science performance

	Mod. 0	Mod. 10a	Mod. 10b	Mod. 10c	Mod. 10d	Mod. 10e
INTERCEPT	522.9	557.9	561.9	583.1	581.3	568.7
STUDENT LEVEL (LEVEL 1)						
ESCS		1.4	-0.2	-0.2	-0.2	-0.1
FEMALE		-16.7***	-17.1***	-18.5***	-18.4***	-17.6***
IMMIG		-20.8***	-22.3***	-22.0***	-21.3***	-21.0***
LANG		-6.2	-6.3	-5.8	-6.0	-5.9
MLANG		-15.7*	-15.8*	-15.5*	-15.6*	-15.5*
GRADE		-40.8***	-38.7***	-38.3***	-37.6***	-37.8***
HOMSCIEH		-2.9*	-2.7*	-2.9*	-2.9*	-3.4**
SCIEEFF		24.6***	24.5***	24.3***	24.4***	24.1***
SCSCIE		11.3***	11.3***	11.1***	11.2***	11.0***
HIGHCONF		5.7*	5.6*	5.8*	5.9*	5.9*
PRGUSE		-10.4***	-10.2***	-10.1***	-10.0***	-10.0***
INTCONF		8.5***	8.3***	8.1***	8.0***	8.0***
INTUSE		-6.3**	-6.4**	-6.6**	-6.5**	-6.6**
SCHOOL LEVEL (LEVEL 2)						
SCHLANG		-37.7**	-54.6***	-53.2***	-36.9***	-34.2***
SCHESCS			86.5***	46.0***	41.7***	49.6***
TECH				-8.4	-7.8	-6.6
VOC				-30.7***	-24.4***	-14.9*
TRA (CFP)				-49.4***	-46.4***	-11.8
HPCTGIRLS					-1.5	6.7
HPCTIMMIG					-36.8***	-37.8***
SCHSCIEH						12.0***
RANDOM COMPONENTS						
Level 1 Variance	4701.7	3621.5	3619.6	3618.7	3618.8	3617.7
Level 2 Variance	3244.0	1637.0	625.2	455.5	401.5	288.0
Level 2 Variance (%)	40.8					
Level 1 Variance explained (%)		23.0	23.0	23.0	23.0	23.1
Level 2 Variance explained (%)		49.5	80.7	86.0	87.6	91.1

* $0.05 < p \leq 0.10$; ** $0.01 < p \leq 0.05$; *** $p \leq 0.01$ (p = p-value)

As for the students variables, when comparing table 4 with table 2 it is clear that the effects of individual indicators remain substantially the same with the exception of language spoken at home (LANG). We will focus then on school level predictors, which anyway are more interesting both in order to understand differing performances across schools and to plan and evaluate educational policies.

In the first model (10a), only the school language group has been placed as an explanatory variable. On its own, it explains almost 50% of the between schools variance. As observed before, if the language of school attended is Italian, all individual conditions being equal, the decrease of students mean science score is about 38 points.

What it is more interesting to note is that, taking under control the language group of the school and its mean socio-economic-cultural status (model 10b), the gap between the performance of a German/Ladin student and an Italian one grows from 38 to 55 points. This is due to the ESCS index of the Italian language group being meanly higher than the German/Ladin, both at a provincial level and within different tracks with the exception of technical schools, as it is clear in table 5 (Thrupp, 1997).

TABLE 5

ESCS in Bolzano by school type and language group

	German/Ladin Group		Italian Group	
	Mean	Standard error	Mean	Standard error
Academic sc.	0.29	0.04	0.40	0.06
Technical sc.	-0.04	0.03	-0.03	0.07
Vocational sc.	-0.33	0.05	-0.15	0.09
Training sc.	-0.42	0.06	-0.36	0.08
All schools	-0.12	0.03	0.11	0.03

The difference in the mean index of the two groups is to be attributed less to the family wealth component than to components regarding parents' education and profession, whose values are usually greater in the Italian than in the German/Ladin group[15].

There is a second aspect to underline, already well known in previous analysis of local and international PISA data, and that is the difference between the effect of the student's personal status on his/her performance and the effect of the school status mean. In the case examined, the net effect of ESCS on science test score at individual level is practically null. Nevertheless, even looking at the only model (see model 1 in table 2) where the personal student's status is significant, the size of the effect is anyway smaller than the effect produced by the school mean ESCS. This confirms one more time the statement of PISA 2006 International report (but also in prior ones) quoted here: «Regardless of their own socio-economic background, students attending schools in which the average socio-economic background is high tend to perform better than when they are enrolled

[15] Indicators of wealth (WEALTH), years of parents instruction (PARED), and parents' occupation (HISEI) present the following mean values respectively in the German/Ladin and in the Italian group:
WEALTH: G/L = -0.25; IT = -0.28. PARED: G/L = 12.8; IT = 13.3. HISEI: G/L = 46.5; IT = 49.9.

in a school with a below-average socio-economic intake. In the majority of OECD countries, the effect of the average economic, social and cultural status of students in a school – in terms of performance variation across students – far outweighs the effect of the individual student's socio-economic background.» (OECD, 2006, p. 194).

Moving on to model 10c, the introduction of the school track variable not only increases the intercept (reference is now a student attending an academic school) but also reduces the impact of social status on performance. Controlling for both the school mean social status and the track, a significant net effect remains only in the case of vocational and training schools but not in the case of technical ones[16]. The difference observed in the effect produced by "school track" variable, controlling or not for students mean background, suggests that track chosen at the moment of enrolling in upper secondary education works as a variable mediating the influence of social background on results.

Unlike a high female proportion, a high percentage of immigrant students (model 10d) has a significant effect decreasing the result of about 37 points. On the contrary, the gap between Italian and German/Ladin language students is now to some extent filled, counterbalancing the effect of the school mean ESCS which, as we have seen, tends to increase it. As seen in table 6, reporting the proportion of immigrant students compared to the total number of students in each type of school and in each language group, not only immigrant students are mostly concentrated in Italian language schools[17], but their distribution across tracks is different in German/Ladin group and in the Italian one. In the former immigrant students attend more often academic schools, less technical and vocational schools and are almost not present in training schools. In the latter it happens the opposite, with the majority of immigrant students attending vocational and training schools. This trend indicates that students' characteristics differ a lot in one case and the other[18].

TABLE 6

Proportion of immigrant students in Bolzano by school type and language group

	German/Ladin Group		Italian Group	
	Proportion	Standard error	Proportion	Standard error
Academic sc.	0.027	0.009	0.061	0.018
Technical sc.	0.014	0.006	0.076	0.027
Vocational sc.	0.018	0.010	0.166	0.048
Training sc.	0.006	0.004	0.144	0.041
All schools	0.016	0.003	0.095	0.015

[16] If a model totally similar to the one examined above is estimated without the school mean ESCS, the decrease of the science score raises immediately to 82 points for a training school student, to 57 for a vocational school student, to 24 for a technical school student, this last difference being significant again.

[17] On the whole, immigrant students represent 3% of the sample of upper secondary school's students in the province of Bolzano. Nevertheless, in German/Ladin language schools, the immigrant students' quota is only 1,6%, raising to 9,5% in Italian language schools. Moreover, out of 11 schools with a high percentage of immigrant students, 10 are in the Italian language group.

[18] Taking away immigrant students from the analyzed sample, science performance remains basically the same in German/Ladin language schools, raising of a mean 10 points in Italian language schools.

Considering the last model in table 4, with all first and second level variables (model 10e), it is opportune to dedicate a brief comment to the last introduced variable, that is the weekly curricular hours of science. The addition of one hour per week meanly increases students' performance by 12 points. Yet what is more interesting to note is that keeping under control this variable makes no more significant the difference in the attainment of training schools students, while on the other hand the gap of vocational schools' students is somehow reduced. It is remarkable also a slight reduction of the gap due to the language group a school belongs. All this is to be ascribed to the different mean number of hours devoted to science teaching from one track to the other and between the two language group schools, as seen in table 7.

TABLE 7

Mean hours of science in Bolzano by school type and language group

	German/Ladin Group (G1)		Italian Group (G2)		Difference		
	Mean hours	St. Err.	Mean hours	St. err..	(G1-G2)	St. err.	*t*-ratio
Academic sc.	3.50	0.06	3.01	0.14	0.49	0.16	3.10
Technical sc.	3.76	0.09	3.38	0.19	0.38	0.21	1.77
Vocational sc.	2.95	0.10	2.40	0.19	0.55	0.21	2.57
Training sc.	1.15	0.08	1.63	0.22	-0.48	0.25	-1.94
All schools	2.81	0.05	2.75	0.10	0.05	0.11	0.42

Significance level of 5%

Looking at table7, it is possible to observe, first, that the average of weekly hours is higher in technical schools, a bit lower in academic schools, definitely low in vocational, and even lower in training schools. The same trend goes for both language groups. Nevertheless in German/Ladin academic, technical, and vocational schools the average of science hours is systematically higher in comparison to the same type of Italian schools, with a significant difference in two cases out of three. The opposite goes for training schools, where the average in the Italian schools is higher than in German/Ladins schools (the difference is close to significance).

CONCLUSIONS

To sum up the main points emerging from the analysis, we underline, first of all, that the final model (10e) explains 23% of the variance among students within schools and a remarkable 91% of the between schools variance. As usual, the amount of level 1 variance explained is far smaller than the level 2 variance. Still, in the latter case, there is a 9% of residual variance, unexplained by considered variables and attributable to peculiar features of the schools.

As showed in many surveys, school contextual variables have a major weight determining the students' performance. In our case, the language group a school belongs plays a relevant role, as it can be ascribed to it about half of the between schools variance. It is worth focusing on this variable to try some hypothesis on how its influence works, although it has to be made clear that an essential piece of information is missing to support our argument, that is any measurement of the cognitive level of students entering upper secondary education - or a measurement of their general ability independent from their PISA results. This is an objective limit to PISA survey, particularly in our opinion for those countries where 15-year-old students attend schools with different curricula and a different requirement level[19]. Having that said, it is possible to affirm that the selection (or self-selection) process at the entrance into upper secondary education for the students of German/Ladin group is more consistent with their proficiency level in comparison to the Italian language group students. If we consider the weighted distribution of students across different tracks by language group, it is possible to observe that, whereas German/Ladin academic schools count 28% of students, the same Italian school type counts 47%. The rest of the student population is so divided within the German/Ladin group: 29% in technical schools, 13% in vocational and 30% in training schools. Corresponding percentages of students attending schools of Italian language group amount respectively to 20%, 16%, and 17%. Assuming that the proficiency levels of students entering upper secondary education are normally distributed in the two groups, even if the mean values in each group would not be significantly different[20], any way as school choice reflects more or less the student ability, it is easy to grasp the logic consequences. From the different student distribution across tracks in the two language groups follows necessarily a gap in the mean ability level of students attending the same track of one group and the other. On the basis of the outputs of multilevel analysis described in the International PISA report, we can argue that school selectivity exercises a positive effect, all other conditions being equal, on the overall attainment, as well. It is possible to assume that school selectivity, making the school intake more homogenous, improves teaching conditions and therefore its efficacy[21].

From this point of view, it is interesting to observe that in German/Ladin language schools, unlike Italian language schools, performance variability tends to decrease once performance levels increase, as it is plain to see in figure 1, where schools mean science scores are put in relation to their standard deviations.

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[19] As the target population of PISA is age-based, because of the different organization of education systems in each country, students often are not found in the same stage of their educational career. In many OECD countries, for example in Finland, and generally in Scandinavian and Anglo-Saxon countries, 15-year-old students still attend comprehensive schools, while in Italy, Germany, Japan, and other countries they attend tracked schools. This is a very important point for its implications and it has to be taken into account when comparing countries on the basis of PISA results.

[20] We think there are clues attesting the better mean proficiency level of the German/Ladin students. Moreover, we can assume that counseling at the end of lower secondary school works differently in the two language groups, even if we do not have evidence of this, like for the previous hypothesis. *En passant*, let's remember that all the sampled students still in lower secondary school at 15 belong to German language group. Finally, we add that if the two hypothesis made before were to be true, this would not contradict the effect generated by differences in the distribution per track, on the contrary, it would only reinforce it.

[21] This is true for schools recruiting students with high ability levels and not for schools where poor ability students are in the majority. It is appropriate to point out that, according to the International PISA report, there is no evidence that educational systems with a higher proportion of selective schools are advantaged in comparison to less selective systems, all other conditions being equal.

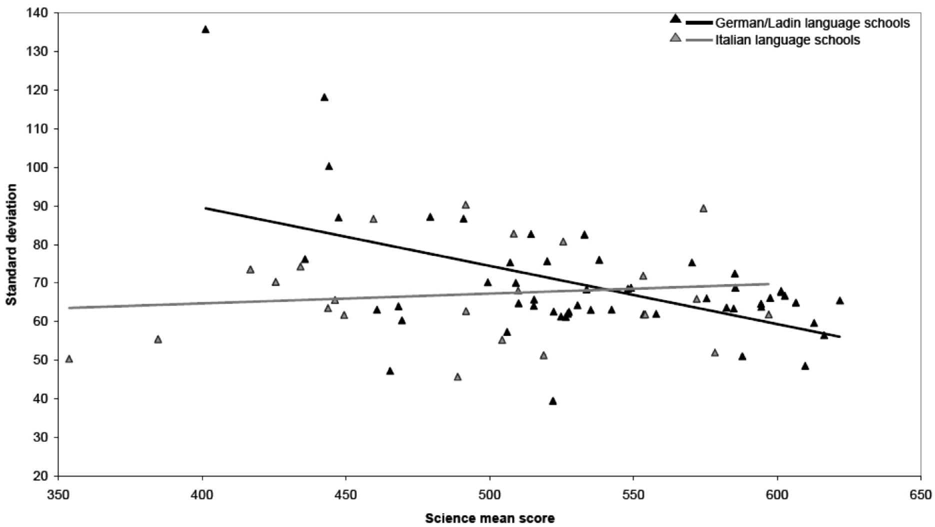

Figure 1 – Relation between school mean science score and scores' standard deviation.

The difference in the performance of German/Ladin students compared to Italian students can be attributed as secondary factors to the lower number of weekly curricular hours of science in Italian schools - except in CFPs - and to the higher proportion of immigrant pupils (particularly in vocational schools). It is not by chance that the greatest performance gap, in comparison to the same type of German/Ladin schools, is found in Italian vocational schools, where these factors' action sums up.

Of course, this interpretation does not exclude in any way the action of other factors related to the functioning of schools, although it would be necessary a specific research as the pieces of information supplied by PISA survey are not sufficient, or relevant in our case.

The second aspect we want to point out in the conclusions is the importance, mainly at school level, of the student's socio-economic-cultural status. While at student level the ESCS effect stops being significant when additional individual variables are considered, at school level the role played by this indicator remains relevant in all the specified models. As it is possible to see in table 4, it explains about 81% of the between schools variance together with the language group factor. As already remarked in the previous paragraph, the composition of the school intake creates a "contextual" effect going beyond the individual student's background effect. Nevertheless, it is important to underline that PISA tends to emphasize the role played by the school mean ESCS because a measurement of the ability of students entering upper secondary education is missing. One more time more specific researches at a local level, for example evaluating the proficiency level of students exiting lower secondary school, might help define the picture and let the contribution of these two factors - and their interaction - come out.

APPENDIX

Variable description	Variable name	Mean	St. Dev.	Min	Max	Missing Values %
LEVEL 1 (STUDENT)						
1) Background variables:						
Student socio-economic-cultural status index	ESCS	-0.05	0.83	-2.85	3.02	0.6
Square socio-economic-cultural status index	ESCS2	0.69	1.00	0.00	9.13	0.6
Student gender is female (male)	*FEMALE*	0.51	0.50	0	1	0.0
Student has an immigrant background (native)	*IMMIG*	0.05	0.22	0	1	1.7
Student does not speak at home test language (speaks test language)	*LANG*	0.34	0.47	0	1	9.7
2) Scholastic variables:						
Student is not at grade (at grade)	*GRADE*	0.25	0.43	0	1	0.0
Student studied a scientific subject in the previous year (did not)	*ANYSCIE1*	0.84	0.37	0	1	4.2
Student studied a scientific subject in the assessment year (did not)	*ANYSCIE2*	0.85	0.36	0	1	3.9
Student has been studying scientific subjects for two years (has not)	*ANYSCIE3*	0.79	0.41	0	1	0.0
Weekly hours spent on science homework	HOMSCIEH	1.38	1.39	0	7	1.6
3) Motivational variables:						
Self efficacy in science	SCIEEFF	-0.20	0.81	-3.77	3.22	0.8
Academic self-concept in science	SCSCIE	0.14	0.94	-2.36	2.24	8.2
Enjoyment of science learning	JOYSCIE	0.05	1.00	-2.15	2.06	0.6
General interest in science	INTSCIE	0.10	0.86	-3.14	3.29	0.9
Instrumental motivation to learn science	INSTSCIE	-0.25	0.96	-2.10	1.82	8.0
Future oriented science motivation	SCIEFUT	-0.10	0.95	-1.42	2.27	1.0
Science related activities at home	SCIEACT	0.15	0.88	-1.69	3.38	0.6
Student expects a science related career at age 30 (does not)	*SCIS5*	0.26	0.44	0	1	1.2
Student attaches importance to succeeding at school in sc. (does not)	*IMPSCIE*	0.74	0.44	0	1	8.2
4) Information and Communication Technologies variables:						
Self-efficacy in ICT high level tasks	HIGHCONF	0.02	0.86	-3.99	2.10	1.4
Use of computer to program or to implement software	PRGUSE	0.07	0.83	-2.58	3.83	1.3
Self-efficacy in Internet tasks	INTCONF	-0.29	0.97	-4.85	0.76	1.4
Use of computer and/or Internet for entertainment	INTUSE	-0.29	0.85	-3.04	3.18	1.3
LEVEL 2 (SCHOOL)						
1) Contextual variables:						
1a) External context variables						
School is located in a town with ≤ 15.000 inhabitants (> 15.000 in.)	*LOC*	0.39	0.49	0	1	2.6
School must not compete with other schools (school must compete)	*COMPET*	0.30	0.46	0	1	3.9
Most of parents press for high marks (none or some)	*PRESSPA*	0.14	0.35	0	1	5.2
1b) Global variables						
Language spoken at school is Italian (German/Ladin)	*SCHLANG*	0.30	0.46	0	1	0.0
School is a technical school (academic)	*TECH*	0.26	0.44	0	1	0.0
School is a vocational school (academic)	*VOC*	0.14	0.35	0	1	0.0
School is a training school (academic)	*TRA*	0.25	0.43	0	1	0.0
1c) Intake variables						
School mean socio-economic-cultural status	SCHESCS	-0.08	0.41	-1.20	1.08	0.0
School size (students number /100)	SCHSIZE	3.08	2.18	0.27	9.98	3.9
Square school size	SCHSIZE2	14.21	18.86	0.07	99.60	3.9
Percentage of girls ≥ 70% (< 70%)	*HPCTGIRLS*	0.23	0.43	0	1	4.0
Percentage of immigrant students ≥ 10% (< 10%)	*HPCTIMMIG*	0.14	0.35	0	1	0.0
2) Human and material resources:						
Number of students per teacher	STRATIO	6.67	2.47	1.82	11.62	5.2
Teacher shortage	TCSHORT	0.45	0.75	-1.06	1.64	0.0
Proportion of computers for educational use > 0,50 (≤ 0,50)	*IRATCOMP*	0.34	0.16	0.03	0.74	7.8
Quality of educational resources	SCMATEDU	0.49	0.95	-1.49	2.14	0.0

Variable description	Variable name	Mean	St. Dev.	Min	Max	Missing Values %
3) Science teaching:						
Mean weekly science hours	SCHSCIEH	2.94	1.34	0.23	5.77	0.0
Number of activities to promote science learning	SCIPROM	-0.21	0.70	-2.27	1.44	2.6
Science teaching focuses on applications or models	SCAPPLY	-0.31	0.48	-2.46	0.59	8.6
Science teaching focuses on hands-on activities	SCHANDS	-0.25	0.69	-2.10	1.27	8.3
Science teaching focuses on student investigations	SCINVEST	-0.24	0.40	-1.26	0.94	8.6

Note: Variables whose names are in italics are dummy variables. The condition described in the first column of table above is codified with "1" (the reference category, codified wit "0", is reported in parenthesis)

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SUMMARY

Individual and school variables effects on science learning: a multilevel analysis of PISA 2006 data in Alto-Adige

The paper describes the outcomes of a two-level regression analysis of the PISA 2006 science test scores in the province of Bolzano (Alto-Adige). They are particularly interesting because of the peculiarity of this province, where the organization of the education system is the same in the whole territory but schools are divided on the basis of language group their students belong: German/Ladin or Italian. More than forty variables from student and school-questionnaires have been analyzed by means of a series of models to

study their effects on science scores and to identify which of them were associated with better performances at student and school level. Some hypothesis are also formulated to try to explain the superior performance of German/Ladin students and schools in comparison with Italian ones.