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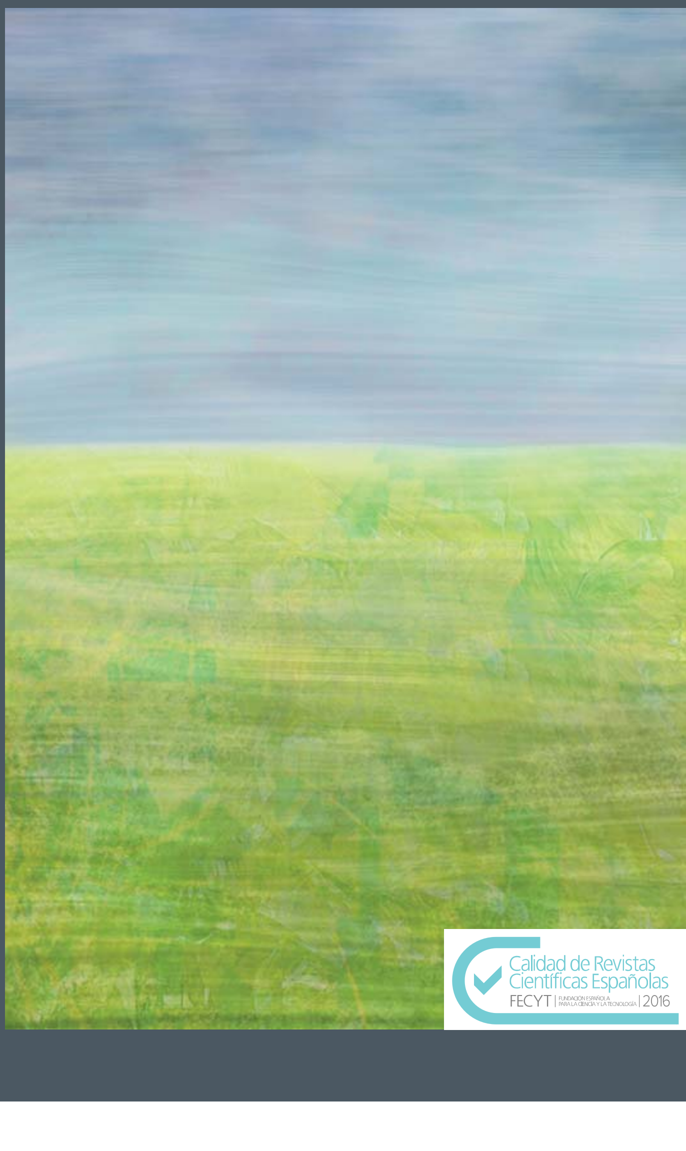

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Assessment of factors related to school effectiveness in PISA 2015. A multilevel analysis[1]

Evaluación de factores relacionados con la eficacia escolar en PISA 2015. Un análisis multinivel

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Abstract

The study of school effectiveness has gained relevance in the past few decades. The availability of data pertaining both to student performance and to the socioeconomic, demographic, organisational and educational characteristics of students and schools has allowed for the proliferation of studies on the relationship of all kinds of variables with student performance, and on the essential practices necessary to provide a quality and equal education.

This research is focused on the study of school effectiveness. To this end, hierarchical linear models (multilevel) are implemented with math, reading and science performance data from the Spanish sample of PISA 2015, aiming to establish which contextual factors have a larger effect on student performance. Gender, socio-economic level, grade, grade repetition, and school changes, together with the school's average socio-economic level, are the variables that consistently appeared as relevant in all three models.

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This information was used to select the schools with the highest and lowest levels of effectiveness, calculated as the difference between their observed performance scores and their expected scores according to the relevant contextual factors. This selection allows for a study on which non-contextual factors (at student and school levels) are related to school effectiveness. There were no significant relationships with the school level variables, although there were some at student level (classroom discipline, self-efficacy, teacher unfairness or parental emotional support).

Keywords: large scale assessment, school effectiveness, contextual effects, hierarchical linear models, academic achievement.

Resumen

El estudio de la eficacia escolar ha ganado relevancia en las últimas décadas. La disponibilidad de datos relativos tanto al rendimiento del alumnado como a las características socio-económicas, demográficas, organizativas y educativas de los alumnos y los centros ha permitido la proliferación de estudios sobre la relación de todo tipo de variables con el rendimiento, y sobre las prácticas que resultan fundamentales para poder ofrecer una educación equitativa y de calidad.

La presente investigación se centra en el estudio de la eficacia escolar, utilizando para ello la aplicación de modelos jerárquicos lineales (multinivel) con los datos de rendimiento de matemáticas, lectura y ciencias de la muestra española de PISA 2015 con el objetivo de determinar qué factores contextuales tienen más efecto en el rendimiento de los estudiantes. El género, el nivel socio-económico, el curso, la repetición de curso y los cambios de escuela, junto con el nivel socio-económico medio del centro, son las variables que aparecen como relevantes consistentemente en los tres modelos realizados.

Dicha información se utiliza para realizar una selección de centros de alta y baja eficacia basada en la diferencia entre la puntuación observada de los centros y su puntuación esperada en función de los factores contextuales relevantes. A partir de esta selección, se realiza un estudio de los factores no contextuales a nivel de estudiante y de centro que se encuentran relacionados con la eficacia de los centros. No se encuentran relaciones significativas con las variables del nivel de centro, aunque sí con algunas a nivel de estudiante (clima de disciplina, auto-eficacia, apoyo emocional parental o nivel de injusticia del profesorado).

Palabras clave: evaluación a gran escala, eficacia escolar, efectos contextuales, modelos jerárquicos lineales, rendimiento académico.

Introduction

The study of school effectiveness has a long history within the field of educational research. Its scientific exploration began with the publication of the Coleman Report (Coleman, 1966), whose conclusions on the small impact of school intervention on student performance in comparison with socioeconomic variables promoted the development of numerous studies that aimed to expand the knowledge basis of this new subject. Some examples of the studies that emerged in the wake of this report are those conducted by Weber (1971), who introduced process variables such as school climate or leadership to a study field that, up until that point, only considered context factors, the works by Brookover, Beady, Flood, Schewitzer and Wisenbaker (1979), which expanded the research by employing large samples, or the findings of Aitkin and Longford (1986), obtained through the use of multilevel statistical analyses. All these authors provided the field of school effectiveness with key contributions, and laid the foundations for what is nowadays considered a well-established topic within educational research.

Currently, a school is defined as effective when it "achieves a comprehensive and integral development of each and every one of its students, even higher that it would be expected taking into consideration their previous performance and the social, financial and cultural situation of their families" (Murillo, 2005, p.25). This definition lays out three key aspects that characterise the research in this field: *equity* (every student's development is sought), *integral development* of the students (we do not only seek to promote academic performance, but also values and student well-being), and *added value* (contextual elements are included in the study of performance) (Murillo, 2003). Several authors employ a broader definition of the term "value added", which advocates the need to assess the results of the schools once the effects of the contextual variables have been controlled, as it results in a more equitable and rigorous practice (Joaristi, Lizasoain & Azpillaga, 2014). However, it is recommended to limit the use of this term to longitudinal studies (OECD, 2008), therefore the present study refers to the model employed as "contextualised model without gain" due to the lack of longitudinal data.

This study subject has achieved a growing interest in the scientific community in the last few decades (Gamazo, Olmos-Migueláñez & Martínez-Abad, 2016), due, in part, to the availability of datasets from

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large-scale assessments (OCDE, 2017). Not only do these tests provide us with data on the performance of the students in different competences, but they also offer a broad catalogue of contextual data, both from students and schools, which enables in-depth studies on the factors that most influence performance, or even school effectiveness. However, some authors suggest that the reliability and validity of the instruments vary, ranging from the high technical guarantees of performance tests to the flawed design of the context questionnaires (De la Orden & Jornet, 2012).

There are many large-scale assessments conducted at an international level which can serve as a basis to carry out this kind of studies. The Progress in international Reading Literacy Study (PIRLS) and the Trends in International Mathematics and Science Study (TIMSS), both from the International Association for the Evaluation of Educational Achievement (IEA), or the Programme for international Student Assessment (PISA) from the Organisation for Economic Co-operation and Development (OECD), are a few examples of international standardised tests that measure the level of competence development among students, and that also gather data on their personal, family, school and social backgrounds.

The open access to the results of these tests enables the study of the impact of the cultural, financial, social, educational and personal factors on student performance, and, through the research of these factors, it also allows us to analyse the effectiveness of schools.

Factors related to student performance

The factors that are most commonly linked to student performance, and those whose information is also provided by the context questionnaires of the abovementioned competence tests, vary in nature. Several authors, such as Murillo (2007) or Jornet, González-Such and Perales (2012) classify these factors in three categories: input (gender, socioeconomic level, mother tongue, school resources, etc.), process (study habits, academic expectations, family support, school climate, teaching methodology, etc.) and product (academic performance). In turn, these factors can also be divided in two levels: student and school.

Several studies have verified the significant effect of some personal *student* factors. Some of them belong to the category of input factors, also referred to as contextual factors, such as gender, migratory status, pre-school education attendance (Karakolidis, Pitsia & Emvalotis, 2016; Özdemir, 2016), socioeconomic index (Cordero, Manchón & Simancas, 2014; Ehmke, Drechsel, & Carstensen, 2008), mother tongue (Özdemir, 2016; Riederer & Verwiebe, 2015) or the education and occupation of the parents (Riederer & Verwiebe, 2015; Tsai, Smith, & Hauser, 2017). Others are classified as process, or non-contextual factors, including emotional and motivational variables such as self-efficacy (Aksu & Güzeller, 2016), anxiety or self-concept (Karakolidis et al., 2016; Risso, Peralbo & Barca, 2010), the opportunities to learn at home (Liu & Whitford, 2011; Santibañez & Fagioli, 2016), study habits and strategies (Risso et al., 2010; Santos, Godás & Lorenzo, 2013) or family support (King et al., 2005; Santos et al., 2013).

School factors are also explored in these kinds of studies, although there is less consensus about the significant effect of these variables (Choi & Calero, 2012; Martínez-Abad & Chaparro-Caso, 2017). However, there is data that supports the influence of some input factors such as the average socioeconomic and cultural level of the school (Perry & McConney, 2010a, 2010b), the school size, or the teacher to student ratio (Nath, 2012), as well as some process factors like student grouping according to their academic performance (Kunz, 2014; Meunier, 2011), teaching methodology (Nath, 2012; Payandeh-Najafabadi, Omidi-Najafabadi, & Farid-Rohani, 2013) or learning environment (Payandeh-Najafabadi et al., 2013; Santos et al., 2013).

The introduction of internal student factors (personal, family, cultural, financial and social) and external school factors in an academic performance model should be guided by a systemic quality model that relates these complex dimensions, so that they can be tested with the empirical data gathered (De la Orden & Jornet, 2012; Jornet, et al., 2012).

Statistical techniques for school effectiveness research

The complexity of the study of the factors related to academic performance and school effectiveness, which is caused by their large number and the network of relationships established among them (Tejedor, 2003), has resulted in the use of a broad variety of statistical techniques to address this research subject.

One of these techniques is multilevel analysis, which is used during the course of this study. Its characteristics allow researchers to

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differentiate the variability contributed by each of the aggregation levels encountered in the hierarchical data, a distinction without which we could incur the over-estimation of coefficients or data interpretation errors (Snijders & Bosker, 2012). For this reason, its use is recommended for cases where the data presents a nested structure, such as the data from large-scale assessments, where students are gathered in higher level structures (Lenkeit, 2013; Lizasoain & Angulo, 2014; Martínez-Arias, 2009; Murillo & Hernández, 2011). Another example of quantitative techniques is structural equation modelling, which facilitates the establishment of relationships between predicting and criterion variables. It also enables the introduction of other variables of a latent nature, or dimensions (factorial confirmation analysis), which are constructs that cannot be directly measured, but which can be studied through the analysis of other observable variables (Castro & Lizasoain, 2012). Data mining techniques are also suitable for the analysis of data from large-scale assessments, given that they allow the researcher to extract relevant information, such as patterns or significant relationships among variables, from datasets with high amounts of information (Castro & Lizasoain, 2012).

Taking this framework into consideration, the *aim* of this research is twofold. On the one hand, we intend to study the effect of certain input variables (contextual) on student performance, thus analysing the variability of the schools according to their effectiveness, which is measured through the difference between their actual score and the score they would be expected to get according to said variables. On the other hand, we will analyse the process variables (non-contextual) that present a higher discrimination power over the residual of the schools.

For each of the aims, the analysis method will differ. For the first aim, *multilevel models* will be used to study the effect of contextual variables on student performance, and to select the schools whose actual score is significantly above (or below) their expected score according to their demographic and socioeconomic characteristics. These schools, referred to as high and low residual or effectiveness, serve as a basis for the second part of the study, in which *logistic regression* techniques are used to figure out which non-contextual variables most influence the level of the schools' residual, revealing which factors have a significant relationship with school effectiveness.

Method

This secondary analysis of PISA 2015 data is of a non-experimental ex-post-facto nature, due to the lack of experimental control over the variable collection. This section offers information of the participating sample and the data-collecting instruments, as well as the data analysis techniques employed.

Sample

The sample for this study was extracted from the dataset provided by the OECD (2017), and it is composed of all 15-year-old students (born between January and December 1999) who participated in the 2015 PISA test in Spain. Although the initial sample was composed of 32,330 students and 976 schools, the students from schools with less than 20 participating students, along with their schools, were removed from the sample in order to ensure the correct analysis of the variables aggregated at school level, as has been done in other similar studies (Joaristi, Lizasoain & Azpillaga, 2014; Martínez-Abad, Lizasoain, Castro & Joaristi, 2017; Meunier, 2011). This study had a final sample of 31,273 students, where 49.4% (15,437) were female and 50.6% (15,836) were male. These students were enrolled in 897 schools. In this edition of the test, all Autonomous Communities decided to broaden their sample so that their data could be compared at an international level (Ministerio de Educación, Cultura y Deporte, 2016).

The distribution of students according to their Autonomous Community is even (between 4.5% and 6% of the total population), except for the Basque Country, which represents 10.7% of the participants. The schools show a similar distribution.

Out of the 897 schools participating, 66.6% are public schools, 28.2% are publicly-funded private schools, and 5.2% are private schools (excluding the 49 missing values of this variable).

Instruments

In order to conduct this research, the specific instruments created for the PISA test were used. There are two main kinds of instruments. On the

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one hand, the competence assessment tests are used to measure the competence level of the students. In 2015, these tests measured student performance in reading, mathematics and science. They are composed of sets of different items that can have three types of answers: open (e.g. explaining the necessary steps to solve a problem), closed (numerical or one-word answers) or multiple choice.

On the other hand, the study also uses information from the context questionnaires administered to students, parents and schools. These questionnaires provide a large amount of information on socioeconomic, cultural and demographic questions, and they also report on other topics of educational interest, such as school climate, student motivation, teacher training, or school assessment practices.

Variables

The criterion variables used to construct the multilevel models are the scores obtained by the students in the competence tests (reading, mathematics, science). These variables are defined by the steering documents of PISA 2015 (OECD, 2016) as follows:

- Reading: "An individual's capacity to understand, use, reflect on and engage with written texts, in order to achieve one's goals, to develop one's knowledge and potential, and to participate in society" (p. 13).
- Mathematics: "An individual's capacity to formulate, employ and interpret mathematics in a variety of contexts. It includes reasoning mathematically and using mathematical concepts, procedures, facts and tools to describe, explain and predict phenomena" (p. 13).
- Science: "A scientifically literate person is willing to engage in reasoned discourse about science and technology, which requires the competencies to explain phenomena scientifically, evaluate and design scientific enquiry, and interpret data and evidence scientifically" (p. 13).

This analysis includes the 10 plausible values provided for each student and each competence. These values are obtained through an imputation method in order to estimate the performance level of a student from the scores obtained in the items. The sampling weights of both students and schools were also included in the analysis to ensure the correct treatment of the data and the proper calculation of the sampling error (OECD, 2012).

For their part, the context factors extracted from the context questionnaires were used as predicting variables for the models. The selection of these variables was based on the literature review conducted for the theoretical framework, and they are divided in two groups: level 1 (students) and level 2 (schools) (Table I). Where nominal or ordinal data was encountered, dummy variables were generated (in a number equal to the number of categories of the original variable minus one, with the most frequent category being the reference).

TABLE I. Predicting variables for the multilevel model.

	Variable	Label	Range
Level 1 - Students	Gender	N1GEN	0: Male 1: Female
	Birth month	N1BMONTH	1 (Jan) – 12 (Dec)
	Grade	N1GRADE	7th – 11th
	Economic, social and cultural status (ESCS)	N1ESCS	Continuous
	Migratory status	N1IMMIG	0: Native 1: 2nd generation immigrant 2: 1st generation immigrant
	Grade repetition	N1REPEAT	0: No 1: Yes
	Number of school changes	N1SCCH	0: No change 1: One change 2: Two or more changes
	Language spoken at home	N1IDIOMA	0: Language of the test 1: Other language
Level 2 - Schools	School size	N2TAMESC	Continuous
	Class size	N2TAMCLS	Continuous
	Resource shortage	N2ESCRES	Continuous
	Staff shortage	N2ESCPER	Continuous
	School ownership	N2TITESC	1: Private 2: Publicly-funded private 3: Public
	Teacher-student ratio	N2RATIO	Continuous
	Average ESCS	N2ESCS	Continuous
	Rate of repeaters	N2REPETI	Continuous
	Rate of immigrant students	N2IMMIG	Continuous
	Percentage of girls	N2PCGIRL	Continuous

Source: Elaborated by the authors.

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On the other hand, the non-contextual variables were used in a later stage of the study (see section on procedure). The variables were selected on the basis of whether they were provided in the form of indices (i.e. those grouping information from several items in one factor) both at student and school levels. The level-1 variables analysed were motivation, disposition for collaborative work, epistemological beliefs, enjoyment and interest in science, competence, interest and autonomy in the use of new technologies, climate of discipline in the classroom, teacher support, environmental awareness and optimism, expected occupational status, sense of belonging to the school, emotional and academic parental support, perceived feedback and teacher fairness. The level-2 variables employed were leadership, curriculum development, professional development, school responsibility over resources and curriculum, teacher participation, school autonomy and creative extra-curricular activities.

Procedure

To obtain the high and low effectiveness schools we used *hierarchical linear models* (Snijders & Bosker, 2012), which enabled the identification of the effect of contextual factors on the schools' average performance. A model was defined for each competence assessed, keeping only the significant predicting variables (α=.05) at both levels, which allowed us to calculate the difference between the actual school score and the expected score according to the socioeconomic and cultural variables, also referred to as school "residual", obtained through empirical Bayes estimators (Raudenbush, Bryk, Cheong, Congdon, & Du Toit ,2011). After a previous collinearity study of the predicting variables, and based on the evidence gathered by Özdemir (2016), who did not appreciate substantial differences between fixed and random slope models built with PISA data, a decision was made to introduce the level-1 contextual variables as fixed effects covariables, without including the random effects.

Afterwards, a protocol was set up with a series of criteria that the schools must meet to be selected as high or low residual schools. The protocol was based in two main research works. The first one is the work of Joaristi et al. (2014), where the 80^{h} percentile was chosen as the cut-off point for the 6 estimated models. The second work is the research conducted by Martínez-Abad et al. (2017), where the lower limit was set at the 66th percentile (high effectiveness) and the upper limit (low effectiveness) was the 33rd percentile, and a school had to comply with the inclusion criterion in 5 of the 8 models estimated in order to be selected. Given the data at our disposal, we opted for an eclectic criterion located somewhere between the abovementioned two. The 33rd and 66th percentiles are taken as limits for the selection, but a school must be included within the limit regions in all three of the estimated models.

Then, we proceeded with the calculation of the correlation between the main process variables (levels 1 and 2) and the dichotomous variable generated (criterion variable: high or low residual school) through a point-biserial correlation. After we ruled out any relevant collinearity effects among the predicting variables of the model, if significant correlations (α=.05) were found, we applied *logistic regression techniques*. These techniques are particularly recommended for dichotomous criterion variables.

The construction of the hierarchical linear models was carried out with the statistical software HLM7[2], and the logistic regression was conducted with SPSS v.20[3].

Results

The first step was to calculate the null model, which is an unconditional model without any predicting variables (Hayes, 2006; Lee, 2000). The estimation of the variance components of this model allows for the calculation of the Intraclass Correlation Coefficient (ICC), which represents the proportion of variance attributable to the second level (Snijders & Bosker, 2012). In order for the use of multilevel models to be deemed a suitable alternative, the value of the ICC must be over 10% (Lee, 2000). The ICC is defined by the following equation (1):

$$CCI = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \qquad (1)$$

(2) Commercial licence of the Research Group of Educational Assessment and Guidance, University of Salamanca.
(3) Commercial licence of the University of Salamanca.

The term τ_{00} refers to the variability among schools, and σ^2 represents the variability among students.

The data from the Spanish sample of PISA 2015 presents an ICC of 12.26% in mathematics, 12,04% in reading, and 12,41% in science, thus making it pertinent to use a procedure based on multilevel analysis.

Performance in mathematics

After applying the procedure described in the previous section, the multilevel model for the performance of the students in the mathematical competence tests is defined by the following equation (2):

$$PV1MATH_{ij} = \gamma_{00} + \gamma_{01}*N2ESCS_{j} + \gamma_{10}*N1GEN_{ij} + \gamma_{20}*N1ESCS_{ij} + \gamma_{30}*N1REPEAT_{ij} + \gamma_{40}*N1GRADE_{ij} + \gamma_{50}*N1IMM2_{ij} + \gamma_{60}*N1SCCH1_{ij} + \gamma_{70}*N1SCCH2_{ij} + u_{0j} + r_{ij} \quad (2)$$

Table II shows the coefficients, t-values and signification values of the variables that were eventually included in the mathematical competence model.

TABLE II. Final estimation of fixed effects with robust standard errors, mathematics.

Fixed Effect	Coefficient	Standard error	t-ratio	*p*-value
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	543.097	1.731	313.758	<.001
SCHOOL ESCS, γ_{01}	12.986	1.906	6.813	<.001
For GENDER slope, β_1				
INTRCPT2, γ_{10}	-22.599	1.972	-11.457	<.001
For ESCS slope, β_2				
INTRCPT2, γ_{20}	9.799	1.123	8.723	<.001
For REPEAT GRADE slope, β_3				
INTRCPT2, γ_{30}	-35.721	4.972	-7.184	<.001
For GRADE slope, β_4				
INTRCPT2, γ_{40}	34.960	3.874	9.024	<.001
For 1st GEN IMMIGRANT slope, β_5				
INTRCPT2, γ_{50}	-11.785	4.863	-2.423	.026
For SCHOOL CHANGES (1) slope, β_6				
INTRCPT2, γ_{60}	-10.690	1.870	-5.716	<.001
For SCHOOL CHANGES (2+) slope, β_7				
INTRCPT2, γ_{70}	-15.512	3.303	-4.696	<.001

Source: Elaborated by the authors.

While the only school factor included is the average ESCS, at student level there are several factors with a significant influence. Gender is the variable with the highest t-value, followed by grade, ESCS and repeating a grade. The variable related to migratory status indicates that only being a 1st generation immigrant is significant.

After estimating the model, the ICC for the mathematical competence is 4.55%, which enables us to confirm that the variables included in the model explain 7.71% of the variance among schools.

Performance in reading

In the case of reading comprehension skills, the variables that finally composed the model are found in the following equation (3):

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$$PV1READ_{ij} = \gamma_{00} + \gamma_{01}*N2ESCS_j + \gamma_{02}*N2REPETI_j + \gamma_{03}*N2PCGIRL_j + \gamma_{10}*N1GEN_{ij} + \gamma_{20}*N1ESCS_{ij} + \gamma_{30}*N1REPEAT_{ij} + \gamma_{40}*N1GRADE_{ij} + \gamma_{50}*N1SCCH1_{ij} + \gamma_{60}*N1SCCH2_{ij} + \gamma_{70}*N1IDIOMA_{ij} + u_{0j} + r_{ij} \quad (3)$$

Table III shows the magnitude and signification values of the relationship between the variables that compose the model and the performance of the students in the reading comprehension test.

TABLE III. Final estimation of fixed effects with robust standard errors, reading.

Fixed Effect	Coefficient	Standard error	t-ratio	*p*-value
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	522.475	6.153	84.912	<.001
SCHOOL ESCS, γ_{01}	20.293	2.658	7.633	<.001
REPEATER RATE , γ_{02}	36.502	10.829	3.371	<.001
GIRL RATE, γ_{03}	24.719	10.572	2.338	.020
For GENDER slope, β_1				
INTRCPT2, γ_{10}	6.776	1.849	3.665	<.001
For ESCS slope, β_2				
INTRCPT2, γ_{20}	8.299	0.949	8.748	<.001
For REPEAT GRADE slope, β_3				
INTRCPT2, γ_{30}	-32.120	5.162	-6.222	<.001
For GRADE slope, β_4				
INTRCPT2, γ_{40}	41.092	3.495	11.757	<.001
For SCHOOL CHANGES (1) slope, β_5				
INTRCPT2, γ_{50}	-8.857	2.127	-4.164	<.001
For SCHOOL CHANGES (2+) slope, β_6				
INTRCPT2, γ_{60}	-20.642	3.224	-6.403	<.001
For LANGUAGE slope, β_7				
INTRCPT2, γ_{70}	-6.718	3.026	-2.220	.033

Source: Elaborated by the authors.

At school level, this model presents more predicting variables than the previous one, with the percentage of repeating students and the percentage of girls joining the average ESCS of the school. At level 1, the variables with a highest t-value are grade, ESCS, grade repetition, and school changes (two or more times).

The ICC of the scores obtained in reading after the application of the model is 5.07%, which means that the model was able to explain roughly 7% of the variance of the second level in this competence.

Performance in science

Lastly, the factors that resulted in a significant relationship with the scientific competence are reflected in the following equation (4):

$$PV1SCIE_{ij} = \gamma_{00} + \gamma_{01}{*}N2TAMESC_j + \gamma_{02}{*}N2ESCPER_j + \gamma_{03}{*}N2ESCS_j + \gamma_{04}{*}N2REPETI_j + \gamma_{05}{*}N2PCGIRL_j + \gamma_{10}{*}N1GEN_{ij} + \gamma_{20}{*}N1ESCS_{ij} + \gamma_{30}{*}N1BMONTH_{ij} + \gamma_{40}{*}N1REPEAT_{ij} + \gamma_{50}{*}N1GRADE_{ij} + \gamma_{60}{*}N1IMM2_{ij} + \gamma_{70}{*}N1SCCH1_{ij} + \gamma_{80}{*}N1SCCH2_{ij} + u_{0j} + r_{ij} \quad (4)$$

Table IV shows the coefficients derived from the implementation of the model.

The resulting model contains several significant school-level variables, with the most relevant being the average ESCS, followed by the rate of students who have repeated a grade. Other variables included in the model are the percentage of girls in the school, school size and the shortage of teaching staff.

At student level, the variables with the highest t-values are ESCS, grade, gender and school changes. Again, the variable related to migratory status indicates significant differences only for 1st generation immigrant students.

Once the model was applied, the calculation of the ICC of the final model (5.6%) revealed that the model for this competence has managed to explain 6.8% of the level-2 variance.

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TABLA IV. Final estimation of fixed effects with robust standard errors, science.

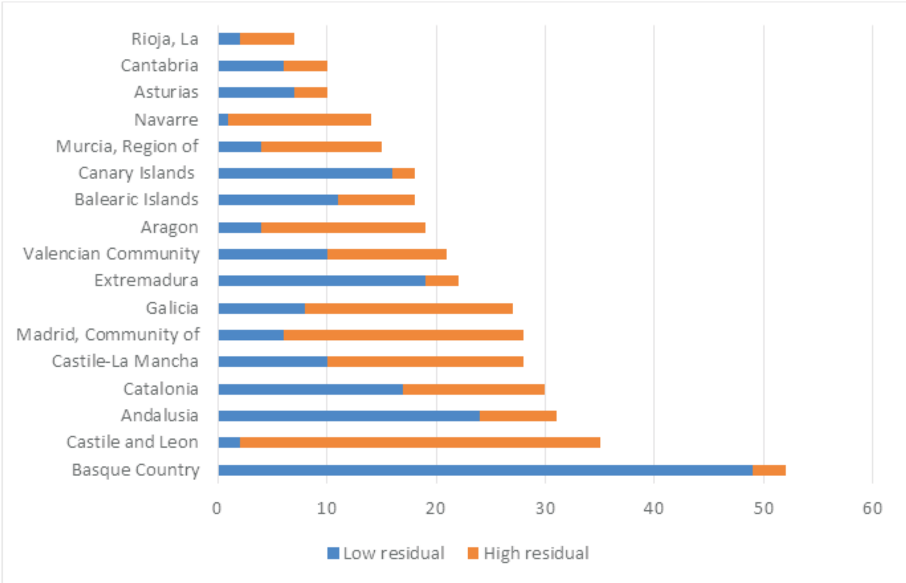
Fixed Effect	Coefficient	Standard error	t-ratio	*p*-value
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	537.733	7.298	73.683	<.001
SCHOOL SIZE, γ_{01}	-0.006	0.003	-2.226	.026
STAFF SHORTA GE, γ_{02}	2.513	1.163	2.161	.031
SCHOOL ESCS, γ_{03}	20.708	2.605	7.949	<.001
REPEATER RATE , γ_{04}	31.815	9.545	3.333	<.001
GIRL RATE, γ_{05}	31.854	11.979	2.659	.008
For GENDER slope, β_1				
INTRCPT2, γ_{10}	-19.782	1.686	-11.730	<.001
For ESCS slope, β_2				
INTRCPT2, γ_{20}	9.792	0.704	13.912	<.001
For BIRTH MONTH slope, β_3				
INTRCPT2, γ_{30}	-0.590	0.228	-2.586	.011
For REPEAT GRADE slope, β_4				
INTRCPT2, γ_{40}	-34.223	3.874	-8.833	<.001
For GRADE slope, β_5				
INTRCPT2, γ_{50}	38.389	2.898	13.248	<.001
For 1st GEN IMMIGRANT slope, β_6				
INTRCPT2, γ_{60}	-9.596	2.886	-3.325	<.001
For SCHOOL CHANGES (1) slope, β_7				
INTRCPT2, γ_{70}	-10.417	1.945	-5.356	<.001
For SCHOOL CHANGES (2+) slope, β_8				
INTRCPT2, γ_{80}	-16.847	2.631	-6.404	<.001

Source: Elaborated by the authors.

School selection

In order to select high and low residual schools, we implemented the previously explained selection procedure with the variables obtained as a result of the difference between the observed score of the schools and the score estimated by the final model of each competence. With this criterion, 196 low-residual schools and 189 high-residual schools were selected. Figure I shows the distribution of these schools by Autonomous Community.

FIGURE I. Distribution of high and low residual schools by Autonomous Community.



Source: Elaborated by the authors.

Regarding the ownership of the selected schools, most of them belonged to the public network (roughly 67%), while private and publicly-funded private schools represented about a third of the sample, with private schools being the smallest group (table V). The goodness-of-fit test show the correspondence between the initial sample and the selection (χ^2=0.016; p.=.992).

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TABLE V. Fit of the school selection to the initial sample, by school ownership.

		Ownership			Total
		Private	Publicly-funded private	Public	
School selection	Count	19	102	245	366
	%	5,2%	27,9%	66,9%	100,0%
Initial sample	Count	44	239	564	847
	%	5,2%	28,2%	66,6%	100,0%

Source: Elaborated by the authors.

Table VI offers descriptive information on the ESCS, rate of repeaters, rate of immigrant students and expected score for each competence, which are variables that characterise the sample of selected schools. Both the indicators of the context variables and the expected scores are fairly similar, with no significant differences being found between the means of both groups for any of the variables (t-test, α=.05), except for the one referred to the rate of immigrants, which was significantly higher in the group of high-residual schools (p=.002).

TABLE VI. Mean, standard deviation, maximum value, minimum value.

	Low residual				High residual			
	Avg.	S.d.	Min.	Max.	Avg.	S.d.	Min.	Max.
Average ESCS	-0,42	0,66	-1,92	0,97	-0,53	0,56	-1,55	1,14
Repeater rate	0,27	0,16	0,00	0,67	0,30	0,14	0,00	0,79
Immigrant rate	0,09	0,13	0,00	0,69	0,13	0,11	0,00	0,58
Exp. Sc. math	537,60	8,77	517,75	556,01	536,18	7,37	522,67	558,19
Exp. Sc. reading	537,39	10,24	513,54	563,23	536,26	8,34	517,89	559,68
Exp. Sc. science	547,87	10,63	518,18	576,41	546,79	8,72	525,10	572,22

Source: Elaborated by the authors.

Effect of the process variables on school effectiveness (logistic regression)

The initial correlational study revealed that none of the process variables extracted from the context questionnaires administered to the leadership teams of the schools (level 2) presented a significant correlation with the school selection variable. For this reason, we did not proceed with the logistic regression analysis at school level.

n order to study the process variables at student level (level 1), the average scores of these variables were aggregated to the school database. In the correlational study, a good part of the variables presented significant correlations with the residual-based school selection variable. Thus, the logistic regression model, obtained after eliminating one by one the variables that were not significant, was composed of the variables reflected in table VII and equation 5.

TABLE VII. Logistic regression.

Variable	Content of the variable	B	Sig.	Odds Ratio
DISCLISCI	Discipline climate (science)	1,435	,001	4,199
TEACHSUP	Teacher support (science)	-1,868	,014	,154
ENVAWARE	Environmental awareness	1,443	,018	4,235
SCIEEFF	Self-efficacy (science)	1,781	,001	5,939
EPIST	Epistemological beliefs	2,017	,007	7,514
BSMJ	Expected occupational status	-,091	,008	,913
BELONG	Belonging to the school	-1,628	,003	,196
COOPERATE	Enjoyment of cooperation	1,628	,029	5,095
EMOSUPS	Emotional parental support	-3,606	,000	,027
PERFEED	Perceived feedback	-1,652	,006	,192
ADINST	Adaptation of instruction	2,466	,004	11,770
USESCH	Use of ICT in the school	-1,330	,001	,264
AUTICT	Autonomy in the use of ICT	2,768	,001	15,920
SOIAICT	ICT as a topic of social interaction	-2,569	,005	,077
unfairteacher	Teacher unfairness	-,882	,000	,414
Constant	Constant	14,223	,000	1502425,583

Source: Elaborated by the authors.

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$$\hat{Y} = 14.223 + 1.435 * DISCCLISCI - 1.868 * TEACHSUP + 1.443 * ENVAWARE + 1.781 * SCIEEFF + 2.017 * EPIST - 0.091 * BSMJ - 1.628 * BELONG + 1.628 * COOPERATE - 3.606 * EMOSUPS - 1.652 * PERFEED + 2.466 * ADINST - 2.569 * SOIAICT - 0.882 * unfairteacher \quad (5)$$

Among the variables included in the model, the most significant ones with a positive effect in school effectiveness, i.e. those variables whose increment produces a higher probability of the school to belong to the high-residual group, were climate discipline, self-efficacy, autonomy in the use of ICT and the adaptation of instruction. The variables that present a highly significant negative effect were the level of teacher unfairness, parental emotional support, ICT use in school, sense of belonging to the school, and perceived feedback.

It is worth noting that the model achieves a good fit, obtaining a R^2=.527 (Nagelkerke index). On the other hand, the accuracy of the predicting model reaches an 80.52% of correct classifications of high and low residual schools, correctly predicting 79.59% for low-residual schools and 81.48% in high residual schools.

Discussion and conclusions

This research had two main aims. The first one resulted in the construction of three models that allowed us to detect the size and significance of the relationship between input variables, both from students and schools, and student performance.

The level-1 variables included in the models match the results of previous studies, with gender being one of the most influencing factors (Karakolidis et al., 2016; Özdemir, 2016; Stoet & Geary, 2014). In mathematics and science, male students outperform females, while in reading the opposite is true, although to a lesser extent. Other relevant variables are the socioeconomic level (Risso et al., 2010), the fact of repeating a grade (Choi & Calero, 2013; Ehmke et al.2008), or the number of school changes in the academic history of a student, a variable which is largely unexplored. Moreover, two of the models (mathematics and science) suggest that migratory status is a relevant variable, but only for 1st generation immigrants, since no differences were found between 2nd generation immigrants and native students. This discrepancy might be due to broader contextual factors, such as the decline in immigration from Spanish-speaking countries and the rise in immigration from other countries (Riederer & Verwiebe, 2015). Among the level-2 variables introduced in the models, the only one that was significant in all of them was the average ESCS of the school, a factor whose relevance has been underlined by other studies (Perry & McConney, 2010a, 2010b). Furthermore, we found that the impact of the input variables presents some differences depending on the performance variable used to make the model. For example, gender has a different influence in reading and mathematics (Stoet & Geary, 2013), and migratory status (Meunier, 2011) or the school's socioeconomic level (Perry & McConney, 2010a) do not influence the three competences to the same extent, so the differences found in this respect have a precedent in the scientific literature.

The distribution of the schools selected with the help of these models presents a good fit with the original sample in almost all the characterisation variables controlled. However, the distribution according to their Autonomous Community is not entirely adjusted to the sample; some Autonomous Communities are underrepresented (Asturias, Cantabria, La Rioja), while others have a higher percentage of representation in the selected sample than in the PISA sample (Andalusia, Castile and Leon, Basque Country). Some of these Communities present a noticeable unbalance between the proportion of high and low residual schools, which suggests the pertinence of an in-depth study of these particular cases to explore which regional factors might be causing these inequalities.

The second aim was to analyse the non-contextual variables according to the previous selection of schools. This analysis revealed that there were no statistically significant differences in the scores of the process variables obtained by high and low residual schools. This conclusion differs from some qualitative studies which concluded that there are many process variables related to school effectiveness in a relevant way, such as the research by Lizasoain and Angulo (2014), conducted with highly effective schools, or the work of Murillo (2007) with high, medium and low residual schools. The causes for this relevant discrepancy may vary in nature. De la Orden and Jornet (2012) highlight the shortcomings presented by the PISA questionnaires to properly measure the contextual factors, which could hinder a correct analysis of the educational reality and lead to wrong conclusions. This issue might point to the necessity to

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search for alternative sources for contextual data which could give the research a higher degree of internal validity.

The level-1 variables that resulted significant in the logistical regression model indicate some transversal issues, such as the disciplinary climate in the classroom, student self-efficacy, the adaptation of instruction or the autonomy in the use of ICT, which would be beneficial to promote within the schools, since the analyses indicate that the perception of the students about these questions is closely related to a positive residual in the measurement of school effectiveness. Although this aggregated analysis has the elimination of inter-school variance as a disadvantage, it allows us to compare the schools at a global level according to the characteristics of their students.

The key strengths of this research are the employment of all the statistical guarantees recommended for the application of multilevel models (consideration of the variance at both levels of analysis, use of plausible values, and introduction of sampling weights), the selection of high and low residual schools through the scores in the three measured competences, and the high explaining percentage of the final models, given that all three of them explained more than 50% of the ICC of the null model. Furthermore, the logistic regression presents very high goodness-of-fit values.

On the other hand, the research also presents some shortcomings, such as the lack of systematicity in the selection of the variables, the occurrence of variables with an opposite effect to that expected in the logistic regression, or the lack of sufficient evidence of the validity and reliability of the context questionnaires, which were one of the main sources of information.

The results obtained in this study suggest the need to encourage in-depth research about the factors related to school effectiveness in our country. This study should always be based on the comparison between high and low residual schools so as to make it possible to eliminate those factors that occur in both types of school, thus making them irrelevant. Therefore, we propose the establishment of new lines of research which, starting from the school selection presented in this study, make use of alternative sources of non-contextual data, such as qualitative research techniques, in order to determine the school factors that are relevant for the study of school effectiveness, thus being able to draw relevant conclusions for educational policies and practices.

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