Identifying the Factors Influencing the Scientific Competence in Andalusia: A Multilevel Study of the PISA 2012 Results

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Abstract: In this paper we investigate the factors that contribute to the performance of Andalusian students in the scientific competence aspect of the PISA 2012 tests. The variables included refer to the students and schools. Multilevel analysis of the variables reveals that between 9.58% and 14.68% of the differences in the performance are due to characteristics of the schools and that most of the variance is explained by the characteristics of the students. The most significant variables with respect to scientific competence, in a negative sense, are grade repetition, immigrant status and female gender; in a positive sense, they are family and sociocultural background and pre-primary schooling. In the light of these results, we discuss implications for education policy actions. This study shows the multilevel analysis model to be a very useful tool in education studies.

Keywords: Education, PISA, Multilevel regression, Performance, Scientific competence, Andalusia

Introduction

Scientific competence, is defined by the Programme for International Student Assessment (PISA) as "An individual's scientific knowledge and use of that knowledge to identify questions, to acquire new knowledge, to explain scientific phenomena, and to draw evidence-based conclusions about science-related issues, understanding of the characteristic features of science as a form of human knowledge and enquiry, awareness of how science and technology shape our material, intellectual, and cultural environments, and willingness to engage in science-related issues, and with the ideas of science, as a reflective citizen" (OECD, 2006).

Traditional conceptual, procedural and attitudinal contents have been used in most educational reforms carried out since the 1990s. According to Gil and Vilches (2006), the PISA project is a new approach, an attempt to improve the scientific training of the citizens of the 21st century during compulsory schooling, irrespective of whether they continue their scientific formation or not. In other words, the aim is to promote scientific literacy.

PISA tests generate a huge amount of data and results, which may be analysed from different perspectives within the educational community. In this respect, two broad viewpoints have been taken. The first is highly critical of the PISA approach, arguing that the performance of these tests does not take a holistic view of education but, rather, an analytic one, dividing global competence into discrete elements, such as reading competence (evaluated in detail in the 2002 and 2009 editions of the study), mathematical competence (evaluated in the 2004 and 2012 editions) or scientific competence (considered in the 2006 and 2015 editions).

Under this analytic approach, each partial competence is defined as a set of capacities that may be evaluated, which simplifies the complex task of conducting an international assessment and provides guarantees for an objective correction of the tests. However, it has been argued that the tests do not take a holistic view of competence and therefore do not really assess it. Other critics claim that the context in which the tests are performed is inappropriate, since acquiring a competence in an academic environment does not assure its mastery and application in non-academic contexts. Traditional pen-and-paper tests are cheap and easy to apply, but their effectiveness is questionable in the sense that they are disconnected from what they seek to evaluate (Yus et al., 2013). The second type of analysis focuses on the usefulness of the data, taking into account that data quality in some cases, such as the information supplied by the heads of education centres or by students' parents, might be significantly improved. The usefulness of these data is influenced by educational policies aimed at enhancing students' performance in education. Performance analyses focus on crucial cultural and socioeconomic factors such as the education level of the parents, the environment, the type of school, the presence of immigrants, grade repetition, the student-teacher ratio and educational resources (Cordero et al., 2013). By means of these analyses, a global evaluation of students' performance can be made, together with one of specific aspects, such as mathematical competence (in PISA 2003) or scientific competence (in PISA 2006) (Calero et al., 2010; Escardíbul, 2008; López et al., 2009). In this analytic process, multilevel logistic models are used, following Choi and Calero (2013) and Cordero et al. (2011) regarding PISA 2009.

The publication of the results of each edition of the PISA study often originates major controversy and intense discussions in the educational environment. The aim of this paper is to present an analysis, using multilevel regression, of the scientific performance of Andalusian students, based on the data collected in the 2012 edition of the PISA project.

Method

Sample and Description of the Variables

The PISA project is a competence evaluation of 15-year-old students, carried out by the OECD every three years. Our study sample is obtained from the 2012 edition of the study, which examined some 510,000 students drawn from a population of 28 million students in 65 countries. In Spain, over 25,000 students from 900 schools located in 14 regions were evaluated. Our analysis focuses on the evaluation of scientific competence according to the data collected for the students in the region of Andalusia.

The PISA project does not evaluate the performance using a single score; rather, the students are scored in each test on a continuous scale. This procedure is based on the item response theory developed by Rasch (1980), according to which the difficulties of each question and the capacities of the student are estimated simultaneously. Under this approach, instead of deriving an average value of the knowledge of each student, five values randomly drawn from the result distribution, called plausible values (PV), are taken (Wu and Adams, 2002). The PV are a representation of the capacities that the student may reasonably be assumed to possess. The multilevel analysis then performed is based on the PV, using the method described in OECD (2003).

The PISA 2012 tests consist of 1076 items that encompass information about variables regarding the school, the household and the socioeconomic context of the student. However, the present study only addresses the variables regarding the student environment and the school environment, which are considered significant in most previous research into education quality. Nevertheless, in addition to the traditional factors, we also consider some innovative aspects, first introduced in PISA 2009, which have received scant attention in previous studies analysing this database. One such question is that of pre-primary schooling, a variable that seems to have made a noticeable impact on the results of the 2009 edition of the PISA study (Cordero et al., 2011). For example, the average difference in performance between the students that attended more than one year of pre-primary courses and those who did not was of 54 points (OECD, 2011).

The variables considered are presented in Table 1. Two types of variables are distinguished: dichotomous (or dummy) and continuous.

Table 1. Variables considered

Student variables		School variables	
Name	*Type*	*Name*	*Type*
Gender	Dummy (0: Male; 1: Female)	Type of school	Dummy (0: Private sch.; 1: Public sch.)
Repeat	Dummy (0: No; 1: Yes, one or more grades)	Does the school "compete" with other surrounding schools?	Dummy (0: No; 1: Yes)
Pre-primary schooling	Dummy (0: No; 1: Yes)	Teacher – students ratio	Continuous
Immigrant	Dummy (0: No; 1: Yes)	Proportion of girls at school	Continuous
Possession of textbooks at home	Dummy (0: No; 1: Yes)	Size of the school	Continuous
Possession of literature at home	Dummy (0: No; 1: Yes)	School location	Dummy (0: Town; 1: City)
Possession of computer at home	Dummy (0: No; 1: Yes)	Is the school's capacity to provide instruction hindered by shortage or inadequacy of science laboratory equipment?	Dummy (0: No; 1: Yes)
Do the language of the test and the language spoken at home match?	Dummy (0: No; 1: Yes)	Responsibility of the school in curriculum design and in evaluation criteria setting	Continuous
Highest educational level of parents	Dummy (0: No; 1: Yes)	Responsibility of the school in resource management	Continuous
Highest parental occupational status	Continuous	Quality of scholar resources	Continuous
Cultural possessions	Continuous		
Index of economic, social and cultural status (ESCS)	Continuous		

The 2012 PISA database is composed of 1,434 entries, with no missing values in the final weight or in the performance estimate of each student. Nevertheless, 80 records contain missing values for some of the variables we have taken as predictors, and these records were removed from the study sample1. In Andalusia, the PISA tests were applied in 52 schools (38 were public schools, with 985 students evaluated, and 14 were private schools, with 369 students evaluated). 48.59% of the students were girls. Thus, 1,354 valid entries were analysed.

Method and Results

In this study, the hierarchical organisation of the educational data is modelled using multilevel regression models, in which individuals belonging to the same subgroup are not independent. Most previous empirical studies have used this type of model (Snijders and Bosker, 2012), which take into account that the students take part, or are "nested", in a superior level represented by the schools.

To facilitate analysis, the data from the PISA report are usually separated into two levels: student and school (in this respect, see, for example, Molina et al. (2015), who analysed financial competence using the data presented

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[1]Missing values are not always random, and therefore the variances between centres and the variances between students obtained from different models cannot be compared (OECD, 2003).

in the 2012 edition of PISA). On the other hand, Ruíz de Miguel (2009) and Blanco-Blanco et al. (2014) used a three-level model, considering the student, the school and the region as separate levels.

In the present paper, we consider an additive approach to constructing the multilevel models (Dronkers and Robert, 2008). This is usually done using hierarchical systems of regression equations and focusing on the regression coefficients β and the variance components.

First, we analyse the "empty" or "null" model (the one that does not include any independent variable), which provides unbiased estimates of the between-centre and within-centre variances. This model takes the form:

$$Y_{ij} = \beta_{0j} + \varepsilon_{ij} \; ; \quad \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$$
$$\beta_{0j} = \beta_0 + U_{0j} \; ; \quad U_{0j} \sim N\left(0, \sigma_{u_n}^2\right) \qquad [1]$$

The complexity of the null model is progressively increased by adding variables from the two levels. Thus, we first consider an independent variable from level 1, x_{1ij} (the i-th student (level 1) from the j-th school (level 2)).

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + \varepsilon_{ij} \qquad [2]$$
$$\beta_{0j} = \beta_{00} + U_{0j} \; ; \quad U_{0j} \sim N\left(0, \sigma_{u_0}^2\right)$$
$$\beta_{1j} = \beta_{10} + U_{1j} \; ; \quad U_{1j} \sim N\left(0, \sigma_{u_1}^2\right)$$

In equation [2], the subindex j in the regression coefficient indicates that it may vary between schools. If $\beta_{1j} = \beta_1$, the slope is the same for all the schools. The intercept β_{0j} is always considered as a random effect since when it is considered as fixed the multilevel model is reduced to the customary linear regression model.

ε_{ij}: Random effect of level 1.

$\sigma_{u_0}^2$: Between-school variance.

σ_ε^2: Within-school variance.

If there is more than one independent level 1 variable, the model is expressed as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + \beta_{2j} X_{2ij} + \cdots + \beta_{Qj} X_{Qij} + \varepsilon_{ij} \qquad [3]$$
$$\beta_{0j} = \beta_{00} + U_{0j} \; ; \quad U_{0j} \sim N(0, \sigma_{u_0}^2)$$
$$\beta_{1j} = \beta_{10} + U_{1j} \; ; \quad U_{1j} \sim N(0, \sigma_{u_1}^2)$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$\beta_{Qj} = \beta_{Q0} + U_{Qj} \; ; \quad U_{Qj} \sim N\left(0, \sigma_{u_Q}^2\right)$$

In the level 2 model, each of the coefficients β_{qj} (q = 0, 1, …, Q) becomes a dependent variable of level 2.

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_{1j} + \cdots + \gamma_{0L} Z_{Lj} + U_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11} Z_{1j} + \cdots + \gamma_{1L} Z_{Lj} + U_{1j}$$
$$\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$
$$\beta_{Qj} = \beta_{Q0} + \beta_{Q1} Z_{1j} + \cdots + \beta_{QL} Z_{Lj} + U_{Qj}$$

$\gamma_{QL} (l = 0, 1, …, L)$: Coefficient of level 2.

Z_{Lj}: Predictor of level 2.

U_{Qj}: Random effect of level 2.

Therefore, the two-level model with Q and L explicative variables associated with the students and the schools, respectively, is expressed as:

$$Y_{ij} = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qj} X_{qij} + \varepsilon_{ij} ; \quad \varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2) \qquad [4]$$

$$\beta_{qj} = \gamma_{q0} + \sum_{l=1}^{L} \gamma_{ql} Z_{lj} + U_{qj}; \qquad U_{qj} \sim N(0, T)$$

where T is a matrix whose diagonal is composed of the variances of U_q and the non-diagonal elements are the covariances between them.

The Null Model

As indicated previously, the null model (which does not include any independent variables) is the starting point in the multilevel regression analysis, after which different blocks of independent variables are introduced.

Due to the absence of independent variables in the null model, the intercepts of the schools, β_{0j}, coincide with the performance means of the schools or are close to these means. The variance of U_{0j} is the between-school variance and the variance of ε_{ij} is the within-school variance, and therefore the predicted score for each student will be the mean of the corresponding school. If σ^2_{u0} and σ^2_{ε} are not statistically significant, there is no reason to include independent variables in any of the levels.

The effect of the school factor may be evaluated by comparing the model that includes that effect (Model IA) with the one that does not (Model IB). Table 2 shows the value of the -2LL (-2 log likelihood) statistic associated with each model. The difference between these two values, 14,322.578, is distributed according to a chi-square distribution with 1 degree of freedom. The probability of finding chi-square values equal to or greater than 14,322.578 is less than 0.0005; therefore, we reject the hypothesis that the effect of the school factor is null.

Our estimation of the parameters associated with the fixed and random effects of the null model is presented in Table 2 (the standard errors are shown in brackets).

Table 2. Comparison of models IA and IB

	Fixed part	Random part		
Model I	β_0	σ^2_{ε}	σ^2_{u0}	*-2LL*
A	490.456 (5.048)	6333.747 (248.150)	1054.078 (257.761)	1578.538
B	491.264 (2.333)	7375.586 (283.466)		15901.116

The value of the intercept, β_0, indicates that the average performance of the students is 490.456. Thus, the mean score obtained in science in the PISA 2012 tests is 490.456 and the standard error[2] of 5.048 shows it is statistically significant.

The significance of the within-school variance indicates differences in the performance of students belonging to the same school. Moreover, the significance of the between-school variance highlights the existence of differences in the average performance of these schools. From the significance of these two variances, we conclude that there is an unexplained relationship between the average performance of the students and that of the schools. This justifies our decision to expand the null model by including independent variables from the two levels to explain the residual variance between schools.

The percentage of the total variance attributable to the school is obtained through the intra-class correlation coefficient, ρ, which explains the degree of variability between the schools in comparison with the variability between students of the same school. That is, it reflects how the schools differ regarding the average performance of the students.

$$\rho = \frac{\sigma^2_{u_0}}{\sigma^2_{u_0} + \sigma^2_{\varepsilon}} = \frac{1054.078}{1054.078 + 6333.747} = 0.1426$$

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[2]A parameter is considered significant ($\alpha = 0.05$) when the ratio between the parameter estimate and its standard error is greater than 1.96 (~2).

In this specific case, 14.26% of the difference in the performance of the students is explained by the school effect. In our context, this is a fairly low percentage, from which we deduce that the inequalities in the students' performance arise more from the students' own characteristics than from those of the schools.

Model Expansion

After confirming the significance of the variances obtained, the next step in our analysis of the multilevel models is to explain as much variance as possible in each of the levels. To do so, independent variables from the two levels are included in the model.

In the model including individual characteristics of the students and the characteristics of the schools (see Table 3), the variables Gender, Repeat, Immigrant, Pre-primary schooling, Cultural Possessions, ESCS, Repeat*Immigrant and Repeat*ESCS proved to be significant with coefficient values of -12.515, -65.582, -40.695, 24.763, 8.259, 20.353, 47.391 and -10.955, respectively.

Regarding the individual characteristics of the students, all the variables considered were significant, with grade repetition being the most important factor in all the models. Another important factor, which had a significantly negative effect on the results, was the immigrant status of the student. The coefficient of this variable barely varied when the variables of the family environment were introduced into the model. The remaining variables all had a positive impact on the results. We emphasise the important influence of the interaction between immigrant status and grade repetition.

Focusing on the characteristics of the family environment, the possession of cultural resources and the students' cultural and socioeconomic status positively affected the results. On the other hand, the interaction between the cultural and socioeconomic status and grade repetition had a negative influence on performance.

Comparison of this model (which includes all the predictors of the student and the school levels) with the null model (Model I) shows that the between-school variance decreased from 1,054.078 to 433.122 and that the within-school variance fell from 6,333.747 to 4,611.280. The joint effect of the student-related and the school-related variables very largely explains the between-class and within-class differences observed in the null model, as evidenced by the significant decrease in the residual variance.

Table 3. Final model with variables of the student level and the school level

Fixed part			
Variables	β_{0j}	β_{aj}	*-2LL*
Gender		-12.515 (3.816)	
Repeat		-65.582 (4.788)	
Immigrant		-40.695 (14.026)	
Pre-primary schooling		24.763 (7.703)	
Cultural possessions		8.259 (2.327)	
ESCS	496.447 (17.171)	20.353 (2.496)	14865.418
Repeat * Immigrant		47.391 (22.917)	
Repeat * ESCS		-10.955 (4.551)	
Competition		13.480 (8.435)	
Teacher-students ratio		1.126 (1.089)	
Language of the test and the language spoken at home match		-12.204 (14.170)	

When both groups of predictors were included, the ρ coefficient decreased from 14.26% in Model I to 9.75% in the final model. Thus, the simultaneous effect of the two groups of variables reduced the variability of the performance that is explained by the between-school variance, and therefore the variability of the performance depends to a lesser extent on the differences observed between schools.

Finally, we evaluated the goodness of fit of the proposed model to the PISA 2012 data. To do this, we compared the likelihood ratio coefficient corresponding to the final model (14,865.418) with their counterpart in the null model (15,780.538). Reduction in the likelihood ratio coefficient is, thus, significant, so we can affirm that the proposed model made a significantly greater contribution than the null model.

Conclusion

This paper discusses the results obtained by students in Andalusia (Spain) in the 2012 PISA tests, and seeks to identify the factors that are relevant to the students' scientific performance in these tests. For this purpose, a multilevel regression model was analysed in order to detect the most significant variables, and the sign of this influence.

In the null model, 14.26% of the differences in the students' performance is explained by the school effect. This value is fairly low, which means that the inequalities detected in the students' results can be attributed more to their own characteristics than to those of their schools. These results are similar to those reported in previous studies, both for Andalusia and for other regions in Spain (Cordero et al., 2010). Nevertheless, these findings, with an average inequality attributable to Spanish schools of 14.7% (with a maximum of 20%) are strikingly different from those obtained in other countries; for example, in the Netherlands and Australia, this value is close to 50%.

The most significant variable was found to be grade repetition, with a strong negative effect (-65.582). This finding means that policymakers should devote considerable thought to grade repetition strategies and relevant factors.

Immigrant status and the interaction Repeat*ESCS also had negative effects on scientific performance (- 40.695 and -11.045). On the other hand, male gender, pre-primary schooling and the variables Cultural Possessions, ESCS and Repeat*Immigrant, all increased the students' scientific performance, by 12.515, 24.763, 8.259, 20.353 and 47.391 points, respectively.

The results obtained with respect to these variables should be taken into consideration in the formulation of education policies. Regarding immigrant students, two groups should be distinguished, in order to assess levels of integration: those who were born abroad (first generation) and their children (second generation). At present, these disaggregated data are not available, but should be obtained, together with knowledge of the students' native language, as both of these questions are fundamental to the acquisition of academic competence. What measures should schools take regarding immigrant students? National and international experience suggests that various alternatives may be considered (Choi and Calero, 2013).

For over 20 years, gender studies in the educational context have shown that girls and boys differ in their perception of science and mathematics. Thus, girls consider these subjects more difficult and believe that studying science is more specific to boys. Differences in attitudes towards science have also been analysed in children of different ages and among different ethnic groups and different countries (Gail et al., 2000; Ford et al., 2006; Buck et al., 2008; Vázquez and Manassero, 2010; Riegle-Crumb et al., 2011). The coefficients of the negative results of girls are not very large. Nevertheless, eradicating this gender bias from scientific performance continues to pose a major challenge.

School attendance rates among children aged 3-5 years are very high and the importance of this early schooling for future academic performance has been highlighted in several empirical studies (Leuven et al., 2010). Accordingly, the more pre-primary places that can be provided, the better. Nevertheless, studies should also be undertaken to consider whether the effect of early schooling on children's later scientific performance is related to the scientific education prompted by their parents (Ho, 2010).

The ESCS has a significant and positive effect on the results, raising scientific performance by 20.353 points. This index is considered one of the most important indicators of students' academic success or failure. Nevertheless, it should be noted that although there is general agreement that the index should be used, a wide range of factors can be included in its estimation (with family income and the education level of the parents being the most commonly employed).

With respect to measuring the parameters in a multilevel model, it is important to note the simultaneous effect of all the predictors included in our model on academic performance. After introducing the independent variable related to socioeconomic status, the variables Gender, Repeat, Immigrant and Pre-primary schooling remained significant, but with lower coefficients; for example, the increase in the performance of non-repeater students decreases from 76.111 points to 65.582 points. The negative effect of grade repetition is emphasised in all studies of this question (Choi and Calero, 2013; Calero et al., 2009, 2010).

Palliative measures for under-performance are neither easy nor cheap, requiring more personalised attention for each student and early detection of problems. In a scientific competence context, this would imply a more appropriate specialisation of primary teachers and further training for secondary teachers.

In conclusion, we emphasise the potential offered by multilevel models for developing new lines of research. The methodological contribution of these models to the specific context of school performance research is very important. A recent review (Liou and Hung, 2015) analysed 51 papers, published in eight SSCI journals from 1996 to 2013, which studied PISA or TIMSS data. This review identified multilevel models as a very powerful technique compared to basic descriptive methodologies and correlation approaches. According to these authors, multilevel models are becoming ever more powerful, and may open up valuable areas for future research, in ways impossible by other means. A multilevel regression approach might also be considered for studying and analysing educational centres which present unpredictable behaviour, for instance where the results of scientific, mathematical and reading performance are uncorrelated, which is quite a common situation.

As a final observation, it would be very interesting to extend this analysis to other regions and to consider a three-level model (students, schools and regions). Such comparisons would be very useful for determining the efficiency of regional educational policies (Cordero et al., 2010). In this respect, authorities at the Andalusian Department of Education (Martínez, 2010) have highlighted the need for rigorous studies to put into context the results obtained by Andalusian students in the PISA tests and thus contribute to reviewing, planning and improving educational procedures.

Acknowledgements

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