TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

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ACRONYMS

Acronym	Explanation
ESJS	European Skills and Jobs Survey
ESCO	European Skills, Competences, Qualifications and Occupations classification system
ISCO	International Standard Classification of Occupations
ISCED1997	International Standard Classification of Education (1997 version)
ISCED2011	International Standard Classification of Education (2011 version)
JS	Job Satisfaction
VET	Vocational Education and Training
ICT	Information and Communication Technology
CEDEFOP	European Centre for the Development of Vocational Training

EXECUTIVE SUMMARY

This report examines critical aspects of educational mismatch, vocational education, and dynamic skill changes in the European labour market, offering valuable insights for policymakers and stakeholders to address skills deficits, improve workforce alignment, and foster adaptability to changing job demands.

The purpose of the report is to assess the incidence and evolution of educational mismatch in Europe before and after the COVID-19 pandemic, evaluate the impact of vocational education and training (VET) on mismatch, investigate determinants of VET choice, and examine the associated labour market outcomes. It also analyses dynamic skill changes within occupations across Europe using online job vacancy data, linking these changes to measures of skill deficits. The report builds on previous deliverables in the TRAILS project, applying theoretical and empirical analyses of skills mismatch to broader questions of upskilling, training, and labour market inclusiveness.

Educational mismatch, both overeducation and undereducation, has declined significantly over the past decade. Using data from the European Skills and Jobs Survey (ESJS), the analysis shows that between 2014 and 2021, overeducation fell from 28% to 21%, while undereducation dropped from 15% to 10%. Increased educational attainment explains about one-third of the reduction in undereducation. However, most of the decline in overeducation remains unexplained, indicating broader structural changes in the labour market, likely driven by the COVID-19 pandemic. To explore this further, we use a novel question in the ESJS data that captures whether an employee experienced an increase in remote working due to the pandemic. We find that remote working has played a significant role in changing educational mismatch. Employees who gained remote working flexibility during the pandemic were 10 percentage points less likely to be overeducated than those without such flexibility. This suggests that remote work may enable workers to better align their skills and qualifications with job demands, providing new opportunities for reducing mismatch.

Vocational education and training in Europe has been examined in terms of its incidence, wage effects, and job satisfaction outcomes. VET participation varies widely across countries, ranging from 80% in Finland and Czechia to 30–40% in Belgium and Ireland. The analysis reveals that, for most countries, vocational education does not have a statistically significant impact on wages.

However, significant wage premiums are observed in six countries including Spain, Greece, Lativa, Austria, Estonia and France, while a wage penalty is found in Slovenia. Regardless of wage outcomes, employees with vocational education consistently report higher job satisfaction compared to those with general education. These findings underscore the importance of tailoring VET strategies to specific labour market contexts in order to maximise their benefits.

Dynamic skill change in the labour market is analysed using online job vacancy data from 2019 to 2023, allowing the development of a novel metric for measuring skill evolution within occupations. This measure, which compares changes in skill demands over time, provides occupation- and country-specific insights into the evolving labour market. The analysis demonstrates that workers in occupations with rapidly changing skill profiles are more likely to experience underskilling, which occurs when employees lack the necessary skills to meet job demands. On-the-job training emerges as a critical factor in mitigating these deficits, showing that continuous learning can bridge skill gaps in dynamic occupations. The economic impacts of underskilling are significant, negatively affecting firm productivity, profits, and employee outcomes such as job satisfaction and future employability.

This report highlights the interplay between educational mismatch, vocational training, and dynamic skill demands in the evolving European labour market. The findings emphasise the role of remote working in reducing overeducation, the need for targeted VET policies to improve labour market outcomes, and the importance of on-the-job training in addressing skill deficits caused by rapid technological and market changes. These insights provide a foundation for future analyses and inform policies aimed at building a more skilled and adaptable European workforce.

1. INTRODUCTION

Skills mismatch, the misalignment between workers' qualifications and the demands of their jobs, has long been a topic of significant concern for policymakers and researchers alike. In today's rapidly evolving labour market, understanding the dynamics of educational mismatch, the role of vocational education, and the impact of changing skill demands is more critical than ever. Against the backdrop of structural labour market changes accelerated by the COVID-19 pandemic, this report seeks to shed light on the extent and implications of these phenomena across Europe.

1.1 PURPOSE OF THE DELIVERABLE

The purpose of this report is to (i) assess the incidence and changes to educational mismatch in Europe pre- and post-COVID-19 pandemic, (ii) examine the impact of VET on mismatch, and study the determinants of VET choice as well as the labour market outcomes associated with vocational education, (iii) use job vacancy data to examine dynamic skill changes within occupations across Europe, and relate this to measures of skills deficits.

1.2 RELATION WITH OTHER DELIVERABLES AND TASKS

This paper draws from other deliverables in the project, particularly from WP1, which reviews existing theoretical work and empirical applications relating to skills mismatch and shortages in Europe (D1.1), and highlights initiatives that use digital applications to promote upskilling and awareness for European citizens' active engagement, as well as related EU funded projects (D1.2). The scope of this deliverable is also related to deliverable (D.2.1) which conducts analyses of core secondary datasets. Early findings from this deliverable were used in D1.3 to report on specifications about TRAILS's technological advances. The findings of this paper will also be used as a basis for analyses in subsequent deliverables in the same work package (D3.2: The interplay between technological change, training and upskilling in Europe; D3.3: Regional and sectoral analysis of training and inclusiveness; D3.4: Behavioural, social, and cultural change for successful development of skills matched to needs).

1.3 STRUCTURE OF THE DOCUMENT

The document is divided into three chapters. The first chapter, entitled 'Educational Mismatch in Europe: Incidence, Determinants and the Impact of an Increase in Remote Working', examines trends in educational mismatch in Europe over time, and the potential effect that the COVID-19 pandemic had on mismatch. The second chapter, 'Vocational Education in Europe: Incidence, Wage Effects and Job Satisfaction', explores vocational education in Europe. We study its incidence and determinants and evaluate its effects on labour market outcomes. In Chapter 3, 'Dynamic Skill Change and Skill Deficits in the Labour Market: An Analysis using Online Job Vacancy Data' we devise a measure of occupation specific dynamic skill change using a large dataset on online job vacancies and link this measure to indicators of skill deficits among employees.

Within each of these sections, there are subsections that summarise existing literature on the study topic, describe the data used in the analyses, outline the method and design of analyses for the research, present the results of the analyses and finally discuss findings of our research, and link them to both previous research and policy.

2. CHAPTER 1: Educational Mismatch in Europe: Incidence, Determinants and the Impact of an Increase in Remote Working

2.1 Introduction

Educational mismatch refers to a situation where there is a discrepancy between the education level possessed by an employee and the education level that is required to do their job. This can take the form of overeducation, where the employee's educational attainment exceeds that which is required to do their job, or undereducation, where the employee's educational attainment is below that which is required to do their job. While both types of mismatch have been shown to be prevalent in the labour market, the incidence of overeducation tends to be higher. In a survey of the international literature, McGuinness et al. (2018) finds that approximately one quarter of employees are overeducated, while the rate of undereducation tends to be between 10 and 20 percent.

Educational mismatch can have consequences for employee satisfaction, job turnover and wages, as well as firm performance. Therefore, understanding the drivers of mismatch and how it is changing over time is important. In this study, we use two waves of the European Skills and Jobs Survey (ESJS) to analyse how educational mismatch—both overeducation and undereducation—changed between 2014 and 2021. We identify instances of mismatch by comparing an employee's highest educational attainment to the education level that they report is required to do their job. Our analysis shows that both forms of educational mismatch have declined over time. From 2014 to 2021, the incidence of overeducation in the EU fell from 28 percent to 21 percent, and the rate of undereducation fell from 15 percent to 10 percent. We attempt to explain the declines over time by carrying out an Oaxaca decomposition. The results of the decomposition reveal that approximately one-third of the reduction in undereducation rates across the EU can be attributed to increasing educational attainment among employees. However, most of the decline in overeducation is unexplained, suggesting that broader structural changes in the labour market—likely influenced by the COVID-19 pandemic—may be important.

One area of the labour market that has been significantly impacted by the COVID-19 pandemic is remote working. This is also an area that has the potential to improve educational mismatch by offering employees greater flexibility in their job search. We examine this by exploiting a unique question in the second wave of the ESJS, which asks employees if they gained greater remote-working flexibility after the pandemic. Using a matching estimator, we find that employees who experienced more remote-working opportunities are 10 percentage points less likely to be overeducated than those whose remote working capabilities remained unchanged. This estimate aligns closely with the observed reduction in overeducation, which declined by 8 percentage points between the two periods. Our findings provide the first direct evidence that the expansion of remote working in the EU, driven by the COVID-19 pandemic, may have contributed to the decrease in overeducation by enabling employees to better align their skills and qualifications with job demands.

2.2 Related Literature

Much of the existing literature on educational mismatch focuses on employee outcomes. Overeducated employees have been found to experience a wage penalty when compared to employees with similar education in matched employment (see, e.g., Cultrera et al., 2023; Bender and Roche, 2018; Sánchez-Sánchez and McGuinness, 2015; McGuinness and Sloane, 2011). Overeducation has also been linked to lower job satisfaction, an increased likelihood of changing jobs, and long-term negative consequences for the employee's future career trajectory (Fleming and Kler, 2008; Sánchez- Sánchez and McGuinness, 2015; Mateos-Romero and Salinas-Jiminéz, 2018; Bender and Heywood, 2009; Scherer, 2004). Other work has looked at the impact on employers. Kampelmann and Rycx (2012) and Mahy et al. (2015) show that an undereducated workforce has a negative impact on a firm's productivity, especially among firms facing economic uncertainty and those with young employees. On the other hand, an overeducated workforce increases firm productivity, particularly among firms operating in tech/knowledge-intensive industries. Kampelmann et al. (2020) find similar effects when looking at firm profits, with bottom lines of firms being positively (negatively) associated with overeducation (undereducation).

A related strand of research has attempted to understand the determinants of educational mismatch. This literature is important for our analysis, as it informs the type of explanatory variables that we use in our empirical strategy to help explain changes in educational mismatch over time. Several factors have emerged in the literature as potentially important determinants of educational mismatch. Firstly, the level of educational attainment within a country is likely to be important. To be overeducated, a person must have a sufficiently high level of education, and vice versa. Therefore, overeducation is likely to be more prevalent among highly educated individuals, while those with lower qualifications are more likely to experience undereducation. In a cross-country study of EU countries, Davia et al. (2017) found that a ten-percentage point increase in tertiary enrolment was associated with a seven-percentage point increase in the incidence of overeducation. However, in a study of 30 European countries from 2000 to 2016, Delaney et al. (2020) found that despite significant increases in the percentage of tertiary graduates across countries, the rate of overeducation actually fell, suggesting that labour markets have been able to absorb increases in university graduate supply.

Field of study has emerged as an important predictor of overeducation. Graduates from fields such as social sciences, arts, and humanities are typically at a higher risk of experiencing overeducation, while those from education, health, and science fields are less likely to be overeducated (Boto-García and Escalonilla, 2022; Aina & Pastore, 2020; Meroni & Vera-Toscano, 2017; Barone & Ortiz, 2011). Despite the evidence on the link between overeducation and field of study, there is a lack of evidence on the relationship between undereducation and field of study.

Others have examined the role of education type—vocational versus general—in influencing overeducation. This relationship appears complex. Vocational education tends to lower the risk of overeducation in a person's first job compared to general education. However, those with general education often use overeducation as a stepping-stone to better-matched roles over time as they are promoted to more senior positions (see, e.g., Verhaest and Schatteman, 2010; Verhaest et al., 2017). Specific or vocational education may act as a direct "entry ticket" to a well-matched job, while general education provides a broader skill set, offering greater career mobility and the potential for advancement through on-the-job learning (Verhaest and Van der Velden, 2013).

Other work has examined the relationship between overeducation and the characteristics of the employee or their job. With respect to gender, the results are mixed. Sloane et al. (1999) find that being a man increases a person’s likelihood of being overeducated. However, Green and McIntosh (2007) and Frenette (2004) find no statistically significant relationship between gender and overeducation. Rossen et al. (2019) also found no strong gender-based differences across 21 EU countries, except in the "Services" field, where women were less likely to be overeducated than men. Longer job tenure and additional years of experience have been found to be associated with a lower risk of overeducation (Tarvid, 2015; Boll et al., 2016; Sloane et al., 1999). This may relate to career mobility; the longer a person stays in a job, the higher the likelihood of advancement. Sloane et al. (1999) find that part-time work reduces the probability of being undereducated and raises the probability of being overeducated. Ortiz (2010) shows that overeducation is more likely among permanent workers than among those on temporary contracts in Spain. This is explained by the fact that people value permanent contracts, especially in settings where they are relatively rare, as they provide security. Employees invest in human capital to acquire a permanent job, often at the expense of a good match, which leads to a positive association between overeducation and holding a permanent contract.

The likelihood of overeducation also differs by occupation and sector. Overeducated workers tend to be overrepresented in jobs that require lower education levels (Green & McIntosh, 2007; Büchel & Mertens, 2004). This has important implications, as it underscores the need to account for occupational shifts when analysing educational mismatch trends. For example, a shift in job composition toward more highly skilled positions could help explain declines in overeducation, as more qualified workers secure matched employment.

Despite substantial research on the impact and determinants of educational mismatch, questions remain about the role of broad institutional or policy factors in shaping mismatch rates. The impact of structural changes in the labour market, particularly after the COVID-19 pandemic, is still not fully understood. Greater remote working flexibility, for instance, has been suggested as a factor that may help improve educational matching (Office for National Statistics, 2021), but empirical evidence remains scarce. One relevant study by Santiago-Vela and Mergener (2022) using 2018 German data shows that remote work reduces the risk of overeducation and may help narrow the gender gap in educational mismatch, in which women often experience a greater likelihood of overeducation.

Pizzinelli and Shibata (2023) examine whether the COVID-19 pandemic led to labour market mismatch in the US and UK due to certain sectors being more adversely affected than others. Labour market mismatch, in this instance, refers to the mismatch between job seekers and job vacancies. Specifically, the COVID-19 pandemic hit the hospitality and retail sectors hardest. If jobless people typically seek work in retail and hospitality, while most vacancies occur in well-performing industries such as ICT, this could create a labour market mismatch that could impact employment dynamics. However, Pizzinelli and Shibata (2023) find a very limited role for this type of mismatch. While there was a rise in labour market mismatch at the onset of the pandemic, this quickly returned to previous levels with little impact on persistent unemployment. In related work, Ciminelli et al. (2024) examine whether the COVID-19 led to mismatches between labour demand and labour supply across 19 countries. Similar to Pizzinelli and Shibata (2023), they find that occupational mismatch initially increased, but quickly reverted to pre-pandemic levels.

Note that the labour market mismatch measure employed by Pizzinelli and Shibata (2023) and Ciminelli et al. (2024) differs from ours. While we focus on the education level of employees relative to the required education level for their jobs, the two aforementioned papers focus on a mismatch between labour supply (i.e., jobseekers) and labour demand (i.e., advertised job vacancies). Therefore, one important dimension along which these two approaches may differ relates to employment. An individual could be unemployed due to labour market mismatches between labour demand and supply. However, educational mismatch focuses only on employees in work. Therefore, it is possible that a reduction in overeducation could, at least to some extent, be due to overeducated workers moving into unemployment (Vecchi et al., 2021). However, it is worth re-stating that both Pizzinelli and Shibata (2023) and Ciminelli et al. (2024) do not find strong evidence for mismatch-induced unemployment. On the contrary, most labour markets in our sample period are performing strongly with low unemployment rates and high employment.

2.3 Data and descriptive statistics

Our analysis utilises data from two waves of the European Skills and Jobs Survey (ESJS), a periodic EU-wide survey designed to collect information on skill requirements, skill mismatches, and both initial and continuing learning among adult workers across EU labour markets. The survey is conducted and compiled by Cedefop (the European Centre for the Development of Vocational Training). It draws a representative sample of adult workers from EU countries, gathering data on sociodemographic characteristics, job characteristics, job-skill requirements, skill mismatches, participation in vocational education and training (VET), and labour market outcomes. The first wave of the ESJS was conducted in 2014, followed by the second wave in 2021.

In our analysis, we employ a self-assessment approach to determine educational mismatch. This method involves comparing a person's realised level of educational attainment to their perceived educational requirement to do their job in order to determine whether they are matched (have a level of education equal to that required), overeducated (have a level of education above that required) or undereducated (have a level of education below that required). Specifically, to measure over- and undereducation, we use two questions from the ESJS. The first asks, "What is the highest level of education you have completed?" The second asks, "What level of education is required to do your job?" Responses are coded using the ISCED1997[1] classification system. Overeducation occurs when an individual's education level exceeds the job requirement, while undereducation occurs when it falls short. A match is recorded when the individual's education level aligns with job requirements.

The self-assessment, or subjective approach, to measuring educational mismatch is only possible in survey data that contains the necessary questions. Other approaches exist for categorising educational mismatch. Each approach has advantages and disadvantages, and the type of approach used is often governed by the type of data available to researchers. Another commonly used method is the "statistical approach". This uses either the mean or modal level of education of all persons in employment within an occupation to determine the average educational requirements for that job, and then compares this to a person's realised level of educational attainment (for a person in that particular occupation). Workers with an education level above (below) their occupation average level are seen as being overeducated (undereducated), otherwise they are matched. The advantage of using this method is that it can be widely applied, including retrospectively to historical data. This is

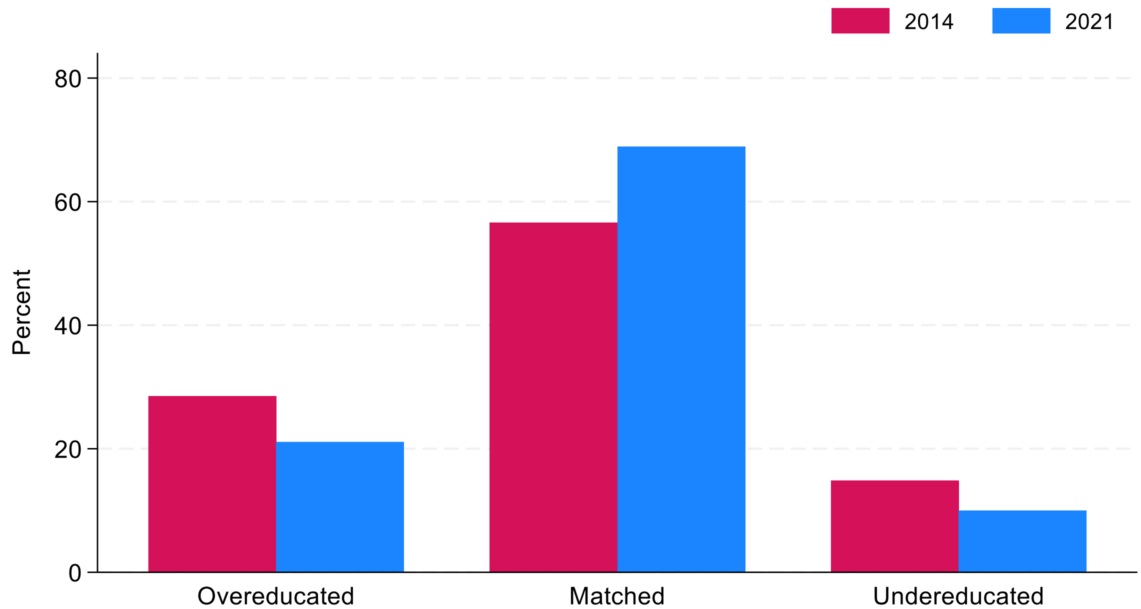
[1] ISCED 1997 refers to the International Standard Classification of Education, developed by UNESCO to provide a framework for comparing education systems internationally. It classifies educational programmes by levels and fields of education, enabling consistent reporting and analysis across countries.

because virtually all labour force surveys capture a person's occupation and education level. However, there are also drawbacks associated with this method. The main drawback is that the application of an average job requirement for large groups of workers does not account for heterogeneity within occupations/occupational groups. Another limitation of the statistical approach is that occupational averages may be strongly influenced by longer tenured workers, as such workers often make up the majority of workers within occupations. As such, the occupation averages may reflect historical, rather than current, entry requirements. Compared to the statistical approach, an advantage of our method - the self-assessment approach - is that job requirements are determined on a case-by-case basis, and so every job is accounted for independently.

Others have used a "normative approach" to defining educational mismatch. With this method, educational requirements for occupations are evaluated by industry experts or job analysts and are then compared to workers' realised education levels. An advantage of this method is that it employs the expertise of industry or job experts to construct the measure. However, it faces the same drawback as the statistical approach in relation to not capturing within-job heterogeneity and can also be quite expensive and requires frequent updating as job requirements change over time.

Using our self-assessment-based measure of mismatch, Figure 1 shows how the incidence of educational mismatch has evolved over time across 25 EU countries (EU-27 excluding Cyprus and Malta). Between 2014 and 2021, the incidence of both overeducation and undereducation decreased significantly. Overeducation fell from 28% in 2014 to 21% in 2021, while undereducation fell from 15% to 10% over the same period.

Figure 1: Education mismatch over time (ESJS)



Source: European Skills and Jobs Survey. Authors' calculations.

While Figure 1 presents the average change in educational mismatch for all EU-25 countries, there is considerable variation at the individual country level in both the incidence of over- and undereducation and the changes over time. Table 1 details overeducation and undereducation rates for each country across both survey waves. The vast majority of countries experienced declines in both overeducation and undereducation. The largest decline, in percentage terms, in undereducation was experienced in Ireland (-55 percent) and the largest decline in overeducation was experienced in Croatia (-56 percent). Out of the 25 countries studied, only three experienced an increase in overeducation, and four saw a rise in undereducation. Italy recorded the highest increase in overeducation (+36 percent), while Luxembourg saw the largest increase in undereducation (+120 percent).

Table 1: Incidence of educational mismatch across EU countries over time

	Overeducation	Undereducation

COUNTRY	2014	2021	Diff		2014	2021	Diff
Austria	36.9	23.2	-13.7		11.3	11.8	0.5
Belgium	23.8	17.3	-6.5		14.9	8.9	-6
Bulgaria	26.3	21.9	-4.4		8.9	8.8	-0.1
Croatia	38.1	16.7	-21.4		7.5	9.4	1.9
Czechia	39.2	22.4	-16.8		6.4	5.1	-1.3
Denmark	24.4	24.6	0.2		14.4	8.4	-6
Estonia	36.6	25.0	-11.6		12.5	12.3	-0.2
Finland	22.0	14.1	-7.9		16.3	10.0	-6.3
France	38.2	19.6	-18.6		19.5	12.1	-7.4
Germany	27.6	26.2	-1.4		12.6	8.5	-4.1
Greece	25.0	22.2	-2.8		13.7	10.4	-3.3
Hungary	29.1	29.4	0.3		5.5	8.0	2.5
Ireland	34.0	21.5	-12.5		16.7	7.5	-9.2
Italy	19.3	26.3	7		26.5	14.9	-11.6
Latvia	27.0	19.9	-7.1		15.7	10.5	-5.2
Lithuania	33.7	25.2	-8.5		10.9	5.5	-5.4
Luxembourg	13.8	12.4	-1.4		6.3	13.9	7.6
Netherlands	14.4	11.2	-3.2		20.7	12.1	-8.6
Poland	27.4	18.3	-9.1		14.2	6.5	-7.7
Portugal	34.1	15.1	-19		24.9	20.1	-4.8
Romania	20.8	18.7	-2.1		10.5	7.6	-2.9
Slovakia	29.4	23.7	-5.7		6.4	5.0	-1.4
Slovenia	26.3	16.3	-10		15.2	11.2	-4
Spain	30.9	25.9	-5		14.0	8.4	-5.6
Sweden	25.3	18.1	-7.2		18.8	12.8	-6
Total	**28.4**	**21.1**	**-7.3**		**14.8**	**10.0**	**-4.8**

Source: European Skills and Jobs Survey. Authors' calculations.

In our analysis, we attempt to explain the determinants of, and changes in, rates of educational mismatch using a range of potentially important explanatory variables. While there are two waves of the ESJS, there were changes over time so that some variables that were in the first wave were either omitted or else changed in the second wave. As such, when constructing a list of explanatory variables, we are restricted to those variables that are measured consistently across both waves. These include a range of factors relating to the employee's personal characteristics (e.g., age, gender), job characteristics (e.g., contract type, firm size), education level and type (vocational or general) and occupation. Descriptive statistics for all of these variables for both waves are presented in Table 2.

Table 2: Descriptive statistics for ESJS1 (2014) and ESJS2 (2021)

Variables	*2014*	*2021*	*Difference (2021-2014)*
Male	51.9%	51.3%	-0.6*
Permanent contract	83.6%	84.2%	0.6**
Part-time	16.3%	20.7%	4.4***
Tenure (years)	10.4	9.9	-0.5***
Vocational education	74.4%	61.1%	-13.3***
Firm size			
1-49 employees	52.1%	49.0%	-3.1***
50-249 employees	25.2%	25.6%	0.4
250 or more employees	22.7%	25.4%	2.7***
Education			
Low	12.9%	11.0%	-1.9***
Medium	51.3%	46.1%	-5.2***
High	35.9%	42.9%	7.0***
Occupations			
Managers	6.5%	9.0%	2.5***
Professionals	18.6%	21.5%	2.9***
Associate professionals	16.4%	16.1%	-0.3
Clerical	21.3%	11.9%	-9.4***
Sales	15.0%	13.2%	-1.8***
Agriculture	0.8%	1.3%	0.5***
Craft & trade	8.7%	11.4%	2.7***
Plant & machine operatives	7.4%	7.6%	0.2
Elementary	5.3%	8.1%	2.8***

Source: European Skills and Jobs Survey. Authors' calculations.

While many of the variables in Table 2 remained relatively stable over both periods, there are notable exceptions. There was a significant decline in the percentage of survey respondents with a vocational education, falling from 74 percent in 2014 to 61 percent in 2021. However, other sources, such as Cedefop's official data[2], report an increase in vocational education over time. This discrepancy may arise from differing definitions of vocational education. Most data sources measure the percentage of graduates with vocational education and often limit the sample to upper-secondary or post-secondary non-tertiary education. In contrast, the ESJS includes all employed adults aged 25 to 64 with an upper-secondary education or above.

There was a large increase in the percentage of respondents with a high level of educational attainment, defined as first and advanced level tertiary. In 2014, 36 percent of employees were recorded as having a high education level, compared to 43 percent in 2021. This is supported by official findings from both Eurostat[3] and Cedefop, who find between a 5 and 6 percentage point increase in the proportion of tertiary graduates across Europe. We also see some change in relation to the distribution of occupations. The percentage of respondents in clerical jobs declined by 9 percent in 2021 compared to 2014, while there were approximately five percent more respondents working in either management or professional occupations.

The timing of the second wave of the ESJS is notable as it was conducted in 2021 during the COVID-19 pandemic. The pandemic brought significant changes to labour markets. One of the most significant was the shift to remote working. This was initially necessitated by public health restrictions but has since become embedded in the working culture of many organisations. Mobility costs in the form of geographic inflexibility, whereby workers are precluded from finding matched employment due to a lack of jobs close to their home, have been found to contribute significantly to overeducation rates (Buchel and van Ham, 2003). The ability to work remotely may mitigate some of these mobility costs, thereby reducing overeducation rates. We can test this by using a novel question that was introduced to the 2021 ESJS data, whereby respondents were asked if they work

[2] For Cedefop statistics, see https://www.cedefop.europa.eu/en/tools/key-indicators-on-vet
[3] For Eurostat statistics, see https://ec.europa.eu/eurostat/databrowser/view/edat_lfse_03__custom_14745479/default/table?lang=en

from home more frequently compared to their pre-pandemic situation. Specifically, respondents are asked, "*Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job?*" with one of the categories being, "*You work more time away from your employer's premises (e.g., remotely from home)*". We create a binary variable to indicate increased remote working, which equals one for those answering "yes", and zero for those answering "no". Overall, 32% of respondents reported increased remote working due to the pandemic. We use this question to test whether those that experience greater flexibility in remote working experience a lower risk of overeducation.

2.4 Empirical strategy

We investigate the determinants of educational mismatch (overeducation and undereducation) by estimating the following probit model,

$$\Pr\left(Y_i = 1 | X_i\right) = \Phi(\alpha + I_i{}'\beta + E_i{}'\gamma + \delta WAVE_i + \textstyle\sum_{\tau=2}^{25} \theta_\tau C_i^\tau) \qquad (1)$$

Our dependent variable, Y_i is a dummy variable which equals one if employee i is mismatched, with separate models estimated for overeducation and undereducation. The intercept is denoted by α and I is a vector of individual characteristics that have been discussed in section 1, including qualification level dummies, field of education dummies, a dummy variable to indicate whether their highest completed education was classed as vocational or general and a gender dummy.[4] E is a

[4] According to our subjective measure of mismatch, it is not possible for those with no education to be overeducated and analogously, for PhD graduates to be undereducated. Therefore, employees with no education are excluded from regression models with overeducation as the dependent variables and PhD graduates are excluded from models with undereducation as the dependent variable.

vector containing the following characteristics of a respondent's employment: occupation (ISCO 1[5]); size of the firm; tenure (in years); contract type (permanent or temporary); and a variable to indicate whether the employee works part-time. *WAVE* is a dummy variable for the wave of the survey that the individual is part of (equal to zero in the 2014 wave and one in the 2021 wave). Dummy variables to indicate the country of the respondent are also included and denoted by C_i^τ.

To investigate the reasons for the change in the rates of educational mismatch over time, we employ an extension of the Blinder-Oaxaca decomposition. This method decomposes the changes in educational mismatch over time into an explained and an unexplained component. The explained component is the change in the rate of mismatch that can be attributed to changes in sample characteristics over time. For example, if a continuous variable X is shown to be negatively associated with overeducation, and if the average level of X within the sample increases over time, then this will explain some of the reduction in the rate of overeducation. The unexplained component captures changes in the rate of educational mismatch that are attributable to changes over time in the relationship between mismatch and the explanatory variables, as well as changes to the constant term. Again, take a continuous variable X. In this case, let the average value of X within the sample populations remains unchanged over time. If in period 1, X was found to have a small negative association with overeducation, but a large negative association was found in period 2, then this would contribute to the unexplained component of the reduction in overeducation. It is termed as an 'unexplained component' because the average value of X within the sample populations was unchanged, while the coefficient describing the relationship between X and overeducation changed, for reasons that cannot be explained by the model.

Specifically, we implement our decomposition with reference to equation (1). To simplify, assume individual characteristics I, Job characteristics E, and country dummies are all collected in one vector X_t and $\hat{\beta}_t$ is the associated vector of coefficients. While we carry out separate

[5] ISCO refers to the International Standard Classification of Occupations, a framework developed by the International Labour Organization (ILO) for organizing jobs into a clearly defined set of occupational groups according to the tasks and duties undertaken. It facilitates international comparisons of labour market statistics and is commonly used for analysing occupational data.

decompositions for both overeducation and undereducation (the outcome variable, Y, in equation (1)), we illustrate the approach by focusing on overeducation, denoted by O. To further help with ease of exposition, assume we estimate equation (1) using a linear probability model. By considering separate regression equations for the 2021 and 2014 samples, and taking expectations, we get $E(O_{21})=\beta_{21}E(X_{21})$ and $E(O_{14})=\beta_{14}E(X_{14})$. Denoting expected values as sample means, i.e., $E(O_{21})=\bar{O}_{21}$, we can write the average change in overeducation over time as,

$$\bar{O}_{21} - \bar{O}_{14} = \beta_{21}\bar{X}_{21} - \beta_{14}\bar{X}_{14} \qquad (2)$$

Finally, by adding and subtracting $\beta_{21}\bar{X}_{14}$, the decomposition can be written as,

$$\bar{O}_{21} - \bar{O}_{14} = (\bar{X}_{21} - \bar{X}_{14})'\hat{\beta}_{21} + \left(\hat{\beta}_{21} - \hat{\beta}_{14}\right)'\bar{X}_{14} \qquad (3)$$

where the average change in overeducation over time $(\bar{O}_{21} - \bar{O}_{14})$ is decomposed into the explained effects due to differences in the average characteristics of respondents between waves $(\bar{X}_{21} - \bar{X}_{14})'\hat{\beta}_{21}$, and an unexplained part due to differences in the coefficients associated with these characteristics $\left(\hat{\beta}_{21} - \hat{\beta}_{14}\right)'\bar{X}_{14}$. In addition to applying the decomposition to the pooled sample comprising all countries, we carry out separate decompositions for each country.

To estimate the impact of an increase in remote working on educational mismatch, we again employ a probit model, with over- and undereducation as outcome variables. We use the same covariates as described in equation (1), with the addition of a variable that captures whether an employee experienced an increase in remote working as a result of the COVID-19 Pandemic. Note that this analysis is restricted to the second wave of ESJS data (for 2021). While the remote working variable only appears in the 2021 wave of the survey, the question is retrospective, allowing us to examine how increased flexibility to work remotely may have impacted a person's probability of being either overeducated or undereducated.

In addition, we employ propensity score matching to account for the fact that workers who experienced increased remote working as a result of the pandemic may be systematically different (in terms of observable characteristics) from those who did not. If this is ignored, we may end up with biased estimates on the impact of remote working on our dependent variables. The first stage of the PSM involves estimating propensity scores $p(X)$ using a probit model to predict the likelihood of a person experiencing increased remote working during the pandemic based on their characteristics X. Defining D as a dummy variable that equals one for those that experienced an increase to remote working, and zero for those that did not, the propensity score is,

$$p(X) = \Pr(D = 1|X) \qquad (4)$$

We use the same covariates as outlined above in equation (1), with one exception – instead of one-digit ISCO occupations, we use the more detailed ISCO two-digit occupations.[6] After propensity scores have been calculated, we compare treated (D = 1) and untreated (D = 0) individuals with similar propensity scores. The average treatment effect on the treated (ATET) is estimated by matching each treated employee (D = 1) with one control employee (D = 0) with a similar propensity score and comparing the average outcomes (in terms of educational mismatch) of both groups.

2.5 Results

2.5.1 Determinants of Educational Mismatch

Table 3 shows the determinants of overeducation according to the probit model outlined in equation (1) of Section 2.4. Three different specifications are shown. The first column includes all employees. The specification in column (2) includes a vocational education dummy variable along with the other control variables. As data on vocational education is only collected for individuals with at least an upper secondary education, column (2) excludes those with lower secondary education or below. In column (3) we include dummy variables to capture the respondent's field of study, which is collected only for post-secondary graduates. The variable ESJS Wave is a dummy variable equal to 1 for the

[6] The reason for this is that we have data on ISCO 2-digit occupations in the second wave, but not the first.

2021 wave and 0 for the 2014 wave. We see that, across all specifications, overeducation shows a statistically significant decline over time, ranging from 5 to 9 percentage points.

There is a positive monotonic relationship between education level and overeducation, with more highly educated workers being more likely to experience this form of mismatch. In terms of occupation, employees in high-skilled jobs are less likely to be overeducated. For example, compared to elementary workers, managers, professionals and associate professionals are approximately 20 to 30 percentage points less likely to be overeducated across all specifications. Company size is consistently found to have a negative relationship with overeducation. This may relate to labour mobility if larger organisations offer greater opportunities for employees to switch between roles, thus making them more likely to settle in a matched position. Part-time workers are more likely to be overeducated, while those on permanent contracts are less likely to be overeducated.

Longer job tenure is associated with a lower likelihood of overeducation. It may be that the longer a person stays in a job, the higher the likelihood of progression. However, this could also reflect grade inflation over time; longer-tenured individuals may have entered the workforce with qualifications that were considered sufficient in the past but are now perceived as insufficient in the current labour market.

Vocational education is associated with a significantly lower likelihood of being overeducated. Those with a vocational qualification are approximately four percentage points less likely to be overeducated compared to those with a general qualification. We also see strong effects when looking at the impact of field of education for graduates (column (6)). Those with a graduate qualification in services, arts & humanities and agriculture are the most likely to be overeducated.

We conduct a similar analysis for undereducation, with results presented in Table 4. The specifications are the same as those used in the overeducation analysis in Table 3. However, the samples are slightly different. Unlike the overeducation analysis, individuals with no formal education are included in the undereducation analysis, while those with PhDs are excluded from the analysis as, by definition, they cannot be classified as undereducated. Across all specifications, we observe a statistically significant decrease in the incidence of undereducation between 2014 and 2021, in the order of between 1 and 3 percentage points.

We observe a negative monotonic relationship between education level and undereducation, meaning individuals with higher levels of education are less likely to be undereducated. Vocational education is also associated with a lower likelihood of undereducation for those with at least an upper-secondary qualification. However, the effect of vocational education is not significant when we look at post-secondary graduates only and include field-of-study as additional explanatory variables (column (3)). Longer job tenure is consistently shown to be associated with a greater likelihood of undereducation. One potential explanation relates to credentialism or qualification inflation. An employee may have been matched at the time they entered their job, but due to credentialism over time, the same job may now require a higher qualification. Another potential explanation relates to the on-the-job accumulation of skills and human capital. An employee that stays with a company for a very long time may gain skills that allow them to progress to a position that is otherwise reserved for those advanced formal qualifications. For example, an employee with a relatively low level of education could, over time, progress up the ranks to a senior management position. If the same organisation was to recruit for this position externally, it is likely that they would require an advanced degree from the applicant. Those in larger firms are also more likely to be undereducated. Again, this may be due to greater opportunities for advancement within larger firms, allowing employees to attain positions that would normally be reserved for those with advanced qualifications.

When examining graduates' field of study, those with a qualification in services or agriculture are least likely to be undereducated. In terms of occupation, all categories show a higher likelihood of undereducation compared to elementary workers. This is expected, as elementary workers typically have the lowest educational qualifications and are therefore the least likely to experience undereducation. Managers, followed closely by professionals, are the most likely to be undereducated.

Table 3: Pooled overeducation determinants

	(1)	(2)	(3)

VARIABLES			
ESJS wave	-0.092***	-0.051***	-0.044***
	(0.004)	(0.004)	(0.006)
Male	-0.007*	-0.005	-0.001
	(0.004)	(0.004)	(0.006)
Tenure	-0.004***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)
Part-time	0.035***	0.033***	0.029***
	(0.005)	(0.006)	(0.007)
Permanent contract	-0.027***	-0.030***	-0.020**
	(0.006)	(0.006)	(0.008)
Vocational education		-0.038***	-0.044***
		(0.004)	(0.006)
Company size (ref: 1 to 49)			
50 to 249	-0.020***	-0.022***	-0.037***
	(0.004)	(0.005)	(0.006)
250 or more	-0.030***	-0.034***	-0.044***
	(0.005)	(0.005)	(0.007)
Education (ref: primary/lower-secondary)			
Upper-/post-secondary	0.151***	-	-
	(0.008)	-	-
Tertiary	0.308***	0.116***	-0.023***
	(0.009)	(0.005)	(0.007)
Occupation (ref: elementary workers)			
Managers	-0.218***	-0.216***	-0.254***
	(0.004)	(0.004)	(0.006)
Professionals	-0.280***	-0.289***	-0.375***
	(0.004)	(0.005)	(0.010)
			Continued on next page
Associate professionals	-0.221***	-0.214***	-0.239***
	(0.005)	(0.005)	(0.009)
Clerical workers	-0.191***	-0.181***	-0.187***
	(0.005)	(0.006)	(0.011)

Sales & Service workers	-0.104***	-0.096***	-0.094***
	(0.007)	(0.008)	(0.014)
Skilled agricultural	-0.089***	-0.119***	-0.152***
	(0.016)	(0.014)	(0.020)
Craft & trade workers	-0.128***	-0.123***	-0.139***
	(0.007)	(0.007)	(0.013)
Plant & machine operators	-0.058***	-0.052***	-0.030
	(0.009)	(0.010)	(0.021)
Education field (ref: Education)			
Arts & humanities			0.088***
			(0.016)
Social sciences & journalism			0.048***
			(0.017)
Business, admin & law			0.011
			(0.012)
Natural sciences & maths			0.033**
			(0.015)
ICT			0.025*
			(0.015)
Engineering, manuf. & const.			-0.022*
			(0.013)
Agri, forestry & fishery			0.034
			(0.023)
Health & welfare			-0.038***
			(0.013)
Services			0.050***
			(0.018)
Other			0.069***
			(0.015)
Country FE	**YES**	**YES**	**YES**
Observations	**78,856**	**67,122**	**36,954**

Note: Pooled probit regression on overeducation. Coefficients reported are marginal effects. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Pooled undereducation determinants

VARIABLES	**(1)**	**(2)**	**(3)**
ESJS wave	-0.026***	-0.022***	-0.011***
	(0.002)	(0.002)	(0.002)

Male	0.007***	0.005***	0.002
	(0.002)	(0.002)	(0.002)
Tenure	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Part-time	-0.005*	-0.002	-0.001
	(0.004)	(0.002)	(0.002)
Permanent contract	0.003	0.000	-0.005**
	(0.003)	(0.003)	(0.003)
Vocational education		-0.006***	-0.000
		(0.002)	(0.002)
Company size (ref: 1 to 49)			
50 to 249	0.010***	0.007***	0.004**
	(0.003)	(0.002)	(0.002)
250 or more	0.011***	0.010***	0.006***
	(0.003)	(0.002)	(0.002)
Education (ref: none/primary/lower-secondary)			
Upper-/post-secondary	-0.094***		
	(0.004)		
Tertiary	-0.282***	-0.177***	-0.173***
	(0.004)	(0.003)	(0.007)
Occupation (ref: elementary workers)			
Managers	0.243***	0.193***	0.077***
	(0.017)	(0.018)	(0.023)
Professionals	0.233***	0.186***	0.057***
	(0.013)	(0.014)	(0.014)
			Continued on next page
Associate professionals	0.175***	0.135***	0.047***
	(0.012)	(0.013)	(0.015)
Clerical workers	0.112***	0.080***	0.032**
	(0.010)	(0.010)	(0.013)
Sales & Service workers	0.040***	0.025***	0.006
	(0.008)	(0.008)	(0.008)
Skilled agricultural	0.045***	0.066***	0.085**
	(0.017)	(0.023)	(0.042)

Craft & trade workers	0.051***	0.032***	0.012
	(0.009)	(0.009)	(0.011)
Plant & machine operators	0.016**	0.006	0.007
	(0.008)	(0.007)	(0.010)
Education field (ref: Education)			
Arts & humanities			-0.005*
			(0.003)
Social sciences & journalism			-0.004
			(0.004)
Business, admin & law			0.000
			(0.003)
Natural sciences & maths			0.005
			(0.005)
ICT			0.002
			(0.004)
Engineering, manuf. & const.			0.003
			(0.004)
Agri, forestry & fishery			-0.008**
			(0.003)
Health & welfare			0.003
			(0.004)
Services			-0.008***
			(0.003)
Other			-0.006**
			(0.003)
Country FE	**YES**	**YES**	**YES**
Observations	**75,469**	**66,162**	**36,354**

Note: Pooled probit regression on undereducation. Coefficients reported are marginal effects. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

2.5.2 Decomposition Results

To better understand the changes in educational mismatch between 2014 and 2021, we employ an Oaxaca decomposition, as outlined in equation (3). This is done separately for overeducation and undereducation. The detailed Oaxaca-Blinder decomposition for overeducation is presented in Table 5. This table displays the incidence of overeducation in both years and the percentage point difference. According to our analysis, overeducation decreased by 7.2 percentage points between

2014 and 2021. We also present the portion of this change that can be 'explained' – i.e., the percentage of the decrease that is attributable to changes in sample characteristics between the two survey waves. Note that the explained component is negative in this instance. This implies that the change in the average characteristics of respondents between 2014 and 2021 would have been expected to increase the overeducation rate, when in fact overeducation decreased. The most significant negative component relates to education. This is because educational attainment has risen over time within the EU, and higher educational attainment tends to be positively correlated with a greater likelihood of overeducation. Despite this, the overeducation rate decreased, and therefore the 'explained' component relating to education is negative.

We also examine the role of education in the Oaxaca decomposition for each country separately. We focus the country-level analysis on the role of educational attainment for brevity, as compared to other factors, educational attainment plays a more prominent role across countries. Figure 2 illustrates the proportion of the change in overeducation that can be explained by changes in educational attainment for each country. The red dots represent the overall change in overeducation (in percentage points), while the blue bars indicate the amount of this change (in percentage points) attributable to changes in educational attainment. The vast majority of countries (apart from Italy and Hungary) experienced a decline in overeducation, with countries such as Croatia, France, Portugal, Czechia and Ireland experiencing the largest declines. With the exception of Lithuania, the explained component relating to educational attainment is either close to zero or works in the opposite direction for all countries. The results are particularly striking in countries such as Croatia, France, Austria and Slovenia where, despite increasing educational attainment within these countries predicting a significant increase in overeducation, the actual overeducation rates declined by between 10 and 20 percentage points between 2014 and 2021.

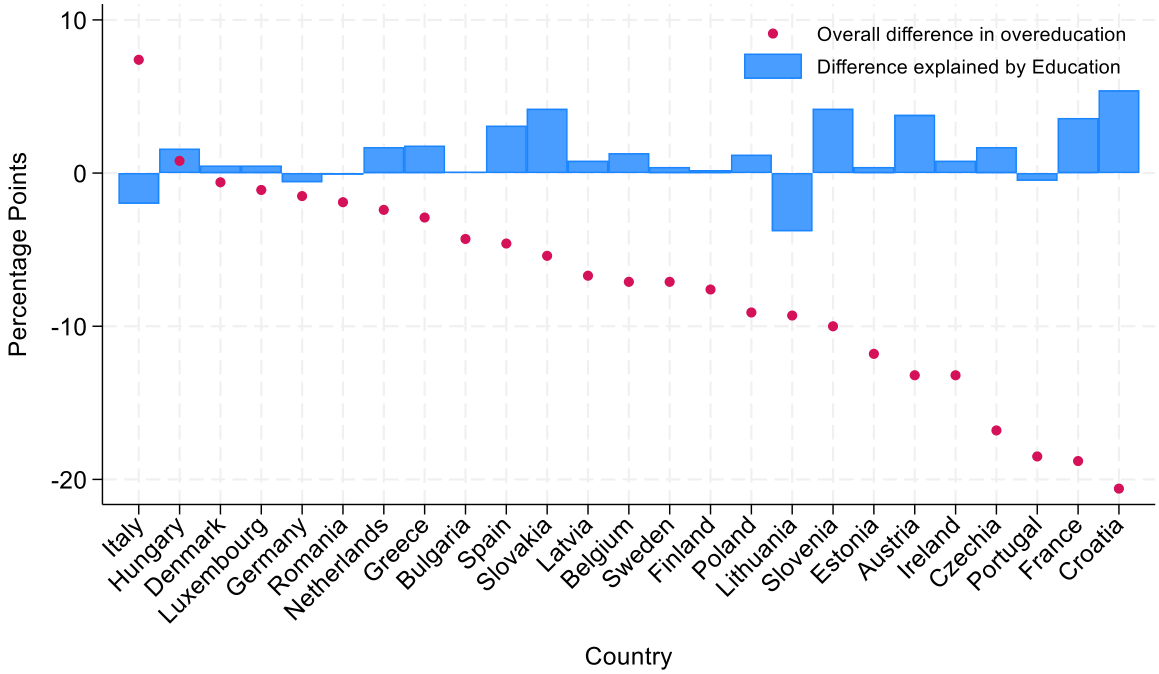
Table 5: Overeducation Oaxaca-Blinder decomposition

	(1) All employees
Overeducation 2014	28.3 %
Overeducation 2021	21.1 %
Difference	7.2 p.p.

(percentage points)	
	Explained (%)
Gender	0
Part-time	-2.8
Tenure	-2.8
Permanent contract	0
Education level	-19.4
Occupation	-5.6
Company size	1.4
Country effects	4.2
Total	**-25.0**
Observations	**78,991**

Source: European Skills and Jobs Survey. Oaxaca-Blinder decomposition of change in overeducation over time. Difference is presented in percentage points and all other coefficients are a percentage.

Figure 2: Role of educational attainment in overeducation country-level decomposition



Source: European Skills and Jobs survey. Based on Oaxaca-Blinder decomposition specification (1) for overeducation. Shows the overall percentage point change in overeducation, as well as the percentage point difference explained by changes in educational attainment over time.

We conduct a similar decomposition for the decline in undereducation and the results are shown in Table 6. In contrast to the results for overeducation, a substantial portion of the decline in undereducation—about 35% of the 5.1 percentage point drop—can be explained by changes in sample characteristics. Nearly all of this comes from improvements in educational attainment, which is consistent with the fact that higher education levels are associated with a lower likelihood of undereducation. Again, we decompose the change in undereducation for each country separately. The gap in undereducation as well as the proportion that is explained by differences in educational attainment are shown in Figure 3. For Slovakia, Greece and Slovenia, virtually all of the decrease in undereducation can be explained by increased educational attainment. For other countries, including Ireland, Netherlands, Finland, Spain, Denmark, Belgium and Latvia, approximately 50 percent (or more) of the decline in overeducation can be explained by increased educational attainment between 2014 and 2021.

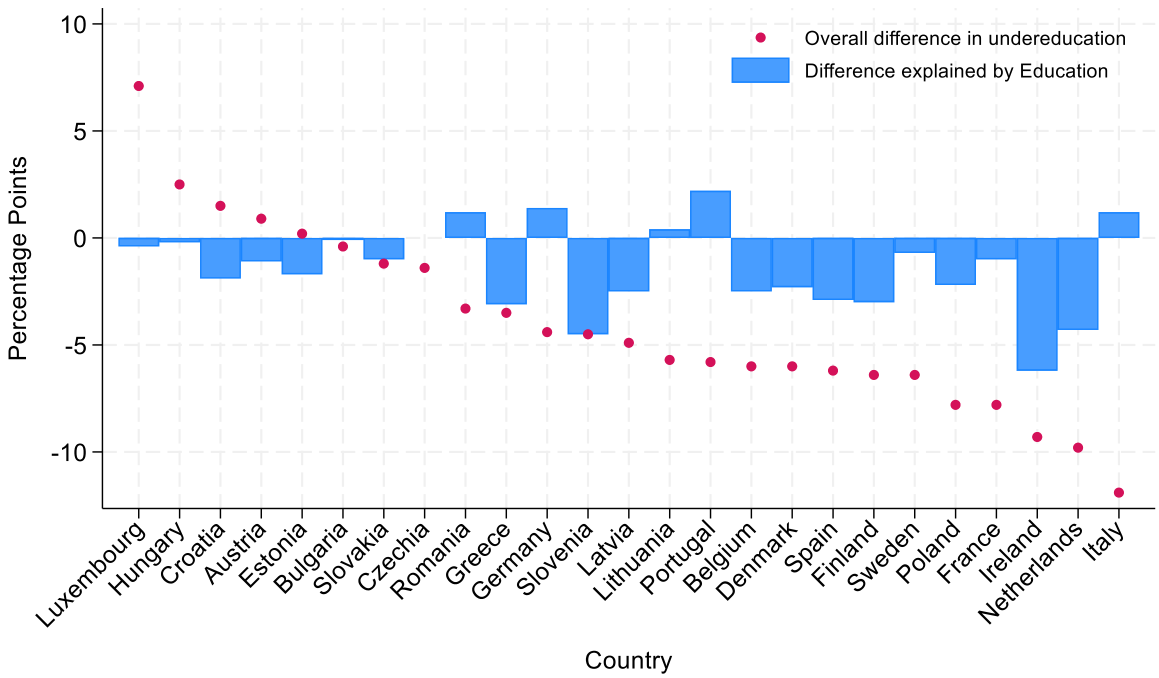
Table 6: Undereducation Oaxaca-Blinder decomposition

	(1)

	All employees
Overeducation 2014	15.0 %
Overeducation 2021	9.9 %
Difference (percentage points)	5.1 p.p.
	Explained (%)
Gender	0
Part-time	0
Tenure	2
Permanent contract	0
Education level	33.3
Occupation	2
Company size	0
Country effects	0
Total	**35.3**
Observations	**78,991**

Source: European Skills and Jobs Survey. Oaxaca-Blinder decomposition of change in undereducation over time. Difference is presented in percentage points and all other coefficients are a percentage. Due to rounding, the figures in the "explained (%)" column do not add up to the exact total of 35.3.

Figure 3: Role of educational attainment in undereducation country-level decomposition

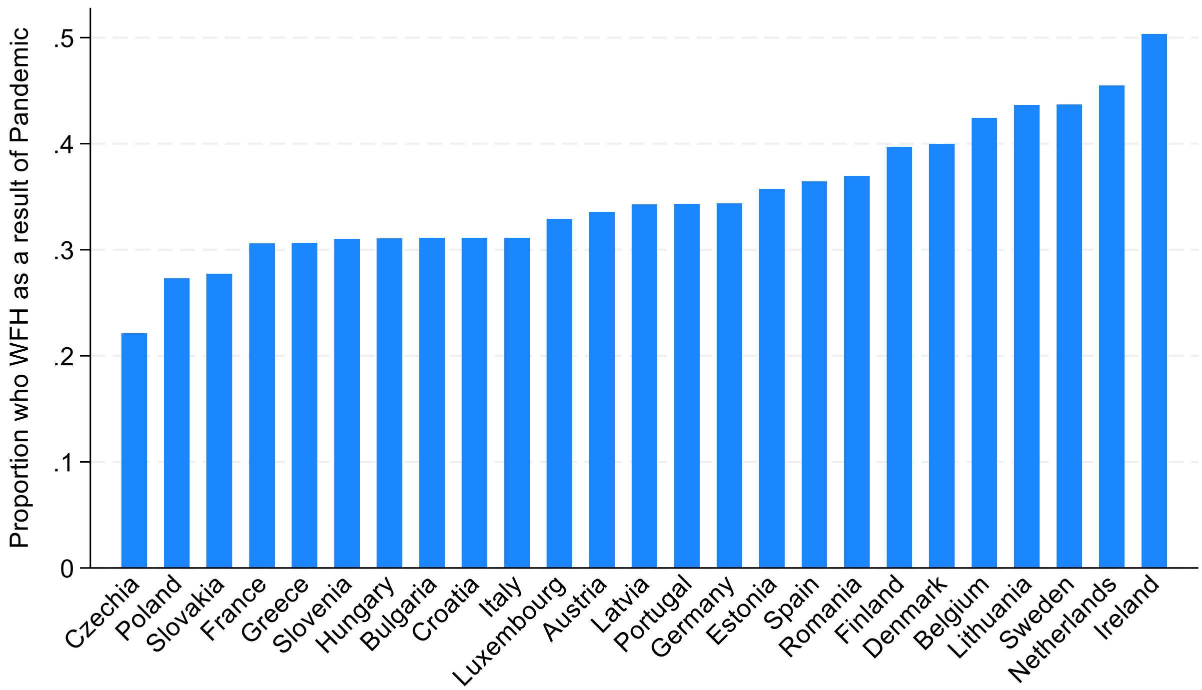


Source: European Skills and Jobs survey. Based on Oaxaca-Blinder decomposition specification (1) for overeducation. Shows the overall percentage point change in overeducation, as well as the percentage point difference explained by changes in educational attainment over time.

2.5.3 The Role of Remote Working

The decomposition analyses showed that while a substantial part of the decline in undereducation can be explained by increased educational attainment, the decline in overeducation cannot be explained. To further explore potential reasons for the decline in overeducation, we use a novel question from the second wave of the ESJS survey, which asks participants whether they work from home more frequently compared to their pre-pandemic situation. Greater flexibility in terms of remote working may remove some of the constraints relating to geographical mobility in the labour market, thereby affording individuals more choice in selecting a matched occupation. Overall, 32% of respondents reported increased remote working due to the pandemic, though this varies significantly by country, as shown in Figure 4. Countries such as Ireland, the Netherlands, and Sweden saw substantial increases in remote working, with between 40 and 50 percent of respondents saying that they spent more time working remotely in 2021 compared to before the pandemic. While Czechia, Poland and Slovakia record the smallest increase in remote working among all countries, the percentages are still quite high, with 20 to 30 percent respondents reporting increased remote working.

Figure 4: Proportion of respondents saying they engage in remote working more frequently due to COVID-19



Source: European Skills and Jobs survey. Authors' Calculations

In Table 7 we show the results of the probit model in which overeducation and undereducation are regressed on the set of covariates shown in earlier models, along with the remote working dummy variable. For brevity, we focus on the remote working coefficient only, as we have seen the impacts of the other variables in the earlier analysis. We estimate this using the full sample of employees (columns (1) and (3)), as well as for a restricted sample consisting only of employees with a company tenure of less than 2 years (columns (2) and (4)). Many people may have moved to a new job during the pandemic to avail of remote working and to find a better education-occupation match, and therefore the impact may be more salient for the group of recent job movers. We see that increased remote working is associated with an 8 percentage-point reduction in the probability of overeducation for all employees, and a 10 percentage-point reduction for the sub-sample of recent movers.

Table 7: Probit regression with WFH variable included

Dep variable:	**Overeducation**			**Undereducation**	
	(1)	(2)		(3)	(4)
VARIABLES					
WFH	-0.083***	-0.102***		0.025***	0.020***
	(0.006)	(0.013)		(0.003)	(0.006)
Limited to Tenure < 2	**NO**	**YES**		**NO**	**YES**
Includes control variables	**YES**	**YES**		**YES**	**YES**
Country FE	**YES**	**YES**		**YES**	**YES**
Observations	**28,536**	**6,607**		**28,536**	**6,607**

Source: European Skills and Jobs Survey. Pooled probit specifications for overeducation {(1) and (2)} and undereducation {(3) and (4)}, including WFH dummy previously described. Coefficients reported are marginal effects. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

When we focus instead on undereducation, as presented in columns (3) and (4) of Table 7, we find that an increase in remote working is associated with a two percentage-point increase in undereducation. It may be that the flexibility of greater remote working allowed some high ability undereducated employees to find better jobs, which exceed their formal qualifications. On the other hand, the rapid transition to remote work may have also exacerbated undereducation by widening the gap in digital literacy skills. As businesses shifted operations online, the reliance on digital tools, platforms, and communication technologies became more important in some occupations. As a result, job requirements may have become more demanding, seeking individuals with the necessary digital skills to operate in a modern business environment. Therefore, it is possible that employers started to seek graduates with more advanced qualifications that included digital learning components over more basic post-secondary and non-tertiary graduates. Therefore, the education requirements for new hires may have increased, while the education level of existing employees remained the same.

To address potential systematic differences between those who experienced increased remote work flexibility due to the COVID-19 pandemic and those who did not, we employ propensity score matching (PSM). The average treatment effects on the treated (ATET) for the remote working variable, based on our PSM specification, are presented in Table 8. We find a strong negative association between remote working and overeducation, consistent across both specifications. The effects are in line with the probit estimates, indicating that increased remote working is associated with an 8-10 percentage point reduction in the likelihood of being overeducated. For undereducation, the impact of increased remote working is positive and significant for the full sample of employees, showing a three-percentage point increase in the likelihood of undereducation for those that experienced an increase in remote working. However, it is not statistically significant for the sub-sample of employees with less than two years of tenure at their companies.

Table 8: Average treatment effects of treated (ATET) for WFH variable

DEPENDENT VARIABLE	**(1)**	**(2)**
Overeducation	-0.08^{***}	-0.10^{***}
	(0.007)	(0.018)
Undereducation	0.03^{***}	0.02
	(0.004)	(0.011)
Limited to Tenure < 2	**NO**	**YES**

Source: European Skills and Jobs Survey. Coefficients from PSM estimator applied to specifications in Table 7. *** p<0.01, ** p<0.05, * p<0.1.

2.6 Conclusion

While most of the existing literature on educational mismatch focuses on overeducation, less is known about undereducation, and how both forms of mismatch have changed over time. In particular, little research has been done on the association between educational mismatch and the COVID-19 Pandemic. In this paper, we examine the incidence, determinants, and trends in educational mismatch in 25 EU countries using data from two waves of the European Skills and Jobs Survey (ESJS). We explore the drivers of educational mismatch as well as the trends in mismatch by decomposing changes in their incidences into explained and unexplained components over two time periods. Moreover, we investigate the possible role of the pandemic in explaining trends in both over- and undereducation over time.

Our findings indicate significant declines in both overeducation and undereducation from 2014 to 2021. A significant portion of the decline in undereducation can be attributed to increased educational attainment among European employees. As the overall education level of the workforce has risen, fewer workers find themselves underqualified for their positions. This trend is consistent across most EU countries, reflecting broader improvements in access to education and the alignment of educational qualifications with job requirements. In contrast, the decline in overeducation is largely unexplained by changes in measurable factors such as educational attainment, occupation, or company size. The fact that we observe a reduction in overeducation, despite greater educational attainment, is consistent with previous work that indicates European labour markets have been able to absorb increases in university graduate supply in recent years.

Our analysis suggests that structural changes in the labour market following the COVID-19 pandemic, namely the increased capacity for remote working, may have played an important role in reducing overeducation. Employees who experienced greater remote-working flexibility were significantly less likely to be overeducated, highlighting the potential of remote work to improve job-education matching, perhaps by expanding geographical job opportunities and enabling better alignment of skills with job requirements.

The findings from our study have important policy implications, as they suggest a role for remote working in mitigating educational mismatch. While remote working likely has both benefits and drawbacks, it may be a useful tool for policymakers in countries where overeducation is prevalent.

Exploring ways to support and enhance this mode of working may present useful opportunities for addressing educational mismatch. Some countries have already implemented policies in this area. In 2024, Ireland passed a law which gave employees the legal right to request remote working from their employers, who have four weeks to issue a response in writing. Employers can refuse the request on a number of broad grounds and, as such, the law has been criticised as being quite limited. Nonetheless, this shows that national governments are recognising the potential benefits and importance of remote working. Future research should continue to explore the long-term impacts of remote working on educational mismatch and other labour market outcomes. It should also investigate the interplay between digital skills, remote work, and job matching to provide deeper insights into how the digital transformation of work environments affects educational and occupational dynamics.

3. CHAPTER 2: Vocational Education in Europe: Incidence, Wage Effects and Job Satisfaction

3.1 Introduction

Vocational education is designed to equip individuals with the practical skills and hands-on training needed for specific trades, crafts, and careers. Unlike traditional academic education, VET focuses on preparing learners with the competencies required to enter the workforce directly and succeed in specialised professions. Over the past few decades, VET has undergone significant changes, adapting to shifting labour market demands and technological advancements, making it an important policy tool for adapting to changing skill demands within the labour market (Cedefop, 2022).

In Chapter 1, we showed that vocational education is associated with a significantly lower probability of experiencing overeducation. It has also been shown to have consequences for wages. Therefore, understanding the take-up of vocational education in Europe and its labour market consequences across countries is important. To help shed light on this issue, we utilise the 2021 wave of the European Skills and Jobs Survey (ESJS) to investigate the incidence and wage effects associated with choosing a vocational education compared to general education, as well as the impact of educational choice (vocational versus general) on an employee's job satisfaction.

An important contribution of our paper is to investigate heterogeneity in the incidence and impact of vocational education across EU countries. Our analysis shows substantial cross-country differences. The incidence of employees with self-reported vocational education ranges from approximately 80 percent in Finland and Czechia to between 30 and 40 percent in Belgium and Ireland. For the majority of countries, there is no statistically significant impact of vocational education on wages. However, we observe a statistically significant impact in seven countries. In six of these countries (Spain, Greece, Lativa, Austria, Estonia and France), vocational education is associated with a wage premium, while it is associated with a wage penalty in Slovenia. Our analysis also shows that employees with a vocational education tend to have higher job satisfaction than those with a general education.

3.2 Related Literature

One strand of VET literature attempts to analyse the impact of vocational education on labour market outcomes, such as employment, wages and educational mismatch. The results are often inconclusive, and therefore this is an area of ongoing debate. In recent work, Oswald-Egg and Renold (2021) find that higher education (HE) graduates in Switzerland with a dual-VET upper-secondary education experience a wage premium and a lower search time for their first job compared to HE graduates that pursued an academic (non-VET) path at upper-secondary level. Specifically, HE graduates with an upper-secondary VET qualification have wages that are 7 to 19 percent higher, and job search time that is two months lower, than those with an academic upper-secondary diploma. However, these effects dissipate within five years of HE graduation. The authors attribute these favourable labour market impacts to the work experience that HE graduates gained when completing their dual-VET upper secondary education. Bishop and Mane (2004) present similar findings from a cross-national study which shows that offering upper-secondary students the option to pursue vocational education increases their subsequent earnings, and this holds whether or not they enter and complete a post-secondary education.

Kriesi and Sander (2024), also for Switzerland, study the long-term (up to 20 years) wage development of academic and vocational tertiary degree holders. They find that, even after one year, tertiary university graduates face a wage premium over tertiary vocational graduates, and this persists in the long term (after 20 years). The authors suggest that this is due to non-vocational university graduates possessing more general skills which allows them move jobs more frequently, eventually ending up in managerial or senior positions.

The impact of education choice (general versus vocational) on labour market outcomes appears to differ depending on the education level that is being considered. Among those with an upper-secondary or a post-secondary non-tertiary education level, having a vocational education is associated with slightly lower earnings, but a higher probability of employment compared to those with a general education (Brunello and Rocco, 2017). However, the picture is very different for tertiary graduates. Brunello and Rocco (2017) find that vocational tertiary graduates face a wage deficit of approximately 20 percent compared to academic (non-vocational) graduates. The authors conclude that, overall, vocational education does not perform as well as academic education with respect to earnings but preforms slightly better with respect to employability.

It is possible that vocational education leads to employment benefits early in a person's career and a disadvantage later on in their career. As vocational education is quite specific, it allows people quick access to employment after graduation. However, the demand for these specific skills may become obsolete over time, and relative to general (non-vocational) graduates that are equipped with broader and more transferable skills, vocational graduates may be at a disadvantage once their specific skillset becomes obsolete. Hanushek et al. (2017) find support for this hypothesis by examining differences in labour market outcomes over the lifecycle among those completing vocational versus general education. Vocational graduates are more likely to be employed when they are young, but this diminishes, and reverses, as they get older. Hanushek et al. (2017) also investigate whether the early employment gains are sufficient to offset later employment disadvantage in terms of a person's lifetime earnings. They find cross-country heterogeneity. In Switzerland, early employment gains are sufficient to lead to higher discounted lifetime earnings for vocational graduates compared to general graduates. However, the opposite is true for Germany and Denmark, where lifetime earnings are higher for general graduates compared to vocational graduates.

The role of vocational education on educational mismatch appears to vary depending on the career stage of the individual. Vocational education is associated with a lower risk of overeducation in a person's first job compared to general education. However, those with general education often use overeducation as a stepping-stone to better-matched jobs as, over time, they get promoted to senior positions (see, e.g., Verhaest and Schatteman, 2010; Verhaest et al., 2017).

A related strand of literature explores the factors influencing an individual's decision to choose a vocational program over a general academic program. While research in this area is somewhat limited, the existing literature identifies three broad categories of factors: individual characteristics, socio-economic status, and regional characteristics, primarily related to labour market conditions. With regard to individual characteristics, women, non-nationals and those with lower test scores have been found to be more likely to enrol in vocational programmes (Ordovensky, 1995; Sá et al., 2011). The relationship between age and vocational enrolment is mixed, with some studies suggesting that enrolment patterns may be more closely related to birth cohorts than age (Sá et al., 2011; Vincent and Rajasekhar, 2023).

Socio-economic factors appear to play an important role in determining vocational enrolment. Parental education and occupation are strongly correlated with the choice to pursue vocational education, with students whose parents hold college degrees or work in white-collar occupations being less likely to choose vocational programs (Ordovensky, 1995; Sá et al., 2011; Nguyen and Taylor, 2003; Vincent and Rajasekhar, 2023). Similarly, students from higher-income households are more likely to attend university rather than vocational institutions, likely due to the perception of university programs as more prestigious. For students with financial means, university is often the preferred option, assuming academic performance permits (Lovšin, 2014; Winch, 2013). Glauser and Becker (2016) examine how regional opportunity structures shape students' educational choices after compulsory education and find that regions with more restricted opportunities are associated with a higher probability of pupils attending VET programmes. Overall, the decision to pursue vocational education is shaped by an interplay of individual, socio-economic, and regional factors.

3.3 Data

To study vocational education in Europe, we use data from the most recent wave of the ESJS in 2021 (as explained in section 1.3 of Chapter 1). In wave 2 of the ESJS, respondents are asked the following question relating to VET:

'Was the qualification obtained as part of your highest level of education you have completed mainly general or vocational? Vocational means it is designed for acquiring knowledge and skills closely linked to a particular job or trade or a particular group of jobs and trades.'

This question is only asked to those who completed upper-secondary education or higher (ISCED2011[7] ≥ 3), and thus applies to more than 90% of the sample. We exclude those with no answer or say that they don't know.

Respondents' job satisfaction and relative level of income are also recorded in the ESJS. For job satisfaction, respondents are asked a series of questions about how satisfied they are with certain aspects of their job: Work-Life balance, Training provided, Promotion/career prospects, Job security and overall job satisfaction. The questions are measured on a 0 to 10 scale, with 0 corresponding to complete dissatisfaction and 10 corresponding to complete satisfaction, and 5 representing a neutral midpoint. For each question, we create a dummy variable to capture job satisfaction: responses above 5 indicate satisfaction and are coded as 1, while responses of 5 or below reflect dissatisfaction or indifference and are coded as 0. Respondents were asked what their usual monthly net pay is in their local currency, after deductions for tax, social insurance and any other compulsory deductions. This value is then converted into Euro.

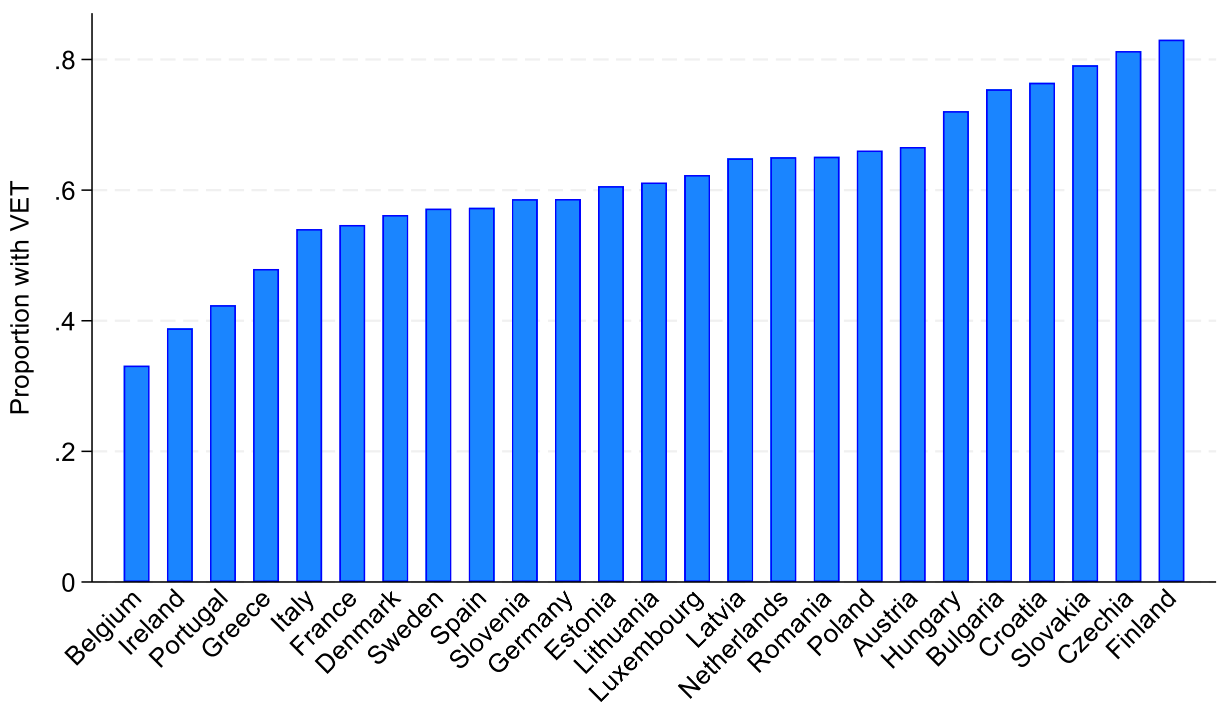
As discussed in the review of the literature surrounding the determinants of VET, many of the key predictors of VET completion are related to socio-demographic factors, such as household income, father's education and whether the primary earner in the house in blue or white collar. The ESJS focuses on employment and education characteristics of employees, and therefore we do not have access to these types of individual level background socio-demographic characteristics. Instead, we link the ESJS data to macroeconomic data from Eurostat, allowing us to identify the characteristics of the region that the employee lives in. In the ESJS data, each respondent's region is recorded either at NUTS 2 or NUTS 3. We collect regional level statistics including GDP per capita and unemployment, in order to capture the average socio-demographic characteristics of the employee's region.

[7] ISCED 2011 refers to the International Standard Classification of Education, updated by UNESCO to replace ISCED 1997.

3.4 Incidence of Vocational Education

Overall, approximately 60% of respondents reported that their highest level of education was vocational in nature. There is notable variation when we look at the incidence of VET across countries (Figure 5). Almost 80 percent of employees in countries including Finland, Czechia and Slovakia report that their highest qualification is vocational in nature. This compares to less than 40 percent in Ireland and Belgium.

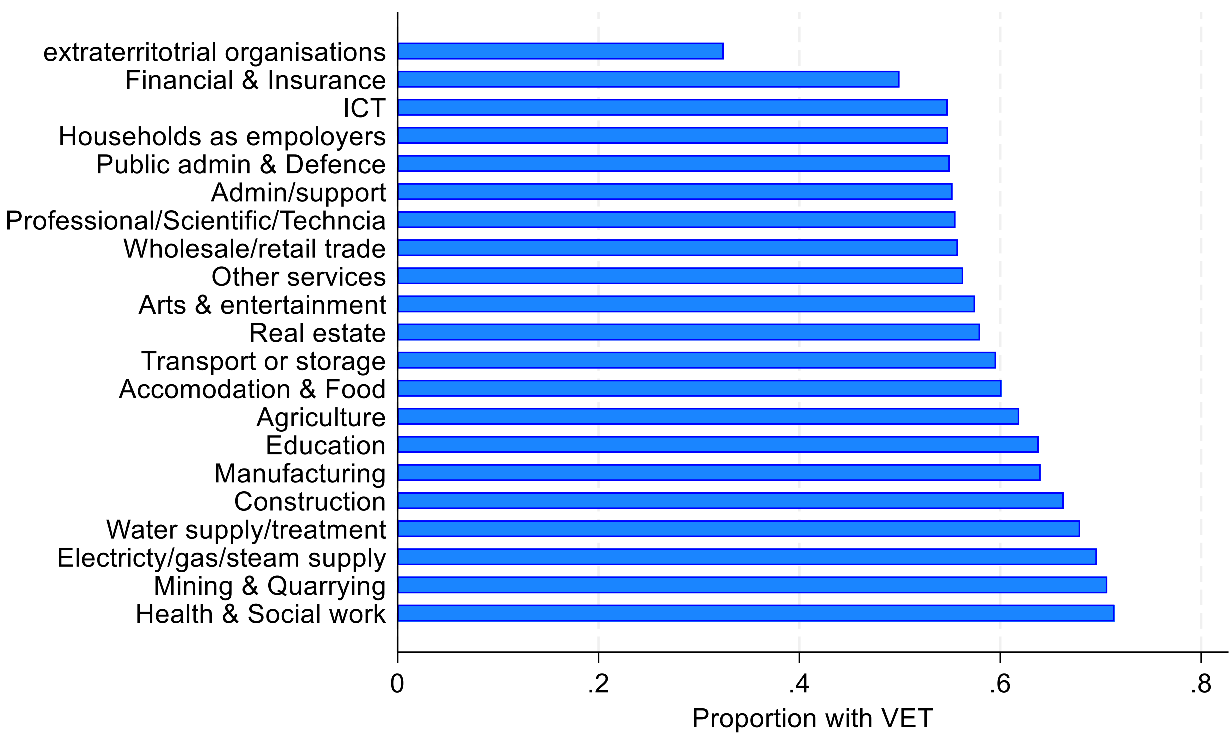
Figure 5: Proportion of respondents with VET by country (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

We also show the incidence of vocational education by Industry (Figure 6). The top five industries with the highest incidence of employees with a vocational education are: health and social work; mining and quarrying; electricity, gas and steam supply; water supply / treatment; construction. Approximately 60 to 70 percent of employees in these sectors report that their highest educational qualification is vocational. The sector with the lowest incidence of vocational education is activities relating to extraterritorial organisations. However, very few employees work in this sector. Other sectors with a relatively low incidence of vocational education include: finance and insurance; ICT; households as employers; public administration and defence. Approximately 50-60 percent of employees in these sectors have a vocational education.

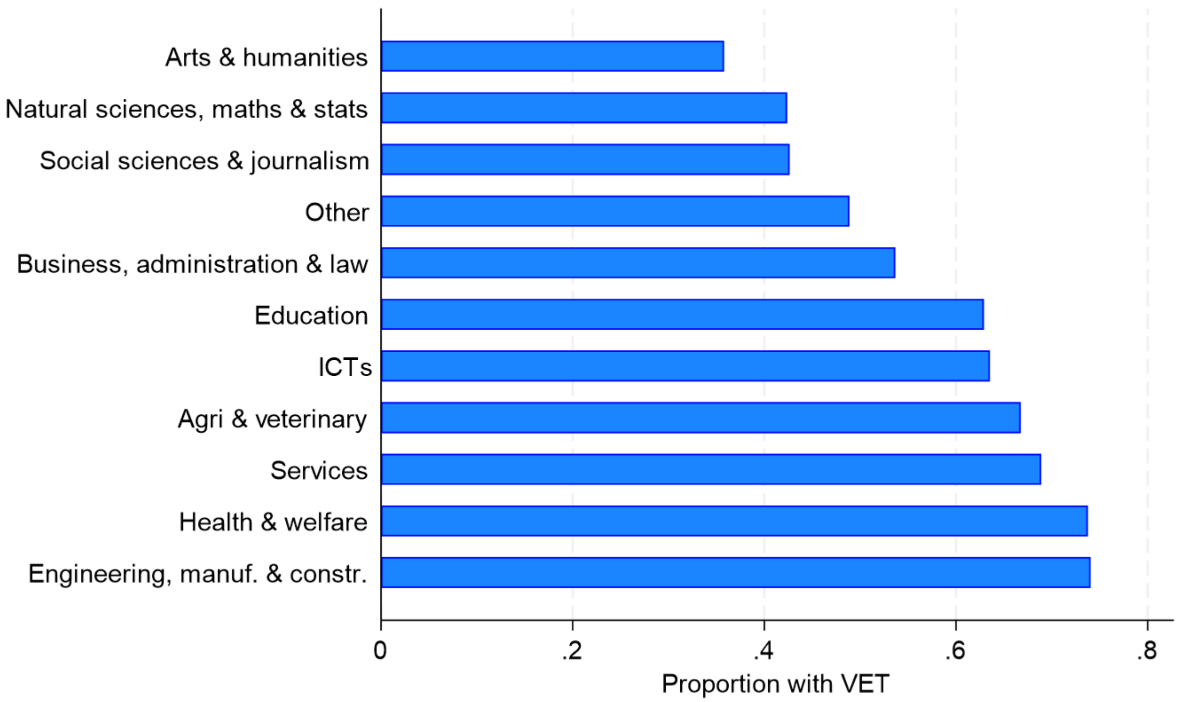
Figure 6: Proportion of respondents with VET by NACE1 Industry (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

In Figure 7, we show the incidence of vocational education by field of study[8]. Over 70 percent of graduates from engineering and health and welfare indicate that they have a vocational qualification. This compares to less than 40 percent of graduates from arts and humanities.

Figure 7: Proportion of respondents with VET by Field of Education (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

[8] Field of education is recorded for those with upper-secondary education or higher

3.5 Empirical strategy

We investigate the determinants of vocational choice by estimating the following probit model using data from the second wave of the ESJS (2021),

$$\Pr\left(Vocational_i = 1 | X_i\right) = \Phi\left(\alpha + I_i{}'\beta + R_i{}'\gamma + \sum_{\tau=2}^{25} \theta_\tau C_i^\tau\right) \quad (5)$$

Where our dependent variable, $Vocational_i$ equals one if employee i reports that their highest level of education they completed was vocational, and zero otherwise. Regional characteristics including regional GDP per capita and total/youth unemployment rates are captured in vector R and individual characteristics are in vector I, while α is the intercept term. We also include dummy variables for each of the 25 countries used in the analysis, with $C_{i\tau}$ indicating whether individual i is employed in country τ.

We then investigate the effects of VET completion on labour market outcomes. First, we estimate the effects of vocational education on monthly earnings using the following linear regression model,

$$\mathrm{Ln}(wage_i) = \alpha + \delta Vocational_i + I_i{}'\beta + E_i{}'\gamma + \sum_{\tau=2}^{25} \theta_\tau C_i^\tau \quad (6)$$

Where our dependent variable is the natural log of monthly wage (in Euros). We include a dummy variable for vocational education, while other individual characteristics are collected in vector I and employment characteristics are present in vector E. The intercept term is denoted by α and we again control for country fixed effects.

Finally, we analyse the determinants of job satisfaction. Job satisfaction is measured on an ordinal scale from 0 to 10, where higher values correspond to greater satisfaction. In line with previous research, we categorise those who are job satisfied and those who are not satisfied into two separate groups. This allows us to estimate a binary probit model in the same vein as equation (1), where this time, our dependent variable is a dummy variable that is equal to one if an employee has a job satisfaction score of 6 out of 10 or above, and zero otherwise. Different aspects of job satisfaction are recorded in the 2nd wave of the ESJS. Aside from overall job satisfaction, job satisfaction in relation to the following job characteristics is also available: job security; career prospects; work-life balance; training provided. Thus, we include a separate specification for the effect of vocational education on each measure of job satisfaction and estimate the effects with the following probit model,

$$\Pr\,(Satisfied_i = 1|X_i) = \ \Phi(\alpha + \delta VET_i + I_i{}'\beta + R_i{}'\gamma + \textstyle\sum_{\tau=2}^{25} \theta_\tau C_i^\tau) \qquad (7)$$

3.6 Results

3.6.1 Determinants of Vocational choice

Table 9 presents regression coefficients from estimating model 4 specified in the previous section. Results from several specifications are presented, as we include different versions of regional GDP per capita and regional unemployment. Columns (1) – (4) include the full sample, while in columns (5) and (6) the sample is limited to people who indicated in the survey that they left education within the last 10 years. This is to capture potential differences in older versus younger graduating cohorts.

Vocational graduates tend to be older than graduates of general educational programmes, with the effect being stronger for more recent graduates. There is no significant difference between genders when it comes to their likelihood of completing VET for the full sample. However, when limiting the sample to employees that graduated from education within the last ten years, women are five percentage points more likely to choose vocational education than men. This is likely related to the large proportion of female VET graduates from health & welfare related programmes. Urbanisation is negatively associated with VET choice, as measured by the indicator variable denoting whether a person lives in a town or city. Those living in large towns or cities are five percentage points less likely to complete vocational education relative to those in rural areas.

Table 9: Determinants of Vocational choice

	(1)	(2)	(3)	(4)	(5)	(6)

VARIABLES						
Age at graduation	0.002***	0.003***	0.003***	0.002***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender (Male)	0.002	0.001	0.002	0.001	-0.049***	-0.050***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.014)
Area of Residence (Ref: Rural)						
Small/medium town	-0.017*	-0.017*	-0.017*	-0.017*	-0.021	-0.022
	(0.010)	(0.010)	(0.010)	(0.010)	(0.020)	(0.020)
Large town/city	-0.050***	-0.052***	-0.050***	-0.050***	-0.053***	-0.055***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.020)	(0.020)
GDP/cap (PPS €10,000s) (2020)	-0.015***	-0.013***				
	(0.004)	(0.005)				
GDP/cap (PPS €10,000s) (2011-2020 mean)			-0.017***	-0.017***	-0.021**	-0.018*
			(0.005)	(0.006)	(0.010)	(0.010)
Unemployment (15-74 y/o) (2020)	-0.003					
	(0.002)					
Unemployment (15-29 y/o) (2020)		-0.002				
		(0.001)				
Unemployment (15-74 y/o) (2011-2020 mean)			-0.002		-0.001	
			(0.002)		(0.003)	
Unemployment (15-29 y/o) (2011-2020 mean)				-0.001		0.000
				(0.001)		(0.002)
Limited to graduates from last 10 years	**NO**	**NO**	**NO**	**NO**	**YES**	**YES**
Country FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Observations	**25,012**	**23,975**	**25,114**	**25,090**	**6,688**	**6,683**

Note: Probit regression on vocational completion. Coefficients reported are marginal effects. Columns 5 and 6 are limited to graduates of the last 10 years. Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Focusing on regional characteristics, GDP per capita (measured as purchasing power standards in €10,000s) is a significant predictor of vocational choice, irrespective of the measure used for GDP (value of the year prior or the average of the previous 10 years). An increase of €10,000 in GDP per capita is associated with a 1.5 to 2 percentage point reduction in the likelihood of individuals completing a vocational qualification. This suggests that, as regions become more prosperous, the proportion of individuals choosing VET decreases. One possible mechanism is that university degrees are seen as more prestigious and valuable than apprenticeships and vocational accreditations, and therefore if people have the resources to attend university, they usually will (Lovšin, 2014; Winch, 2013). Of course, university courses generally have higher academic entry requirements than vocational courses, but regional level economic activity also determines schooling resources and thus will also be highly correlated with student performance (Wößmann, 2003; Hanushek and Woessmann, 2011). Unemployment remains insignificant across all specifications. Interestingly, magnitude of effect sizes is larger for the limited sample for all significant variables.

3.6.2 Wage effects of VET completion

Table 10 shows the effects of vocational education on the log of monthly earnings, with the effects for completion of vocational education highlighted in bold. The marginal effects of VET on wages, at various levels of education are shown in adjoining columns. Specification (1) applies the model (5) to the entire sample for which wage data is available, while specification (2) limits the sample to people who left education within 10 years of data collection. Across both specifications, industry, occupation, education and other important determinants are controlled for. The coefficient for Vocational represents the effect of Vocational education on wages overall, when controlling for individual ICSED2011 categories of education level. The marginal effects of each individual level of post-secondary education are also calculated using this specification. The marginal effects of upper-secondary education and aggregated post-secondary education are calculated based on a model where all post-secondary education levels are aggregated into a single variable.

Looking at the full sample, completion of vocational education is associated with a wage premium of 1.8 percent. When looking at the marginal effects at different levels of education, the only statistically significant effect is for PhD graduates.

Table 10: Marginal Effects of Vocational education on wages across education levels

Dependent variable: **log (monthly wages)** VARIABLES	**(1)**	**(2)**
Vocational	0.018**	-0.017
	(0.008)	(0.016)
Marginal effects of VET at:		
Upper-secondary	0.008	-0.024
	(0.014)	(0.036)
Post-secondary	0.006	-0.026
	(0.010)	(0.018)
- Non-tertiary	0.001	-0.070
	(0.023)	(0.058)
- Short-cycle tertiary	0.052	-0.049
	(0.033)	(0.064)
- Bachelors	0.021	0.028
	(0.014)	(0.029)
- Masters	0.011	-0.026
	(0.015)	(0.028)
- PhD	0.193**	-0.015
	(0.088)	(0.094)
Employment/Education controls	**YES**	**YES**
Country FE	**YES**	**YES**
Limited to graduates from last 10 years	**NO**	**YES**
R-squared	**0.599**	**0.556**

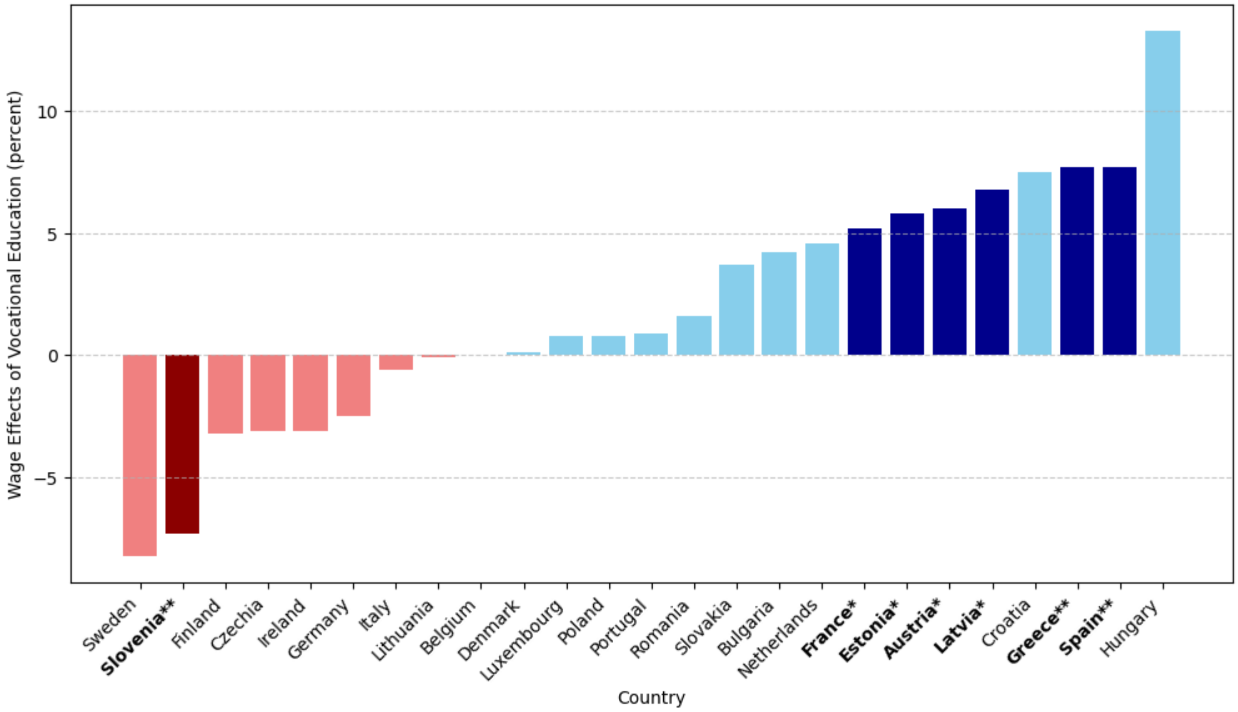
Note: OLS regression on log of monthly wages. Coefficients reported are for Vocational, but all necessary covariates are controlled for. Marginal effects of vocational education at different levels of education are shown underneath. Columns 1 and 2 include the full sample, while columns 3 and 4 are for employees who have completed their highest level less than 10 years before the time of data collection. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

When focusing on the sample that graduated in the last ten years (column 2), the wage effect is not statistically significant. It may be that recent graduates face a labour market shaped by technological change and automation, which may have reduced the relevance of many traditional vocational skills (OECD, 2020). Older workers, on the other hand, may have established their careers when their skills were in higher demand and have since advanced into stable, well-paying roles (Hanushek et al., 2017). It may also be that the degree to which employers favour the adaptability and broader competencies associated with academic qualifications, relative to those with a vocational qualification, has become more pronounced in recent years (Terrier et al., 2020).

We also present the wage effects of vocational education by country, in Figure 8. There is notable variation in wage effects across countries. We detect statistically significant wage effects in seven of the 25 countries. This ranges from a wage premium of 7.7% in Spain and Greece to a wage penalty of 7.3% in Slovenia.

Additionally, we present the effects of each additional level of education on wages for the pooled sample, this time differentiating by whether the education is vocational or general/academic in nature (Table 11). Compared to the reference category of lower secondary education completion, each corresponding education level (whether vocational or general in nature) is associated with a significant wage premium, with the size of the premium monotonically increasing with education level. Consistent with our previous findings, each vocational ISCED education level is similar to the wage premium associated with its general education counterpart, with the exception of short-cycle tertiary and PhD, where the vocational track is associated with a higher wage premium.

Figure 8: Wage effects of vocational education across countries



Source: European Skills and Jobs Survey. Authors' calculations. Countries with significant wage effects are in darker colours. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Wage effects by level and orientation of education

	(1)

VARIABLES	log (monthly wage)
Level and orientation of highest education (ref: Lower Secondary)	
Upper Secondary General	0.040*
	(0.020)
Upper Secondary Vocational	0.049***
	(0.018)
Post-secondary non-tertiary General	0.065**
	(0.026)
Post-secondary non-tertiary Vocational	0.067***
	(0.022)
Short-cycle tertiary General	0.112***
	(0.036)
Short-cycle tertiary Vocational	0.165***
	(0.022)
Bachelors General	0.192***
	(0.021)
Bachelors Vocational	0.212***
	(0.019)
Masters General	0.273***
	(0.021)
Masters Vocational	0.282***
	(0.021)
PhD General	0.296***
	(0.088)
PhD Vocational	0.486***
	(0.038)
Education and employment controls	**YES**
Country FE	**YES**
Observations	**29,605**
R-squared	**0.586**

Note: OLS regression on log of monthly wages. Coefficients reported are for different orientations and levels of education, but all necessary covariates are controlled for. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

3.6.3 Association between VET completion and Job Satisfaction

Table 12 presents regression results showing the association between vocational education and overall job satisfaction, as well as job satisfaction in relation to specific aspects of one's job (work-life balance, career prospects, training provided and job security). Marginal effects of vocational education at upper- and post-secondary level education are also presented. Again, there are separate specifications for the full sample and employees who graduated in the last ten years.

Vocational graduates are more likely to be happier in their job overall. Those with a vocational qualification are approximately 1.5 to 2.5 percentage points more likely to indicate they are satisfied in their job. Results are strongest for recent upper-secondary graduates. Looking at more specific aspects of job satisfaction, vocational graduates are more likely to be satisfied with their work-life balance for the full sample. Decomposing this further identifies that this result is entirely driven by graduates of post-secondary education. Upper secondary vocational graduates in the last ten years are marginally more likely to be more satisfied with their future career prospects, while there are no significant effects for 'training provided'. Vocational graduates are more likely to be satisfied with their job security, both in the overall sample and limiting our sample to graduates from the last ten years. This effect seems to be driven by graduates of post-secondary VET programmes rather than upper-secondary.

Differing levels of significance, directions, and magnitudes of results between recent graduates and the full sample, as well as between upper- and post-secondary graduates, likely illustrate how outcomes evolve over one's career and educational trajectory. For instance, in the full sample, vocational graduates experience a significant improvement in work-life balance compared to non-vocational graduates, while recent graduates do not. This may be due to similar demands placed on workers in entry-level vocational and general-oriented roles, with a gap emerging later in one's career as roles suited to general education graduates become more strenuous or demanding. Alternatively, this could reflect shifting labour market conditions that favour vocationally trained workers at different stages of their careers.

Post-secondary vocational graduates, rather than upper-secondary graduates, experience significant job security advantages, both in the full sample and among recent graduates. This could be due to the higher specialisation and advanced training associated with post-secondary vocational education, which may better align with industries offering stable, well-defined career paths. By contrast, upper-secondary vocational graduates may enter roles with less specialisation and higher exposure to sectors prone to economic fluctuations, resulting in comparatively less job security. This suggests that the level of vocational training plays a critical role in shaping labour market outcomes.

Table 12: Vocational education as a determinant of different aspects of job satisfaction (and marginal effects across education levels)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Overall Job Satisfaction		Work-life Balance		Career Prospects		Training Provided		Job Security	
Vocational	0.012**	0.023**	0.024***	0.015	0.003	-0.004	0.011	0.009	0.021***	0.027*
	(0.006)	(0.011)	(0.008)	(0.016)	(0.009)	(0.016)	(0.008)	(0.016)	(0.008)	(0.015)
Marginal effects of VET at:										
Upper-secondary	0.012	0.052**	0.013	0.027	0.008	0.055	0.003	0.053	0.008	0.010
	(0.010)	(0.024)	(0.014)	(0.037)	(0.015)	(0.038)	(0.015)	(0.039)	(0.013)	(0.036)
Post-secondary	0.012*	0.011	0.031***	0.011	0.000	-0.022	0.017*	-0.004	0.029***	0.032**
	(0.006)	(0.012)	(0.010)	(0.017)	(0.010)	(0.017)	(0.010)	(0.017)	(0.009)	(0.016)
Employment/Education controls	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Country FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Limited to graduates from last 10 years	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Observations	**19,306**	**4,868**	**19,306**	**4,876**	**19,310**	**4,879**	**19,310**	**4,876**	**19,310**	**4,876**

Note: Probit regression on Job satisfaction. Coefficients reported are marginal effects. Certain columns are limited to graduates of the last 10 years. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

3.7 Discussion

Our research on vocational education provides valuable insights into the incidence and determinants of vocational attainment in Europe, as well as its role in influencing labour market outcomes and job satisfaction. We find that completion of vocational education programmes is partly shaped by regional economic conditions, particularly GDP per capita, suggesting that prosperity discourages participation in vocational pathways. Our analysis of labour market outcomes reveals a marginally significant wage premium for vocational education graduates in the full sample, but this benefit is not observed for recent graduates. Notably, the wage premium seems to be driven by post-secondary non-tertiary vocational graduates and PhD vocational graduates, highlighting the importance of higher-level vocational qualifications for securing better wages. At the country level, there is variation in the wage effects. Seven of the 25 countries show a statistically significant effect – six countries show a wage premium associated with vocational education while one country shows a wage penalty.

When examining job satisfaction, we find that vocational graduates are generally more satisfied with their jobs, with post-secondary graduates benefiting from a better work-life balance and greater job security. These findings demonstrate that vocational education offers not only economic benefits but also improved job quality, particularly for those with post-secondary qualifications. Therefore, our research suggests that access to and participation in post-secondary vocational education could, for some individuals, lead to higher earnings and greater job satisfaction. Future research could further explore the long-term impacts of this progression to better understand its implications for career advancement and economic mobility.

4. CHAPTER 3: Dynamic Skill Change and Skill Deficits in the Labour Market: An Analysis using Online Job Vacancy Data

4.1 Introduction

In recent years, rapid digitalisation and the diffusion of disruptive emerging technologies have greatly accelerated the rate at which skill requirements evolve in the labour market. Rapid shifts in skill demand place an ever-increasing requirement on workers to up- or re-skill in order to secure competitive wages. As such, it is important for policymakers to monitor the demands of the labour market to accurately target education and training policy.

New data sources, specifically the use of large online job vacancy data, have emerged which help researchers identify the demand for specific skills in the labour market. We leverage the near-universe of online job vacancies in the EU-27 to estimate skills demand between 2019 and 2023 and measure the extent to which the skills demanded within occupations have changed over time. Specifically, our measure of dynamic skills change computes a separate skill change score for each 3-digit ISCO occupation for each EU country. Our measure of skills change within occupations is closely related to Deming and Noray (2020), who pioneered the use of large-scale job advertisement data to track shifts in skills demand. In essence, our measure compares the prevalence of specific skills between one year and another. The idea is that some jobs may experience little to no change in required skills over a specified period of time, while other jobs require an almost entirely new skillset.

By linking our skills change measure with survey data for EU employees, we show that employees within occupations with a rapidly changing skills profile are more likely to experience skill deficits. Our dynamic skills measure may, therefore, provide an early warning signal for identifying occupations likely to experience skills shortages and skill deficits. Moreover, our occupation and country-level dynamic skills measure, which we make freely available, should be a useful data source for further studies in this area.

A further contribution of our work relates to the impacts of employee training, and how this may mitigate negative consequences associated with a changing skills environment. Specifically, we explore the potential for on-the-job training to mitigate the extent to which workers experience underskilling in a dynamically changing occupation. Accepting that occupational skill change occurs, and that workers will not always be adequately skilled relative to their occupational requirements, firms may respond by investing in training in order to remedy employee underskilling. If training is appropriately targeted and sufficient in quality, it is possible to bridge the gap between new skill requirements and employee skills, in turn alleviating underskilling. Our results indicate that the provision of on-the-job training to employees in rapidly changing jobs lowers the likelihood of skills deficits.

By linking dynamic skill change to skills deficits, our work also makes an important contribution to the literature on skills mismatch. Skill deficits, which are often referred to as 'underskilling' in the literature, refers to a condition where workers feel that their current skillset falls short of what is required to perform their job effectively, captured through self-reported survey responses (McGuinness et al., 2018). While overskilling (in which workers possess skills beyond what their job requires) has been widely studied, underskilling remains relatively understudied both in terms of its incidence and its economic impact. Across Europe, national estimates of underskilling vary significantly, ranging from less than 2% in Croatia to over 50% in Portugal (McGuinness et al., 2018; Sanchez-Sanchez & McGuinness, 2015; Livanos and Nunez, 2015; Quintini, 2011). It has been noted in the literature that underskilling is generally less common than overskilling in Europe, which may partially explain the dearth of research examining the phenomenon in Europe. However, while it may be less prevalent than overskilling, recent studies have highlighted serious consequences associated with underskilling. Kampelmann and Rycx (2012) and Mahy et al. (2015) show that an undereducated workforce negatively impacts on a firm's productivity. Kampelmann et al. (2020) find similar effects when looking at firm profits, with bottom lines of firms being negatively impacted by an undereducated workforce. Therefore, understanding these types of skill deficits is clearly important.

Underskilling has also been shown to have consequences for employees. Data from the European Skills and Jobs Survey indicates that workers whose skills are well-matched to their jobs experience better labour outcomes (in terms of wages, employment or job satisfaction) compared to both underskilled and overskilled workers (Cedefop, 2018). Furthermore, 33% of underskilled employees believe their skills will become obsolete in the near future, which may fuel anxiety about job loss.

4.2 Data and Descriptive Statistics

In this section, we outline the data sources and methods used to measure changing skill requirements, underskilling and training. We first discuss how we measure changing occupational skill requirements using online job vacancy data. We then outline how we characterise underskilling and training using survey data. Descriptive statistics for all measures are provided throughout.

4.2.1 Changing Skill Requirements: Lightcast Data

We use data from Lightcast (formerly Burning Glass Technologies) to estimate a measure of changing skill requirements. Lightcast collects vacancy data from a huge variety of online job postings billboards and websites, and parses information into ready-to-use, organised variables such as job title, occupation category, industry, salary, location, date of the posting, and education/experience/skill requirements. We focus on job postings from 2019 and 2023. We choose 2019 as our base year as it represents the earliest year for which there is a sufficient volume of vacancy data available to conduct meaningful analysis, and 2023 as our end year as it is the latest complete year of data at the time of writing. Table 13 shows the number of job postings by country in each year.

The cross-national distribution of vacancies is generally in line with the population of each country. However, there is a substantial jump between years. In total, there are 15,373,250 job postings in 2019 and 39,180,516 in 2023. This jump may be attributed to several factors. First, Lightcast's algorithm for scraping vacancies has become more sophisticated over time, expanding its reach to include vacancies posted on an increasing number of portals. Second, labour demand naturally fluctuates between years. Third, companies may be more likely to use online job portals in 2023 when compared to 2019 (i.e. due to hiring norms). Finally, population growth may partially explain the difference between years.

Table 13: Number of Vacancies by Country

	Vacancies	
Country	2019	2023
Austria	554,082	880,062
Belgium	616,329	2,335,774
Bulgaria	128,142	164,216
Cyprus	10,988	12,527
Czechia	243,740	430,421
Germany	6,422,733	8,697,191
Denmark	52,132	587,259
Estonia	30,605	31,082
Greece	22,336	103,248
Spain	944,212	1,289,819
Finland	61,133	120,753
France	2,674,887	12,180,200
Croatia	45,277	168,676
Hungary	79,322	422,787
Ireland	318,050	712,780
Italy	1,007,406	3,525,488
Liechtenstein	1,473	4,026
Lithuania	63,605	67,897
Luxembourg	42,855	58,615
Latvia	50,838	64,901
Malta	6,264	23,376
Netherlands	550,203	2,825,843
Norway	34,425	261,693
Poland	272,885	1,256,142
Portugal	129,331	582,420
Romania	185,621	384,233
Sweden	703,047	1,832,150
Slovenia	28,229	66,486
Slovakia	93,100	90,451
Total	**15,373,250**	**39,180,516**

Source: Lightcast Job Advertisement data. Authors' calculations.

We include the occupational distribution of online job vacancies in the appendix (Table 1A). Postings are concentrated in what could be considered more highly skilled, professional occupations. It is noted in the literature that certain occupations are inaccurately represented in the Lightcast data (Vermeulen and Amaros, 2024; Cammeraat and Squicciarini, 2021). Specifically, agricultural workers may be underrepresented in online job vacancies, while more professional occupations (e.g. managers, technicians, professionals) may be comparatively overrepresented. Since the calculation of the skill change measure is conducted at the ISCO 3-Digit level and is only derived from information relating to that specific occupation (i.e. does not depend on the occupation's relative incidence regarding other occupations), this is not a concern for our study.

Skills

Lightcast categorises skills (derived from vacancy descriptions) according to the European Skills, Competences, Qualifications and Occupations (ESCO) skills taxonomy[9]. At the broadest level, skills can be grouped into six different subcategories: 'Hard Skills', 'Application of Knowledge', 'Thinking', 'Social Interaction', 'Attitudes and Values', and 'Language'. While all these categories reflect various dimensions of job requirements, not all are equally relevant when measuring the specific skill demands of particular roles or occupations. For the purpose of capturing occupation-specific skills, we concentrate on 'Hard Skills'. This category was chosen because it represents the most direct and measurable aspects of job-specific capabilities that are tied to particular roles. 'Hard Skills' generally refer to technical abilities or knowledge required to perform certain tasks or operate particular tools and technologies, which are usually unique to certain occupations.

In contrast, other categories like 'Application of Knowledge', 'Thinking', 'Social Interaction', 'Languages', and 'Attitudes and Values' encompass more universal skills that are applicable across a

[9] The ESCO skills taxonomy is part of the European Skills, Competences, Qualifications and Occupations (ESCO) classification system, developed by the European Commission. It categorises and standardises skills, competences, and qualifications to improve transparency, comparability, and mobility across European labour markets and education systems. See https://esco.ec.europa.eu/en/classification

wide range of occupations. While these are important for overall employability, they do not provide a focused view of the specific competencies that differentiate one occupation from another. Therefore, they are excluded from this analysis to ensure the results reflect a clearer picture of the unique skill demands associated with different jobs.

In total, 2,967 unique hard skills appear in job vacancies across both years. Table 14 shows the top twenty skills demanded in each year, by proportion of job ads that they appear in. As expected, these are generally a mixture of basic digital skills (e.g. "have computer literacy", "use microsoft office") and transversal skills that might be consistent with a professional position (e.g. "think proactively", "communication", "problem solving"). This is consistent with the occupational profile of online job vacancies listed previously.

We also examine skills that have increased in importance over time (with regard to the proportion of total job advertisements they appear in) and conversely, skills that appear less important (Table 15). The top twenty skills by demand share growth and decline across the EU-27 are listed Table 15 below. Interestingly, the majority of the skills that grew significantly are considered to be transversal/social skills (e.g. "brainstorm ideas", "think proactively", "think analytically"). That said, general technical skills also feature ("perform data analysis", "Analysing data or information", "use CAE software"). On top of this, most of the skills that exhibited relatively sizeable declines in their demand shares are more technical in nature (e.g. "excel", "Use communication and collaboration software", "administer ICT system").

Table 14: Top ESCO LEVEL 3 skills by proportion of Job ads they appear in

	2019		2023	
Rank	ESCO Level 3 Skill	Percentage of total ads	ESCO Level 3 Skill	Percentage of total ads
1	*have computer literacy*	36.05%	*have computer literacy*	33.84%
2	*use microsoft office*	22.96%	*use microsoft office*	20.95%
3	*problem solving*	16.30%	*think proactively*	18.69%
4	*customer service*	14.64%	*problem solving*	16.18%
5	*think proactively*	14.47%	*communication*	15.04%
6	*office software*	14.23%	*use office systems*	14.65%
7	*communication*	13.37%	*customer service*	13.17%
8	*project management*	12.69%	*office software*	12.98%
9	*use office systems*	12.69%	*brainstorm ideas*	12.46%
10	*use spreadsheets software*	10.19%	*project management*	10.91%
11	*use communication and collaboration software*	8.65%	*quality standards*	10.62%
12	*computer programming*	7.94%	*use spreadsheets software*	9.88%
13	*brainstorm ideas*	7.82%	*tolerate stress*	8.22%
14	*quality standards*	7.71%	*think analytically*	7.73%
15	*excel*	7.56%	*database*	7.72%
16	*office administration*	7.32%	*proactivity*	7.41%
17	*sales activities*	6.78%	*develop animations*	7.06%
18	*economics*	6.05%	*customer relationship management*	6.52%
19	*business ICT systems*	5.99%	*sales strategies*	6.35%
20	*sales strategies*	5.84%	*office administration*	6.19%

Source: Lightcast Job Advertisement data. Authors' calculations.

Table 15: Top ESCO LEVEL 3 Skills by Proportion of Vacancies

Source: Lightcast Job Advertisement data. Authors' calculations.

Most Growing Skills		**Most Declining Skills**	
Skill	ΔPrevalence (2019-2023)	Skill	ΔPrevalence (2019-2023)
develop animations	5.47%	*use communication and collaboration software*	-7.34%
brainstorm ideas	4.64%	*excel*	-3.86%
think proactively	4.22%	*administer ICT system*	-3.16%
proactivity	3.42%	*use communication techniques*	-2.45%
sell products	3.41%	*manage data, information and digital content*	-2.28%
think analytically	3.32%	*have computer literacy*	-2.21%
Getting Information	2.96%	*web programming*	-2.21%
quality standards	2.91%	*computer programming*	-2.19%
sell services	2.85%	*use microsoft office*	-2.01%
perform data analysis	2.58%	*ABAP*	-1.95%
tolerate stress	2.42%	*consultation*	-1.95%
plan	2.38%	*project management*	-1.78%
Analyzing Data or Information	2.20%	*precision measuring instruments*	-1.63%
use CAE software	2.07%	*use software design patterns*	-1.53%
recruit employees	1.98%	*object-oriented modelling*	-1.51%
use office systems	1.95%	*customer service*	-1.47%
database	1.89%	*business ICT systems*	-1.46%
customer relationship management	1.85%	*financial products*	-1.40%
Guiding, Directing, and Motivating Subordinates	1.80%	*CSS*	-1.30%
Handling and Moving Objects	1.74%	*economics*	-1.29%

The magnitude of skills demand differs by occupation, with certain jobs requiring more skills than others. The top twenty most skill-intensive occupations (i.e. those that have the highest average number of skills per ad) in both 2019 and 2023 are shown in Figures 8 and 9 below. In both years, occupations in the ICT sector have the highest skill requirements.

Figure 8: Average Skills Per-Vacancy (2019-2023, Top Ten 2023)

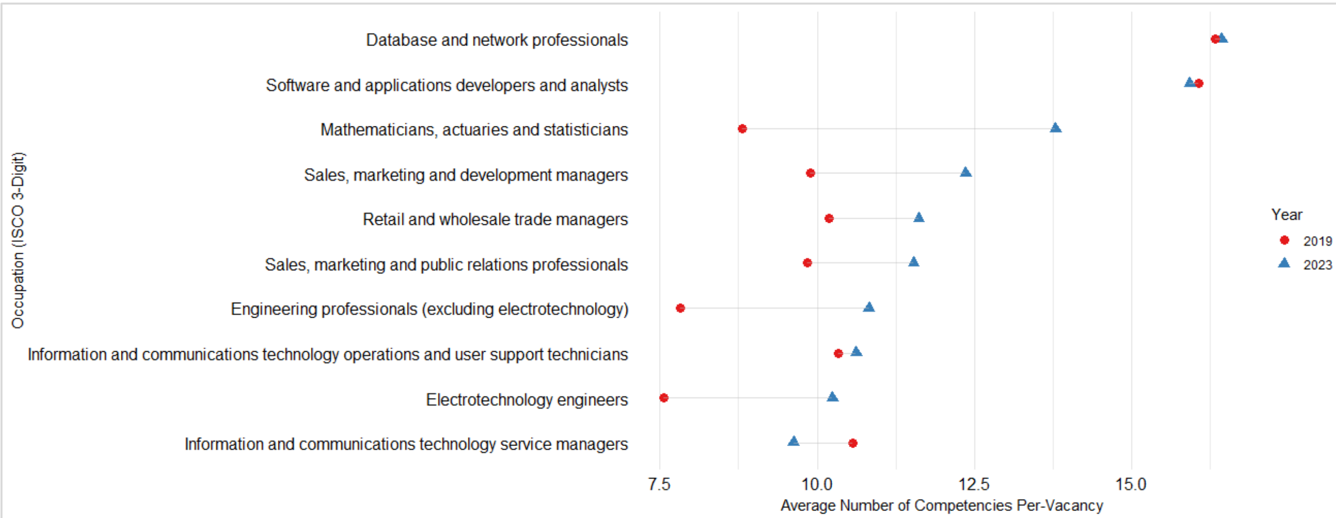
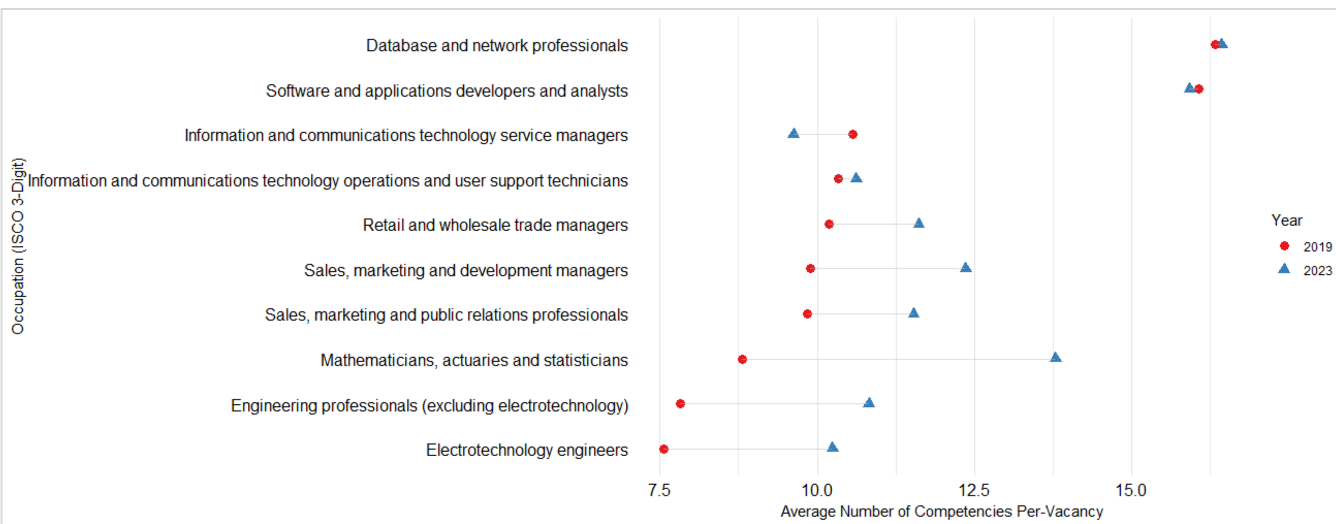


Figure 9: Average Skills Per-Vacancy (2019-2023, Top Ten 2019)



Source: Lightcast Job Advertisement data. Authors' calculations.

4.2.2 Measuring Changing Skill Requirements

We estimate a measure of skill change over time for each ISCO 3-Digit occupation in each EU country using the Lightcast data. We examine changes in skills in EU-27 countries between 2019 and 2023.[10] The measure is based on previous work by Deming and Noray (2020) and is formalised in equation (8) below.

$$SkillChange_{o,c} = \sum_{s=1}^{S} \left\{ Abs \left[\left(\frac{Skill_{o,c}^{s}}{Vacancies_{o,c}} \right)_{2023} - \left(\frac{Skill_{o,c}^{s}}{Vacancies_{o,c}} \right)_{2019} \right] \right\} \quad (8)$$

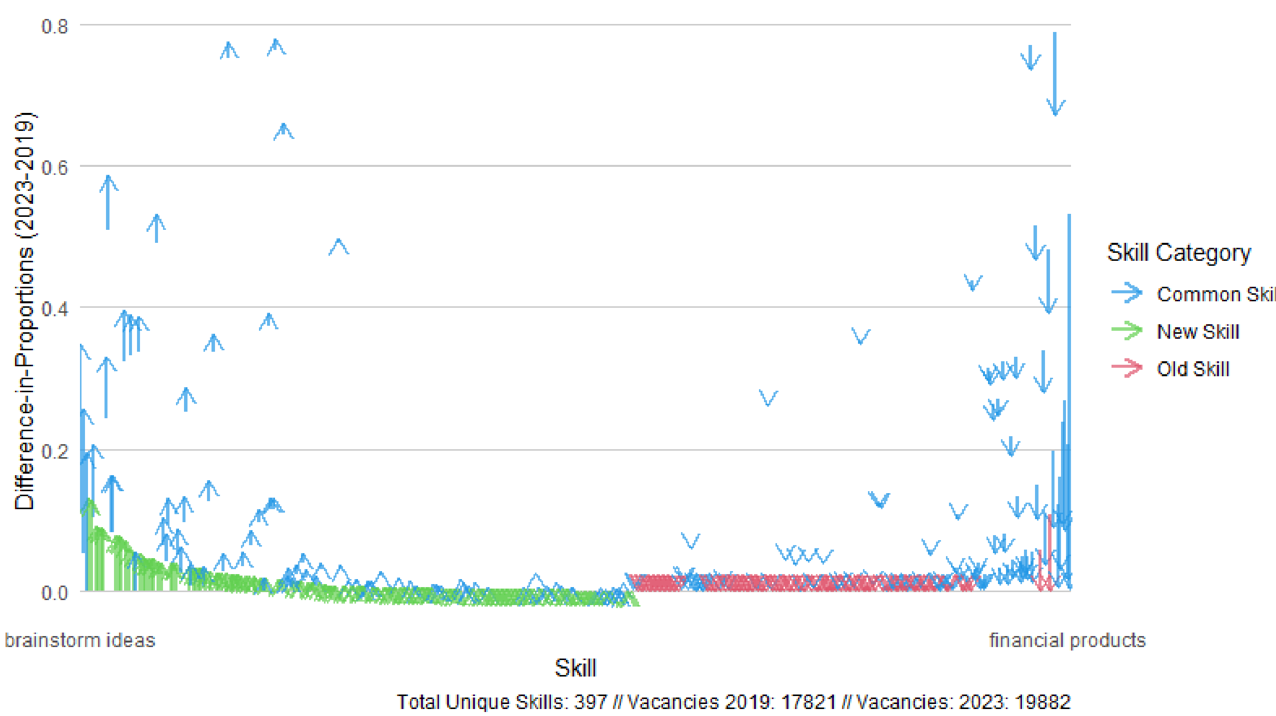
Where $Skill$ is the number of times skill s appears in vacancies posted in a given occupation o and country c ($Vacancies_{o,c}$). Put simply, $\frac{Skill_{o,c}^{s}}{Vacancies_{o,c}}$ represents the prevalence of the skill in question in the given year, occupation and country. For example, suppose there were thirty vacancies for Software Developers in Ireland in 2019, and five in 2023. If the skill "Python" was present in zero of the five vacancies for Software Developers in Ireland in 2023, but was present in ten of the thirty vacancies in 2019, this gives the absolute difference-in-proportions of |0 – 0.3| = 0.3 (or 30%). We calculate absolute differences in proportions for all skills and aggregate changes in skill popularity for each country and occupation, giving us a measure of overall changes in skill requirements over time for jobs in countries.

To further illustrate how this measure works, we graph the difference-in-proportions for all skills in the occupational category 'Finance Professionals' in Ireland between 2019 and 2023 (Figure 10). On the x-axis, each skill is included, ordered by the size of the simple difference in proportions, with higher values on the left, and lower values on the right. We only include axis labels for the largest positive and negative values for brevity, with 'brainstorm ideas' showing the most growth and

[10] We select these years as they represent the years that are furthest apart within the data for which there is adequate data coverage for all EU-27 countries

'financial products' showing the largest decline. The starting point of each arrow is the prevalence of the corresponding skill in 2019, with the end point representing the prevalence in 2023. In other words, longer arrows contribute greater values to the final $SkillChange$ figure for this occupational category/country. Green arrows indicate that the skill in question is a completely new skill relative to the base year (i.e. was not present in 2019, but was present in 2023), and red arrows represent the opposite case. Blue arrows refer to skills that are present in both years.

Figure 10: Difference-in-Proportions (Finance Professionals, Ireland)



Source: Lightcast Job Advertisement data. Authors' calculations.

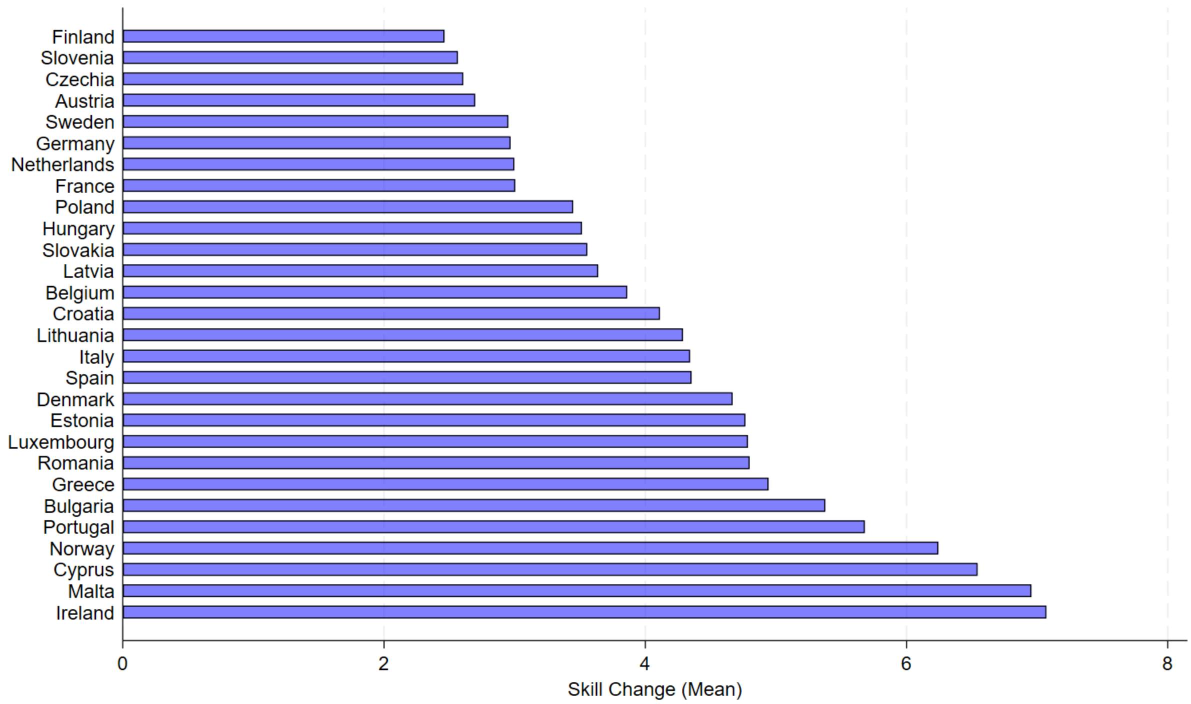
In this case, we note that the majority of skill changes arise from skills that are present in both 2019 and 2023 (as indicated by the concentrations of long, blue arrows on either side of the graph). There are also a number of new skills of moderate importance, while complete skill obsolescence (red arrows) plays less of a role in the overall $SkillChange$ value. The skill with the largest positive proportional change was "brainstorm ideas", rising from being present in just over 10 percent of vacancies in 2019 to 35 percent in 2023. In contrast, "financial products" fell from being present in

53 percent of vacancies in 2019 to less than one percent in 2023. Since our measure of skill change is agnostic to the direction of change (i.e. whether a skill becomes more or less important), both of these skills will contribute relatively heavily toward the final $SkillChange$ figure for Finance Professionals in Ireland.

In this case, we note that the majority of skill changes arise from skills that are present in both 2019 and 2023 (as indicated by the concentrations of long, blue arrows on either side of the graph). There are also a number of new skills of moderate importance, while complete skill obsolescence (red arrows) plays less of a role in the overall $SkillChange$ value. The skill with the largest positive proportional change was "brainstorm ideas", rising from being present in just over 10 percent of vacancies in 2019 to 35 percent in 2023. In contrast, "financial products" fell from being present in 53 percent of vacancies in 2019 to less than one percent in 2023. Since our measure of skill change is agnostic to the direction of change (i.e. whether a skill becomes more or less important), both of these skills will contribute relatively heavily toward the final $SkillChange$ figure for Finance Professionals in Ireland.

We calculate $SkillChange$ for all country/occupation combinations. By taking an average of our occupation level measures within each country, we can graph the average value of $SkillChange$ for each EU-27 country (Figure 11 overleaf). On average, occupations in Ireland exhibit the highest levels of skill change across time, while those in Finland experience the least change, on average.

Figure 11: Average Skill Change Values (EU-27)[11]



Source: Lightcast Job Advertisement data. Authors' calculations.

In Table 16, we show the country-occupation combinations with the highest values of $SkillChange$. The vast majority of the top occupations are associated with digital/technical competencies (e.g. Software and Applications Developers and Analysts, Database and Network Professionals, Engineering Professionals). Aside from these, we note the presence of several largely non-digital occupations, namely Legislators and Senior Officials (Ireland), Mining and Mineral Processing Plant Operators (Ireland), Refuse Workers (Croatia), Administrative and Specialised Secretaries (Malta) and Retail and Wholesale Trade Managers (Bulgaria). When examining these specific categories, we note that these values are generally equally driven by combinations of the emergence of new, important (i.e. high prevalence) skills and obsolescence of previously important skills. One

[11] These figures are the average $SkillChange$ values calculated from the linked Lightcast/ESJS data.

exception to this appears to be Refuse Workers in Croatia, where obsolescence of previously important skills predominantly drives the high value of $SkillChange$.

Table 16: Top Occupations/Countries with Changing Skill Requirements (2019-2023)

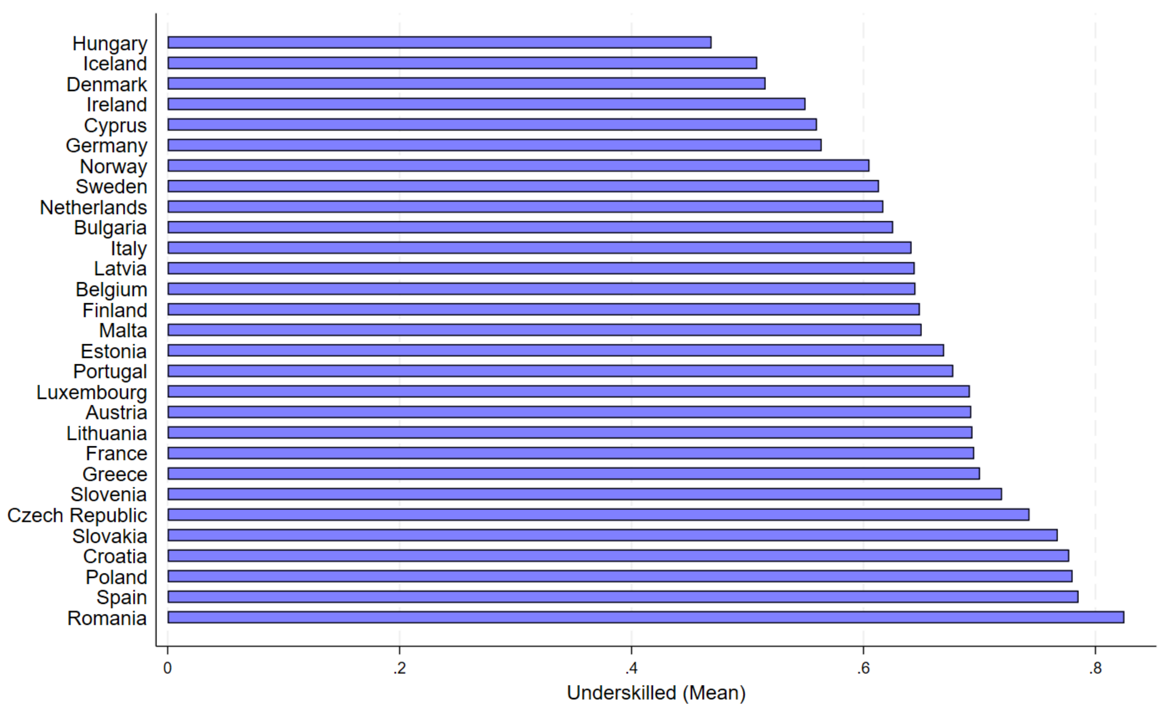
Country	ISCO 3-Digit Occupation	SkillChange
BG	*Software and applications developers and analysts*	17.36
IE	*Legislators and senior officials*	16.92
BG	*Database and network professionals*	15.39
IE	*Mining and mineral processing plant operators*	14.47
HR	*Refuse workers*	14.43
CY	*Software and applications developers and analysts*	14.39
PT	*Database and network professionals*	14.30
ES	*Database and network professionals*	13.78
EE	*Software and applications developers and analysts*	13.28
MT	*Administrative and specialised secretaries*	13.05
PT	*Software and applications developers and analysts*	12.65
LT	*Database and network professionals*	12.57
EL	*Software and applications developers and analysts*	12.46
LT	*Software and applications developers and analysts*	12.09
MT	*Software and applications developers and analysts*	11.97
IE	*Database and network professionals*	11.52
PT	*Engineering professionals (excluding electrotechnology)*	11.35
EL	*Engineering professionals (excluding electrotechnology)*	11.31
BG	*Retail and wholesale trade managers*	11.20
EE	*Engineering professionals (excluding electrotechnology)*	11.17

Source: Lightcast Job Advertisement data. Authors' calculations. Occupations/Countries Excluded where less than 500 vacancies were posted in either year.

4.2.3 Underskilling & Training

We derive a binary measure of underskilling ($Underskilled$) from 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?"* (Q63) in the ESJS. We consider a respondent to be underskilled if they responded, "Great extent" or "Moderate extent". This is simply modelled as a binary variable (i.e. equal to one if the respondent is underskilled, and zero if not). Figure 12 shows the incidence of underskilling by country. Underskilling ranges from just under 45 percent in Hungary to approximately 80% in Romania.

Figure 12: Proportion of underskilled employees by country (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

Table 17 contains the incidence of underskilling among European employees by ISCO 2-Digit Occupation. Underskilling is most prevalent among occupations requiring more cognitive or technical competencies (e.g. professionals, ICT workers, technicians) and least prevalent among occupations associated with more manual tasks (e.g. farmers, services workers, cleaners).

Table 17: Top 20 Underskilled Occupations (ISCO 2-Digit Occupation)

ISCO 2-Digit Category	N	% Underskilled
Information and communications technology professionals	1,789	77.8%
Information and communications technicians	860	77.6%
Science and engineering professionals	1,767	75.8%
Teaching professionals	3,612	74.3%
Electrical and electronic trades workers	646	73.1%
Health professionals	1,539	73.0%
Business and administration professionals	2,668	72.7%
Chief executives, senior officials and legislators	567	72.6%
Production and specialised services managers	2,178	70.5%
Administrative and commercial managers	1,813	69.9%
Legal, social and cultural professionals	1,520	69.7%
Health associate professionals	730	69.5%
Science and engineering associate professionals	984	67.9%
Legal, social, cultural and related associate professionals	596	67.7%
Hospitality, retail and other services managers	709	67.0%
General and keyboard clerks	2,142	66.8%
Business and administration associate professionals	3,817	66.7%
Numerical and material recording clerks	1,628	65.9%
Assemblers	327	64.4%
Metal, machinery and related trades workers	842	64.1%

Source: European Skills and Jobs Survey. Authors' calculations.

To measure training, we make use of the variable *E_TRAIND* in the ESJS, which is a binary variable that denotes whether or not respondents reported having undergone training for work in the past twelve months. Training can consist of courses, workshops, seminars or on-the-job training. We note that the occupational distribution of training receipt is similar to the occupational distribution of underskilling, in that professional occupations were more likely to receive training as compared to jobs with a more manual focus (see Table 18 overleaf).

Table 18: Top 20 Occupations by Training Incidence (ISCO 2-Digit Occupation; ESJS)

ISCO 2-Digit Category	N	% Trained
Teaching professionals	3,612	82.2%
Health professionals	1,539	79.5%
Chief executives, senior officials and legislators	567	76.5%
Administrative and commercial managers	1,813	73.6%
Production and specialised services managers	2,178	73.1%
Information and communications technicians	860	72.6%
Science and engineering professionals	1,767	71.4%
Business and administration professionals	2,668	71.4%
Information and communications technology professionals	1,789	71.3%
Health associate professionals	730	71.0%
Legal, social and cultural professionals	1,520	70.4%
Commissioned armed forces officers	57	70.2%
Science and engineering associate professionals	984	67.9%
Hospitality, retail and other services managers	709	66.9%
Armed forces occupations, other ranks	53	64.2%
Legal, social, cultural and related associate professionals	596	63.9%
Protective services workers	824	63.1%
Customer services clerks	1,763	63.0%
Personal care workers	1,635	61.2%
Business and administration associate professionals	3,817	60.6%

Source: European Skills and Jobs Survey. Authors' calculations.

Descriptively, we identify a discrepancy in the incidence of underskilling between those who receive training and those who do not. Specifically, the cohort that received training (of any kind) exhibit a substantially higher incidence of self-reported underskilling (approximately 77 percent) when compared to those who did not receive training (approximately 53%). It is likely that skill-intensive occupations require more training but may also increase the likelihood of self-reported underskilling due to the complexity of their skill requirements.

4.3 Empirical strategy

2.3.1 Identification Strategy

To examine the relationship between changing skill requirements, training and underskilling, we estimate the following probit model using data from the 2021 wave of the ESJS:

$$\Pr\left(Underskilled_{i,o,c} = 1 \middle| X_{i,o,c}\right) = \Phi\left(\alpha + \delta SkillChange_{i,o,c} + Z'_{i,o,c}\beta_z + \sum_{\tau=2}^{28} \theta_\tau C_i^\tau\right) \quad (9)$$

Where $Underskilled$ is a binary variable indicating whether employee i in occupation o and country c is underskilled. The variable $SkillChange$ captures the corresponding occupational skill change measure based on the occupation that employee i works in. The vector Z'_i includes demographic control variables at the employee level; gender (as a binary in which female status is equal to one), sector (at the NACE 1 level), tenure in current position (in years), hours worked (modelled as a dummy variable equal to one if the respondent worked part time), and education level (as a factor variable). We also include country dummy variables, denoted C_i^τ. The main coefficient of interest is δ, which captures the relationship between $SkillChange$ and the probability of that an employee is underskilled. To understand the role of training in the relationship between changing skill requirements and underskilling, we estimate this model for 1) the full cohort of respondents in the ESJS, 2) the cohort that received on-the-job training (of any kind) and 3) the cohort that did not receive any on-the-job training.

4.3.1 Results

Table 19 presents the probit model results based on equation (9). The analysis is conducted for three groups: the full sample, individuals who received some form of training within the past 12 months, and those who did not receive any training during the same period. The estimated coefficients for these groups are shown in Columns (1), (2), and (3), respectively.

In the full sample, we find a significant positive association between $SkillChange$ and underskilling. Specifically, a one-point increase in the value of $SkillChange$ – equivalent to one skill that was present for all jobs in one year and present in none in the other – is associated with a 1 percentage point increase in the likelihood of reporting underskilling. This suggests that changes in job-specific skill requirements contribute, at least in part, to the incidence of underskilling. In other words, workers whose jobs demand evolving skills are more likely to be underskilled if they cannot keep pace with these changes.

When we focus on the subsample of individuals who have received training, we still observe a significant relationship between underskilling and $SkillChange$, though the magnitude of the coefficient is considerably smaller. This finding implies that training plays a crucial role in alleviating the negative effects of job-specific skill change on underskilling.[12] Training may equip workers with the necessary tools to adapt more effectively to shifting skill demands in their jobs. Conversely, in the group of workers who have not received any training, the relationship between $SkillChange$ and underskilling is stronger. Workers in this category, particularly those in jobs with high skill change demands, are more likely to be underskilled than those in the full sample or the trained group. This highlights the importance of ongoing skill development in addressing underskilling. Overall, these results suggest that training may mitigate some of the adverse impact of changing skill

[12] To verify that the coefficients in the specifications in Columns 2 and 3 are statistically different from one another, we estimate an additional model in which we include $SkillChange$, a training dummy ($Trained$, equal to one if the respondent received training and zero otherwise) and an interaction term (i.e. $SkillChange \times Trained$) as independent variables, as well as the other covariates included in Equation 8. We find that the coefficient on the interaction term is negative and statistically significant ($\delta = -0.009$, $p < 0.01$). This verifies that the coefficient estimates that we observe in the sub-sampled models are statistically different from one another. Full estimates are available in the Appendix (Table 2A).

requirements on underskilling. In the absence of training, workers may be more vulnerable to falling behind in skill requirements as their jobs evolve.

Table 19: $SkillChange$ as a determinant of Underskilling

Outcome Variable: Underskilling	**(1)** *Full Sample*	**(2)** *Trained*	**(3)** *Not Trained*
SkillChange	**0.010*** **	**0.006*** **	**0.013*** **
	(0.001)	(0.001)	(0.002)
Female	-0.024***	-0.026***	-0.003
	(0.005)	(0.006)	(0.009)
Tenure	-0.001***	-0.001***	-0.001
	(0.000)	(0.000)	(0.000)
Part-Time	-0.045***	-0.023***	-0.058***
	(0.006)	(0.007)	(0.010)
Education (Ref: None/Primary/Lower-Secondary)			
Upper-/Post-secondary	0.044***	0.016	0.066***
	(0.009)	(0.011)	(0.013)
Tertiary	0.110***	0.062***	0.106***
	(0.009)	(0.012)	(0.014)
Industry controls	YES	YES	YES
Country FE	YES	YES	YES
Pseudo R-Squared	0.05	0.04	0.05
Observations	40,546	26,091	14,455

Note: Probit regression on underskilling. Coefficients reported are marginal effects. Columns (2) and (3) are limited to those who have received training in the last year and those who have not, respectively. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.4 Conclusions

In this paper, we sought to examine the relationship between changing skill requirements, underskilling and training. We first estimated occupation-specific skill change across European countries by analysing a large dataset of online job advertisements. We employed a measure of skill change to capture how the skill requirements of jobs have evolved over time and linked this measure to underskilling data obtained from a workforce survey. The goal was to understand whether changes in job-specific skill demands contribute to underskilling, and to explore the role of training in addressing this issue.

Occupations with a higher emphasis on digital/technical competencies exhibited higher levels of skill change over time. This is likely due to the skill diversity (i.e. complexity) associated with such positions. Our estimates suggest that higher levels of skill change were associated with an elevated likelihood of experiencing underskilling. Intuitively, this makes sense. While the data gives insight into the skill requirements imposed upon newly hired employees, it is reasonable to assume that these skill requirements apply (at least to some degree) to existing employees as well. As more new skills are required, the likelihood of employees not possessing adequate competency in such new skills increases. This is borne out empirically in the pooled model, represented by the positive associative relationship between skill change and the probability of underskilling.

Importantly, our findings highlight the critical role of training in mitigating the effects of skill change on underskilling. Those who had experienced training exhibited a lower likelihood of experiencing underskilling (as a result of greater skill changes) than those who had not received training. This suggests that training can insulate workers from the adverse impacts of large changes in occupational skill requirements and may supplement employees' human capital.

Overall, this research provides important insights into how changing skill demands influence underskilling in the workforce and demonstrates the value of training in addressing this challenge. The notable variation in the skill change measure across countries also raises important questions about the role of national labour markets, policies, and education systems in shaping occupational skill demands. Future research could explore these cross-country differences and investigate how specific national frameworks either facilitate or hinder worker adaptability to evolving job requirements.

In conclusion, as jobs continue to evolve, particularly in skill-intensive and highly technical fields, the need for continuous skill development becomes more pressing. Without effective training systems in place, workers are at risk of being left behind as job demands change. Addressing underskilling will require coordinated efforts from employers, policymakers, and educators to ensure that workers have access to the training and resources they need to stay current in their roles.

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Appendix

Table 1A: Proportion of Vacancies by ISCO 2-Digit Occupation

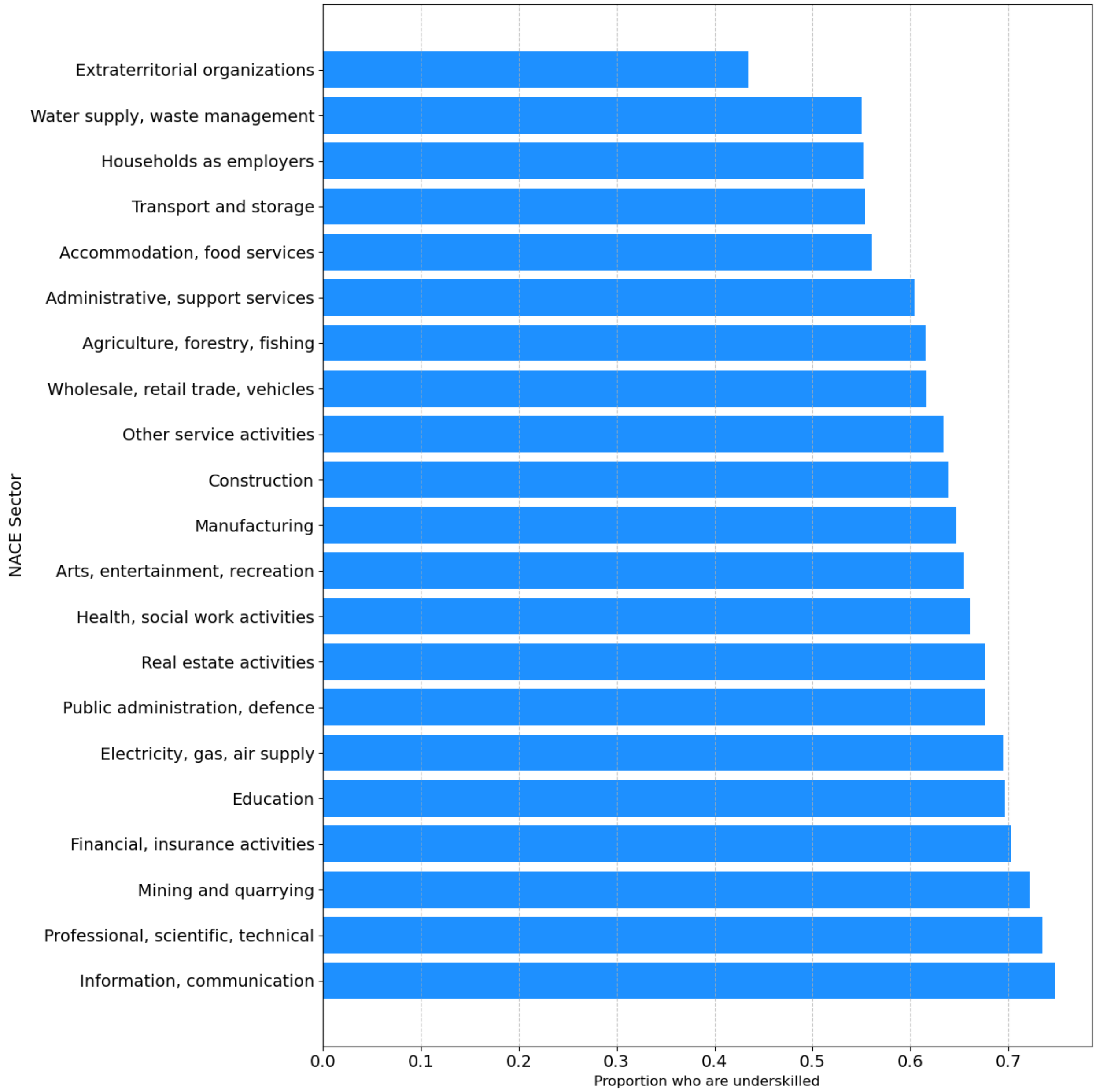
	2019		2023	
ISCO 2-Digit Occupation	**Vacancies**	**%**	**Vacancies**	**%**
Administrative and commercial managers	683,771	4.45%	1,946,352	4.97%
Agricultural, forestry and fishery labourers	33,815	0.22%	63,366	0.16%
Assemblers	193,286	1.26%	484,959	1.24%
Building and related trades workers, excluding electricians	249,347	1.62%	725,194	1.85%
Business and administration associate professionals	1,752,626	11.40%	3,617,707	9.23%
Business and administration professionals	1,194,573	7.77%	2,811,114	7.17%
Chief executives, senior officials and legislators	152,970	1.00%	241,525	0.62%
Cleaners and helpers	51,972	0.34%	445,362	1.14%
Customer services clerks	397,253	2.58%	945,336	2.41%
Drivers and mobile plant operators	244,057	1.59%	959,133	2.45%
Electrical and electronic trades workers	349,038	2.27%	905,136	2.31%
Food preparation assistants	49,851	0.32%	241,436	0.62%
Food processing, wood working, garment and other craft and related trades workers	145,882	0.95%	509,377	1.30%
General and keyboard clerks	295,913	1.92%	676,654	1.73%
Handicraft and printing workers	53,043	0.35%	79,418	0.20%
Health associate professionals	227,988	1.48%	740,866	1.89%
Health professionals	275,204	1.79%	956,266	2.44%
Hospitality, retail and other services managers	243,578	1.58%	507,779	1.30%

Continued on next page

Information and communications technicians	262,600	1.71%	382,377	0.98%
Information and communications technology professionals	1,548,710	10.07%	2,651,054	6.77%
Labourers in mining, construction, manufacturing and transport	428,629	2.79%	1,693,239	4.32%
Legal, social and cultural professionals	337,634	2.20%	826,182	2.11%
Legal, social, cultural and related associate professionals	283,782	1.85%	773,040	1.97%
Market-oriented skilled agricultural workers	24,542	0.16%	79,659	0.20%
Market-oriented skilled forestry, fishery and hunting workers	17,647	0.11%	4,576	0.01%
Metal, machinery and related trades workers	531,813	3.46%	1,516,372	3.87%
Numerical and material recording clerks	508,382	3.31%	1,518,188	3.87%
Other clerical support workers	320,243	2.08%	930,941	2.38%
Personal care workers	235,769	1.53%	835,900	2.13%
Personal service workers	464,299	3.02%	1,313,621	3.35%
Production and specialised services managers	313,420	2.04%	868,201	2.22%
Protective services workers	52,823	0.34%	225,598	0.58%
Refuse workers and other elementary workers	45,403	0.30%	160,465	0.41%
Sales workers	785,031	5.11%	2,419,646	6.18%
Science and engineering associate professionals	953,978	6.21%	2,148,677	5.48%
Science and engineering professionals	1,107,479	7.20%	2,329,461	5.95%
Stationary plant and machine operators	331,098	2.15%	1,033,367	2.64%
Street and related sales and service workers	2,855	0.02%	7,872	0.02%
Subsistence farmers, fishers, hunters and gatherers	0	0.00%	52	<0.01%
Teaching professionals	222,946	1.45%	605,048	1.54%
Total	**15,373,250**	**--**	**39,180,516**	**--**

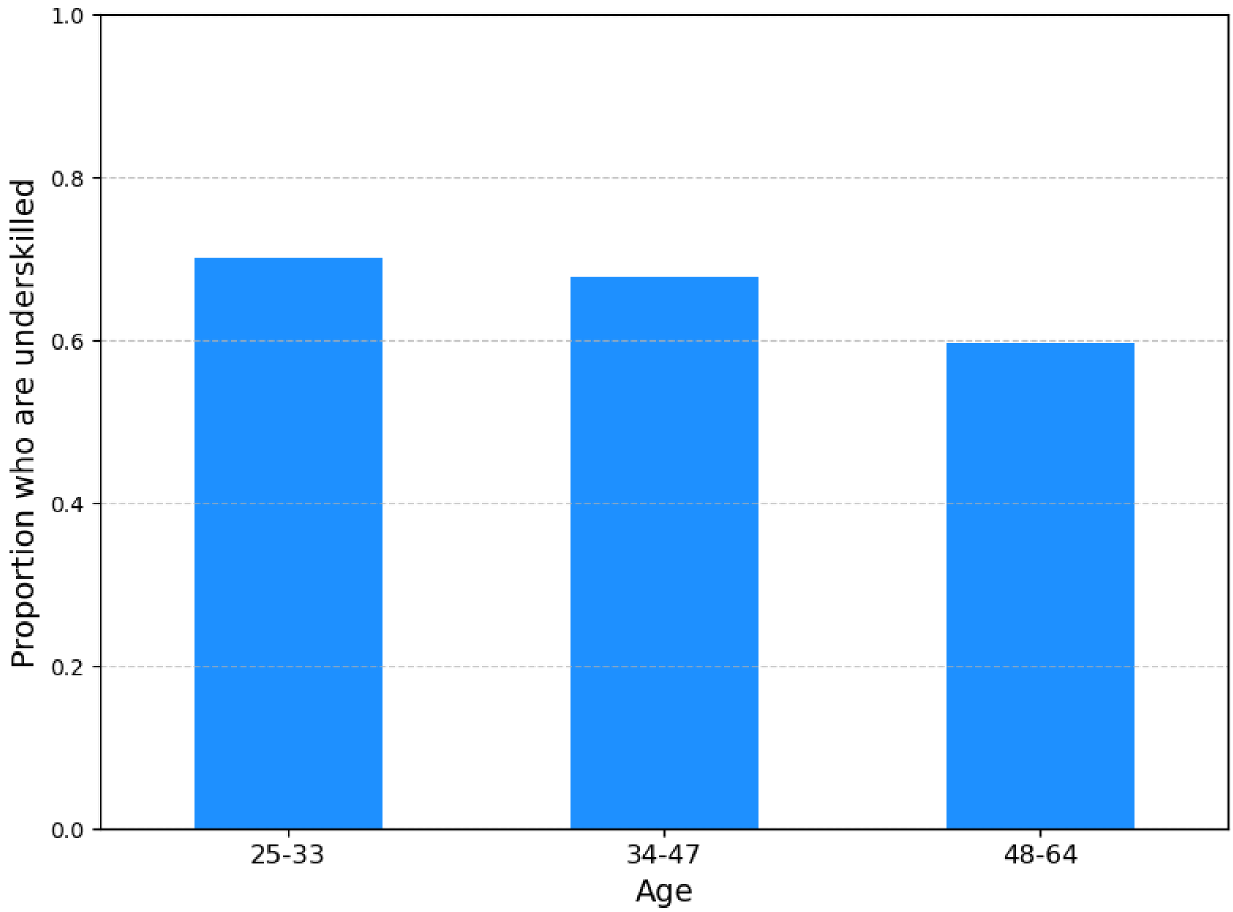
Source: Lightcast Job Advertisement data. Authors' calculations.

Figure 1A: Proportion of underskilled employees by NACE 1-Digit Industry (ESJS2021)



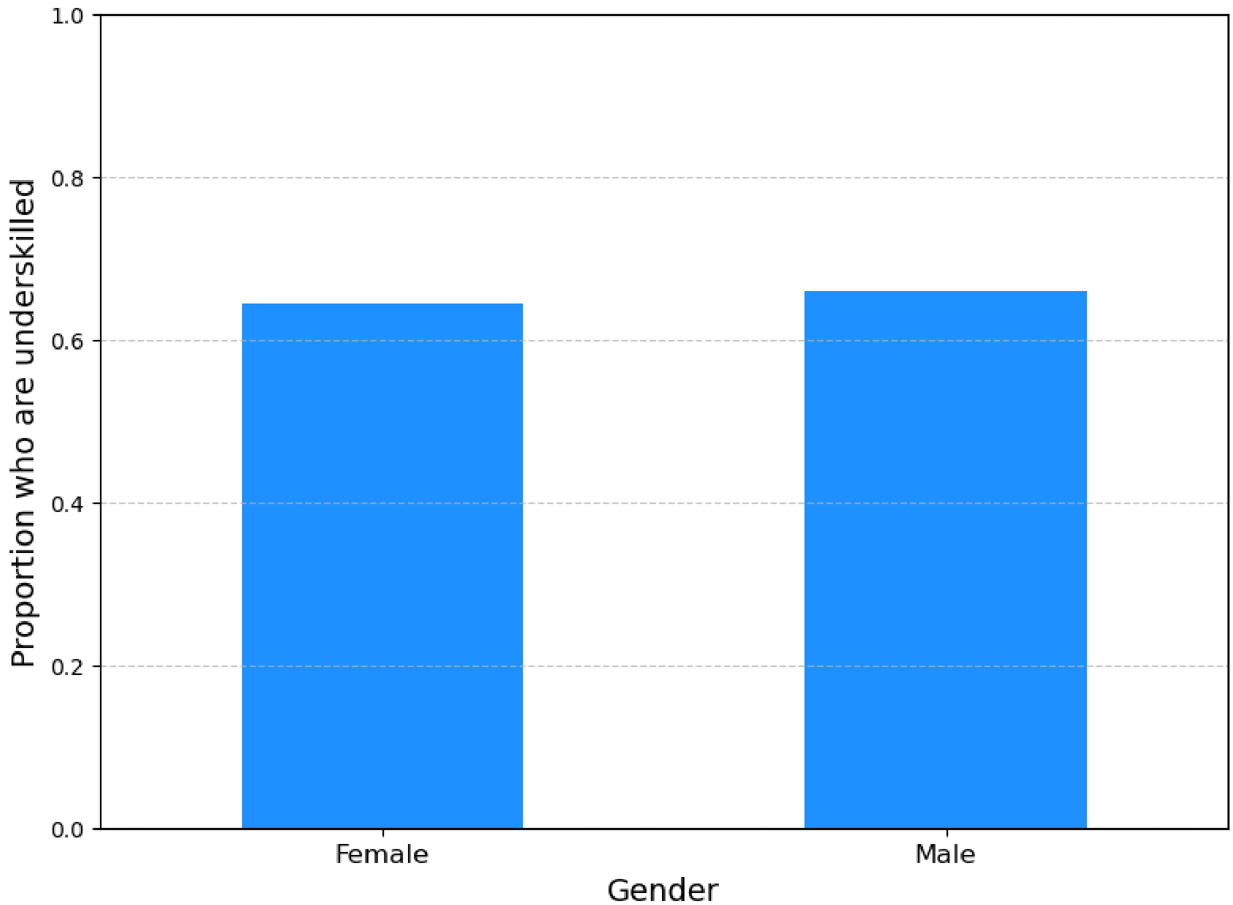
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 2A: Proportion of underskilled employees by age group (ESJS2021)



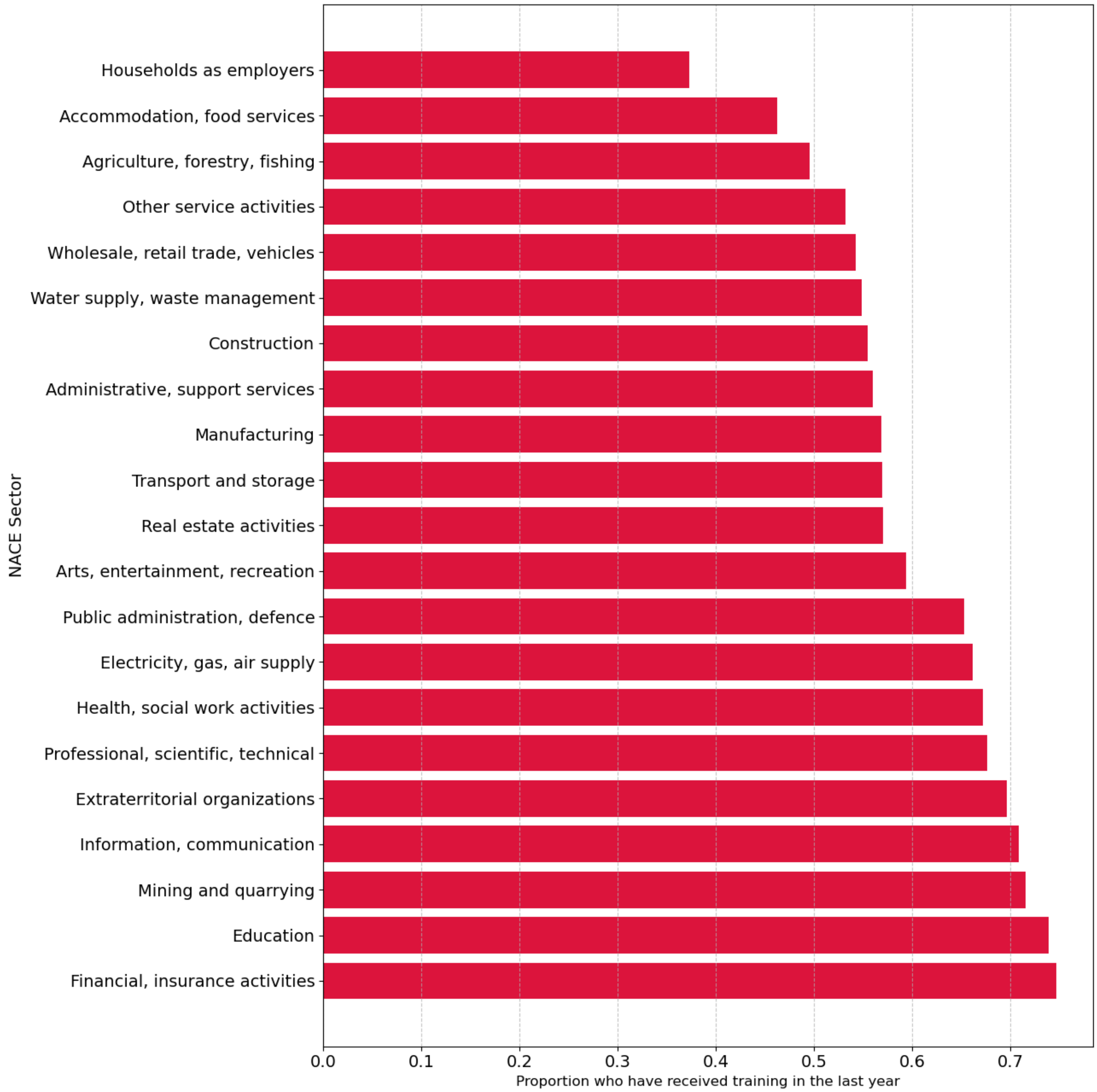
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 3A: Proportion of underskilled employees by gender (ESJS2021)



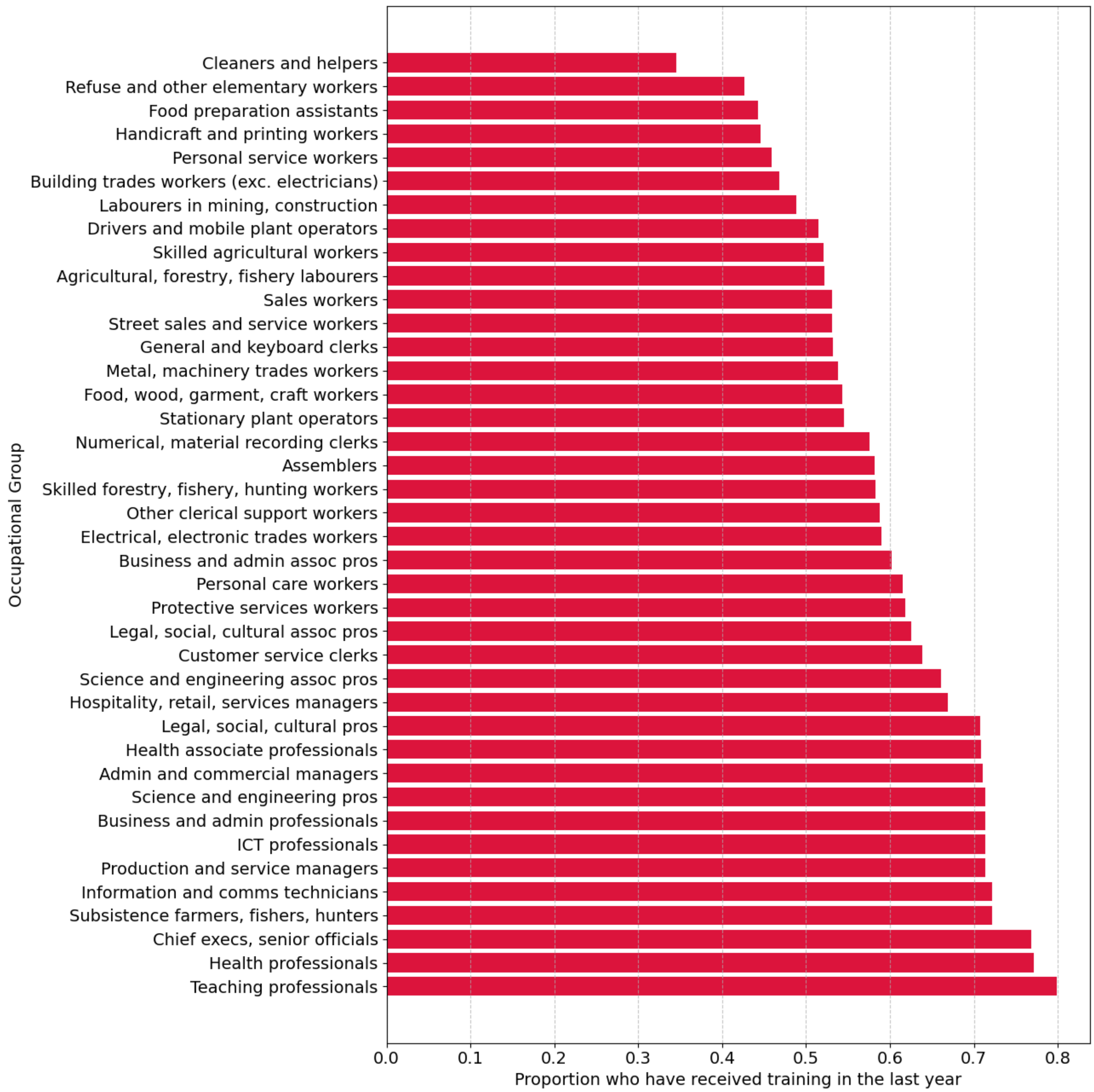
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 4A: Proportion of employees that have received training this year by Industry (ESJS2021)



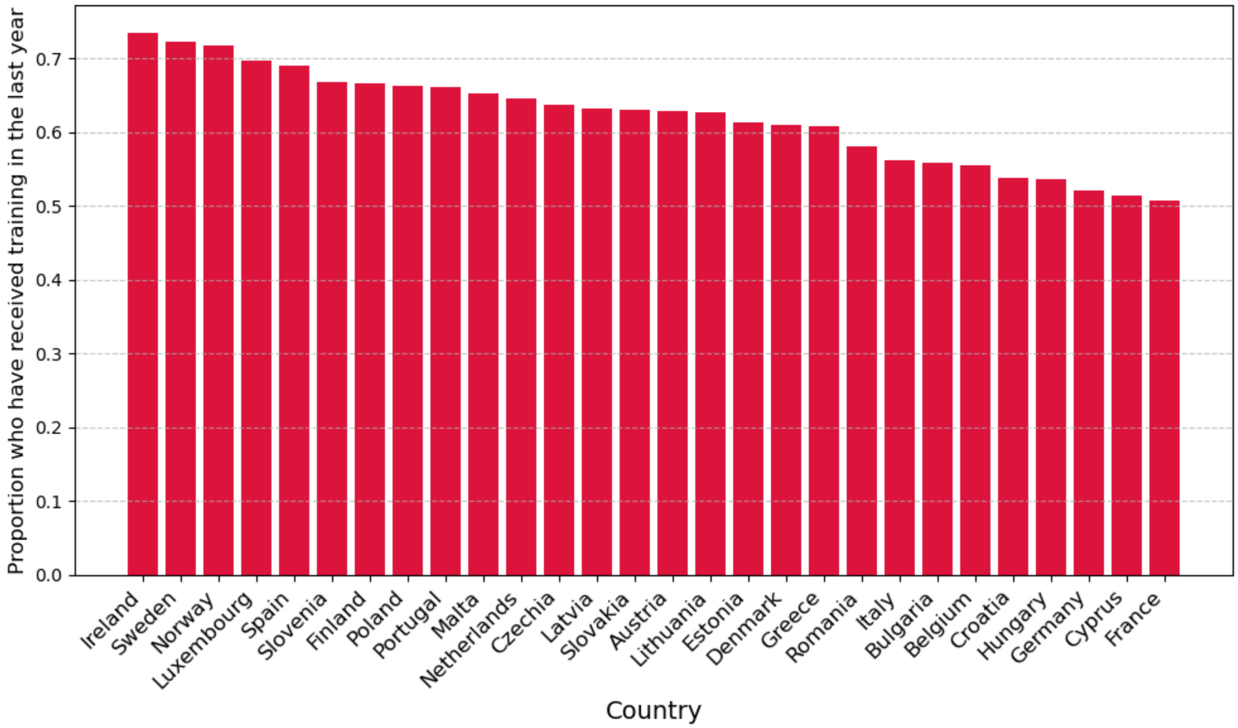
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 5A: Proportion of employees who have received training in the last year by Occupation (ESJS2021)



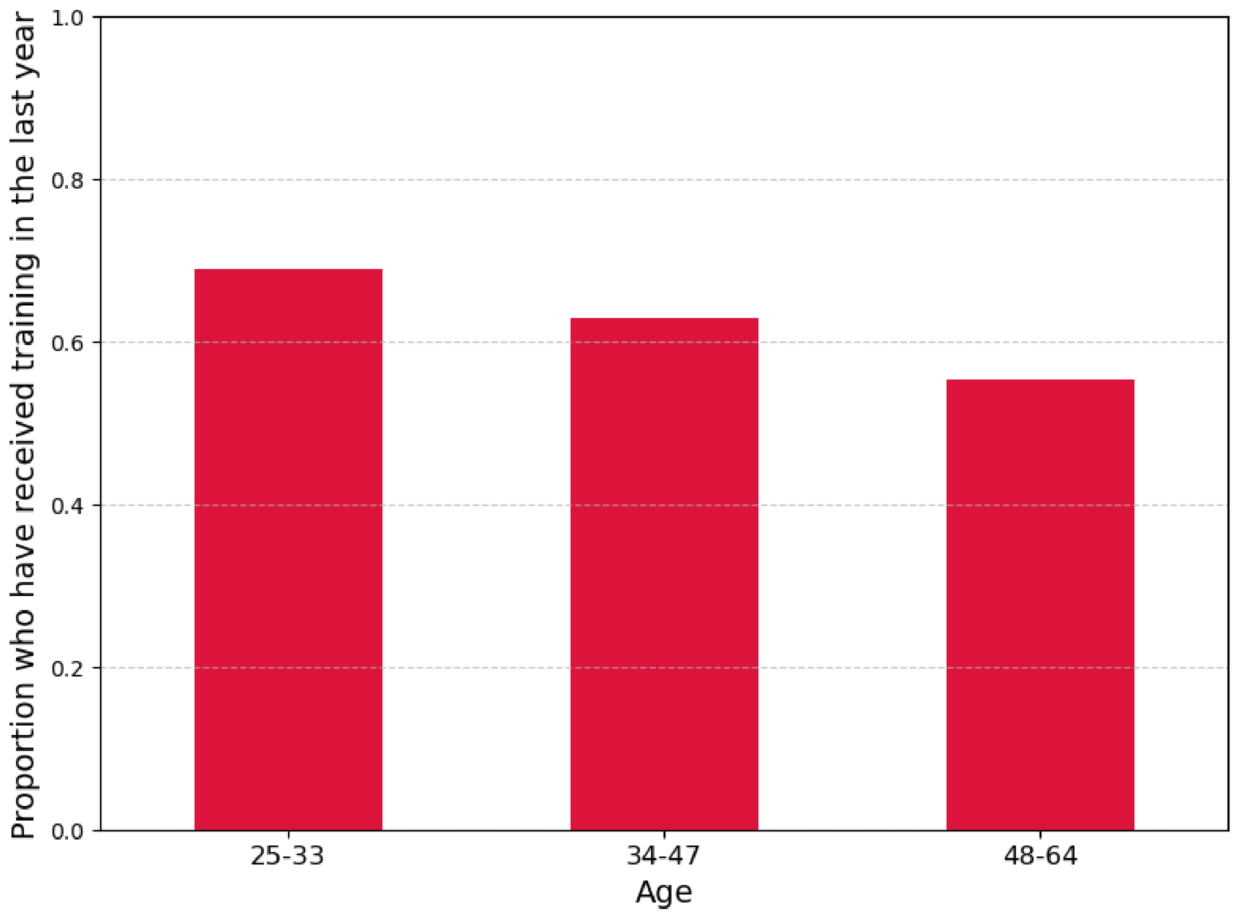
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 6A: Proportion of employees that have received training in the last year by country (ESJS2021)



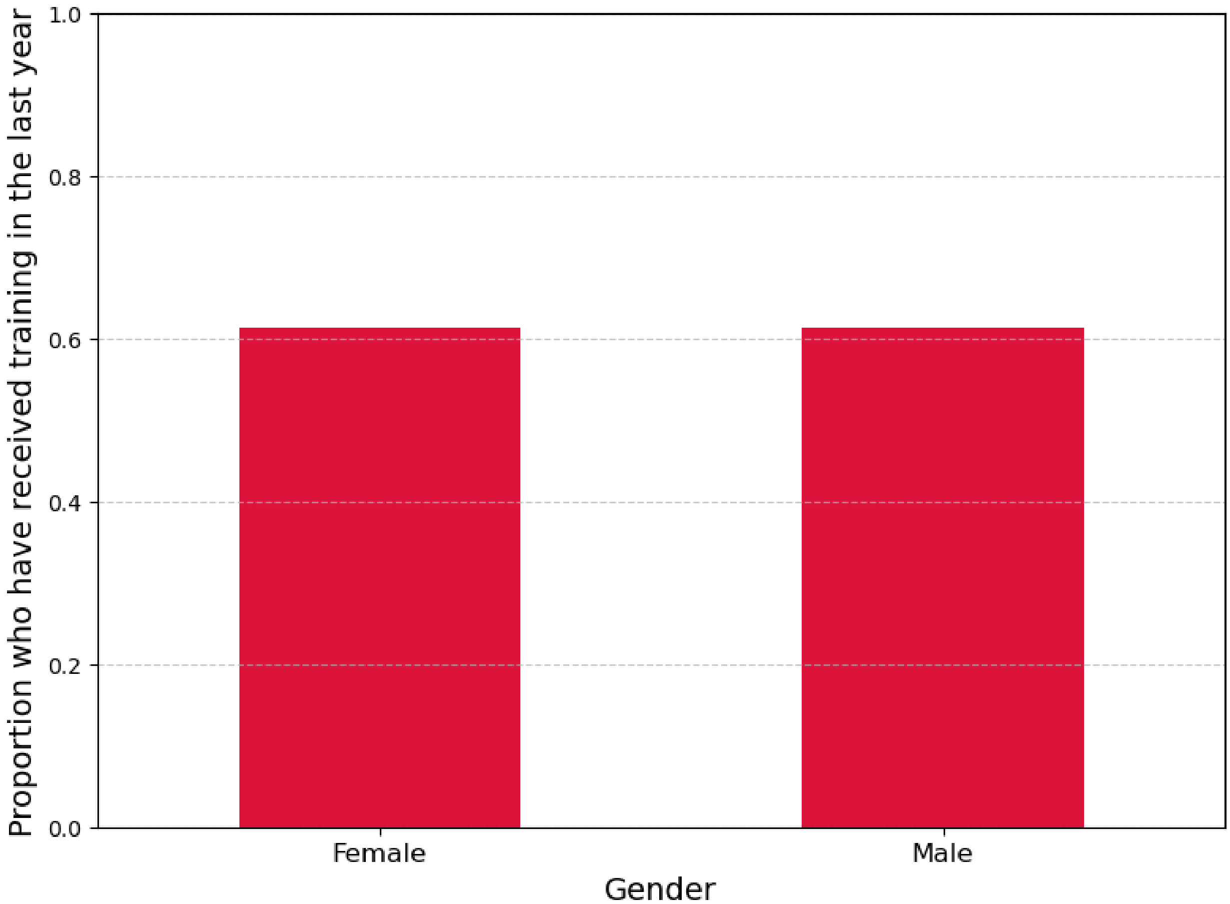
Source: European Skills and Jobs Survey. Authors' calculations.

Figure 7A: Proportion of employees that have received training in the last year by age group (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

Figure 8A: Proportion of employees that have received training in the last year by gender (ESJS2021)



Source: European Skills and Jobs Survey. Authors' calculations.

Table 2A: *SkillChange* and Underskilling (Differing Forms of Training, Marginal Effects)

Outcome Variable: Underskilling	**(1)** Training
$\boldsymbol{SkillChange}$	0.015***
	(0.002)
$\boldsymbol{Trained}$	0.194***
	(0.010)
$\boldsymbol{SkillChange \times Trained}$	-0.009***
	(0.003)
Female	-0.019***
	(0.006)
Tenure	-0.001***
	(0.000)
Part-Time	-0.035***
	(0.008)
Education (Ref: Low Education)	
Upper/Post-Secondary	0.038***
	(0.009)
Tertiary	0.080***
	(0.009)
Country FE	**YES**
Industry Controls	**YES**
Psuedo R-Squared	**0.071**
Observations	**40,581**

Note: Probit regression on underskilling. Coefficients reported are marginal effects. Country clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.