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Abstract

We explore the cognitive skill gap between the adult population in Spain and in the rest of European Union countries using the Programme for the International Assessment of Adult Competencies. We find that differences in schooling account for about a third of the average difference in cognitive test scores, whereas differences in socio-economic background explain about one fourth of the average score gap. While cognitive skill gaps are increasing along the distribution of test scores, differences in educational stocks and socio-economic factors explain a larger fraction of the gap at the bottom than at the top of the skill distribution.

Keywords: human capital, cognitive skills, PIAAC, Oaxaca-Blinder decomposition.

JEL classification: J24, J10.

Resumen

Utilizando datos del Programa de Evaluación de Competencias de Adultos (PIAAC, por sus siglas en inglés) de la Organización para la Cooperación y el Desarrollo Económicos, analizamos la brecha en habilidades cognitivas de la población adulta en España con respecto al resto de los países de la Unión Europea. Encontramos que la menor escolarización y el peor contexto socioeconómico de la población española explican, en promedio, respectivamente, un tercio y un cuarto del diferencial en las puntuaciones. La brecha española en las habilidades cognitivas aumenta a lo largo de la distribución de la puntuación PIAAC. Sin embargo, la escolarización y los factores socioeconómicos explican una proporción más grande de esa brecha en la parte baja que en la parte alta de la distribución de habilidades.

Palabras clave: capital humano, habilidades cognitivas, PIAAC, descomposición Oaxaca-Blinder.

Códigos JEL: J24, J10.

1. INTRODUCTION

Human capital is often regarded as one of the main determinants of the productivity and economic growth of a country. Classical growth theory suggests that higher human capital levels can foster economic growth by increasing the productivity of the labor force (Mankiw et al. 1992), by facilitating the development of new technologies (Romer 1990) or the diffusion of existing ones (Benhabib and Spiegel 2005). Empirically, an extensive number of studies have found that differences in human capital levels across countries explain a substantial fraction of cross-country differences in economic growth (Hanushek and Woessmann 2008), income (Manuelli and Seshadri 2014) and wage growth (Lagakos et al. 2018a, 2018b).

In this paper, we take the relationship between human capital and growth as a motivating fact, and analyze to what extent differences in human capital across countries are related to cross-country differences in the socio-economic characteristics of the population. Because human capital is often regarded as a latent, possibly multidimensional, object, a central issue in the literature concerns its definition and measurement. This is especially important in cross-country studies like ours, which rely on the existence of comparable measures of human capital across countries. In this respect, international standardized examinations are usually thought to provide a better measure of human capital than previously used proxies which only took into account some quantitative measure of schooling (e.g., years of schooling or enrolment rates). Compared to the latter, international test scores capture skills acquired outside school, embed not only the quantity but also the quality of the education system, and allow to exploit cross-country variation in skills at each level of education (Hanushek and Woessmann 2008; Hanushek et al. 2015).

In our paper, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC), which provides comparable measures of cognitive skills, measured by means of numeracy and literacy tests, of the adult population across 24 countries. As a starting point for our analysis, we document the gap in cognitive skills of the adult population in Spain, a developed country performing at the bottom of the PIAAC rankings, vis-à-vis an aggregate group of other European Union (EU) countries assessed in PIAAC. Our main objective is to assess to what extent such differences in cognitive test scores can be explained by differences in the stock of education, socio-economic background (as proxied by the level of education of the parents) and the demographic structure (age and immigrant status) of the adult population in Spain with respect to the adult population of other EU countries.

Spain represents an interesting case study for several reasons. First, cognitive skill gaps are particularly pronounced: compared to other EU countries, Spain scores on average 0.36 standard deviations less in the PIAAC numeracy module and 0.34 standard deviations less in literacy. Second, compared to other advanced economies, the Spanish population is characterized by lower educational levels (OECD 2019a) and a high persistence of low human capital stocks across generations (Petrongolo and San Segundo 2002), both of which are important factors in the accumulation of human capital. Third, the productivity growth in Spain is one of the lowest relative to other OECD countries (Cuadrado et al. 2020), and the empirical evidence for Spain from a macroeconomic perspective shows that human capital is positively related to income per capita and labour productivity (Doménech 2008). Fourth, returns to cognitive skills in Spain are among the highest of OECD countries (Hanushek et al. 2015). All these reasons together imply that compositional differences in the education and socio-economic background of the population might explain a substantial fraction of the cognitive skill gaps of Spanish adults, and that such compositional effects might have important implications for wage and productivity growth both at the micro and at the macro level.

In order to study to what extent differences in cognitive test scores can be accounted for by differences in observable characteristics, we carry out counterfactual exercises based on several decomposition methods (Oaxaca 1973; Blinder 1973; Chernozhukov et al. 2013; Firpo et al. 2009). These allow to quantify, both at the average and throughout the distribution of test scores, the contribution of differences in education stocks, socio-economic background and demographics in explaining the Spanish cognitive skill gaps with respect to other EU countries. We document three main facts. First, compositional effects explain more than half of the average Spanish cognitive skill gaps in the numeracy and literacy tests. Second, about 34% of the average gap is accounted for by differences in the stock of education of the Spanish population, and 23% by differences in the level of education of the parents. Third, compositional effects are significantly larger at the bottom of the test score distribution: differences in characteristics explain more than 70% of the performance gap at the lower percentiles, whereas at higher percentiles they account for about 40%.

We also present some results investigating the heterogeneity in the compositional effects for different demographic groups. We document three findings. First, composition effects are larger for men than for women, a result which is related to the comparatively larger education gap of Spanish males with respect to other EU countries. This difference is particularly relevant for males at the lower percentiles of the distribution of test scores, as differences in educational levels and socio-demographic factors account for the entire performance gap with respect to males in the rest of the EU. Second, cognitive skill gaps are significantly larger for older cohorts (55-65 years old), and the importance of compositional differences in educational levels and socio-economic background varies substantially across cohorts. In particular, for younger cohorts the contribution of differences in educational levels to the cognitive skill gap is lower than for older cohorts, whereas differences in socio-economic background have a comparatively larger weight. Third, the cognitive skill gap of immigrants (defined as those individuals born in a foreign country) is positive, but significantly smaller than the gap for natives. Interestingly, when we control for our set of education, socio-economic and demographic variables, the cognitive skill gap of immigrants disappears, and particularly so at the lowest percentiles of the distribution of cognitive test scores. This might suggest the existence of differences in the selection patterns of migrants across countries, with relatively more educated immigrants being less likely to migrate to Spain than to other EU countries.

Our paper is mainly related to the literature studying the determinants of cross-country differences in cognitive skill levels. This includes studies that relate the size of the differences in students' achievements to the quality of teachers (Hanushek et al. 2018); to institutional factors such as the degree of school autonomy (Hanushek et al. 2013), instruction time (Lavy 2015; Rivkin and Schiman 2015) or class size (Woessmann and West 2006); or to differences in socioeconomic factors (Schütz et al. 2008; Guiso et al. 2008; Bedard and Dhuey 2006; Ammermueller and Pischke 2009; Fryer and Levitt 2010; Dustmann et al. 2012).[1] In this literature, decomposition methods have been used in order to explore how family-background could explain performance differences in international standardized examinations across countries. For example, McEwan and Marshall (2004) use a Oaxaca-Blinder decomposition in order to explain why primary school students in Cuba score higher than students in Mexico. Their findings suggest that more than 30% of the difference can be explained by differences in family characteristics, peer groups and school variables. Ammermüller (2007) analyses the difference in student reading performance between Germany and Finland. His results show that German students have a more favorable background, but their returns to these background characteristics are lower than for Finnish students.

These studies mainly used measures of cognitive skills from international assessments of primary and secondary school students. By contrast, studies exploiting the existence of cross-country differences in the cognitive skills of the adult population have mainly focused on the consequences of such differences for labor market-related outcomes (Denny et al. 2004; Leuven et al. 2004; Blau and Khan 2005; Hanushek and Zhang 2009; Hanushek et al. 2015), inequality (Brocke et al. 2017) or productivity growth (Hidalgo-Cabrillana et al. 2017). In contrast, relatively little attention has been paid to the relationship between cross-country differences in cognitive skills of adults and differences in socio-economic factors across countries. In our paper, we contribute to this literature by using PIAAC data in order to assess to what extent composition effects related to differences across countries in socioeconomic backgrounds and educational attainments can explain the differences in the cognitive skills of the Spanish population.

2. DATA AND STYLIZED FACTS

2.1. Data and sample selection

The Programme for the International Assessment of Adult Competencies (PIAAC) provides internationally comparable data about the cognitive skills of the adult population (16 to 65 years)

[1] Hanushek and Woessmann (2011) and Woessmann (2016) provide extensive reviews of this literature.

in 24 participating countries: Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Slovak Republic, Spain, Sweden, Russian Federation, United Kingdom, and the United States. The PIAAC design was developed by the OECD, and data were collected between August 2011 and March 2012. Cognitive skills are assessed through standardized tests in two main domains: numeracy and literacy.[2]

Individuals were examined through a computer-based assessment, although respondents with low familiarity with the use of a computer were instead given a paper-based version of the literacy and numeracy tests.[3] One characteristic of the computer-based test is the use of a multistage adaptive algorithm in which subsequent clusters of test items depend on the respondent's score on previous clusters of items. This adaptive procedure has the advantage of tailoring the test difficulty to the test taker's performance, thus allowing to acquire more information about the respondent's proficiency in a given domain. The final score on each domain is measured on a 500-point scale.[4]

In addition to the skills assessment, PIAAC also gathers information about respondents' demographic characteristics, socio-economic background, level of education and labor market status. This information was collected through a background questionnaire administered by an interviewer before taking the test. A country-specific stratified sampling design was used in order to obtain a representative sample of the adult population in each country. The number of strata varies across countries, with larger countries typically having more strata than smaller countries (see OECD 2013; OECD 2019b for further details).

In order to compare the cognitive skills of the adult population in Spain with those of other advanced economies, we rank countries participating in the PIAAC test based on their average numeracy and literacy scores (Figure 1). Spain is located at the bottom of both rankings, obtaining 23 points less in numeracy and 20 points less in literacy as compared to the average of the OECD countries examined in PIAAC. The poor performance of Spanish adults occurs throughout the entire distribution of test scores. When ranking countries according to different percentiles of the test score distribution, Spain is consistently at the bottom of the ranking for most percentiles and for both modules (see Figure A1 and A2 in the Appendix).

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[2] A third, optional, domain aimed to assess problem-solving skills, but, as some countries (i.e., Cyprus, France, Italy and Spain) did not administer the corresponding module, we do not consider it in the following analysis.

[3] On average, about 78% of respondents took the computer-based test and 22% the paper-based test. A field test, conducted prior to the data collection, suggests that the mode of assessment had no impact on respondent's performance on the test. Moreover, after controlling for several socio-economic characteristics, there is no evidence that the test scores of respondents who took the paper-based assessment differ systematically from those of respondents who took the computer-based assessment (OECD 2013).

[4] In PIAAC, skills are a latent variable that is estimated using item-response-theory models (see OECD 2013 for details). PIAAC provides 10 plausible values, instead of only one individual score, for each respondent and each skill domain. Throughout our empirical analysis, we use estimation techniques using the 10 plausible values in order to get unbiased estimates of the statistics of interest.

Figure 1. Ranking of countries by average PIAAC score

We quantify the Spanish cognitive skill gap, and the size of the compositional effects, with respect to a reference group including all the other EU countries assessed in PIAAC.[5] Our choice rests on two main reasons. First, we believe that defining a benchmark group that includes several countries provides a more robust way to assess cognitive skill gaps adjusted for compositional effects than comparing Spain vis-à-vis only one single country, as results would be less prone to compositional differences which might exist only with respect to that country. Second, in order to work with a more homogenous benchmark group, we selected only countries from the EU as they arguably have a more similar institutional framework among each other than other countries assessed in PIAAC, such as Japan or the US. Based on this criterion, our sample includes 96,493 test takers, of which 5,775 in Spain and 90,718 in other EU countries.

In Table 1, we present summary statistics for the PIAAC scores of the adult population in Spain and in our reference group and for several socio-economic factors: education stocks, as measured by the number of attained years of schooling;[6] socio-economic background, which we proxy with the attained education level of the parents; and differences in the demographic structure of the population with respect to age and immigration status. The average cognitive skill gap of Spain with respect to the group of EU countries is slightly higher in numeracy (19 points) than in literacy (16 points). Adults in the group of EU countries have, on average, 1 more year of schooling. This

[5] This group includes the following 16 countries: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, and United Kingdom.
[6] In PIAAC, the number of years of schooling is associated with the highest level of education attained. All reported national categories in the achieved level of education are converted into the nominal years of schooling needed to achieve that particular level of education (see OECD 2019b for more details).

Table 1. Descriptive statistics

	EU countries		Spain		Difference	
Variables	Mean	SD	Mean	SD	Mean	SE
Numeracy score	265.98	52.65	246.84	50.82	19.13***	0.724
Literacy score	268.96	47.56	252.52	48.70	16.45***	0.776
Years of schooling	12.35	3.28	11.35	3.54	1.00***	0.028
Level of education						
Lower secondary and less	0.25	0.43	0.47	0.50	-0.21***	0.002
Upper secondary	0.47	0.50	0.24	0.42	0.23***	0.003
Tertiary	0.28	0.45	0.30	0.46	-0.02***	0.002
Female	0.50	0.50	0.50	0.50	0.00	0.002
Immigrant	0.11	0.31	0.13	0.34	-0.02***	0.002
Age						
15-24 years	0.17	0.37	0.12	0.32	0.05***	0.002
25-34 years	0.20	0.40	0.21	0.41	-0.02***	0.004
35-44 years	0.22	0.41	0.25	0.43	-0.03***	0.003
45-54 years	0.22	0.41	0.22	0.41	-0.00	0.003
55-65 years	0.21	0.40	0.20	0.40	0.01***	0.002
Parental education						
Lower secondary or less	0.36	0.48	0.72	0.45	-0.36***	0.007
Upper secondary	0.43	0.49	0.15	0.36	0.28***	0.006
Tertiary	0.22	0.41	0.13	0.34	0.09***	0.005
No. of observations	90,718		5,775			

Notes. EU countries include: Austria. Belgium. Cyprus. Czech Republic. Denmark. Estonia. Finland. France. Germany. Ireland. Italy. Netherlands. Poland. Slovak Republic. Sweden. United Kingdom. SD = standard deviation. SE = standard error.

gap in schooling levels is even more apparent when we look at the differences in the proportion of individuals with a given attained level of education: whereas the proportion of individuals with tertiary education is only 2 percentage points lower in Spain, in other EU countries the proportion of individuals attaining at most lower secondary education is only 25% as compared to 47% in Spain.

Differences in educational attainments are even more striking if we look at the level of education of the parents. We measure parental education as the highest of father or mother's level of education and define three indicators corresponding to the following options: (i) Both parents attained at most lower secondary education; (ii) At least one parent attained upper secondary education; (iii) At least one parent attained tertiary education.[7] We observe that the percentage of individuals whose parents have not attained upper secondary education is 72% in Spain while in

[7] We cannot convert these categorical variables for parental education into attained years of schooling because the years of schooling required to complete a given education level in a country might change over time (e.g., because of a reform of the education system in the country) and we do not observe demographic characteristics of the parents (e.g., age, year of completion of the highest level of schooling) which could be used to construct reasonable conversion factors.

2.2. Cognitive skill gaps

In order to get a more detailed picture about human capital differences in Spain vis-à-vis other EU countries, in Table 2 we analyze the cognitive skill gaps in numeracy and literacy for different groups of individuals.

Both in EU countries and in Spain, males score significantly higher than females in numeracy, whereas within-country gender differences in test scores are much smaller for literacy. This fact is consistent with previous studies with PISA data showing that male students tend to outperform female students in math and science (Guiso et al. 2008; Fryer and Levitt 2010), a finding that some recent literature links to the existence of gender stereotypes (Carlana 2019). Nevertheless, across countries cognitive skill gaps are similar for males and females: in numeracy, the gap for males is one point lower than the gap for females, while in literacy males in Spain score about four points less than females in relation to their counterparts in other EU countries.

Table 2. Numeracy and literacy scores by individual characteristics

	Numeracy				Literacy			
	EU countries	Spain	Diff.	SE	EU countries	Spain	Diff.	SE
Gender								
Male	272.0	253.3	18.7***	1.073	269.6	254.9	14.7***	1.055
Female	260.0	240.3	19.6***	1.154	268.3	250.1	18.3***	1.203
Nationality								
Native	269.4	249.6	19.9***	0.662	272.1	255.4	16.7***	0.732
Immigrant	237.8	229.0	8.7***	3.016	243.0	233.7	9.3***	2.873
Age								
15-24 years	270.1	256.1	14.0***	2.007	277.7	264.7	13.0***	1.715
25-34 years	277.3	258.0	19.3***	1.492	280.6	263.3	17.3***	1.562
35-44 years	271.5	255.9	15.5***	1.502	273.2	260.4	12.8***	1.593
45-54 years	262.5	243.5	18.9***	1.837	264.0	249.2	14.8***	1.672
55-65 years	249.8	221.6	28.2***	1.865	251.5	227.5	24.0***	2.054
Level of education								
Lower secondary and less	233.8	221.5	12.3***	1.414	241.8	228.8	13.0***	1.448
Upper secondary	265.7	257.7	8.0***	1.357	267.9	261.9	6.0***	1.238
Tertiary	296.0	278.2	17.7***	1.167	295.7	282.5	13.2***	1.190
Parental education								
Lower secondary or less	243.5	238.1	5.3***	1.034	248.4	243.9	4.4***	1.102
Upper secondary	271.5	261.2	10.3***	1.575	273.8	267.6	6.2***	1.610
Tertiary	292.4	278.4	14.0***	1.875	293.6	282.6	11.0***	1.853
Total	266.0	246.8	19.1***	0.724	269.0	252.5	16.4***	0.776

Notes. EU countries include: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom.

Immigrants, which are defined as individuals born in a foreign country, obtain on average lower test scores than natives both in Spain and in other EU countries.[8] We observe positive cognitive

[8] Because our definition of immigrants includes only individuals born in a foreign country, second generation of immigrants are included in the native group. Second generation of immigrants account for about 3% of the adult population in EU countries, and less than 1% in Spain.

skill gaps between immigrants in Spain and those in other EU countries, which might be related to different patterns of selection into migration across countries. Nevertheless, the cognitive skill gaps of immigrants are between 45% and 55% lower than those of natives in both PIAAC modules.

The within-country cognitive skill profiles by age groups are also very similar for Spain and our reference group: in both countries, adults who are 25-34 years old obtain the largest scores in both numeracy and literacy and, consistently with other studies highlighting the depreciation of human capital past age 34 (Anghel and Lacuesta 2020), cognitive skills decline as individuals get older. Looking at differences across countries, the Spanish cognitive skill gaps in both numeracy and literacy are particularly large among the 55-65 years old (28 points and 24 points respectively).

As for the attained education level, not surprisingly average test scores are increasing in the level of education in both countries. However, compared with their respective counterparts in EU countries, more educated adults in Spain perform comparatively worse in numeracy than less educated individuals: the gap is about 30% higher for adults with tertiary education than for those with at most lower secondary education. Cognitive skill gaps are also increasing with the level of education of the parents: adults whose parents attained tertiary education obtain 14 points less in numeracy and 11 points less in literacy with respect to adults with similar socio-economic background in EU countries; by contrast, these differences are between 4 and 5 points for adults whose parents have not obtained upper secondary education.[9]

3. EMPIRICAL STRATEGY AND MAIN RESULTS

In order to assess to what extent the cognitive skill gaps documented in the previous section are related to differences in observable characteristics between the adult population in Spain and in other EU countries, we carry out several decomposition exercises. As a first step, we estimate Oaxaca-Blinder decompositions, which allow to quantify the contribution of different observed characteristics to the cognitive skill gap at the mean (Section 3.1). This method has been frequently used in the education literature to explain cognitive skill gaps both across (McEwan and Marshall, 2004; Ammermüller, 2007) and within countries (e.g., Martins and Veiga, 2010; Baird, 2011; Lounkaew, 2013). Next, in Section 3.2 we compute analogous decompositions over the entire distribution of test scores following the work of Chernozhukov et al. (2013) and Fortin et al. (2011). Finally, in Section 3.3 we present some results about the heterogeneity of the compositional effects for different groups of individuals.

3.1. Oaxaca-Blinder decomposition

In this section, we present the results of the Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973). The starting point of our analysis is the estimation of the following regressions:

[9] Note that, when we condition on the education levels, the average conditional gaps in Table 2 are lower than the average unconditional gaps for all three education groups. Obviously, this is due to the different distribution of educational attainments between Spain and the group of other EU countries (see Table 1).

$$score_{ic} = \beta_c x_{ic} + v, \;\; c \in \{EU, S\}. \tag{1}$$

In our preferred specification, x_{ic} is a vector including a constant and the following explanatory variables: years of schooling; a gender dummy; age dummies corresponding to the 15-24, 25-34, 45-54, 55-65 age groups; a dummy for the individual being foreign born; and parental education dummies corresponding to parents having attained at most lower secondary or having attained upper secondary education. We estimate this regression separately for the EU countries (EU) and for Spain (S), and we denote with $\hat{\beta}_{EU}$ and $\hat{\beta}_S$ the estimated parameters for the EU group and Spain, respectively.

Next, the average score difference can be decomposed as follows:

$$\overline{score}_{EU} - \overline{score}_S = (\bar{X}_{EU} - \bar{X}_S)\hat{\beta}_S + (\hat{\beta}_{EU} - \hat{\beta}_S)\bar{X}_{EU}. \tag{2}$$

The first term on the right-hand side shows the component of the cognitive skill gap which is accounted for by differences in observed characteristics, where $\bar{X}_{EU}$ and $\bar{X}_S$ are vectors of the average characteristics of individuals in the EU group and Spain, respectively. The second term is an unexplained component which is given by differences in “returns” to observed characteristics.

The results of the Oaxaca-Blinder decomposition are reported in Table 3. Columns 1 and 2 focus on the numeracy test while columns 5 and 6 on the literacy test. The decomposition analysis is remarkably similar for both PIAAC modules in that more than 60% of the gap in performance between the EU group of countries and Spain could be explained by differences in characteristics. In particular, differences in educational attainments contribute the most, as they account for about 34% of the cognitive skill gap. Differences in the level of education of the parents are also very relevant, explaining about 23% of the cognitive skill gap. Finally, other socio-demographic variables (gender, nationality and age) explain altogether a much smaller proportion, between 5% and 8%. Overall, the results of this counterfactual exercise suggest that, if the Spanish adult population had the same educational level, socio-economic background and demographic structure of the adult population in other EU countries, the average cognitive skill gaps would be 62% lower than the actual one.

Table A1 in the Appendix shows a detailed decomposition of the unexplained component. The negative estimates associated with schooling and socio-economic background suggests that returns to these characteristics are more favorable in Spain than in other EU countries. In other words, the process through which one extra year of schooling or better parental education are transformed into higher human capital is relatively more efficient in Spain, on average. Instead, the larger constant in other EU countries as compared to Spain is suggestive that other unobserved factors, which could be related to institutional differences or to the quality of the education system, are likely important to explain the residual part of the cognitive skill gaps which is not accounted for by differences in socio-economic backgrounds and educational attainments.

Table 3. Oaxaca-Blinder decomposition

	Numeracy				Literacy			
	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive skill gap	19.134		19.584		16.445		16.811	
Explained	11.772***	61.52%	12.217***	62.38%	10.359***	62.99%	10.098***	60.07%
	(0.345)		(0.453)		(0.316)		(0.417)	
Years of schooling	6.513***	34.04%	6.969***	35.58%	5.527***	33.61%	5.921***	35.22%
	(0.197)		(0.222)		(0.172)		(0.192)	
Female	-0.023	-0.12%	-0.088***	-0.45%	-0.002	-0.01%	0.004	0.02%
	(0.019)		(0.027)		(0.002)		(0.005)	
Immigrant	0.698***	3.65%	0.677***	3.45%	0.648***	3.94%	0.632***	3.76%
	(0.072)		(0.089)		(0.065)		(0.082)	
Age								
15-24 years	0.177***	0.92%	0.176***	0.90%	0.407***	2.47%	0.236***	1.40%
	(0.048)		(0.045)		(0.042)		(0.048)	
25-34 years	0.009	0.92%	-0.066**	-0.34%	-0.030**	2.47%	-0.077***	-0.46%
	(0.013)		(0.026)		(0.014)		(0.027)	
45-54 years	0.020	0.10%	-0.025	-0.13%	0.024	0.14%	-0.022	-0.13%
	(0.015)		(0.032)		(0.018)		(0.028)	
55-65 years	-0.064***	-0.33%	-0.323***	-1.65%	-0.075***	-0.46%	-0.295***	-1.76%
	(0.024)		(0.053)		(0.029)		(0.049)	
Parental education								
Lower secondary or less	8.242***	43.07%	6.717***	34.30%	7.497***	45.58%	6.043***	35.95%
	(0.368)		(0.393)		(0.362)		(0.395)	
Upper secondary	-3.799***	-19.86%	-3.373***	-17.22%	-3.636***	-22.11%	-3.125***	-18.59%
	(0.231)		(0.261)		(0.219)		(0.245)	
Labor market characteristics								
Experience			0.666***	3.40%			0.286***	1.70%
			(0.095)				(0.079)	
Employed			0.464***	2.37%			0.187**	1.11%
			(0.098)				(0.079)	
On the job training			0.073**	0.37%			0.079**	0.47%
			(0.036)				(0.038)	
Open/distance education			-0.175*	-0.89%			-0.298***	-1.77%
			(0.105)				(0.092)	
Seminars or workshops			0.492***	2.51%			0.501***	2.98%
			(0.069)				(0.068)	
Private lessons			0.033	0.17%			0.028	0.16%
			(0.035)				(0.029)	
Unexplained	7.362***	38.48%	7.368***	37.62%	6.087***	37.01%	6.712***	39.93%
	(0.709)		(0.796)		(0.795)		(0.901)	
No. of observations	96,493		80,516		96,493		80,516	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Standard errors, computed using the jacknife replication method, are reported in parentheses.

Robustness and alternative specifications. As it is well-known, the decomposition in equation (2) is not unique as one could write an alternative decomposition in which the difference in observed characteristics is evaluated using the estimated coefficient for the EU countries, and Spain is the reference group to assess the contribution of the differences in the "returns" of the observed characteristics. We report the results of this alternative decomposition in the Appendix (see Table A2). Results are similar to those in Table 3 in that observed characteristics explain 55% and 64% of the numeracy and literacy gaps, respectively.

Moreover, we also investigate if individual characteristics related to the labor market could explain at least partly the residual difference in cognitive test scores. We augment the vector of covariates x_{ic} in equation (1) with the following variables: years of labor market experience; an indicator for the individual being currently employed; and four dummies capturing different types of job-related training (i.e., on the job training, attendance to open education, attendance to seminars and workshops, attendance to private lessons). The reason why we have not included these variables in our preferred specification is that they are potentially endogenous in equation (1). For example, while differences across countries in the distribution of training might also reflect exogenous institutional differences in the labor market, individuals might choose to participate into training depending on their cognitive skills, giving rise to a reverse causality problem. For this reason, caution is required in the interpretation of these results.

Columns 3-4 and 7-8 of Table 3 show the results for this extended specification. As can be seen, the inclusion of labor market characteristics changes very little the proportion of the cognitive skill gap which can be explained by differences in observed characteristics. Experience, employment status and training altogether account for just 4% to 7% of the cognitive skill gaps in numeracy and literacy. The table also shows that, although parental education has a slightly lower weight as compared to our preferred specification, the contributions of differences in educational attainments and socio-economic background are also quite robust to the inclusion of labor market variables.

3.2. Decomposition of the score gap along the distribution of scores

In this section, we conduct decomposition exercises of the cognitive skill gaps across the distribution of test scores. This is relevant because the Oaxaca-Blinder decomposition only shows how compositional effects account for differences in test scores at the mean, whereas these might vary throughout the distribution of test scores. Our first approach follows the work of Chernozhukov et al. (2013). Intuitively, this allows to decompose the difference between the τ-th quantile of the unconditional distribution of the cognitive skill of the EU countries and Spain into an effect due to differences in characteristics and an effect due to differences in coefficients:

$$Q_{\tau}^{EU} - Q_{\tau}^{S} = \underbrace{[Q_{\tau}^{C} - Q_{\tau}^{S}]}_{characteristics\ effect} + \underbrace{[Q_{\tau}^{EU} - Q_{\tau}^{C}]}_{coefficients\ effect}, \qquad (3)$$

where Q_{τ}^{EU} and Q_{τ}^{S} denote, respectively, the unconditional τ-th quantile of the cognitive score distribution in the EU group of countries and Spain; and Q_{τ}^{C} is the counterfactual τ-th quantile function of the distribution that would be observed if adults in the group of EU countries would have the same cognitive skills of adults in Spain. Formally, Q_τ^C is defined as follows

$$Q_\tau^C = inf\left\{score\colon \tau \leq \int_{\chi_{EU}} F_{score_S}(score|x)dF_{X_{EU}}(x)\right\}.$$

This is a counterfactual quantile function in the sense that it is obtained by integrating the conditional distribution of cognitive skills for Spain, $F_{score_S}(score|x)$, with respect to the distribution of characteristics in EU countries, $F_{X_{EU}}$. Therefore, the first term on the right-hand side of equation (3) is interpreted as the effect of characteristics as it is obtained by netting out the (τ-th quantile of the) distribution of scores of Spanish adults from the (τ-th quantile of) distribution of scores that Spanish adults would have obtained had they faced the same characteristics of EU adults. The vector of characteristics x includes the usual variables from our preferred specification (i.e., schooling, socio-demographic and parental background).

We present the results of this decomposition for the numeracy and literacy tests in Figure 2. The solid lines show the total cognitive skill gap between the group of EU countries and Spain. The dashed lines show the effects of characteristics, whereas the dotted lines show the effects of coefficients. In numeracy, we observe that the total difference increases across the distribution of scores, while in literacy the total gap is relatively flat. The effect of characteristics is clearly decreasing across the test score distribution. In particular, the differences in observed characteristics explain more than 70% of the cognitive skill gap at lower test score percentiles. By contrast, at higher percentiles differences in composition explain only between 40% and 50% of the score gap.

Our analysis suggests that a large fraction of the cognitive skill gap among Spanish adults with lower levels of human capital is driven by lower educational attainments and worse socio-economic backgrounds. Instead, for Spanish individuals with higher levels of human capital, differences in characteristics with respect to EU countries explain a smaller proportion of the performance gap and, as a result, other unobserved factors are comparatively more important. In order to better understand how educational and socio-demographic differences contribute to the cognitive skill gaps across the distribution, we also present another decomposition exercise based on the methodology by Firpo et al. (2009).[10] Whereas Chernozhukov et al. (2013) allows to compute an exact decomposition of the counterfactual effect on the unconditional quantile, the methodology of Firpo et al. (2009) holds only as a first order approximation. Nevertheless, the latter method has the advantage of allowing a straightforward detailed decomposition of the effect of each covariate included in the model.[11]

[10] The methodology of Firpo et al. (2009) is based on the estimation of Recentered Influence Functions (RIF) regressions of the unconditional quantile on the explanatory variables.
[11] In contrast, in Chernozhukov et al. (2013) detailed decompositions are path dependent, i.e., they depend on the order in which the decomposition is performed. See Fortin et al. (2011) for an in-depth discussion of these decomposition methods.

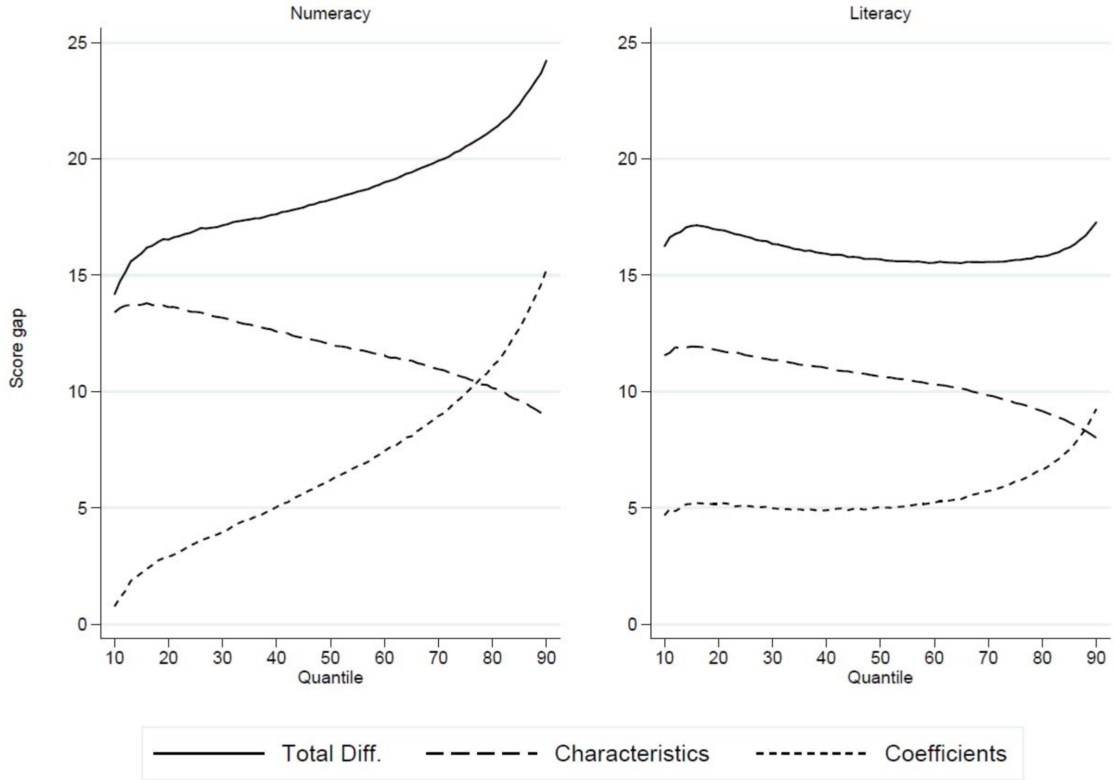

Figure 2. Decomposition of differences in PIAAC score between the group of EU countries and Spain

In Table 4, we present the results of this decomposition for the numeracy score gap at the 10th, 50th and 90th percentile. For expositional reasons, we group together the contribution of all demographic factors and of the parental education dummies. As before, we note that differences in educational attainments and in socio-economic background explain almost the entire cognitive skill gap for individuals with low levels of human capital, whereas the contribution of these factors decreases as one moves towards the top of the test score distribution. In particular, differences in the stock of education account for about 47% of the gap at the 10th percentile, but for just 21% at the 90th percentile. Another important factor explaining the Spanish cognitive skill gap at the bottom of the distribution is given by differences in parental education, which explain about 34% of the observed gap. By contrast, the contribution of such differences becomes relatively smaller, although statistically significant, at the 50th and 90th percentile, accounting for 27% and 11% of the cognitive skill gap, respectively.

3.3. Heterogeneity

In this section, we analyze in more detail the cognitive skill gaps by gender, age and nationality. For expositional reasons, in the main text we only show the results for the numeracy test.[12] The first four columns of Table 5 report Oaxaca-Blinder decomposition results for males and females.[13] As discussed in Section 2.2, gender differences in cognitive skills are small. Overall,

[12] The results for literacy are similar and they are available in the Appendix (see Table A3 and Figures A1, A2 and A3).
[13] In order to ease readability, in the results for the Oaxaca-Blinder decompositions presented in this section we aggregate the contributions of the single items within the following three groups: years of schooling, parental education and the rest of socio-demographic factors.

Table 4. Quantile decomposition of the cognitive skill gap in numeracy

	10th quantile		50th quantile		90th quantile	
	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained
Cognitive skill gap	17.773		18.327		21.782	
Explained	16.107***	91%	11.955***	65%	7.135***	33%
	(0.758)		(0.502)		(0.423)	
Years of schooling	8.357***	47%	6.405***	35%	4.625***	21%
	(0.476)		(0.335)		(0.280)	
Demographic characteristics	1.699***	10%	0.665***	4%	0.064	0%
	(0.267)		(0.163)		(0.141)	
Parental education	6.051***	34%	4.885***	27%	2.445***	11%
	(0.573)		(0.321)		(0.267)	
Unexplained	1.666	9%	6.372***	35%	14.648***	67%
	(1.777)		(0.839)		(1.151)	

Notes. *** p<0.01, ** p<0.05, * p<0.1. The decomposition method is based on Fortin et al. (2011). Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Demographic characteristics include a gender dummy, a dummy for the individual being foreign born and four age dummies. Parental education include two indicators for parental education, corresponding to lower secondary education or less and upper secondary education. Standard errors, computed using the jacknife replication method, are reported in parentheses.

71% of the score gap for males and 53% for females are accounted for by differences in observed characteristics. The contribution of differences in educational attainments is larger for males (42% of the total gap) than for females (27% of the total gap). This is consistent with the fact that the gap in educational attainments with respect to other EU countries is larger for men (1.1 years of schooling) than for women (0.9 years; see Table A4 in the Appendix). Moreover, compositional effects are larger for men than for women throughout the entire distribution of test scores (see Figure 3).

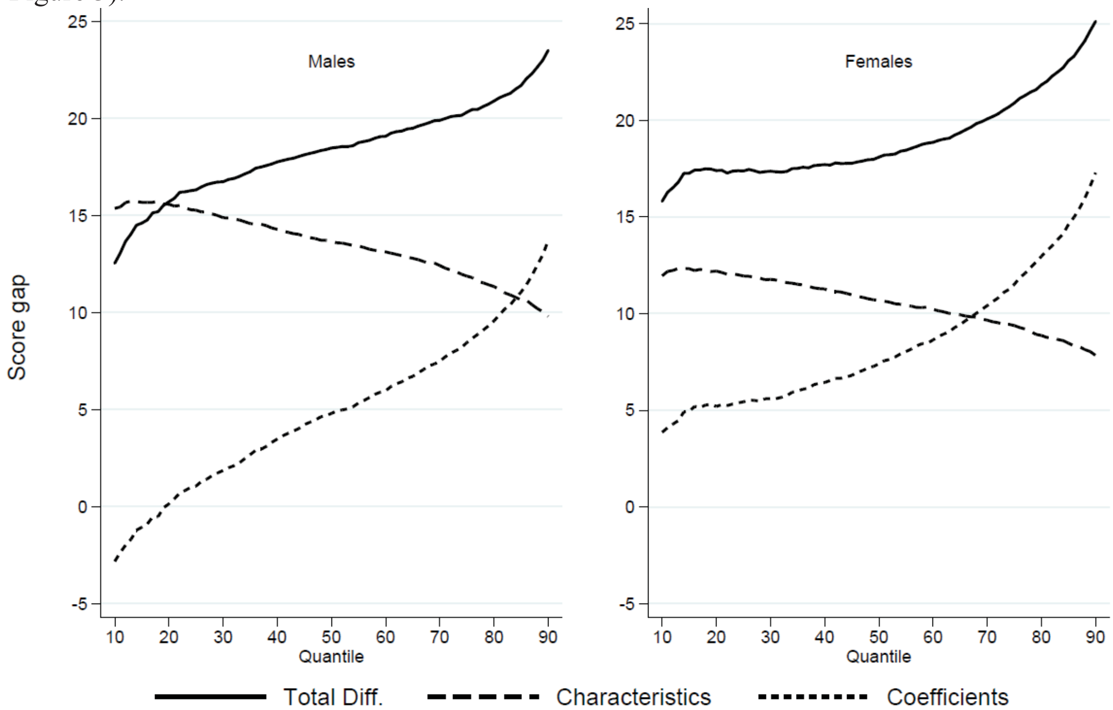

Figure 3. Decomposition of differences in PIAAC score in numeracy between the group of EU countries and Spain, by gender

Table 5. Oaxaca-Blinder decomposition by demographic groups: numeracy test score

	Gender				Age						Nationality			
	Females		Males		Less than 35		35-54		55 and more		Immigrants		Natives	
	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained
Cognitive skill gaps	19.629		18.691		16.650		16.817		28.162		8.748		19.863	
Explained	10.473***	53.4%	13.260***	70.9%	12.346***	74.1%	11.516***	68.5%	12.738***	45.2%	9.244***	105.7%	11.157***	56.2%
	(0.56)		(0.60)		(0.66)		(0.68)		(0.98)		(1.44)		(0.42)	
Years of schooling	5.273***	26.9%	7.861***	42.1%	3.569***	21.4%	7.005***	41.7%	11.491***	40.8%	5.665***	64.8%	6.562***	33.0%
	(0.37)		(0.37)		(0.33)		(0.50)		(0.85)		(1.06)		(0.22)	
Parental education	4.017***	20.5%	4.888***	26.2%	6.966***	41.8%	4.040***	24.0%	2.014***	7.2%	3.687***	42.2%	4.378***	22.0%
	(0.40)		(0.43)		(0.55)		(0.44)		(0.46)		(0.68)		(0.34)	
Other socio-demographic charact.	1.183***	6.0%	0.512***	2.7%	1.811***	10.9%	0.470**	2.8%	-0.768***	-2.7%	-0.109	-1.2%	0.216***	1.1%
	(0.19)		(0.18)		(0.28)		(0.19)		(0.23)		(0.39)		(0.07)	
Unexplained	9.156***	46.6%	5.431***	29.1%	4.304***	25.9%	5.302***	31.5%	15.425***	54.8%	-0.496	-5.7%	8.707***	43.8%
	(1.03)		(0.98)		(1.12)		(1.02)		(1.68)		(2.57)		(0.69)	
No. of observations	50,499		45,994		37,905		38,199		20,389		9,807		86,686	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Standard errors, computed using the jacknife replication method, are reported in parentheses.

Next, we split the sample into three age groups: the 15-34, 35-54 and 55-65 years old. Columns 5-10 of Table 5 suggest that compositional effects vary substantially across cohorts: for younger cohorts (15-34 years old), they account for 74% of the observed cognitive skill gap, whereas for the 55-65 years old they account for 45%. Differences in years of schooling are the most relevant factor in explaining the cognitive skill gaps of older generations, contributing to 41% of the numeracy skill gap. In contrast, differences in the socio-economic background have a substantially higher weight (42% of the observed gap) for younger generations. This finding is consistent with a higher persistence of low education stocks in Spain vis-à-vis other countries (Petrongolo and San Segundo, 2002). As can be seen in Table A5 from the Appendix, across cohorts the proportion of individuals whose parents have a tertiary education level has increased at a smaller rate in Spain (14 percentage points) than in the group of EU countries (21 percentage points). Similar patterns can be observed from a decomposition on the distribution of test scores (Figure 4). First, for the younger (16-34 years) and middle (35-54 years) age groups, differences in characteristics account practically for the whole performance gap at the lowest percentiles of the cognitive skill distribution. Second, the older age group exhibits a higher cognitive skill gap with respect to that of younger cohorts along the whole distribution of scores, with the effect of characteristics explaining about half of the total difference throughout the distribution of test scores.

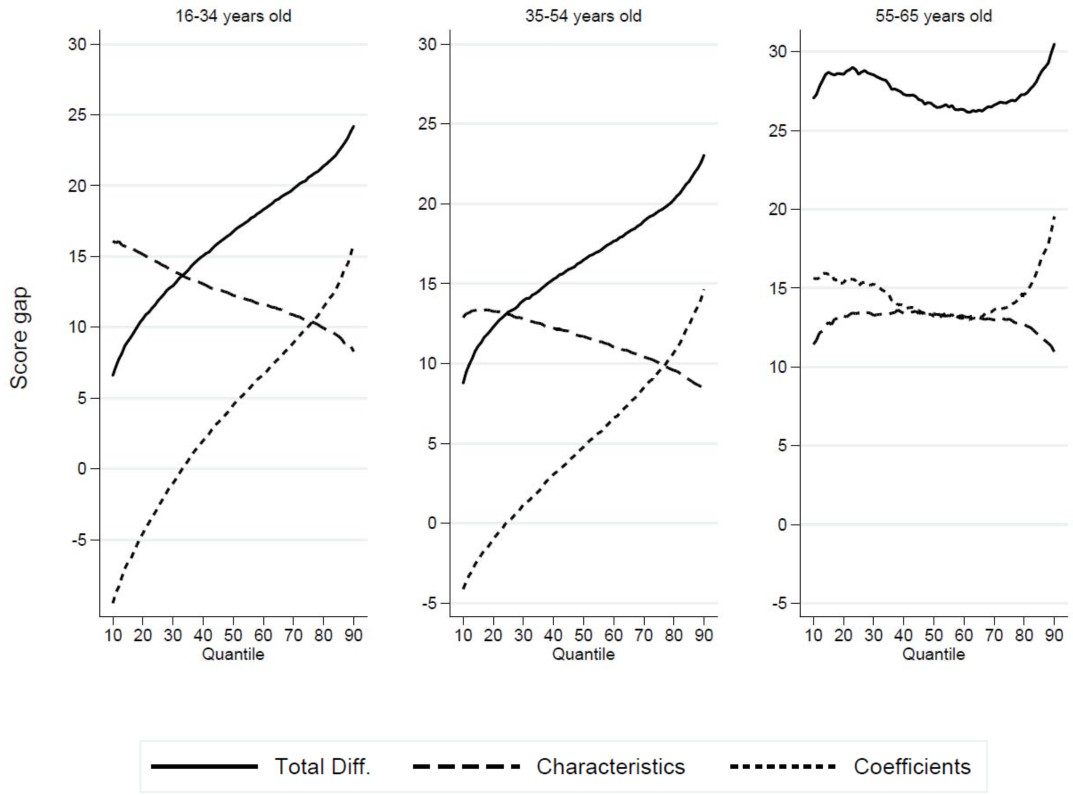

Figure 4. Decomposition of differences in PIAAC score in numeracy between the group of EU countries and Spain, by age

Finally, the cognitive skill gap of immigrants is significantly lower than the gap for natives, but it is nevertheless positive and significant (see columns 11-14 of Table 5). This could arise for several reasons. First, immigrants with different characteristics might select into different countries. Second, exposure to institutional factors of the host country might imply different patterns of human capital accumulation among immigrants in different countries. The Oaxaca-Blinder decomposition suggests that differences in characteristics completely account for the observed differential in test scores for immigrants. In other words, if EU immigrants had the same cognitive skills of Spanish immigrants, the score gap would be about 106% larger than the observed gap. Because socio-economic background and educational levels account for the entire cognitive skill gaps of immigrants, a possible interpretation for these findings points to differential selection patterns of migration across countries, with more educated individuals being more likely to migrate to other EU countries than to Spain. In fact, Spanish immigrants accumulate, on average, about 0.8 years of education less than immigrants in the other EU countries, and are more likely to come from relatively less educated families (see Table A6 in the Appendix). Moreover, Figure 5 suggests that this is particularly true for immigrants at the bottom quantiles of the test score distribution as the characteristics effect is larger than the total observed difference in test scores up to the 50th quantile.

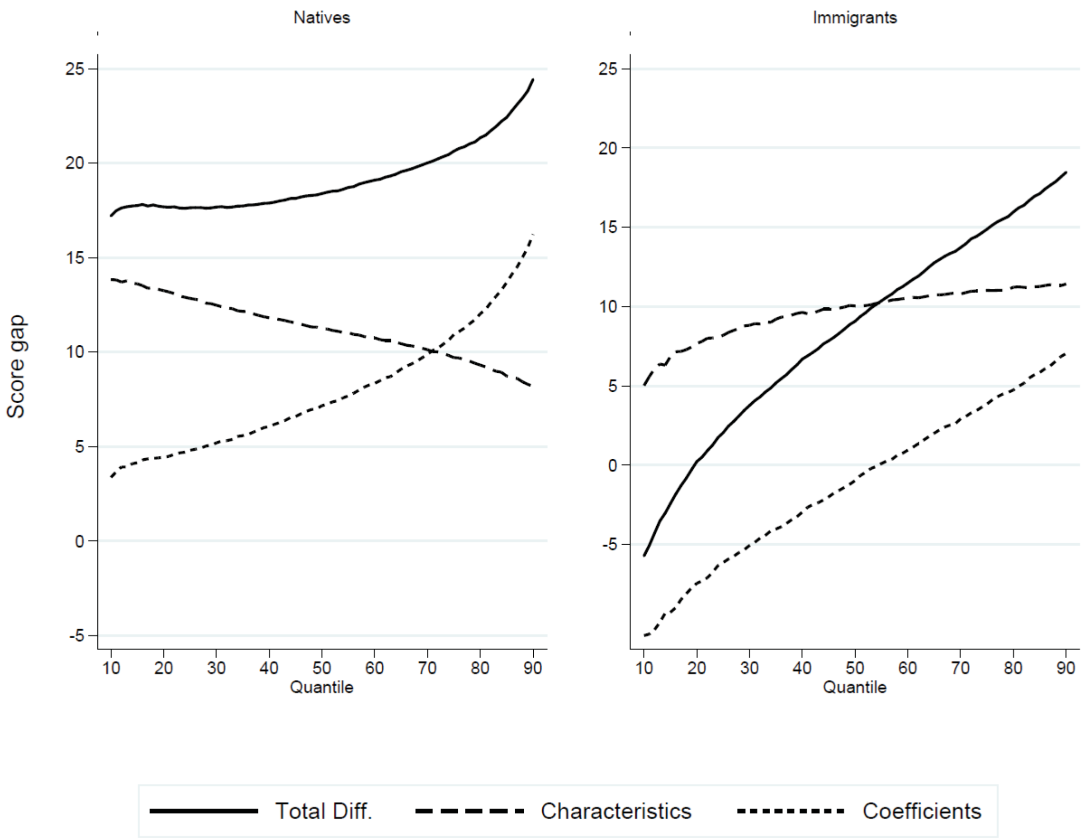

Figure 5. Decomposition of differences in PIAAC score in numeracy between the group of EU countries and Spain, by nationality

4. CONCLUSIONS

Our paper analyzes the differences in performance in PIAAC tests between Spain and other EU countries who took the PIAAC assessment, and identifies to what extent differences in cognitive skills can be explained by differences in educational attainments, socio-economic background and demographic structure of the adult population. We find that the cognitive test scores of Spanish adults are, on average, 0.35 standard deviations lower than those of adults in other EU countries. Oaxaca Blinder decompositions show that about 60% of the average performance gap is explained by differences in observed socio-economic characteristics, among which the number of years of schooling explains about 34% and the level of education of the parents explains about 23% of the average score gap.

We also carry out an analogous decomposition over the distribution of test scores. We find that the differences in educational attainments and socio-economic background between Spain and other EU countries explain almost the entire performance gap at the lower percentiles of the test score distribution. A heterogeneity analysis reveals that this finding is mostly driven by males, individuals below 54 years of age and immigrants performing at the lower part of the distribution of test scores. Moreover, differences in education levels seem relatively more important for older cohorts, whereas for younger cohorts the cognitive skill gaps are mainly related to differences in parental education.

Overall, our results suggest that a large fraction of the documented score gaps of the Spanish population are related to lower education stocks and to a larger persistence of low education levels across generations with respect to other EU countries. This finding is coherent with studies highlighting the high repetition rate and early dropout in the Spanish education system (Miyako and Garcia 2014), and the high persistence of low human capital levels (Petrongolo and San Segundo 2002). Although with the inherent limitations of the counterfactual exercises we presented, the results in our paper point to the importance of policies aiming at increasing the accumulated stock of education of new generations in Spain. Nevertheless, it is important to remark that about 40% of the score gap between Spain and other EU countries is not accounted for by the observable characteristics we analyzed in our study. Other unobserved factors, which could be related to the quality of the education system, are likely to play an important role in explaining the residual cross-country differences in cognitive test scores, an issue which certainly deserves further research.

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ONLINE APPENDIX

Figure A1 and A2 rank countries examined in PIAAC according to different percentiles (i.e., 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles) of the distribution of numeracy and literacy scores, respectively.

Table A1 shows the full estimation results of the Oaxaca-Blinder decomposition reported in Table 3 in the main text. Table A2 shows the results of the alternative Oaxaca-Blinder decomposition given by the following equation

$$\overline{score}_{EU} - \overline{score}_{S} = (\bar{X}_{EU} - \bar{X}_{S})\hat{\beta}_{EU} + (\hat{\beta}_{EU} - \hat{\beta}_{S})\bar{X}_{S}.$$

Table A3 is analogous to Table 5 in the main text, and shows the results of the Oaxaca-Blinder decomposition for the literacy test score by gender, age and nationality.

Table A4 reports descriptive statistics about the differences in education, socio-demographic characteristics and parental education between Spain and the group of other EU countries by gender. Tables A5 and A6 show the same descriptive statistics by age and nationality, respectively.

Figures A3, A4 and A5 are analogous to, respectively, Figure 3, 4 and 5 and show the results of the quantile decomposition by Chernozhukov et al. (2013) for the literacy test score.

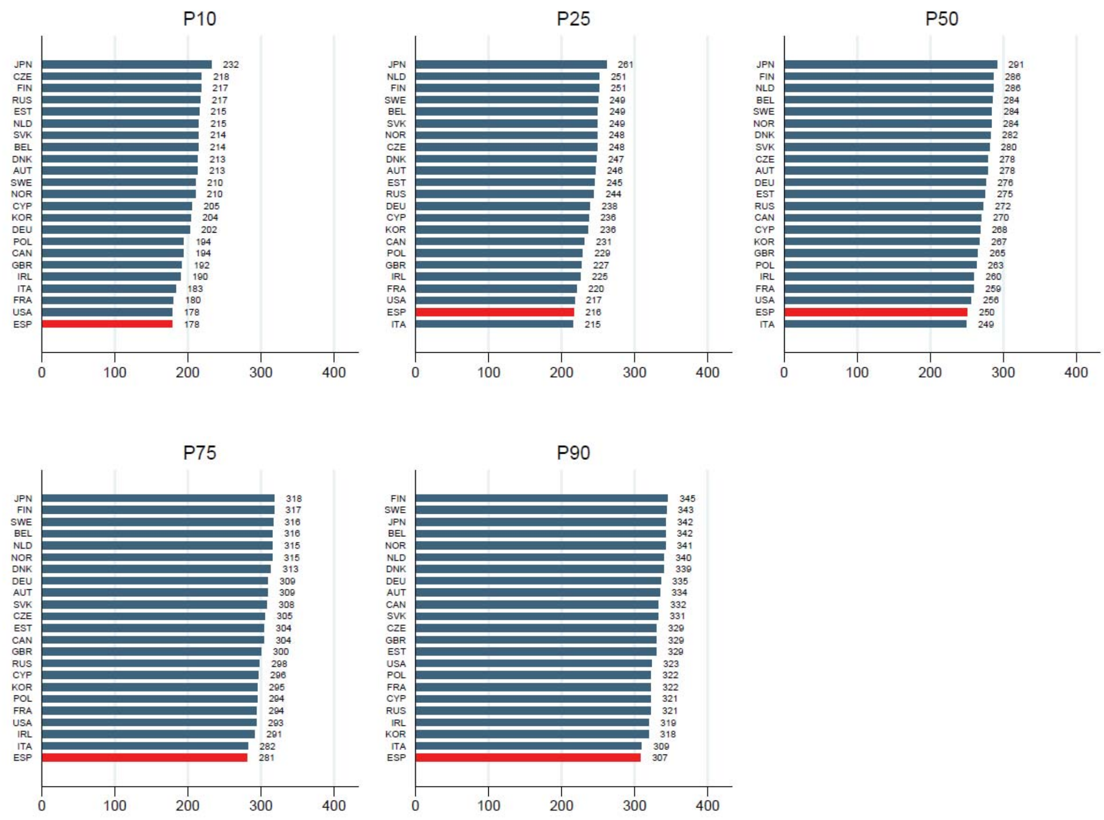

Figure A1. Ranking of countries by percentiles of PIAAC score in numeracy

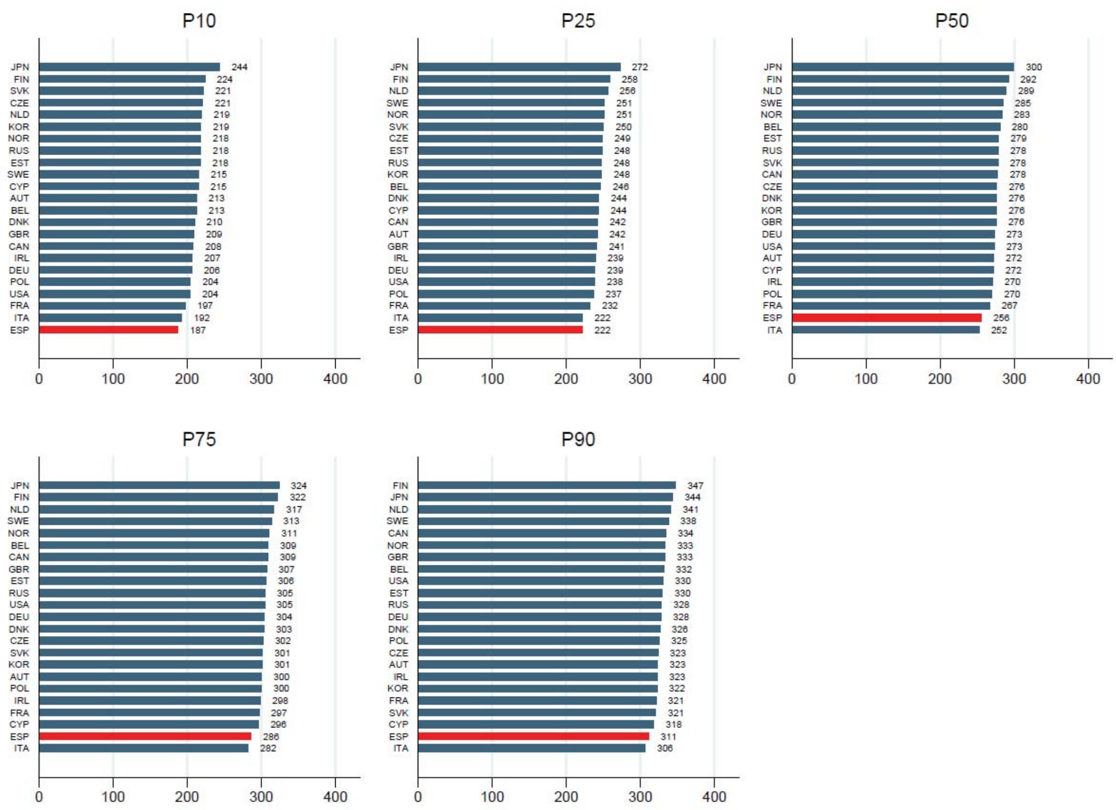

Figure A2. Ranking of countries by percentiles of PIAAC score in literacy

Table A1. Oaxaca-Blinder decomposition

	Numeracy		Literacy	
	PIAAC points	% explained	PIAAC points	% explained
Cognitive skill gap	19.134		16.445	
Explained	11.772***	61.52%	10.359***	62.99%
	(0.35)		(0.32)	
Years of schooling	6.513***	34.04%	5.527***	33.61%
	(0.20)		(0.17)	
Female	-0.023	-0.12%	-0.002	-0.01%
	(0.02)		(0.00)	
Immigrant	0.698***	3.65%	0.648***	3.94%
	(0.07)		(0.07)	
Age				
15-24 years	0.177***	0.92%	0.407***	2.47%
	(0.05)		(0.04)	
25-34 years	0.009	0.92%	-0.030**	2.47%
	(0.01)		(0.01)	
45-54 years	0.020	0.10%	0.024	0.14%
	(0.02)		(0.02)	
55-65 years	-0.064***	-0.33%	-0.075***	-0.46%
	(0.02)		(0.03)	
Parental education				
Lower secondary or less	8.242***	43.07%	7.497***	45.58%
	(0.37)		(0.36)	
Upper secondary	-3.799***	-19.86%	-3.636***	-22.11%
	(0.23)		(0.22)	
Differences in returns to characteris	-0.01	-48.87%	-0.01	-74.71%
Years of schooling	-4.894*	-25.58%	-10.477***	-63.71%
	(2.71)		(2.75)	
Female	1.291*	6.75%	2.565***	15.60%
	(0.69)		(0.67)	
Immigrant	-0.843**	-4.41%	-0.350	-2.13%
	(0.34)		(0.32)	
Age				
15-24 years	-0.094	-0.49%	0.082	0.50%
	(0.28)		(0.25)	
25-34 years	0.130	0.68%	0.459	2.79%
	(0.39)		(0.46)	
45-54 years	0.590	3.08%	0.264	1.61%
	(0.44)		(0.44)	
55-65 years	1.756***	9.18%	1.424***	8.66%
	(0.42)		(0.49)	
Parental education				
Lower secondary or less	-6.353***	-33.20%	-5.197***	-31.60%
	(1.65)		(1.50)	
Upper secondary	-0.934**	-4.88%	-1.057***	-6.43%
	(0.37)		(0.37)	
Constant	16.713***	87.34%	18.373***	111.72%
	(4.07)		(4.15)	
No. of obs.	96,493		96,493	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Standard errors, computed using the jacknife replication method, are reported in parentheses.

Table A2. Oaxaca-Blinder alternative decomposition

	Numeracy		Literacy	
	PIAAC points	% explained	PIAAC points	% explained
Cognitive skill gap	19.134		16.445	
Explained	10.549***	55.13%	10.471***	63.67%
	(0.535)		(0.54)	
Years of schooling	6.944***	36.29%	6.449***	39.21%
	(0.30)		(0.27)	
Female	-0.028	-0.15%	-0.012	-0.07%
	(0.02)		(0.01)	
Immigrant	0.548***	2.87%	0.586***	3.57%
	(0.08)		(0.08)	
Age				
15-24 years	0.214**	1.12%	0.374***	2.27%
	(0.10)		(0.09)	
25-34 years	0.019	1.12%	0.004	2.27%
	(0.03)		(0.03)	
45-54 years	0.031	0.16%	0.028	0.17%
	(0.03)		(0.02)	
55-65 years	-0.118**	-0.62%	-0.119**	-0.72%
	(0.05)		(0.05)	
Parental education				
Lower secondary or less	5.048***	26.38%	4.884***	29.70%
	(0.75)		(0.71)	
Upper secondary	-2.109***	-11.02%	-1.724***	-10.48%
	(0.66)		(0.65)	
Differences in returns to characteristics	-0.01	-42.48%	-0.01	-75.40%
Years of schooling	-5.325*	-27.83%	-11.399***	-69.31%
	(2.95)		(2.99)	
Female	1.296*	6.77%	2.575***	15.66%
	(0.69)		(0.67)	
Immigrant	-0.694**	-3.63%	-0.288	-1.75%
	(0.28)		(0.26)	
Age				
15-24 years	-0.131	-0.68%	0.115	0.70%
	(0.39)		(0.36)	
25-34 years	0.121	0.63%	0.425	2.58%
	(0.36)		(0.42)	
45-54 years	0.579	3.03%	0.259	1.58%
	(0.43)		(0.44)	
55-65 years	1.810***	9.46%	1.467***	8.92%
	(0.44)		(0.50)	
Parental education				
Lower secondary or less	-3.159***	-16.51%	-2.584***	-15.71%
	(0.82)		(0.75)	
Upper secondary	-2.625**	-13.72%	-2.970***	-18.06%
	(1.03)		(1.03)	
Constant	16.713***	87.34%	18.373***	111.72%
	(4.07)		(4.15)	
No. of obs.	96,493		96,493	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Standard errors, computed using the jacknife replication method, are reported in parentheses.

Table A3. Oaxaca-Blinder decomposition by demographic groups: literacy test score

	Gender				Age						Nationality			
	Females		Males		Less than 35		35-54		55 and more		Immigrants		Natives	
	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained	PIAAC points	% explained
Cognitive skill gap	18.257		14.655		15.447		13.437		24.047		9.318		16.746	
Explained	9.171***	50.2%	11.652***	79.5%	11.969***	77.5%	9.641***	71.8%	10.517***	43.7%	7.828***	84.0%	9.866***	58.9%
	(0.51)		(0.53)		(0.60)		(0.59)		(0.83)		(1.24)		(0.39)	
Years of schooling	4.571***	25.0%	6.550***	44.7%	3.071***	19.9%	5.903***	43.9%	9.409***	39.1%	4.866***	52.2%	5.554***	33.2%
	(0.32)		(0.32)		(0.30)		(0.43)		(0.66)		(0.92)		(0.20)	
Parental education	3.345***	18.3%	4.399***	30.0%	7.091***	45.9%	3.242***	24.1%	1.754***	7.3%	3.309***	35.5%	3.761***	22.5%
	(0.40)		(0.39)		(0.48)		(0.36)		(0.45)		(0.60)		(0.32)	
Other socio-demographic charact.	1.254***	6.9%	0.702***	4.8%	1.807***	11.7%	0.497***	3.7%	-0.646***	-2.7%	-0.347	-3.7%	0.552***	3.3%
	(0.17)		(0.17)		(0.26)		(0.16)		(0.18)		(0.28)		(0.06)	
Unexplained	9.086***	49.8%	3.002***	20.5%	3.478***	22.5%	3.796***	28.2%	13.530***	56.3%	1.490	16.0%	6.879***	41.1%
	(1.09)		(1.01)		(1.08)		(1.09)		(1.97)		(2.41)		(0.76)	
No. of observations	50,499		45,994		37,905		38,199		20,389		9,807		86,686	

Notes. *** p<0.01, ** p<0.05, * p<0.1. Cognitive skill gaps in Spain are measured with respect to a group of EU countries including: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom. Standard errors, computed using the jacknife replication method, are reported in parentheses.

Table A4. Descriptive statistics by gender

	Females			Males		
Variables	EU countries	Spain	Diff.	EU countries	Spain	Diff.
Years of schooling	12.39	11.53	0.86	12.32	11.18	1.13
Level of education						
Lower secondary and less	0.26	0.45	-0.19	0.25	0.49	-0.24
Upper secondary	0.46	0.23	0.22	0.48	0.24	0.25
Tertiary	0.29	0.32	-0.03	0.27	0.28	-0.01
Immigrant	0.11	0.14	-0.03	0.11	0.12	-0.02
Age						
15-24 years	0.16	0.12	0.05	0.17	0.12	0.05
25-34 years	0.20	0.21	-0.02	0.20	0.21	-0.02
35-44 years	0.21	0.24	-0.03	0.22	0.26	-0.04
45-54 years	0.22	0.22	-0.01	0.21	0.22	0.00
55-65 years	0.21	0.21	0.00	0.20	0.19	0.01
Parental education						
Lower secondary or less	0.36	0.72	-0.35	0.35	0.72	-0.37
Upper secondary	0.43	0.16	0.27	0.43	0.15	0.28
Tertiary	0.21	0.13	0.08	0.22	0.13	0.09
No. of ob.	47555	2944		43163	2831	

EU countries include: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom.

Table A5. Descriptive statistics by age

Variables	Less than 35			35-54			More than 54		
	EU countries	Spain	Diff.	EU countries	Spain	Diff.	EU countries	Spain	Diff.
Years of schooling	12.48	11.85	0.63	12.65	11.69	0.96	11.50	9.74	1.76
Level of education									
Lower secondary and less	0.26	0.41	-0.15	0.21	0.44	-0.23	0.33	0.63	-0.30
Upper secondary	0.47	0.30	0.18	0.48	0.21	0.27	0.44	0.19	0.25
Tertiary	0.27	0.29	-0.03	0.31	0.35	-0.04	0.23	0.18	0.05
Female	0.49	0.49	0.00	0.50	0.49	0.01	0.51	0.52	0.00
Immigrant	0.11	0.17	-0.06	0.12	0.14	-0.02	0.08	0.05	0.03
Parental education									
Lower secondary or less	0.18	0.53	-0.35	0.41	0.78	-0.38	0.57	0.88	-0.31
Upper secondary	0.51	0.26	0.25	0.41	0.11	0.29	0.33	0.06	0.27
Tertiary	0.31	0.20	0.11	0.19	0.10	0.08	0.10	0.06	0.04
No. of ob.	35812	2093		35544	2655		19362	1027	

EU countries include: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom.

Table A6. Descriptive statistics by nationality

Variables	Immigrants			Natives		
	EU countries	Spain	Diff.	EU countries	Spain	Diff.
Years of schooling	12.11	11.30	0.81	12.38	11.36	1.02
Level of education						
Lower secondary and less	0.32	0.47	-0.15	0.25	0.47	-0.22
Upper secondary	0.38	0.31	0.06	0.48	0.22	0.26
Tertiary	0.30	0.21	0.09	0.27	0.31	-0.04
Female	0.51	0.53	-0.02	0.50	0.49	0.01
Age						
15-24 years	0.11	0.11	0.00	0.17	0.12	0.05
25-34 years	0.25	0.31	-0.06	0.19	0.20	-0.01
35-44 years	0.27	0.31	-0.04	0.21	0.24	-0.03
45-54 years	0.21	0.19	0.02	0.22	0.22	-0.01
55-65 years	0.16	0.08	0.08	0.21	0.22	-0.01
Parental education						
Lower secondary or less	0.45	0.62	-0.17	0.35	0.73	-0.39
Upper secondary	0.30	0.21	0.09	0.44	0.14	0.30
Tertiary	0.25	0.17	0.08	0.21	0.12	0.09
No. of ob.	9054	753		81664	5022	

EU countries include: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Netherlands, Poland, Slovak Republic, Sweden, United Kingdom.

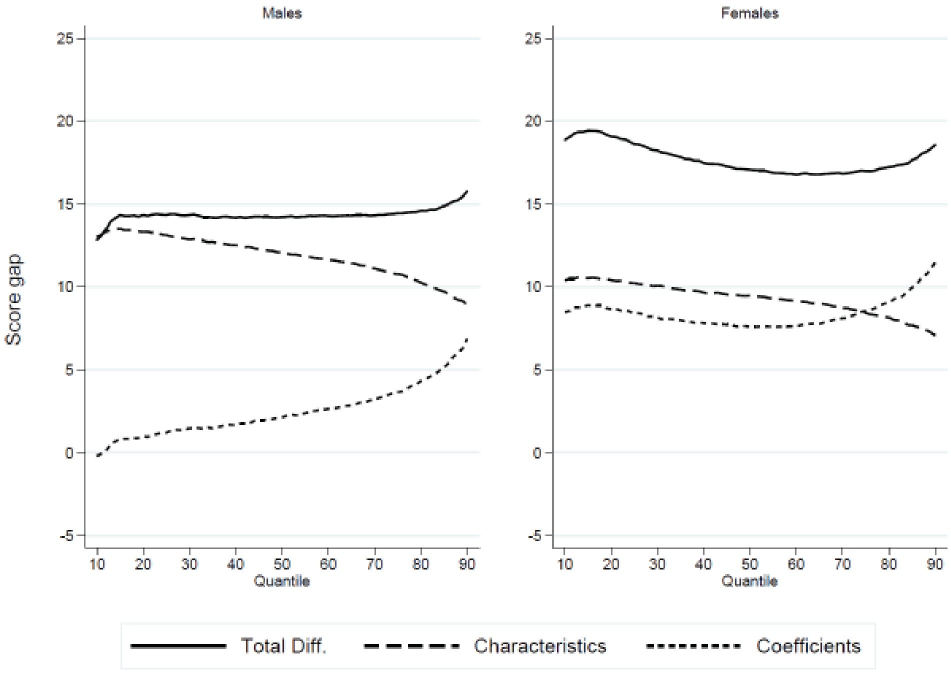

Figure A3. Decomposition of differences in PIAAC scores in literacy between the group of EU countries and Spain, by gender

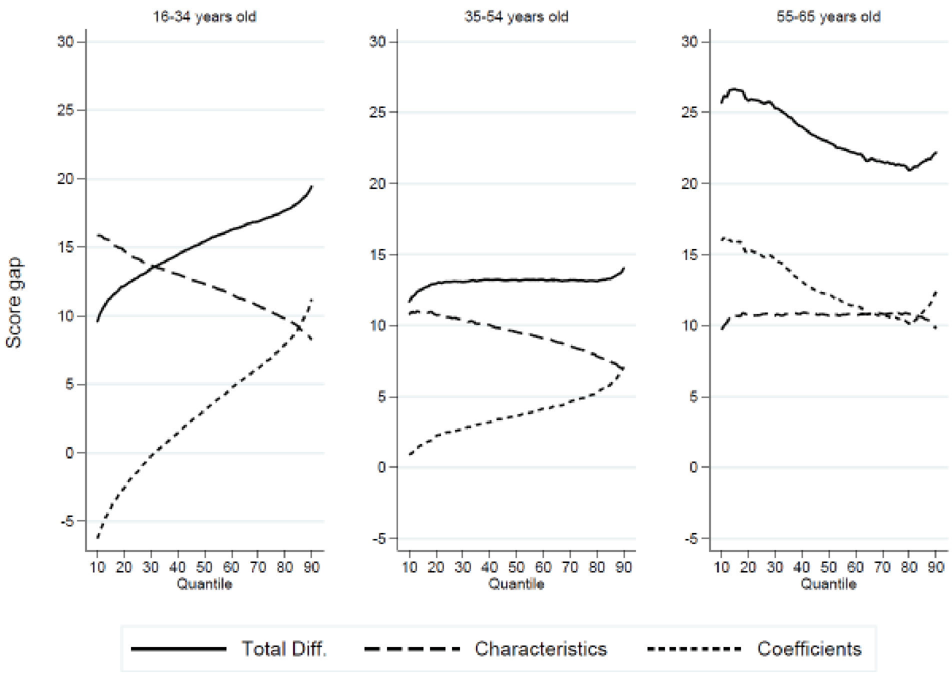

Figure A4. Decomposition of differences in PIAAC scores in literacy between the group of EU countries and Spain, by age

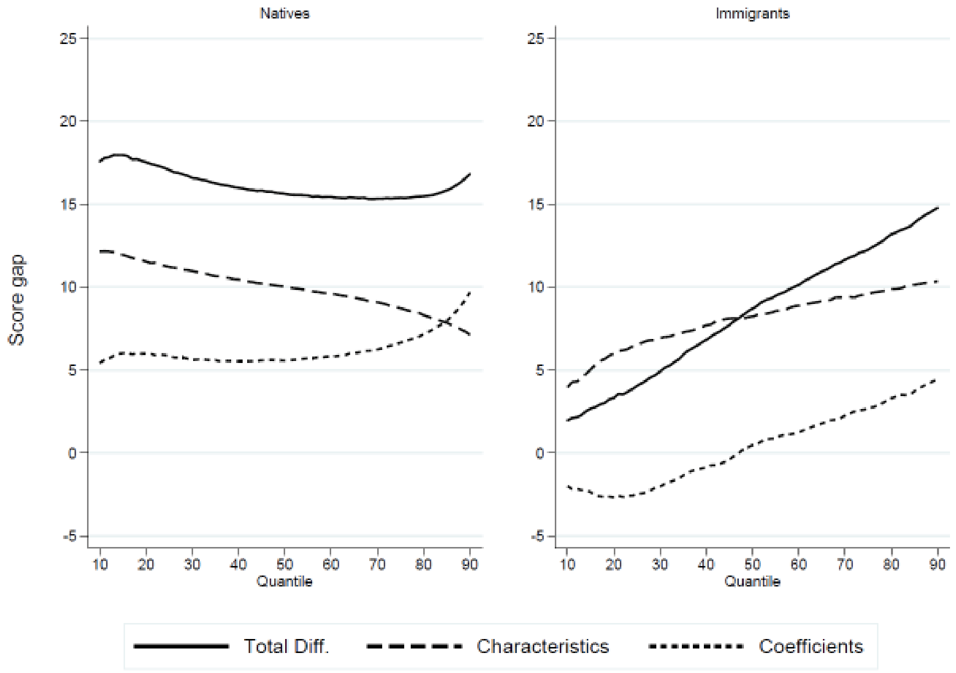

Figure A5. Decomposition of differences in PIAAC scores in literacy between the group of EU countries and Spain, by nationality

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