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Abstract

This paper examines resilient students, i.e., students with high academic achievement in spite of their unfavorable socioeconomic circumstances. To do this, we focus on schools with students from more disadvantaged backgrounds of which we select students that are higher academic achievers with the aim of finding some common traits with respect to student characteristics and skills, as well as the activities carried out by schools. The aim behind this strategy is to single out issues that can be influenced by educational policy measures rather than structural factors for analysis. For this purpose, we use information from Spanish students participating in PISA 2012. After identifying resilient students according to a criterion endorsed by previous theoretical literature, we estimate a multilevel logistic model including several student and school explanatory variables in order to identify which variables are associated with the likelihood of students belonging to the group of resilient students. The results show that, apart from several individual variables, schools with a higher proportion of resilient students are characterized by having small classes, strict discipline and low levels of school absenteeism. All these variables are related to teaching quality. Thus this factor can be considered as a key driver motivating students to overcome the adversities of an unfavorable socioeconomic background and develop their potential to the full.

Keywords: Education, PISA, Determinants of educational performance, Multilevel analysis, Educational policy.

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Resumen
Este trabajo se centra en el estudio de los alumnos resilientes; es decir, aquellos que obtienen buenos resultados académicos a pesar de pertenecer a un entorno socioeconómico desfavorable. Con esa finalidad, nos concentramos en aquellas escuelas que desarrollan su labor con un alumnado que pertenece a entornos socioeconómicos más adversos y, dentro de ellas, elegimos a los alumnos que alcanzan mejores resultados académicos con la idea de encontrar algunos rasgos comunes entre ellos, tanto en lo que se refiere a sus características y habilidades personales, como en lo relativo a las actividades desarrolladas por esas escuelas. Con esta estrategia, se pretende focalizar el análisis sobre aspectos en los que sea posible incidir mediante medidas de política educativa en lugar de otros factores de carácter estructural. Para ello, se utiliza información procedente de los alumnos españoles participantes en PISA 2012. Tras la identificación de los alumnos resilientes según un criterio que cuenta con sustento teórico en la literatura previa, se estima un modelo logístico multinivel en el que se incluyen como regresores tanto variables individuales como escolares con el propósito de determinar qué variables están asociadas con la probabilidad de pertenecer al grupo de los alumnos resilientes. Los resultados obtenidos muestran que, además de una serie de variables individuales, los centros donde se concentra un mayor porcentaje de esta tipología de alumnos se caracterizan, en general, por impartir docencia en aulas de tamaño más reducido, con notable disciplina y con bajas tasas de absentismo escolar. Todas estas variables están relacionadas con la calidad de la docencia, lo que confirma a este factor como un elemento clave en la motivación de los alumnos para poder superar las adversidades de un entorno socioeconómico desfavorable y poder sacar el máximo rendimiento posible a su potencial.

Palabras clave: Educación, PISA, Determinantes del rendimiento educativo, Análisis multinivel, Política educativa

Introduction

Ever since the first studies were conducted in the field of education economics, one of the main concerns of researchers has been to investigate the determinants of academic performance (Coleman et ál., 1966). In recent years, this question has been addressed from a comparative perspective as an increasing number of international databases have become available (Hanushek and Woessman, 2011). A general conclusion of these studies is that family socioeconomic

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background play an important role in explaining students' academic performance (Sirin, 2005).

This factor is usually defined by indicators representing parents' educational level, employment qualifications and family wealth (Yang and Gustafsson, 2004). In the specific case of the Programme for International Student Assessment (PISA), developed by the Organization for Economic Cooperation and Development (OECD), this factor is approximated by the so-called index of economic, social and cultural status (ESCS), composed of the highest educational and occupational level of either parent and an indicator of cultural possessions at home. This variable is closely associated with student academic performance. According to the data reported in the latest wave of the report (OECD, 2013a, p. 34), ESCS index differences account for about 15% of the variation observed in mathematics scores across OECD countries.

Student socioeconomic status and educational outcomes are related to such an extent that it is common to use the relationship of the outcomes to socioeconomic status as a measure of the degree of equity in education systems (Rumberger, 2010). In this respect, an education system will be fairer and will better guarantee equal opportunities if it is effective at neutralizing the effects of the ESCS index of students on their school performance (Levin, 2010).

However, we should not assume that students from disadvantaged socioeconomic environments are inexorably condemned to school failure because these variables are related. Fortunately, there are a significant number of students who are able to overcome a disadvantaged socioeconomic background and perform well. These students, known in the literature as resilient students (Wang, Haertel and Walberg, 1994), are the focus of our research. PISA 2012 classifies students as resilient if they are in the bottom quarter of the ESCS index in the country of assessment and perform internationally in the top quarter of students after accounting for socioeconomic status. As shown in Figure I, Asian countries have the highest percentage of resilient students (between 15% and 20%), and the value for Spain, with a percentage of 6.5%, is, according to this definition, very close to the OECD average.

To be precise, our study aims to identify which factors, apart from their low socioeconomic status, are characteristic of resilient students. To do this, we focus on schools with students from disadvantaged socioeconomic environments, of which we select students with better academic achievement. The idea is to find some common traits, related to student characteristics and skills, as well as the activities developed at those schools. This strategy should eliminate the effects related to the socioeconomic background of both the students themselves and the school, known in the literature as the peer effect[1], which has an even greater influence on performance than student socioeconomic status per se (Willms, 2004). Our ultimate aim is to analyze specifically the less structural factors characterizing resilient students which can be modified by means of education policy measures with the goal of improving academic performance.

Almost all of the studies on this type of students so far have focused on identifying personal characteristics (Krovetz, 2007). Those studies generally suggest that motivation or self-confidence as the main factors explaining the phenomenon of resilience (Borman and Overman, 2004). However, we must not overlook some school factors that may also play a key role, as highlighted by other papers that push for measures to encourage regular class attendance and participation (Masten and Coatsworth, 1998), keep the number of students per classroom (Robinson, 1990) and per school down (Noguera, 2002) or implement innovative teaching practices to try to engage students from disadvantaged backgrounds and encourage them to develop their capabilities (Tajalli and Opheim, 2004).

In the United States, a lot of literature has examined special educational interventions for students at risk of school failure (Harris, 2007), an issue which has received special attention since the adoption of the No Child Left Behind (NCLB) Act in 2001. One of the main purposes of this law was to improve the performance of the most disadvantaged students. The fields of psychology and sociology have made lots of progress on the characterization of resilient students (Martin and Marsh, 2006), whereas contributions in the field of education economics are few and far between. The studies by Agasisti and Longobardi (2014a; 2014b) are an exception. Based on the educational production function, they conduct an econometric analysis to try to identify some school characteristics linked with there being a greater rate of resilient students at the schools using PISA 2009 data.

In our research we use a similar method applied to Spain using PISA 2012 data with respect to the competence of mathematics. The 2012 wave focused on this competence, which accounted for two-thirds of the

[(1)] Usually calculated from the average socioeconomic level of the classmates or schoolmates. For a review of peer effect studies, see van Ewijk and Sleegers (2010).

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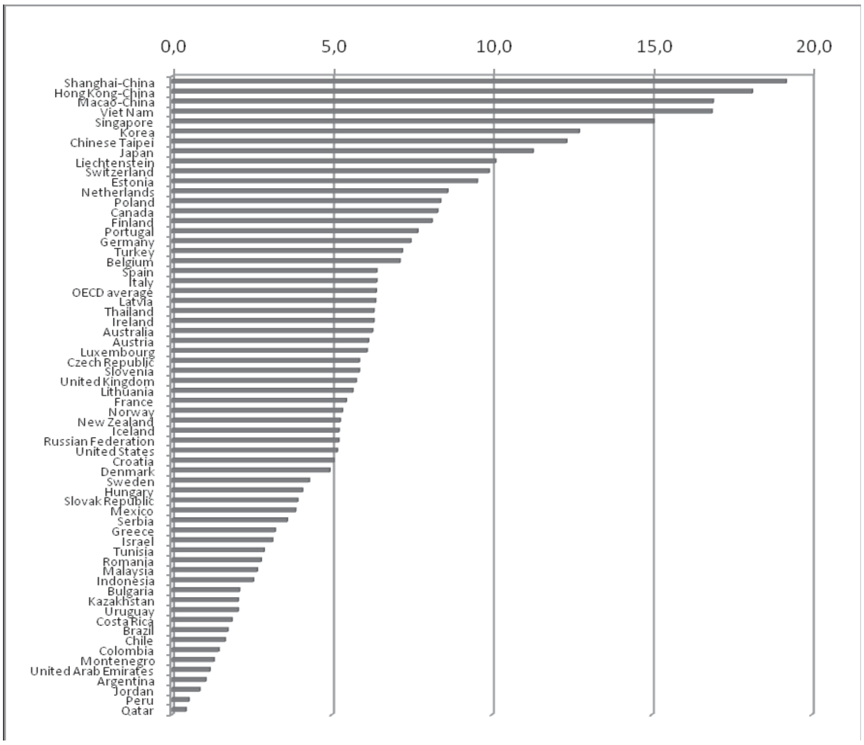
assessment tests, and included quite a few questions related to students' specific attitude towards and engagement in the subject. In anticipation of the 2015 scenario, when PISA tests will be completely administered by computer, we used the sample of students who completed the PISA 2012 computer based-assessment (CBA) in our study. Students completing this test require skills to interact with data presented in numerical, tabular and graphical format, and may have to use pull-down menus and databases with associated calculation tools. There is the question then of whether students who are more familiar with new technologies might have an edge over the others and achieve better results. This issue may have a major impact with respect to our study, since students from disadvantaged socioeconomic backgrounds are less likely to have access to these technologies.

FIGURE I. Percentage of resilient students in countries participating in PISA 2012



Source: OECD (2013a), Table II.2.7a

The procedure used to select the analysis group is to segment the available sample and focus on schools with a lower socioeconomic status. At these schools, we consider only those students whose socioeconomic status no higher than the bottom rung defined by the segmentation of the selected schools. Thus, we aim to isolate the socioeconomic component of the analysis in order to focus on other relevant factors both at student and school level. Once the sample has been segmented, students are considered as resilient if the score they achieved for mathematics is one the best in the score distribution. Next, we estimate a multilevel logistic model that includes both student and school variables as explanatory variables in order to determine which variables are associated with the likelihood of a student belonging to the group of resilient students.

The remainder of the study is organized as follows. Section 2 provides a description of the database used and a detailed explanation of the approach adopted to identify the schools and students under analysis. Section 3 explains the methodology used in the empirical analysis. The main results of the estimations are reported and discussed in Section 4. Finally, the conclusions at the end of the paper give some educational policy recommendations based on the results.

Database and variables

The source of the database used in our analysis is PISA (Programme for International Student Assessment), designed and launched by the OECD in the late nineties as a comparative, international, regular and continuous study of certain characteristics and competences of 15-year-old pupils (Turner, 2006). Our research is based on the last wave, PISA 2012, and is confined to Spain, providing information on a total of 25,313 students from 902 schools. The PISA 2012 report assesses student performance in mathematics, reading comprehension, sciences and problem solving, dealing more thoroughly with the competence of mathematics. On this ground, we will use the results for this competence as a benchmark for identifying resilient students.

Of the total sample of Spanish students participating in the PISA 2012 report, only 10,175 students from 368 schools took the computer-based assessment. It is these students that are the subject of this research. Table

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I shows the distribution of the computer-based assessment sample of students and schools compared to the total PISA 2012 survey sample by regions. As Table I shows, there are two regions that are overrepresented in the selected database, Catalonia and especially the Basque Country, whose students account for almost half of the sample. This is because these regions decided to participate with an enlarged representative sample in the specific computer-based assessment of competences which would enable them to conduct worldwide comparisons.

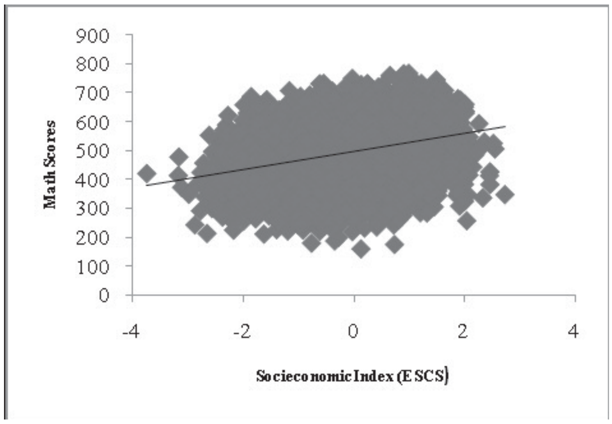
TABLE I. Spanish computer-based assessment sample of students in PISA 2012 by regions

	PISA 2012		**PISA CBA[a]**	
	Students	**Schools**	**Students**	**Schools**
Balearic Islands	1.435	54	100	4
Cantabria	1.523	54	111	4
Castilla y León	1.592	55	201	7
Basque Country	4.739	174	4.739	174
La Rioja	1.532	54	85	4
Madrid	1.542	51	592	20
Galicia	1.542	56	202	8
Navarra	1.530	51	135	4
Murcia	1.374	52	141	6
Andalucía	1.434	52	910	33
Extremadura	1.536	53	150	5
Asturias	1.611	56	120	4
Aragón	1.393	51	159	6
Catalonia	1.435	51	1.435	51
Others	1.095	38	1.095	38
Total	**25.313**	**902**	**10.175**	**368**

[a] Computer-based assessment.

Although a very wide range of factors may be influencing these results, the socioeconomic status of families is usually identified as the key factor. As mentioned in the introduction, this factor is approximated in PISA by the ESCS index, which takes the value 0 for the average of the OECD countries. Therefore, negative values denote a below average ESCS and positive values an above average ESCS. Figure II shows the relationship between students' mathematics scores and socioeconomic status. The correlation is clearly positive.

FIGURE II. Relationship between the socioeconomic status and mathematics (total sample)



As already mentioned in the introduction, the aim of this research is to isolate the effect of socioeconomic status in order to study the factors that characterize students who are higher academic achievers despite unfavorable circumstances. To do this, the strategy that we applied was to segment the total sample in such a way as to select the schools with the lowest average socioeconomic status out of the 368 schools that participated in the PISA computer-based assessment. This preliminary selection left us with the bottom third (33rd percentile) of the sample in terms of the ESCS variable[2]. Specifically, 125 schools attended by a total of 3,116 students were available for our analysis. To ensure that our study only included students in adverse socioeconomic circumstances, we then selected only students whose individual socioeconomic status did not

(2) Although the PISA definition given in the introduction considers that resilient students are students in the bottom quartile of the ESCS variable, we have opted for the bottom third in order to reduce the loss of observations. Agasisti and Lomgobardi (2014a) adopted this same criterion.

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exceed the criterion used to select schools. This reduced the sample to 2,054 observations. Finally, we decided to discard schools that had a small number of students (fewer than 10). Therefore, the final sample used in our empirical analysis consists of 1,917 students from 105 schools.

Predictably, the results achieved by the students belonging to this segmented sample are very poor. Specifically, the average score for mathematics decreases from 483 points to 453 points. These lower average values can be largely explained by a number of variables linked to the selected students' socioeconomic status. Tables II and III, for example, show the differences between the total sample (10,175 pupils) and the segmented sample (1,917 pupils) with respect to their parents' educational level and the number of books in the family home. The total sample is characterized by having a middle socioeconomic status, where the majority of both fathers and mothers are university educated and half of the households own more than 100 books, whereas the segmented sample has a very negative average value for the ESCS index (-1.12), the parents' average educational level is compulsory secondary education (only 10% have university degrees) and families own a small number of books (fewer than 100 in 80% of the cases).

TABLE II. Educational levels of the parents of the students assessed in PISA 2012 for the total sample and the segmented sample selected in the study

	Total sample		**Segmented sample**	
	Father's educational level (%)	**Mother's educational level (%)**	**Father's educational level (%)**	**Mother's educational level (%)**
None	2.44	1.80	7.07	5.94
Primary education	8.70	6.96	22.16	19.68
Secondary education	21.78	20.33	37.59	40.46
Upper secondary or secondary-level vocational education	21.87	25.89	21.54	24.59
Higher education	45.22	45.02	11.65	9.32

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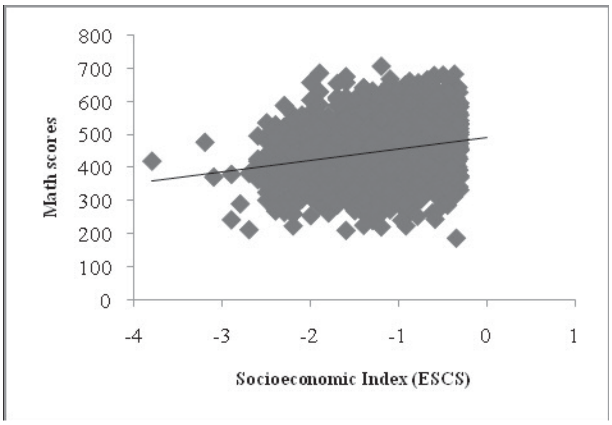
TABLE III. Distribution of the number of books at home for the total sample and for the segmented sample selected in the study (percentage)

Books at home	Total sample (%)	Segmented sample (%)
0-10	6.99	18.35
11-25	12.30	23.47
26-100	29.85	35.86
101-200	22.08	13.92
201-500	17.66	6.22
More than 500	11.13	2.16

With a subsample that is much more homogeneous with respect to the socioeconomic status of the families, the relationship between the results in mathematics and ESCS becomes much weaker, as shown in Figure III. As a result, we can focus on the study of other variables related to the results.

FIGURE III. Relationship between the socioeconomic status and results after segmentation



As mentioned above, our goal is specifically to identify the resilient students within the sub-sample of the most disadvantaged schools and

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students in terms of the ESCS variable, i.e., students who achieve good scores. To do this, we generate a dummy variable called *resilient* that will be the dependent variable of our models. This variable takes the value 1 if the student is in the top quartile of the mathematics score distribution. To do this, we generated five possible dependent variables, one for each plausible value for mathematics following the recommendations of PISA technical reports (OECD, 2009). We find that there are huge differences in the academic achievement of groups of students with a very similar average socioeconomic status. This is an inducement to investigate whether or not other factors related to both individual student characteristics and school-related issues might explain such discrepancies in the scores.

Firstly, we selected three control variables that, as far as we can infer from the previous literature on the determinants of student performance, should have some influence on the dependent variable. These are gender, represented by a dummy variable that takes the value 1 if the student is a girl, first-generation immigrant status and family structure, also represented by a dummy variable that takes the value 1 if the student is a member of what is known as a traditional family, i.e., a household formed by both parents and their children. We have also included the student-level ESCS variable in order to check whether, after selecting schools and students with a lower socioeconomic status, it is still a key factor in explaining student resilience. Apart from these control variables, we have, in view of the main goal of this study, tested the option of adding a number of student indicators related to teaching quality at schools to the model. Finally, we decided to include a composite index representing the classroom disciplinary climate, built from student responses about the frequency of disruptions in class. Also, our interest in testing the influence of computer resources has led us to adopt household computer ownership as a possible explanatory variable.

The next block is composed of variables which should in principle be related to mathematics scores. Of these, we selected several dummy variables such as students' liking of mathematics, attention paid in class and hard work by classmates on this subject.

The school variables include several composite indicators, based on the responses of principals concerning the degree of autonomy with which the school operates (power to hire and fire teachers, set salaries and wage rises, or draw up and allocate school budgets) or the quality of educational resources (availability of computers for educational purposes, educational software, calculators, books, audiovisual resources and laboratory equipment)[3]. Additional school variables were also considered, such as the relationship between students and their teachers, the level of absenteeism at the school based on the principals' opinion about how regularly students attend classes or the average class size at the school. After analyzing the between-school frequency distribution within the analyzed sample, class size was set to a value of less than 20 students in order to select schools with a small class size.

Finally, only two specific variables were selected. Firstly, hours of mathematics instruction, represented by a continuous variable reflecting the average weekly duration (in minutes) of mathematics classes, was adopted as an indicator that should be associated with high academic achievement in this subject. Secondly, the number of computers available for instruction was selected as a variable that might be related to the scores achieved in the computer-based assessment.

Table IV shows the main descriptive statistics of all the variables considered in our analysis, distinguishing between dependent, student and school variables.

Looking at the values of the descriptive statistics, we find that there are hardly any differences in the gender composition of the sample. The percentage of immigrant students in the sample (16.1%) is considerably greater than the 9.9% recorded in the national sample for PISA 2012 (INEE, 2013), which is a predictable result in view of the relationship between immigrant condition and low socioeconomic status. Also noteworthy is the low proportion of students who claim to like mathematics or whose classmates make an effort and work hard at this subject and the high level of absenteeism, considering that the variable refers to schools where students tend not to attend class regularly. As for the rest of the school variables, perhaps the most striking result is that 23% of schools have classes with a rather small average size (fewer than 20 students).

(3) In order to make the parameters associated with these indices easier to interpret, they have been transformed into dummy variables that take the value 1 if the schools are at the very top of the distribution in each case.

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TABLE IV. Descriptive statistics of the variables included in the empirical analysis

VARIABLES / Dependent variable	Minimum	Maximum	Mean	Std. Dev.
Resilient in mathematics	0.00	1.00	0.2499	0.4331
Student-level variables **General variables**				
Gender	0.00	1.00	0.5013	0.5001
Immigrant	0.00	1.00	0.1607	0.3673
Traditional family	0.00	1.00	0.8164	0.3873
Computer	0.00	1.00	0.9259	0.2620
Climate	-2.48	1.85	-0.1196	0.8607
Socioeconomic status	-3.75	-0.31	-1.1245	0.5418
Specific variables				
Enjoy Maths	0.00	1.00	0.2374	0.4256
Peers work hard at mathematics	0.00	1.00	0.2796	0.4489
Attention in mathematics class	0.00	1.00	0.5467	0.4979
School-level variables **General variables**				
Autonomy	0.00	1.00	0.2358	0.4246
School resources	0.00	1.00	0.2932	0.4553
Absenteeism	0.00	1.00	0.3933	0.4886
Teacher -student relationship	0.00	1.00	0.1137	0.3176
Small class size	0.00	1.00	0.2306	0.4213
Specific variables				
Hours of mathematics instruction	157.14	298.08	210.2599	27.1170
Number of computers	12.00	200.00	43.0498	26.9030

Methodology

The model used in the empirical application is a multilevel regression (Goldstein, 1995), where the students are grouped (nested) at a higher level represented by the schools. This technique avoids possible biases in the estimations derived from the correlation between the values of the school variables of pupils from the same school (Hox, 2002). Since the dependent variables are categorical, these regressions adopt a binomial logistic model structure.

This approach has been used before in different studies using the PISA database to analyze the main factors related to the probability of occurrence of a particular event, such as school failure (Calero, Choi and Waisgrais, 2010) or grade retention (Goos et al., 2012; Carabaña, 2013; Cordero, Manchón and Simancas, 2014).

In this model, the dependent variable represents the group of students with higher scores in PISA (first quartile within the selected subsample), where the variable to be estimated is the probability of student *i* from school *j* being a member of the respective group: $P(Y_{ij} = 1 \mid \beta) = P_{ij}$. This probability can be modeled using the following logistic function (Equation 1):

$$\log\left[\frac{P_{ij}}{(1-P_{ij})}\right] = \beta_{0j} + \beta_{ij} X_{ij} + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_1 \qquad [1]$$

In Equation 1, the probability of the student meeting the established requirement depends on a vector of independent variables at student level (Xij) and a vector of school variables (Zj), but also takes into account the deviation of the school *j* (uj) with respect to the average scores for all the schools (ã0) and the deviation of student *i* with respect to the average scores achieved by students attending the same school *j*.

The values of the coefficients estimated in the model cannot be interpreted directly as in a linear regression, and we have to estimate the odds ratios of each independent variable. These statistics measure the relationship between the probability of an event occurring or not occurring when the value of the variable considered increases by one unit, while the others are constant. Therefore, the odds ratios associated with an explanatory variable will be greater than one if that variable increases the probability of a student being a member of the group of higher academic performers, and less than one if that variable decreases

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the probability of occurrence of that event, where the odds are associated with positive coefficients in the first case and with negative coefficients in the second case.

An additive approach is the most commonly used strategy for calculating the results in this type of study, where the different blocks of explanatory variables are added one by one to a baseline specification (Dronkers and Robert, 2008), adding, first, the variables related to student level and, then, the variables corresponding to the school level.

Analysis and discussion of results

In this section, we present the results of applying the multilevel logistic regression model to the sample of selected students according to the above criteria. For the purposes of this estimation, the problem of non-response for some of the variables (missing data) has been addressed using the method of imputation by regression recommended by the OECD (2008). The estimations were performed using HLM 6 software (Raudenbush, Bryk, Cheong and Congdon, 2004), by means of which it is possible to incorporate the sample weightings in the estimations to ensure that sampled students adequately represent the analyzed total population (Rutkowski, González, Joncas and von Davier, 2010)[4]. Thus, the results of the analysis refer to the entire Spanish population, even though there are some regions (Basque Country and Catalonia) that are overrepresented in the sample because they entered an enlarged sample.

The dependent variable takes the value 1 if the student is considered as a resilient student with respect to the mathematics competence and the model has been estimated sequentially as described in the previous section[5]. Firstly, only student-level variables were added to the analysis, distinguishing between general and specific variables. The results of these estimations are shown in Table V.

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(5) Following the recommendations in the PISA technical report (see OECD, 2009), each plausible value is estimated separately. The results tables show the average statistics for each value.

TABLE V. Results of the estimation with variables at student level

VARIABLES	Coeff.	SE	Odds Ratio	
Constant	-1.09	0.45	0.34	**
STUDENT LEVEL **General variables**				
Gender-female	-0.49	0.13	0.61	***
Immigrant	-0.82	0.30	0.44	***
Traditional family	0.54	0.18	1.72	***
Computer	0.54	0.36	1.71	
Climate	0.30	0.10	1.35	***
Socioeconomic index	0.70	0.14	2.01	***
Specific variables				
Enjoy Maths	0.35	0.16	1.25	*
Peers work hard at mathematics	0.25	0.16	1.28	
Attention in mathematics class	-0.02	0.14	0.98	

*** The variable is significant at 99%; ** 95%; * 90%.

As expected, the three control variables added to the analysis have a significant influence on the dependent variable. Both female gender and immigrant status are negatively linked to the probability of the student belonging to the group of resilient students, whereas membership of a traditional family has the opposite effect. These results are consistent with the previous literature, since there are many studies that have identified these factors as good predictors of results. However, we should stress that our dependent variable is measuring the possibility of students from disadvantaged socioeconomic backgrounds being ranked among the best rather than the influence of such variables on scores.

One result to which we would like to draw attention is that, even after the school and student selection process, the value of the odds ratio for socioeconomic status is very high and clearly significant. Therefore, ranking at the top of the bottom socioeconomic status is a factor clearly associated with resilience. This result is surely due to the fact that the sample is still very heterogeneous, as denoted by the values of the standard deviation shown in Table IV. The classroom disciplinary climate

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is also positively and significantly associated with the likelihood of achieving better scores, although its relative importance is much lower. This finding is consistent with the results reported by Padron, Waxman and Huang (1999), who concluded that resilient students in primary education are more sensitive to the learning climate and spend more time working with teachers on aspects related to education than other students. Finally, we found that there is no significant relationship between having a computer at home and student resilience, which is consistent with the results reported by Marcenaro (2014) and Mediavilla and Escardíbul (2015) using the total sample of students in the PISA 2012 computer-based assessment.

After exploring the associations between different selected student indicators and the dependent variable, we added the school-related variables in the next step of the empirical analysis. The results of this new estimation are reported in Table VI.

Generally, most of the parameters associated with the student variables are unchanged when the school variables are added. Therefore, the discussion of the results of this new model will focus on the school-related variables.

The two factors showing a higher level of correlation with the dependent variable are the relationship between students and their teacher and membership of a small class, which carry a significantly greater weight than the other variables. Although the analysis cannot establish causal relationships between these variables and academic achievement, this result is consistent with evidence found in previous studies. On the one hand, most previous studies about the relationship between teaching staff and students consistently point out that it is a key factor in achieving greater engagement and commitment, particularly with respect to students from disadvantaged socioeconomic backgrounds (Roorda, Koomen, Spilt and Oort, 2011). There is also a lot of literature examining class size[6] that suggests that class size has a bigger influence in schools attended by students from more disadvantaged socioeconomic backgrounds (Heinesen, 2010). In these cases, attention is more personalized in classes with a smaller number of students, and this may, to some extent, compensate for the fact that their parents cannot give them as much help at home as students in more favorable circumstances receive (Fredriksson, Öckert and Oosterbeek, 2014).

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61) See Chingos (2013).

TABLE VI. Results of the estimations with variables at student and school level

VARIABLES	Coeff.	SE	Odds Ratio	
Constant	-0.15	0.77	0.86	
STUDENT LEVEL				
General variables				
Gender-female	-0.51	0.13	0.60	***
Immigrant	-0.87	0.32	0.42	***
Traditional family	0.55	0.19	1.73	***
Computer	0.59	0.38	1.80	
Climate	0.32	0.11	1.37	***
Socioeconomic index	0.71	0.14	2.04	***
Specific variables				
Enjoy Maths	0.37	0.16	1.28	**
Peers work hard at mathematics	0.25	0.17	1.28	
Attention in mathematics class	-0.03	0.14	0.97	
SCHOOL LEVEL				
General variables				
Autonomy	0.37	0.19	1.45	**
School resources	0.11	0.22	1.11	
Absenteeism	-0.44	0.18	0.65	**
Teacher -student relationship	1.10	0.31	2.99	***
Small class size	0.91	0.24	2.49	***
Specific variables				
Hours of mathematics instruction	-0.01	0.00	0.99	**
Number of Computers	0.01	0.00	1.01	

*** The variable is significant at 99%; ** 95%; * 90%.

School absenteeism is another factor that has a significant influence, although the direction of the effect is, of course, opposite in this case. This finding is consistent with the empirical evidence existing worldwide (OECD, 2013b). This phenomenon has led to the proposal of a number

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of strategies to encourage class attendance, but it has had relatively little success to date (Reid, 2013).

We found that the number of computers available for instruction is a factor that has no significant effect. This is consistent with the findings of other previous studies (Calero and Escardíbul, 2007) using information on Spanish students in previous waves of PISA without computer-based assessment. Using computer-based assessment data, however, Mediavilla and Escardíbul (2015) detected that this variable had a significant relationship, whereas other studies found that the relationship between this variable and student achievement was significant and negative (Jimenez and Villaplana, 2014). Therefore, it would be risky to venture whether or not policies based on indiscriminately increasing computer provision at schools are a good thing.

The degree of autonomy with which the schools operate appears to be statistically significant. This is in line with previous results reported in other studies focusing on only one country (Verschelde, Hindriks, Raypand and Schoors, 2015) and in international comparisons (Hanushek, Link and Woessmann, 2013), although the international study only detects a relationship between school autonomy and school performance in the most developed countries.

Finally, the hours of mathematics instruction is clearly significant, although, with values close to 1%, its odds ratio suggests that it does not have much impact on the results. Here the Spanish results diverge from the international evidence, where this factor is often associated with better student academic performance, especially of students from more developed countries (Lavy, 2010; Riykin and Schiman, 2013).

Conclusions

In this study we have analyzed the determinants of the academic performance of Spanish students considered as mathematically resilient in the PISA 2012 computer-based assessment. Resilient students are students who, despite coming from a socioeconomically adverse background, perform well academically.

In view of the importance of socioeconomic circumstances in explaining academic achievement, we have tried to isolate this component by selecting only schools with a low average socioeconomic status in order to more clearly highlight the effect of other factors that are normally concealed by the influence of socioeconomic status.

Despite the fact that students from these schools are, a priori, very likely to achieve low scores in PISA, we were able to identify some factors characterizing more successful schools. According to our results, these schools teach to smaller class sizes (fewer than 20 students), enforce some level of discipline (good climate) and have low rates of absenteeism. All these variables appear to be clearly related to teaching quality, which confirms that this is a key factor in motivating students to effectively overcome the adversities of a disadvantaged socioeconomic background and to be able to fully develop their potential (Hanushek, 2011).

These results provide some keys to the design of educational policies aimed at schools whose students have a relatively low socioeconomic status. In this respect, they should increase the size of the teaching staff so that they have attend to fewer students per class or, alternatively, establish some kind of incentive system (positive or negative) targeting both school teachers and principals with a view to getting students to attend class regularly.

As regards student variables, it is noteworthy that, even after selecting schools and students from a disadvantaged background, socioeconomic status is still a key factor for explaining academic performance. Additionally, immigrant status and female gender have a significant and negative influence on the performance of students from more disadvantaged backgrounds. As regards gender, it is known from other studies that this result has to do with the assessed competence (mathematics). In any case, the above findings should be viewed with caution because they are the result of an analysis performed on cross-sectional data which cannot be interpreted in a causal sense. Educational policies should be evaluated based on causal inference techniques which can be used to precisely measure the possible impact of the implemented policies (Angrist and Pischke, 2008). Randomized or controlled trials would be ideal, although, in view of their high cost, we recommend that efforts be focused on the development longitudinal databases which could be used to evaluate the impact of particular educational measures, such as the modification of class size, over time (Fredriksson Öckert and Oosterbeek, 2013).

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