SkillsPULSE

SKILLS - PREDICTING, UNDERSTANDING, AND LOCATING SHORTAGES IN EUROPE

D2.2 Empirical investigation of skill gaps in Europe

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Abbreviations

CO: Confidential

D: Deliverable

DEM: Demonstrator

DoA: Description of the Action

DoW: Description of Work

EC: European Commission

ESJS: European Skills and Jobs Survey

EU: European Union

GA: Grant Agreement

IPR Intellectual Property Rights

M: Month

PC: Project Coordinator

PM: Project Manager

PO: Project Officer

PP: Programme Participants

PU: Public

RE: Restricted

SC: Steering Committee

TM: Technical Manager

WP: Work Package

1. Introduction

Skill gaps in the labour market arise when existing employees the lack necessary skills for doing their job. Within the literature, skill gaps measurement is usually based on assessing whether employees require additional training in order to do their jobs or whether their skills are sufficient for what is required in order to do their job effectively. From a policy perspective, skill gaps are a concern as they potentially inhibit firm-level performance, employee level career progression and human capital development and, as a consequence of both firm and employee level impacts, macroeconomic performance. The measurement of skill gaps can be based on either employee perception of their own capabilities or employer perceptions of their workforce's competency levels. Given this, measurements of skill gaps can be undertaken in employee, employer or linked employee-employer surveys. Skill gaps can also be potentially proxied by undereducation, i.e., a situation where a worker possesses a level of education that is lower than the level of education required for their job. However, such measures do not account for the fact that workers may compensate for education with higher skills acquired through labour market experience. The main difficulty in this research space is that there is no consistent approach taken to measuring skill gaps directly and the research base is extremely underdeveloped, which in turn means that policy approaches to resolving skill gaps tend not to be strongly grounded in evidence. In a recent review of the academic literature on skill gaps McGuinness et al. (2025)[1] estimate that between 2002 and 2022 there were just seven academic studies published on the topics.

This study builds on previous research from McGuinness et al. (2024), who used the first wave of the European Skills and Jobs Survey (2014) to investigate the extent to which existing workers in the EU countries do not have the skills and basic competencies to perform their current jobs to an adequate standard. McGuinness et al. (2024) adopted a measure of skill gaps based on the following question addressed to employees *'How would you best describe your skills in relation to what is required to do your job?'*. Based on survey responses, just six per cent of employees were classified as having a skill gap, having indicated that *"their skills are lower than what is required for their job and need to be further developed"*. In addition to examining general skill gaps, McGuinness et. al (2024) also assess the extent of skill gaps in basic literacy and numeracy skills based on similar questions within the survey that focused on these specific competencies. The authors found low incidence across the EU of basic skill gaps: only 2.7 per cent of employees reported a level of basic numeracy skills lower than what is required to do their jobs, and 1.8 per cent reported basic literacy gaps, with variation across countries. Evidence from multivariate models found that basic numeracy gaps were a dominant factor determining general underskilling. No evidence of any wage effect (a proxy for productivity) was found to be associated with general underskilling, but basic literacy gaps were associated with a 10 per cent pay penalty. Findings from the first wave of the European Skills and Jobs Survey suggested that Europe is not experiencing a major skills deficiency problem, at least in terms of the basic competency levels of the existing workforces.

This report aims at updating the analysis on skill gaps using the second wave of the European Skills and Jobs Survey (2021), and, where possible, compare results from the two waves of data[2]. There was a change of questions in wave 2 questionnaire, which caused some measurement inconsistencies and made it not feasible to compare some relevant outcomes over time, however, we do assess undereducation patterns across time and countries as an indicator of the general trend.

[1] Deliverable 2.1 of the SkillsPulse project.
[2] See https://www.cedefop.europa.eu/en/projects/european-skills-and-jobs-survey-esjs.

2. Data and methods

The data used in this study comes from the 2014 and the 2021 European Skills and Jobs Survey (ESJS), administered by CEDEFOP, which contains information on skill requirements and mismatches, as well as workers' working experiences and characteristics, across all EU countries. For both waves, the survey's respondents are adult employees, aged 24 to 65, and the total sample is over 46,000 observations.[3]

In terms of our methodological approach, we initially measure skills mismatch and deficit in human capital in terms of under-education across the two waves. We compare the highest level of education completed by the employee to the education level required by their job (according to ISCED classification). Under-education occurs when the level of education of the worker is lower than the level education required by the job. This is the only indicator that can be compared across both the 2014 and the 2021 waves.

We then focus on the 2021 wave and examine the extent to which employees report to have a skill gap. General under-skilling is based on the response to the question *"To what extent do you need to further develop your overall level of knowledge and skills to do your main job even better?".* Possible responses are to a *"great extent"*, a *"moderate extent"*, a *"small extent"*, or *"not at all"*. In this study we identify a skill gap when individuals report the need to develop their skills and knowledge at a great extent. The way the question is asked creates an inconsistency with respect to the measure produced in the first wave of the ESJS: Ideally, skill gap measures reflect a situation where workers do not have the adequate skills and competencies to perform their current jobs, while in this case the question refers to the development of skills to do their job even better. As such, the current measure will reflect (a) persons with skills that do not meet basic job requirements and (b) workers with skills that meet basic job requirements but have insufficient skills to perform their current job optimally. In addition to our general measure of skill gaps, we also examine measures of numeracy, social or technical skill gaps based on a similar questioning approach. They are measured in response to the question: *"Do you feel the need to further develop any of the following skills to do your main job even better?".* Numeracy skills imply working with numbers and quantities and doing calculations using maths; social skills imply working with and dealing with co-workers and other people; technical skills are job-specific skills. Workers responding "*yes*" are considered as having a skill gap in the relevant area. The ESJS is performed through both computer assisted telephone interviewing (CATI) and computer assisted web interviewing (CAWI) methods. The specific questions related to skill gaps are only asked in the CAWI questionnaire. Therefore, the questions are not asked to everybody, leading to a smaller sample size (over 30,000 observations).

We then use individual level data to estimate the determinants of general skill gaps, focusing on the extent to which they are correlated with numeracy, social or technical skill gaps. Finally, we assess the extent to which general skill gaps, and competency specific skill gaps are associated with wage penalties, which will give us some insights into the relationship between these skill gaps and productivity. A pay penalty, which will reflect worker performance, will provide a strong indication of the extent to which skill gaps are limiting worker productivity and, by extension, firm-level performance.

[3] UK was present in the first wave but not in the second, while Norway and Iceland appear only in the second: therefore when the analysis compares results across the two waves, only the EU-27 countries are considered.

3. Results

3.1 Descriptive statistics

In Table 1, we measure the extent of educational mismatch in Europe across the two waves of data, focusing on undereducation. We measure undereducation by comparing a person's educational attainment with the perceived level of education required for their job, which was collected as a survey question. A person is identified as being undereducated (overeducated) if their actual level of schooling lies below (above) their jobs' educational requirement. We use undereducation as an indirect proxy for skill gaps here in order to get a sense of whether the share of workers with a deficit in human capital is changing over time. The share of employees having a level of education lower than the level required by the job was over 14 per cent in 2014, and over 12 per cent in 2021. Therefore, the average rate of undereducation has been slightly declining over time across the EU.

Table 1: Incidence of undereducation – EU27 (+ U.K. in wave 1; + Norway and Iceland in wave 2)

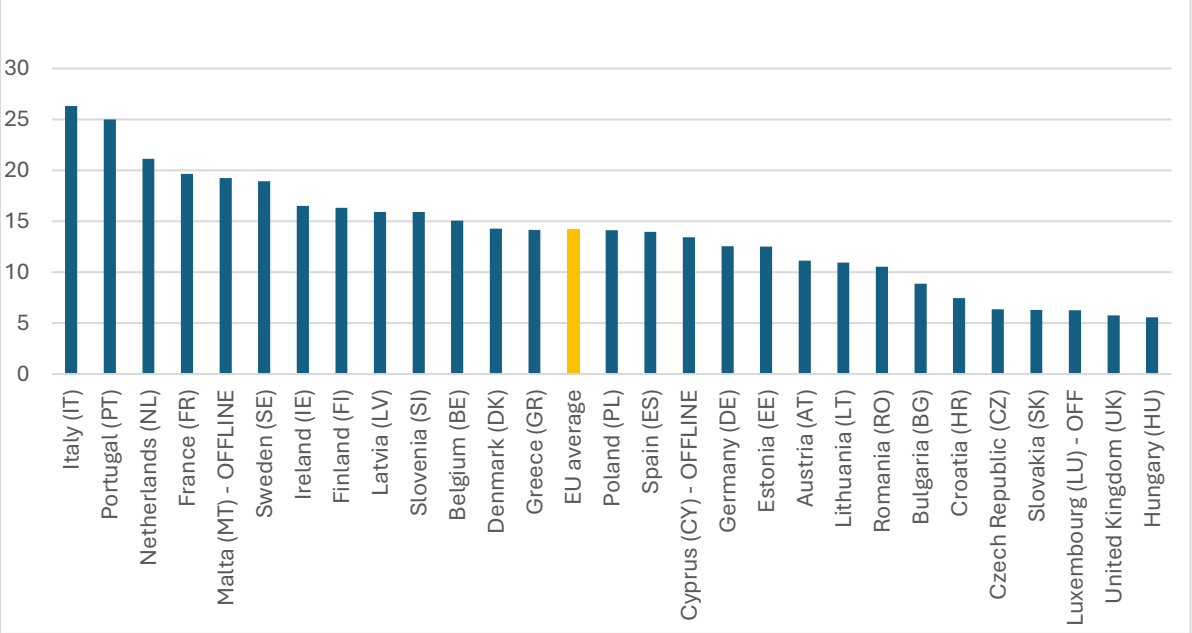
	Wave 1		**Wave 2**	
Educational Mismatch	N	%	N	%
Undereducation	5,239	14.16	5,527	12.34
Matched	26,976	56.12	28,914	62.57
Overeducated	13,734	29.72	11,772	25.47
	45,949	100	46,213	100

Source: 2014 and 2021 European Skills and Jobs Survey (authors' calculations).

Note: weights have been applied.

Figure 1 shows the extent of undereducation by country in wave 1 data. Rates ranged from over 25 to over 5 per cent. Countries such as Italy, Portugal, Netherlands and France had the highest share of undereducated employees in 2014, while Hungary, the U.K., Luxembourg and Slovakia had the lowest.

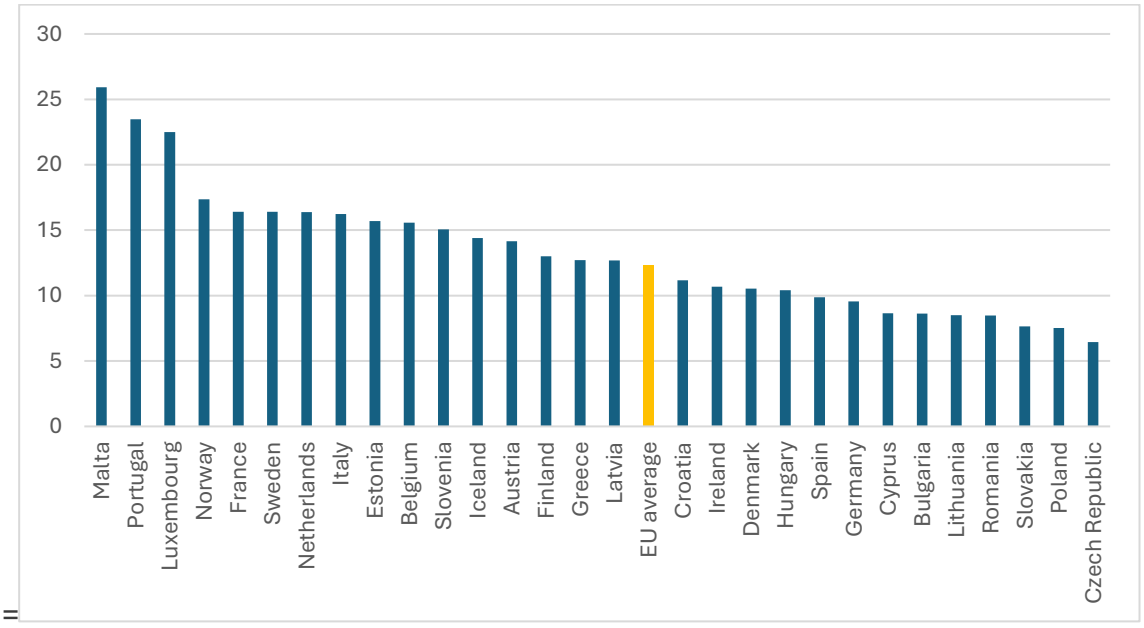
Figure 1: Undereducation by country, wave 1



Source: 2014 European Skills and Jobs Survey (authors' calculations).

Figure 2 shows the variation across countries of undereducation in wave 2 based on 2021 data. Rates ranged from over 25 to over 5 per cent. Countries such as Malta, Portugal, Luxembourg and Norway reported the highest share of overeducation in 2021, while Czechia, Poland, Slovakia and Romania the lowest.

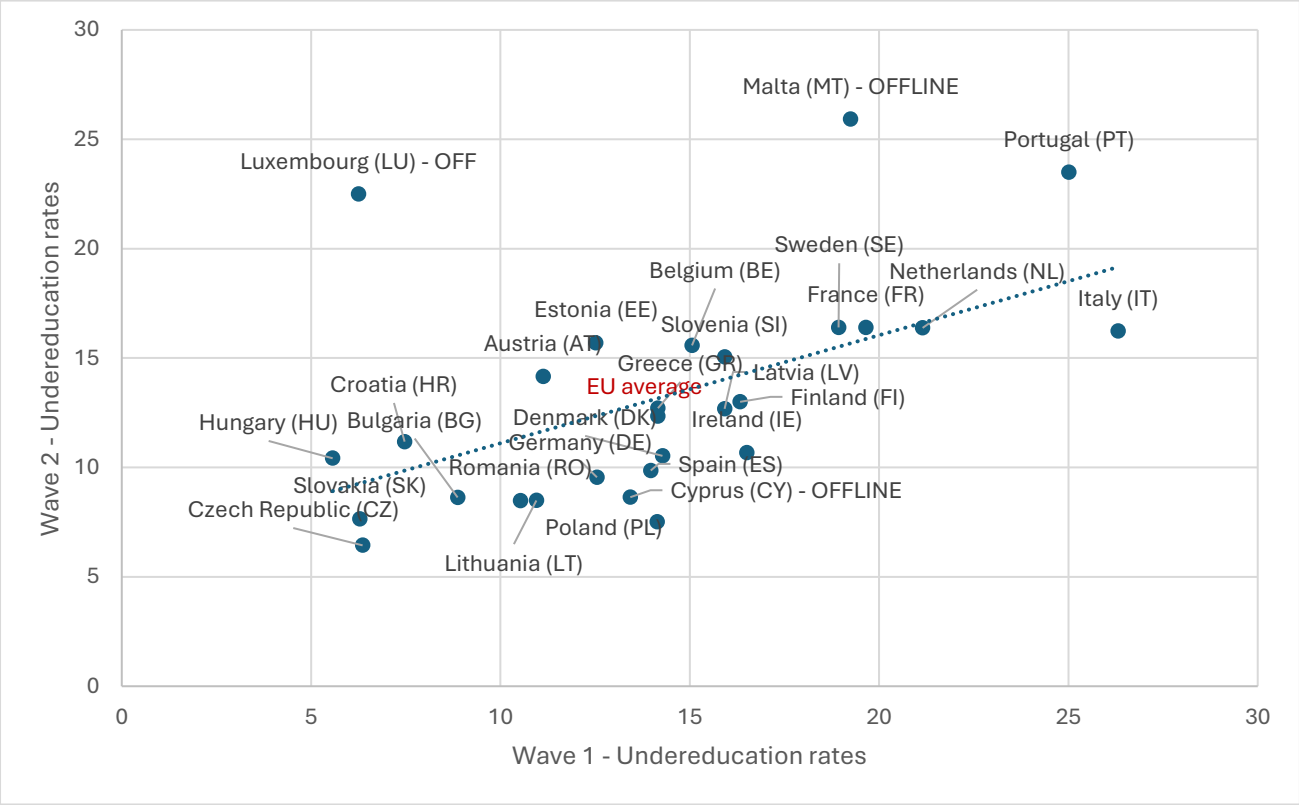
Figure 2: Undereducation by country, wave 2



Source: 2021 European Skills and Jobs Survey (authors' calculations).

In Figure, 3 we plot rates of undereducation in wave 1 against rates in wave 2 at country level. We find a positive correlation: countries with high (low) shares of undereducation in 2014, generally have high (low) rates of undereducation in 2021, although with some outliers such as Luxembourg, Malta and Portugal. Figure 3 demonstrates that while there is a strong consistency in undereducation rates across countries over time, the majority of countries experienced a decline in undereducation rates between 2014 and 2021. A small number of countries, in particular Luxembourg and Malta, experienced a relatively substantial increase in undereducation rates over the period.

Figure 3: Undereducation by country- wave 1 against wave 2



Source: 2014 and 2021 European Skills and Jobs Survey (authors' calculations).

However, while the data suggests some decline in deficit human capital over recent years, the focus of our analysis is the measurement of skill gaps in the 2021 data. We then analyse the extent of underskilling in Europe, using the 2021 ESJS. The proportion of employees reporting that they need to further develop their level of knowledge and skills to do their main job even better to a great extent stands at 16.20 per cent (see Table 2). It is noticeable that the average incidence of skill gaps in Europe in 2021 is similar to the rates of undereducation, however, the country level distribution is somewhat different. It is also important to note that the incidence of skill gaps using this measure is very different from the 6 per cent average incidence generated by the stricter definition contained in the 2014 data.

Table 2: Incidence of underskilling – EU27 + Norway, Iceland

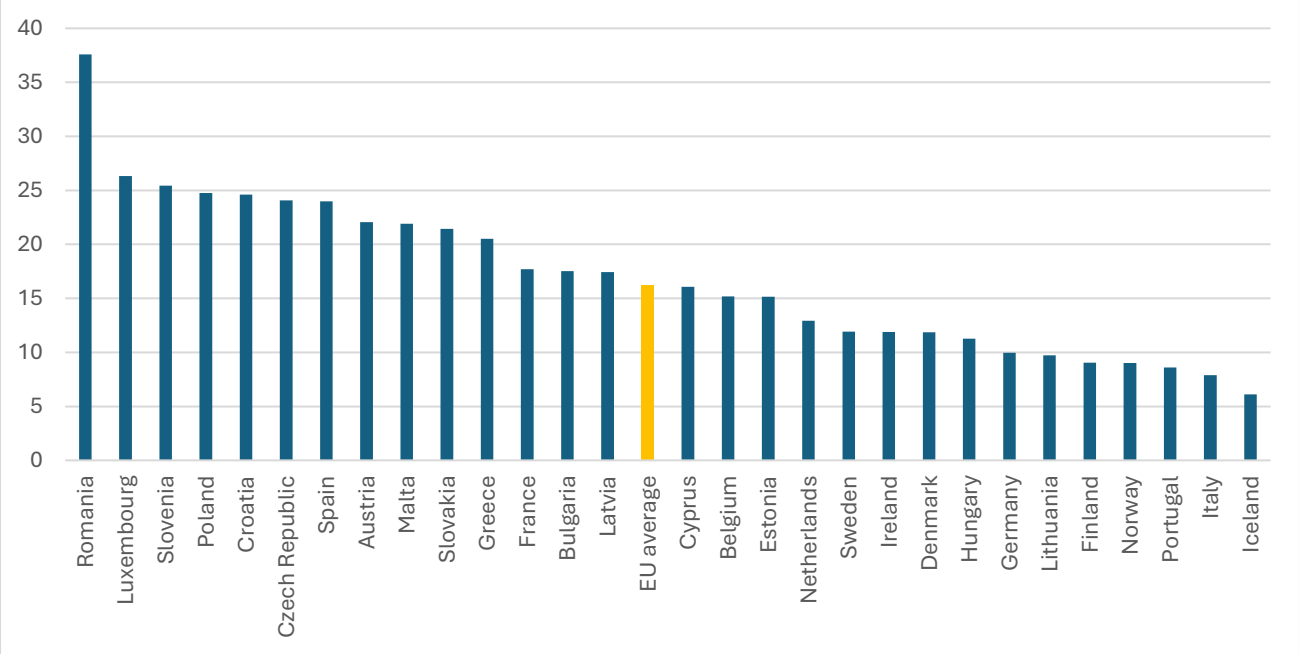
Underskilling	N	%
A great extent	8771	16.20
A lower extent or not at all	37442	83.80
Total	46212	100

Source: 2021 European Skills and Jobs Survey (authors' calculations).

Note: weights have been applied.

We analyse the incidence of underskilling by country. As stated, our indicator will capture employees who have a skill gap relative to their jobs essential requirements as well as those who have a perceived skill gap relative to their job optimal performance. There is substantial variation across countries. Rates vary from 37 per cent in Romania to over 5 per cent in Iceland, and it is noticeable that while the average incidence of skill gaps in 2021 (16 per cent) closely aligns with the average incidence of undereducation (14 per cent) in that year, the distribution across countries is very different. For instance, while Poland and Slovakia have one of the lowest incidences of undereducation in 2021, they also have some of the highest incidences of skill gaps.

Figure 4: Underskilling by country, wave 2



Source: 2021 European Skills and Jobs Survey (authors' calculations).

As outlined in Section 2, the question to measure underskilling changed from wave 1 to wave 2 data, therefore it is not possible to compare results with findings from McGuinness et al. (2024). The way the question is asked likely captures not only severe skill gaps, but also workers who simply would like to improve their skills to have more optimal performance on work. To better investigate the

characteristics of employees experiencing skill gaps we analysed their level of education. As shown in Table 3, almost half of workers reporting skill gaps possess a tertiary level of education; while 40 per cent have an upper-secondary or post-secondary level. As many workers reporting skill gaps are highly educated, it may be the case that they work in highly demanding/complex jobs where they often need to update their skills. This is a matter that we will return to later.

Table 3: Underskilling by education level

Level of education	%
Primary education or below (ISCED 0-1)	1.0
Lower secondary (ISCED 2)	8.6
Upper secondary/post upper (ISCED 3-4)	40.6
Tertiary (ISCED 5 and above)	49.8
N.	8,760

Source: 2021 European Skills and Jobs Survey (authors' calculations).

We next focus on the competency specific skill gaps among the European employees. The incidence of skills gaps in numeracy skills was 29.50 per cent; for social skills it was 49.4 per cent while for technical skills was 39.7 (see Table 4). We can contrast numeracy gaps from the 2014 wave of the ESJS, which was 2.7 per cent, and the 29.5 per cent estimate generated by 2021 data. As the questions in the 2014 captured essential numeracy gaps and the 2021 data essential and non-essential numeracy gaps, it is reasonable to conclude that the vast majority of employees reporting numeracy skill gaps have sufficient numeracy skills to meet their basic job requirements. The same conclusion can be drawn with regard to general skill gaps. We again investigate the characteristics of employees reporting these specific gaps by analysing their level of education (see Table 5). Similarly to general skill gaps, workers reporting specific skill gaps have either a tertiary (45/46 per cent) or upper secondary/post-secondary (43/44 per cent) level of education. This reinforces our conclusion that workers with essential skill gaps necessary to meet basic job requirements account for a small minority of those reporting skill gaps: as these workers are higher educated, it may be the case that they work in highly demanding/complex jobs where they often need to update their skills in essential competency areas in order to meet essential and non-essential job requirements.

Table 4: Incidence of numeracy, social or technical skill gaps, EU average

Skill gaps	N	%
Numeracy skill gaps	10,479	29.5
Social skill gaps	16,174	49.39
Technical skill gaps	13,505	39.73
Total	30,695	100

Source: 2021 European Skills and Jobs Survey (authors' calculations).

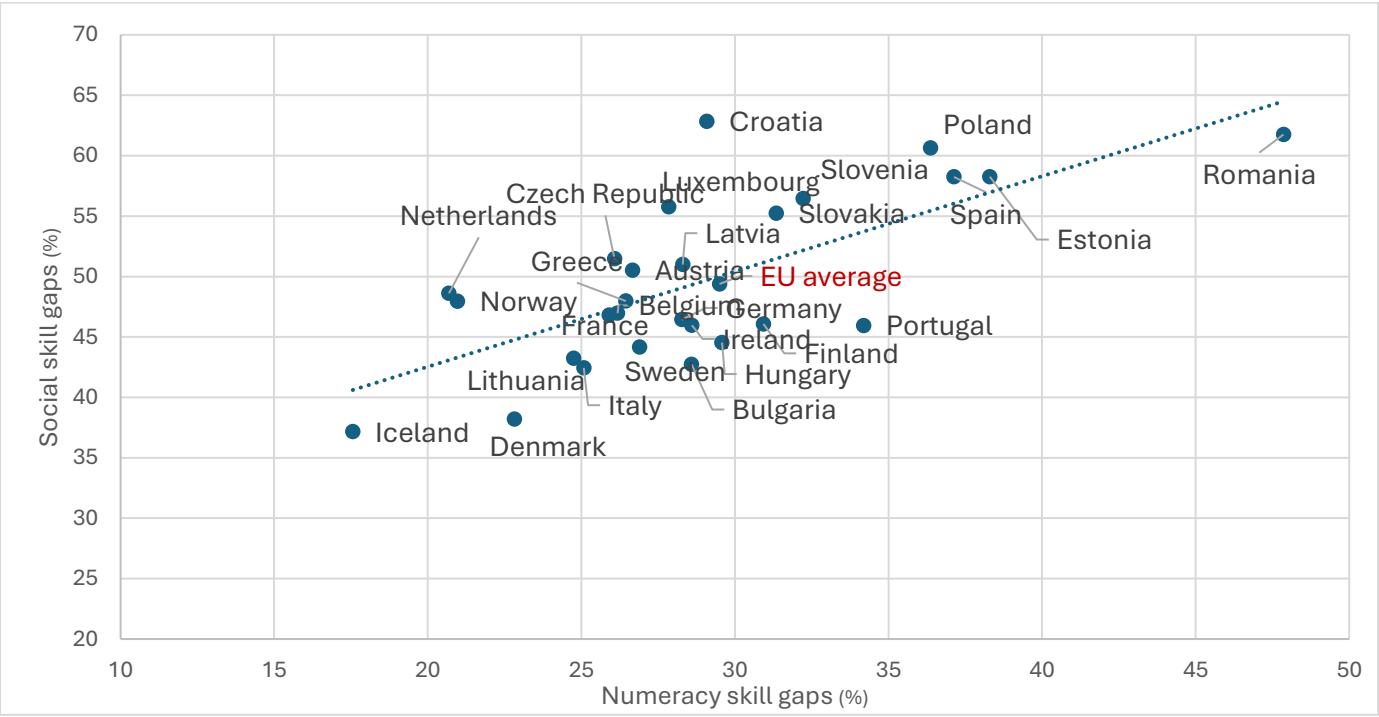
Table 5: Numeracy, social or technical skill gaps by education level

Level of education	Numeracy skill gaps (%)	Social skill gaps (%)	Technical skill gaps (%)
Primary education or below (ISCED 0-1)	1.9	1.5	1.4
Lower secondary (ISCED 2)	9.6	9.4	8.4
Upper secondary/post upper (ISCED 3-4)	43.4	43.3	44.1
Tertiary (ISCED 5 and above)	45.2	45.8	46.1
N	10,474	16,166	13,498

Source: 2021 European Skills and Jobs Survey (authors' calculations).

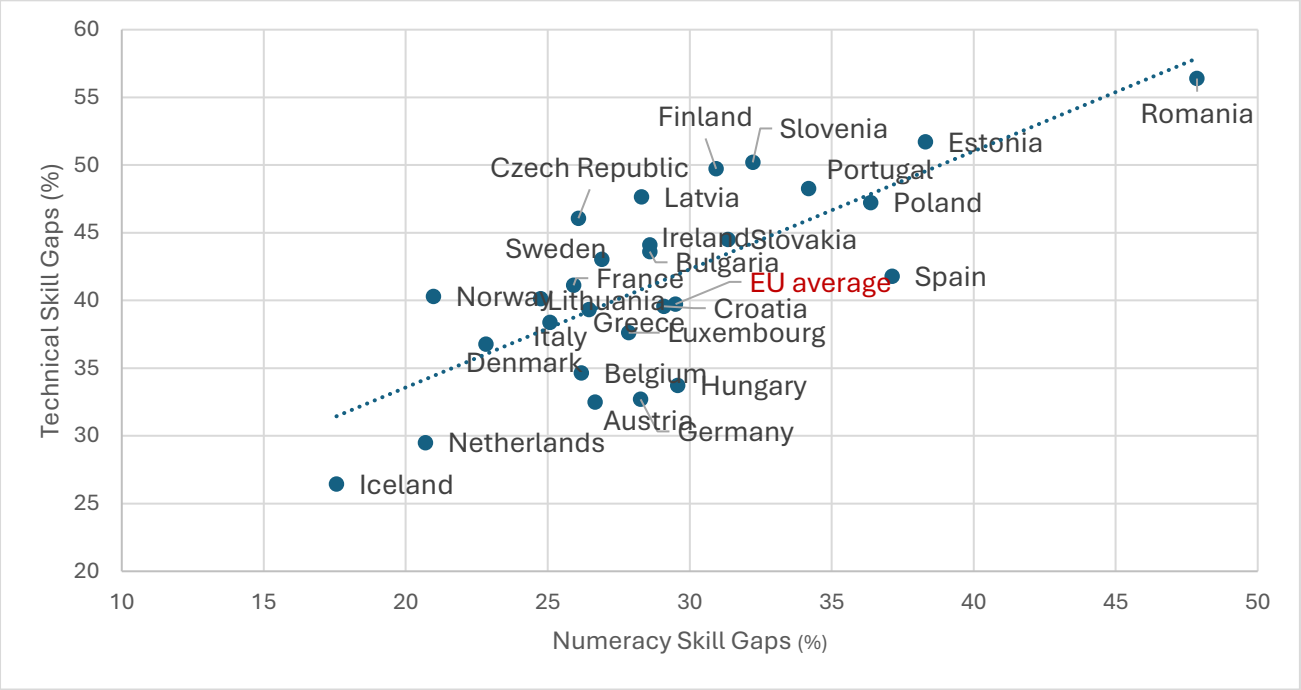
We next investigate the relationship between different measures of skill gaps competency-related. In Figure 5, we plot rates of numeracy skill gaps against social skill gaps at country level; in Figure 6 we plot rates of numeracy skill gaps against technical skill gaps at country level; in Figure 7 we plot social skill gaps against technical skill gaps rates at country level. There is a clear positive correlation among the skill gap measures at country level: countries reporting a skills gap in one competency area are likely to report a skills gap in other areas.

Figure 5: Numeracy skill gaps against social skill gaps by country



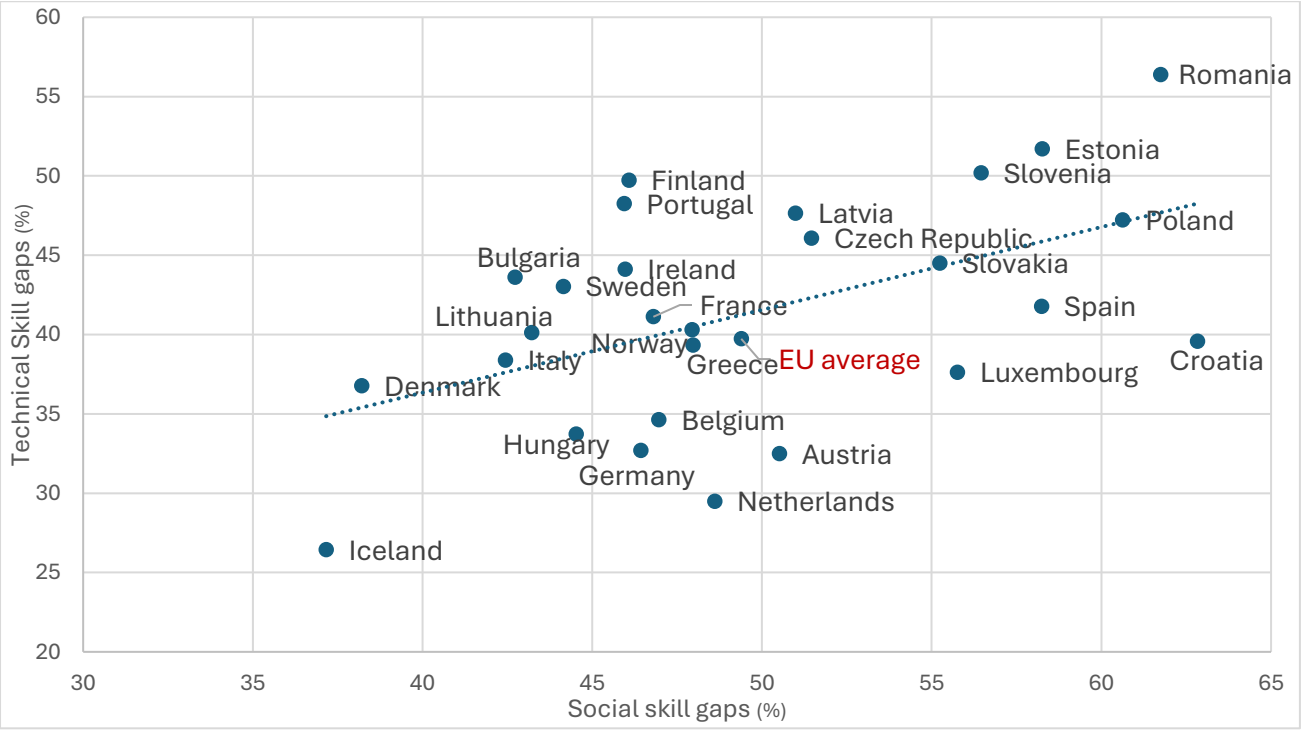
Source: 2021 European Skills and Jobs Survey (authors' calculations).

Figure 6: Numeracy skill gaps against technical skill gaps by country



Source: 2021 European Skills and Jobs Survey (authors' calculations).

Figure 7: Social skill gaps against technical skill gaps by country



Source: 2021 European Skills and Jobs Survey (authors' calculations).

3.2 Multivariate estimates

3.2.1 Probit model for general skill gaps

It is important to assess the extent to which general skill gaps are correlated with skill gaps in key competency areas, as this information is important for the design of any policies aimed at tackling skill gaps at a national level. We also examine the extent to which general skill gaps vary by worker characteristics, including age, gender, educational attainment, contractual status and labour market history. We also examine the extent to which general skill gaps are correlated with other measures of mismatch, such as overeducation and undereducation. In this section, we use 2021 ESJS data to model the relationship between general skill gaps and numeracy, social or technical skill gaps among employees in the EU27 + Norway and Iceland. The multivariate analysis is based on the following equation,

$$U_{ic} = a + \beta_1 \, Num_{ic} + \beta_2 \, Soc_{ic} + \beta_3 \, Tech_{ic} + X_{ic}{}' \, \beta_4 \; + \delta_c + e_{ic} \qquad (1)$$

Where U_{ic} is a dummy variable that takes value 1 for respondent i in country c who is classified as having a skill gap, that is when they state that they need to further develop their level of knowledge and skills to do their main job even better to a great extent, zero otherwise; $Num_{ic}$is a dummy variable indicating numeracy skills gaps (that is when they need to further develop numeracy skills to do their main job even better; Soc_{ic} is a dummy variable that indicates if the respondent has social skills gaps and; $Tech_{ic}$ is an indicator of technical skills gaps.; $X_{ic}{}'$ represents a vector of additional covariates including gender, age, educational attainment, part-time work, temporary contract, previous unemployment status, undereducation and overeducation; δ_c are country level fixed effects[4]. As the dependent variable is binary, we implement probit models. We show the models in Table 6. Our approach is forward stepwise, which allows us to observe model stability and potential collinearity: in particular, our controls for competency level skill gaps are added sequentially to the model.

We do find that general skill gaps are negatively correlated with gender and age, specifically males and older workers have a lower probability of a general skill gap. The age impact suggests that general skill gaps are likely to decline with labour market experience. Workers previous spells of unemployment have a lower probability of general skill gaps, which may reflect the possibility that they are more likely to be employed in lower skilled occupations. Being on a temporary contract is associated with a higher probability of general skill gaps, which may also reflect the fact that some contractual arrangements limit the accumulation of job specific human capital. We do not find any relationship between general skill gaps and educational attainment, indicating that general skill gaps tend to be distributed across jobs of varying productivity intensity. We do find that general skill gaps are highly correlated with other forms of worker mismatch, specifically, overeducated workers have a lower probability of skill gaps, while undereducated workers are more likely to have skill gaps.

Importantly we find that general skill gaps are strongly positively correlated with individual skill competency gaps. We find that having a skill gap in numeracy, technical or social skills raises the probability of a general skill gap by 40 percentage points respectively.

[4] The model standard errors account for clustering at country level.

Table 6: Determinants of general underskilling, Probit model for EU-27+ Norway, Iceland, 2021

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**Being underskilled**	**Being underskilled**	**Being underskilled**	**Being underskilled**	**Being underskilled**
Male	0.04*	-0.01	0.05**	-0.04	-0.04**
	(0.023)	(0.021)	(0.020)	(0.024)	(0.020)
Age	-0.01***	-0.01***	-0.01***	-0.01***	-0.00***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lower secondary ed	-0.13	-0.07	-0.10	-0.10	-0.05
	(0.081)	(0.073)	(0.081)	(0.076)	(0.075)
Upper secondary/post upper ed	-0.14*	-0.08	-0.11	-0.14*	-0.07
	(0.078)	(0.075)	(0.079)	(0.078)	(0.078)
Tertiary ed	0.07	0.11	0.06	0.04	0.09
	(0.078)	(0.072)	(0.081)	(0.074)	(0.074)
Undereducated	0.13***	0.12***	0.12***	0.11***	0.11***
	(0.028)	(0.028)	(0.028)	(0.029)	(0.028)
Overeducated	-0.21***	-0.15***	-0.19***	-0.17***	-0.14***
	(0.021)	(0.020)	(0.021)	(0.020)	(0.019)
Part-time	-0.01	-0.02	-0.02	-0.00	-0.01
	(0.028)	(0.026)	(0.029)	(0.028)	(0.028)
Temporary contract	0.05*	0.07**	0.04	0.07**	0.07**
	(0.028)	(0.027)	(0.027)	(0.028)	(0.028)
Previous unemployment	-0.14***	-0.11**	-0.11**	-0.11**	-0.08*
	(0.051)	(0.047)	(0.045)	(0.047)	(0.043)
Numeracy Skill Gap		0.63***			0.39***
		(0.031)			(0.032)
Social Skill Gap			0.60***		0.42***
			(0.032)		(0.029)
Technical Skill Gap				0.59***	0.40***
				(0.019)	(0.014)
Constant	-0.31***	-0.72***	-0.77***	-0.62***	-1.09***
	(0.100)	(0.093)	(0.103)	(0.096)	(0.097)
Observations	30,697	30,692	30,692	30,669	30,668
r2_p	0.0628	0.105	0.0996	0.0995	0.138

Source: European Skills and Jobs Survey 2021 (authors' elaboration).

*Note: Includes country level fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Specification (1) estimates a model with only controls; specification (2) estimates a model with controls and numeracy skills gaps dummy; specification (3) estimates a model with controls and social skills gaps dummy; specification (4) estimates a model with controls and technical skills gaps dummy: specification (5) estimates a model containing controls and the three skills gap measures.*

As mentioned in Section 3.1, workers who reported either general or competency specific skill gaps are more likely to be highly educated, with the majority having a tertiary level of education or upper

secondary/post upper education level. While we find no statistical relationship, the descriptive data points to the possibility that employees who work in more demanding/complex jobs are more likely to feel that they need to update and improve their skills more frequently to meet job requirements.

In order to examine the relationship between general skill gaps and job complexity we have developed a “job complexity” measure in order to try to account for this in our models. In the ESJS, employees are asked whether they read, write or do mathematical computations (so called “foundational” skills) as part of their job and at what intensity. For each skill, three dummies with different intensity levels are derived: basic, intermediate and high level of skill use. We create a composite index with intermediate and high-level dummies for reading, writing and math skills (the index is made up by six dummies and the value ranges from 1 to 6). High index levels represent the intense use of higher-level key competencies within the job. We now re-estimate equation 1 with the additional control for job complexity.

The models are shown in Table 7 and confirm that the coefficient for job complexity is positive and statistically significant: the more complex the job, the higher the probability for workers to report their need to develop their skills and knowledge. After controlling for job complexity, general skill gaps remain positively correlated with numeracy, social and technical skill gaps, with the marginal effects broadly comparable with the previous estimates. However, when job complexity is added to our model, other controls that were significant in our previous models, such as gender, age, previous unemployment and contract status, are no longer significant, suggesting that these variables were merely proxying job complexity impacts. For instance, we might predict that job complexity will be higher in jobs with higher tenure (proxied previously by age and temporary contracts) and lower in jobs in lower paid occupations (which are more likely to be undertaken by employees with previous unemployment histories). The importance of job complexity in determining general skill gaps is also demonstrated by the fact that the model fit (proxied by the pseudo r squared statistic) improves when this variable is added to the model.

Table 7: Determinants of general underskilling with job complexity measure, Probit model for EU-27+ Norway, Iceland, 2021

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**Being underskilled**	**Being underskilled**	**Being underskilled**	**Being underskilled**	**Being underskilled**
Male	0.04	0.01	0.03	-0.00	-0.01
	(0.039)	(0.038)	(0.035)	(0.042)	(0.038)
Age	-0.01***	-0.00**	-0.00***	-0.00***	-0.00
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Lower secondary ed	-0.21	-0.21	-0.21	-0.21	-0.22
	(0.200)	(0.208)	(0.213)	(0.204)	(0.218)
Upper secondary/post upper ed	-0.33*	-0.29	-0.29	-0.32*	-0.28
	(0.194)	(0.201)	(0.196)	(0.184)	(0.196)
Tertiary ed	-0.30	-0.21	-0.24	-0.26	-0.18
	(0.205)	(0.210)	(0.208)	(0.194)	(0.204)
Undereducated	0.04	0.05	0.05	0.05	0.06
	(0.046)	(0.045)	(0.044)	(0.047)	(0.044)
Overeducated	-0.08	-0.05	-0.08	-0.07	-0.05
	(0.050)	(0.051)	(0.050)	(0.048)	(0.049)
Foundational index	0.21***	0.15***	0.17***	0.17***	0.12***
	(0.023)	(0.020)	(0.023)	(0.022)	(0.021)
Part-time	0.07	0.04	0.05	0.07	0.03
	(0.056)	(0.057)	(0.061)	(0.056)	(0.060)
Temporary contract	0.05	0.06	0.06	0.06	0.06
	(0.060)	(0.064)	(0.063)	(0.063)	(0.067)
Previous unemployment	-0.06	-0.05	-0.06	-0.04	-0.05
	(0.104)	(0.089)	(0.096)	(0.100)	(0.088)
Numeracy Skill Gap		0.62***			0.39***
		(0.041)			(0.038)
Social Skill Gap			0.66***		0.46***
			(0.045)		(0.044)
Technical Skill Gap				0.54***	0.34***
				(0.039)	(0.035)
Constant	-0.81***	-1.03***	-1.14***	-0.97***	-1.26***
	(0.185)	(0.200)	(0.191)	(0.194)	(0.207)
Observations	6,703	6,701	6,702	6,696	6,696
r2_p	0.0839	0.119	0.122	0.109	0.147

Source: European Skills and Jobs Survey 2021 (authors' elaboration).

*Note: Includes country level fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Specification (1) estimates a model with only controls; specification (2) estimates a model with controls and numeracy skills gaps dummy; specification (3) estimates a model with controls and social skills gaps dummy; specification (4) estimates a model with controls and technical skills gaps dummy: specification (5) estimates a model containing controls and the three skills gap measures.*

3.2.2 Determinants of wages

In order to assess potential productivity impacts arising from skill gaps, we next include the measures in a wage model. If workers with skill gaps are less productive than their adequately matched counterparts, we would expect to see this lower productivity translated into a pay penalty. We estimate an OLS model where log hourly earnings are our dependent variable. The analysis is based on the following specification which adds a series of skill gap related controls into a wage specification that follows a Mincer type specification that account for both education and age. Controls are also included for other factors related to labour market history, contractual status etc that will also potentially impact earnings:

$$\ln(W)_{ic} = a + \beta_1 U_{ic} + \beta_2 Num_{ic} + \beta_3 Soc_{ic} + \beta_4 Tech_{ic} + X_{ic}' \beta_5 + \delta_c + e_i \quad (2)$$

The dependent variable, $\ln(W)_{ic}$, are log hourly earnings for respondent i in country c; U_{ic} is a dummy variable for general under-skilling; Num_{ic}, Soc_{ic} and $Tech_{ic}$ are the numeracy, social and technical skills gaps measures; X_{ic}' represents a vector of additional covariates including gender, age, educational attainment, part-time work, temporary contract and previous unemployment status; δ_c are country level fixed effects.

We again adopt a forward stepwise approach, sequentially adding our measures of underskilling and skill gaps (see Table 8). As expected, our results show that wages are positively correlated with age, level of education, male gender, and negatively correlated with part-time, temporary employment contracts and previous unemployment. The coefficients on overeducation, undereducation are consistent with the wider literature (Sanchez-Sanchez and McGuinness, 2015; McGuinness et al., 2018). Undereducated workers earn a wage premium of 9 per cent relative to employees with the same level of schooling who are matched, while overeducated workers experience a wage penalty of 13 per cent relative to the same reference category. Interestingly, we do find a wage premium associated with our measure of general skill gaps. We also find weak evidence of wage premium associated with a gap in numeracy skills, and a stronger significant wage premium associated with technical skill gaps. According to our analysis, it seems that workers who report the need to develop to a great extent their skills and knowledge, and improve specific skills areas, are associated with higher wages, and higher productivity levels, which one would not expect. Nevertheless, we can conclude at this point that there is no evidence of adverse productivity impacts, proxied by wage returns, arising from either general or competency specific skill gaps. We next estimate the same wage equation (2) but by different levels of education, to investigate whether the pattern of returns varies by level of educational attainment.

Table 8: Determinants of earnings, OLS model for EU-27+Norway, Iceland, 2021

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**
Underskilling		0.07***				0.06***
		(0.017)				(0.017)
Male	0.17***	0.17***	0.17***	0.17***	0.16***	0.16***
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
Age	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Age squared	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary ed	0.04	0.04	0.04	0.04	0.03	0.04
	(0.050)	(0.050)	(0.050)	(0.049)	(0.049)	(0.050)
Upper secondary/post upper ed	0.15***	0.15***	0.15***	0.15***	0.14***	0.15***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)
Tertiary ed	0.40***	0.40***	0.40***	0.40***	0.40***	0.40***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.040)	(0.040)
Undereducated	0.10***	0.10***	0.10***	0.10***	0.10***	0.09***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Overeducated	-0.14***	-0.14***	-0.14***	-0.14***	-0.14***	-0.13***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
Part-time	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***
	(0.056)	(0.055)	(0.055)	(0.055)	(0.055)	(0.054)
Temporary contract	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Previous unemployment	-0.11***	-0.11***	-0.11***	-0.11***	-0.11***	-0.11***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Numeracy Skill Gap			0.04***			0.02*
			(0.010)			(0.012)
Social Skill Gap				0.03***		0.01
				(0.007)		(0.008)
Technical Skill Gap					0.04***	0.03***
					(0.007)	(0.009)
Constant	5.39***	5.37***	5.38***	5.38***	5.38***	5.35***
	(0.112)	(0.108)	(0.109)	(0.110)	(0.112)	(0.107)
Observations	22,661	22,661	22,658	22,659	22,648	22,648
R-squared	0.496	0.497	0.496	0.496	0.496	0.497

*Source: European Skills and Jobs Survey 2021 (authors' elaboration). Includes country level fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*

Note: specification (1) estimates a model with only controls; specification (2) estimates a model with controls and general under-skilling dummy; specification (3) estimates a model with controls and numeracy skills gap dummy; specification (4) estimates a model with controls and social skills gaps dummy; specification (5) estimates a model with controls and technical skills gaps dummy; specification (6) estimates a model containing controls, general under-skilling dummy and the three skills gap measures.

Table 9 presents the results from the wage models estimated by different level of education (specification 1 at tertiary; specification 2 at upper secondary/post-upper secondary; specification 3 at lower secondary; specification 4 at primary or below). Hourly wages are positively correlated with our measure of general skill gaps at tertiary and upper secondary/post-upper secondary level of

education, not surprisingly given the earlier descriptives the effect disappears at the lowest level of education. The wage premium would be explained by the fact that underskilled employees with higher educational attainment work in more qualified jobs, that likely require them to often update their skills. The evidence supports the view that skill gaps are not associated with low skills or relatively low paying employment. At upper/post-upper secondary level of education, we find evidence of wage premium associated with gaps in numeracy and technical skills. There is no evidence of wage premiums associated with competency specific skill gaps among graduates.

Table 9: Determinants of earnings by level of education, OLS model for EU-27+Norway, Iceland, 2021

	(1)	(2)	(3)	(4)
VARIABLES	**Hourly wage (tertiary)**	**Hourly wage (uppersec/postupp)**	**Hourly wage (lowersec)**	**Hourly wage (primary)**
Underskilling	0.05**	0.07***	0.02	-0.01
	(0.020)	(0.015)	(0.051)	(0.160)
Numeracy Skill Gap	0.00	0.05***	-0.01	-0.18
	(0.020)	(0.015)	(0.032)	(0.144)
Social Skill Gap	0.02	0.00	-0.02	-0.06
	(0.020)	(0.010)	(0.054)	(0.146)
Technical Skill Gap	0.02	0.03***	0.05*	0.15*
	(0.022)	(0.010)	(0.024)	(0.074)
Male	0.15***	0.16***	0.26***	0.11**
	(0.020)	(0.026)	(0.020)	(0.051)
Age	0.03***	0.02***	0.01	-0.03
	(0.006)	(0.006)	(0.020)	(0.033)
Age squared	-0.00***	-0.00***	-0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)
Undereducated	-0.00	0.14***	0.11***	0.07
	(0.037)	(0.022)	(0.025)	(0.098)
Overeducated	-0.19***	-0.09***	-0.04	-0.12
	(0.017)	(0.019)	(0.025)	(0.214)
Part-time	-0.40***	-0.42***	-0.36***	-0.36***
	(0.069)	(0.051)	(0.023)	(0.086)
Temporary contract	-0.18***	-0.16***	-0.13***	0.04
	(0.022)	(0.023)	(0.041)	(0.104)
Previous unemployment	-0.14***	-0.09***	-0.11**	-0.13
	(0.017)	(0.022)	(0.051)	(0.124)
Constant	5.57***	5.63***	5.64***	6.78***
	(0.118)	(0.123)	(0.439)	(0.760)
Observations	11,964	8,623	1,812	235
R-squared	0.466	0.525	0.434	0.352

Source: European Skills and Jobs Survey 2021 (authors' elaboration).

*Note: Includes country level fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Specification (1) estimates the full wage model at tertiary level of education; specification (2) estimates the full wage model at upper secondary/post upper secondary level of education; specification (3) estimates the full wage model at lower secondary level of education; specification (4) estimates the full wage model at primary or no level of education.*

Similarly to what we did for general underskilling, we introduce as a control in our wage equation (2) the job complexity indicator previously developed, based on reading, writing and math skills. Results

from the models are shown in Table 10. Again, we use a stepwise approach, sequentially adding our measures of underskilling and skill gaps. Consistently with our previous wage models, wages are positively correlated with age, level of education, and being a man, and negatively correlated with part-time, temporary employment contracts and previous unemployment. Undereducated workers experience a wage premium, while overeducated a wage penalty. Interestingly, the coefficient for the measure of job complexity is positive and statistically significant: the more complex/skills intensive the job, the higher the wage premium. Any wage premia associated with underskilling or numeracy, social and technical gaps disappear when controlling for job complexity. We, therefore, find no evidence that skill gaps (as measured in the 2021 ESJS) are associated with negative productivity impacts (proxied by wages). In particular, we find that where skill gaps exist, they are likely to be driven by workers motivated to keep pace with evolving requirements in more complex jobs. In this context, the skill gaps observed here, which are likely to be overwhelmingly non-essential, can be viewed as a positive outcome that reflects employees' desire to undertake their job in a more optimal way. This is very different from a deficiency that prevents workers from meeting the basic requirements of their role, which is the traditional perception of skill gaps.

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Table 10: Determinants of earnings with job complexity measure, OLS model for EU-27+Norway, Iceland, 2021

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**	**Hourly wage**
Underskilling		0.04				0.03
		(0.027)				(0.027)
Male	0.19***	0.19***	0.19***	0.19***	0.19***	0.19***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)
Age	0.02**	0.02**	0.02**	0.02**	0.02**	0.02**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Age squared	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower secondary ed	0.22	0.22	0.22	0.23	0.22	0.23
	(0.207)	(0.202)	(0.205)	(0.206)	(0.206)	(0.201)
Upper secondary/post upper ed	0.34*	0.34**	0.34*	0.34*	0.34*	0.34**
	(0.168)	(0.164)	(0.166)	(0.167)	(0.167)	(0.162)
Tertiary ed	0.57***	0.57***	0.57***	0.57***	0.57***	0.57***
	(0.167)	(0.163)	(0.165)	(0.166)	(0.166)	(0.159)
Foundational Index	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Undereducated	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
Overeducated	-0.09***	-0.08***	-0.09***	-0.09***	-0.09***	-0.08***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Part-time	-0.23***	-0.23***	-0.23***	-0.23***	-0.22***	-0.22***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)	(0.036)
Temporary contract	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***
	(0.038)	(0.041)	(0.039)	(0.038)	(0.039)	(0.042)
Previous unemployment	-0.17**	-0.17**	-0.17**	-0.17**	-0.17***	-0.17**
	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)	(0.064)
Numeracy Skill Gap			0.00			-0.01
			(0.018)			(0.020)
Social Skill Gap				0.01		0.01
				(0.011)		(0.017)
Technical Skill Gap					0.01	0.01
					(0.010)	(0.010)
Constant	5.14***	5.12***	5.14***	5.13***	5.14***	5.13***
	(0.271)	(0.271)	(0.274)	(0.273)	(0.271)	(0.274)
Observations	5,072	5,072	5,070	5,071	5,066	5,066
R-squared	0.555	0.556	0.555	0.555	0.555	0.556

*Source: European Skills and Jobs Survey 2021 (authors' elaboration). Includes country level fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*

Note: specification (1) estimates a model with only controls; specification (2) estimates a model with controls and general under-skilling dummy; specification (3) estimates a model with controls and numeracy skills gap dummy; specification (4) estimates a model with controls and social skills gaps dummy; specification (5) estimates a model with controls and technical skills gaps dummy; specification (6) estimates a model containing controls, general under-skilling dummy and the three skills gap measures.

4. Conclusion

In this research, we investigate the extent of skill gaps among the European workforce and examine the relationship between skill gaps and workers characteristics, as well as employment conditions. We use data from the 2014 and 2021 European Skills and Jobs Survey, administered by CEDEFOP. In the second wave of the data, there has been a change in several questions, which caused some measurement inconsistencies and made it not feasible to compare some relevant outcomes over time.

We initially measure skills mismatch and deficit in human capital in terms of under-education across the two waves. It is the only indicator that can be compared across the 2014 and the 2021 waves. We found that undereducation has been slightly declining at both the EU and member state levels between 2014 and 2021 (from 14.2 to 12.3 per cent).

When we compare the definitional changes in the measure of skill gaps between the 2014 and 2021 waves of the ESJS, we argue that the 2014 question captures essential skill gaps while the 2021 question captures essential and non-essential skill gaps. The fact that we observe skill gap measures increasing from 6.7 to 16 percent across the two waves, over a period when undereducation has been declining, leads us to conclude that the majority of skill gaps reported in the 2021 data are predominantly non-essential. This is even more the case for competency specific skill gaps based on the increase in numeracy skill gaps between the waves. We conclude that the majority of workers reporting skill gaps in numeracy, social skills and technical skills have the skill levels to meet their basic job requirements and that both general and competency specific skill gaps generally reflect employees' desire to perform their job in a more optimal way.

We focus on the 2021 wave of the ESJS and analyse underskilling and skill gaps in specific areas. We find relatively high rates of general skill gaps: around 16.2 per cent of EU employees reported they need to develop their overall level of knowledge and skills to do their job even better. High shares of skill gaps were also found in specific areas: 29.5 per cent of workers have numeracy skill gaps; 49.4 per cent have social skill gaps; and 39.7 per cent have technical skill gaps. A data limitation needs to be acknowledged: the way the questions on general underskilling and gaps are asked could be somehow misleading from the general meaning of skill gaps: ideally, a skill gap should feature a situation where workers do not have the adequate skills and competencies to perform their jobs, while in this case the ESJS question refers to development of skills to do their job even better. Although this goes beyond the skill gap concept, we are confident that among the workers reporting the need to develop their skills to do their job even better, we are also capturing genuine underskilling and gaps in specific areas. Measures of skill gaps were found to be highly correlated with each other at member state level.

Within probit models estimated at worker level, general underskilling appear to be highly correlated with numeracy, social and technical skills gaps. Moreover, the more complex the job, the higher the probability for workers to report being underskilled.

We assessed the extent to which general under-skilling, and skill gaps are associated with wage penalties or not. Interestingly, when estimating a basic wage model, underskilling and specific skill gaps were found to be associated with wage premia, specifically for workers at tertiary or upper secondary/post-upper secondary level of education. However, these premia disappeared when job complexity was introduced in the model: wage premia seem to be driven solely by the fact that skill gaps are occurring in more complex jobs. Consequently, we find no evidence that skill gaps (as measured in the ESJS2) are associated with negative productivity impacts (proxied by wages).

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