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Socioeconomic inequality and regional disparities in educational achievement: The role of relative poverty

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ABSTRACT

The relationship between PISA 2012 maths test scores and relative poverty was tested in a sample of 35 Italian and Spanish regions, together with a larger sample that included Australian, Belgian, and Canadian regions. The correlation between mean scores in mathematics, adjusted for students' socioeconomic and cultural backgrounds, and poverty rates is -−0.84 for the Italian and Spanish sample, and −0.68 for the complete sample. In the regressions, the effect of relative poverty on mean scores in mathematics is highly significant ($p < 0.01$), robust to different specifications, and independent from students' backgrounds and regional development levels. It is proposed that disparities in average scores in mathematics across regions depend on the shares of low-performing students which, in turn, depend on the degree of relative poverty within regions. The implications for the thesis according to which, in Italy and Spain, regional disparities in educational achievements reflect genetic differences in the IQ of populations are discussed.

1. Introduction

In all countries for which data are available, regional disparities exist in educational achievement (OECD, 2013a, 2016a, 2019a). For the magnitude of regional disparities in students' achievements, Italy and Spain represent two relevant case studies among the economically developed countries.

In the Programme for International School Assessment (PISA) 2012, both in Italy and Spain, the range of variations in mean regional scores in mathematics was as large as that which can be found between nations with very different levels of economic development. In Italy, the difference in mean scores in mathematics between the best and the worst performing regions was of 94 points, similar to that between Italy as a whole and Brazil. The 55 point-difference between the Spanish regions of Navarra and Extremadura was roughly as great as that between Spain and Kazakhstan (OECD, 2013a). In order to assess these differences, consider that, in the PISA metric, test scores are standardized with a mean of 500 points and a standard deviation of 100 points for all OECD countries, and that a difference of 39 points corresponds to one year of education.

Significant regional disparities in achievement scores were found in subsequent assessments, and, in the case of Italy, derive from national evaluation programmes (Invalsi, 2019a). In PISA 2018, the mean score in mathematics in the north-eastern Italian macro-region (515 points) was close to that of Switzerland; conversely, in the south-islands Italian macro-region, the average score (445 points) was similar to that of the Karagandy region of Kazakhstan and to that of Malaysia (OECD, 2019a). In Spain, the difference in average scores in mathematics between Navarra and Andalusia was of 35 score points. Mean regional PISA scores in mathematics, like those in science and reading, also vary, to different degrees, within other countries, including Australia, Canada, Belgium, Kazakhstan, and Mexico (OECD, 2013a, 2016a, 2019a).

At the individual level, students' educational attainments depend on the interaction between genetic and environmental factors (Haworth, Asbury, Dale & Plomin, 2011; Bueno, 2019). Among the latter, students' families' socioeconomic and cultural status (SES) plays a prominent role (Chiu, 2010; Rasbash, Leckie, Pillinger, & Jenkins, 2010; Broer, Bai, & Fonseca, 2019). Educational achievements are also influenced by other factors, such as pre-primary school attendance, the time devoted by students to homework, parental support with homework or truancy (Hemmerechts, Agirdag, & Kavadias, 2017; Hippe, Jakubowski, & Araújo, 2018). Furthermore, performances by students with immigrant backgrounds are, on average, comparatively poorer (OECD, 2016b, 2019b).

Students' educational outcomes also depend on environmental factors beyond immediate family backgrounds, such as the quality of

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teaching and the average SES of schools attended, and the social environment where students have lived since infancy (Bradley & Corwyn, 2002; Goldhaber, 2013; Perry & McConney, 2010; Rasbash et al., 2010).

Within each country, however, regional disparities in PISA mean scores remain large, also when students' familial backgrounds are taken into account (OECD, 2013a, 2019a). This implies that there are regional-specific factors, different from students' SES, that affect students' mean performances. Studies on Italy and Spain suggest that regional differentials in achievements are, in fact, related to overall economic conditions, as measured by GDP per capita, and to labour market indicators (Bratti, Checchi, & Filippin, 2007; Agasisti & Vittadini, 2012; Seta, Pipitone, Gentile, & Allegra, 2014; Hippe et al., 2018; Martini, 2020). The relevance of regional factors seems to be higher in Italy than in Spain (Agasisti & Cordero-Ferrera, 2013), although, in Spain too, variation in educational achievements is greater between regions than schools (González-Betancor & López-Puig, 2020). The way in which regional socioeconomic variables affect individual educational performances remains unclear, however.

From a psychological perspective, it has been proposed that, in Italy and Spain, regional differences in school achievements reflect genetic differences in the average intelligence quotient (IQ) of populations (Lynn, 2010, 2012a, 2012b; Piffer & Lynn, 2014). Due to lack of cognitive abilities test scores for Italian regions, Lynn (2010) used PISA 2006 scores as a proxy of mean regional IQs, concluding that in the south the mean PISA-IQ is 9–10 points lower than in the north. Analogously, PISA scores were taken as a measure of mean IQs in Spanish regions by Lynn (2012b), and in Italian regions by Piffer and Lynn (2014).

The use of PISA scores as a measure of a population's mean IQ is based on the strong correlation between educational assessment tests and standard IQ tests. Studies on large samples of individuals typically report correlations ranging from 0.5–0.7, and sometimes higher (Lynn & Mikk, 2007). For example, by using data on a sample of 70,000 English children, Deary, Strand, Smith, and Fernandes (2007) found a correlation of 0.81 between cognitive ability tests at age 11 and educational achievement at age 16, concluding that general cognitive ability makes a large contribution to educational achievement. Across countries, school assessment scores, such as PISA and TIMMS, are very strongly correlated ($r \sim 0.90$) with national mean IQ test scores (Lynn & Meisenberg, 2010; Lynn & Mikk, 2007, 2009; Rindermann, 2007). On the basis of these studies, it has been proposed that student achievement tests and IQ tests measure a common cognitive ability (namely a national *g*-factor) at the macro-social level (Rindermann, 2007).

In line with the theory of racial differences in intelligence (Lynn, 2015; Lynn & Becker, 2019), Lynn attributed the comparatively lower IQ of southern Italians to the genetic legacy of the Phoenicians and Arabs who, in different eras, settled in some areas of the south of Italy.

To corroborate his thesis, Lynn (2012a) showed how, across Italian regions, PISA 2009 regional scores were positively correlated with the percentages of the populations with blonde hair, a marker for northern European ancestry, and negatively with the frequency of the haplogroup E1b1 allele, a marker for North African ancestry, which is higher in southern regions. Analogously, in the case of Spain, Lynn (2012b) proposed that PISA scores were lower in those regions, such as Andalusia or Extremadura, with higher fractions of alleles typical of North African populations, and where the Arab domination lasted longer.

Lynn's findings were supplemented by Templer (2012), who reported the correlations between PISA scores and some biological variables across Italian regions, and by Piffer and Lynn (2014) who estimated a difference of 9.2 IQ points between northern and southern Italy, attributed by them to genetic factors.

Lynn's thesis on north-south disparities in Italy raised much criticism. It has been observed, in particular, that PISA tests measure scholastic achievements, not general intelligence, and, furthermore, that the north-south disparities in achievements and in socioeconomic development are due to historical and economic factors (Beraldo, 2010; Cornoldi, Belacchi, Giofrè, Martini, & Tressoldi, 2010; Cornoldi, Giofrè, & Martini, 2013; D'Amico, Cardaci, Di Nuovo, & Naglieri, 2012; Daniele, 2015; Daniele & Malanima, 2011; Felice & Giugliano, 2011).

The purpose of this article is not to discuss whether, across nations or regions, average scores on PISA tests are a reliable measure of the average intelligence of populations (Baumert, Luedtke, Trautwein, & Brunner, 2009; Cornoldi et al., 2013). Rather, the purpose is to re-examine Lynn's (2010, 2012b) thesis, showing how differences in mean PISA scores among Italian and Spanish regions essentially depend on socioeconomic factors. In particular, the analysis focuses on the role of relative poverty, a measure closely related to inequality in income distribution. Notwithstanding the evidence that shows how poverty and inequality affect cognitive abilities and educational outcomes (Van der Berg, 2008; Chmielewski & Reardon, 2016; OECD, 2017a), the role of relative poverty in interregional disparities in achievements is still unexplored.

2. Empirical analysis

2.1. Methods and data

In the subsequent analysis, the relationship between relative poverty rates and mean regional scores in mathematics was tested through multiple regressions in a sample of 35 Italian and Spanish regions, and, to check the results, in a larger sample that included a further 20 regions of Australia (8), Belgium (2) and Canada (10), developed countries for which PISA 2012 data are available.[1] The approach followed was analogous to that of cross-country analyses that used national PISA scores (e.g. Chmielewski & Reardon, 2016); furthermore, average regional scores from PISA, or from national school assessments, were used in studies on Italy and Spain (Lynn, 2010, 2012b; Beraldo, 2010; Piffer & Lynn, 2014) and on other countries, including the UK (Carl, 2016) and Japan (Kura, 2013).

The psychometrics properties, the reliability and the comparability of PISA results across countries, and student groups (e.g. natives and immigrants), have been investigated by diverse studies (Costa & Araújo, 2012; Kreiner & Christensen, 2014; Zwitser, Glaser, & Maris, 2017). Analyses have been devoted, in particular, to assessing the measurement equivalence of PISA tests and the presence of *differential item functioning* (DIF), an occurrence which could influence the comparability of results among countries and student groups (Feskens, Fox, & Zwitser, 2019; Huang, Wilson, & Wang, 2016; Zwitser et al., 2017). For example, the presence of DIF in PISA 2006 was found by Kreiner and Christensen (2014), while in-equivalence in PISA 2009 tests, especially affecting countries' scores in the reading scale, was found by Kankaraš and Moors (2010). However, there is no evidence of the measurement of in-equivalence in regional PISA 2012 scores, whose comparability is, in any case, validated by the OECD (2014: 43).

Moreover, due to the principle of cultural proximity, according to which groups of individuals sharing the same history, the same language and the same culture tend to have analogous results, the comparability of educational achievements between regions is, at least in principle, greater than between countries with very different cultures (Hui & Triandis, 1989; Kankaraš & Moors, 2010).

2.1.1. Dependent variables

Regional mean test scores in mathematics, adjusted for students' families' economic, social and cultural status (ESCS), were taken from the OECD-PISA 2012 online database. The ESCS is a composite index, derived from three indices: highest parental occupation, highest parental education level and home possessions indices. In turn, this last index was derived from sub-indices: the measure of family wealth

[1] The regional classification of the OECD was used. For Australia, the six states, the Australian Capital Territory and the Northern Territory were considered.

possessions, cultural possessions and home educational resources, as well as the number of books in a student's home (OECD, 2014: 263; Avvisati, 2020). Data on the percentage of low-performing students, that is below level 2 of proficiency (with a score under 420 points) were also taken from PISA 2012. Furthermore, maths scores and school-related variables from PISA, 2018, for a subsample of 33 regions for which data are available, were also used to check the results. Regional mean scores were derived from a large sample of 15-year-old students. In PISA 2012, the samples of participating students were 38,142 in Italy and 25,335 in Spain, while in PISA, 2018 the participants were 11,785 and 35,493, respectively (OECD, 2020).[2]

2.1.2. Regressors

The regressor of interest was the relative poverty rate in the year 2012, taken from the OECD Income Distribution Database (IDD, online at https://stats.oecd.org/). The poverty rate is given by the share of people whose disposable income, after taxes and transfers, is lower than the poverty threshold, set at 50% of the national median household income. Incomes were equalised, in order to ensure comparability across households, setting a two-adult household as the reference to compare living standards. Diversely from absolute poverty, that refers to a minimum living standard, defined on the basis of a given basket of goods and services, relative poverty is computed with reference to a relative income threshold and, thus, can be considered a measure of inequality at the lower tail of income distribution (Niemietz, 2011: 40, 41; Piacentini, 2014).

The regressions control for regional GDP per capita in Purchasing Power Parity (PPP) in the year 2012, taken from the OECD Regional Database, and five school-related variables taken from PISA datasets. Three variables measure the endowment of human and material resources: the index of teacher shortages, that measures the lack of qualified teachers (higher values indicating higher teacher shortages); the index of quality of educational resources, such as computers, software, instructional and library materials; and the index of the quality of schools' physical infrastructures, including buildings, heating/cooling systems and classrooms. Higher values in these two last indices denote a better quality of educational resources and infrastructures (OECD, 2013b: 140–141).

The other two variables were: the index of school responsibility over resources allocated, and the index of school responsibility over curriculum and assessments. These indices, derived from questionnaires administered to school principals, measure the degree of responsibility of schools, with respect to the national and regional educational institutions, in the management of the school's human and economic resources and in the determination of some aspects related to curricula (course contents, textbooks used….) and assessment policies (OECD, 2013b: 139–140).

2.2. Results for Italian and Spanish regions

The analysis was first performed on a sample from PISA 2012, composed of 21 Italian regions (including the two autonomous provinces of Trento and Bolzano) and 14 autonomous Spanish communities. It is noteworthy that in the subsequent PISA editions (2015, 2018), data on test scores for Italy cover only 4 regions. Italy and Spain present many similarities. They have roughly the same development level (in 2012, GDP per capita PPP in Spain was about 90% of that of Italy and 96% in, 2018), and both are characterised by wide and historically-rooted regional development disparities (Daniele & Malanima, 2014; Felice, 2011, 2012; Tirado, Díez-Minguela, & Martinez-Galarraga, 2016).

Reflecting the degree of decentralisation between central and regional governments, the organisation of the educational systems in Italy and Spain shows some differences. In Italy, the educational system is historically centralised, both in the allocation of resources and personnel and in funding (Agasisti & Cordero-Ferrera, 2013); furthermore, up to secondary school (10th grade) the curricula are identical in the whole country for each type of school (Lyceums, technical schools, etc.). The Spanish educational system is, instead, more decentralised. The central government establishes the legal framework regulating the objectives and organisation of schools and sets the minimum core curricula content, while the autonomous communities manage their education systems within the national policy framework (OECD, 2018). Notwithstanding these differences, the educational performances of these two countries are very similar. In PISA 2012, the mean score in maths was 485 points (s.d. 93) in Italy and 484 (s.d. 88) in Spain; in PISA, 2018, mean scores were 487 (s.d. 94) and 481 (s.d. 88), respectively.

As shown in Table 1, in PISA 2012 educational achievement presented ample regional variations in both countries. In Italy the gap in mean regional mathematics scores between the highest and lowest performing regions was of 92 points, and of 55 points for mathematics scores adjusted for student's ESCS. In Spain, the gaps in mathematics scores were, respectively, of 89 and 43 points. It is worthy of note that in Spain, regional disparities in GDP per capita, as measured by the coefficient of variation, are slightly lower than in Italy.

The partial correlation between relative poverty rates and adjusted mathematics scores is plotted in Fig. 1 ($R^2 = 0.71$). From the graph we can note how in Italy the range of variation in relative poverty rates is larger than in Spain. In Sicily and Campania, two southern regions, the poverty rates were 29% and 27%, respectively; by contrast, in the province of Trento and in Friuli-Venetia-Giulia, as in other northern regions, poverty rates were about 5%. These notable differences in the shares of people in relative poverty corresponded to large differences in mean PISA scores. In Spain, the autonomous communities with the highest poverty rates were Andalusia and Extremadura (21%), while the lowest rates were recorded in Navarra (5%) and in the Basque Country (8.4%).

Table 2 reports the correlations among the variables used in the regressions for the sample of 35 regions. Unadjusted PISA scores are highly correlated with the ESCS index ($r = 0.51$), with relative poverty rates (−0.87) and with regional GDP per capita (0.71); mathematics scores adjusted for students' backgrounds are highly correlated with poverty rates (−0.84) and with GDP per capita (0.72) and, surprisingly, moderately with the average ESCS index (0.34). Adjusted mathematics scores are also moderately correlated with school educational resources (0.28) and with school infrastructures (0.36), and negatively with school autonomy over curriculum (−0.26). Importantly, poverty rates are negatively and highly correlated (−0.81) with GDP per capita.

The results of regressions for mathematics scores, adjusted for students' socioeconomic backgrounds, are presented in Table 3. Due to the

Table 1
Descriptive statistics for regional mathematics scores, mathematics scores adjusted for ESCS (PISA 2012) and GDP per capita (PPP) – Italy and Spain.

	Mathematics scores unadjusted		Mathematics scores adjusted		GDP per capita PPP	
	Italy	Spain	Italy	Spain	Italy	Spain
Min.	430	461	436	478	13,603	11,850
Max	524	517	525	521	24,852	20,989
Max-Min	94	55	89	43	11,249	9139
Max/min	1.22	1.12	1.20	1.09	1.83	1.77
St. dev.	26.3	17.4	24.9	13	3760	2825
CV	0.054	0.035	0.051	0.026	0.195	0.174

Note: 35 regions: 21 Italian and 14 Spanish. CV = coefficient of variation. Sources: Mathematics scores from PISA 2012; GDP per capita in PPP 2012 from OECD Regional database online (retrieved on 12.10.2019).

[2] In PISA surveys, the comparability of regional data is ensured by the oversampling of participating students (Fernandez-Cano, 2016; OECD, 2017b). In Italy, the sample of students participating in PISA, 2018 was representative of the 521,000 15-years-old students from all macro-regions (Invalsi, 2019b).

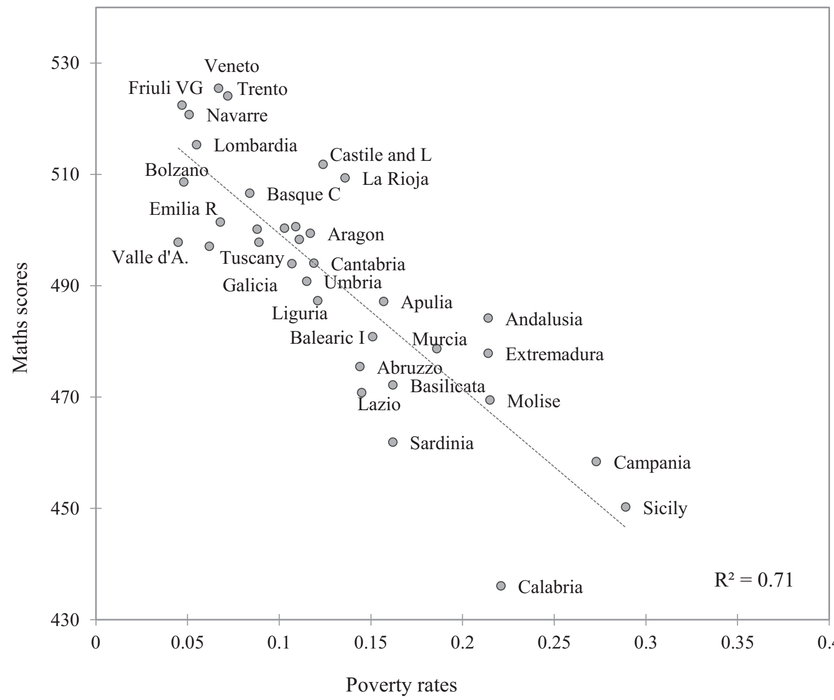

Fig. 1. Relative poverty and adjusted PISA 2012 mathematics scores in 21 Italian and 14 Spanish regions.

Table 2
Correlation coefficients among variables.

		1	2	3	4	5	6	7	8	9	10
1	Maths scores unadj.	1.00	0.98	0.51	−0.87	0.71	−0.05	0.28	0.36	−0.09	−0.26
2	Maths scores adjusted		1.00	0.34	−0.84	0.62	−0.14	0.34	0.42	−0.05	−0.35
3	ESCS index			1.00	−0.51	0.72	0.32	−0.16	−0.11	−0.22	0.26
4	Poverty rates				1.00	−0.81	−0.10	−0.19	−0.33	0.14	0.19
5	GDP per capita					1.00	0.44	0.22	0.06	−0.11	0.18
6	Teacher shortage						1.00	−0.20	−0.61	−0.20	0.83
7	Educ. resources							1.00	0.47	0.15	−0.35
8	School infrastructures								1.00	0.27	−0.69
9	Autonomy over resources									1.00	−0.11
10	Autonomy over curricula										1.00

Table 3
Regressions for mathematics scores adjusted for students' ESCS.

	(1)	(2)	(3)	(4)	(5)	(6)
Const.	719*** (5.82)	527*** (120)	525*** (119)	527*** (120)	530*** (91.8)	526*** (117)
Poverty rate	−330*** (−7.27)	−287*** (−8.73)	−268*** (−8.16)	−262*** (−7.66)	−283*** (−8.29)	−267*** (−8.19)
Ln GDP pc	−18.9 (−1.55)					
Teacher shortage		−9.07** (−2.61)				
Educational resources			15.8* (1.80)			
School infrastructures				11.7* (1.84)		
Autonomy over resources					5.68 (0.806)	
Autonomy over curricula						−9.42** (−2.35)
n	35	35	35	35	35	35
R^2	0.72	0.76	0.74	0.73	0.72	0.75

OLS - Heteroskedasticity-robust standard errors; t-statistics in parentheses.
[*] $p < 0.10$;
[**] $p < 0.05$;
[***] $p < 0.01$.

relatively low number of observations, control variables are included individually. In all specifications, poverty rates are negatively related to the dependent variable at the 1% level of significance, and the regressions explain 72%–76% of variance in mathematics scores. GDP per capita is not significant. Although poverty rates and GDP per capita are highly correlated, this result is not affected by collinearity, as indicated by the variance inflation factor that, for the specification in col. 1, has the value of 2.9.

As expected, the teacher shortage index is significantly and negatively related to lower mathematics scores ($p < 0.01$), while schools' resources and infrastructures are positively associated ($p < 0.05$). Finally, school autonomy over curriculum is negatively linked to mathematics scores, a result that contrasts with the positive association between these two variables that instead is found across OECD nations (OECD, 2013c: 51).

How does relative poverty affect average regional school achievement? A possible way is that higher poverty rates (or higher "inequality" levels) result in a higher share of low-performing students, that is performing below level 2 of proficiency, and, consequently, in lower mean regional achievements. In fact, as shown by Fig. 2, across Italian and Spanish regions, a strong positive relationship exists between relative poverty rates and the regional shares of low performing students ($r = 0.88$). In turn, the percentage of low-performing students is correlated −0.97 with mean scores in mathematics adjusted for students' socioeconomic backgrounds, measured by the ESCS index.

The regressions confirm how the poverty rate is a predictor of the share of low-performing students across Italian and Spanish regions, controlling for the average ESCS of students and the other variables (Table 4). In the diverse specifications, R^2 is substantially stable (0.74–0.78); GDP per capita is not significant, while, among the school-related factors, teacher shortages, poorer infrastructures and higher school autonomy over curricula are associated, on average, with higher shares of low-performing students. Overall, these findings are perfectly in line with the previous ones regarding test scores.

2.3. Results for 55 regions

In the sample of 55 regions, regional relative poverty rates are strongly and negatively correlated with unadjusted mathematics scores ($r = -0.71$) and with mathematics scores adjusted for students' socioeconomic backgrounds (−0.68), and positively with the percentage of low-performing students (0.72). These correlations are, however, influenced by the data from the Northern Territory of Australia (Fig. 3).[3] In fact, excluding this region from the sample, relative poverty rate is correlated −0.77 with adjusted mathematics scores, and 0.79 with the share of low-performing students.

In multiple regressions, with mathematics scores adjusted for students' ESCS as a dependent variable, the poverty rate is significant at the 1% level (Table 5). GDP per capita is not significant, while teacher shortages negatively and significantly affects students' mean results in mathematics. Schools' resources and infrastructures, and schools' autonomy over resource management, are positively related to the dependent variable at the 5% level of significance, while schools' autonomy over curricula is not significant. Adjusted R^2 values range between 0.48 and 0.50 depending on the specifications; excluding the data of the Northern Territory from the sample, R^2 would increase to 0.60–0.64.

Table 6 reports the results of regressions for the share of low-performing students. The relative poverty rate is positively and significantly related to the dependent variable ($p < 0.01$) in all the specifications. Even though the simple correlation between GDP per capita and the percentage of low-performing students is negative ($r = -0.38$), in the regressions that control for relative poverty and students' socioeconomic background, the coefficient of GDP per capita is positive. This result, that should be interpreted in the light of the previous one (Table 5), indicates that poverty rate and average students' background, more than average regional income, account for educational performances.

In this sample, regions with a higher teacher shortages, lower educational resources and poor school infrastructures have, on average, higher shares of low-performing students. This confirms the importance of qualified teachers and school resources for educational achievement, while higher school autonomy over curricula has a detrimental effect. Overall, these findings are in line with those obtained for the Italian and Spanish regions, notwithstanding the socioeconomic and cultural differences, as well as those in school systems across the countries and regions included in the sample.

2.4. Results for PISA 2018 mathematics scores

The PISA 2018 online database provides mathematics scores for only 4 Italian regions (the autonomous provinces of Trento and Bolzano, Sardinia and Tuscany), while there is no data for Australian regions. Data are available for 17 Spanish autonomous communities and for the cities of Ceuta and Melilla that, given their demographic sizes and locations, were excluded from the sample. The sample is thus composed of 33 regions (including 2 Belgian and 10 Canadian). There are, furthermore, no data for maths scores adjusted for students' ESCS or for the school-related variables previously considered. In the analysis, therefore, unadjusted mathematics scores are used, while the ESCS index is included as a control variable. Despite these limitations, the data allowed us to check the robustness of the link between poverty and achievement. In the sample of 21 regions (17 Spanish and 4 Italian), average scores in mathematics and relative poverty are very highly correlated ($r = -0.89$), while for the sample of 33 regions the correlation is −0.75.

Fig. 4 plots the partial correlation for unadjusted scores in mathematics and regional poverty rates for the Italian and Spanish regions, while Table 7 contains the results of the regressions that show how poverty rates are negatively and significantly related, at the 1% level, to average scores, controlling for mean students' ESCS both in the sample of 21 Italian and Spanish regions (coll. 1–2), and in the sample of 33 regions (coll. 3–5). Due to the limited number of observations, GDP per capita is included only in the full sample, even though this variable is not significant.

Finally, regression analysis is replicated by using the share of low-performing students as a dependent variable (Table 8). The results are perfectly consistent with previous ones.

3. Discussion

The present analysis shows how, across Italian and Spanish regions, and on a larger sample that includes Australian, Belgian and Canadian regions, relative poverty rates and mean PISA scores in mathematics are significantly and negatively related. This relationship is independent from students' socioeconomic and cultural backgrounds and from some school-related factors, and is found for PISA 2012 and 2018 scores. Even though relative poverty rates are negatively correlated with GDP per capita, the impact of poverty on mean scores in mathematics is also independent from regional development levels.

In the samples under examination, regions with higher poverty rates have a greater share of low-performing students, whose proficiency is below level 2 on the OECD scale, and, consequently, this results in lower mean PISA scores. The relationship between poverty rates and the share of low-performing students holds independently from students' familial backgrounds, as measured by the ESCS index, and it is robust to the inclusion of GDP per capita and school-related variables.

Overall, these findings are consistent with the literature that shows how educational performances are notably affected by socioeconomic

[3] The Northern Territory of Australia presents some peculiarities. This region has about 229,000 inhabitants: 25.5% are Aboriginals (including a small group of indigenous Torres Strait Islanders). In the PISA 2012 tests, the mean score in mathematics in the Northern Territory was of 452 score points, significantly lower than the Australian mean score (504 points). In Australia, the mean score in mathematics of Aboriginals was of 417 score points compared to the 507 score points of non-indigenous students. According to the OECD estimates, the relative poverty rate in the Northern Territory was just 7%, although, among the Aboriginal households, the poverty rate is 30%, and reaches 54% among those living in very remote communities, many of which are in the Northern Territory (Davidson, Saunders, Bradbury, & Wong, 2018); 48% of Aboriginal students participating in PISA 2012 were, in fact, classified in the lowest quartile of socioeconomic backgrounds, compared to 24% of non-indigenous students (Thomson, De Bortoli, & Buckley, 2013).

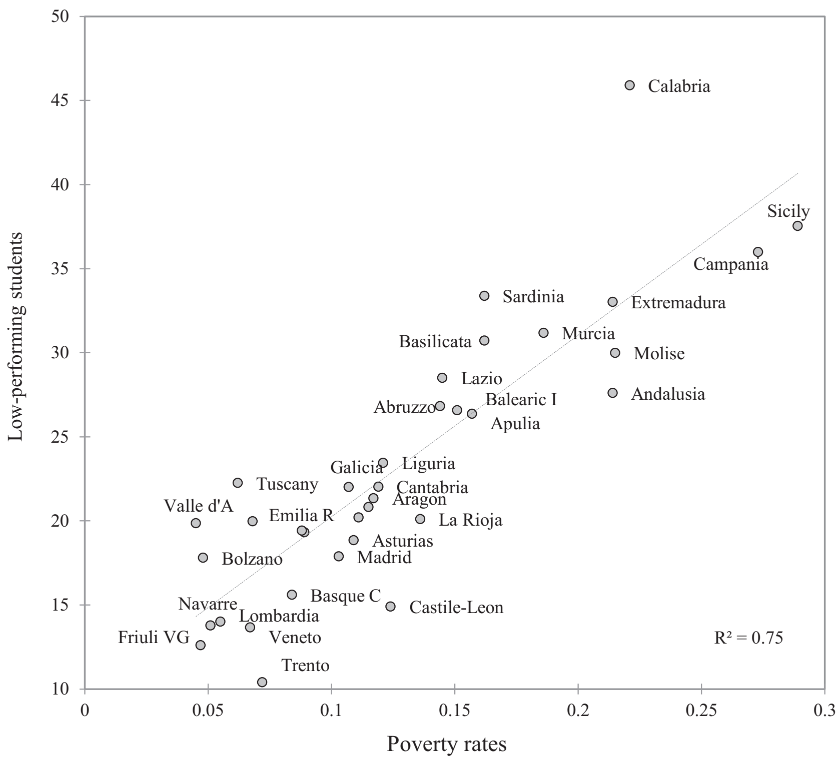

Fig. 2. Relative poverty rates and share of low-performing students in 21 Italian and 14 Spanish regions.

Table 4
Regressions for the share of low-performing students.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
const	9.65*** (6.32)	−43.3 (−0.745)	10.0*** (6.61)	10.3*** (6.19)	10.0*** (6.54)	8.60*** (3.97)	10.5*** (6.66)
Poverty rates	104*** (7.82)	114*** (6.89)	101*** (7.63)	98.6*** (6.97)	93.0*** (6.86)	104*** (7.88)	93.2*** (6.94)
ESCS index	−3.64 (−0.937)	−7.08 (−1.38)	−7.87* (−1.98)	−5.71 (−1.39)	−6.93 (−1.63)	−4.56 (−1.15)	−8.72* (−1.96)
Ln GDP pc		5.25 (0.908)					
Teacher shortage			3.35*** (2.78)				
Educational resources				−3.69 (−1.17)			
School infrastructures					−4.60* (−1.99)		
Autonomy over resources						−2.54 (−0.942)	
Autonomy over curricula							3.43** (2.17)
n	35	35	35	35	35	35	35
Adj. R^2	0.74	0.73	0.78	0.74	0.75	0.74	0.76

OLS - Heteroskedasticity-robust standard errors; t-statistics in parentheses;
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

and educational inequalities. This kind of inequality exerts its effects on individuals' educational outcomes in diverse and interrelated ways (Schmidt, Burroughs, Zoido, & Houang, 2015). The main one is the socioeconomic and cultural status of parents, which influences children's cognitive development, as measured by IQ tests (Von Stumm & Plomin, 2015) and by educational achievement tests (Willms, 2006).

Despite its relevance, the role of students' socioeconomic backgrounds in achievement, as measured by the ESCS index, should not, however, be overstated in interregional comparisons. In PISA 2012, students' backgrounds explained the 10% of variance in students' performances in mathematics tests in Italy and the 15.8% in Spain (OECD, 2013b: 36), while in PISA, 2018, the students' backgrounds explained the 9% variance in reading performance in Italy (OECD, 2019b: 17).[4]

Moreover, as previously noted, regional differences persist also when test scores are adjusted for the students' socioeconomic and cultural statuses. Consequently, the causes of regional differences in school test scores have to be sought outside students' immediate family backgrounds, that is considering the role of those environmental factors that affect learning, educational achievement and cognitive competencies.

It is well known how individual-students' performances depend not only on their families' SES, but also on the SES of their peers attending the same school (Perry & McConney, 2010). In particular, students from low SES families attending schools with a low mean SES, perform worse than they would have if they had attended schools with a higher mean SES, or with a heterogeneous composition (Willms, 2006: 63). There is, furthermore, a large literature showing how social contexts where children grow up, commencing with the neighbourhoods where they live, influence school achievements and other individual outcomes, including infant health and youth delinquency (Bradley & Corwyn, 2002; Chetty & Hendren, 2018; Dupéré, Leventhal, Crosnoe, & Dion,

[4] For an in-depth discussion of the role of the socioeconomic status on students' performance across countries, see OECD (2019b, 49-60).

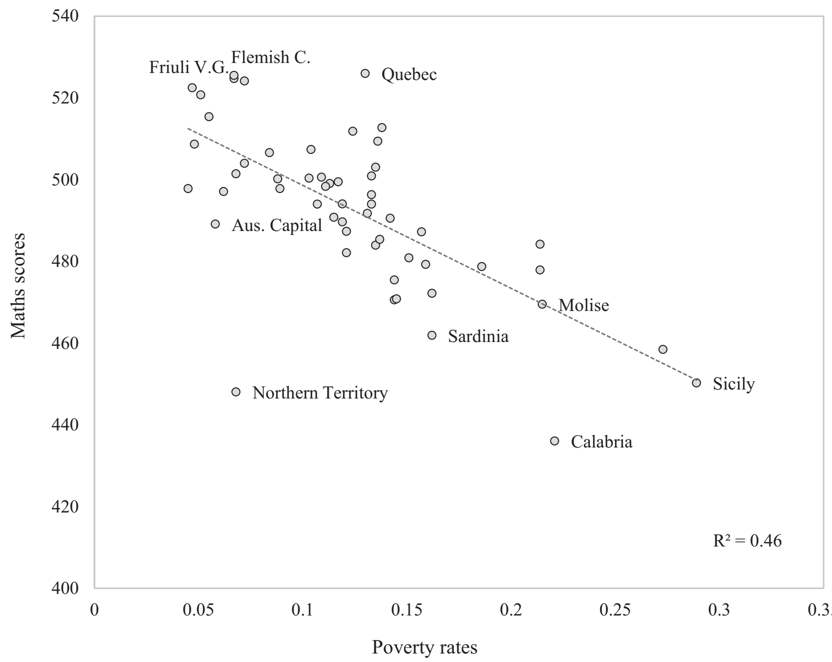

Fig. 3. Relative poverty and adjusted PISA 2012 mathematics scores across 55 regions.

Table 5
Regressions for mathematics scores adjusted for students' ESCS.

	(1)	(2)	(3)	(4)	(5)	(6)
const	697*** (6.57)	524*** (105)	520*** (88.9)	522*** (89.7)	529*** (92.0)	523*** (92.8)
Poverty rates	−306*** (−8.42)	−264*** (−8.00)	−240*** (−6.26)	−233*** (−5.85)	−256*** (−6.89)	−246*** (−6.60)
Ln GDP pc	−16.9 (−1.59)					
Teacher shortage		−11.7*** (−2.69)				
Educational resources			11.8** (2.40)			
School infrastructures				13.1** (2.22)		
Autonomy over resources					11.9** (2.31)	
Autonomy over curricula						−4.29 (−1.23)
n	55	55	55	55	55	55
Adj. R^2	0.50	0.55	0.50	0.50	0.49	0.48

OLS - Heteroskedasticity-robust standard errors; *t*-statistics in parentheses; *$p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

Table 6
Regressions for the share of low-performing students.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
const	11.7*** (6.43)	−112* (−1.99)	11.9*** (6.89)	12.2*** (6.25)	11.9*** (6.34)	10.3*** (5.42)	12.2*** (6.51)
Poverty rates	84.9*** (6.48)	112*** (8.43)	87.0*** (7.28)	83.6*** (6.22)	80.8*** (6.06)	85.5*** (6.59)	83.2*** (6.38)
ESCS index	−9.59*** (−3.93)	−17.4*** (−4.04)	−11.4*** (−4.96)	−8.67*** (−3.28)	−6.86*** (−3.19)	−9.92*** (−4.04)	−8.64*** (−3.78)
Ln GDP pc		12.3** (2.16)					
Teacher shortage			4.65*** (3.15)				
Educational resources				−2.50 (−1.47)			
School infrastructures					−5.58*** (−3.14)		
Autonomy over resources						−3.77** (−2.15)	
Autonomy over curricula							2.31** (2.09)
n	55	55	55	55	55	55	55
Adj. R^2	0.58	0.63	0.67	0.58	0.62	0.59	0.59

OLS - Heteroskedasticity-robust standard errors; t-statistics in parentheses;
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

2010; Leventhal & Dupéré, 2019; Nieuwenhuis & Hooimeijer, 2016).

Differences in educational outcomes between students from advantaged and disadvantaged neighbourhoods have multiple origins: within each neighbourhood, the SES of families, the involvement of parents in school activities, the educational opportunities offered to children, the quality of social relationships and that of the schools attended, produce

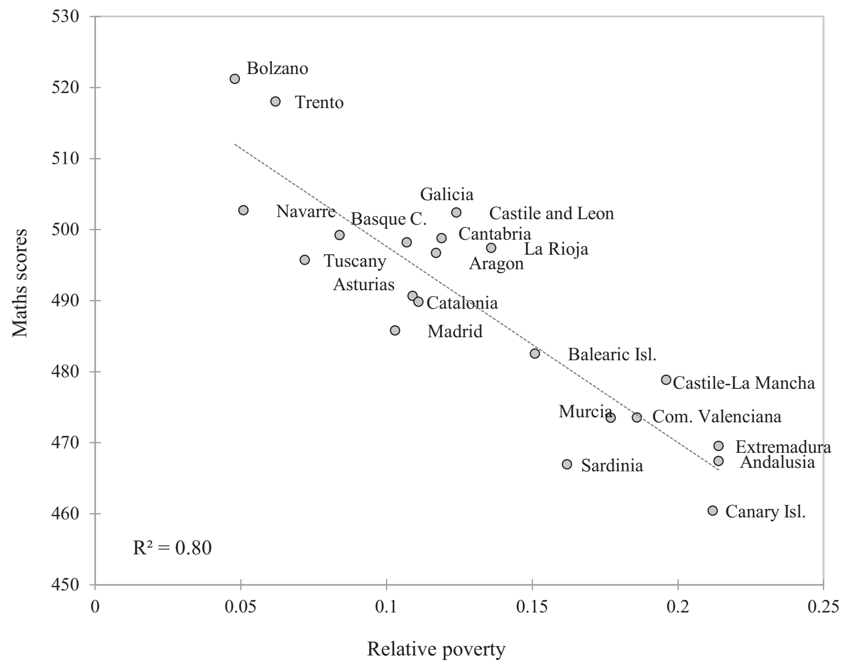

Fig. 4. Relative poverty rates and PISA 2018 mathematics scores in 4 Italian and 17 Spanish regions.

Table 7
Regressions for unadjusted mathematics scores.

	(1)	(2)	(3)	(4)	(5)
const	525***	526***	529***	523***	676**
	(110)	(94.4)	(122)	(94.4)	(2.73)
Poverty rates	−276***	−289***	−280***	−241***	−279***
	(−9.04)	(−5.84)	(−9.60)	(−5.83)	(−5.03)
ESCS index		−6.12		17.6*	24.0 (1.38)
		(−0.38)		(1.84)	
Ln GDP pc					−15.0
					(−0.60)
n	21	21	33	33	33
Adj. R^2	0.79	0.78	0.55	0.60	0.64

In columns 1–2, results for 4 Italian regions and 18 Spanish autonomous communities; in columns the sample includes a further 2 Belgian and 10 Canadian regions. OLS - t-statistics in parentheses;
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

Table 8
Regressions for the share of low-performing students.

	(1)	(2)	(3)	(4)	(5)
const	10.0***	10.1***	9.88***	11.3***	−32.8
	(6.65)	(5.88)	(7.75)	(6.83)	(−0.456)
Poverty rates	92.4***	91.7***	89.3***	78.5***	89.6***
	(9.35)	(6.02)	(9.81)	(6.49)	(5.33)
ESCS index		−0.343		−4.81*	−6.69
		(−0.063)		(−1.94)	(−1.37)
Ln GDP pc					4.35
					(0.606)
n	21	21	33	33	33
Adj. R^2	0.79	0.78	0.63	0.67	0.67

In columns 1–2, results for 4 Italian regions and 18 Spanish autonomous communities; in columns the sample includes a further 2 Belgian and 10 Canadian regions. OLS - t-statistics in parentheses; **$p < 0.05$;
* $p < 0.10$;
*** $p < 0.01$.

interrelated effects, difficult to disentangle, on cognitive development and on learning. Children who live in advantaged neighbourhoods not only benefit from the advantages that derive from their family backgrounds; they also have more educational opportunities, including child-care and pre-school services, and receive more educational *stimuli* than children from disadvantaged neighbourhoods (Bradley & Corwyn, 2002; Dupéré et al., 2010). In addition, in affluent neighbourhoods, the quality of schools is higher than in poor neighbourhoods and, for obvious reasons, students attending the same school generally come from high SES families; this peer-effect, in turn, produces a further positive effect on learning and on educational achievement (Dupéré et al., 2010).

As one may expect, the quality of teaching also tends to adapt to the levels of competence and knowledge that students have acquired in their previous years of schooling, and this exacerbates, over time, initial differences between advantaged and disadvantaged students. The cumulative advantage process, known as the “Matthew effect”, that results in a growing gap in achievements – and in cognitive abilities – between students over their school career, may occur at both the individual level and group levels (Rigney, 2010; Ceci & Papierno, 2005; Baumert, Nagy, & Lehmann, 2012), and was found between schools in different neighbourhoods in US cities (Kozol, 1991).

It can be argued that the multiple factors that determine inequality in achievement across neighbourhoods – and that, ultimately, reflect the degree of socioeconomic inequality within an urban community - also act, in a similar fashion, on a larger scale, that is within and across regions. The present analysis has shown, in fact, how the less developed regions have, on average, higher relative poverty rates, a higher share of low-performing students and, thus, lower mean test scores.

In the analysed samples, interregional differences in mean PISA scores are also explained by school-related factors: the shortage of qualified teachers, the availability of educational resources, and the quality of school infrastructures, all affect regional educational performances. A greater school autonomy over curricula is, instead, negatively related to mean scores in mathematics, and is associated with a higher share of low-performing students: a result consistent with other studies that indicate how school autonomy may increase inequality in educational opportunities (Marks, Cresswell, & Ainley, 2006; Van de Werfhorst & Mijs, 2010; Dumay & Dupriez, 2014).

Moreover, it is reasonable to argue that, analogously to what occurs at the neighbourhood level, in regions with a higher share of people living in relative poverty, and poor school resources, the quality of teaching is also comparatively lower. All in all, the relative poverty rate within each region, together with school-related factors, contributes to explain cross-regional differences in school achievement.

The use of relative poverty as an explanatory variable of regional differences in mean test scores deserves some consideration. As previously mentioned, being computed with respect to median income, relative poverty can be considered a measure of inequality in the bottom half of income distribution (Niemietz, 2011: 30). In this respect, it can be noted that differences in cognitive abilities and in educational achievements among students with different socioeconomic backgrounds can be found within countries with very different levels of economic development. In fact, children from families with higher SES outperform those from families with lower SES, both in wealthy countries and in poor countries. A socioeconomic gradient in children's cognitive development, increasing with age, was found, for example, in India, Indonesia, Madagascar, Peru and Senegal (Fernald et al., 2011; Fernald et al., 2012).

This paper's findings are in line with studies that show how, at the international level, greater inequality in income distribution (typically measured by the Gini index) is associated to lower achievements in standardized school tests such as PISA and TIMMS (Admson, 2010; OECD, 2015; Broer et al., 2019. In particular, cross-countries research indicates how increasing inequality and poverty tend to be associated with an increasing gap in school test scores between students from high-income and low-income families (the 'socioeconomic achievement gap'). Moreover, countries with less differentiated school systems and with standardized curricula have, on average, a lower socioeconomic achievement gap (Chmielewski & Reardon, 2016).

The strong negative relationship between relative poverty rates and mean test scores in mathematics across Italian and Spanish regions, and the fact that this relationship can be found across regions of other countries, has implications for the thesis according to which regional inequalities in school achievements in Italy and Spain are due to genetic differences in the populations' IQ (Lynn, 2010, 2012a; Piffer & Lynn, 2014). As mentioned, with reference to Italy, this thesis has already been criticized (Beraldo, 2010; Cornoldi et al., 2010, 2013; Felice & Giugliano, 2011; D'Amico et al., 2012; Daniele, 2015). In addition to the previous criticisms, further considerations can be made.

First, while it is established that genes, together with environmental factors, contribute to explaining the differences in educational achievement and cognitive abilities *among* individuals within a population (Asbury & Plomin, 2014; Kovas et al., 2013; Tucker-Drob, Briley, & Harden, 2013; Krapohl et al., 2014), there is no direct scientific evidence concerning differences *between* populations or races (Sternberg, Grigorenko, & Kidd, 2005; Hunt, 2012; Shawneequa & Bonham, 2015).

Second, as is known, the interaction between genes and environment (G × E) in a population is related to the degree of socioeconomic inequality. In contexts characterised by high inequality, heritability explains more variance in educational outcomes among people with high SES than among those with lower SES (Asbury & Plomin, 2014; Tucker-Drob & Bates, 2016; Selita & Kovas, 2019). Therefore, as inequality increases, differences in cognitive abilities and educational achievement among individuals are explained less by genetic factors and more by environmental ones (Colodro-Conde et al., 2015; Selita & Kovas, 2019).

This implies that estimates of heritability in IQ differences between groups or populations could, possibly, be obtained under identical environmental conditions: but these conditions vary between groups with different socioeconomic status and, obviously, even more so between countries. Thus, in principle, IQ differences between groups and populations could be entirely due to environmental factors (Dickens & Flynn, 2001; Hunt, 2012).

Even more, it is entirely plausible that differences in educational achievements between regions can be explained by those environmental factors that affect learning and students' performances, and that the role of these factors is as great as the degree of inequality in environmental conditions is wider. Since in Italy and Spain, as in other countries, regional socio-economic contexts are heterogeneous, the explanation according to which regional differentials in average school test scores depend on any genetic differences between populations is purely conjectural.

In the perspective of the thesis of racial differences in intelligence, it could be argued that the mean intelligence of populations is a main determinant of poverty rates, as well as of the socioeconomic development of nations and regions (Lynn, 2010, 2012a, 2012b; (Lynn, & Vanhanen, 2006). If so, poverty could be considered as a mediating variable of the relationship between IQ and scholastic results. Effectively, at the country or regional levels, mean IQ test scores are negatively correlated with absolute and relative poverty rates, and positively with average income (Lynn, Fuerst, & Kirkegaard, 2018, for a review). However, while correlations do not establish a causal nexus running from a population's IQ to poverty rates, there is sound evidence that socioeconomic and educational poverty negatively affects children' cognitive abilities and educational outcomes (Alivernini, Manganelli, & Lucidi, 2016; Ferguson, Bovaird, & Mueller, 2007; Reardon, 2011; Tine, 2014).

The effect of environment on populations' mean IQs is shown by the Flynn effect, documented for many nations and regions (Flynn, 2012, 2020; Pietschnig & Voracek, 2015). Notably, IQ gains are larger in the first phase of countries' social and economic modernization, when socioeconomic and educational conditions improve faster, and gradually decrease as countries develop (Bratsberg & Rogeberg, 2018; Flynn, 2012). As well exemplified by the case of East Germany after reunification, socioeconomic development and improvement in education may have a powerful effect on mean IQ. Over the period 1992–1998, the mean IQ of the conscripts of the former East Germany increased by 0.66 points per year, almost closing the initial gap of 5 IQ points with West Germany (Roivainen, 2012).

In conclusion, this paper shows how at the regional level, analogously to what occurs on smaller territorial scales, such as between neighbourhoods or urban and rural areas, there is a socioeconomic gradient in mean educational achievements. Within each region, the incidence of relative poverty captures the effects of multiple and interrelated factors on students' educational performances. Summing up, it could be said that inequalities in academic achievement are an aspect of socioeconomic inequalities among individuals and geographical areas.

Regional disparities in school achievements have relevant implications for educational and social policies: they reflect, in fact, inequality in social conditions and/or in the effectiveness of school systems and, in turn, represent a channel of reproduction of social inequality (Croizet, Autin, Goudeau, Marot, & Millet, 2019; Van de Werfhorst & Mijs, 2010). Furthermore, since human capital is a key factor for economic growth (Castelló & Doménech, 2002), large disparities in education may influence regional economic development prospects.

In countries in which regional disparities in achievements are large, the improvement of national educational performances can hardly be pursued by intervening on factors such as educational curricula or school organisation, homogeneous to the entire nation. Rather, it would require policies expressly devoted to the regions with low performances. Furthermore, public policies should not intervene only with regard to school-related factors, such as providing adequate numbers of qualified teachers and material resources, but also address those economic and social causes that result in differences in educational outcomes between regions.

Finally, a question regarding the measurement of educational performances. On the basis of the overwhelming evidence showing how socioeconomic factors affect educational achievements, one may wonder what school tests, such as PISA, really measure. That is, whether these tests do really measure the quality of schools or do they, instead, reflect the degree of inequality between individuals, social classes, and territories.

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