European Centre for the Development of Vocational Training

2022 European Skills Index

Technical report

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Note: This is not an official Cedefop publication. For any further information please contact Cedefop Expert Ilias Livanos who has been responsible for developing the European Skills Index.

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Note

The technical report was drafted during the update of the European Skills Index 2022.

List of abbreviations

EEA	European Economic Area
ESI	European Skills Index
ET2020	Education and Training 2020
EU	European Union
HCI	Human Capital Index
JRC	Joint Research Centre
NEET	Not in Education, Employment or Training
OECD	Organisation for Economic Co-operation and Development
PISA	Programme for International Student Assessment
VET	Vocational education and training
WEF	World Economic Forum
Cedefop	European Centre for the Development of Vocational Training
EU-LFS	European Union Labour Force Survey
EU-SILC	European Union Statistics on Income and Living Conditions
ISCED	International Standard Classification of Education
PCA	Principal component analysis

Part One: Constructing the Index

1. Introduction

This technical report accompanies the release of the 2022 version of the European Skills Index (ESI, henceforth also called the Index) developed by Cedefop.

The methodological decisions made in constructing the Index have implications for the subsequent interpretation and understanding of the results. The first part of this report outlines the scope, structure and results of the Index. The second part of the report discusses the analysis motivating some of the methodological decisions made in constructing the Index.

The 2022 ESI updates the work undertaken for the two previous ESI reports in 2020 ESI, (Cedefop, 2020), and 2018 ESI, (Cedefop, 2019). The new Index builds on the methodology described in the 2018 ESI Technical Report (Cedefop, 2018) and the JRC Statistical Audit performed by the European Commission's Competence Centre on Composite Indicators and Scoreboards (Norlén & Saisana, 2018). The changes made compared to the 2020 update are explained in Part 2 of this report; briefly, they include the most recent data available, replacing two indicators, and the updating of the bounds and the weights. The 2022 ESI has gone through an independent statistical audit from the Joint Research Centre and has benefited from the pre-audit notes that were discussed with JRC. The conclusions of the JRC audit are presented in the Annex and can serve as a basis for improvements of subsequent releases.

2. Theoretical framework

2.1. Developing a framework to conceptualise a country's skills system

The ESI is intended to measure the performance of EU Members States, Iceland, Norway, Switzerland and the United Kingdom (hereinafter to be referred as EU-27+4) skills formation and matching systems to enable a comparative assessment across countries. The concept of a *skills system* is a multifaceted and complex one, and there is no single all-encompassing measure of the system's performance.

2.2. Defining a skills system

A country's skills system delivers enhanced skills to its population through compulsory education, and post-compulsory education and training. The skills system includes a variety of formal and informal training and education, secondary, further (continuing) and higher education, and both academic and vocational education and training (VET). It also includes lifelong learning, including on-the-job training and the acquisition of competences accrued through years working in a job. It also includes the activation of skills of different groups into the labour force to increase the skills base of the economy. The skills system's role is to ensure, as far as is feasible, that skills demand is met by skills supply in a way that optimises the use of the skills available in the labour force.

A country's skills system can be seen to fulfil several different roles, including:

(a) delivering the skills the country needs and/ or is anticipated to need in the future (including re-skilling and up-skilling);

(b) activating the skills in the labour market, by providing enough job opportunities to different groups in the population;

(a) matching, as far as possible, individuals' aspirations, interests, and abilities to the needs of the labour market.

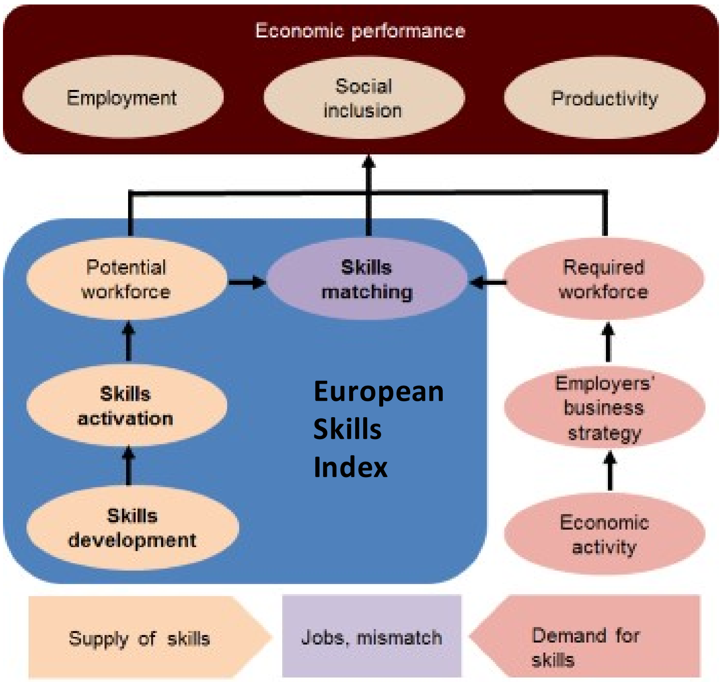
The capacity of a skills system to realise these ends has traditionally been measured with respect to individuals' propensities to avoid unemployment, obtain relatively high-wage work, and secure progression in the labour market. Accordingly, indicators have concentrated on measures of employment status and wages. The role that a skills system has in matching interests, aspirations, and abilities to labour market demand points to a wider range of outcomes that focus, more or less, on non-pecuniary measures relating to the quality of employment and working life.

These have driven the design of the ESI.

2.3. Our theoretical framework

In Figure 2.1 the theoretical framework to characterise a country's skills system is presented. The framework developed for ESI is based on a human capital approach in which both the individual and society derive economic benefits from investing in skills. The framework identifies the various dimensions of skills that can be acquired by an individual through both formal and informal learning. The starting point is that these skills drive economic performance through employment, social inclusion and productivity. Within the framework, social inclusion stands as a desired outcome because success in improving employment and productivity outcomes will depend on the latter being shared across the population as a whole. In other words, outcomes are socially as well as economically optimal.

Figure 2.1 Theoretical framework for the skills system



Source: European Skills Index (2019), Cedefop.

The role of the skills system is to bring together and match a suitably skilled **potential workforce** (supply) with the needs of employers (the **required workforce**, demand). The required workforce and the skills needed are determined by the nature and scale of **economic activity** and by **employers' business strategies**. The potential workforce is determined by **skills development** (education and training, and lifelong learning) and by the **activation** (or participation) of workers in the labour market. It is through the interplay between skills supply and demand that the degree of successful **matching** of skills is observed.

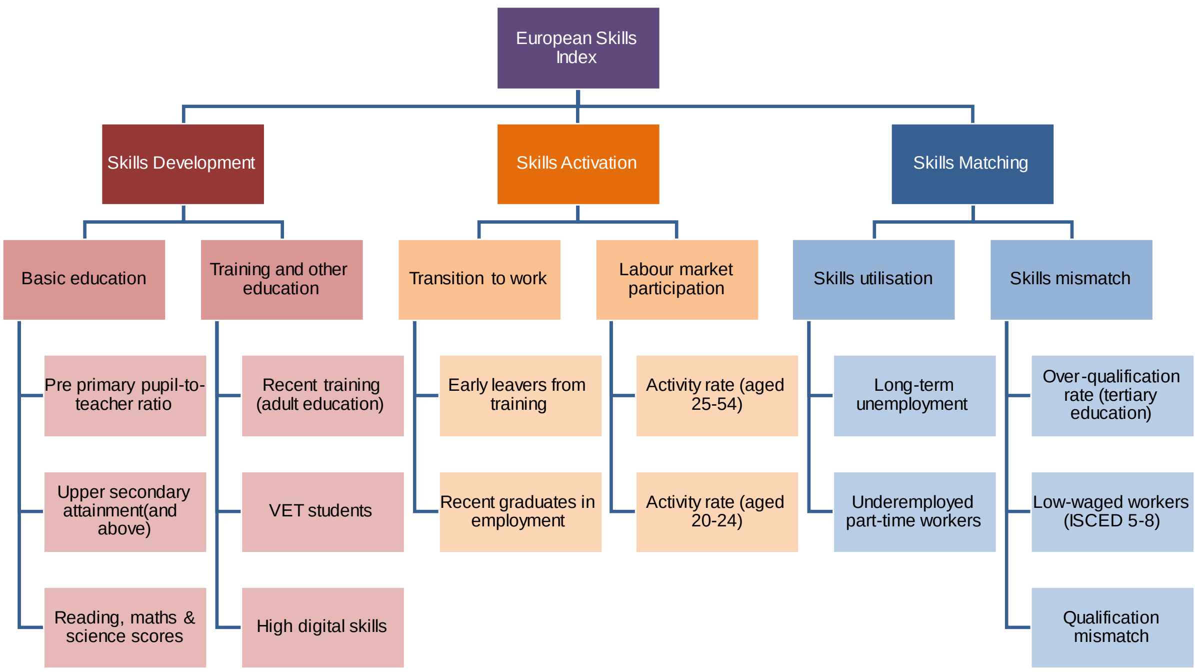
3. Scope of the European Skills Index (ESI)

3.1. Structure of the Index

In Figure 2.1 above, the area highlighted in the blue box indicates the aspects of the skills system that are included in the ESI. The ESI has three pillars (highlighted in bold in Figure 2.1 above) to assess how well the skills formation and matching systems of EEA Member States are performing in relation to the degree to which they are **developing**, **activating** and **matching** skills reserves within their economies. The ESI focuses on these supply and matching aspects of the skills system. Within the ESI, the demand for skills is captured most clearly in the matching of skills, and in the extent to which it influences decisions to invest in training and to activate skills.

Each pillar is broken down further into sub-pillars, to further organise the indicators into related groups. In total, the ESI has three pillars, six sub-pillars, and 15 indicators. The rationale and definition of each indicator are outlined in Table 3.2 below (Section 3.4). The structure of the Index is represented in Figure 3.1.

Figure 3.1 European Skills Index structure



Source: European Skills Index (2022), Cedefop.

3.1.1. Skills development

This pillar represents the training and education activities of the country and the immediate outputs of that system in terms of the skills developed and attained. This pillar has two sub-pillars:

- basic education; and

- training and other education.

3.1.2. Skills activation

The potential workforce of a country is determined not only by the development of skills in the population, but also by the activation (or participation) of skills in the labour market. This pillar includes indicators of the transition from education to employment, together with labour market activity rates for different groups of the population. This pillar has two sub-pillars:

- transition to work; and
- labour market participation.

3.1.3. Skills matching

Finally, the skills matching pillar represents the degree of successful utilisation of skills, the extent to which skills are effectively matched in the labour market. This can be observed in the form of jobs and mismatches which include unemployment, skills shortages, and skills surpluses or underutilisation of skills in the labour market. This pillar has two sub-pillars:

- skills utilisation; and
- skills mismatch.

3.1.4. Interpretation of the pillars

The pillars represent different aspects of the skills system and they organise our understanding of the system and the indicators that will be used to measure it. In reality, inter-relationships exist between the different pillars of the ESI. This is evident in all composite indices, for example, other composite indices (in a similar domain to ESI) also include pillars that are inter-related: the WEF's Human Capital Index (World Economic Forum, 2017) (pillars include education; health and wellness; workforce and employment; and enabling environment); and the European Commission's Social Scoreboard for the European Pillar of Social Rights (Joint Research Centre, 2018) (pillars include education, skills and lifelong learning; gender equality in the labour market; inequality and upward mobility; living conditions and poverty; and youth).

In our framework, the pillars can be interpreted as a process: the development of an individual's skills influences their activation in the labour market and consequently their matching to employment. However, as in other composite indices, there are also complex inter-relationships that run in the opposite direction: for example, an individual's decision to invest in training may be influenced by the likelihood of training improving their employment opportunities (matching).

3.2. Country coverage

The Index covers the EU-27+4, at the country level. The specific countries covered within the ESI are outlined in Table 3.1 below.

Table 3.1 Country coverage

Countries (country code)			
Belgium (BE)	Greece (EL)	Lithuania (LT)	Portugal (PT)
Bulgaria (BG)	Spain (ES)	Luxembourg (LU)	Romania (RO)
Czech Republic (CZ)	France (FR)	Hungary (HU)	Slovenia (SI)
Denmark (DK)	Croatia (HR)	Malta (MT)	Slovakia (SK)
Germany (DE)	Italy (IT)	Netherlands (NL)	Finland (FI)
Estonia (EE)	Cyprus (CY)	Austria (AT)	Sweden (SE)
Ireland (IE)	Latvia (LV)	Poland (PL)	United Kingdom (UK)
Iceland (IS)	Norway (NO)	Switzerland (CH)	

Source: European Skills Index (2022), Cedefop.

3.3. Time coverage

The 2022 European Skills Index draws on annual data, up to 2020. The Index is back-cast over 2018-2019 data to gauge how countries have performed over recent history (see Section 6.2 below).

3.4. Indicators in the Index

The details of each indicator in the Index are summarised in Table 3.2 below[1].

[1] For the UK, some indicators had to be computed from national sources, while data for 2020 had to be imputed for other indicators, see Section 4.1 below.

Table 3.2 Details of the indicators

Indicator (unit of measurement)	Description	Relevance of indicator (direction of effect)*	Source of data (and dataset code, if applicable)	Country coverage	Time coverage
Development					
Pre-primary pupil-to-teacher ratio (students per teacher)	Ratio of pupils and students to teachers and academic staff at the pre-primary education level (ISCED11 level 0, 3 years to the start of primary education.)	Proxy for the quality of teaching at pre-primary education level. (-) A lower value for Pre-primary pupil-to-teacher ratio is interpreted as a better outcome.	Eurostat, Collected by the UNESCO, OECD, Eurostat joint data collection (Eurostat code educ_uoe_perp04)	EU 27 plus Iceland, Liechtenstein, Norway, United Kingdom, Switzerland, Macedonia, Serbia, Turkey,	2013-2019
Upper secondary education (and above) (%)	Share of population aged 15-64 with at least upper secondary education (ISCED11 level 3-8)	Proxy for the education attainment level of the country (+)A higher value for Upper secondary education (and above) is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code edat_lfse_03)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1992 - 2020
Reading, maths & science scores (PISA score)	Average PISA scores (15-year olds) for reading, maths and science.	Proper levels of basic competences are key outcomes of initial education because they build the foundation for long-term economic growth of societies and social inclusion of individuals. Average across three separate indicators. (+) A higher value for Reading, maths & science scores is interpreted as a better outcome.	OECD PISA programme	OECD plus other partner countries for a total of 78 countries in the 2018 edition.	6 rounds, every three years, starting in 2000, last one being in 2018
Recent training (%)	Share of population aged 25-64 who stated that they received formal or non-formal education or training in the four weeks preceding the survey.	Continued learning after initial education is crucial for raising productivity levels of the working-age population and tackling skill mismatches and bottlenecks on the labour market. Matches EC E&T Monitor Target 6. (+) A higher value for Recent training is interpreted as a better outcome.	Eurostat - Labour Force Survey, (Eurostat code trng_lfse_01)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1992 - 2020
VET students (%)	Share of the population at ISCED11 level 3 attending vocational training	Evidence shows that within the group of graduates from upper secondary education, graduates from vocational education and training (VET) programmes have better employment prospects, particularly in countries where work-based learning is a strong component of VET programmes. EC E&T Monitor Target 13. (+) A higher value for VET students is interpreted as a better outcome.	Eurostat, Collected by the UNESCO, OECD, Eurostat joint data collection (Eurostat code educ_uoe_enra13)	EU 27 plus Iceland, Liechtenstein, Norway, Switzerland, United Kingdom, Macedonia, Turkey, with a further breakdown at NUTS 2 level	2013 - 2019
High digital skills (%)	Share of individuals who performed more than one activity in all skills domain (information, communication, problem-solving, software)	Digital competences are required for employability and active participation in society. (+) A higher value for High digital skills is interpreted as a better outcome.	Eurostat Community survey on ICT usage in households and by individual (Eurostat code isoc_sk_dskl_i)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Montenegro, Macedonia, Serbia, Turkey, Bosnia, Albania, Kosovo	2015, 2016, 2017, 2019
Activation					
Early leavers from training (%)	Early leavers from education and training (work status 'not in employment') as a share of the population, aged 18-24 having attained ISCED11 level 0, 1, 2 or 3c short and not receiving any formal or non-formal	Early leavers experience reduced lifetime earnings and longer and more frequent unemployment spells; early leaving also brings large public and social costs. (-)	Eurostat - Labour Force Survey (Eurostat code edat_lfse_14)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1992-2020

	education or training in the four weeks preceding the survey.	A lower value for Early leavers from training is interpreted as a better outcome.			
Recent graduates in employment (%)	Share of employed people aged 20-34 having successfully completed upper secondary or tertiary education 1 to 3 years before the reference year of the survey and who are no longer in education or training.	Although education and training cannot compensate for the economic downturn, the quality and relevance of education can be strengthened to better meet the needs of the modern labour market. Matches EC E&T Monitor Target 5 (+ A higher value for Recent graduates in employment is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code edat_lfse_24)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	2000-2020
Activity rate (aged 25-54) (%)	Employed/active persons as a share of same age total population	The supply of skills can be increased through higher activation. (+) A higher value for Activity rate (aged 25-54) is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code lfsa_argaed) For the UK : Annual Population Survey	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1983-2020
Activity rate (aged 20-24) (%)	Employed/active persons as a share of same age total population	Integrating under-represented groups into the labour force can increase the skills base in an economy. (+) A higher value for Activity rate (aged 20-24) is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code lfsa_argaed) For the UK : Annual Population Survey	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1983-2020
Matching					
Long-term unemployment (%)	Share of unemployed persons since 12 months or more in the total number of active persons in the labour market	Gives some indication of structural mismatch and of the effectiveness of a skills system in responding to skill obsolescence. (-) A lower value for Long-term unemployment is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code une_ltu_a) For the UK : computed from dataset YBWH and Labour Force Survey Table A02 SA, ONS	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	1996-2020
Underemployed part-timers (%)	Underemployed part-time workers aged 15-74 as share of active population. Persons working on an involuntary part-time basis are those who declare that they work part-time because they are unable to find full-time work	Ineffective use of skills - labour is underutilised among persons already employed and willing to work more hours. (-)A lower value for Underemployed part-timers is interpreted as a better outcome.	Eurostat - Labour Force Survey (Eurostat code lfsa_sup_age and lfsa_agan)	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, Macedonia, Turkey, Serbia, Montenegro	2008-2020
Overqualification rate (tertiary education) (%)	Share of employed people aged 25-34 with ISCED11 level 5 and 6 that occupy jobs NOT corresponding to ISCO 1, 2 or 3	Gives an indication of ineffective use of skills – highly-educated employees working in lower skilled jobs (-) A lower value for Over-qualification rate is interpreted as a better outcome.	Skills Panorama, from Eurostat – Labour Force Survey	EU 27 plus Iceland, Norway, Switzerland, United Kingdom	2011-2019

Low waged workers (ISCED 5-8) (%)	This is defined as the proportion of low wage earners out of all employees of ISCED11 level 5-8 qualification level, where low wage is defined as “those employees (excluding apprentices) earning two-thirds or less of the national median gross hourly earnings in that particular country”	Gives an indication of the ineffective use of skills - high-educated employees in low wage employment (-) A lower value for Low-waged workers (ISCED 5-8) is interpreted as a better outcome.	Elaboration of EU-SILC microdata	EU-27 plus Iceland, Norway, Switzerland, United Kingdom	2014-2019
Qualification mismatch (%)	The measure is calculated by taking the modal education attainment level for each occupation in each industry and assessing whether each employee’s education attainment level matches it	Measures incidences of both underqualification and overqualification, which provides an indication of ineffective use of skills, or the need for upskilling. (-) A lower value for Qualification mismatch is interpreted as a better outcome.	OECD WISE database	EU 27 plus Iceland, Norway, Switzerland, United Kingdom, South Africa	2015-2016

Source: European Skills Index (2022), Cedefop.

3.4.1.1. New indicators replacing existing ones

The ESI 2022 update includes the following changes in indicators compared to the ESI 2020:

- “High digital skills”, replacing the old “High computer skills”; and
- A “Low waged workers (ISCED 5-8)” indicators constructed on a different data source.

The change of indicators does not affect the ESI theoretical framework (see section 2) and structure see (see Section 3.1), since the new “High digital skills” and “Low-waged workers (ISCED 5-8)” cover the same concepts as the previous indicators.

3.4.1.2. High digital skills

The “High computer skills” indicator (Eurostat code isoc_sk_cskl_i) used in ESI 2018 and 2020 belongs to the “Training and other education” sub-pillar, and captures the level of computer skills of the population. The indicator measures the share of population that carried out five out of six of the following activities: coping or moving a file or folder, using copy and paste tools, using basic arithmetic formula in a spreadsheet, compressing (or zipping) files, connecting and installing new devices, writing a computer program using a specialised programming language[2]. Eurostat discontinued the update of the indicator in 2015 and replaced it with a new digital skills indicator (Eurostat code isoc_sk_dskl_i), based on the Digital Competence Framework developed by the JRC and DG EAC[3]. The “High digital skills” indicator measures the share of population with above basic digital skills, meaning those people who performed a sufficient number of activities in the skills domain of information, communication, problem-solving and software. The “High digital skills” indicator broadly measures the same concept as the “High computer skills” indicator and is updated from the same survey (i.e. the Community survey on ICT usage in households and by individual). The “High digital skills” in 2015 has a correlation of 0.78 with the previous “High computer skills” in 2014.Therefore, its inclusion in the ESI framework does lead to any conceptual changes.

The “High digital skills” indicator correlates at the 1% significance level with five other ESI indicators (see Figure 8.1), i.e. better pairwise correlation with other ESI indicators than “High computer skills” indicator.

3.4.1.3. Low-waged workers (ISCED 5-8)

The “Low-waged workers (ISCED 5-8)” indicator (Eurostat code earn_ses_pub1i) used in ESI 2018 and 2020 belongs to the “Skills mismatch” sub-pillar and was derived from the Structure of Earning Survey (SES). The SES covers a sample of enterprises with more than 10 employees and provides detailed and comparable information on the level of employees’ remunerations and characteristics of both employees and employers[4]. The indicator was defined as: “the proportion of low-wage earners out of all employees of ISCED11 level 5-8 qualification level, where low wage is defined as those employees (excluding apprentices) earning two-thirds or less of the national median gross hourly earnings in that particular country”. The SES is updated every four years, the latest version dating back to 2018. The indicator in the ESI 2020 dates from 2014. The four-year publishing period does not allow a meaningful update of the ESI every two years, since new information would be included in the index only every four years. Therefore, a readily-updated indicator broadly measuring the same concept, i.e. share higher educated receiving lower wages than 60% of the median

[2] https://digital-agenda-data.eu/datasets/digital_agenda_scoreboard_key_indicators/indicators#digital-skills

[3] https://digital-strategy.ec.europa.eu/en/library/new-comprehensive-digital-skills-indicator

[4] https://ec.europa.eu/eurostat/web/microdata/structure-of-earnings-survey

wage was sought out. Eurostat publishes income indicators based on the European Union Statistics on Income and Living Conditions (EU-SILC) at the household level, but not at the individual level[5]. Since no other similar publicly available indicator was identified, the new indicator was constructed based on EU-SILC microdata[6]. The following rules were followed for each country:

- Keep only employees;
- Drop individuals with zero income .
- Keep only individuals working either only full-time or only part-time for one year or less.
- Calculate monthly wage income from annual wage income by dividing annual wage income by the number of months worked during the year.
- Compute hourly wages as:

$$hourly\ wage = \frac{monthly\ wage\ income}{\left(\frac{52}{12}\right) * weekly\ hours\ worked}$$

With 52/12 being the average number of weeks in a month.

- Drop individuals in the first and last percentile of the hourly wage distribution to avoid outliers.
- Compute the median of the hourly wage distribution.
- Determine the low-wage threshold (i.e. two third of the median income).
- Compute the percentage of tertiary graduates earning less than the low-wage threshold.

Table 3.3 shows summary statistics for the computed indicator. Overall, the values of the indicator range from 1% to 19%, with cross-country differences. The mean and the median are around 8% for the whole sample (all years and all countries). The three countries with the lowest share (i.e. the top performing as average in the six years available) are in order Romania, Slovakia and Malta, while those with the highest share (i.e. worst performing as average in six years) are Estonia, Spain, and Ireland.

Table 3.3 Statistics for new “Low waged workers (ISCED 5-8)” indicator in 2014-19, %

Country	Median	Mean	Standard deviation	Min	Max
AT	9.8	9.5	1.2	7.9	10.7
BE	5.6	6.1	1.1	5.1	8.1
BG	9.3	7.8	2.7	3.4	9.8
CH	8.7	8.7	0.9	7.7	10.0
CY	13.5	13.5	1.3	11.5	14.9
CZ	3.5	3.6	0.7	2.9	4.5
DE	9.1	9.1	0.3	8.6	9.6
DK	5.5	5.7	0.8	4.9	7.0
EE	15.4	15.1	1.2	13.4	16.6
EL	9.2	8.9	0.7	7.5	9.5
ES	15.0	14.9	0.6	13.9	15.4
FI	4.0	4.0	0.4	3.6	4.5

[5] The “In-work poverty by educational attainment” indicator (Eurostat code ilc_iw04) was tested but showed insufficient correlation with the index to be included.
[6] Release of November 2020, which contains cross-sectional data up to 2019.

Country	Median	Mean	Standard deviation	Min	Max
FR	6.7	7.0	0.6	6.6	8.1
HR	5.1	5.4	0.9	4.4	6.5
HU	3.8	5.5	5.1	2.3	15.8
IE	14.8	14.8	0.7	14.0	15.8
IS	7.9	7.8	0.2	7.5	8.0
IT	11.8	11.8	0.9	10.4	12.7
LT	12.0	11.8	1.1	10.1	12.8
LU	12.3	11.8	2.6	7.9	15.3
LV	9.5	9.1	0.9	7.7	9.8
MT	3.2	3.3	0.8	2.1	4.4
NL	7.4	7.5	1.1	6.1	8.9
NO	9.5	9.8	0.7	9.0	10.8
PL	7.2	7.2	0.9	6.2	8.5
PT	5.0	4.9	0.6	4.1	5.4
RO	2.3	2.1	0.7	1.1	2.8
SE	11.3	11.3	2.1	8.9	13.8
SI	8.0	8.0	0.6	7.3	8.9
SK	2.8	2.9	0.9	1.6	4.3
UK	11.8	13.8	3.2	11.3	18.6
All sample	8.2	8.4	3.9	1.1	18.6

Source: Cedefop elaboration based on EU-SILC microdata

Table 3.4 compares the SES “Low-waged workers (ISCED 5-8)” indicator with the EU-SILC one in 2018. The shares of low-waged tertiary graduates are higher in the EU-SILC-based indicator, and in some cases (e.g. Belgium, Luxembourg and Spain) the differences are large between the two indicators. However, the correlation between the two indicators is 0.48 at the 1% significant level[7]. The median wages in the two sources is of similar magnitude. Given the small difference in median wages, the difference in shares can be attributed to the different composition of individuals in the sample between the two surveys; for example, the SES being administered at firm-level and EU-SILC at household level. EU-SILC covers also individuals working in firms with less than ten employees, which are not covered by SES. Despite the difference in magnitude of the shares, a significant correlation at the 1% level between the two indicators and similar median wage makes the EU-SILC-based indicator a good replacement for the SES-based indicator in the ESI framework.

[7] The critical value for a 1% two-tailed test of Pearson correlation with 29 degrees of freedom (31 countries minus 2) is 0.456.

Table 3.4 Comparison SES and EU-SILC, 2018

	Share of low waged ISCED 5-8 (%)			Median wage (€)		
	SES	EU SILC	pp diff	SES	EU SILC	diff
AT	5.3	10.2	4.9	15.0	17.2	2.2
BE	0.8	6.5	5.6	18.0	19.7	1.7
BG	5.4	9.2	3.8	2.4	2.1	-0.3
CH	2.0	9.2	7.2	31.4	33.1	1.7
CY	4.9	12.8	7.9	8.4	8.3	-0.1
CZ	2.5	3.1	0.6	6.2	5.7	-0.5
DE	5.7	9.1	3.5	16.9	16.2	-0.7
DK	2.7	5.8	3.0	27.1	26.6	-0.5
EE	12.7	13.4	0.6	6.5	6.1	-0.4
EL	7.4	9.2	1.9	7.0	7.8	0.8
ES	4.8	14.7	9.8	10.0	9.7	-0.3
FI	1.5	4.4	2.9	17.5	18.4	0.9
FR	4.0	6.6	2.6	15.2	14.3	-0.9
HR	2.5	4.4	1.8	5.4	4.9	-0.5
HU	1.3	4.9	3.6	4.4	3.4	-1.0
IE	13.0	14.8	1.8	17.8	18.3	0.5
IS	3.1	14.8	11.7	21.8	26.8	5.0
IT	2.8	10.4	7.6	12.5	12.1	-0.3
LT	7.8	11.4	3.5	4.4	4.1	-0.3
LU	1.7	12.4	10.7	19.5	21.6	2.1
LV	9.8	9.7	-0.1	4.9	4.9	0.0
MT	4.1	3.9	-0.2	10.0	9.5	-0.5
NL	4.3	7.6	3.3	16.4	21.3	4.9
NO	3.1	7.6	4.5	26.2	26.9	0.8
PL	7.2	6.2	-1.1	5.0	4.2	-0.8
PT	0.3	5.3	5.0	5.4	5.3	-0.1
RO	5.9	2.6	-3.3	3.7	2.8	-1.0
SE	1.5	9.1	7.6	18.2	18.5	0.4
SI	3.8	8.3	4.5	8.0	8.6	0.6
SK	3.9	2.5	-1.5	5.6	4.5	-1.1
UK	7.9	15.6	7.7	15.1	13.8	-1.3

Source: Cedefop elaboration based on EU-SILC microdata and SES

4. Treatment of indicators

4.1. Missing data and imputation methods

4.1.1. Method for data imputation in our dataset

For the ESI, a complete dataset for the latest year would mean 31 observations per indicator and 15 observations per country. Since the dataset is not complete, cold deck imputation is used, i.e. replacing missing values with values from a previous year. After that, by indicator, the lowest data availability is 93% for qualification mismatch indicator (Croatia and Malta have missing data).

For back-casting the Index, in addition to cold-deck imputation, linear interpolation is used to fill in missing data for which data are available in preceding and subsequent years in the same indicator.

4.1.2. Practical rules

In determining whether additional imputation methods are necessary, some practical rules are followed:

- a requirement for at least 60-65% indicator, pillar and sub-pillar coverage per country. This can be relaxed or made stricter depending on the degree of correlation between indicators within a dimension; for example, for each country, if there are more than 20% missing values in one dimension, then the country may be removed;
- there is a requirement for at least 75-80% data coverage per indicator.

Several imputation methods are available, each one with its advantages and disadvantages. The cold deck imputation replaces missing values with values from the nearest available previous year. Hot deck imputation replaces the missing values for a country with actual values taken from a "similar" country for the same period. The hot deck method requires the choice of auxiliary variables to identify the similar unit whose data will replace that of the missing unit, and the choice of distance to minimise once the auxiliary variables are identified[8]. In the context of the ESI, the identification of auxiliary variables would be difficult to achieve. Other imputation methods, such as model-based imputation methods, rely on explicit statistical modelling. The simplest method in this class is the unconditional mean imputation, whereby the missing data is imputed with the mean of the available observations. Other more sophisticated methods, such as regression or expectation-maximisation imputations, require distributional assumptions (OECD/EC JRC, 2008) that need to be justified. When data for a country is missing in single year within an indicator, it is judged that the best approximation to that missing data is the closest observation for the same country, therefore, cold deck imputation is applied, given also its simplicity both in terms of implementation and communication.

Once cold deck imputation is applied, **no imputation** approach is adopted thereafter (see Table 4.1 below). This is conceptually equivalent to imputing the missing value with the weighted mean of the values observed for that unit on the other indicators included in the same lower dimension (mean-row). This applies even if the indicators are assigned different weights. Other imputation methods described above complicate the communication of results. Moreover, imputing values based on other countries' performance would not reflect truthfully

[8] https://ec.europa.eu/eurostat/cros/content/handbook-methodology-modern-business-statistics_en

the developments in the country with the missing data, given that the purpose of ESI is to rank countries according to the effectiveness of their skills system.

As shown in Table 4.1, there are many instances where data for the UK were imputed in the year 2020. Eurostat stopped disseminating new data for the UK after 2019 until a new arrangement on statistical cooperation with the British statistical authorities is established in the context of Brexit[9]. It was possible to derive 2020 values for the indicators “Activity rates (25-54)”, “Activity rates (20-24)” and “Long-term unemployment” from the UK Office for National Statistics (ONS) data. Cold-deck imputation was applied in 2020 for the rest of the indicators. In the case Eurostat stops altogether to disseminate UK data, the removal of UK from the sample is recommended.

[9] https://ec.europa.eu/eurostat/help/faq/brexit

Table 4.1: Data coverage (most recent year, 2020)

Indicator (unit)	Missing data after imputation	Year of data for the Index
Pre-primary pupil-to-teacher ratio (students per teacher)	IE	2019 except: CH - 2018
Upper secondary education (and above) (%)	0	2020 except: UK - 2020
Reading, maths & science scores (PISA score)	0	2018 except: ES -2015
Recent training (%)	0	2020 except: UK - 2020
VET students (%)	0	2019
High digital skills (%)	0	2019
Early leavers from training (%)	0	2020 except: UK - 2020
Recent graduates in employment (%)	0	2020 except: UK - 2020
Activity rate (aged 25-54) (%)	0	2020
Activity rate (aged 20-24) (%)	0	2020
Long-term unemployment (%)	0	2020
Underemployed part-timers (%)	0	2020 except: UK - 2020
Over-qualification rate (tertiary education) (%)	0	2019
Low waged earners (ISCED 5-8) (%)	0	2019
Qualification mismatch (%)	HR, MT	2016

Source: European Skills Index (2022), Cedefop.

4.2. Outliers

Table 4.2 below presents the main summary statistics for the indicators for the latest year of data[10].

Table 4.2: Summary statistics

Indicator (unit)	Range	Median	Mean	Standard deviation	Skewness	Kurtosis
Pre-primary pupil-to-teacher ratio (students per teacher)	[5, 39.7]	12.4	13.6	6.2	2.7(*)	10.5(*)
Upper secondary education (and above) (%)	[55.5, 89.2]	79.3	77.8	8.5	-1.2	1.1
Reading, maths & science scores (PISA score)	[426.7, 525.5]	492.0	485.8	24.2	-1.1	0.8
Recent training (%)	[1, 28.6]	10.0	11.3	7.7	0.8	-0.1
VET students (%)	[16.9, 70.8]	48.1	47.9	15.8	0.0	-1.2
High digital skills (%)	[10, 62]	34.0	34.6	12.1	0.1	-0.2
Early leavers from training (%)	[1.8, 9.7]	4.3	4.6	2.0	1.1	0.7
Recent graduates in employment (%)	[54.9, 92.2]	82.2	80.6	8.6	-1.5	2.9
Activity rate (aged 25-54) (%)	[76.5, 92.4]	87.5	87.0	3.1	-1.2	3.4
Activity rate (aged 20-24) (%)	[39.7, 78.9]	61.2	60.5	12.1	-0.2	-1.4
Long-term unemployment (%)	[0.5, 10.9]	1.5	2.0	2.0	3.5(*)	14.4(*)
Underemployed part-timers (%)	[0.3, 7.3]	3.0	2.8	1.7	0.4	-0.2
Over-qualification rate (tertiary education) (%)	[9.7, 48]	21.1	23.6	8.3	1.1	1.5
Low-waged earners (ISCED 5-8) (%)	[2.4, 15.6]	8.1	8.4	3.8	0.3	-0.6
Qualification mismatch (%)	[17.1, 44]	35.0	33.6	7.0	-0.7	-0.1

(*) Instances where skewness is greater than 2 or kurtosis greater than 3.5.
Source: European Skills Index (2022), Cedefop.

Outliers can polarise the scores and bias the rankings. All variables are checked for absolute skewness greater than 2, and kurtosis greater than 3.5. The 2020 value for the UK in indicator "Pre-primary pupil-to-teacher ratio" is a outlier, while 2020 value for Greece is an outlier within "Long-term unemployment". In the previous editions of the ESI (Cedefop, 2019), the value for Greece in Long-term unemployment was winsorised[11] before normalisation step. Since it was observed that the 2020 normalised values of these two indicators satisfy the double criterion for skewness and kurtosis, no winsorisation was applied before normalisation, as suggested by the JRC Statistical Audit of the ESI (Norlén & Saisana, 2018). The 2019 value of the "Low-waged earners (ISCED 5-8)" indicator for Hungary was deemed unreliable and was substituted with the 2018 value.

4.3. Normalisation – Distance to frontier

The distance-to-frontier normalisation method is a special case of min-max normalisation method with bounds, where a country's performance in a variable is compared with the value of a logical "best case" as well as that of a logical "worst case". As a result, the country's

[10] The latest year of data in this instance refers to figures for 2020, including imputed values.
[11] Winsorisation entails replacing an outlier value with the closest non-outlier value. In previous editions of the ESI the value for long-term unemployment for Greece was replaced with the long-term unemployment value for Spain.

relative position can be captured by the generated distance-to-frontier scores. If the upper and lower bounds are time-invariant, then this approach enables easier comparison of Index scores over time. A country's distance-to-frontier score for each indicator is calculated using the formula:

$$\frac{I_{ij} - worst\ case}{best\ case - worst\ case}$$

where I_{ij} is the raw value of country i in indicator j.

The normalised scores for every indicator calculated using the formula above range from zero to one.

4.4. Bounds for the indicators

The ESI 2022 follows the methodology already implemented in the ESI 2018 update, and derives the fixed bounds for each indicator, i.e. best case and worse case, from statistical considerations. Some bounds could have been aligned with targets identified in policy papers at the EU level, in instances where they exist and can provide a target that countries can aspire to. However, it was decided not to use policy targets because of statistical coherence issues and it would not reward improvement of performance on either side of the bound. Regarding the first problem, many policy bounds are expressed as “at least” and they are average targets for the EU as a whole (e.g. at least 40% of people aged 30-34 should have completed some form of higher education). If such as target is used as a maximum bound, countries score full marks as soon as they achieve that bound, but no more if they exceed it – we do not reward the country performing better than the (EU-wide) target. If such a target is used as a minimum bound, countries score no points until they achieve that bound – we do not reward the country for making progress towards that (EU-wide) target. Regarding the second point, using policy bounds as described above causes a lack of variation in the scores of some indicators and this might be an issue for the index calculation. Moreover, policy targets are not available for all indicators. Therefore, statistical bounds are set close to the maximum and minimum values observed at indicator level, across EU+4 countries, and observed over 2014-2020, in instances where data are available. Table 4.3 below presents the bounds used for each Indicator in the Index and the rationale behind the choice of bounds, which are statistically computed bounds.

Table 4.3: Worst case and best case bounds

Indicator (unit)	Rationale for bounds	Worst case	Best case
Pre-primary pupil-to-teacher ratio (students per teacher)	There is no clear evidence on worst nor optimal student-to-teacher ratios, hence the best case is simply put at the minimum value of the ratio found in the data. The worst case is set around the 95th percentile, since the maximum (the UK value) is a clear outlier.	22	5
Upper secondary education (and above) (%)	Best outcome bound close to the maximum across the years. The Education and Training 2020 target was 40% attainment for tertiary education (of 30-34-year-olds), so in the long-term we would expect that the share of population with at least upper secondary education should be higher than this target. The worst case was rounded up to the level corresponding to the 5th percentile, while the best case is the rounding of the maximum value over seven years.	55	90

Indicator (unit)	Rationale for bounds	Worst case	Best case
Reading, maths & science scores (PISA score)	Bounds close to the (EU) 5th percentile and maximum. Both bounds are chosen to maintain a challenging but feasible level of ambition among Member States.	440	525
Recent training (%)	Bounds set close to the minimum and maximum across the seven years, which provide a reasonable benchmark given the underlying Member States' performance in this indicator.	1	32
VET students (%)	Bounds set close to the minimum and maximum across the seven years, which provide a reasonable benchmark given the underlying Member States' performance in this indicator.	17	75
High digital skills (%)	Bounds set at the minimum and maximum across the seven years, which provide a reasonable benchmark given the underlying Member States' performance in this indicator.	9	62
Early leavers from training (%)	It was decided to use a number close to the 95th percentile as the worst frontier across the years in order to increase Member States' ambitions in a feasible way, given that the indicator has been trending downward in most of them. For the best frontier a figure close to the minimum scored across the years was chosen, given that it is difficult to improve on such a low level.	9	1
Recent graduates in employment (%)	Bounds close to the 10th percentile and maximum across the seven years, in order to maintain a challenging and feasible level of ambition, given that the indicator has trended upward in most Member States.	65	95
Activity rate (aged 25-54) (%)	Bounds close to the 5th percentile and maximum across the seven years, in order to maintain a challenging and feasible level of ambition among Member States.	80	95
Activity rate (aged 20-24) (%)	Bounds close to the minimum and 95th percentile across the seven years. There is no clear trend of improvement among Member States, so the minimum is deemed appropriate as worst case. The 95th percentile was chosen as best case because the top 5% of observations belong to only one top-performer, and choosing the maximum would have excessively penalised the other Member States.	40	80
Long-term unemployment (%)	Bounds close to the minimum and 90th percentile (after excluding Greece as an outlier) across the seven years, in order to maintain a challenging and feasible level of ambition among Member States. The best case is kept close to the minimum because it is difficult to improve on such a low level.	5	0.5
Underemployed part-timers (%)	Bounds close to the minimum and maximum across the seven years. The worst case is kept around the maximum because many Member States are close to it, and proposing a more challenging bound would be excessively penalising. The best case is kept close to the minimum because it is difficult to improve on such a low level.	7	0.5

Indicator (unit)	Rationale for bounds	Worst case	Best case
Over-qualification rate (tertiary graduates) (%)	Bounds close to the 5th and 90th percentile across the seven years in order to maintain a challenging and feasible level of ambition among Member States.	35	10
Low waged earners (ISCED 5-8) (%)	Bounds close to the minimum and maximum across the seven years. There is no clear trend of improvement among Member States, so the maximum is deemed appropriate as worst case. The best case is kept close to the minimum because it is difficult to improve on such a low level.	19	1
Qualification mismatch (%)	Bounds close to the minimum and maximum across the seven years, which provide a reasonable benchmark given the underlying Member States' performance in this indicator.	44	16

Source: European Skills Index (2022), Cedefop.

The bounds in Table 4.3 have been modified compared to ESI 2020 update to take stock of the improvements occurred with the addition of years of data. In practice, bounds should be changed if a high number of countries moved away from the worst case or reached/surpassed the best case previously set. In this way, an appropriate level of ambition is maintained.

4.5. Transformation

No transformations are applied to the normalised scores. Although some of the normalised indicators present left or right skewness, it is considered that a sample of 31 countries is prone to such types of distribution. However, most indicators show values of the mean and the median between 0.3 and 0.7, therefore no transformation is deemed necessary. One indicator stands out: "Long-time unemployment" has both a high median and mean. A log transformation would ensure a more uniform distribution, but would also make an evaluation by country across time less clear.

5. Aggregation

5.1. Aggregation method

The aggregation method is not changed for the 2022 ESI update. A mixture of weighted arithmetic and geometric means is used at different levels of the Index.

The Index score is computed as the weighted geometric average of three pillar scores. Pillar scores are derived from calculating the weighted arithmetic average of the sub-pillar scores. Sub-pillar scores are calculated as the weighted arithmetic average of the Indicator scores.

The weighted arithmetic average method is easy to interpret, but makes a key assumption of perfect compensability between indicators as it assumes that the score in one indicator/sub-pillar can fully offset the score in another. At the indicator and the sub-pillar level, the interpretation of perfect compensability of scores is considered reasonable and adequate. The use of weighted arithmetic average also has precedence in the creation of other composite indices in which a distance-to-frontier normalisation approach is chosen[12].

The choice to use the weighted geometric average to combine the three pillar scores into an Index score stems from the consideration that perfect compensability at this level is more problematic. By using weighted geometric average, unbalanced profiles are penalised - that is, with pillar scores of two and eight, the weighted geometric average would be four, whereas pillar scores of five and five would score higher (five). Moreover, the geometric average gives more incentive for policymakers to improve those pillars with low values.

5.2. Weights

During the ESI 2018 update, it was decided that assigning equal weights to all indicators would not be satisfactory from a methodological point of view, given the different degree of correlation between indicators and the Index. Therefore, weights were chosen with the aim to ensure that the highest number of indicators would contribute in a meaningful way to variation in the Index score. The weights (and bounds) remained unchanged in the ESI 2020 update. During the ESI 2022 update, it was decided to update the bounds to better reflect the shift in the distribution of the data, and two indicators were replaced. Therefore, the weights required updating and the same procedure implemented in the ESI 2018 was followed, as described below.

As a starting point, equal weights were assigned at all levels[13]. The weights of each indicator were then adjusted (informed by PCA factor loadings calculated at sub-pillar level) as follows: the higher the PCA factor loading of an indicator, the lower the weights used and the opposite (see Section 8.4). Then, the correlation between the sub-pillar index and each indicator in the sub-pillar was checked so that no indicator is “driving” the sub-pillar and that each indicator is significantly correlated[14] with its sub-pillar. The weights were then adjusted to achieve these objectives. This check was repeated for the upper dimensions, i.e. sub-pillar, pillar and Index, to ensure that both sub-pillar correlation with its corresponding pillar, the individual indicators’

[12] See for instance Doing Business from World Bank (World Bank, 2016) and the Legatum Prosperity Index 2016 (Legatum Institute, 2016). The Human Development Index (United Nations, 2016) uses simple arithmetic average at sub-pillar level and then simple geometric average at pillar level.

[13] In previous versions of the index, engagement with thematic experts on possible weights concluded that no strong case could be made to assign greater or lesser weighting to any pillar, sub-pillar or indicator.

[14] i.e. significant Pearson’s correlation at 1% level.

correlation with their pillar and finally with the Index. Again, the weights were adjusted so that no indicator or sub-pillar would "drive" the score of the pillar or the Index. The whole purpose of this exercise was to ensure that indicator, sub-pillar and pillar scores contribute as equally as possible to sub-pillar, pillar and the Index scores.

The ESI has also been back-cast (see Section 6.2). The variation of each indicator over time has been reviewed; any indicators that are particularly volatile might cause low correlations and so warrant an adjustment to the corresponding weight. No such adjustments to weights were made because none of the indicators were judged to show problematic volatility in scores.

The final weights for each indicator and pillar are given in Table 5.1 below.

Table 5.1 Pillar, sub-pillar and indicator weights

Pillar/ *sub-pillar*/ indicator	Weights
Skills Development	**0.3**
Basic education	*0.5*
Pre-primary pupil-to-teacher ratio	0.4
Upper secondary education (and above)	0.3
Reading, maths & science scores (aged 15)	0.3
Training and other education	*0.5*
Recent training	0.3
VET students	0.35
High digital skills	0.35
Skills Activation	**0.27**
Transition to work	*0.5*
Early leavers from training	0.6
Recent graduates in employment	0.4
Labour market participation	*0.5*
Activity rate (aged 25-54)	0.5
Activity rate (aged 15-24)	0.5
Skills Matching	**0.43**
Skills utilisation	*0.4*
Long-term unemployment	0.4
Underemployed part-timers	0.6
Skills mismatch	*0.6*
Over-qualification rate	0.4
Low waged earners (ISCED 5-8)	0.1
Qualification mismatch	0.5

Source: European Skills Index (2022), Cedefop.

All ESI sub-pillars correlate strongly with their respective pillars (correlation coefficients close to 0.85 or greater, except the sub-pillar "Basic Education" which has a 0.78 correlation with "Skills Development") and all three ESI pillars correlate strongly and in a balanced way with the ESI (correlations ranging between 0.72 and 0.75) – see Figure 8.2 in Section 8.3. The correlation analysis confirms the choice to use uneven weights for the three pillars (0.30, 0.27 and 0.43) in order to ensure that all three pillars are placed on equal footing when it comes to calculating a summary measure for the performance of a country's skills system.

Sensitivity analysis was undertaken to test the potential change in ranks and scores of countries given alternative aggregation and weighting procedures than the one used above (see Sections 9.2 and 9.3 below).

6. Results

6.1. The 2022 Index

The rankings of the Index for 2022 are presented in **Figure 6.1** below. At the Index level, Czech Republic is ranked highest, and Italy is ranked lowest. At the pillar level, Finland is ranked highest and Cyprus lowest in terms of Skills Development, Switzerland is ranked highest and Italy lowest in Skills Activation, and Czech Republic highest and Spain lowest in Skills Matching.

The dispersion of ranks at the pillar level indicates that there is not one single country far outperforming other countries. For example, Austria is ranked fifth in Skills Activation, but ranks 16th at the Index level. Similarly, Malta ranks second in Skills Matching, but ranks 14th at the Index level.

Figure 6.1 Index, pillar and sub-pillar rankings (*)

	Index	Skills Development	Skills Activation	Skills Matching	Basic education	Training and other education	Transition to work	Labour market participation	Skills utilisation	Skills mismatch
Czech Republic	1	11	16	1	10	13	6	21	1	1
Finland	2	1	15	11	2	1	22	11	21	5
Estonia	3	2	11	13	1	14	17	8	5	19
Denmark	4	4	13	12	4	9	15	13	13	11
Netherlands	5	6	2	17	19	3	2	6	18	16
Slovenia	6	15	9	8	21	11	4	15	10	10
Luxembourg	7	13	20	5	20	8	16	19	7	3
Norway	8	7	6	15	12	4	3	14	15	14
Iceland	9	5	3	19	9	7	10	2	17	21
Poland	10	18	17	4	8	24	7	22	2	9
Sweden	11	8	4	18	14	5	5	3	20	15
Croatia	12	12	22	3	15	12	8	26	12	2
Germany	13	10	8	14	5	16	11	9	11	17
Malta	14	26	7	2	29	22	13	4	4	4
Switzerland	15	3	1	25	18	2	1	1	29	18
Austria	16	9	5	23	13	6	9	5	16	24
Latvia	17	19	10	20	7	26	12	10	19	22
Hungary	18	22	24	6	16	25	27	23	3	7
Slovakia	19	16	26	10	11	17	25	25	14	6
Lithuania	20	21	14	21	6	27	19	12	8	25
Belgium	21	17	25	16	17	15	20	28	24	13
United Kingdom	22	20	12	26	23	10	18	7	22	27
France	23	25	23	22	27	18	26	17	26	20
Portugal	24	27	21	24	31	20	21	18	23	23
Romania	25	30	28	7	30	28	28	27	9	8
Ireland	26	14	19	29	3	23	14	20	25	29
Bulgaria	27	29	30	9	24	29	29	29	6	12
Cyprus	28	31	18	28	28	31	23	16	27	28
Greece	29	28	27	30	22	30	24	30	30	31
Spain	30	23	29	31	25	19	30	24	31	30
Italy	31	24	31	27	26	21	31	31	28	26

(*) Sorted from highest Index score to lowest.
Source: European Skills Index (2022), Cedefop.

Table 6.1 and Figure 6.3 displays the distribution of Index, pillar and sub-pillar scores. Figure 6.2 shows the index ranking and scores.

Table 6.1 Index, pillar and sub-pillar scores, 2022(*)

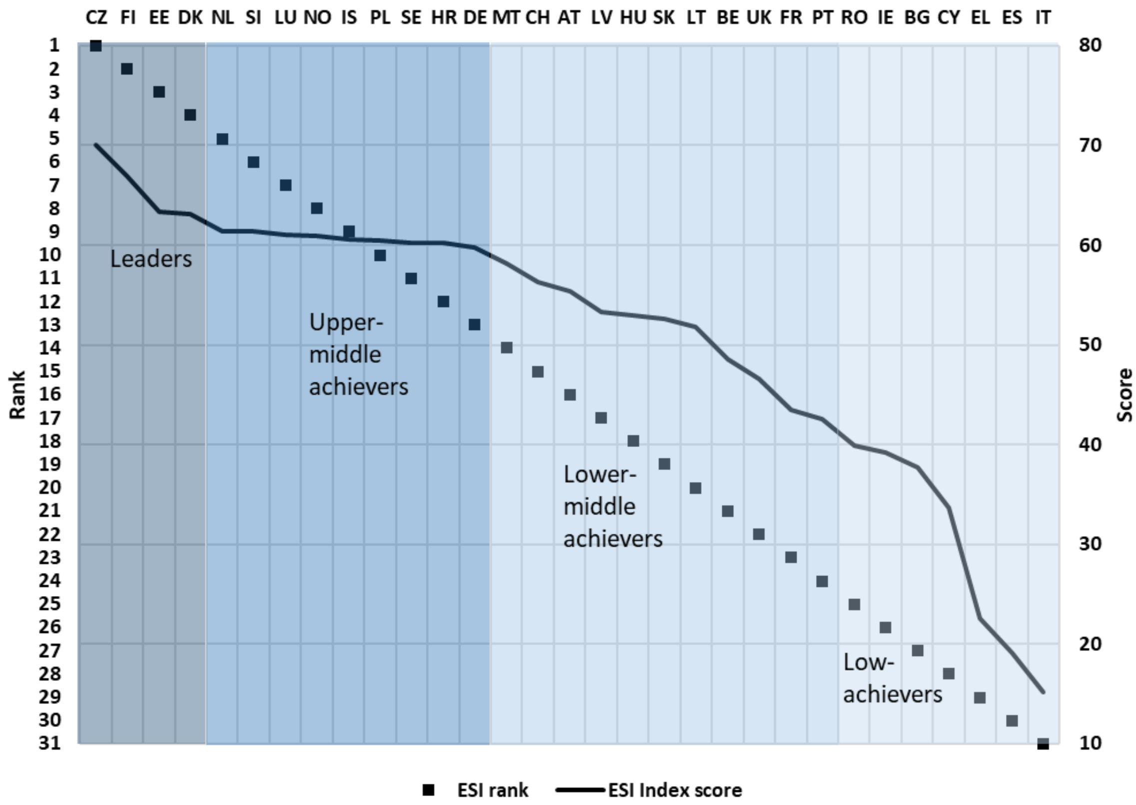
	Index	Skills Development	Skills Activation	Skills Matching	Basic education	Training and other education	Transition to work	Labour market participation	Skills utilisation	Skills mismatch
Czech Republic	70.0	58.3	54.3	93.3	68.8	47.9	68.0	40.6	99.1	89.5
Finland	67.0	82.9	57.5	63.5	82.0	83.7	53.5	61.5	62.2	64.3
Estonia	63.3	67.8	62.5	60.9	87.8	47.8	58.0	67.1	89.0	42.1
Denmark	63.1	65.6	59.9	63.4	74.2	57.1	59.3	60.5	73.7	56.5
Netherlands	61.4	64.4	73.4	53.1	53.9	74.8	78.9	67.8	64.2	45.8
Slovenia	61.4	53.0	64.8	65.7	51.9	54.2	72.5	57.2	77.8	57.6
Luxembourg	61.1	56.0	50.8	72.9	52.2	59.7	58.9	42.6	80.4	67.9
Norway	61.0	62.3	67.8	56.2	61.8	62.7	76.4	59.3	70.0	47.0
Iceland	60.6	65.0	72.8	51.4	69.5	60.6	65.9	79.6	65.6	42.0
Poland	60.5	51.4	53.4	73.2	70.9	32.0	67.9	38.9	95.8	58.2
Sweden	60.3	61.9	71.6	53.1	61.7	62.1	68.3	75.0	63.0	46.4
Croatia	60.2	56.0	47.6	73.5	61.4	50.7	67.6	27.5	76.0	71.8
Germany	59.8	58.8	65.0	57.4	72.6	45.1	64.0	66.0	77.3	44.1
Malta	58.2	35.7	66.6	75.2	36.1	35.3	61.8	71.5	89.1	65.9
Switzerland	56.3	67.1	84.0	38.8	54.2	80.1	85.9	82.2	31.1	43.9
Austria	55.4	61.6	68.0	45.2	61.7	61.4	66.5	69.5	67.4	30.5
Latvia	53.3	50.0	63.2	50.2	71.5	28.5	63.8	62.6	64.0	40.9
Hungary	53.0	44.1	39.2	72.7	57.4	30.8	40.2	38.3	92.9	59.2
Slovakia	52.6	53.0	37.9	64.3	61.8	44.1	45.5	30.3	71.0	59.9
Lithuania	51.8	49.4	58.3	49.8	72.0	26.7	55.4	61.2	79.8	29.8
Belgium	48.5	51.9	38.6	53.5	57.1	46.6	55.4	21.8	59.2	49.7
United Kingdom	46.6	49.6	62.5	37.2	44.6	54.6	57.2	67.7	61.4	21.1
France	43.5	39.0	44.9	46.1	38.4	39.6	41.7	48.0	52.0	42.1
Portugal	42.6	35.2	50.3	43.8	33.1	37.2	54.0	46.5	60.8	32.4
Romania	39.9	29.3	24.8	66.6	34.3	24.3	23.9	25.7	78.1	58.9
Ireland	39.2	53.4	51.3	26.7	74.3	32.6	60.6	42.0	55.8	7.2
Bulgaria	37.7	33.3	18.1	65.2	43.4	23.1	20.5	15.7	84.0	52.7
Cyprus	33.6	26.1	53.4	30.1	38.0	14.1	50.4	56.3	44.8	20.2
Greece	22.5	35.0	31.7	13.4	50.5	19.5	48.8	14.7	23.1	6.9
Spain	19.1	41.0	19.0	11.2	42.8	39.2	6.1	31.8	17.5	7.0
Italy	15.1	39.0	1.7	31.0	41.7	36.3	2.3	1.1	36.2	27.5

(*) Sorted from highest Index score to lowest.
Source: European Skills Index (2022), Cedefop.

It is possible to distinguish four groups of countries:

A first group of four top performers with scores above 63. A second group of nine upper-middle achievers with scores between 59 and 61. A third group of eleven lower-middle achievers with scores between 58 and 42. A last group of seven low-achievers with scores between 39 and 15.

Figure 6.2 Index ranking and scores (*)

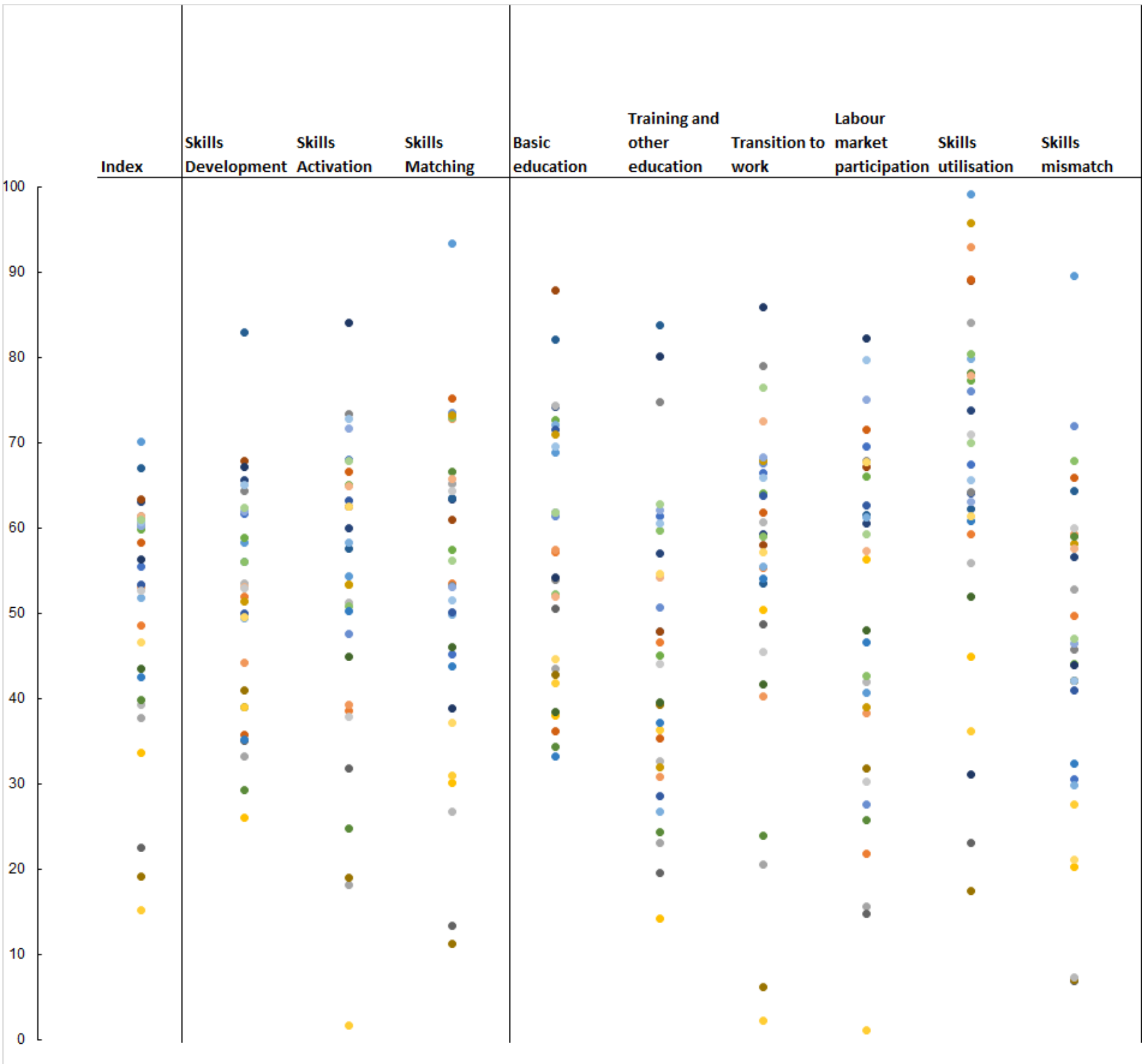


(*) Sorted from highest Index score to lowest.
Source: European Skills Index (2022), Cedefop.

There is a wider distribution of scores across the EU-27 + 4 countries in the second and third pillars (Skills Activation and Matching), than in the first pillar (Skills Development).

At the sub-pillar level, there are some “lagging” countries with scores close to zero in “Transition to work”, “Labour market participation” and “Skills mismatch”. The “Skills utilisation” sub-pillar shows the highest average score among sub-pillars, with scores ranging from 17 to 99. In the “Basic education” sub-pillar, none of the scores falls below 30, reflecting the relatively good performance in 2020 in most countries in providing basic skills. The sub-pillar “Training and other education” has the lowest average score together with “Skills mismatch”, highlighting difficulties to provide effective training beyond basic education in many countries.

Figure 6.3 Distribution of index, pillars and sub-pillars scores, ESI 2022



Note: each dot represents a country.
Source: European Skills Index (2022), Cedefop.

6.2. Back-casting the Index

Table 6.2 shows the changes in the ESI score, the ESI ranking and the ranking by pillar over the period 2018-2020. As can be observed in the first four columns below, not all increases in the ESI score translate to an increase in the position in the ranking. Belgium (21), United Kingdom (22), Portugal (24), Cyprus (28), Portugal (24), and Greece (29) have not changed their position in the ranking during this period, although their scores increased over time.

Czech Republic and Finland maintained the first and second positions throughout the three-years period, respectively. Estonia was on fourth position in 2018 and improved to third in 2019 at the expense of Luxembourg (now sixth). Luxembourg decreased in score in all three pillars, which led to losing in ranking.

The bottom of the ranking is occupied by Greece, Spain and Italy throughout the period. In Italy, small improvement in the “Skills Developments” pillar (a one position increase in the rank) was not enough to offset the decline in the other two pillars’ scores in 2020, despite positive developments in 2019. In particular, Italy occupies the last position in the “Skills

Activation" pillar over the whole period. Both Greece and Spain saw improvements in the first and third pillars' scores and a decline in the "Skills Activation" pillar score, occupying the 27th and 29th position respectively in 2020.

Table 6.2 Back-cast Index, 2018-2020

	ESI				Skills development	Skills activation	Skills matching
	2018 score	2019 score	2020 score	2018-2020 rank change	2018-2020 rank change	2018-2020 rank change	2018-2020 rank change
Czech Republic	72.2	72.2	70.0				
Finland	67.0	69.0	67.0				
Estonia	64.7	65.2	63.3				
Denmark	63.0	64.2	63.1				
Netherlands	60.0	62.3	61.4				
Slovenia	61.9	63.3	61.4				
Luxembourg	65.1	64.5	61.1				
Norway	61.0	62.3	61.0				
Iceland	60.8	64.9	60.6				
Poland	60.5	61.8	60.5				
Sweden	64.3	63.1	60.3				
Croatia	53.3	59.5	60.2				
Germany	58.0	59.9	59.8				
Malta	57.2	58.8	58.2				
Switzerland	56.2	57.1	56.3				
Austria	56.3	57.9	55.4				
Latvia	54.6	52.9	53.3				
Hungary	53.3	54.3	53.0				
Slovakia	52.4	52.7	52.6				
Lithuania	54.9	54.5	51.8				
Belgium	48.2	49.3	48.5				
United Kingdom	45.5	46.3	46.6				
France	43.5	43.8	43.5				
Portugal	41.4	43.3	42.6				
Romania	36.9	39.1	39.9				
Ireland	36.8	39.9	39.2				
Bulgaria	36.2	39.8	37.7				
Cyprus	32.1	35.0	33.6				
Greece	19.9	21.4	22.5				
Spain	19.5	20.2	19.1				
Italy	17.3	19.5	15.1				

Source: European Skills Index (2022), Cedefop.

The highest-ranking countries in "Skills Development" are Finland (1) (in all three years), Estonia (2) and Switzerland (3). In "Skills Activation", Switzerland maintained the first position in all three years, while Netherlands became second only in 2020 at the expense of Iceland, which is third in 2020. Czech Republic is first in "Skills Matching" in all years, followed by Malta (since 2019) and Croatia in 2020.

In "Skills Development", the low achievers are Bulgaria (29) (since 2019), Romania (30) and Cyprus (31) (in all years). Spain (29), Bulgaria (30) and Italy (31) are at the bottom of the "Skills Activation" pillar, while Italy and Bulgaria occupy the same position in all three years. Spain did saw a decline in the "Skills Activation" score, exchanging positions with Romania in 2020. Ireland (29), Greece (30) and Spain (31) occupy the bottom position in "Skills Matching" in all three years.

Despite being one of the low achievers (i.e. in the last three/four positions) in skills development and activation, Romania manages to stay among the first half ranked Member States in skills matching and thus ranks between 25th and 27th at ESI level. Switzerland occupies the 25th position in “Skills Matching” but is among the top three performers in the other two pillars, thus occupying the 15th position in the overall ESI ranking.

Part Two: Statistical coherence analysis

7. Considerations since the last Index update

The current ESI builds on the work undertaken for the previous ESI, published by Cedefop in 2018, and the theoretical and methodological framework remain unchanged from the one described in the 2018 technical report that accompanied the ESI 2018.

In this update, the indicator “High computer skills”, now discontinued, has been replaced by the indicator “High digital skills”, while the “Low-waged workers (ISCED 5-8)” is now computed from EU-SILC microdata instead of SES data publicly available on Eurostat, as discussed in Section 3.4.1. The two new indicators were chosen to measure the same phenomenon as the previous indicators in line the theoretical framework of ESI.

Beside adding more data up to 2020, this update changed bounds and weights as discussed in Sections 4.4 and 5.2.

8. Descriptive statistics

8.1. Summary statistics

Summary statistics on the unprocessed data for the 15 indicators can be found in Table 8.1 below.

Table 8.1 Summary statistics, 2014-2020

	Range	Mean	Median	Observations (2014-2020)	Skewness and kurtosis check (*)
Pre-primary pupil-to-teacher ratio	[5; 40.6]	13.1	12.4	170	2018, 2019, 2020
Upper secondary attainment (and above)	[43.7; 89.2]	75.8	78.3	216	-
Reading, maths & science scores (aged 15)	[426.7; 525.5]	486.8	492.2	61	-
Recent training	[0.9; 34.3]	12.3	9.7	216	-
VET students	[15.1; 73.4]	48.7	49.3	180	-
High digital skills	[9; 62]	32.3	31.0	119	-
Early leavers from training	[1.8; 14.4]	4.8	4.2	216	-
Recent graduates in employment	[44.3; 96.2]	80.1	82.1	216	-
Activity rate (aged 25-54)	[76.5; 92.4]	86.8	87.2	217	-
Activity rate (aged 20-24)	[39.7; 86.3]	61.8	61.6	217	
Long-term unemployment	[0.3; 19.5]	3.3	2.2	215	2015, 2016, 2017, 2018, 2019, 2020
Underemployed part-time workers	[0.3; 7.8]	3.2	2.9	216	-
Over-qualification rate (tertiary graduates)	[4.6; 48]	24.1	21.8	186	-
Low-wage workers (ISCED 5-8)	[1.1; 18.6]	8.4	8.2	182	-
Qualification mismatch	[16; 44.1]	33.6	35.2	58	-

(*) Skewness and kurtosis checks relates to years where the absolute skewness is greater than 2 and absolute kurtosis is greater than 3.5.
Source: European Skills Index (2022), Cedefop.

8.2. Correlation analysis

Correlation analysis is used to assess to what extent the selected indicators support the ESI framework. From the analysis of the correlation matrix within an Index, an indicator should be more correlated to:

- indicators from its own dimension than to indicators from other dimensions;
- its own dimension than to other dimensions.

Figure 8.1 below displays the correlation matrix of the list of indicators. Directional adjustments were accounted for in the matrix figure below. That is, it controls for differences in direction of impact, in instances where a lower value indicates a more positive outcome, by ensuring that the correlation calculation treats both indicators as if they are moving in the same direction for positive outcomes.

From the correlation analysis, it is evident that there are no indicators that are highly correlated with each other (i.e. correlation coefficient greater than 0.92), and that there are no indicators that are negatively and significantly correlated with each other.

Figure 8.1 Correlation matrix of the 15 ESI indicators (*)

15	Pre-primary pupil-to-teacher ratio	Upper secondary attainment (and above)	Reading, maths & science scores (aged 15)	Recent training	VET students	High digital skills	Early leavers from training	Recent graduates in employment	Activity rate (aged 25-54)	Activity rate (aged 20-24)	Long-term unemployment	Underemployed part-time workers	Over-qualification rate (tertiary graduates)	Low-wage workers (ISCED 5-8)	Qualification mismatch
Pre-primary pupil-to-teacher ratio	1.000														
Upper secondary attainment (and above)	-0.051	1.000													
Reading, maths & science scores (aged 15)	-0.127	0.213	1.000												
Recent training	-0.029	-0.043	0.562	1.000											
VET students	-0.089	0.300	0.186	0.006	1.000										
High digital skills	-0.027	-0.062	0.577	0.829	-0.020	1.000									
Early leavers from training	0.009	0.431	0.416	0.293	0.092	0.384	1.000								
Recent graduates in employment	-0.077	0.269	0.319	0.383	0.226	0.510	0.276	1.000							
Activity rate (aged 25-54)	-0.095	0.301	0.266	0.412	0.000	0.384	0.490	0.583	1.000						
Activity rate (aged 20-24)	-0.056	0.134	0.455	0.678	-0.218	0.772	0.381	0.664	0.482	1.000					
Long-term unemployment	-0.107	0.245	0.348	0.321	0.201	0.353	0.130	0.821	0.383	0.558	1.000				
Underemployed part-time workers	0.272	0.224	-0.165	-0.532	0.228	-0.469	-0.121	0.096	0.000	-0.365	0.208	1.000			
Over-qualification rate (tertiary graduates)	0.104	0.037	0.364	0.426	0.432	0.390	0.178	0.583	0.278	0.275	0.709	0.305	1.000		
Low-wage workers (ISCED 5-8)	0.267	-0.001	-0.230	-0.194	0.360	-0.173	0.017	0.166	0.010	-0.167	0.091	0.339	0.267	1.000	
Qualification mismatch	0.115	0.531	-0.155	-0.323	0.581	-0.400	-0.084	0.276	0.144	-0.334	0.299	0.656	0.272	0.542	1.000

(*) The full names of each indicator are available in Figure 3.1 above. Green figures denote significant Pearson's correlation at 1% level.
Source: European Skills Index (2022), Cedefop.

8.3. Correlation analysis following normalisation

Correlation analysis is also performed on the normalised indicators.

Figure 8.2 below outlines the correlation results of the Index, based on the indicators, normalisation, weights and aggregation procedure outlined in Part 1 of the technical report. Given the lack of highly collinear (i.e. Pearson correlation coefficient greater than 0.92) pairs of indicators within the same sub-pillar, the correlation analysis of normalised indicators suggests that there is no redundancy of information in the ESI framework.

Figure 8.2: Correlation analysis of normalised scores (*)

	Index	Skills Development	Skills Activation	Skills Matching	Basic education	Training and other education	Transition to work	Labour market participation	Skills utilisation	Skills mismatch
Index	1.00									
Skills Development	0.72	1.00								
Skills Activation	0.75	0.62	1.000							
Skills Matching	0.75	0.27	0.21	1.00						
Basic education	0.59	0.78	0.42	0.26	1.00					
Training and other education	0.60	0.85	0.58	0.19	0.34	1.00				
Transition to work	0.77	0.60	0.91	0.31	0.44	0.53	1.00			
Labour market participation	0.62	0.54	0.93	0.08	0.33	0.54	0.69	1.00		
Skills utilisation	0.69	0.18	0.23	0.90	0.34	-0.02	0.29	0.14	1.00	
Skills mismatch	0.71	0.30	0.16	0.95	0.18	0.30	0.28	0.03	0.73	1.00
Pre-primary pupil-to-teacher ratio	0.18	0.29	-0.01	0.17	0.59	-0.04	-0.02	0.00	0.20	0.13
Upper secondary attainment (and above)	0.48	0.42	0.34	0.32	0.61	0.12	0.43	0.21	0.36	0.26
Reading, maths & science scores (aged 15)	0.48	0.74	0.48	0.06	0.60	0.61	0.45	0.44	0.09	0.03
Recent training	0.40	0.70	0.60	-0.09	0.29	0.81	0.42	0.68	-0.20	-0.01
VET students	0.39	0.42	0.01	0.48	0.11	0.54	0.18	-0.15	0.25	0.59
High digital skills	0.47	0.72	0.70	-0.08	0.34	0.80	0.55	0.72	-0.14	-0.04
Early leavers from training	0.55	0.47	0.74	0.10	0.41	0.36	0.89	0.48	0.09	0.09
Recent graduates in employment	0.77	0.52	0.76	0.49	0.28	0.55	0.70	0.71	0.48	0.44
Activity rate (aged 25-54)	0.58	0.33	0.75	0.23	0.15	0.37	0.59	0.77	0.22	0.21
Activity rate (aged 20-24)	0.51	0.55	0.84	-0.02	0.37	0.52	0.61	0.92	0.07	-0.08
Long-term unemployment	0.81	0.49	0.71	0.61	0.38	0.42	0.66	0.64	0.67	0.50
Underemployed part-time workers	0.34	-0.10	-0.19	0.76	0.18	-0.31	-0.07	-0.26	0.85	0.61
Over-qualification rate (tertiary graduates)	0.72	0.53	0.38	0.69	0.25	0.59	0.41	0.29	0.52	0.73
Low-wage workers (ISCED 5-8)	0.31	-0.03	-0.02	0.56	-0.09	0.03	0.09	-0.13	0.35	0.64
Qualification mismatch	0.43	0.07	-0.08	0.80	0.14	-0.02	0.04	-0.18	0.63	0.82

(*) Figures in blue denote significant Pearson's correlation at 1% level.
Source: European Skills Index (2022), Cedefop.

Figure 8.2 indicates that the Index is not overly dominated by specific pillars, sub-pillars, or indicators. Moreover, Figure 8.2 confirms the expectation that the indicators are more associated with their own sub-pillar than to any of the other sub-pillars. Similarly, the sub-pillars are more associated within their respective pillar than across the three pillars. Therefore, the correlation analysis suggests that the allocation of ESI indicators to the specific sub-pillar, and allocation of sub-pillars to pillars, is consistent both from conceptual and statistical perspectives.

Nine out of 15 indicators are also positively and significantly correlated with the overall Index (see values in blue in Figure 8.2). Some indicators have low correlation at the Index level (e.g. "Pre-primary pupil-to-teacher ratio), but some remain significantly correlated at both sub-pillar level and pillar level (e.g. "Underemployment part-time workers" and "Low-waged workers (ISCED 5-8)".

8.4. Principal Component Analysis (PCA)

The correlation analysis is followed by a statistical procedure called Principal Component Analysis (PCA).

In this update, PCA is used to assess to what extent the conceptual framework is confirmed by statistical approaches. For each sub-pillar and pillar, loadings with eigenvalues greater than one were considered for the factor matrix, which is rotated using varimax rotation. Ideally, this rotation should result in one single latent component that captures more than 60% of the total variance and all the loadings in the same component have the same sign. In addition, the restriction is added that each individual component with eigenvalue greater than one. If eigenvalue less and equal to one then the component has to explain more than 10% of the variance (see OECD/EC JRC (2008)).

The PCA gives indication about whether the choice of weight described in Section 5.2 is appropriate in terms of statistical coherence of the ESI framework.

The PCA analysis shows the presence of a single statistical dimension between the three pillars that explains around 60% of the total variance, thus justifying the three-pillar structure and the aggregation of these three pillars into one number:

European Skills Index			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.85	0.62	0.62
Factor2	0.83	0.28	0.89
Factor3	0.32	0.11	1.00

The factor loadings suggest that the third pillar should have the greatest weight among the three pillars to increase its influence on the Index:

Index	Factor 1
Pillar 1 Score	0.90
Pillar 2 Score	0.84
Pillar 3 Score	0.59

The sections below look at the unidimensionality at pillar and sub-pillar level.

8.4.1. Pillar 1 – Skills Development

For the two sub-pillars in Skills Development, the results of the PCA show the presence of two latent components in the first sub-pillar and one latent component in the second sub-pillar using eigenvalues greater than 1 as a criterion:

Basic education			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.25	0.42	0.42
Factor2	1.01	0.34	0.75
Factor3	0.74	0.25	1.00
Training and other education			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.79	0.60	0.60
Factor2	0.98	0.33	0.92
Factor3	0.23	0.08	1.00

The second factor in the "Basic education" pillar has a eigenvalue marginally higher than one, while in the ESI 2020 update it was marginally lower than one. As suggested by the rotated factor loading shown in the table below, this is due to the low correlation of the indicator "Pre-primary pupil-to-teacher ratio" with the other indicators in the same sub-pillar.

The factor loadings are presented in the table below:

Basic education			
Indicators	Variable	Factor1	Factor 2
Pre-primary pupil-to-teacher ratio	Ind01	0.00	0.95
Upper secondary attainment (and above)	Ind02	0.73	0.33
Reading, maths & science scores	Ind03	0.83	-0.18
Training and other education			
Indicators	Variable	Factor1	
Recent training	Ind04	0.94	
VET students	Ind05	0.20	
High digital skills	Ind06	0.93	

As in the previous version of ESI, the PCA factor loadings suggest a weak relationship between "VET students" and the other two indicators in the "Training and other education" sub-pillar.

PCA at the pillar level confirms unidimensionality of the first pillar: the single latent dimension captures 71% in Pillar 1 Skills Development of the total variance of the underlying sub-pillars:

Skills Development			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.37	0.69	0.69
Factor2	0.63	0.31	1.00

Thus, the structure of the pillar is justified, and the presence of another factor in the first sub-pillar does not affect the aggregation at the pillar level. Moreover, the loadings of the two sub-pillars would suggest that the use of equal weights for the two sub-pillars is appropriate:

Skills Development	Factor 1
Basic education Score	0.83
Training and other education Score	0.83

8.4.2. Pillar 2 – Skills Activation

The PCA confirms the unidimensionality in each of the sub-pillars: single latent dimension captures more than 60% of the variance of the underlying indicators:

Transition to work			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.46	0.73	0.73
Factor2	0.54	0.27	1.00
Labour market participation			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.37	0.68	0.68
Factor2	0.63	0.32	1.00

As expected, the loadings of each indicator of the two sub-pillars indicate equal weighting:

Transition to work	
Indicators	Factor1
Early leavers from training	0.85
Recent graduates in employment	0.85
Labour market participation	
Indicators	Factor1
Activity rate (aged 25-54)	0.83
Activity rate (aged 15-24)	0.83

The conceptual framework for this pillar is confirmed by the fact that almost 82% of the variance of the underlying sub-pillars is captured by a single latent component:

Skills Activation			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.66	0.83	0.83
Factor2	0.34	0.17	1.00

And the loadings suggest equal weighting when the two sub-pillars are to be aggregated at pillar level:

Skills Activation	Factor 1
Transition to work Score	0.91
Labour market participation Score	0.91

8.4.3. Pillar 3 – Skills Matching

The PCA analysis confirms the unidimensionality in both sub-pillars capturing over 50% of the variation of the underlying indicators:

Skills Utilisation			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.07	0.53	0.53
Factor2	0.93	0.47	1.00
Skills mismatch			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.80	0.60	0.60
Factor2	0.76	0.25	0.85
Factor3	0.44	0.15	1.00

The factor loadings suggest that equal weights could be a used:

Skills Utilisation	
Indicators	Factor1
Long-term unemployment	0.73
Underemployed part-timers	0.73
Skills mismatch	
Indicators	Factor1
Over-qualification rate	0.66
Low waged earners (ISCED 5-8)	0.85
Qualification mismatch	0.80

PCA analysis confirms the unidimensionality at the pillar level: the single latent dimension captures 82% in Pillar 3 Skills Matching of the total variance of the underlying sub-pillars:

Skills Matching			
Factor	Eigenvalue	Proportion	Cumulative
Factor1	1.59	0.80	0.80
Factor2	0.41	0.20	1.00

The loadings of the two sub-pillars would suggest the use of equal weights:

Skill Matching	Factor 1
Skills utilisation Score	0.89
Skills mismatch Score	0.89

9. Sensitivity analysis

The robustness of rankings and the manner in which a composite index is interpreted are greatly influenced by the many methodological choices that are made during its development, for example, the selection of pillars and indicators, the selection of weights and the method of aggregation. These choices require assumptions to be made that introduce uncertainty into the final results. As in any modelling exercise, it is good practice to assess the uncertainties associated with the modelling process and the methodological choices made.

The robustness of the composite index calculation is checked using different scenarios in which one step in the calculation is varied with respect to the original version. Our analysis focussed on varying the:

1. bounds used in normalisation;
2. aggregation method;
3. weights.

Each of these scenarios are explained in the sections below and the results are discussed in Section 9.4.

9.1. Bounds used in normalisation

There is a lot of flexibility on how to choose the “frontier”, i.e. the best and worst cases, and different ways of defining the frontier can be applied to different indicators.

As described in Section 4.4 above, the method used for the 2022 ESI version was to use statistically-defined bounds, i.e. close to the maximum and minimum values over seven years (2014-2020) for EU-27+4.

In this scenario, the impact of using the actual (rather than close to) minimum and the maximum value over a 7 year period (2014-2020) for among all countries, is tested.

9.2. Aggregation method

The Index is calculated using weighted arithmetic mean to calculate the score of the sub-pillar and then using weighted arithmetic mean of sub-pillar scores to obtain the score for each pillar. The pillar scores are then aggregated using weighted geometric mean to obtain the overall ESI score.

In this scenario, the impact on the composite index results of varying the method of aggregation only from pillar to index is tested; weighted arithmetic mean (rather than weighted geometric mean in the baseline) is used. In other words, the only change made is to allow full compensability between pillars.

9.3. Equal weights

Equal weights are applied when there is no clear reference in the literature about the importance of elements the composite indicator. Under the equal weighting scheme all indicators should be equally important in classifying countries with respect to the sub-dimension; sub-dimensions should be equally important in classifying countries with respect to the dimension etc.

In this scenario, the impact on the composite index of using equal weights at sub-pillar, pillar and index level is tested.

9.4. Findings

In this sensitivity analysis, different scenarios are considered to test the robustness of countries' ranking by varying different steps in the calculation of the composite index. In this section, the original composite index presented in Part 1 is referred to as the "baseline" index. Five other variations of this index were calculated with the changes to the calculation as explained in sections 9.1 - 9.3 above and summarised in the table below:

Table 9.1 Description of scenarios

Scenario	Short description
Baseline	Composite index calculated as presented in Part 1.
Scenario 1 (Section 9.1)	Baseline with normalisation bounds changed to the actual (rather than close to) minimum and maximum over 7 years.
Scenario 2 (Section 9.1 combined with 9.2)	Scenario 1 with weighted arithmetic mean at the index level.
Scenario 3 (Section 9.2)	Baseline plus weighted arithmetic mean at the index level.
Scenario 4 (Section 9.3)	Baseline with simple means (equal weights) at all levels of aggregation.
Scenario 5 (Section 9.3 combined with 9.2)	Scenario 4 with weighted arithmetic mean at the index level.

Source: European Skills Index (2022), Cedefop.

Table 9.2 shows the results of the sensitivity analysis. The "ranks" columns show the ranking of the index and the pillars in the baseline scenario, while the "range" columns display the best and worst rankings obtained by the country among the scenarios considered in the sensitivity analysis. This table shows to what degree a country's rank depends on the modelling choices.

In the baseline index, Czech Republic is the top performer, followed by Finland and by a group of countries with a similar overall score until the 4th position. The last position in the baseline is occupied by Italy, preceded by Spain and Greece. Scenarios 1, 2 and 3 produce higher scores than the baseline for all the countries, while in scenarios 4 and 5 a few countries have lower scores. Note that at the pillar level the changes in ranking are relatively smaller than at the Index level. However, changes in weights and aggregation method at the Index level may magnify the changes at pillar levels, producing wide ranges of Index ranking as in the case of Slovenia or Croatia.

Table 9.2: Distribution of ranks and scores, sensitivity analysis (*)

	Composite index			Pillar 1			Pillar 2			Pillar 3		
Country	Rank	Rank range	Score range	Rank	Rank Range	Score range	Rank	Rank Range	Score range	Rank	Rank Range	Score range
Czech Republic	1	[1,2]	[67,77]	11	[10,11]	[58,65]	16	[16,17]	[54,66]	1	[1,1]	[92,94]
Finland	2	[1,2]	[67,73]	1	[1,1]	[83,86]	15	[14,15]	[58,70]	11	[9,11]	[63,68]
Estonia	3	[3,8]	[63,68]	2	[2,4]	[68,72]	11	[11,11]	[62,74]	13	[13,14]	[61,63]
Denmark	4	[4,8]	[63,68]	4	[4,6]	[65,70]	13	[13,13]	[60,71]	12	[8,12]	[63,69]
Netherlands	5	[3,10]	[61,68]	6	[3,6]	[64,73]	2	[2,4]	[73,81]	17	[16,20]	[53,61]
Slovenia	6	[3,11]	[61,70]	15	[12,15]	[53,64]	9	[9,9]	[64,75]	8	[8,10]	[66,72]

	Composite index			Pillar 1			Pillar 2			Pillar 3		
Country	Rank	Rank range	Score range	Rank	Rank Range	Score range	Rank	Rank Range	Score range	Rank	Rank Range	Score range
Luxembourg	7	[6,15]	[58,68]	13	[12,13]	[55,64]	20	[20,20]	[50,64]	5	[5,8]	[70,73]
Norway	8	[8,12]	[61,67]	7	[7,8]	[62,70]	6	[6,7]	[68,76]	15	[15,18]	[56,62]
Iceland	9	[4,14]	[61,66]	5	[5,8]	[63,69]	3	[2,3]	[73,82]	19	[17,22]	[51,60]
Poland	10	[6,14]	[60,68]	18	[16,18]	[51,59]	17	[17,18]	[53,65]	4	[4,4]	[73,78]
Sweden	11	[6,13]	[60,67]	8	[5,8]	[62,70]	4	[3,4]	[72,81]	18	[18,19]	[53,59]
Croatia	12	[5,16]	[57,68]	12	[12,14]	[55,62]	22	[22,23]	[45,60]	3	[3,5]	[74,77]
Germany	13	[9,15]	[60,65]	10	[10,11]	[58,64]	8	[8,8]	[65,75]	14	[13,15]	[57,64]
Malta	14	[4,15]	[58,68]	26	[26,27]	[34,46]	7	[5,7]	[67,77]	2	[2,2]	[75,82]
Switzerland	15	[5,17]	[56,66]	3	[2,3]	[67,77]	1	[1,1]	[84,90]	25	[25,26]	[39,44]
Austria	16	[12,17]	[55,64]	9	[9,9]	[61,69]	5	[5,6]	[68,78]	23	[20,23]	[45,54]
Latvia	17	[17,19]	[53,63]	19	[19,20]	[50,56]	10	[10,12]	[62,74]	20	[14,23]	[50,60]
Hungary	18	[17,20]	[52,63]	22	[22,22]	[44,52]	24	[24,24]	[39,56]	6	[3,6]	[73,78]
Slovakia	19	[15,21]	[51,65]	16	[16,17]	[52,60]	26	[25,26]	[38,54]	10	[5,11]	[64,76]
Lithuania	20	[18,20]	[52,61]	21	[20,21]	[49,56]	14	[14,15]	[56,71]	21	[17,21]	[50,59]
Belgium	21	[21,22]	[48,58]	17	[15,19]	[52,61]	25	[25,26]	[39,53]	16	[16,19]	[53,59]
United Kingdom	22	[19,24]	[47,54]	20	[18,21]	[50,53]	12	[10,12]	[62,74]	26	[25,27]	[37,44]
France	23	[22,24]	[43,55]	25	[23,25]	[39,52]	23	[22,23]	[44,61]	22	[21,24]	[46,54]
Portugal	24	[23,26]	[43,54]	27	[26,27]	[35,48]	21	[19,21]	[49,65]	24	[22,24]	[44,54]
Romania	25	[23,26]	[38,54]	30	[30,30]	[28,38]	28	[27,28]	[25,45]	7	[6,10]	[67,73]
Ireland	26	[23,27]	[39,50]	14	[14,18]	[53,58]	19	[19,21]	[50,64]	29	[28,29]	[27,36]
Bulgaria	27	[24,28]	[35,54]	29	[29,29]	[32,40]	30	[29,30]	[18,40]	9	[7,12]	[65,73]
Cyprus	28	[27,28]	[34,47]	31	[31,31]	[26,37]	18	[16,18]	[53,67]	28	[27,28]	[30,40]
Greece	29	[29,31]	[23,35]	28	[28,28]	[34,43]	27	[27,28]	[28,45]	30	[30,31]	[13,22]
Spain	30	[29,31]	[19,40]	23	[23,24]	[41,52]	29	[29,30]	[19,41]	31	[30,31]	[11,30]
Italy	31	[29,31]	[12,40]	24	[24,25]	[38,49]	31	[31,31]	[2,19]	27	[25,29]	[31,47]

(*) Sorted from highest baseline Index score to lowest.
Source: European Skills Index (2022), Cedefop.

Table 9.3 shows the changes in ranking in each scenario relative to the baseline.

Scenario 1 (using the winsorised minimum and maximum values across seven years for the bounds) does not lead to a change in the top two compared to the baseline, while Estonia falls from the 3rd rank in the baseline to the 4th, replaced by Slovenia. Norway, Netherlands and Iceland lose the most in terms of ranking (three, four and five positions respectively), while Greece falls to the last rank, surpassed by Italy and Spain which gain one rank.

Scenario 2 (Scenario 1 with weighted arithmetic mean at the index level) looks like Scenario 1 ranking results at the top of the ranking, while at the bottom Greece falls to last in Index ranking, replaced by Italy at the 29th position. Malta experiences the highest relative improvement, gaining ten positions compared to the baseline, followed by Croatia (seven positions) and Poland (four positions).

Scenario 3 (baseline with aggregation at the index level using the weighted arithmetic mean) does not show any changes at the top of the ranking compared to the baseline, with the only sizeable movement being Norway losing three positions. Italy becomes the third to last country at the expense of Greece and Spain that lose one position each (Spain become the bottom-ranked country).

Scenario 4 (baseline with equal weights at all levels of aggregation) sees Finland exchanging places with Czech Republic at the top, while Netherlands gains two ranks compared to the baseline thus becoming 3rd. The bottom of the ranking remains the same as in the baseline. Luxembourg, Slovenia and Croatia lose seven, five and four ranks respectively, while Iceland and Switzerland both gain five ranks.

Scenario 5 (equal weights at all levels of aggregation and arithmetic mean at the index level) has again Finland as first and Czech Republic as second in the ranking, while nothing changes at the bottom of the ranking. Luxembourg and Slovenia lose eight and five ranks respectively, while Switzerland and Iceland gain ten and five ranks respectively.

The last row of Table 9.3 shows the average rank shift as described in Saisana et al. (2005), which measures the relative shift in the position of the entire system of countries in a single number. It is computed as the average of the absolute differences in countries' ranks with respect to the baseline, in each scenario. Scenario 5 shows the highest average ranks shift (2.5), which is expected given that it differs from the baseline both in terms of weighting and aggregation schemes. Scenarios 1, featuring changes in statistical bounds for normalisation has a relatively lower average rank shift, which is increased in Scenario 2 when arithmetic mean instead of geometric mean is added at the index level. The scenario with the lowest average rank shift (0.8) is Scenario 3, since it differs from the baseline only in the use of the arithmetic mean to aggregate the pillars' score into the index.

Table 9.3 Changes in ranking relative to baseline (negative is an improvement in ranking)

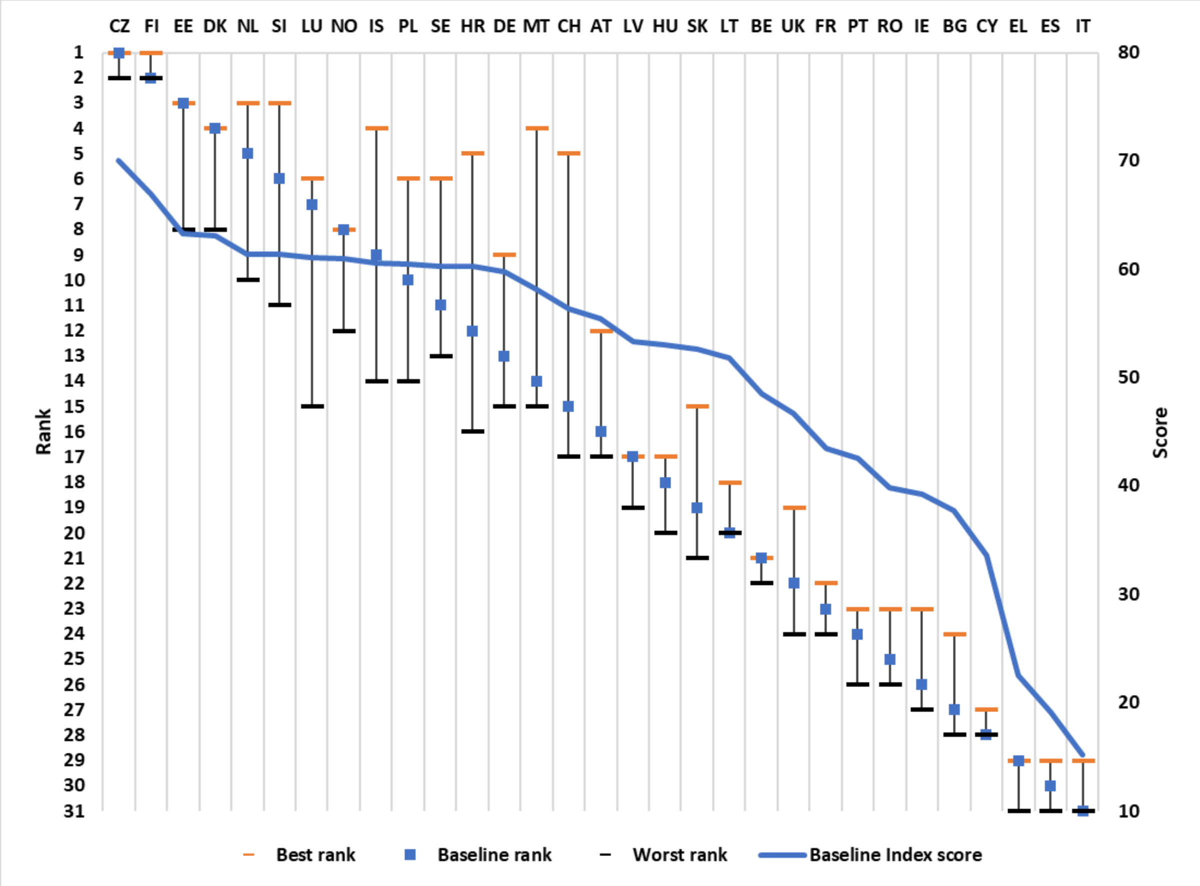
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Czech Republic	0	0	0	1	1
Finland	0	0	0	-1	-1
Estonia	1	4	0	3	5
Denmark	1	4	0	1	3
Netherlands	4	5	0	-2	-2
Slovenia	-3	-3	1	5	5
Luxembourg	1	2	-1	7	8
Norway	3	4	3	0	1
Iceland	5	5	0	-5	-5
Poland	-4	-4	-2	3	4
Sweden	1	0	2	-4	-5
Croatia	-5	-7	-2	4	4
Germany	0	2	1	-4	-3
Malta	-4	-10	-2	1	-2
Switzerland	2	-2	0	-5	-10
Austria	0	1	0	-4	-3
Latvia	1	2	2	0	0
Hungary	1	0	-1	2	0
Slovakia	-4	-3	-1	2	2
Lithuania	0	0	0	-2	-1

Belgium	0	0	0	1	1
United Kingdom	2	1	0	-3	-2
France	-1	-1	1	1	1
Portugal	-1	2	1	1	1
Romania	0	0	-2	1	1
Ireland	1	1	1	-3	-3
Bulgaria	-1	-3	-1	1	0
Cyprus	0	0	0	-1	0
Greece	2	2	1	0	0
Spain	-1	0	1	0	0
Italy	-1	-2	-2	0	0
Avg. rank shift	1.6	2.3	0.9	2.2	2.4

Source: European Skills Index (2022), Cedefop.

Figure 9.1 shows the ranking variation of the composite index across different scenarios. The countries experiencing the highest variation are Switzerland (ranging from 5th to 17th position), Croatia (ranging from 5th to 16th position) and Malta (ranging from 4th to 15th position) followed by the Iceland and Luxembourg, which change by ten and nine positions respectively. The average range of rank change is 4.9.

Figure 9.1: Index rank range (*)



(*) Sorted from highest Index score to lowest.
Source: European Skills Index (2022), Cedefop.

Table 9.4 shows the rank correlation[15] between the baseline and the scenarios. Despite the observed variation in ranks, the rank correlation is higher than 0.9 in all scenarios. In other words, countries that in the baseline occupy the top (bottom) ranks tend to remain in the top (bottom) ranks also in the scenarios.

Table 9.4 Rank correlation between the baseline and each scenario

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Rank correlation	0.97	0.94	0.99	0.95	0.93

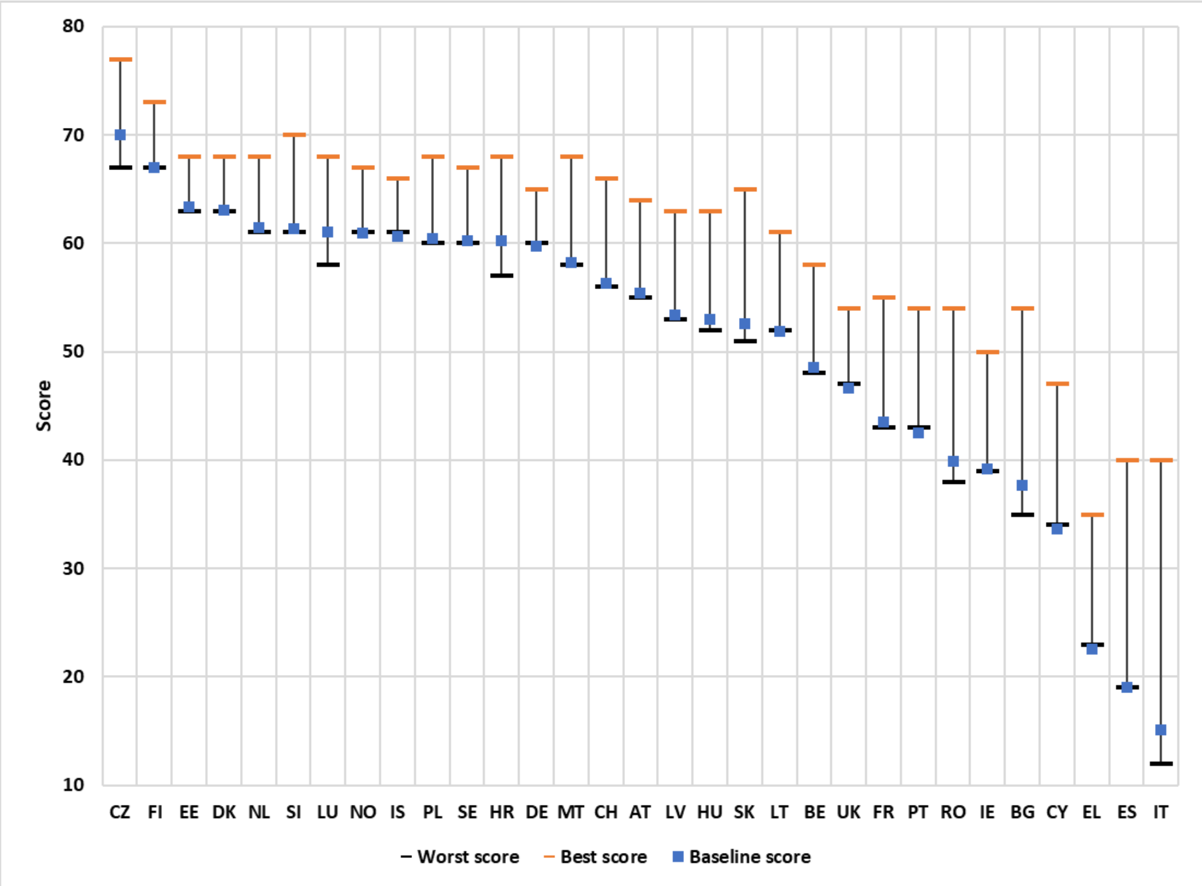
Source: European Skills Index (2022), Cedefop

From this sensitivity analysis of ranks, it can be acknowledged that in some cases there are large variations in Member State (maximum being twelve positions) performance particularly in the upper half of the distribution, excluded the top two positions. This is due to Member States having particularly strong or weak performance in an individual indicator or pillar, which may be magnified by different weighting and aggregation schemes. For example, Luxembourg in the baseline ranks 8th with an Index score of 61, and performs particularly well in the "Skills Matching" pillar, which has a weight of 0.43. In Scenarios 4 and 5, equal weighting means that the weight on "Skills Matching" passes from 0.43 to 0.33, which for Luxembourg implies a significant weakening of the dimension where it has the best performance, with a consequence

[15] I.e. the Spearman rank correlation coefficient.

loss of ranks from the 8th to the 14th /15th position. This emphasises the need to look into the detail of the Index to see which indicators are driving a Member State's performance. The rankings are most sensitive for those upper-ranking Member States that are clustered around a very similar baseline score so that *small changes in the score can have an exaggerated impact on the rankings*. Figure 9.2 explore this issue by showing the scores range across scenarios. It is possible to see that variations in score in the upper-half of the rankings are relatively limited and of a comparable magnitude, and produce noticeable changes in rankings given the clustering around a similar score in the baseline. The lower the baseline ranking, the higher the range of variation in the scores, reflecting in particular the impact of the arithmetic mean aggregation (which allows for perfect compensation between indicators) versus the geometric mean aggregation (which does not allow for perfect compensation). However, the higher variation in scores in the bottom half of the ranks does not create a change in ranks of a similar magnitude because of the different baseline score.

Figure 9.2 Index score range (*)



(*) Sorted from highest Index score to lowest.
Source: European Skills Index (2022), Cedefop.

Notwithstanding some sizable variations, it remains possible to distinguish the same four groups of countries: the top two performers across all scenarios (with scores around 70); a large group of upper-middle countries clustered around a score of 60 with high rank variation; a group of middle-low performers with limited rank variation; and the bottom three performers in all scenarios, with scores around 20. The sensitivity analysis highlighted some variation in ranks within each groups, but the composition of the groups remains fairly stable across scenarios. Therefore, it is possible to conclude that the ESI consistently categorise each country according to the efficiency of their skills system.

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ANNEX: The JRC audit of the 2022 European Skills Index

The box below shows the conclusions of the independent statistical audit of the JRC on the 2022 ESI. These will be used to further refine and improve the European Skills Index in subsequent releases. The full JRC audit report is available on JRCs webpage and a link to it is provided in the European Skills Index webpage.

The JRC statistical audit delves into the extensive work carried out by the developers of the ESI to suggest improvements in terms of data characteristics, structure and methods used. In addition, the analysis aims to ensure the transparency of the index methodology and the reliability of the results.

The data coverage of the framework is excellent. Most indicators contain no missing values for this edition because the developers rely on data from previous years. Only one indicator uses data from 2016.

A few indicators present outliers that are implicitly treated with goalpost normalisation by the developers. The analysis suggests that the ESI is statistically balanced within its pillars. There are mostly positive correlations between indicators and their corresponding sub-pillar, thus suggesting that most of the indicators provide meaningful information on the variation of the scores. This result is due to the decision to use weights to balance each element's role in the composite indicator, especially the pillars.

Indicators Pre-primary pupil-to-teacher ratio and VET students, respectively from sub-pillar 1.1. and 1.2, show shallow, when not negative, correlations with the other indicators in their sub-pillars. This may suggest that these indicators do not entirely cooperate with the others, and this may cause a conflict in results and reduce the impact of the aggregate to which they belong in the following aggregations.

The JRC analysed a series of different choices made during the construction of the index. The uncertainty analysis results reveal that the ESI is a robust summary measure for many countries. The simulated intervals are narrow enough for meaningful inferences to be drawn from the index on most countries; there is a shift of fewer than five positions for about 73% of the countries included in the index. This means nine countries have 90% confidence interval widths of at least five positions. Thus, their ranks vary significantly with changes in weights, data treatment and aggregation method, as also observed in the sensitivity analysis. Nevertheless, it would be unfair to identify this instability in the nine countries as a structural problem of the ESI since most have very similar scores (a difference of 1.6 or less on a 0-100 scale). JRC-COIN has no change to suggest in this sense, but very special care in interpreting those ranks.

Taking into account the points above, this audit confirms that the ESI is reliable and that the framework has a good statistical coherence. The audit also acknowledges the significant efforts by the developers' team to obtain a balanced and transparent result.

Source: JRC audit of the 2022 European Skills Index