Efficiency in the transformation of schooling into competences:

A cross-country analysis using PIAAC data

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Abstract

This study (i) compares the competence levels of the adult population in a set of OECD countries; (ii) assesses the comparative efficiency with which the education system in each country transforms schooling into competences, distinguishing by educational level, and (iii) tracks the evolution of this efficiency by birth cohorts. Using PIAAC data, the paper applies standard parametric frontier techniques under two alternative specifications. The results obtained identify Finland, Sweden, Denmark and Japan as being the most efficient and Spain, the United Kingdom, Italy, Ireland and Poland as the least efficient.

Key words: adult population competences; efficiency; PIAAC; parametric frontier techniques.

JEL codes: I21, C13.

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1. Introduction

The consideration of human capital as a key factor both in the economic growth of countries and in the labour outcomes of individuals represents a long-standing tradition in the literature. Similarly, the limitations researchers face as they seek to measure this human capital – typically by resorting to the number of years of schooling (or, alternatively, the level of education attained) on the basis of Mincer's (1970; 1974) proposal – have been well documented. More recently, various studies have recommended considering the cognitive skills or competences acquired by individuals – as well as the number of years of schooling – when measuring human capital. Borghans et al. (2001) discuss the advantages of such an approach, stressing that the level of education achieved by an individual is an imperfect indicator of their human capital at any one point in time. Indeed, several studies provide empirical support for such arguments and show that cognitive competences can account for a large part of a country's growth in productivity (Hanushek and Kimko 2000; Barro 2001; Hanushek and Woessmann 2008) and for a part of an individual's labor achievements that cannot be explained by their educational attainments (McIntosh and Vignoles 2001; Green, and Riddell 2003).

If, therefore, we assume that an individual's skills are defined not only by the quantity of education they have received (measured in terms of the number of years of schooling), but also by the quality of that education (measured in terms of the cognitive competences acquired), it is of great interest to researchers to (i) determine which factors account for the acquisition of competences throughout an individual's life cycle and (ii) identify the greater performance that some individuals derive from their schooling in terms of competences than is obtained by others. The first of these issues has been broadly analyzed by estimating education production functions (Hanushek 1979; 1997). It has been concluded that not only the number of years of formal education received but other relevant variables, including an individual's personal characteristics and his/her socio-economic environment, can determine the acquisition of cognitive competences (Björklund and Salvanes 2011; Mazzona 2014). When estimating education production functions, however, it is assumed that all the units included in the sample obtain the same benefit from each of the explanatory variables considered. In international comparisons, this means, for example, assuming that an additional year of schooling in two countries with different institutional environments – and, more specifically, with different education systems – is equally effective, on average, in translating higher levels of schooling into competences for their populations. In order to refine this assumption, we need to determine whether the efficiency in the transformation of the number of years of schooling received into competences varies by country. The estimation of production frontiers is useful for this purpose since it indicates, for a given reference unit, the distance from that unit to the frontier, estimated using the most efficient units in the sample. For a given set of countries, this technique would provide a sorting of countries as a function of their distance from the frontier, or what is the same, as a function of the efficiency with which their education systems transform an additional year of schooling into competences[1].

The importance attached to the analysis of efficiency in education has grown notably in recent years (see De Witte and López-Torres 2017, for an exhaustive review of the literature). The bulk of the work in this regard has focused on estimating the efficiency of different units (districts, schools or students) operating within the same country, with far fewer studies comparing the efficiency of education systems across countries. However, among the latter, the most relevant draw on information provided by the OECD's PISA program as they compare from different perspectives the efficiency with which the education systems of different countries operate. For example, Afonso and Aubyn (2005; 2006) and Sutherland et al. (2009) analyse the efficiency of public spending on education for a group of OECD countries, and emphasize the role played by the institutions of each country in accounting for the disparity in the results reported. The influential role played by a country's institutions is similarly stressed by De Jorge and Santín (2010), who, like Deutsch et al. (2013), consider an analysis of efficiency at the student level as the best approach to optimize the use of available information. Agasisti and Zoido (2015) assess efficiency at both the national and school level for a broad set of OECD countries. They document a notable heterogeneity both between and within countries in terms of the degree of efficiency achieved by their respective education systems and schools. Giambona et al. (2011), in contrast, focus on the role played by the students' socio-economic characteristics in the determination of their competences. The authors assess the efficiency of the education systems of several EU countries with particular regard to their ability to help students from a poor family background achieve optimal development of their cognitive competences. The importance of the socio-economic environment is similarly stressed in Thieme et al. (2012). The authors compare the efficiency of a broad set of countries taking into account not only the results obtained by the students but also the degree of dispersion in the distribution of those results as an indicator of the equity of the system. Other studies use several waves of cross-sectional data in order to evaluate the evolution of a given output over time. This is the case of Agasisti (2014) when comparing the efficiency of public expenditure on education in twenty European countries between 2006 and 2009. In a similar vein, Giménez et al. (2017) examine student progress in terms of competences between 2003 and 2009, as they assess the extent to which their progress can be accounted for by the availability of better resources and/or the enhanced efficiency of their respective education systems. Other databases that have been used to evaluate the efficiency of education systems in an international setting include the Third International Mathematics and Science Study (TIMSS) – see Clements (2002) and Giménez et al. (2007); and the Progress in International Reading Literacy Study (PIRLS) – see Cordero et al. (2017).

The aforementioned papers adopt different methodologies (mainly non-parametric, but also semi-parametric and parametric) to calculate the efficiency with which different inputs are combined (at the country, school and/or student levels) in the production of various outputs related to student competences. However, despite this multiplicity of tools and results, they share a common limitation derived from their use of cross-sectional data that

[1] A review of papers using parametric boundary techniques to analyze various issues related to education can be found in Worthington (2001).

refer to individuals belonging to the same birth cohort. This means that we can only evaluate the efficiency of the education system for a given academic year (as in the case of TIMSS or PIRLS) or for a specific age (as in the case of PISA). In contrast, to the best of our knowledge, this paper is among the first that seeks to undertake an efficiency analysis for the education system as a whole, distinguishing by country and by level of education[2]. This is possible as we draw on data from the Program for the International Assessment of Adult Competencies (PIAAC), a survey conducted by the OECD among individuals aged 16-65 that have received a varied number of years of schooling. By estimating standard stochastic frontier functions, our objectives are as follows: (i) to compare the competence levels of the adult population in a set of OECD countries; (ii) to assess the comparative efficiency with which the education system in each country transforms schooling into competences, distinguishing by educational level, and (iii) to track the evolution of this efficiency by birth cohorts.

The rest of the paper is structured in four sections: sections 2 and 3 outline the methodology and the database used, section 4 reviews the main results obtained and, finally, section 5 presents the study's main conclusions.

2. Methodology

Here we propose an education production function and employ standard stochastic frontier techniques to calculate the distance from each country to the frontier. In this way, a classification of the countries is obtained as a function of the (in)efficiency with which they transform schooling into competences. Our unit of analysis is, thus, the country. The education production function can be expressed as follows:

$$\begin{aligned} Y_{iJ} &= \beta' X_{iJ} + w_{iJ} = \beta' X_{iJ} + \left(v_{iJ} - u_{iJ}\right) \\ E\left[u_{iJ} / w_{iJ}\right] &= \delta_{iJ} = h_i + \theta_J \end{aligned} \tag{1}$$

in which the competences of individual 'i' living in country 'J' are accounted for by the variables included in 'X_{iJ}' plus a term of inefficiency or of distance with respect to the frontier, 'u_{iJ}'. The expected value of this distance from the frontier, for individual 'i', is given by 'δ_{iJ}', which is the result of the standard calculation of frontier distances when using stochastic frontiers.

The distance to the frontier for individual 'i' living in country 'J' has two components: the individual component 'h_i', which gathers the innate ability of individual 'i', and 'θ_J', a component of the country that includes the average efficiency with which the country's

[2] Gupta and Verhoeven (2001) use information on adult population competences to make international comparisons of efficiency indicators. However, the aim of their study is not to evaluate the efficiency with which schooling is translated into competences, as is the case in our paper, but rather to compare the efficiency with which public expenditure on education and health improve a series of social development indicators, for some thirty African countries. For the specific case of education, the outputs assessed are school attendance rates in primary and secondary education and adult population competences.

education system transforms schooling into competences plus other surrounding cultural factors such as work ethic or the sense of responsibility. When calculating the average of the individuals living in country 'J', we obtain:

$$\frac{\sum_{i=1}^{M} \delta_{iJ}}{M} = \frac{\sum_{i=1}^{M} h_i}{M} + \theta_J \rightarrow \theta_J \tag{2}$$

In other words, for individuals from country 'J', insofar as the innate ability of the individuals within the same country tends to be compensated for, the average of the individual distances to the frontier will come closest to the average distance from the component country's derived frontier, which may represent a way to approach the efficiency of that country's education system.

In the form of an example, Graph 1 shows the mean of the efficiency evaluated in terms of proximity to the frontier for higher education for Belgium and Italy (the countries with the highest and lowest efficiency scores, respectively). The example focuses on numerical skills after controlling by a group of relevant explanatory variables (those included in our education production function).

[GRAPH 1 about here]

In the specific case of the comparison of the two countries with the lowest and highest average score, the distribution of skills for Italy in terms of proximity to the frontier is on the left of the distribution for Belgium. If we accept that persons in both countries share the same biological brain capacity, the innate average ability must be the same and, consequently, what explains the observed difference in skills must, basically, be attributed to the two factors mentioned above: on the one hand, quality of the educational system and, on the other, surrounding cultural factors such as work ethic or the sense of responsibility. With the available data from PIAAC, it is not possible to differentiate between these two components. Hence, we will refer to the sum of both as 'efficiency of the educational system', a term which includes the surrounding cultural factors. In the case of Belgium and Italy, the difference between the averages is 6.5 points with a 't' statistic of 20.0.

The functional specification for the education production function suggests that using a linear, as opposed to a semi-logarithmic model, provides the best fit for the available data. Moreover, it appears that age and experience – two of the explanatory variables included in the model – have a free effect on the competences when creating dummy specific variables for age (i.e. a dummy for each age in years) and experience (i.e. a dummy for each experience in years), compared to a more standard specification that suggests a linear effect for age and a quadratic effect for experience. We estimate both options with the available data and conclude that the latter gives the better outcomes (see Annex 1).

Standard stochastic frontier techniques are applied to Equation 1 under two different specifications. In the first, the influence of the explanatory variables is accounted for, which means the equation is estimated using the standard frontier function technique and that the estimated coefficients are common to all the countries considered. In the second, the frontier functions methodology is adapted so as to allow the coefficients (other than formal education) that affect the transformation of inputs into competences (including, for example, number of years of experience or type of occupation) to vary from country to country. This approach, which can be consulted in Annex 2, means we can isolate more precisely the (in)efficiency of the formal education system in transforming years of education received into competences. This said, both approaches in fact give very similar results.

3. Data

The data used in the present paper are drawn from the first wave of the PIAAC (corresponding to 2012), an OECD initiative aimed at assessing the competences of the population aged 16-65. This database follows in the wake of others that have measured the competences of the adult population (including IALS and ALL), although the number of participating countries is in this case greater and the competences evaluated refer not only to language skills, but also to mathematical skills and the use of new technologies. All these competences are measured using specific tests, the results of which are presented in terms of plausible values (ten for each skill). These plausible values indicate the performance of each individual on a scale of 0 to 500 points and are grouped into six levels. The survey, designed to facilitate a comparative analysis of the participating countries, also offers harmonized information on the use of the competences assessed in the workplace and in daily life; on the socio-demographic characteristics of the individuals surveyed (e.g. gender, age, nationality, level of education of parents); and on their training and job characteristics (e.g. education level, work experience throughout their working life, work situation: employed, inactive, unemployed, salary and other characteristics of the job: type of contract and working day, performance of supervision tasks, and even variables that allow for the identification of eventual educational or skill mismatches).

We have excluded from the sample those countries that give rise to any kind of concern regarding the reliability of the data they provide and those which fail to provide information on some of the variables considered in our study. Our model's dependent variable is numeracy competences rescaled to 1000 so as to facilitate the interpretation of the results[3]. The explanatory variables provide information about age, number of years of schooling, work experience (in quadratic terms), gender, first or second generation immigrant status, (the absence of) coincidence between the mother tongue and the language in which the survey is carried out, the level of studies of the parents, type of occupation and possible attendance on non-regulated training courses.

[3] All of the study's estimations have been replicated using literacy skills as the dependent variable. The results obtained (available upon request) are, to a large extent, quantitatively and qualitatively similar to those presented here for numeracy.

Table 1 presents the descriptive statistics for the variables in the overall sample (excluding observations without information regarding any of the variables considered in the analysis, which limits the sample to around 79,000 observations). The average value of the numeracy competence is c. 542 points, with a marked standard deviation of around 96 points. The average number of years of schooling stands at 12.73 for individuals whose average age is 40 years old and who have an average work experience of 18.21 years. The proportion of first generation immigrants is 7.9% (falling to 1.7% for second generation immigrants), most individuals (92%) respond to the survey in their mother tongue and 38% (22%) have at least one ascendant with post-compulsory (higher) secondary education. Roughly two-thirds of the individuals in the sample work in a skilled occupation and, finally, around 40% reported participating on non-regulated training courses in the 12 months prior to the survey.

[TABLES 1, 2 AND 3 ABOUT HERE]

Table 2 shows the average competences by country, with values ranging from 491 for Spain to 576 points for Japan. Table 3 ranks the countries by competences, with Japan and the Nordic countries heading the classification and Ireland, Spain and Italy finding themselves at the bottom of the ranking.

Finally, and given that throughout this study the efficiency indices are estimated distinguishing by level of education, Graph 2 presents average numeracy scores for each level of education contemplated. Note that the rankings of countries according to their average competences per level of study (see Table 4) present considerable similarities to those obtained as a function of the efficiency indices (see Graphs 3 and 4).

[GRAPH 2 AND TABLE 4 ABOUT HERE]

4. Results

Graph set 3 shows the results of the estimation of the efficiency indices for specification 1 (see methodology, section 2), in which the influence of the explanatory variables is taken into account. Graph set 4 corresponds to specification 2, which also incorporates a frontier function but in which the coefficients (with the exception of formal education) that affect the transformation of inputs into outputs are allowed to vary from country to country[4]. In each case, the results are broken down into the three educational levels completed by the individuals: up to lower secondary; higher secondary, and higher education. Note that the results obtained from the two specifications are largely similar, with only minor differences.

[4] Table A.3.1 of Annex 3 gathers the numerical indices calculated according to specification 1, and Table A.3.2 the numerical indices according to specification 2.

Focusing on Graph set 3, similar patterns are found for the three levels of education (Graphs 3a, 3b and 3c). The efficiency in the transformation of the number of years of schooling into competences is greatest in three of the Nordic countries analyzed (Finland, Sweden and Denmark), Japan and Belgium. In contrast, the lowest levels of efficiency are recorded in Spain, Italy, Ireland, Poland, Korea and the United Kingdom. This pattern is repeated with only minor differences across the three levels of education: the order of the countries is largely similar, with some notable differences, (for example, in the case of higher education Italy presents an especially low level of efficiency and Poland presents a slightly higher level of efficiency).

Graph set 4 (Graphs 4a, 4b and 4c) presents the efficiency indices using specification 2 (in which the coefficients that affect the transformation of inputs into outputs vary from country to country). As in Graph set 3, the Nordic countries present the highest rates of efficiency, these indices being slightly higher than those reported for specification 1. Japan and Belgium present very similar levels of efficiency to those obtained with specification 1, but they fall in the overall ranking of countries by rates of efficiency. The United Kingdom and Italy present the lowest levels of efficiency, while Spain, Ireland and Poland present indices that are similarly low for both specifications. Here the differences in the efficiency indices between the three levels of education (which are small in the case of specification 1) are even smaller. All in all, the positions occupied by the countries in the rankings are very similar across the three levels of education.

Graph set 5 tracks the evolution of the efficiency levels over the different age cohorts for the three levels of education considered. In the case of higher education, it can be seen that in most of the countries considered the levels of efficiency in generating competences are higher among the younger cohorts. This increase in the index is most significant in Spain and Italy, but is also appreciable in the Nordic countries (with the exception of Denmark), Belgium, Holland and Korea. In the cases of the United Kingdom and Ireland, the increase is less pronounced. However, there are hardly any changes in the levels of efficiency in the remaining countries: Japan, Denmark and the four Eastern European countries considered (i.e. Czech Republic, Estonia, Poland and the Slovak Republic).

In the case of higher secondary education, the pattern presented is one of general stability across all the cohorts. The only deviations from this trend are recorded in the cases of Italy and the United Kingdom, where there has been a fall in efficiency among the youngest cohorts, and in that of Finland, where there has been an increase in efficiency.

Likewise, in the case of lower secondary education, efficiency levels in most countries remain stable across all the cohorts. There are exceptions to this general pattern. For example, in Spain and Korea efficiency levels have increased among younger cohorts, whereas in Italy and the United Kingdom there has been a fall in efficiency levels for these same cohorts. In the Eastern European countries, the pattern of stability is interrupted in the cohort aged between 46 and 55 (26-45 in Slovakia) with marked declines in efficiency, associated in all probability with the historic evolution of the education systems in these countries

5. Conclusions

The aim of this study has been to compare the degree of efficiency with which the OECD countries produce competences from the schooling provided and from other inputs and, also, to monitor how this efficiency has evolved over different age cohorts. To do so, we have estimated standard stochastic frontier functions applied to OECD data from the PIAAC. In order to estimate this frontier we used two specifications so as to verify the robustness of our results. In the first specification, the influence of the explanatory variables has been taken into account and a function was estimated whose coefficients are common to all of the countries considered; in the second, the frontier functions methodology has been generalized to allow the coefficients (other than formal education) that affect the transformation of inputs into competences (including, years of experience and type of occupation) to vary from country to country.

The levels of efficiency reported by the analyses were similar for both specifications. Furthermore, the results by level of education show that in most cases the efficiency indices are similar for all three levels of education. However, efficiency in the transformation of schooling into competences is greatest in Finland, Sweden, Denmark, Japan and Belgium, while the lowest levels of efficiency are to be found in Spain, the United Kingdom, Italy, Ireland and Poland.

Finally, as regards the evolution in the levels of efficiency associated with different age cohorts, we found that in the case of higher education, levels are higher among younger cohorts, whereas in the cases of lower and upper secondary education, the general pattern, albeit with some exceptions, is one of stability for all the cohorts considered.

[GRAPH SET 3, GRAPH SET 4 AND GRAPH SET 5 ABOUT HERE]

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Graph 1. Kernel distribution of efficiency scores for two extreme countries: Belgium and Italy

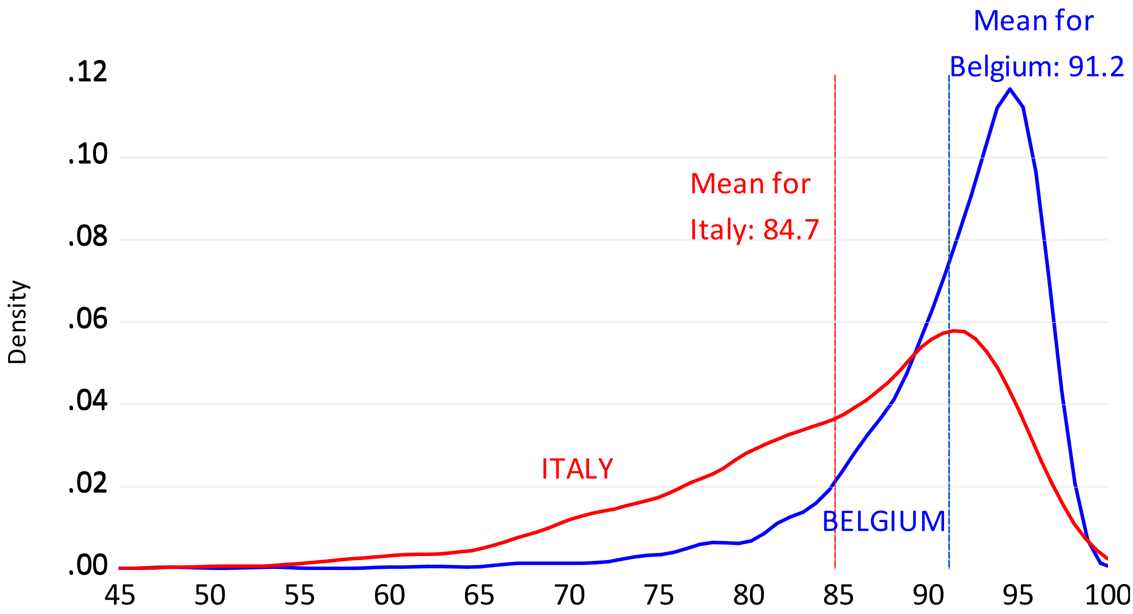


Table 1. Descriptive statistics

Variable	Average	Standard dev.	Min	Max
Mathematics Comp.	542.0646	96.1126	49.6917	888.2642
Schooling	12.7323	3.0259	3.0000	22.0000
Age	39.9555	14.4749	16.0000	65.0000
Experience	18.2143	13.1439	0.0000	55.0000
Man	0.4783	0.4995	0.0000	1.0000
Immigrant 1st gen.	0.0796	0.2707	0.0000	1.0000
Immigrant 2nd gen.	0.0173	0.1304	0.0000	1.0000
Mother tongue	0.9233	0.2660	0.0000	1.0000
Parents higher secondary ed.	0.3815	0.4858	0.0000	1.0000
Parents higher ed.	0.2232	0.4164	0.0000	1.0000
Qualified occupation	0.6122	0.4873	0.0000	1.0000
Non-regulated training	0.3919	0.4882	0.0000	1.0000

Table 2. Average competences by country

Country	Average Competences
Belgium	560.7724
Czech. Rep	551.4677
Denmark	556.5568
Estonia	546.239
Finland	564.4532
Ireland	511.1808
Italy	494.2578
Japan	576.3407
Korea	526.7724
Holland	560.6922
Norway	556.5957
Poland	519.5378
Slovak Rep.	551.6152
Spain	491.6435
Sweden	558.1049
United Kingdom	523.4517

Table 3. Ranking of countries by competences

Country
Japan
Finland
Belgium
Holland
Sweden
Norway
Denmark
Slovak Rep.
Czech Rep.
Estonia
Korea
United Kingdom
Poland
Ireland
Italy
Spain

Graph 2. Average competences by country and level of studies

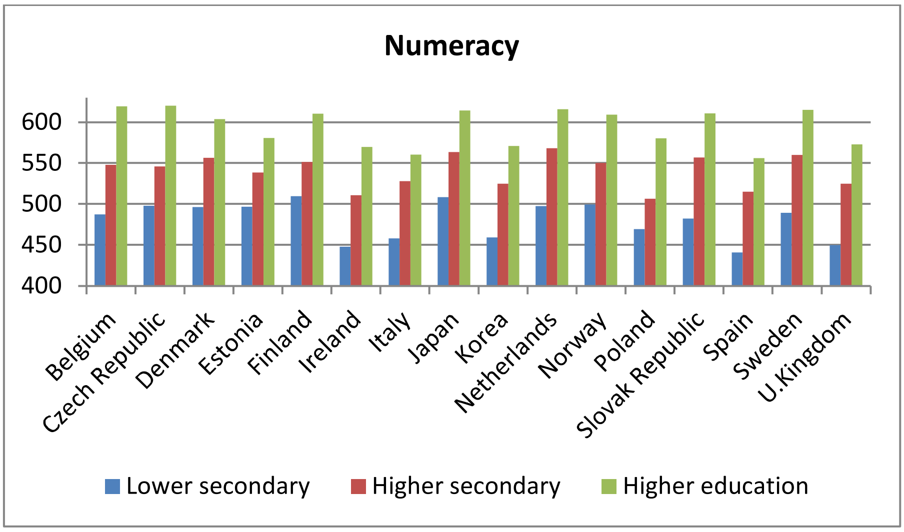
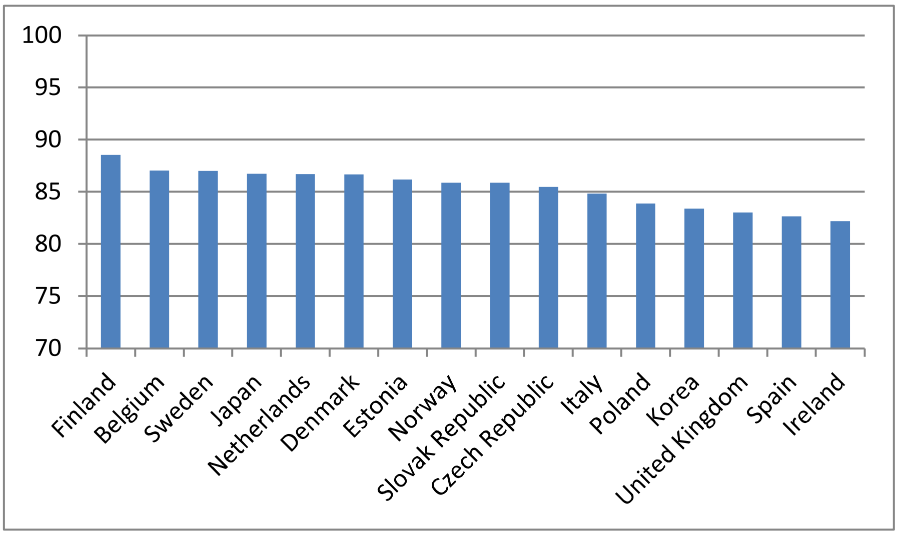


Table 4. Classification of countries as a function of their competence level, by level of studies

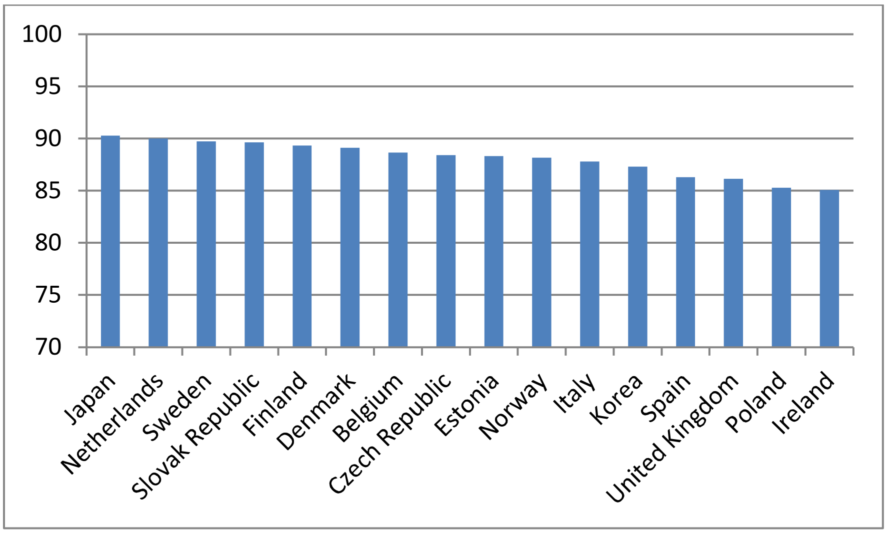
Lower Secondary	Higher Secondary	Higher education
Finland	Holland	Belgium
Japan	Japan	Holland
Norway	Sweden	Sweden
Czech Rep.	Slovak Rep.	Japan
Holland	Denmark	Slovak Rep.
Estonia	Finland	Finland
Denmark	Norway	Norway
Sweden	Belgium	Denmark
Belgium	Czech Rep.	Estonia
Slovak Republic	Estonia	Poland
Poland	Italia	United Kingdom
Korea	Korea	Korea
Italia	United Kingdom	Ireland
United Kingdom	Spain	Italy
Ireland	Ireland	Spain
Spain	Poland	Belgium

Graph set 3. Efficiency indices for competence in mathematics. Specification 1.

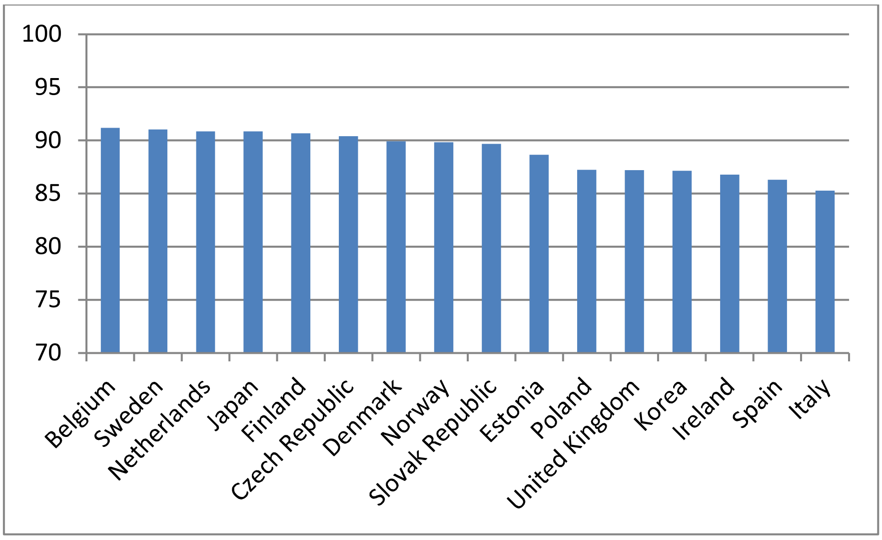
Graph 3.a. Lower secondary



Graph 3.b. Higher secondary

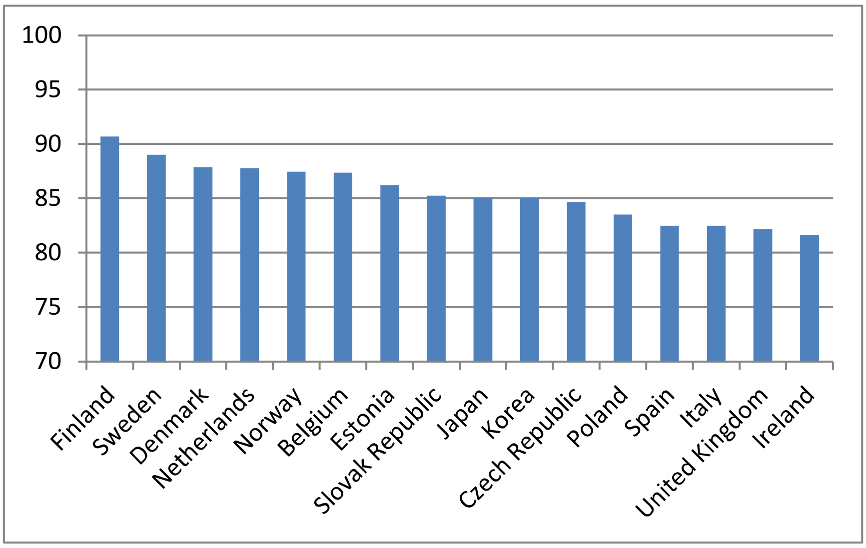


Graph 3.c. Higher education

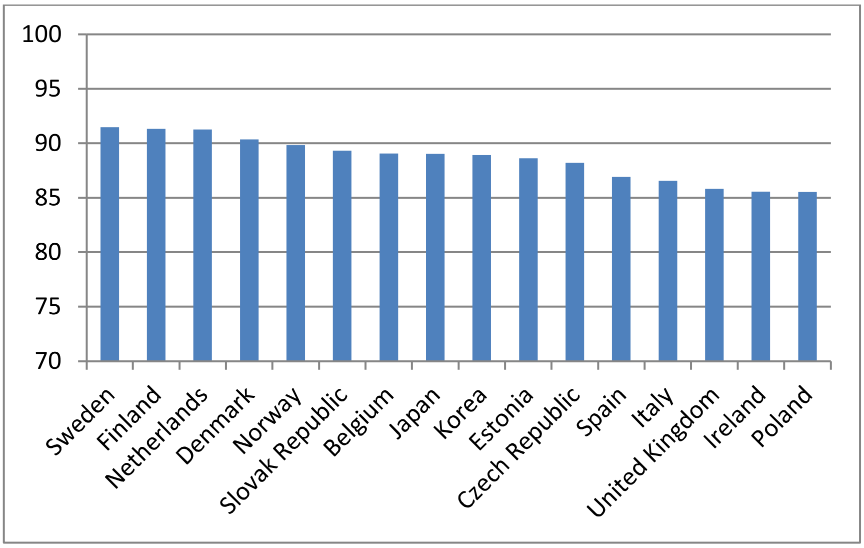


Graph set 4. Efficiency indices for competences in mathematics. Specification 2.

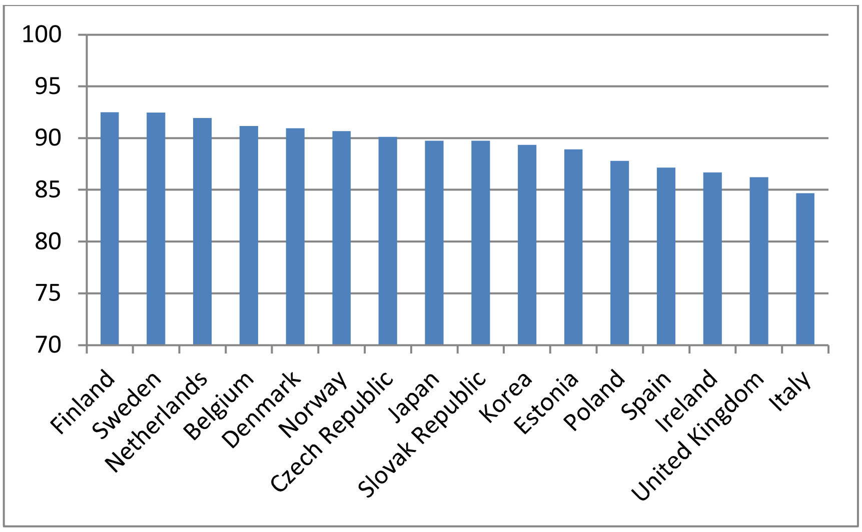
Graph 4.a. Lower secondary



Graph 4.b. Higher secondary



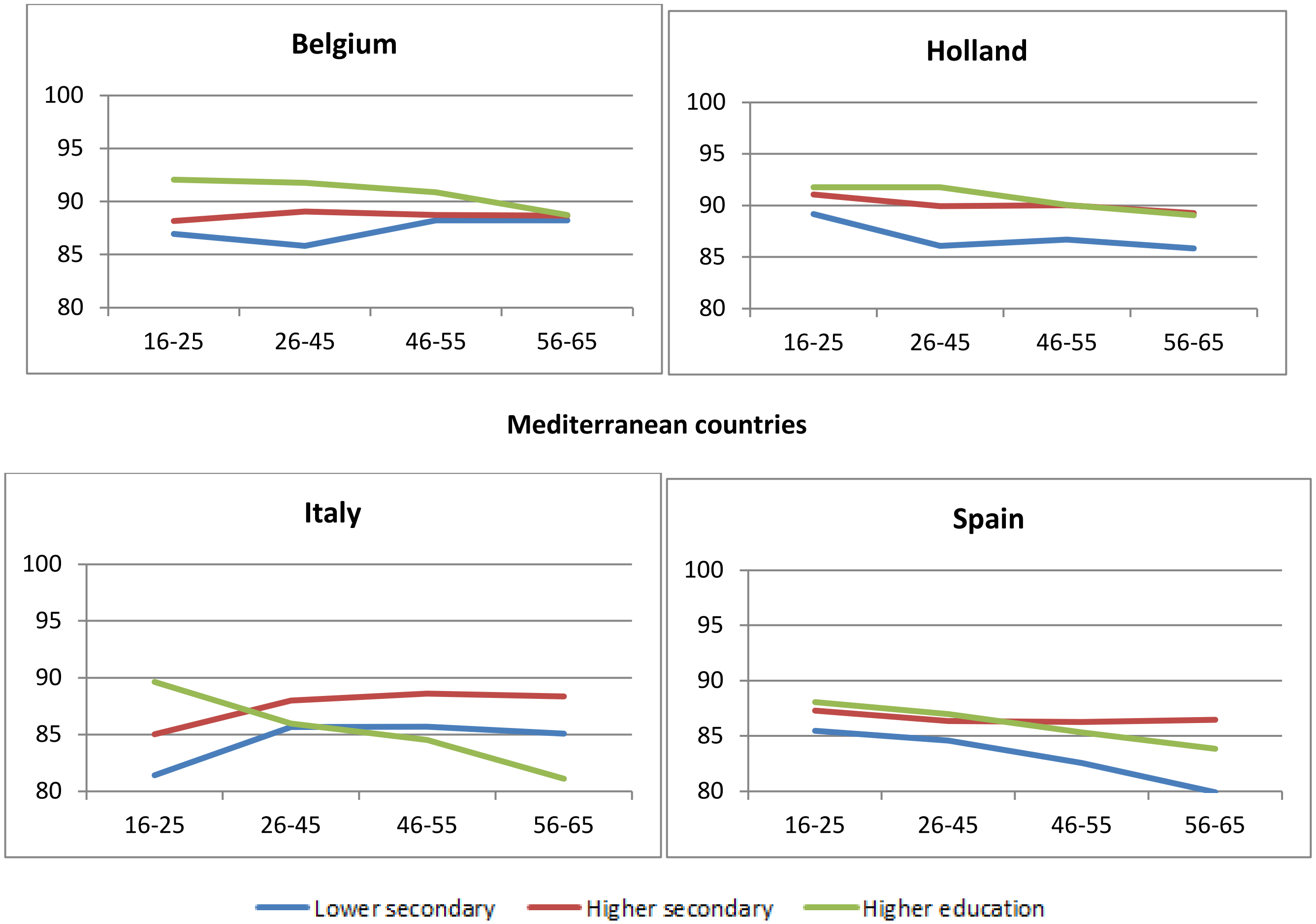
Graph 4.c. Higher education



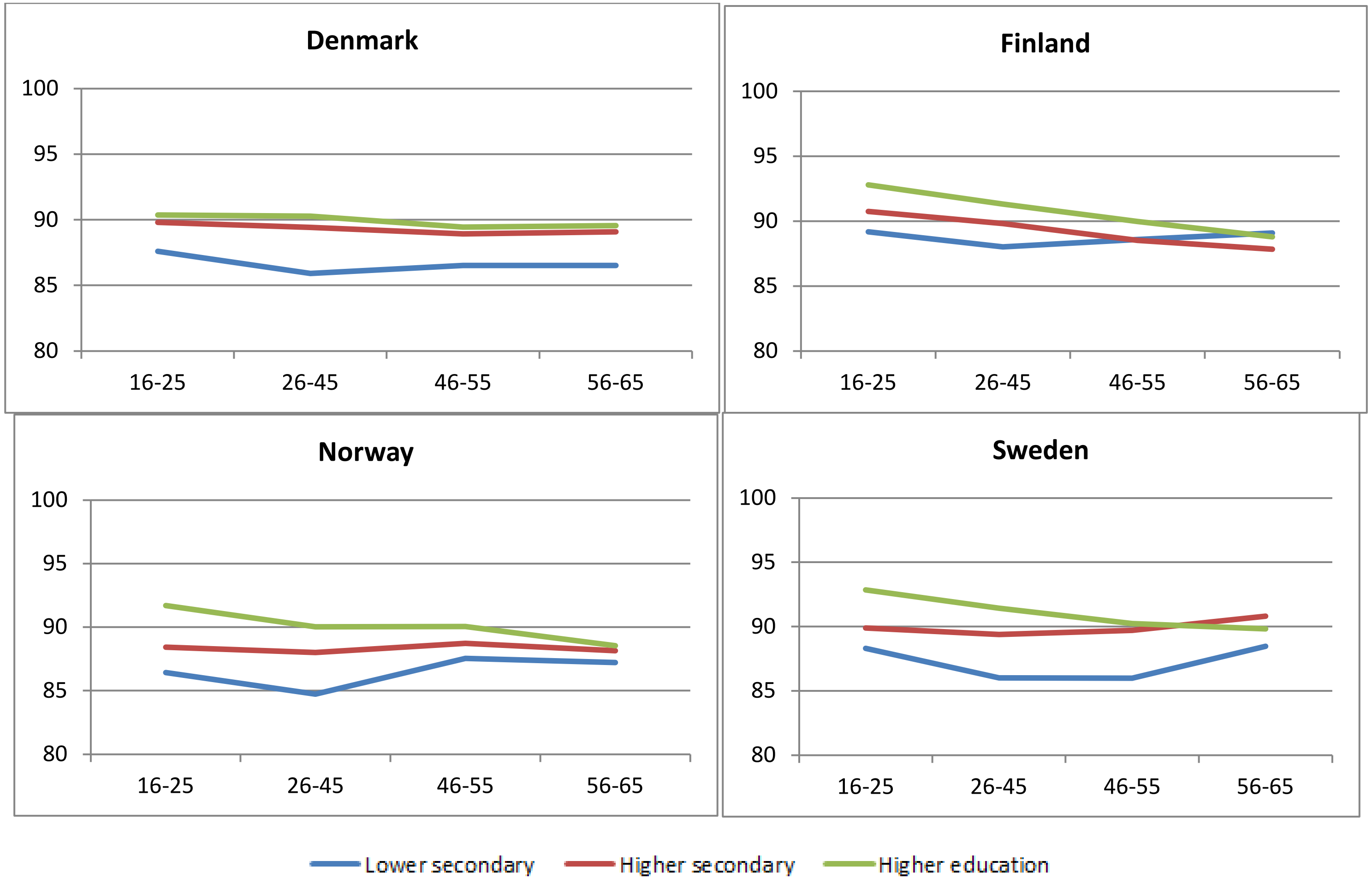
Graph set 5. Efficiency indices for competence in mathematics according to level of education and cohort

Continental countries

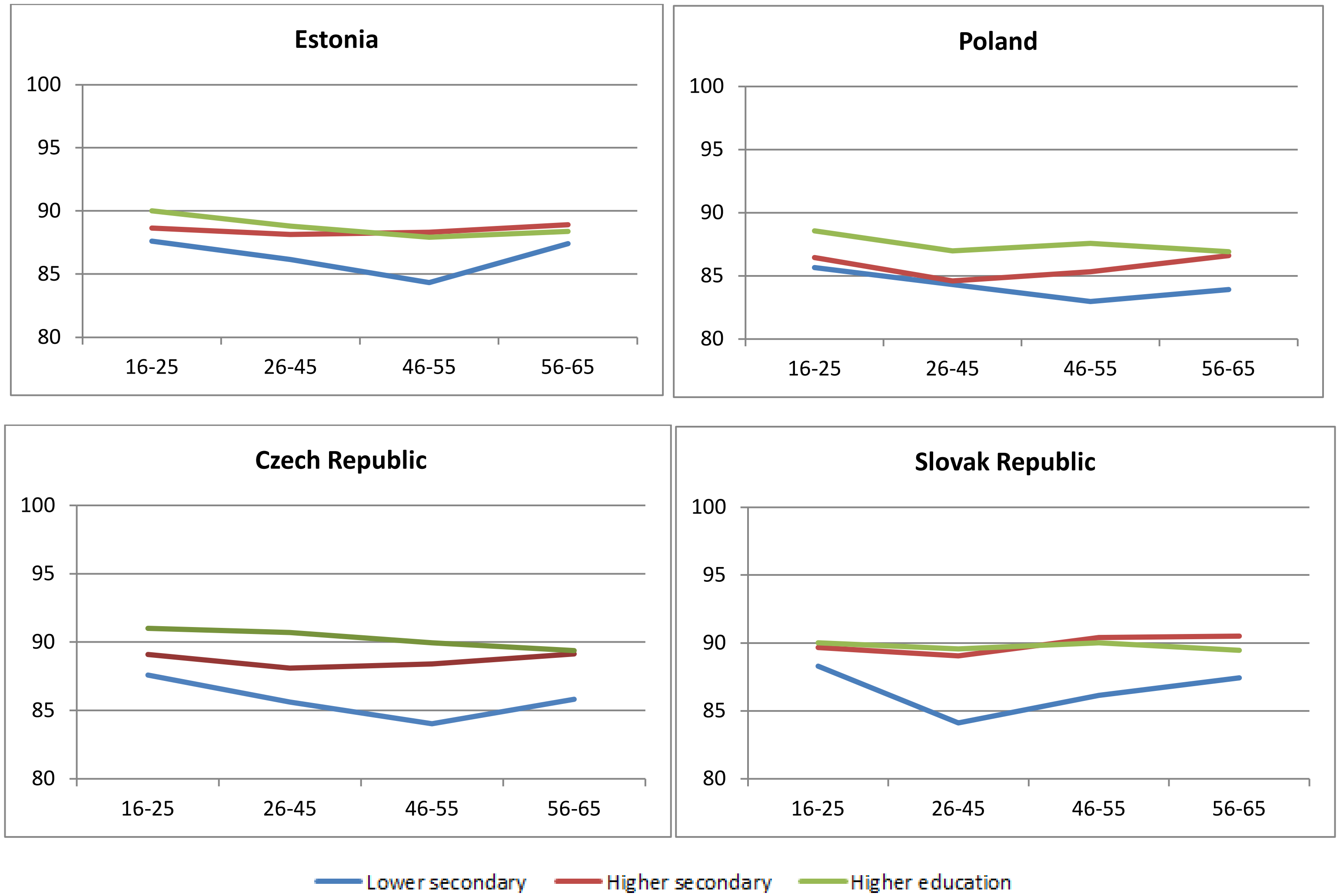
Mediterranean countries



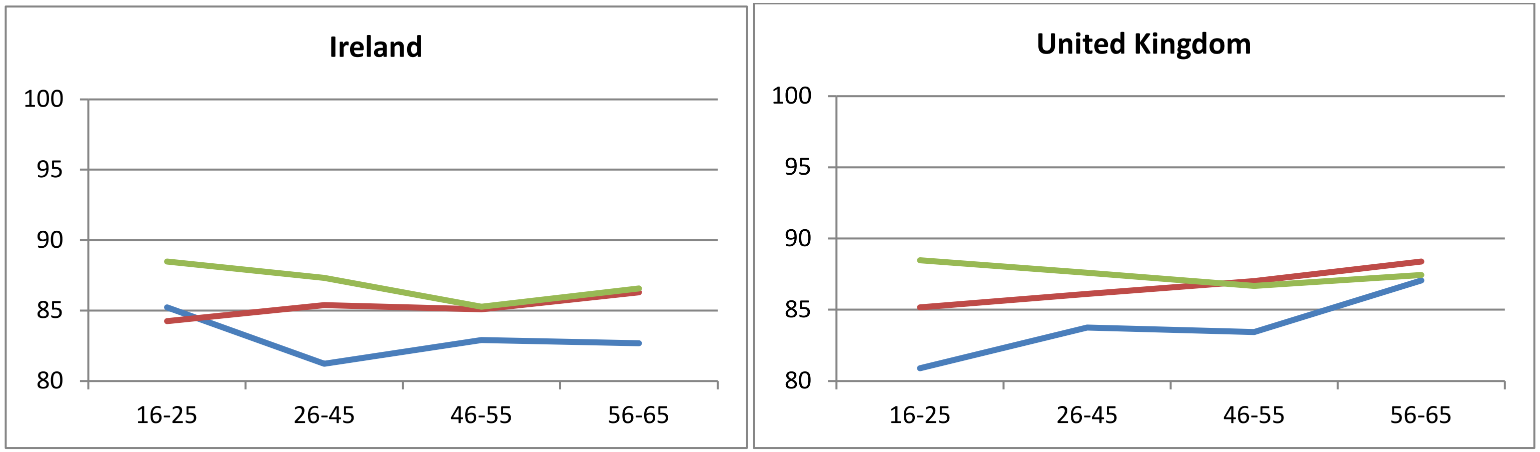
Nordic countries



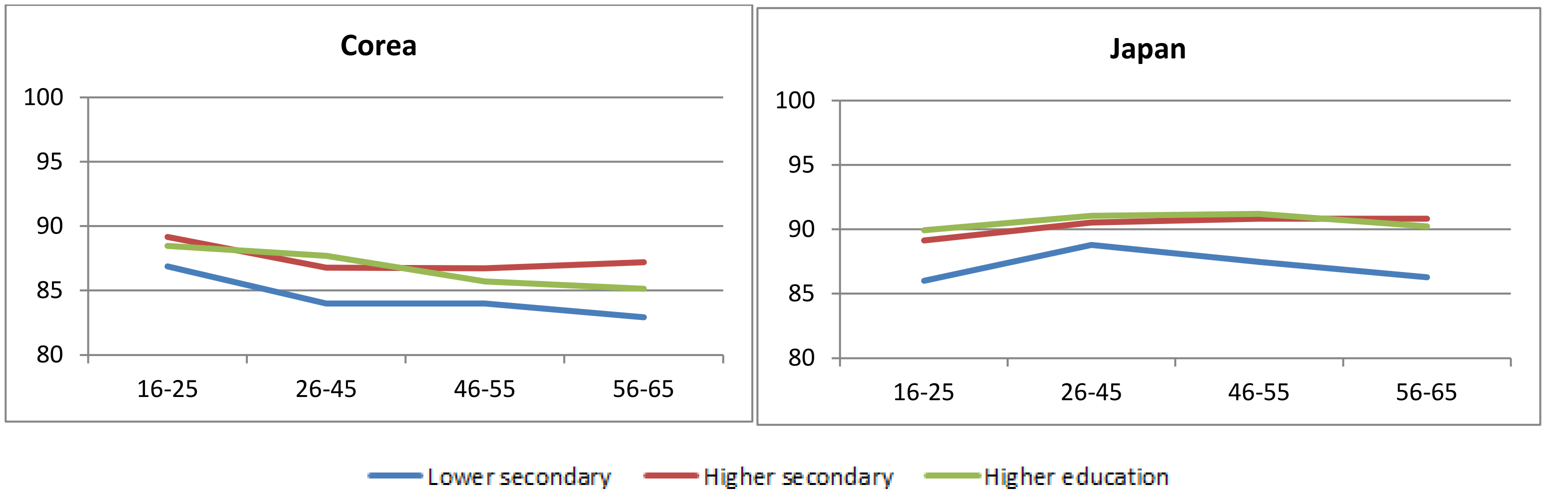
Eastern European countries



Anglo-Saxon countries



Asian countries

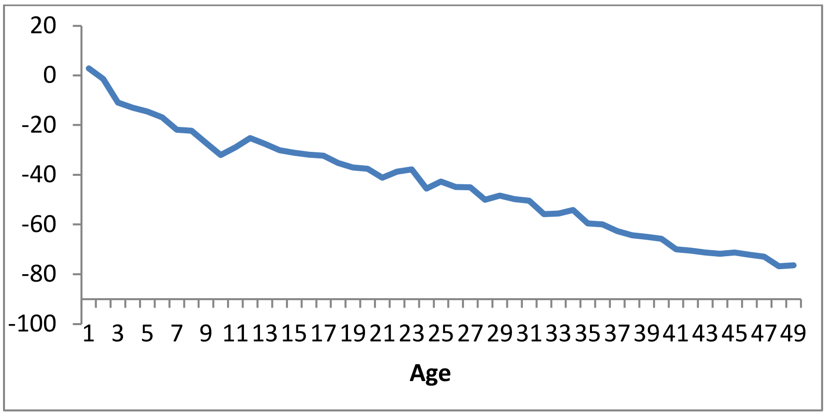


ANNEX 1. Selection of the functional form of age and experience in education production

Table A.1.1. Free Effect of age and experience

Variables	Estimated coefficients
Schooling	9.93***
	87.65
Age dummies: see Graph A.1	
Experience dummies: see Graph A.2	
Woman	-21.31***
	-39.57
Immigrant 1st gen.	-33.73***
	-23.93
Immigrant 2nd gen.	-7.42***
	-3.65
Mother tongue	-19.92***
	-13.64
Parents basic ed.	-30.98***
	-40.98
Parents secondary ed.	-15.13***
	-22.42
Unqualified occupation	-27.94***
	-43.79
Without non-regulated training	-12.84***
	-22.56
Constant	585.52***
	155.09
Schwarz Statistic	907087.7
Observations	78,825

Graph A.1. Effect of age



Graph A.2. Effect of experience

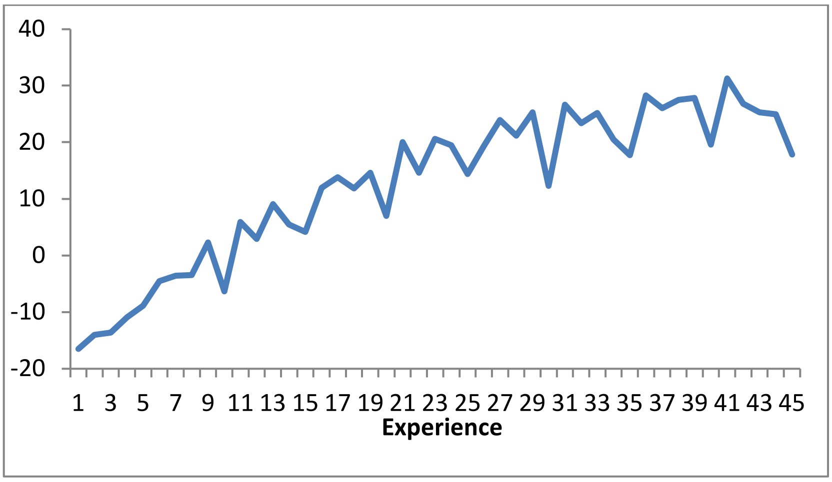


Table A.1.2. Linear effect of age and quadratic effect of experience

Variables	Estimated coefficients
Schooling	9.70***
	87.39
Age	-1.50***
	-31.94
Experience	1.85***
	20.42
Squared experience	-0.02***
	-11.88
Woman	-21.23***
	-39.38
Immigrant 1st gen.	-34.24***
	-24.25
Immigrant 2nd gen.	-7.51***
	-3.68
Mother tongue	-20.05***
	-13.69
Parents basic ed.	-31.87***
	-42.28
Parents secondary ed.	-15.82***
	-23.44
Unqualified occupation	-28.31***
	-44.37
Without non-regulated training	-12.33***
	-21.78
Constant	590.32***
	275.42
Schwarz Statistic	906532.7
Observations	78,825

ANNEX 2. A proposal to generalize the frontier production function (Approach 2)

The starting point is the competence production functions at the country level:

(1) $Y_{iJ} = \mu_J + \beta_J' X_{iJ} + \alpha_J S_{iJ} + w_{iJ}$

where "i" is the individual and "J" the country. X_{iJ} are the characteristics of the individual and S_{iJ} are the number of years of education. From this, we obtain:

(2) $Y_{iJ} - \beta_J' X_{iJ} = \mu_J + \alpha_J S_{iJ} + w_{iJ}$

(3) $Y_{iJ}^{*} = \mu_J + \alpha_J S_{iJ} + w_{iJ}$

If "Y_{ij}^{*}" of equation (3) were directly observable, this equation could be estimated using the standard frontier function technique and assuming a common α_J. As this is not the case, the proposal is:

a) Estimate (1) by OLS for the different countries. This enables us to obtain a consistent estimation of the "β" coefficients.

b) From this consistent estimation of "β", we obtain an estimation of $\hat{Y}_{ij}^{*} = Y_{ij} - \hat{\beta}_j' X_{ij}$. This variable "$\hat{Y}_{ij}^{*}$" is an estimation of the competences of individual "i" living in country "J" after excluding the effects of experience, age, sex, and all the other variables on the competences acquired.

c) Given that "$\hat{Y}_{iJ}^{*}$" is the net of the contribution of the remaining variables of education, a frontier function can be estimated for this variable using the number of years of schooling as the only explanatory variable. Following this approach, the efficiency term estimated from this frontier will also refer uniquely to the years of schooling.

ANNEX 3. Efficiency indices calculated according to specifications 1 and 2

Table A.3.1. Efficiency indices by levels of study. Specification 1

	Lower		Upper		Higher	
	Mean	SD	Mean	SD	Mean	SD
Belgium	87.023	8.476	88.660	6.985	91.174	5.707
Czech Republic	85.463	0.950	88.399	0.325	90.400	0.635
Denmark	86.664	0.858	89.107	0.585	89.910	0.647
Estonia	86.177	2.293	88.310	1.126	88.653	1.263
Finland	88.549	1.088	89.322	0.570	90.650	0.636
Ireland	82.195	1.021	85.060	0.679	86.770	0.748
Italy	84.839	0.208	87.803	0.209	85.258	0.339
Japan	86.712	0.284	90.281	0.128	90.840	0.132
Korea	83.386	0.350	87.295	0.193	87.148	0.214
Netherlands	86.689	0.468	90.009	0.348	90.841	0.395
Norway	85.869	0.941	88.176	0.666	89.830	0.717
Poland	83.868	0.546	85.274	0.196	87.234	0.278
Slovak Republic	85.855	1.303	89.648	0.482	89.680	0.859
Spain	82.652	0.228	86.290	0.278	86.301	0.243
Sweden	86.993	0.738	89.720	0.413	91.011	0.556
United Kingdom	83.015	0.371	86.139	0.196	87.206	0.206

Table A.3.2. Efficiency indices by levels of study. Specification 2

	Lower		Upper		Higher	
	Mean	SD	Mean	SD	Mean	SD
Belgium	87.359	7.773	89.066	6.268	91.172	5.007
Czech Republic	84.658	0.924	88.205	0.318	90.129	0.619
Denmark	87.862	0.834	90.361	0.572	90.937	0.630
Estonia	86.209	2.229	88.630	1.103	88.894	1.232
Finland	90.683	1.058	91.312	0.558	92.489	0.620
Ireland	81.616	0.993	85.553	0.665	86.691	0.729
Italy	82.473	0.202	86.563	0.205	84.667	0.330
Japan	85.055	0.276	89.028	0.125	89.742	0.129
Korea	85.044	0.341	88.912	0.189	89.337	0.209
Netherlands	87.775	0.455	91.267	0.341	91.951	0.385
Norway	87.441	0.915	89.835	0.652	90.657	0.699
Poland	83.497	0.531	85.523	0.191	87.785	0.271
Slovak Republic	85.248	1.267	89.328	0.472	89.737	0.837
Spain	82.474	0.221	86.919	0.272	87.149	0.237
Sweden	88.996	0.717	91.477	0.405	92.450	0.542
United Kingdom	82.140	0.361	85.827	0.192	86.214	0.201