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ABSTRACT

Measuring the Incidence and Impacts of Skill Gaps Among European Workers*

In this paper, we examine the incidence of skill gaps among European employees. We identify the worker and firm level characteristics most commonly associated with skill gaps and investigate the extent to which this particular form of skill mismatch is associated with wage penalties. In 2021, we find that 16.2% of EU employees had essential and non-essential general skill gaps. The incidences for competency specific skill gaps were 29.5% for numeracy skills, 39.7% for technical skills and 49.4% for social skills. Among employees we find that general skill gaps were highly correlated with numeracy, social and technical skills gaps. The more complex the job, the higher the probability for workers to report having a general skill gap or a domain specific skill gap. We find no evidence that skill gaps are associated with negative productivity impacts (proxied by wages). 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. This is very different from the usual view of skill gaps as being concentrated among poorly educated workers in low value-added employment lacking essential skills.

JEL Classification: J20, J24, J31, J38
Keywords: skill gaps, wages, job complexity, measurement, policy

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1 Introduction

Skill gaps in the labour market arise when existing employees lack the 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. There appears to be a working assumption among policy makers that economic performance is persistently threatened by skill gaps among existing employees and / or a lack of suitably qualified candidates to fill vacancies external to the firm (skill shortages), however, there is a remarkable lack of empirical evidence to support either assertion (McGuinness et. al (2018, 2025). The research space is further complicated by the fact that, even within the limited literature, no consistent empirical approach is adopted to the measurement of skill gaps.

This study builds on previous research from McGuinness et al. (2024), who used the first wave of the European Skills and Jobs Survey (ESJS) (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) concluded that, based on the measurement approach adopted in the 2024 ESJS, there was limited evidence of substantial basic skill gaps among European employees. In the present paper, we employ the second wave of the European Skills and Jobs Survey (2021) to perform a similar analysis of skill gaps among the European workforce. We will show that even a very minor change in the question used to assess skill gaps within the survey produces very different results and that careful consideration needs to be given to the exact wording of survey questions when interpreting results and the implications for policy. The research highlights the importance of adopting consistent survey tools for the measurement of skill gaps both within and across countries.

2. Existing Literature

Despite the issue of workforce human capital development being a constant concern for policy makers, there is a very limited literature examining the extent to which employees have sufficient skills and competencies to meet the requirements of their current job. In a recent review of the literature on skills mismatches over the period 2002 to 2022, McGuinness et al. (2025) reported finding only seven academic papers on skill gaps, accounting for approximately two per cent of skill mismatch studies published over the period. McGuinness et. al (2025) summarise the existing literature as being consistent in terms of findings with skill gaps being an important determinant of firm-level training expenditures and labour costs. Furthermore, there is consistent evidence, from the UK Employer Skills Survey, that skill gaps act as a barrier to the introduction of new products.[1] Moreover, with respect to geographical concentration, Zarifa et al. (2019) found that skill gaps are

[1] For further information, please see: https://skillssurvey.co.uk/.

more prevalent in rural areas and small population centres in Canada, reflecting the lower post-secondary education in such areas.

Importantly, within this extremely limited literature, there is a lack of a consistently adopted measurement approach to skill gaps. It is undoubtedly the case that the scarcity of studies on skill gaps and the lack of measurement consistency is wholly a consequence of data constraints. Rikala et al. (2024), in a recent review of the skill gaps literature, confirmed the need for common understanding of skill gaps and for a consistent measurement approach to be adopted.

Two primary methods to measure skill gaps have emerged in the literature: employer-reported skill deficiencies and employee-reported skill gaps. The former relies on direct employer assessments of their workforce's competency shortfalls, while the latter leverages data from employees to identify areas of skill misalignment. Few studies utilise employer surveys as a primary method to measure skill gaps. For instance, Forth and Mason (2006) measure ICT skill gaps among UK businesses' workforce using data from the 1999 International Benchmarking Survey. In the survey, employers are asked whether they perceive a deficiency in the ICT skills of their existing employees; the authors find that ICT skill gaps negatively affect firm performance indirectly by limiting ICT adoption and utilisation. Jackson and Chapman (2012) measure skill gaps by comparing the perceptions of employers and academics regarding the performance levels of Australian business graduates across 20 non-technical skills. Malik et al. (2019) employ data from the 2009 Talent Management Study, a survey of US workplaces, where HR directors are asked to rate the extent to which specific skills are in short supply at their organisation. The authors find that, when they exist, skill gaps do not directly impact firms' profitability. In terms of employee-reported skill gaps, existing surveys tend to focus on asking employees the extent to which their skills are adequate to perform their current job or need to be developed, either generally or in specific competency areas. Examples of surveys that contain information on employee skill gaps included PIAAC and REFLEX for the OECD, the European Skills and Jobs Surveys (ESJS) for EU countries, HILDA survey for Australia.

A potential weakness of skill gap measurement approaches is that they tend to be highly subjective in nature, as they capture either employee perception of their own capabilities or employer perceptions of their workforce's competency levels. As we will see in this paper, in the cases that skill gap questions are included in surveys, the form of the question tends to vary considerably, with substantial implications for measurement. Furthermore, it is also unclear the extent to which skill gaps are more accurately measured from the perspective of the employer or employee. McGuinness and Ortiz (2016) address this question using linked Irish employer-employee data that posed similar questions regarding skill gaps to both employees and employers. They report that while the responses of employers and employees were highly correlated, employee responses were potentially prone to higher bias as they may incorporate training requirements to meet future career objectives as well as those related directly to their current jobs.

Nevertheless, there is little evidence to show that, despite being a major concern for policy makers, skill gaps are widespread or have adverse impacts on earnings or productivity. McGuinness et al. (2024) adopted a measure of skill gaps, based on a question in the 2014 wave of the ESJS, and estimated that just six per cent of employees had a general 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/underskilling, McGuinness et. al (2024) also assessed 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 countries 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. Based on their analysis, McGuinness et al. (2024) conclude that Europe is not experiencing a major skills gap problem, at least in terms of the basic competency levels of the existing workforce.

Finally, it is worth pointing out that measures of undereducation, for which there exists a somewhat more extensive literature (see McGuinness et al., 2018 for a review), is generally considered to represent an objective proxy measure of skill gaps. Undereducation describes a situation where a worker possesses a level of education that is lower than the level of education required for their job, therefore a deficit in human capital accumulation. However, such measure does not account for the fact that workers may compensate for lower levels of education with higher (unobserved) workplace skills acquired through labour market experience. Therefore, it is entirely possible that an employee can simultaneously be undereducated and well matched to their job in terms of skill requirements. The general finding that undereducation is not associated with wage impacts (McGuinness, et al., 2018), which will reflect productivity, suggests that this particular form of mismatch is not particularly damaging to firm-level performance.

3. Data and Methods

The data used in this study comes primarily 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.[2]

In terms of our methodological approach, we initially compare measures of both skill gaps and under-education across the 2014 and 2021 waves of the ESJS. In wave 2021, few questions asked to employees were changed, and we demonstrate the implications of making relatively minor changes to the questions used to measure skill gaps. 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. 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

[2] 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.

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 somewhat smaller sample size (over 30,000 observations).

After an initial examination of the descriptive statistics, the paper sets out to address the following questions (1) *what are the drivers of general skill gaps and are how are these correlated with skill gaps in particular domains (numeracy, social and technical)* and (2) *are there any wage consequences arising from skill gaps, relative to a base case of adequately skilled workers, as the presence of a wage penalty would support the view that skill gaps are damaging from a productivity perspective*. The multivariate analysis for question one 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.[3] 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.

With respect to wage impacts, 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:

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

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

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

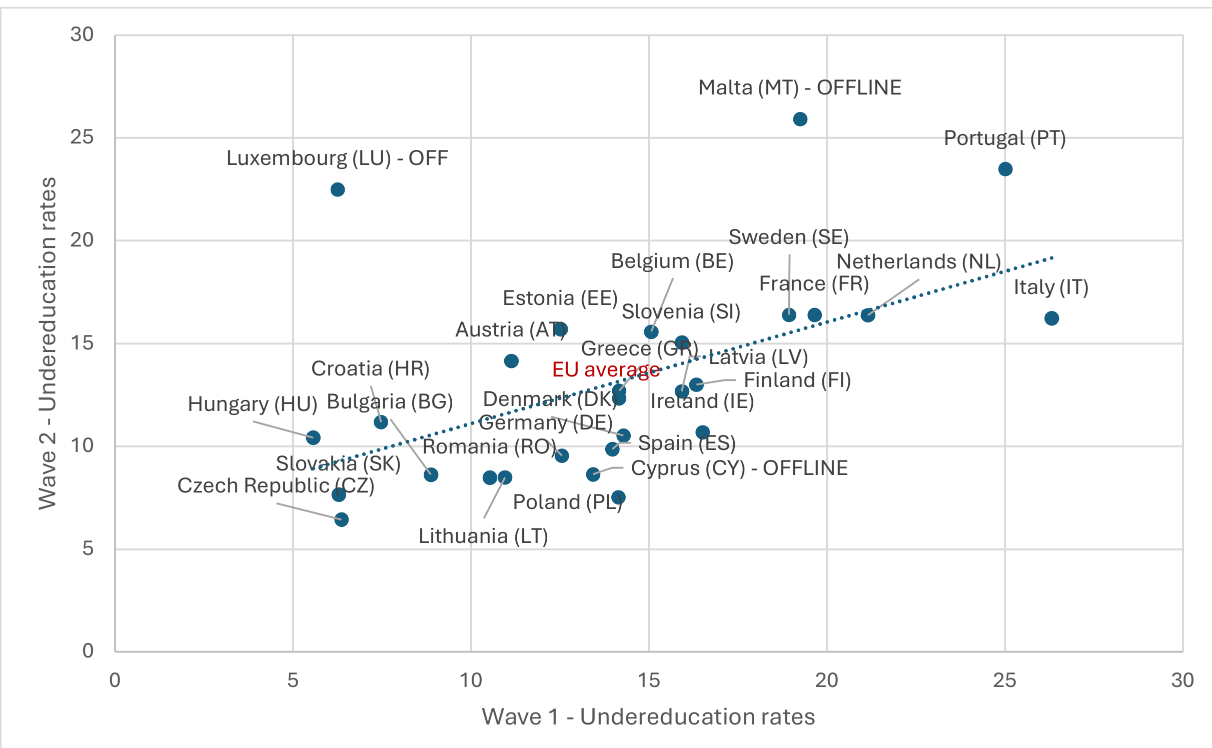
are country level fixed effects. We again adopt a forward stepwise approach, sequentially adding our measures of underskilling and skill gaps.

4. Results

4.1 Descriptive statistics

When measurement approaches to skill mismatch remain consistent, we find that rates are generally stable over time. For instance, if we identify undereducated workers in both waves of the ESJS if their actual level of schooling lies below their jobs' educational requirement, the share of EU 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. In Figure 1, where 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 1 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 1: Undereducation by Country- wave 1 against wave 2



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

However, there was some change in the measurement of skill gaps and overskilling over both waves of the ESJS and, we argue, this has major implications for the interpretation of the data with respect to what is actually being measured. The question administered in the first wave was "*How would you best describe your skills in relation to what is required in your job"* and the response capturing a skill deficiency was *"Some of my skills are lower than what is required".* It is indisputable that workers falling into the skill deficiency category do no possess all the skills necessary to meet basic skill requirements and, as such, we can define such workers as experiencing a basic skills gap. According to the data, across EU countries, just over 6 per cent of employees had a basic skills gap in 2014 (see Table 1). Conversely. Almost 40 per cent of employees had skills higher than those required for their job, i.e., were overskilled in 2014. In the 2021 data, the question that most adequately captures the extent of potential skill gaps is *"To what extent do you need to further develop your overall level of knowledge and skills to do your main job even better"* and the distribution of responses (which are structured as "great extent", "moderate extent", "small extent", "not at all") are given in Table 2. Taking the "to a great extent" response as classifying a general skill gap, we find that the incidence of skill gaps in 2021 was 16.2 per cent, some 10 percentage points above the estimate based on the 2014 data. It is implausible, particularly given the findings on undereducation rates across both waves, that this reflects a genuine increase in skill gaps over time, and it merely reflects the change in measurement approach. There is a clear contrast between the response statements across the two surveys, i.e. *"some of my skills are lower that what is required in my main job"* and *"I need to develop my overall level of knowledge and skills to a large extent in order to do my job event better".* While, as stated, the 2014 measure reflects a basic skill gap relative to current job requirements, the second definition will certainly capture workers who fail to meet the basic requirements of their jobs i.e. workers who do not meet the basic skill requirements of their job, but also those with moderate skill gaps, i.e., workers who meet basic skill requirements of their job but could improve their efficiency levels with further upskilling. Thus, the movement from asking respondents about the skill required to *"do their main jobs"* to the skills required *"to do their main job even better"* completely changes the context of what is being measured. The change in the measurement approach completely alters the estimated incidence of skill gaps and emphasises the need for a consistent approach to the subjective measurement of skill gaps. Therefore, our analysis based on the 2021 measurement approach should be interpreted as a study of ***essential and non-essential skill gaps***, whereby a non-essential skill gap reflects upskilling not related to the basic competency requirements of the job. Such skill gaps will also be a concern from a policy perspective as they reflect workers operating below their productive potential. What is noticeable from the results is that just 11 per cent of employees stated that they did not need to increase their skills at all in order to do their job better, suggesting that rates of overskilling in the labour market are relatively low.

Table 1: Incidence of Overskilling, Underskilling and Matched Employment EU-28 (2014)

How would you best describe your skills in relation to what is required in your job?	%
My skills are higher than required (‘overskilling’)	38.90
My skills are matched to what is required	55.05
Some of my skills are lower than what is required (‘underskilling/skill gaps’)	6.05
Total	100

Source: European Skills and Jobs Survey 2014 (authors’ elaboration). Weights have been applied.

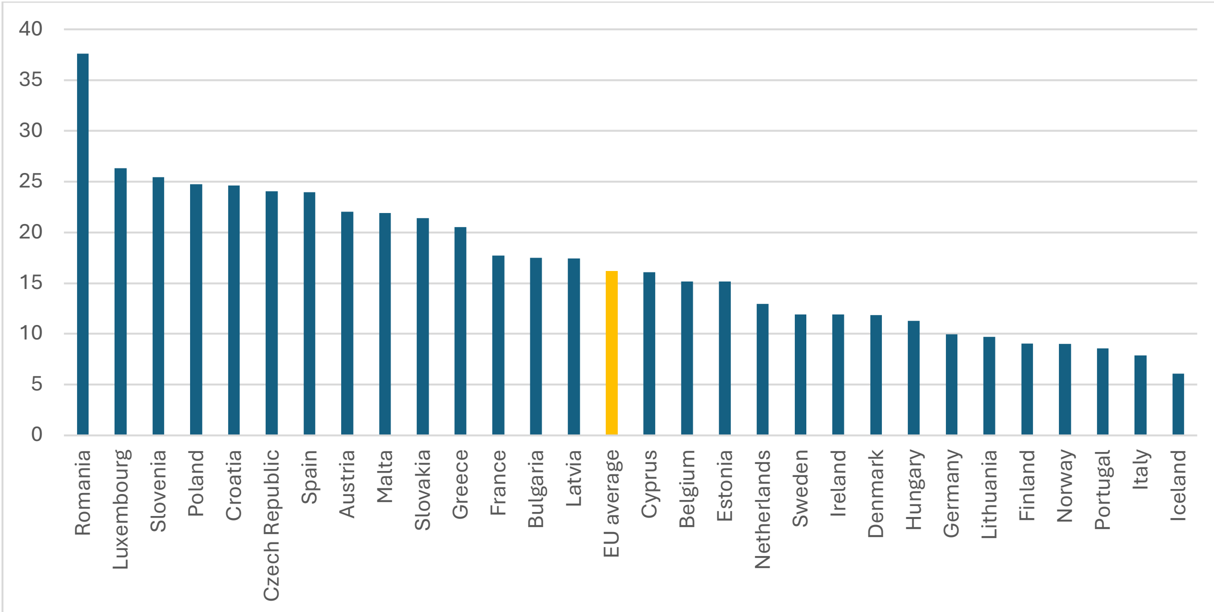
Table 2: Incidence of Skill Gaps – EU27 + Norway, Iceland

To what extent do you need to further develop your overall level of knowledge and skills to do your main job even better	N	%
Great extent	8,771	16.24
Moderate extent	21,983	47.58
Small extent	10,622	24.97
Not at all	4,710	11.21
Total	46,086	100

Source: 2021 European Skills and Jobs Survey (authors’ calculations). Weights have been applied.

In Figure 2 we show the incidence of essential and non-essential skill gaps by country. There is substantial variation in the incidence of these skill gaps across countries. Rates vary from 37 per cent in Romania to just over 5 per cent in Iceland, and it is noticeable that that Eastern European countries tend to report the highest incidences of skill gaps, while peripheral and central European countries tend to be more concentrated among countries reporting low rates of skill gaps.

Figure 2: Perceived Skill Gaps by Country, 2021



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

As outlined, the structure of the skill gaps 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 such 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. Less than 10 per cent of those reporting skill gaps are educated to lower secondary level or below. As most 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. It is clearly not the case that the observed skill gaps are being driven by workers in low value-added jobs lacking basic 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. Again, the questions were posed regarding the need to improve specific skills in order to do their job even better, thus these metrics will also incorporate both essential and non-essential skill gaps in specific domains. 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. Less than 2 per cent of workers reporting these skill gaps are educated to primary level only. 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
	30,695	

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

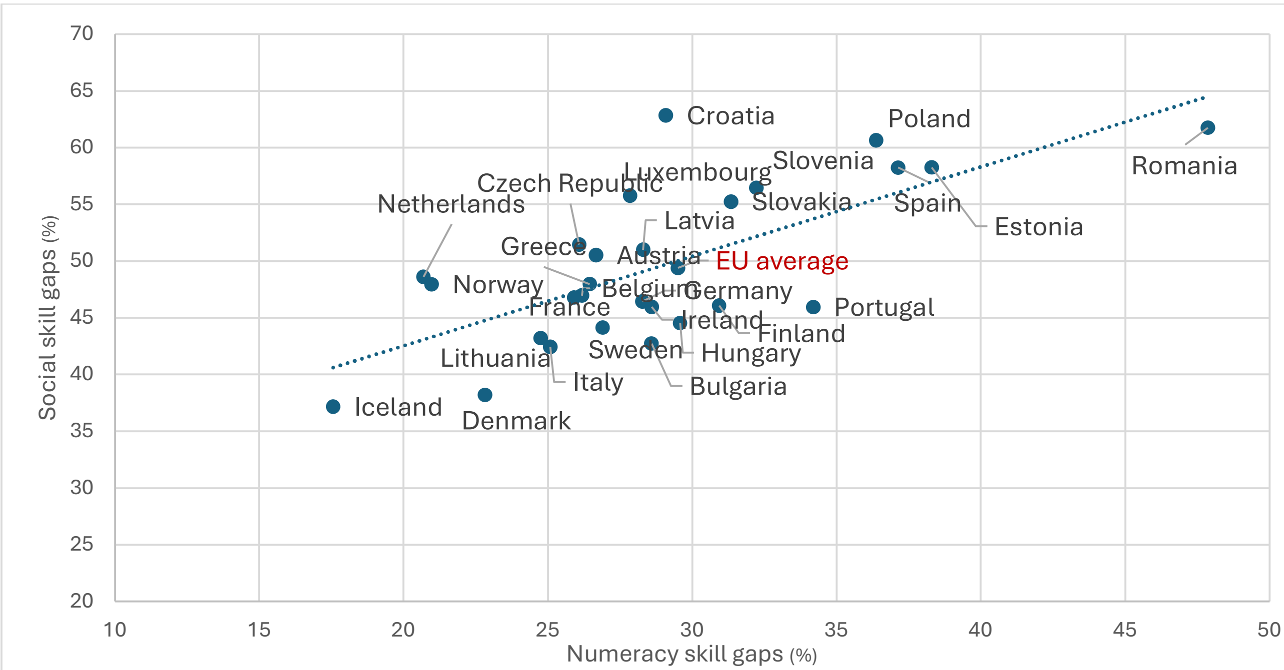
Table 5: Numeracy, social or technical skill gaps by education level

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).

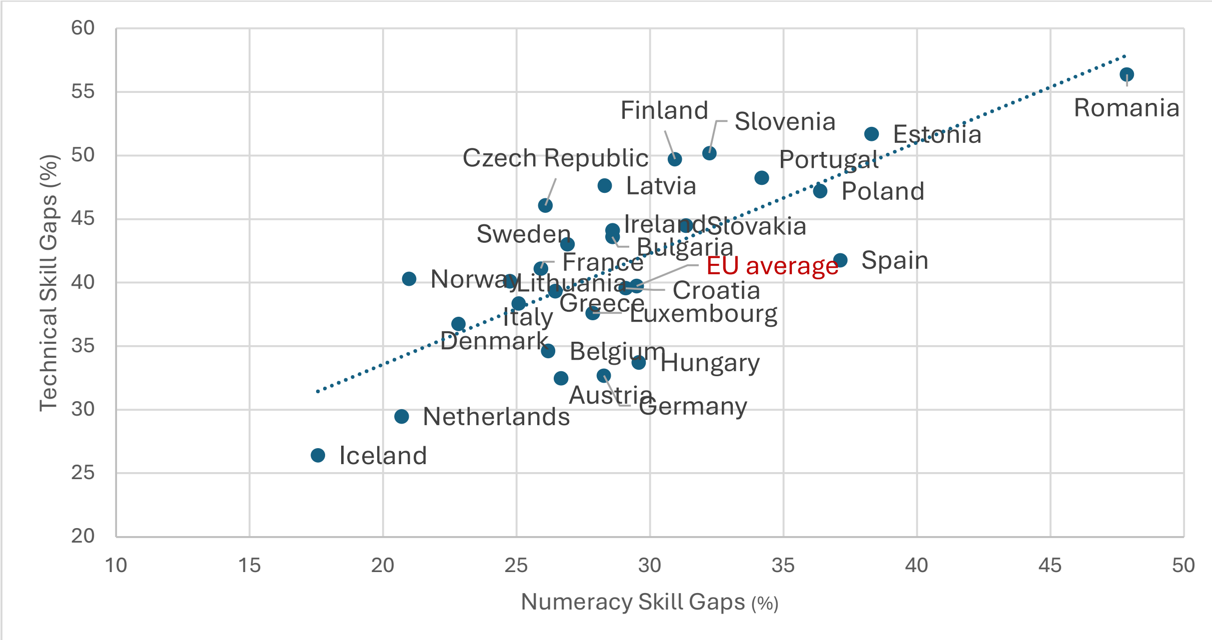
We next investigate the relationship between different measures of skill gaps competency related. In Figure 3, we plot rates of numeracy skill gaps against social skill gaps at country level; in Figure 4 we plot rates of numeracy skill gaps against technical skill gaps at country level; in Figure 5 we 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 relatively high (low) skill gap in one competency area are likely to report a high (low) skill gap in other areas.

Figure 3: Numeracy skill gaps against social skill gaps by Country



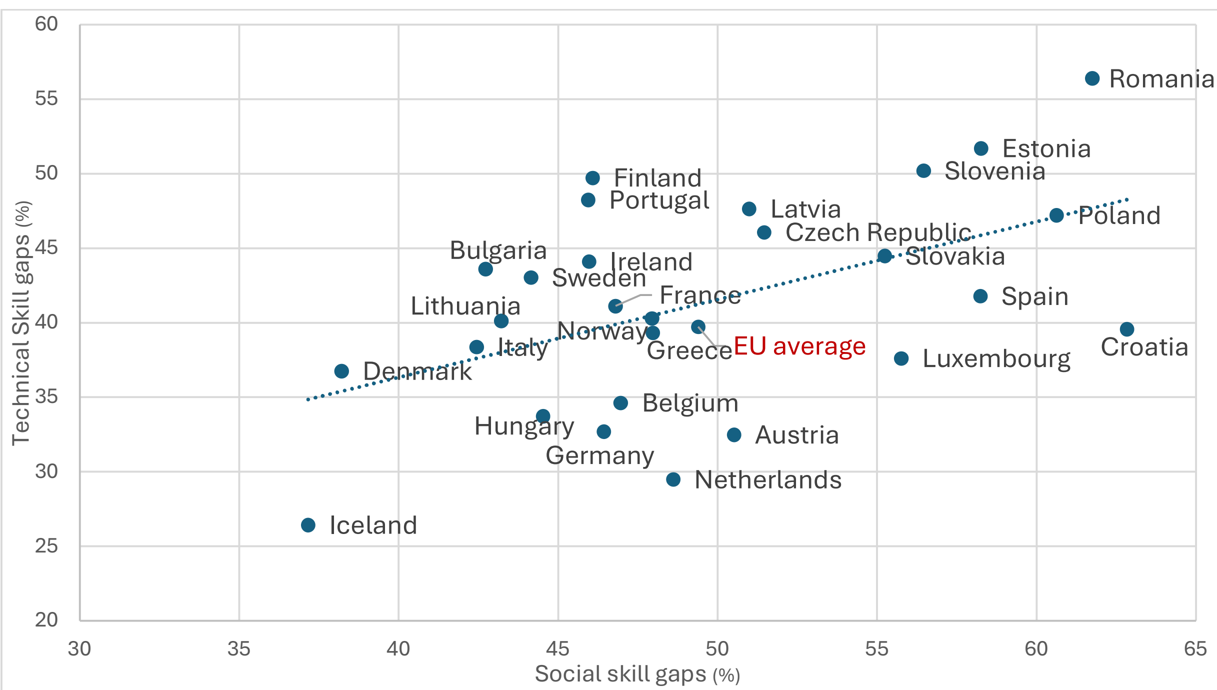
Source: 2021 European Skills and Jobs Survey (authors' calculations).

Figure 4: Numeracy skill gaps against technical skill gaps by Country



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

Figure 5: Social skill gaps against technical skill gaps by Country



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

4.2 Multivariate Estimates

4.2.1 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. In Table 6, we show the results of our probit models for general skill gaps.

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 with 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 that are less likely to require upskilling. 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 after controlling for other characteristics. 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.

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
Pseudo R2	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 4.1, 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)
Job Complexity	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

Pseudo R2	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.*

4.2.2 Skill Gaps and 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. In this case the reference category will be workers with similar levels of education who do not have skill gaps. We estimate an OLS model where log hourly earnings are our dependent variable (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. These covariates remain relatively stable in subsequent specifications when the skill gap controls are included, suggestion that collinearity bias is not an issue. 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 by extension 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.

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
Skill Gap - general		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.

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 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 that shows the incidence of skill gaps falling close to zero at the lowest level of education. The evidence here certainly supports the view that skill gaps are not associated with low skills levels or relatively low paying employment. At upper/post-upper secondary level of education, we find also evidence of wage premium associated with gaps in numeracy and technical skills. There is no evidence of wage premia 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)
Skill Gap - general	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.*

The wage premium could potentially be explained by the employees with higher educational attainment work in more complex jobs, that likely require them to often update their skills. However, without controls for job complexity in the wage model, these impacts are being proxied by the skill gap controls. To investigate this, similar to our earlier models, 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 general skill gaps or skill gaps in numeracy 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. This is very different from the usual view of skill gaps as being concentrated among poorly educated workers in low value-added employment lacking essential skills. 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 challenging jobs in a more optimal way.

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.

4.3 Robustness checks

We must be mindful that our OLS estimates for hourly earnings could be distorted by sample selection bias, particularly, if our skill gaps measures are correlated with other right hand side controls which, are themselves, related to the outcome variable. To address this issue and as a robustness check, we estimate the relationship between hourly earnings and skill gaps using Propensity Score Matching (PSM) methods, which is a non-parametric approach that is robust to the influences of selection bias.

The PSM approach is a two-step procedure. In step one, each individual's probability (or propensity score) of having general or specific skill gap ('*treatment'*) is assessed conditional on a set of explanatory variables. 'Treatment' group individuals (i.e., those reporting skill gaps) and 'control' group individuals (i.e., those not experiencing skill gaps) are then matched on their propensity scores, which is equivalent to matching the control and treatment members on individual observable characteristics. In the second step, the average outcome measures (earnings) of the treatment and control groups are compared. We carry out this operation separately for general skill gaps and skill gaps in each of the three specific domains.

The propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics,

$$P(X) = \Pr(D = 1|X) = E(D|X) \quad (3)$$

Where D indicates exposure to the treatment and X is a vector of determining characteristics. In our case, reporting general skill gaps or specific competency areas skills gaps are the treatment variables. The covariates are the same as reported in Equation (2), with the inclusion of the job complexity index.

We show the results for the estimated coefficients from the PSM model in Table 11, along with our OLS results and covariates balancing diagnostics tests. PSM estimates are not significant, therefore general or specific skills gaps do not impact employees' wages. Our results confirm that there is no evidence that skill gaps (as measured in the 2021 ESJS) are associated with negative productivity impacts (proxied by wages). The post-estimation tests (Rubin's and Rubin's R) are within the recommended thresholds, therefore signalling that covariates are well balanced among treated and control group.

Table 11: Determinants of Earnings with job complexity measure (OLS estimates, PSM estimates and post-estimation tests for balancing covariates).

	OLS Wage estimate	PSM Wage estimate	Rubin's B	Rubin's R
General skill gaps	0.03	-0.006	19.6	1.22
	(0.027)	(0.04)		
Numeracy skill gaps	0.00	-0.047	19.1	1.13
	(0.018)	(0.04)		
Social skill gaps	0.01	0.001	25.5	0.95
	(0.011)	(0.04)		
Technical skill gaps	0.01	0.05	21.4	1.09
	(0.010)	(0.04)		

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

Note: for well-balanced covariates B<25% and R in [0.5 and 2].

5. Conclusion

In this paper, 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 predominantly use data from the 2021 European Skills and Jobs Survey, administered by CEDEFOP. Comparing the definitional changes in the measure of skill gaps that have occurred 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 per cent 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 non-essential in nature. This is also the case for competency specific skill gaps measured in the realms of literacy, numeracy and social skills. We conclude that the majority of workers reporting general skill gaps, as well as skill gaps in numeracy, social skills and technical skills possess the competencies levels to meet their basic job requirements but perceive a need for upskilling in order to perform their current job in a more optimal way.

In the 2021 wave of the ESJS, we find relatively high rates of general essential and non-essential 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. The measures of competency specific skill gaps were found to be highly correlated with each other at member state level.

Within probit models estimated at worker level, general skill gaps 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 having a skill gap either generally or in a specific domain. Finally. we assessed the extent to which general and specific skill gaps are associated with wage penalties, as an indication of the productivity implications of this form of skill mismatch. Interestingly, when estimating a basic wage model, both general and domain specific skill gaps were found to be associated with wage premia, with these premia restricted to employees with tertiary or upper secondary/post-upper secondary level of education. However, these premia disappeared when job complexity was introduced in the model, suggesting that the previous wage premia were the result of a failure to control for the fact that skill gaps occur predominantly in more complex jobs and that job complexity is associated with higher productivity and high wages. Therefore, we 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. This is very different from the usual view of skill gaps as being concentrated among poorly educated workers in low value-added employment lacking essential skills. 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 challenging jobs in a more optimal way.

References

Forth, J., and Mason, G. (2006). “Do ICT skill shortages hamper firms’ performance?”. National Institute of Economic and Social Research.

Jackson, D., and Chapman, E. (2012). “Non-technical skill gaps in Australian business graduates”. *Education + Training*, 54(2/3), 95–113.

Malik, A. R., Manroop, L., and Patel, P. C. (2019). “An empirical examination of the relationship between skills shortage and firm performance: The role of high-performance work systems”, *Journal of Management & Organization*, 25(5), 695–710.

McGuinness, S., and Ortiz, L. (2016). “Skill gaps in the workplace: measurement, determinants and impacts”. *Industrial relations journal*, 47(3), 253–278.

McGuinness, S., Pouliakas, K. and Redmond, P. (2018). “Skills mismatch: concepts, measurement and policy approaches” Journal of Economic Surveys, Vol. 32(4). 985-1015.

McGuinness, S., Redmond, P., Staffa, E., Devlin, A., and Whelan, A. (2025). "15: Skills mismatch: what do we already know and what do we need to know?". In *Handbook of Education and Work*. Cheltenham, UK: Edward Elgar Publishing. Retrieved Jan 20, 2025, from https://doi.org/10.4337/9781035309917.00024.

McGuinness, S., Staffa, E. and Redmond, P. (2024). “Is there a skills problem in Europe?”, *Re-thinking Europe’s Skill Needs: Reflections following the European Year of Skills*, Quaderno 67 Fondazione Giacomo Brodolini

Rikala, P., Braun, G., Järvinen, M., Stahre, J. and Hämäläinen, R. (2024). "Understanding and measuring skill gaps in Industry 4.0 — A review," *Technological Forecasting and Social Change*, Elsevier, vol. 201(C).

Sanchez-Sanchez, N. and McGuiness, S. (2015).” Decomposing the impacts of overeducation and overskilling on earnings and job satisfaction: An analysis using REFLEX data”. *Education Economics* 23: 419–432

Zarifa, D., Seward, B., and Milian, R. P. (2019). “Location, location, location: Examining the rural-urban skills gap in Canada”. *Journal of Rural Studies*, 72, 252–263.