Enabling Data Analytics for Actions Tackling Skills Shortages & Mismatch

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QUESTION I – Review and Analytics of the Core Secondary Datasets

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ACRONYMS

ACRONYM	EXPLANATION
AES	Adult Education Survey
CVTS	Continuing Vocational Training Survey
DA	No answer
DK	Don't know
ECB	European Central Bank
EIB	European Investment Bank
EIBIS	European Investment Bank Investment Survey
ESCO	European Skills, Competences, Qualifications and Occupations
ESJS	European Skills and Jobs Survey
EU	European Union
EU-LFS	European Union Labour Force Survey
EU-SILC	European Union Statistics on Income and Living Conditions
EU-SES	European Union Structure of Earnings Survey
HFCS	Household Finance and Consumption Survey
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
NA	Not available
QLFS	Quarterly Labour Force Survey
SAFE	Survey on the Access to Finance of Enterprises
SMEs	Small & Medium-sized Enterprises
WBES	World Bank Enterprise Surveys
YLFS	Yearly Labour Force Survey

EXECUTIVE SUMMARY

The deliverable task D2.1 is labelled core data analytics as it provides the preliminary analysis of most of the core secondary datasets that will be used throughout the TRAILS project. It enables the visual inspection of country-level differences in aspects of primary interest, alongside differences across key population groups, e.g., by gender, age, and income/wealth/financial status. The domain of primary interest is the incidence of skills mismatching and its evolution over time in European labour markets. Moreover, D2.1 offers an overview of the incidence of training and its types across countries and available datasets, along with the relevant group differences. The review offers a range of preliminary insights based on individual, household, firm, matched employer-employee, and vacancy data. TRAILS project intends to fully operationalise these core secondary datasets in better understanding the precedents, antecedents and likely remedies of skills mismatching in its aim to inform the relevant literature, policy and practice.

1. INTRODUCTION

Skills mismatch is an imbalance between the skills that are sought by employers and the skills that are possessed by individuals, i.e., it is a mismatch between skills and jobs. This means that education and training are not providing the skills demanded in the labour market, or that the economy does not create jobs that correspond to the skills of individuals. Skills and competencies per se are not measured by the regular statistical programmes of most countries. That is why skill proxies are used, such as qualifications and years of education at the supply side, and occupations at the demand side (ILO, 2014).

There are various types of skills mismatches, including: (a) Over/under-skilling. This often happens when the field of education does not correspond to the field of occupation. A person can be simultaneously overqualified and underskilled. (b) Skills obsolescence often accompanies digitalization and technological advancement but can also occur when skills are not being regularly practiced and become obsolete after time. Both of the above can be a result of changing demands in the labour market.

The consequences of skills mismatch reach all levels of the labour market.

- At the individual and household micro level there are serious wage penalties especially for overqualification that eventually affect both job and life satisfaction. For example, assume that in developing countries overqualification should not be a problem because of a lack of sufficient training opportunities. However, people receive training and are still unable to find a job that corresponds to their skill level, which means they are not employed at their full productivity potential. In addition, skill deficiencies decrease chances of landing a job altogether.
- At the firm micro level, skills mismatch has negative consequences for productivity and competitiveness, which affects their ability to implement new products, services or technologies. What is more, skills mismatch causes higher staff turnover and sub-optimal work organization. Eventually skills mismatch leads to the loss of profits and markets.
- At the macro and regional level, skills mismatch can increase unemployment, and affect competitiveness and attractiveness to investors, meaning lost opportunities on the pathway to productive transformation and job creation. Public or private resources are invested in training with the assumption that achieved qualifications will yield positive results in terms of employment insertion or wages. Yet, if skills mismatch is present, these expectations often do not materialize, leading to returns on investment that are lower than expected.

According to ILO (2014) estimates of mismatch between qualifications and skills of the employed and those required by their work typically vary widely. In country studies reported in the literature, between 10% and one-third of the employed are found to be overeducated and around 20% are undereducated, which results in a total mismatch of between 30% and 50% of the employed in European countries.

Furthermore, Cedefop (2015) reported that the economic crisis has made skill mismatch worse. Due to weak employment demand, more people are taking jobs below their qualification or skill level. Their 2014 ESJS data showed that around 25% of highly qualified young adult employees are overqualified for their job in the EU. Those graduating after 2008 are almost twice as likely to be overqualified for their first job as those who graduated between 1991 and 2000. The concern is that economic downturns will undermine the long-term potential of the EU's skilled workforce. Unemployed people returning to work and individuals returning from career breaks, e.g., due to maternity, are also more likely to enter less skill-intensive jobs that may not utilize their skills. 42% of adult workers looking for a job in the years following the crisis had few opportunities to find jobs suitable for their skills and qualifications.

Hence, the importance of training and work-based learning can not be overstated. People whose studies involved work-based learning are more likely to go directly from education to their first job and into more skill-intensive jobs. Based on the ESJS, Cedefop (2015) reports that around 40% of adult employees have completed education or training involving some work-based learning, but this varies considerably across countries and fields of study. Only about 25% of those aged 24-34 with degrees in humanities, languages and arts, economics, business and law have participated in work-based learning. There is also large variation based on the sector of economic activity. Some 62% of adult employees in professional, scientific or technical services completed studies only in an educational institution. Employees in services relating to education or health are more likely to have completed study that involved some workplace learning (48%).

Nikolov, et al. (2018) emphasise that efficient and more popular vocational education and training (VET) practices and greater emphasis on lifelong learning and effective labour intermediation are the key. According to Cedefop (2022), in order to avoid skill mismatch, 53% of adult employees in the EU need to learn new things continuously, as the variety of their tasks has significantly increased since they started their job. More than one in five adult employees in the EU have not developed their skills since starting their job. Overall, around 26% of EU adult employees have significant skill deficits, i.e. their skills are much lower compared to those an average worker needs to be fully proficient in their job. The figure leaves much scope to improve skills and productivity. Countries with the highest shares of adult employees suffering from skill deficits have lower levels of labour productivity. The estimated annual productivity loss is 2.14 percent due to existing mismatches, which equates to EUR 0.80 per hour worked in 2014 in nominal terms (Nikolov, et al., 2018).

Hence, good jobs develop good skills and Europe needs more jobs that fully use and develop the skills of its workforce. Skill-intensive jobs with complex tasks that provide opportunities to acquire skills continuously are a sign of a healthy labour market. However, the ESJS surveys show that some 40% of adult employees only need basic literacy skills to do their job and 33% need only basic or no ICT skills at all. In some sectors, job complexity is stable or decelerating. Over a third of jobs in sectors such as hotels and restaurants, transport, and wholesale and retail trades have stagnant skill needs, where the variety of tasks has not changed significantly over time.

Noting the gaps in the measurement and understanding of skills, competencies, and their antecedents, the TRAILS project engages in this interesting agenda aiming to provide enabling data analytics for tacking skills shortages and mismatched in EU labour markets. The deliverable task D2.1 is at the core of the project's agenda, by setting the stage via reviewing the state of the art in existing datasets in Europe, and beyond.

1.1 PURPOSE OF THE DELIVERABLE

The deliverable task D2.1 provides core data analytics via the preliminary analysis of the vast majority of the core secondary datasets that will be used throughout the TRAILS project. It enables the visual inspection of country-level differences in aspects of primary interest, alongside differences across key population groups of primary interest, e.g., by gender, age, and income/financial status. An aspect of primary interest is the incidence of skills mismatching and its evolution across time in European labour markets. Although the in-depth analysis of skills mismatching and its various aspects will be the theme of follow-up deliverables, D2.1 offers an overview based on mismatching approximations. Moreover, D2.1 offers an overview of the incidence of formal and informal training across countries and available datasets, along with related domains that are pivotal to the choice of VET and study programmes and the organization of training. Finally, D2.1 outlines the systematic literature of each dataset.

1.2 RELATION WITH OTHER DELIVERABLES AND TASKS

Task 2.1 receives input from D1.1–Theoretical and empirical questions for tackling skills shortages and mismatch in Europe (REVIEW-I) and D1.2–Innovative initiatives for tackling skills shortages and mismatch in Europe (REVIEW-II) and outputs D2.1–Review and Analytics of the Core Secondary Dataset (QUESTION-I). This document of D2.1 (QUESTION-I) will contribute to the production of deliverables D2.2 and D2.3 and will inform workpackages 3, 4, 5, 6, and 7.

It is relevant to the following deliverable tasks of workpackage 2 as it reviews the state of the art in the content of questionnaires for survey design and stated-preference techniques, i.e.:

- D2.2 – QUESTION-II – Design of Survey Instruments (M12)
- D2.3 – QUESTION-III – Design of Interventions and Experimental Protocols (M14)
- D2.4 – QUESTION-IV – Survey Data Generation and Analytics (M21)

It is relevant to all following deliverable tasks of workpackage 3 as it describes the secondary datasets that will be used to produce its outputs, particularly the individual and household-level datasets, i.e.:

- D3.1 – COMPARE-I: Skills mismatching in Europe pre- and post-pandemic (M12)
- D3.2 – COMPARE-II: Technological change, training and upskilling in Europe (M24)
- D3.3 – COMPARE-III: The impact of skills mismatching on well-being across sectors (M28)
- D3.4 – COMPARE-IV: Behavioural, social, and cultural change for successful development of skills matched to needs (M32)

It is relevant to all deliverable tasks of workpackage 4 as it presents with several individual and matched employer-employee datasets that will be used for its tasks, as stated below:

- D4.1 – NOVEL-I: Using machine learning to measure skills matched to needs (M18)
- D4.2 – NOVEL-II: Teleworking, digitization and labour market segmentation (M24)
- D4.3 – NOVEL-III: Skills matching and firm resilience in the post-Covid era (M30)

- D4.4 – NOVEL-IV: Technological empowerment of skills matching (M33)

This document also presents firm-level, individual and household-level datasets that will be used to complement inquiries using the novel primary data of the TRAILS project as part of workpackage 5, and its tasks below:

- D5.1 – PORTFOLIO-I: Training for labour market inclusiveness and resilience (M18)
- D5.2 – PORTFOLIO-II: Resilient education and training in the era of automation and climate change (M23)
- D5.3 – PORTFOLIO-III: Skills portfolios and new types of labour (M26)
- D5.4 – PORTFOLIO-IV: Skills portfolios in times of change (M34)

The task also produces a very large number of 82 tables and 157 figures presenting the state-of-the art regarding skills matching and training across key demographic groups in Europe, which can be used for potential dissemination activities of the TRAILS project to the wider public as part of workpackage 6:

- D6.1 – SYNTHESIS-I: Dissemination & Business Plan (M09)
- D6.2 – SYNTHESIS-II: Dissemination & Business Report (M36)

Finally, the illustrations of the 82 tables and 157 figures in this deliverable task can be used to feed content into the web portal of the TRAILS project as part of workpackage 7 and its following tasks:

- D7.1 – INTEGRATE-I: TRAILS portal architecture, design and integration documentation (M15)
- D7.2 – INTEGRATE-II: TRAILS portal (M24)

1.3 STRUCTURE OF THE DOCUMENT

The remainder of this deliverable is organized as follows:

Section 2 presents the review and core analytics of the individual-level secondary datasets to be used in the remainder of the TRAILS project, namely:

- The European Union Labour Force Survey (EU-LFS), in both its yearly and quarterly version.
- The European Skills and Jobs Survey (ESJS).
- The Adult Education Survey (AES).

Section 3 presents the review and core analytics of the household-level secondary datasets to be used in the remainder of the TRAILS project, namely:

- The European Union Statistics on Income and Living Conditions (EU-SILC), in both its cross-sectional and panel version.
- The Household Finance and Consumption Survey (HFCS).

Section 4 presents the review and core analytics of the firm-level secondary datasets to be used in the remainder of the TRAILS project, namely:

- The World Bank Enterprise Surveys (WBES).
- The Survey on the Access to Finance of Enterprises (SAFE).
- The Eurobarometer 2023: 81.3 - Skills and Qualifications (EUROBAROMETER).
- The European Investment Bank Investment Climate Survey (EIBIS).
- The Continuing Vocational Training Survey (CVTS).

Section 5 presents the review and core analytics of the matched employer-employee secondary datasets to be used in the remainder of the TRAILS project, namely:

- The European Union Structure of Earnings Survey (EU-SES).
- The matched employer-employee database by Statistics Sweden (LISA/FEK).
- The matched employer-employee database by INSEE France (INSEE).
- The matched worker-firm database by Central Bureau Voor De Statistiek Data (CBS - Netherlands).
- The Italian matched worker-firm database (INPS/CERVED).
- The linked employer-employee database of the IAB in Germany (LIAB).
- The Quadros de Pessoal matched dataset by Statistics Portugal (QdP)/INE).

Section 6 presents the review and core analytics of the vacancy datasets to be used in the remainder of the TRAILS project, namely:

- SKILLSOVATE
- LIGHTCAST

Section 7 presents an overview of the taxonomies to be used in the remainder of the TRAILS project, namely:

- The European Union Structure of Earnings Survey (ESCO).
- The EU Taxonomy of Sustainable Activities

Section 8 concludes the presentation of the deliverable D2.1.

Finally, the penultimate non-numbered section presents the bibliography of the deliverable D2.1 used for the systematic literature reviews and worldcloud analysis of the relevant literature to each dataset.
Table 1-1 offers the overview of the 21 datasets discussed in D2.1.

Table 1-1: Core secondary datasets in a nutshell

#	ACRONYM	NAME	TYPE	FREQUENCY	PANEL
1	EU-LFS	European Union Labour Force Survey	Individual	Annual & Quarterly: 1983-2022	Limited
2	ESJS	European Skills and Jobs Survey	Individual	2014, 2021	No
3	AES	Adult Education Survey	Individual	Every 4 years: 2007, 2011, 2016, 2022	No
4	EU-SILC	European Union Statistics on Income and Living Conditions	Household	Annual: 2004-2021	Yes
5	HFCS	Household Finance and Consumption Survey	Household	2010, 2014, 2017, 2021	Limited
6	WBES	World Bank Enterprise Surveys	Firm	Every 2-4 years: 2005-2021	Limited
7	SAFE	Survey on the Access to Finance of Enterprises	Firm	Half-yearly: 2009-2024	Yes
8	EIBIS	European Investment Bank Investment Climate Survey	Firm	Application pending approval	
9	EUROBAROMETER	Flash Eurobarometer 529 - Skills and Qualifications	Firm	2023	No
10	CVTS	Continuing Vocational Training Survey	Firm	Application granted approval on 09/2024	
11	EU-SES	European Union Structure of Earnings Survey	Matched	Every 4 years: 2004, 2008, 2012, 2016, 2020	No
12	LISA/FEK	Statistics Sweden	Matched	Annual: 2001-2010	Yes
13	INSEE	INSEE DATABASE (FRANCE)	Matched	Application pending approval	
14	CBS	Central Bureau Voor De Statistiek Data (CBS - Netherlands)	Matched	Application pending approval	
15	INPS/CERVED	INPS/CERVED – Matched Worker-Firm Database (Italy)	Matched	Application pending approval	
16	LIAB	LIAB – Linked Employer-Employee Data of the IAB (Germany)	Matched	Application pending approval	
17	QdP/INE	Quadros de Pessoal (QdP) dataset (INE: Statistics Portugal)	Matched	Application pending approval	
18	SKILLSOVATE	Cefefop's Skills-OVATE job advertisement data	Vacancy	2019-2023	No
19	LIGHTCAST	Lightcast labor market analytics data	Vacancy	Application granted approval on 09/2024	
20	ESCO	European Skills, Competences, Qualifications and Occupations	Taxonomy	2023	No
21	EU Taxonomy	EU Taxonomy of Sustainable Activities	Taxonomy	2020	No

Notes: For the datasets for which there is an application that is pending approval, the applications were submitted early, i.e., in the beginning of the TRAILS project.

2. INDIVIDUAL-LEVEL DATASETS

In this section, we present the two pan-European databases, which enable labour market analysis at the individual level. These are the European Union Labour Force Survey (EU-LFS) and the European Skills and Jobs Survey (ESJS).

Although the EU-LFS entails a household-level potential, it is primarily used for the compilation of statistics on employment, unemployment and related outcomes through the analysis of weighted averages at the individual level. The database covers a long timespan, between 1983-2022, with lesser coverage in terms of countries and numbers of observations in earlier years. The database is available in two versions. The first version is the yearly database, which entails a greater number of variables, due to demographic questions being covered once in the quarterly data and additional questions being asked in special modules every year. The second is the quarterly database, which entails a smaller number of questions/variables, but a higher number of observations. Both versions of the data entail sampling weights which enable the analysis of the data to be representative at the country level.

Analysing the EU-LFS at its entirety is a novelty of the TRAILS project and its deliverable task D2.1. The mere size of the pooled datasets was restrictive until now. Indicatively, the pooled dataset for the yearly EU-LFS requires 64,9 GB of space, and the size recently of the pooled version of the quarterly EU-LFS is 27,0 GB.

The European Skills and Jobs Survey is a smaller database, which also provides sampling weights to render the data representative at the country level. The database is by design only representative at the individual level, and the survey designers, i.e., Cedefop, have collected two waves of data, in 2014 and 2021. The survey is richer in terms of questions related to skills matching and training experience.

Section 2 entails three subsections, namely 2.1 presenting the EU-LFS, 2.2 presenting the ESJS, and 2.3 presenting the AES. The contents of both sub-sections follow a similar structure. The begin with (1) presenting the data and frequencies, and (2) the employed sample and summary statistics. Then, (3) they present the most relevant statistics on skills (mis)matching and training, and differences in these statistics by (4) gender, (5) age, and (6) income. Each subsection concludes by (7) presenting a short systematic literature review of the literature using each of the two databases.

2.1 EUROPEAN UNION LABOUR FORCE SURVEY (EU-LFS)

The EU Labour Force Survey (EU-LFS) is a large-scale, continuous household sample survey conducted across the European Union, as well as in countries of the European Free Trade Association (EFTA). It is the primary source of information on the labour market in the EU, providing comprehensive data on employment, unemployment, and the characteristics of the working population.

The survey aims to gather reliable, timely, and comparable statistics on the labour market, including details on employment, unemployment, underemployment, and various socio-economic characteristics of the labour force. These are crucial for policy-making and monitoring employment trends at the national and EU levels.

The EU-LFS covers all individuals aged 15 and over living in private households. It provides data at national and regional levels, with special attention to different population groups, such as youths, women, and older workers.

The survey collects detailed information on:

- Demographic characteristics: age, gender, education level, etc.
- Labour market: employed, unemployed, or economically inactive.
- Employment characteristics: type of employment, working hours, occupation, industry, etc.
- Job search activity: for those unemployed or seeking work.
- Additional variables: income decile, health status, and working conditions, inter alia.

The survey is conducted quarterly and/or annually, depending on the country. Each survey wave typically involves a large, representative sample of individuals, ensuring the accuracy and reliability of the data.

The survey is harmonized across participating countries, meaning that the methodology, definitions, and classifications are standardized to ensure that the data are comparable across different countries and over time. The data from the EU-LFS are widely used by the European Commission, national governments, researchers, and other stakeholders to analyse labour market trends, assess the impact of policies, and inform decisions related to employment and social policy.

The EU-LFS is crucial for understanding the dynamics of the labour market in the EU, particularly in assessing the effectiveness of employment policies, the impact of economic crises, and structural changes in the economy. It also helps in monitoring progress towards EU-wide targets, such as those related to employment and social inclusion.

2.1.1 THE DATA AND FREQUENCIES

The pooled EU-LFS for all countries and years/quarters is a massive dataset. Table 2-1 presents its sample size for both the yearly dataset and the quarterly dataset. We present the number of observations overall and by country in two variants, i.e., before and after sample selection. Our sample selection strategy comprises of 5 stages, as follows. We select: (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.

In the pooled yearly dataset (YLFS), the total number of observations is 117,150,835 before and 71,427,117 after sample selection. In the pooled quarterly dataset (QLFS), the number of observations adheres to 175,420,056 before and 133,994,871 after sample selection. Table 2-1 shows that there are differences in sample sizes between countries, with the countries with the largest sample sizes being Italy, Spain, Germany, France, and the Netherlands, along EU countries, and the UK among the non-EU countries. The countries with the smallest number of observations are Malta, Estonia, Cyprus, Latvia and Croatia among EU countries and Iceland among non-EU countries.

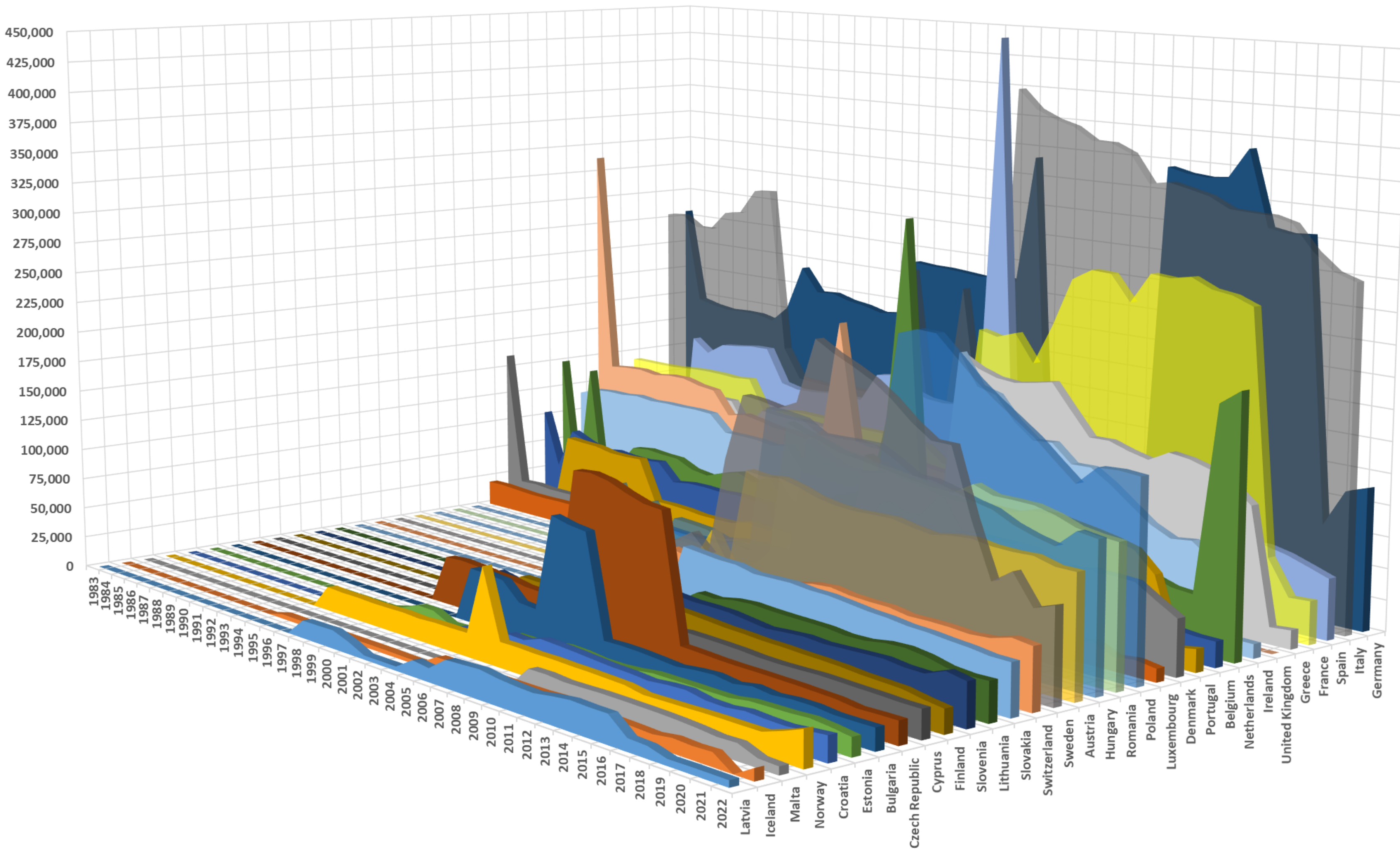
Figure 2-1 presents the evolution of the sample size by year for the YLFS. Countries at the left of the right horizontal axis were included in the dataset post-1995 and have a smaller number of observations by year, while those at the right of the figure, which are also the countries with the highest number of observations have much higher coverage in the majority of the years between 1983-2022. Figure 2-2 presents the overview of the sample size by quarter. It indicates that for the earlier period before 2000 the majority of the countries do not have data in all quarters but have coverage for one quarter every year. In the years after 2000, the majority of the countries have coverage in all quarters.

In the following subsections we examine economic activity post sample-selection, and we present statistics regarding the incidence of skills mismatching and training based on the employed sample of individuals, for what there is data on the highest level of education obtained, which can also be converted to years of schooling. The education/schooling variable is available for the years 2006-2022, which further reduces our sample size to 29,652,164 observations in the yearly dataset and 44,674,341 in the quarterly dataset.

Table 2-1: EU-LFS – Sample size

EU-LFS		YEARLY DATASET		QUARTERLY DATASET	
		SAMPLE SELECTION		SAMPLE SELECTION	
COUNTRY	ACRONYM	PRE	POST	PRE	POST
All countries	***Pooled***	***117,433,218***	***71,357,248***	***175,420,056***	***133,894,076***
Italy	IT	16,957,384	10,042,298	21,043,765	15,684,979
Germany	DE	11,524,415	7,961,474	14,263,403	10,908,075
France	FR	10,945,302	6,016,538	12,338,335	8,778,191
Greece	EL	7,038,463	4,153,063	20,065,604	15,069,846
Spain	ES	6,000,240	4,039,052	9,016,369	6,745,374
Ireland	IE	6,111,994	3,673,371	8,539,619	6,049,230
Poland	PL	5,906,311	3,234,929	6,741,858	5,107,115
Sweden	SE	3,873,057	3,177,961	4,312,791	4,250,538
Hungary	HU	5,418,296	2,834,733	6,872,919	5,232,559
Netherlands	NL	4,178,840	2,767,978	10,238,215	7,886,983
Romania	RO	4,593,815	2,490,651	5,446,725	4,253,535
Portugal	PT	3,776,712	2,224,060	5,204,880	3,907,540
Austria	AT	3,927,403	2,205,140	4,865,885	3,635,953
Belgium	BE	2,916,278	1,752,685	4,005,016	3,035,709
Denmark	DK	3,158,093	1,732,726	2,832,969	1,923,038
Czech Republic	CZ	2,479,357	1,314,118	5,966,042	4,513,727
Slovakia	SK	1,966,728	1,022,577	2,595,428	2,013,058
Finland	FI	1,424,296	805,326	3,508,279	3,076,032
Bulgaria	BG	1,146,839	751,172	3,306,173	2,570,448
Slovenia	SI	1,346,006	709,371	1,698,879	1,319,512
Lithuania	LT	1,110,220	656,218	1,251,907	993,443
Luxembourg	LU	971,310	609,098	1,093,591	842,444
Cyprus	CY	781,882	471,866	802,709	968,383
Croatia	HR	744,281	368,377	996,592	749,228
Latvia	LV	595,430	336,130	890,002	662,234
Estonia	EE	511,436	302,082	571,461	443,922
Malta	MT	317,276	190,925	339,592	257,835
Non-EU					
United Kingdom	UK	5,384,686	3,680,306	11,985,585	8,900,686
Switzerland	CH	1,372,247	1,048,821	2,190,250	1,934,487
Norway	NO	710,473	570,925	2,158,954	1,910,550
Iceland	IS	244,148	213,277	276,259	269,422

Notes: Our sample selection strategy comprises of 5 stages, as follows: (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.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Belgium
Netherlands
Ireland
United Kingdom
Greece
France
Spain
Italy
Germany

Figure 2-1: EU-LFS$_{Yearly}$ – #Observations by country and year

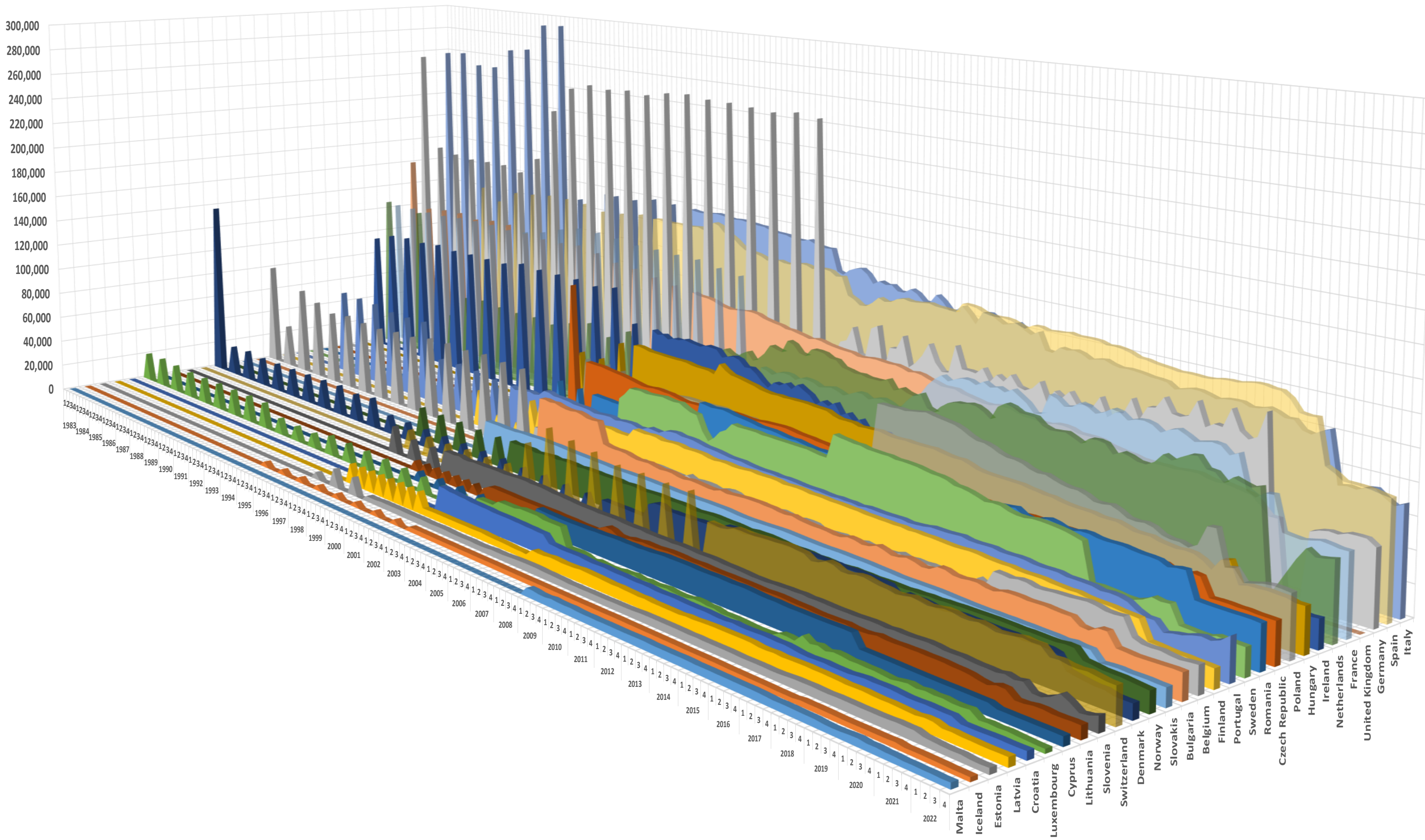

Figure 2-2: EU-LFS$_{Quarterly}$ – #Observations by country and quarter

2.1.2 THE EMPLOYED SAMPLE AND SUMMARY STATISTICS

Table 2-2 describes the 10 categories of economic activity that we distinguish at the pooled EU-LFS sample. In the yearly dataset, the unweighted sample comprises of 71,357,248 observations and the weighted sample comprises of 66,557,824 observations. The respective figures in the quarterly dataset are 133,894,076 and 132,974,403, respectively. The weighted figures show that 46.4% of the individuals in the pooled YLFS are in full-time employment (39.7% in the quarterly dataset) and 9.6% are in part-time employment (8.8% in the QLFS). 8.6% are in full-time self-employment and 1.3% are in part-time self-employment (7.5% and 1.3% in the QLFS, respectively). Moreover, 1.3% identify as unpaid family workers (1% in the QLFS). These top 5 categories of economic activity comprise the employed group in the remainder of the analysis in this section.

In the weighted YLFS, 6.3% of the individuals are unemployed and 19.5% are inactive (5.5% and 35.5% in the QLFS). The highest fraction of inactive in the QLFS compared to the YLFS can be justified by the thorough interviews conducted in the latter, which emphasize among the economically active population. 1.9% are disabled, 1% are students, and 4.1% are homemakers in the YLFS. The respective figures in the QLFS are 0.2%, 0.1%, and 0.4%. The small fraction of students is justified by our sample selection strategy, in which we exclude any students that are not actively searching for employment.

Table 2-2: EU-LFS – Economic activity

	YEARLY DATASET		QUARTERLY DATASET	
ECONOMIC ACTIVITY	UNWEIGHTED	WEIGHTED	UNWEIGHTED	WEIGHTED
Employed FT	**46.86%**	**46.35%**	**37.83%**	**39.69%**
	33,437,355	*30,848,309*	*50,645,596*	*52,778,722*
Employed PT	**9.00%**	**9.64%**	**8.47%**	**8.79%**
	6,424,434	*6,418,988*	*11,345,736*	*11,693,397*
Self-employed FT	**9.48%**	**8.61%**	**7.69%**	**7.46%**
	6,767,848	*5,728,106*	*10,295,135*	*9,922,351*
Self-employed PT	**1.33%**	**1.30%**	**1.27%**	**1.32%**
	949,330	*865,971*	*1,696,771*	*1,748,745*
Family worker (unpaid)	**1.47%**	**1.29%**	**1.15%**	**1.03%**
	1,049,290	*857,984*	*1,536,779*	*1,365,352*
Unemployed	**5.91%**	**6.25%**	**5.29%**	**5.50%**
	4,219,375	*4,158,454*	*7,087,055*	*7,316,929*
Inactive	**16.12%**	**19.47%**	**37.84%**	**35.58%**
	11,504,646	*12,959,379*	*50,666,535*	*47,306,128*
Disabled	**2.67%**	**1.92%**	**0.14%**	**0.18%**
	1,905,158	*1,279,539*	*189,385*	*244,799*
Student	**1.26%**	**1.04%**	**0.06%**	**0.09%**
	898,754	*693,911*	*79,622*	*124,718*
Homemaker	**5.89%**	**4.13%**	**0.26%**	**0.36%**
	4,201,058	*2,747,183*	*351,462*	*473,263*
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**
	71,357,248	*66,557,824*	*133,894,076*	*132,974,403*

Notes: The sampling weights are provided by the data collectors and render the analysis representative at the country level and overall. Weighted averages and number of observations are presented.

Table 2-3 and Table 2-4 present the distribution, among the 10 categories for employment activity, in the pooled country sub-samples for the YLFS and the QLFS respectively. In both tables, countries are presented at an ordering based on the highest fraction of individuals in paid full-time employment of all years (1983-2022 for countries that have observations in all years). The ordering of the countries in Table 2-3 is as follows: Slovenia, Czech Republic, Estonia, Slovakia, Lithuania, Hungary, Latvia, Finland, Croatia, Cyprus, Bulgaria, Austria, Sweden, Denmark, Malta, Luxembourg, Portugal, Poland, Romania, France, Germany, Ireland, Belgium, Spain, Italy, Netherlands, Greece. Among non-countries, the ordering goes as follows: Iceland, Norway, Switzerland, United Kingdom.

The countries with the highest fractions of individuals in full-time self-employment are: Greece (18.6%), Italy (12.7%), Portugal (12.7%), Poland (12.5%), Czech Republic (12.4%), Romania (11.2%), Ireland (10.2%). The countries with the highest fractions of individuals in unemployment at the weighted pooled sample are: Spain (11.4%), Slovakia (10.6%), Croatia (9.4%), Lithuania (8.8%), Greece (8.7%), Latvia (8.1%).

In Table 2-4, the ordering in terms of higher full-time paid employment is the following: Estonia, Germany, Italy, Czech Republic, Sweden, Lithuania, Romania, Bulgaria, Greece, Denmark, Slovakia, Luxembourg, Croatia, Latvia, Poland, Austria, Finland, Spain, Cyprus, Hungary, Netherlands, Portugal, Slovenia, Belgium, Ireland, Malta, France. Among non-EU countries, the order is the following: Iceland, Norway, United Kingdom, Switzerland. The countries with the highest fractions of individuals in full-time self-employment are: France (14.70%), Ireland (10.50%), Poland (9.80%), Netherlands (9.60%), Germany (9.30%). The countries with the highest fractions of individuals in unemployment are: Slovenia (10.30%), France (8.50%), Romania (8.10%), Italy (7.20%), Cyprus (6.90%).

Tables 2-5 and 2-6 present the summary statistics of selected variables of interest from the YLFS and the QLFS, respectively. Table 2-5 shows that in the weighted average of the pooled sample, there are 97.4% residents of EU countries and 37.7% are residents of Eurozone countries in the post-Euro era. 49.1% are males and 42.1% reside in rural areas. The average is 41.5 years and the average years of schooling are 11.8. 7.5% are migrants. 4.5% work in a region different than their region of residence, and 2.6% are disabled. In the weighted average of the employed, 3.6% hold more than one job, 84.2% are full-time and 84.7% have a permanent job. 12.4% have a managerial/supervisory role.

Table 2-6 shows only small differences for the larger quarterly dataset, compared to the yearly dataset. 3.6% of the weighted pooled sample are part of generation Z (born on or after 1996), 25.8% are part of generation Y (born between 1977 and 1995), 23.3% are part of generation X (born between 1965 and 1976), 32.5% are baby boomers (born between 1946 and 1964), and 15% are part of the older traditionalist or silent generation (born on or before 1945). Among the employed 12.7% work in agriculture, 21.2% work in manufacturing, 13.1% in wholesale, retail trade and repairs, and the remainder are distributed in smaller fractions in the remaining 14 industries. It is worth commending the sample for which industry codes are provided is a much smaller sample and for later years in the dataset.

Table 2-3: EU-LFS$_{Yearly}$ – Economic activity by country (weighted)

AXTIVITY	EMPLOYED FULL–TIME	EMPLOYED PART–TIME	SELF-EMPLOYED FULL–TIME	SELF-EMPLOYED PART–TIME	FAMILY WORKER (UNPAID)	UNEMPLOYED	INACTIVE	DISABKED	STUDNENT	HOMEMAKER
All Countries	*46.3%*	*9.6%*	*8.6%*	*1.3%*	*1.3%*	*6.2%*	*19.5%*	*1.9%*	*1.0%*	*4.1%*
Slovenia	67.4%	4.0%	8.7%	0.6%	2.1%	5.7%	5.9%	1.4%	2.2%	2.0%
Czech Republic	65.9%	3.2%	12.4%	0.6%	0.4%	4.6%	3.1%	4.4%	0.6%	4.8%
Estonia	65.7%	6.3%	5.7%	1.1%	0.2%	6.4%	2.1%	5.4%	1.1%	5.9%
Slovakia	64.1%	2.3%	9.8%	0.2%	0.1%	10.6%	3.5%	4.8%	0.5%	4.1%
Lithuania	61.9%	4.0%	8.2%	1.6%	1.5%	8.8%	4.0%	5.7%	1.0%	3.4%
Hungary	60.8%	2.8%	8.7%	0.4%	0.3%	5.3%	8.3%	6.2%	1.5%	5.8%
Latvia	60.2%	4.3%	5.9%	1.6%	1.4%	8.1%	9.2%	3.4%	0.7%	5.3%
Finland	59.6%	7.6%	8.6%	1.3%	0.3%	6.4%	4.7%	6.2%	3.0%	2.4%
Croatia	59.1%	1.2%	8.7%	1.8%	1.2%	9.4%	6.2%	2.1%	2.5%	7.8%
Cyprus	58.4%	4.0%	9.5%	2.4%	1.1%	6.2%	2.9%	2.7%	1.2%	11.4%
Bulgaria	56.5%	0.9%	6.7%	0.4%	0.7%	6.9%	22.2%	2.1%	1.0%	2.7%
Austria	55.6%	16.1%	7.7%	1.3%	1.0%	4.0%	4.6%	1.4%	1.8%	6.5%
Sweden	55.5%	16.5%	6.6%	1.6%	0.2%	5.0%	4.6%	5.5%	3.6%	0.9%
Denmark	55.2%	14.6%	6.2%	0.7%	0.8%	4.7%	10.1%	5.0%	2.3%	0.5%
Malta	54.8%	7.4%	9.0%	1.6%	0.0%	2.9%	2.2%	2.1%	0.4%	19.6%
Luxembourg	54.3%	8.6%	5.1%	0.7%	0.6%	2.4%	16.7%	1.8%	1.8%	8.0%
Portugal	54.1%	3.1%	12.7%	2.6%	1.1%	5.9%	12.9%	1.1%	1.4%	5.0%
Poland	52.2%	3.4%	12.5%	1.3%	2.5%	7.7%	5.5%	7.9%	1.3%	5.6%
Romania	51.8%	0.4%	11.2%	4.3%	9.8%	5.1%	7.9%	0.3%	1.5%	7.8%
France	51.4%	9.9%	7.2%	0.8%	1.0%	7.2%	17.5%	1.0%	0.9%	3.2%
Germany	46.2%	12.9%	5.5%	1.0%	0.7%	4.7%	27.3%	0.5%	0.6%	0.7%
Ireland	44.9%	8.3%	10.2%	1.1%	0.7%	6.4%	15.7%	3.0%	0.8%	9.0%
Belgium	44.4%	11.5%	8.9%	0.5%	1.2%	5.5%	18.1%	3.8%	1.2%	4.9%
Spain	40.3%	5.3%	9.4%	0.7%	1.1%	11.4%	23.4%	2.0%	1.2%	5.3%
Italy	38.6%	5.2%	12.7%	1.2%	1.8%	6.2%	19.9%	1.3%	2.0%	11.0%
Netherlands	37.0%	24.4%	6.2%	3.0%	0.6%	3.4%	16.2%	4.0%	0.6%	4.5%
Greece	34.4%	2.1%	18.6%	0.9%	5.1%	8.7%	16.7%	1.6%	1.3%	10.6%
Non–EU										
Iceland	56.9%	16.7%	9.9%	2.1%	0.1%	2.6%	4.9%	3.6%	1.7%	1.4%
Norway	53.6%	18.5%	4.1%	1.3%	0.3%	3.0%	10.3%	6.2%	1.7%	1.1%
Switzerland	44.3%	22.8%	7.7%	3.2%	1.5%	2.9%	11.8%	1.5%	0.8%	3.5%
United Kingdom	43.8%	14.0%	6.8%	1.9%	0.2%	5.1%	27.4%	0.8%	0.1%	0.0%

Notes: Countries are ordered based on the fraction of individuals in full-time employment, from highest to lowest.

Table 2-4: EU-LFS$_{Quarterly}$ – Economic activity by country (weighted)

AXTIVITY	EMPLOYED FULL–TIME	EMPLOYED PART–TIME	SELF-EMPLOYED FULL–TIME	SELF-EMPLOYED PART–TIME	FAMILY WORKER (UNPAID)	UNEMPLOYED	INACTIVE	DISABKED	STUDNENT	HOMEMAKER
All Countries	39.70%	8.80%	7.50%	1.30%	1.00%	5.50%	35.60%	0.20%	0.10%	0.40%
Estonia	51.50%	5.30%	4.60%	1.00%	0.20%	5.90%	31.00%	0.30%	0.10%	0.30%
Germany	48.90%	2.90%	9.30%	0.60%	0.40%	3.80%	33.80%	0.00%	0.00%	0.30%
Italy	48.40%	3.40%	4.90%	1.30%	1.00%	7.20%	32.90%	0.30%	0.00%	0.50%
Czech Republic	48.00%	3.60%	7.60%	2.20%	1.00%	6.20%	30.70%	0.20%	0.10%	0.40%
Sweden	47.60%	3.60%	6.30%	0.60%	2.30%	4.30%	35.00%	0.10%	0.10%	0.10%
Lithuania	47.40%	3.20%	5.90%	1.30%	1.10%	6.70%	33.90%	0.30%	0.00%	0.10%
Romania	47.40%	1.90%	7.30%	0.10%	0.10%	8.10%	34.50%	0.30%	0.00%	0.20%
Bulgaria	46.40%	0.80%	5.50%	0.30%	0.50%	5.80%	40.10%	0.20%	0.10%	0.30%
Greece	46.20%	7.30%	6.60%	1.30%	0.30%	5.70%	31.90%	0.20%	0.20%	0.10%
Denmark	46.00%	15.00%	5.00%	0.70%	0.40%	4.20%	28.10%	0.30%	0.20%	0.00%
Slovakia	45.70%	14.70%	5.30%	1.50%	0.20%	5.10%	26.90%	0.30%	0.30%	0.10%
Luxembourg	45.60%	8.90%	4.00%	0.90%	0.40%	3.00%	36.60%	0.10%	0.20%	0.30%
Croatia	45.20%	2.30%	6.20%	0.40%	0.20%	3.90%	41.20%	0.20%	0.10%	0.20%
Latvia	45.20%	6.60%	7.40%	1.40%	0.00%	3.00%	34.40%	0.30%	0.00%	1.70%
Poland	44.80%	2.90%	9.80%	2.90%	0.80%	5.50%	32.80%	0.20%	0.10%	0.30%
Austria	43.30%	12.50%	6.00%	1.10%	1.10%	3.30%	32.30%	0.10%	0.10%	0.20%
Finland	42.10%	14.20%	5.20%	1.10%	0.50%	4.20%	32.20%	0.20%	0.10%	0.30%
Spain	41.90%	8.90%	5.70%	0.70%	0.50%	5.70%	35.90%	0.30%	0.10%	0.20%
Cyprus	41.40%	1.00%	6.30%	1.90%	1.00%	6.90%	40.80%	0.20%	0.10%	0.40%
Hungary	40.90%	9.70%	8.50%	1.10%	0.50%	5.60%	32.90%	0.40%	0.10%	0.40%
Netherlands	39.80%	2.70%	9.60%	1.10%	1.90%	6.20%	38.00%	0.30%	0.10%	0.30%
Portugal	38.70%	0.30%	8.30%	3.30%	7.00%	4.00%	37.70%	0.10%	0.10%	0.80%
Slovenia	37.50%	5.30%	8.30%	0.60%	0.70%	10.30%	36.40%	0.10%	0.10%	0.50%
Belgium	35.80%	11.00%	6.90%	0.60%	0.80%	4.50%	39.60%	0.40%	0.10%	0.30%
Ireland	32.00%	5.30%	10.50%	1.20%	1.20%	5.40%	43.50%	0.10%	0.10%	0.80%
Malta	30.30%	26.40%	5.80%	3.40%	0.40%	3.40%	29.70%	0.40%	0.10%	0.20%
France	29.40%	2.10%	14.70%	0.70%	3.40%	8.50%	40.40%	0.10%	0.10%	0.60%
Non–EU										
Iceland	52.70%	15.70%	8.40%	1.80%	0.00%	3.30%	17.00%	0.70%	0.20%	0.10%
Norway	47.60%	17.40%	3.50%	1.20%	0.20%	2.60%	26.40%	0.70%	0.20%	0.10%
United Kingdom	41.40%	13.90%	6.40%	2.10%	0.20%	4.20%	31.70%	0.00%	0.00%	0.00%
Switzerland	39.40%	22.40%	6.40%	3.20%	1.40%	3.30%	22.90%	0.30%	0.20%	0.50%

Notes: Countries are ordered based on the fraction of individuals in full-time employment, from highest to lowest.

Table 2-5: EU-LFS$_{Yearly}$ – Summary statistics of key variables

	POOLED SAMPLE				EMPLOYED SAMPLE			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean
EU country	71,357,248	97.4%	66,557,824	97.9%	48,628,257	97.0%	45,410,505	97.5%
Eurozone country/year	71,357,248	43.8%	66,557,824	37.7%	48,628,257	45.4%	45,410,505	39.4%
Rural	71,357,248	46.8%	66,557,824	42.1%	48,628,257	44.9%	45,410,505	40.1%
Male	71,357,248	48.4%	66,557,824	49.1%	48,628,257	55.5%	45,410,505	56.4%
Years of schooling	40,737,025	11.66	37,336,297	11.82	29,989,976	12.16	27,448,884	12.33
Age	71,357,248	42.42	66,557,824	41.54	48,628,257	41.53	45,410,505	40.36
Migrant	71,357,248	7.3%	66,557,824	7.5%	48,628,257	7.4%	45,410,505	8.0%
Disabled	71,357,248	3.2%	66,557,824	2.6%	48,628,257	0.2%	45,410,505	0.1%
Reference person	71,357,248	31.6%	66,557,824	31.5%	48,628,257	36.5%	45,410,505	36.5%
Reference couple	71,357,248	53.6%	66,557,824	51.6%	48,628,257	57.2%	45,410,505	55.6%
Financially dependent children	71,357,248	15.5%	66,557,824	14.8%	48,628,257	17.2%	45,410,505	16.6%
Spouse/ partner lives in same household	71,357,248	30.8%	66,557,824	28.1%	48,628,257	34.0%	45,410,505	31.5%
Father and mother live in same household	71,357,248	9.0%	66,557,824	7.7%	48,628,257	8.6%	45,410,505	7.0%
Child(ren) live(s) in same household	71,357,248	23.4%	66,557,824	20.6%	48,628,257	26.1%	45,410,505	23.5%
Long-term unemployed	71,357,248	3.0%	66,557,824	3.0%	48,628,257	0.0%	45,410,505	0.0%
Searching for employment in last 4 weeks	71,357,248	9.6%	66,557,824	9.8%	48,628,257	0.0%	45,410,505	0.0%
Not searching for employment	71,357,248	14.6%	66,557,824	14.7%	48,628,257	0.0%	45,410,505	0.0%
Registered at a public employment service	71,357,248	7.3%	66,557,824	7.8%	48,628,257	2.2%	45,410,505	2.3%
Receives benefit or assistance	71,357,248	3.5%	66,557,824	4.7%	48,628,257	1.0%	45,410,505	1.9%
Carer	71,357,248	1.7%	66,557,824	1.4%	48,628,257	1.8%	45,410,505	1.5%
Absentee	71,357,248	5.5%	66,557,824	5.3%	48,628,257	8.0%	45,410,505	7.8%
Number of jobs	71,357,248	0.76	66,557,824	0.74	48,628,257	1.11	45,410,505	1.10
Income decile	12,955,624	5.51	12,938,918	5.51	12,955,624	5.51	12,938,918	5.51
Number of children	34,100,786	0.66	33,013,878	0.66	24,472,269	0.67	23,784,263	0.67
Moonlighter	48,802,568	3.8%	45,410,503	3.6%	48,628,255	3.8%	45,410,503	3.6%
Full-time	48,483,723	84.2%	45,388,097	83.1%	48,483,723	84.2%	45,388,097	83.1%
Permanent job	40,911,079	84.7%	38,068,414	84.9%	40,911,079	84.7%	38,068,414	84.9%
Supervisor	40,911,079	12.4%	38,068,414	10.8%	40,911,079	12.4%	38,068,414	10.8%
Home worker	48,628,255	11.2%	45,410,503	11.8%	48,628,255	11.2%	45,410,503	11.8%
Internal migrant (nomad)	48,628,255	5.7%	45,410,503	4.9%	48,628,255	5.7%	45,410,503	4.9%
Wish to work more hours	48,628,255	5.6%	45,410,503	5.7%	48,628,255	5.6%	45,410,503	5.7%
Not looking for another job	47,670,998	95.4%	44,973,790	94.0%	47,670,998	95.4%	44,973,790	94.0%
Hours of work (actual)	48,285,460	34.78	45,212,367	34.64	48,285,460	34.78	45,212,367	34.64
Overtime hours of work	21,148,714	0.85	19,551,208	1.11	21,148,714	0.85	19,551,208	1.11
Labour market experience	46,313,493	24.05	42,898,752	22.93	33,973,931	22.77	31,368,826	21.56
Time since started work (months)	41,654,597	131.38	38,954,321	123.80	41,654,597	131.38	38,954,321	123.80
Education/training received in last 4 weeks	63,939,924	13.1%	60,395,827	14.5%	44,993,006	11.4%	42,405,434	12.1%
Formal education/training in last 4 weeks	47,329,418	5.8%	43,494,579	7.4%	34,562,945	4.0%	31,582,110	4.9%
Informal job-related training in last 4 weeks	47,887,015	7.2%	43,556,239	7.8%	34,562,945	8.4%	31,582,110	9.0%
Inf. non-job-related training in last 4 weeks	47,887,015	0.2%	43,556,239	0.2%	34,562,945	0.2%	31,582,110	0.2%
Education/training received in last 12 months	1,266,850	28.7%	1,262,228	28.1%	996,797	31.9%	993,210	30.6%
Formal education/training in last 12 months	1,273,214	6.5%	1,268,054	7.2%	1,002,171	5.4%	998,078	6.2%
Informal job-related training in last 12 months	1,265,637	20.7%	1,261,102	19.4%	995,859	24.9%	992,319	22.9%
Inf. non-job-related training in 12 months	1,265,637	3.7%	1,261,102	3.5%	995,859	3.7%	992,319	3.5%
Self-employed in 2nd job	1,697,276	39.9%	1,574,885	38.8%	1,697,276	39.9%	1,574,885	38.8%
Paid employee in 2nd job	1,697,276	52.2%	1,574,885	54.6%	1,697,276	52.2%	1,574,885	54.6%
Family worker in 2nd job	1,697,276	7.9%	1,574,885	6.6%	1,697,276	7.9%	1,574,885	6.6%

Table 2-6: EU-LFS$_{Quarterly}$ – Summary statistics of key variables

	POOLED SAMPLE				EMPLOYED SAMPLE			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean
EU country	133,894,07	96.8%	132,974,4	97.6%	75,520,017	96.0%	75,147,451	97.1%
Euro country/year	133,894,07	46.0%	132,974,4	50.5%	75,520,017	47.5%	75,147,451	51.2%
Rural	133,894,07	42.1%	132,974,4	33.6%	75,520,017	40.8%	75,147,451	32.7%
Male	133,894,07	48.6%	132,974,4	49.3%	75,520,017	55.2%	75,147,451	55.4%
Years of schooling	76,207,294	11.35	75,799,74	11.53	45,011,428	12.19	44,805,964	12.31
Age	133,894,07	43.94	132,974,4	43.23	75,520,017	41.45	75,147,451	40.92
Gen Z, iGen, or Centennials	133,894,07	3.0%	132,974,4	3.6%	75,520,017	1.6%	75,147,451	1.9%
Millennials or Gen Y	133,894,07	21.8%	132,974,4	25.6%	75,520,017	22.3%	75,147,451	27.1%
Generation X	133,894,07	22.2%	132,974,4	23.3%	75,520,017	29.6%	75,147,451	30.7%
Baby Boomers	133,894,07	34.9%	132,974,4	32.5%	75,520,017	38.9%	75,147,451	34.7%
Traditionalists or Silent Gen	133,894,07	18.1%	132,974,4	15.0%	75,520,017	7.6%	75,147,451	5.6%
Migrant	133,894,07	5.5%	132,974,4	7.7%	75,520,017	7.0%	75,147,451	9.6%
Disabled	133,894,07	0.2%	132,974,4	0.3%	75,520,017	0.0%	75,147,451	0.0%
Long-term unemployed	133,894,07	2.6%	132,974,4	2.8%	75,520,017	0.0%	75,147,451	0.0%
Searching for employment in last 4 weeks	133,894,07	9.1%	132,974,4	9.6%	75,520,017	0.0%	75,147,451	0.0%
Not searching for employment	133,894,07	28.9%	132,974,4	27.9%	75,520,017	0.0%	75,147,451	0.0%
Registered at a public employment service	133,894,07	0.3%	132,974,4	0.5%	75,520,017	0.1%	75,147,451	0.2%
Receives benefit or assistance	133,894,07	0.5%	132,974,4	1.2%	75,520,017	0.5%	75,147,451	1.5%
Absentee	133,894,07	4.9%	132,974,4	5.3%	75,520,017	8.6%	75,147,451	9.0%
Number of jobs	133,894,07	0.63	132,974,4	0.65	75,520,017	1.11	75,147,451	1.11
Moonlighter	75,520,015	3.9%	75,147,44	3.8%	75,520,015	3.9%	75,147,449	3.8%
Full-timer worker	75,470,957	82.1%	75,101,88	82.0%	75,470,957	82.1%	75,101,881	82.0%
Permanent job	63,528,111	83.8%	63,199,32	84.3%	63,528,111	83.8%	63,199,329	84.3%
Internal migrant (nomad)	75,520,015	6.1%	75,147,44	4.6%	75,520,015	6.1%	75,147,449	4.6%
Wish to work more hours	75,520,015	6.1%	75,147,44	7.4%	75,520,015	6.1%	75,147,449	7.4%
Hours of work (actual)	75,015,851	34.03	74,664,20	33.78	75,015,851	34.03	74,664,206	33.78
Overtime hours of work	31,113,295	1.01	31,008,77	1.06	31,113,295	1.01	31,008,770	1.06
Time since person started to work (months)	67,227,641	129.1	67,104,09	123.6	67,227,641	129.1	67,104,095	123.62
Education/training received in last 4 weeks	120,679,17	17.8%	120,516,7	17.7%	69,722,114	13.2%	69,678,650	13.1%
Formal job-related training in last 4 weeks	89,858,876	11.9%	89,572,27	11.7%	52,618,188	5.9%	52,453,189	5.6%
Informal job-related training in last 4 weeks	89,132,248	7.6%	89,079,97	7.4%	52,303,522	9.4%	52,282,757	9.0%
Inf. non-job-related training in last 4 weeks	89,132,248	0.1%	89,079,97	0.2%	52,303,522	0.2%	52,282,757	0.2%
Self-employed in 2nd job	2,778,007	39.0%	2,767,898	38.9%	2,778,007	39.0%	2,767,898	38.9%
Paid employee in 2nd job	2,778,007	54.2%	2,767,898	54.8%	2,778,007	54.2%	2,767,898	54.8%
Family worker in 2nd job	2,778,007	6.8%	2,767,898	6.3%	2,778,007	6.8%	2,767,898	6.3%
Industry: Agriculture, hunting and forestry	9,694,079	9.5%	9,694,078	12.7%	9,694,079	9.5%	9,694,078	12.7%
"-": Fishing	9,694,079	0.1%	9,694,078	0.1%	9,694,079	0.1%	9,694,078	0.1%
"-": Mining and quarrying	9,694,079	0.7%	9,694,078	0.9%	9,694,079	0.7%	9,694,078	0.9%
"-": Manufacturing	9,694,079	21.4%	9,694,078	21.2%	9,694,079	21.4%	9,694,078	21.2%
"-": Electricity, gas and water supply	9,694,079	1.4%	9,694,078	1.5%	9,694,079	1.4%	9,694,078	1.5%
"-": Construction	9,694,079	7.4%	9,694,078	7.1%	9,694,079	7.4%	9,694,078	7.1%
"-": Wholesale and retail trade; repairs	9,694,079	13.2%	9,694,078	13.1%	9,694,079	13.2%	9,694,078	13.1%
"-": Hotels and restaurants	9,694,079	3.6%	9,694,078	3.3%	9,694,079	3.6%	9,694,078	3.3%
"-": Transport, storage and communication	9,694,079	6.7%	9,694,078	6.6%	9,694,079	6.7%	9,694,078	6.6%
"-": Financial intermediation	9,694,079	2.1%	9,694,078	2.0%	9,694,079	2.1%	9,694,078	2.0%
"-": Real estate, renting and business	9,694,079	6.8%	9,694,078	6.4%	9,694,079	6.8%	9,694,078	6.4%
"-": Public administration and defence; CSS	9,694,079	6.1%	9,694,078	6.0%	9,694,079	6.1%	9,694,078	6.0%
"-": Education	9,694,079	7.3%	9,694,078	6.7%	9,694,079	7.3%	9,694,078	6.7%
"-": Health and social work	9,694,079	9.3%	9,694,078	8.2%	9,694,079	9.3%	9,694,078	8.2%
"-": Other community, social & personal	9,694,079	4.0%	9,694,078	3.9%	9,694,079	4.0%	9,694,078	3.9%
"-": Activities of households	9,694,079	0.3%	9,694,078	0.2%	9,694,079	0.3%	9,694,078	0.2%
"-": Extra-territorial organizations and bodies	9,694,079	0.1%	9,694,078	0.0%	9,694,079	0.1%	9,694,078	0.0%

2.1.3 SKILLS MATCHING AND TRAINING STATISTICS

In this section, we present weighted statistics related to skills matching and training. Skills matching statistics are possible to compute for the years 2006-2022, due to the variable capturing the highest education qualification obtained only being available post 2006. Statistics on training during the last four weeks are available for the full period 1983-2022, and there are additional variables capturing the incidence of training and during the last year its type, which are available only for the year 2022.

We employ two definitions of vertical skills matching. Our primary definition I for an employee whose skills match their occupation is defined based on the highest educational qualification attained being equal to the median educational qualification by country, year and 3-digit ISCO code. Over if higher, under if lower. The second definition II, which is only used as an alternative, captures skills matching based on the years of schooling being equal to the mean ± one standard error of the years of schooling by country, year and 3-digit ISCO code (matched). The countries with the highest matching are highlighted in blue, and those with the lowest matching in red.

Tables 2-7 and 2.8 present weighted statistics and rankings on skills matching and employment using the YLFS and the QLFS, respectively. In the pooled sample for 31 counties for the YLFS, 67.2% are employed, 57.5% are at an occupation that matches their educational qualifications (60.3% according to the definition II), 26.1% are overeducated (20.4% by definition II), and 24.6% are undereducated (19.2% by definition II). In Table II for the QLFS, 58.3% are employed, 57.5% are at an occupation that matches their educational qualifications (60.3% according to the definition II), 21% are overeducated (20.5% by definition II), and 21.4% are undereducated (19.2% by definition II).

Table 2-7 presents the list of 31 countries at the YLFS, ranked based on the level of employment among the sample. The employed are considered as all paid employees, the self-employed, and the few unpaid family workers. The countries with the highest levels of employment between 1983-2022 are Iceland (85.8%), Slovenia (82.9%), the Czech Republic (82.6%), Austria (81.7%) and Sweden (80.4%). The countries with the lowest levels of employment are Spain (56.7%), Italy (59.5%), Greece (61.1%), Ireland (65.1%), Bulgaria (65.2%), and Germany (66.3%).

Based on the definition I, the countries with the highest levels of skills matching in the pooled sample between 2006-2022. are: Czech Republic (80.6%), Slovakia 79.5%), Croatia (77.1%), Poland (72.3%), and Bulgaria (70.8%). The countries with the lowest levels of skills mismatching are: Cyprus (50.6%), Iceland (50.2%), Greece (50.1%), Malta 47.9%), Spain (47.6%), and Ireland (41.6%).

The countries with the highest levels of overeducation based on the definition I are: United Kingdom (33.8%), Malta (30.0%), Ireland (28.0%), Estonia (27.8%), and Cyprus (27.0%). The countries with the lowest levels of overeducation are: Austria (14.3%), Spain (13.6%), Switzerland (13.1%), Poland (12.4%), Netherlands (11.7%), and Luxembourg (10.5%).

The countries with the highest levels of undereducation based on the definition I are: Cyprus (28.4%), France (26.1%), Sweden (25.6%), Norway (25.2%), Croatia (24.9%). The countries with the lowest levels of undereducation are: Italy (14.9%), Hungary (14.1%), Austria (14.1%), Latvia (11.2%), Slovakia (8.9%), Poland (8.1%).

Observing the rankings using definition II, based on the years of schooling there are mostly similarities and differences. Moreover, only a few rankings are similar when using the quarterly data, as shown in Table 2-8.

Table 2-7: EU-LFS$_{Yearly}$ – Skills Matching statistics by country (weighted)

	EMPLOYED		MATCHED				OVEREDUCATED				UNDEREDUCATED			
			Definition I		Definition II		Definition I		Definition II		Definition I		Definition II	
All Countries	*67.2%*	*(Rank)*	*57.5%*	*(Rank)*	60.3%	*(Rank)*	26.1%	*(Rank)*	20.4%	*(Rank)*	24.6%	*(Rank)*	19.2%	*(Rank)*
Austria	81.7%	(4)	57.9%	*(13)*	64.8%	(11)	14.3%	(26)	17.0%	(20)	14.1%	(28)	18.1%	(20)
Belgium	66.5%	(25)	55.3%	(17)	59.5%	(18)	23.5%	(8)	21.9%	(12)	20.9%	(18)	18.7%	*(17)*
Bulgaria	65.2%	(27)	70.8%	(5)	69.2%	(8)	16.0%	(25)	14.9%	*(27)*	22.2%	(14)	15.9%	(24)
Croatia	72.0%	(19)	77.1%	(3)	72.8%	(2)	21.9%	(13)	14.6%	*(29)*	24.9%	(5)	12.6%	(30)
Cyprus	75.5%	(14)	50.6%	(26)	54.8%	(26)	27.0%	(5)	25.3%	(5)	28.4%	(1)	19.9%	(10)
Czech Republic	82.6%	(3)	80.6%	*(1)*	73.3%	(1)	18.6%	*(21)*	14.6%	(28)	23.7%	(10)	12.1%	*(31)*
Denmark	77.4%	(10)	61.7%	(9)	62.2%	(15)	22.7%	*(9)*	16.2%	*(23)*	19.3%	(21)	21.6%	(5)
Estonia	79.1%	(7)	52.8%	(24)	*62.0%*	(16)	27.8%	(4)	*18.3%*	(16)	24.4%	(7)	*19.7%*	(12)
Finland	77.3%	(11)	60.5%	(11)	64.7%	(12)	24.8%	(7)	16.5%	(22)	23.4%	(11)	18.8%	*(15)*
France	70.2%	(22)	53.7%	(20)	58.5%	(19)	22.6%	(10)	22.7%	(10)	26.1%	(2)	18.8%	(16)
Germany	66.3%	(26)	55.5%	*(16)*	62.8%	(14)	16.2%	(23)	18.2%	*(17)*	24.0%	(8)	19.0%	(14)
Greece	61.1%	(29)	50.1%	*(28)*	54.4%	(28)	19.8%	(19)	25.7%	(3)	22.1%	(15)	19.8%	(11)
Hungary	73.0%	(17)	67.3%	(8)	68.1%	(9)	26.5%	*(6)*	17.8%	(18)	14.1%	(27)	14.1%	(26)
Ireland	65.1%	(28)	41.6%	*(31)*	54.9%	(25)	28.0%	*(3)*	26.0%	(2)	19.9%	(19)	19.1%	*(13)*
Italy	59.5%	(30)	58.9%	(12)	58.2%	(20)	16.1%	*(24)*	23.6%	(8)	14.9%	(26)	18.2%	*(19)*
Latvia	73.3%	(16)	57.0%	(14)	64.5%	(13)	21.6%	(16)	17.2%	*(19)*	11.2%	(29)	18.3%	(18)
Lithuania	77.2%	(12)	53.2%	(23)	71.5%	(4)	19.3%	(20)	15.4%	*(25)*	19.2%	(22)	13.2%	*(29)*
Luxembourg	69.3%	(23)	61.1%	*(10)*	65.5%	(10)	10.5%	(31)	16.8%	*(21)*	*21.5%*	(17)	17.7%	*(21)*
Malta	72.8%	(18)	47.9%	(29)	56.5%	(24)	30.0%	(1)	26.1%	(1)	22.9%	(12)	17.4%	(22)
Netherlands	71.2%	(21)	53.4%	*(22)*	56.7%	(23)	11.7%	*(30)*	22.8%	(9)	22.5%	(13)	20.6%	(7)
Poland	71.9%	(20)	72.3%	*(4)*	70.1%	(6)	12.4%	(29)	14.4%	(30)	8.1%	(31)	15.5%	*(25)*
Portugal	73.7%	(15)	54.2%	*(19)*	54.6%	(27)	*21.0%*	*(18)*	25.2%	(6)	24.4%	(6)	20.2%	(9)
Romania	77.5%	(9)	69.2%	(6)	70.7%	(5)	22.1%	(11)	15.6%	(24)	22.1%	(16)	13.7%	*(27)*
Slovakia	76.4%	(13)	79.5%	(2)	71.6%	(3)	21.9%	*(15)*	15.0%	(26)	8.9%	(30)	13.4%	(28)
Slovenia	82.9%	(2)	68.4%	*(7)*	69.3%	(7)	21.1%	(17)	13.6%	*(31)*	18.3%	(23)	17.1%	*(23)*
Spain	56.7%	(31)	47.6%	(30)	51.3%	(31)	13.6%	*(27)*	25.7%	(4)	16.1%	(25)	23.0%	(4)
Sweden	80.4%	(5)	53.7%	(21)	60.5%	(17)	16.8%	(22)	18.9%	(14)	25.6%	(3)	20.5%	(8)
Non-EU														
Iceland	85.8%	(1)	50.2%	(27)	51.8%	(30)	21.9%	(14)	24.1%	(7)	17.3%	(24)	24.1%	(2)
Norway	77.7%	(8)	55.1%	(18)	57.7%	(21)	22.0%	*(12)*	18.4%	*(15)*	25.2%	(4)	23.9%	(3)
Switzerland	79.5%	(6)	55.6%	(15)	57.1%	(22)	13.1%	(28)	21.3%	(13)	23.7%	(9)	21.6%	(6)
United Kingdom	66.6%	(24)	51.8%	*(25)*	52.8%	(29)	33.8%	(1)	22.5%	(11)	19.4%	(20)	24.7%	(1)

Notes: Definition I of skills mismatching is based on the highest educational qualification attained being equal to the median educational qualification by country, year and 3-digit ISCO code. Definition II is based on the years of schooling being equal to the mean ± one S.E. of the years of schooling by country, year and 3-digit ISCO code (matched). The countries with the highest matching are highlighted in blue, and those with the lowest matching in red.

Table 2-8: EU-LFS$_{Quarterly}$ – Skills matching statistics by country (weighted)

	EMPLOYED		MATCHED				OVEREDUCATED				UNDEREDUCATED			
			Definition I		Definition II		Definition I		Definition II		Definition I		Definition II	
All Countries	***58.3%***	*(Rank)*	***57.5%***	*(Rank)*	***60.3%***	*(Rank)*	***21.0%***	*(Rank)*	***20.5%***	*(Rank)*	21.4%	*(Rank)*	***19.2%***	*(Rank)*
Austria	63.9%	(8)	57.5%	(13)	64.5%	(12)	22.7%	(11)	17.1%	(20)	19.8%	(19)	18.3%	(18)
Belgium	55.0%	(25)	55.2%	(16)	59.1%	(18)	20.1%	(19)	22.2%	(12)	24.7%	(7)	18.7%	(17)
Bulgaria	53.5%	(27)	70.8%	(5)	69.5%	(7)	13.1%	(28)	14.9%	(27)	16.2%	(25)	15.6%	(24)
Croatia	51.6%	(29)	76.4%	(3)	72.5%	(2)	12.4%	(29)	14.7%	(28)	11.2%	(29)	12.7%	(30)
Cyprus	62.4%	(11)	51.1%	(26)	55.3%	(25)	24.8%	(8)	25.3%	(6)	24.1%	(10)	19.4%	(13)
Czech Republic	62.0%	(12)	80.3%	(1)	73.0%	(1)	10.7%	(31)	14.6%	(29)	8.9%	(30)	12.3%	(31)
Denmark	67.1%	(5)	60.7%	(10)	62.3%	(15)	18.5%	(21)	17.7%	(19)	20.8%	(18)	20.0%	(10)
Estonia	62.5%	(10)	52.9%	(22)	61.6%	(16)	23.6%	(9)	18.4%	(15)	23.5%	(12)	20.1%	(8)
Finland	61.8%	(13)	59.4%	(11)	63.3%	(13)	16.2%	(24)	16.6%	(23)	24.4%	(9)	20.1%	(9)
France	57.7%	(21)	53.8%	(20)	58.6%	(19)	21.2%	(18)	22.8%	(10)	25.0%	(5)	18.7%	(16)
Germany	63.0%	(9)	55.9%	(15)	63.2%	(14)	21.6%	(17)	17.8%	(18)	22.5%	(14)	19.0%	(15)
Greece	50.3%	(30)	49.9%	(28)	54.4%	(28)	27.9%	(3)	25.8%	(1)	22.2%	(15)	19.9%	(12)
Hungary	54.3%	(26)	67.2%	(8)	68.0%	(9)	18.5%	(22)	17.8%	(17)	14.3%	(28)	14.2%	(26)
Ireland	60.7%	(15)	42.0%	(31)	55.1%	(26)	29.6%	(2)	25.5%	(4)	28.4%	(1)	19.3%	(14)
Italy	50.1%	(31)	58.8%	(12)	58.2%	(20)	22.0%	(15)	23.6%	(7)	19.1%	(21)	18.2%	(20)
Latvia	59.2%	(19)	57.3%	(14)	64.7%	(11)	21.8%	(16)	17.1%	(21)	20.9%	(17)	18.2%	(19)
Lithuania	58.9%	(20)	53.5%	(21)	71.5%	(3)	26.8%	(5)	15.2%	(25)	19.6%	(20)	13.4%	(29)
Luxembourg	59.8%	(18)	61.1%	(9)	65.2%	(10)	17.3%	(23)	17.0%	(22)	21.6%	(16)	17.8%	(21)
Malta	60.7%	(16)	48.0%	(29)	57.2%	(22)	33.9%	(1)	25.8%	(2)	18.1%	(23)	17.0%	(23)
Netherlands	66.3%	(6)	52.4%	(25)	55.5%	(23)	22.7%	(10)	22.8%	(9)	24.9%	(6)	21.7%	(6)
Poland	55.1%	(24)	72.1%	(4)	70.0%	(6)	13.4%	(27)	14.5%	(30)	14.5%	(27)	15.5%	(25)
Portugal	61.2%	(14)	54.3%	(18)	54.6%	(27)	26.6%	(6)	25.4%	(5)	19.1%	(22)	20.0%	(11)
Romania	57.5%	(22)	69.0%	(6)	70.4%	(5)	16.2%	(25)	15.8%	(24)	14.8%	(26)	13.8%	(27)
Slovakia	56.8%	(23)	79.3%	(2)	71.4%	(4)	12.4%	(30)	15.0%	(26)	8.3%	(31)	13.6%	(28)
Slovenia	60.4%	(17)	68.0%	(7)	69.5%	(8)	14.6%	(26)	13.5%	(31)	17.4%	(24)	17.1%	(22)
Spain	52.4%	(28)	47.6%	(30)	51.2%	(31)	27.8%	(4)	25.6%	(3)	24.7%	(8)	23.2%	(4)
Sweden	67.4%	(4)	52.7%	(23)	59.8%	(17)	22.1%	(13)	19.1%	(14)	25.2%	(4)	21.0%	(7)
Non-EU														
Iceland	78.8%	(1)	50.4%	(27)	52.2%	(30)	26.1%	(7)	23.6%	(8)	23.5%	(11)	24.2%	(2)
Norway	70.0%	(3)	54.6%	(17)	57.5%	(21)	19.3%	(20)	18.1%	(16)	26.0%	(2)	24.4%	(1)
Switzerland	72.7%	(2)	54.2%	(19)	55.4%	(24)	22.6%	(12)	21.8%	(13)	23.3%	(13)	22.8%	(5)
United Kingdom	64.1%	(7)	52.5%	(24)	53.5%	(29)	22.0%	(14)	22.6%	(11)	25.5%	(3)	24.0%	(3)

Notes: Definition I of skills mismatching is based on the highest educational qualification attained being equal to the median educational qualification by country, year and 3-digit ISCO code. Definition II is based on the years of schooling being equal to the mean ± one S.E. of the years of schooling by country, year and 3-digit ISCO code (matched). The countries with the highest matching are highlighted in blue, and those with the lowest matching in red.

Figure 2-3 presents the evolution of employment by year in the YLFS. The figure documents a rise in employment after the mid-1990s to most of the countries, a decline in the post-2010 period, and a rise in employment in most of the countries in the post-Covid-19 era. Countries at the right of the figure have higher and more stable figures for employment. Then, Figure 2-4 presents the evolution of employment by quarter of each year in the QLFS and confirms these patterns by presenting them in greater detail at the quarterly level.

Figure 2-5 presents the evolution of skills matching by year in the YLFS. The figure is adamant regarding the detrimental impact of the 2010 crisis on skills matching in European labour markets. At the peak of the Eurozone debt crisis between 2013 and 2014, all countries experienced large declines in skills matching ranging between -3.2% (Czech Republic) and -29.5% (Ireland). The absolute magnitude of the increase in skills mismatching was between 2.7 and 15.5 percentage points. The only exception was Iceland, which started experiencing large rises in mismatching gradually between 2010 and 2014, in the aftermath of the global financial crisis. Figure 2-6 presents the evolution of skills matching by quarter of each year in the QLFS and confirms that it was the first quarter of 2014 which brought about the biggest drops in skills matching in labour markets across Europe.

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Figure 2-5 presents the evolution of skills matching by year in the YLFS. The figure is adamant regarding the detrimental impact of the 2010 crisis on skills matching in European labour markets. At the peak of the Eurozone debt crisis between 2013 and 2014, all countries experienced large declines in skills matching ranging between -3.2% (Czech Republic) and -29.5% (Ireland). The absolute magnitude of the increase in skills mismatching was between 2.7 and 15.5 percentage points. The only exception was Iceland, which started experiencing large rises in mismatching gradually between 2010 and 2014, in the aftermath of the global financial crisis. Figure 2-6 presents the evolution of skills matching by quarter of each year in the QLFS and confirms that it was the first quarter of 2014 which brought about the biggest drops in skills matching in labour markets across Europe.

The notable increase in skills mismatching in 2014, as opposed to previous years, can be understood in the context of several economic, political, and structural factors that either fully materialized or became more evident around that specific year. While the groundwork for these mismatches was laid earlier, particularly in the aftermath of the global financial crisis and Eurozone debt crisis, the specific dynamics converged in 2014 for the following reasons: (i) Delayed economic recovery and labour market lag after the Eurozone debt crisis; (ii) Shift from crisis management to long-term restructuring; (iii) Impact of structural reforms becoming evident; (iv) Youth unemployment peaking and lingering "Lost-Generation" effects; (v) Intensified migration and labour mobility patterns; (vi) Accelerating technological change and digital transformation.

It is clear from figure 2-5 that European labour markets have not yet recovered from the mismatching shock that occurred in 2014. The recovery has been modest and can be seen mostly in the new member states of Eastern Europe, which were affected the least in 2014. This pattern can not be seen in other datasets that only provide snapshots at different points in time post-2014 from smaller samples.

Figure 2-7 presents the evolution of overeducation by year in the YLFS. There are varying patterns in the evolution of overeducation, which is based on definition I of vertical mismatching used above. Four new member states saw drops in overeducation occurring at later years of the sample, i.e., post 2017, namely Romania, Bulgaria, Croatia, and the Czech Republic. For most of the remaining EU countries, but also for the four non-EU counties in our sample (Iceland, Switzerland, Norway and the United Kingdom) overeducation appears to have increased between 2010 and 2016, and to be remaining at these higher levels until 2022. The five countries with consistently higher rates for overeducation are Cyprus, Greece, Spain, Ireland, and Malta. It appears that overeducation has increased a lot in Sweden, the United Kingdom, Latvia and Lithuania, bringing these three countries among those with the highest rates for overeducation by 2022. Figure 2-8 presents the evolution of overeducation by quarter of each year in the QLFS. The patterns observed confirm the analysis of the dominos in the previous figure, and the data in this figure shed further light into the exact quarters in which the biggest changes occurred.

Figure 2-9 presents the evolution of undereducation by year in the YLFS, and figure 2-10 presents the evolution of undereducation by quarter of each year in the QLFS. The counties with the lowest rates of undereducation are the 9 Eastern European EU counties, namely Slovakia, the Czech Republic, Croatia, Hungary, Poland, Romania, Bulgaria, Slovenia, and Lithuania. The nine countries experienced an increase in undereducation after 2013, which appears to decline in later years for Croatia, Slovenia and Lithuania. The counties with the highest rates for undereducation are Sweden, Finland, Norway, Estonia, the United Kingdom, Germany, Ireland and Iceland. For Estonia, Germany and Iceland, there are rises in undereducation post 2017, i.e., in the last five years of the sample.

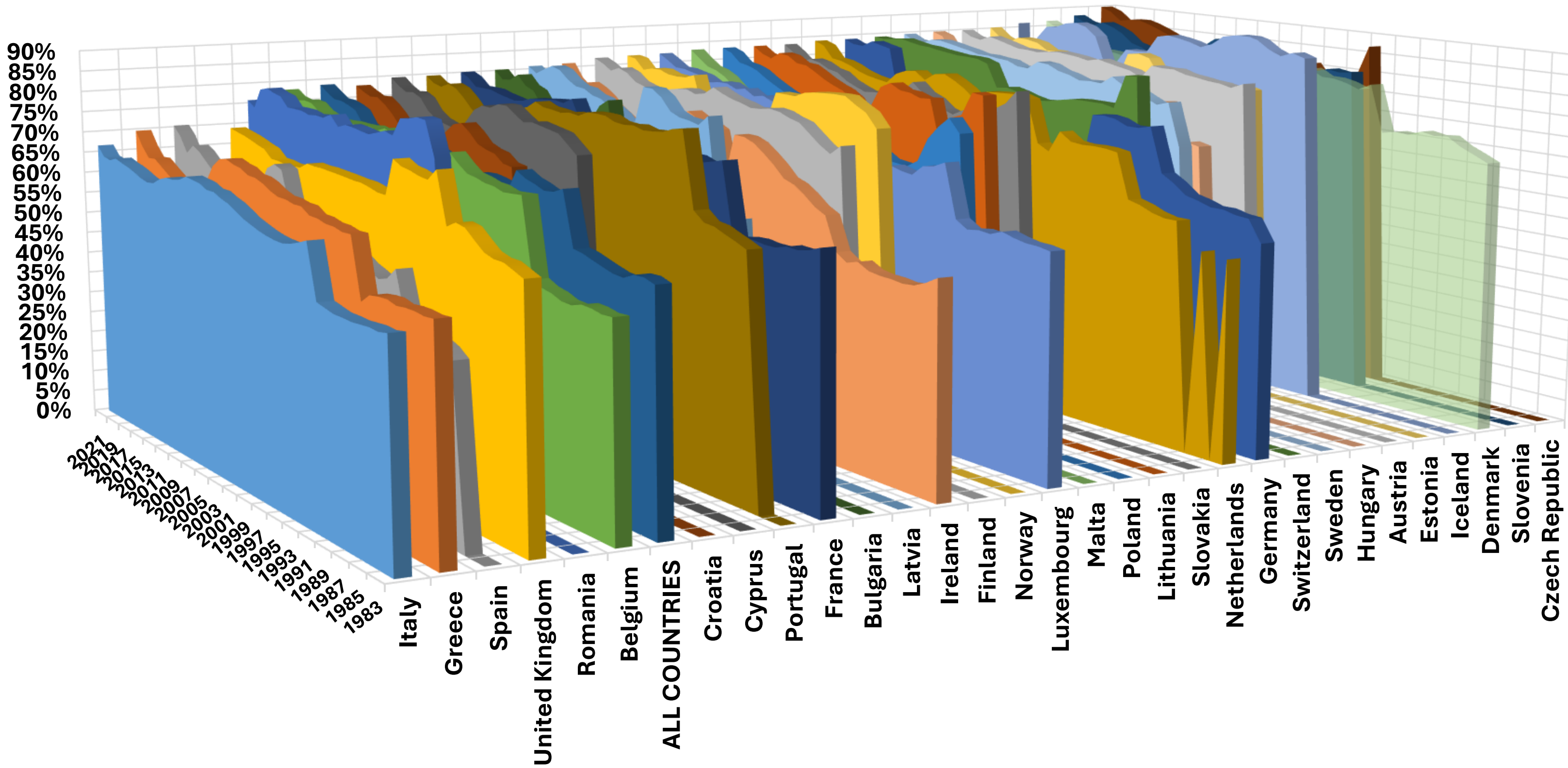
Column 1 of Table 2-9 presents weighted averages of the key variables in the YLFS for the four sub-samples of employees whose level of education is matched to the median level of skills of employees in their 3-digit ISCO occupational code in their country every year. Then, column 2 presents the weighted averages of key variables for mismatched employees. Columns 3 and 4 show the weighted average for the overeducated and the undereducated. Columns 5 and 6 present a weighted t-test and the level of significance for differences in means between skills matched and mismatched employees.

The inspection of the rows of the table suggests that matching is slightly higher in EU countries, and it is quite a bit lower in the Eurozone country-years. Among matched employees 28.3% reside in rural areas, while of the mismatched 24.3% are in rural areas. 54.7% of the matched employees are male, compared to 53.9% of the mismatched employees. 12.9% of the matched employees are migrants, compared to 17.1% of the mismatched employees. 18.4% of the overeducated are migrants, compared to 15.8% of the undereducated. A higher fraction of the matched employees is likely to have financially dependent children, to be living with a spouse or partner, and/or a parent in the same household. Matched employees are less likely to be registered at a public employment service or to be receiving benefits or assistance. Matched employees are less likely to have more than one job, and they are more likely to be at a higher income decile, compared to mismatched employees. The overeducated are more likely to be at higher income decile, and the undereducated are more likely to be at a lower income decile. A higher fraction of overeducated and a lower fraction of undereducated are moonlighting at a second job or more, i.e., 4.6% versus 3.6%.

82.6% of the matched employees are full-timers and 86.7% have a permanent contract, compared to 79.7% and 83.5% among the mismatched, respectively. 20.5% of the matched employees have a managerial/supervisory role, compared to 22.5% among the mismatched. This is an interesting pattern, as it might indicate that they are more mismatched employees among those who have more responsibilities within firm, and that is likely to have important negative consequences. Among the overeducated, 25.5% have a supervisory role, compared to 19.6% among the undereducated.

Fewer workers among the matched employees work from home, compared to the mismatched, i.e., 14.6% compared to 16.7% respectively. Matched employees are more likely not to be looking for another job, and to be working more hours on average, compared to the mismatched. They are less likely to want to work more hours in their main job and less likely to work overtime hours. Matched employees have fewer years of labour market experience, but higher tenures at their current job. They are less likely to receive training of all sorts. Finally, among the moonlighters, matched employees are more likely to be self-employed, and less likely to be paid employees. This is likely to entail interesting repercussions regarding the view of moonlighting as a skill diversification instrument for future transitions to own entrepreneurial activity (Panos, et al., 2013).

Table 2-10 repeats the previous illustration for the same four sub-samples of employees in the QLFS. Most of the results from the previous analysis hold. In addition, the inspection of the quarterly data shows that there are more matched employees among generation X and the baby boomers, compared to generations Y and Z, and the oldest silent generation. Moreover, there are more matched employees in mining and quarrying, manufacturing, electricity, gas and water supply, construction, wholesale and retail trade, hotels and restaurants, transport, education, health and social work. There are fewer matched employees in the fishing, financial intermediation, public administration and defence, extra-territorial organisations, activities of household and other community, social and personal work industries.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Italy
Greece
Spain
United Kingdom
Romania
Belgium
ALL COUNTRIES
Croatia
Cyprus
Portugal
France
Bulgaria
Latvia
Ireland
Finland
Norway
Luxembourg
Malta
Poland
Lithuania
Slovakia
Netherlands
Germany
Switzerland
Sweden
Hungary
Austria
Estonia
Iceland
Denmark
Slovenia
Czech Republic

Figure 2-3: EU-LFS$_{Yearly}$ – %Employment by country and year

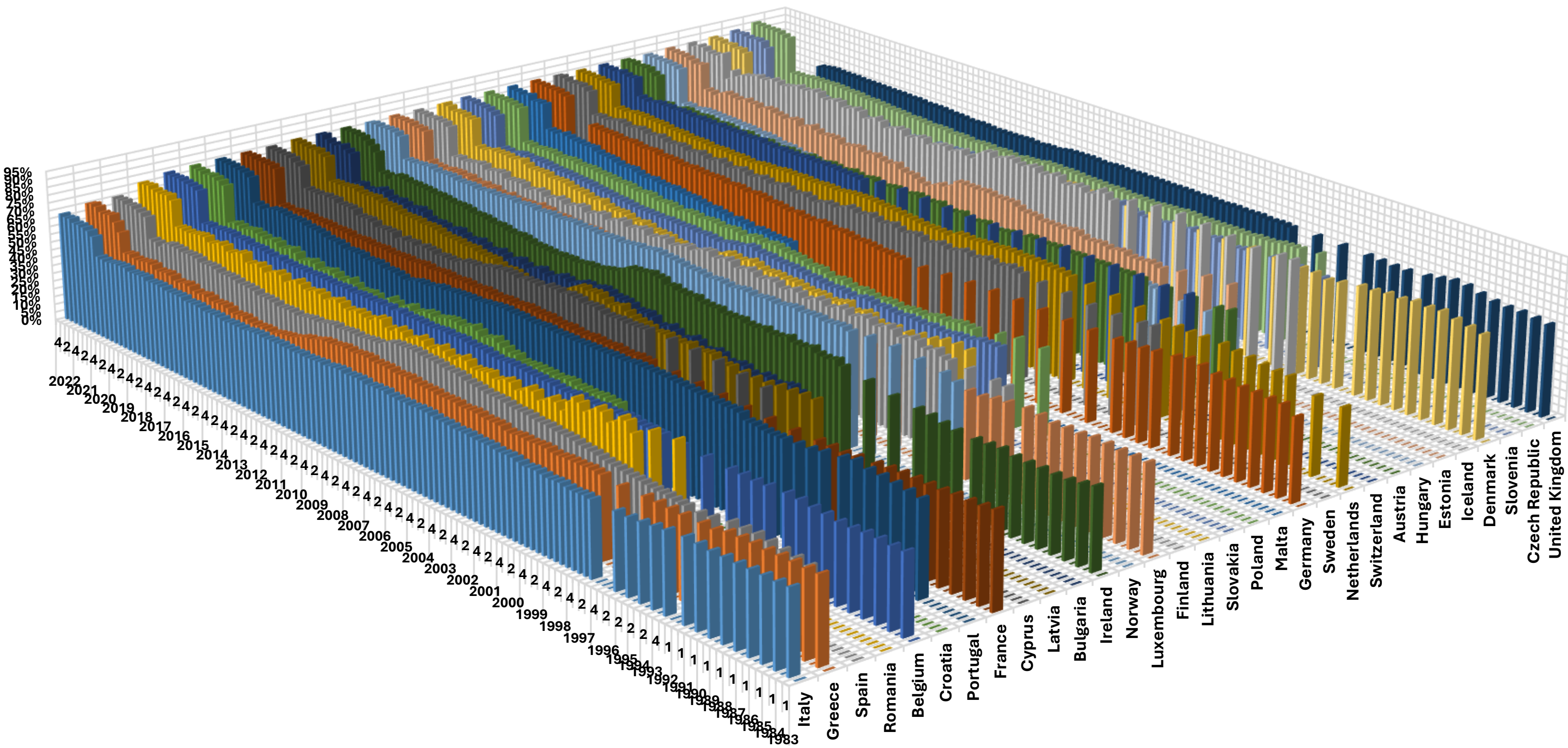


Figure 2-4: EU-LFS$_{Quarterly}$ – %Employment by country and quarter

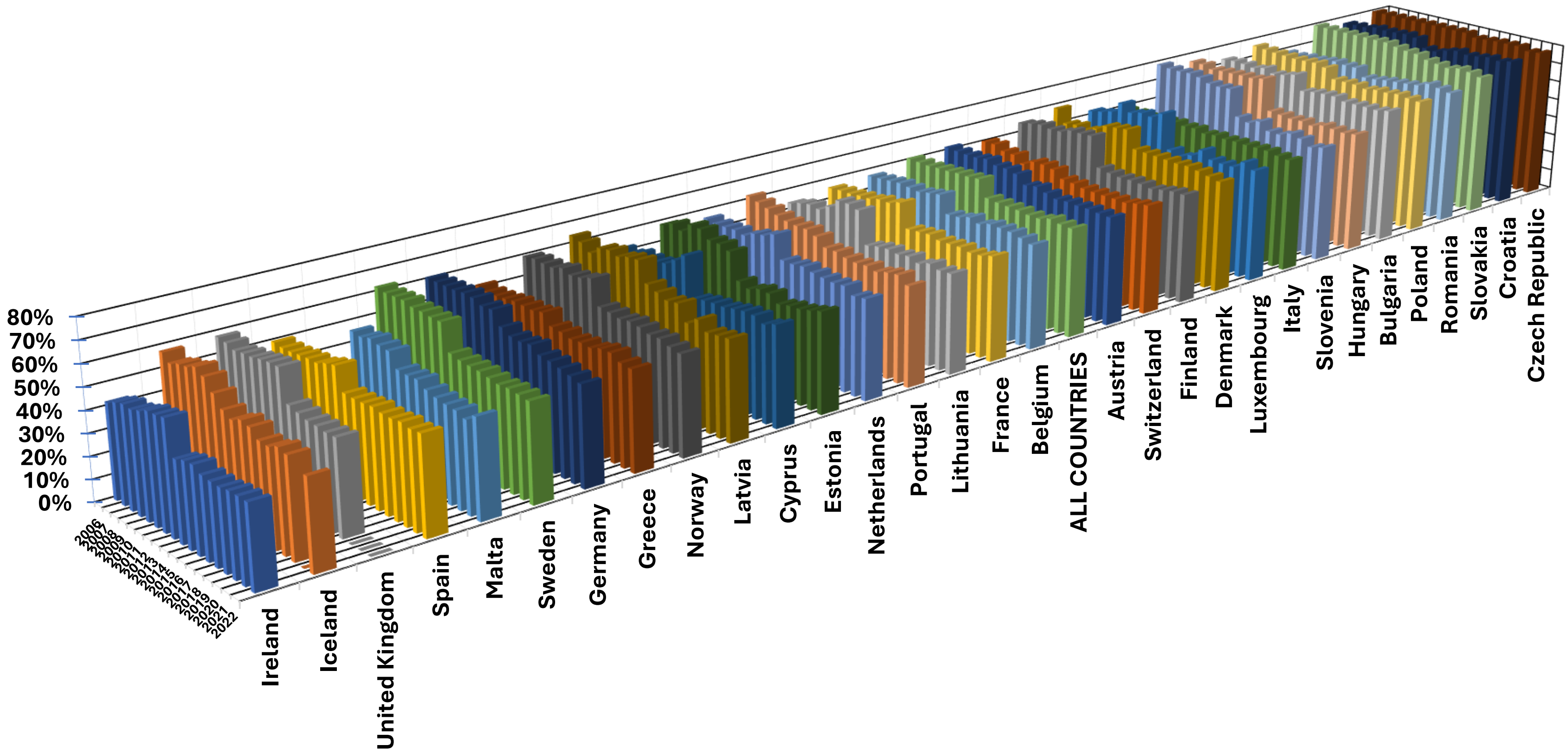


Figure 2-5: EU-LFS$_{Yearly}$ – %Skills matching by country and year

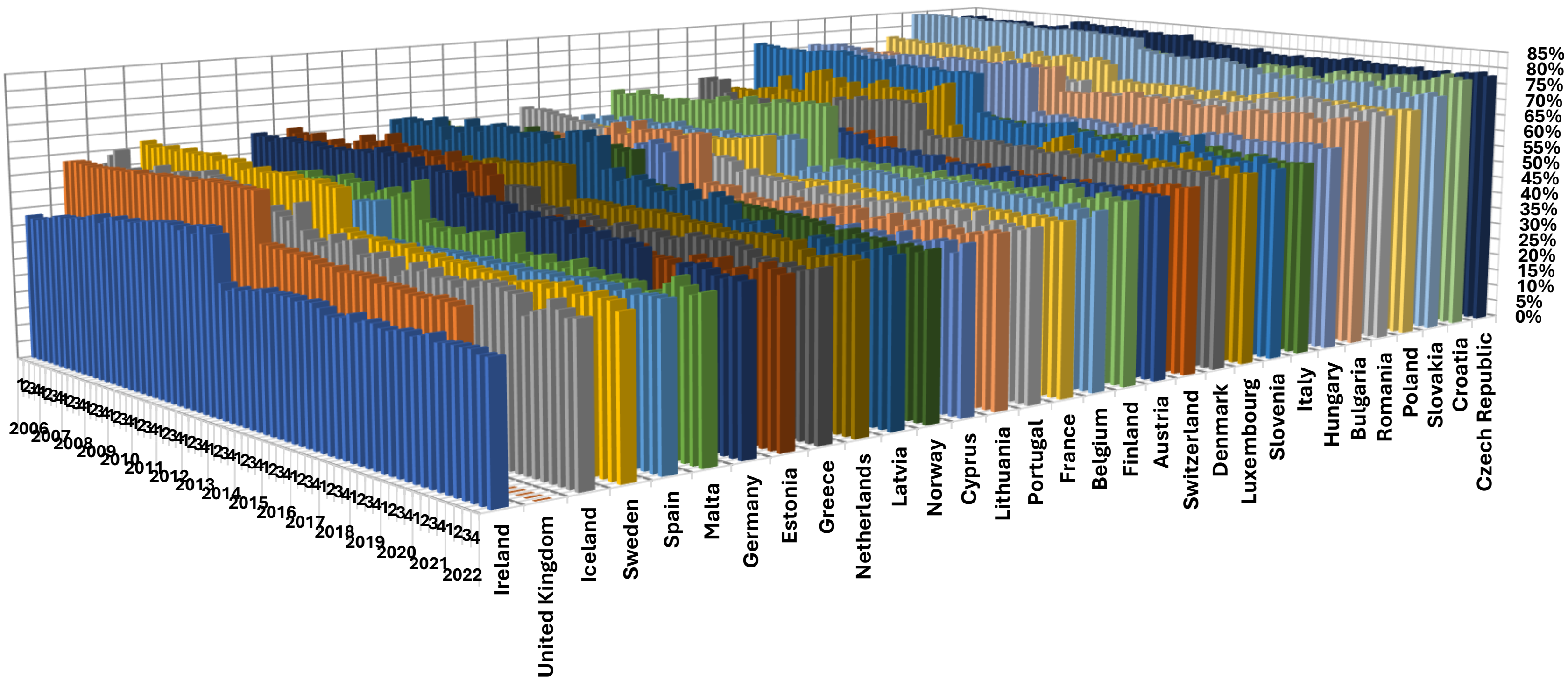


Figure 2-6: EU-LFS$_{Quarterly}$ – %Skills matching by country and quarter

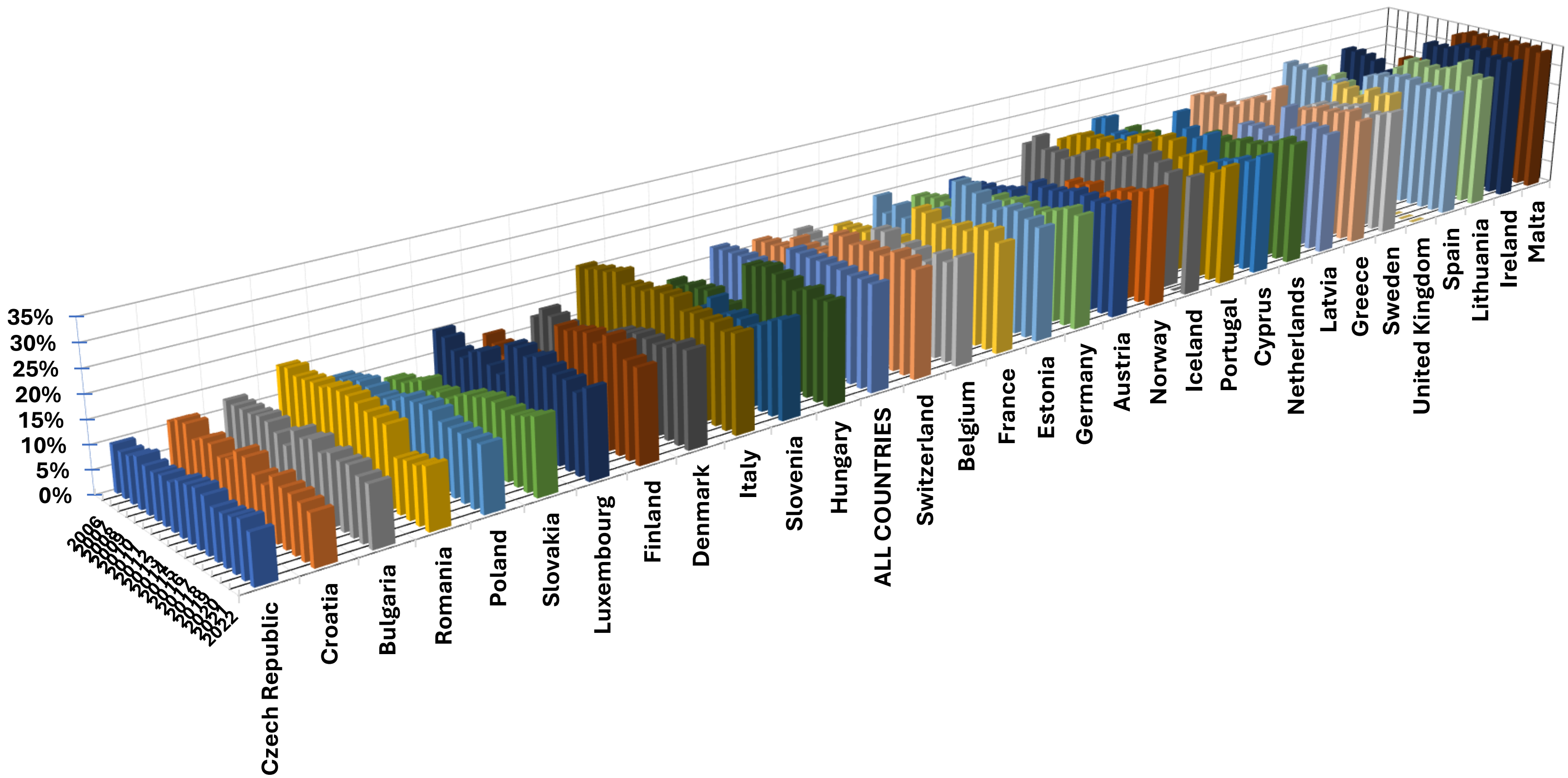


Figure 2-7: EU-LFS$_{Yearly}$ – %Overeducation by country and year

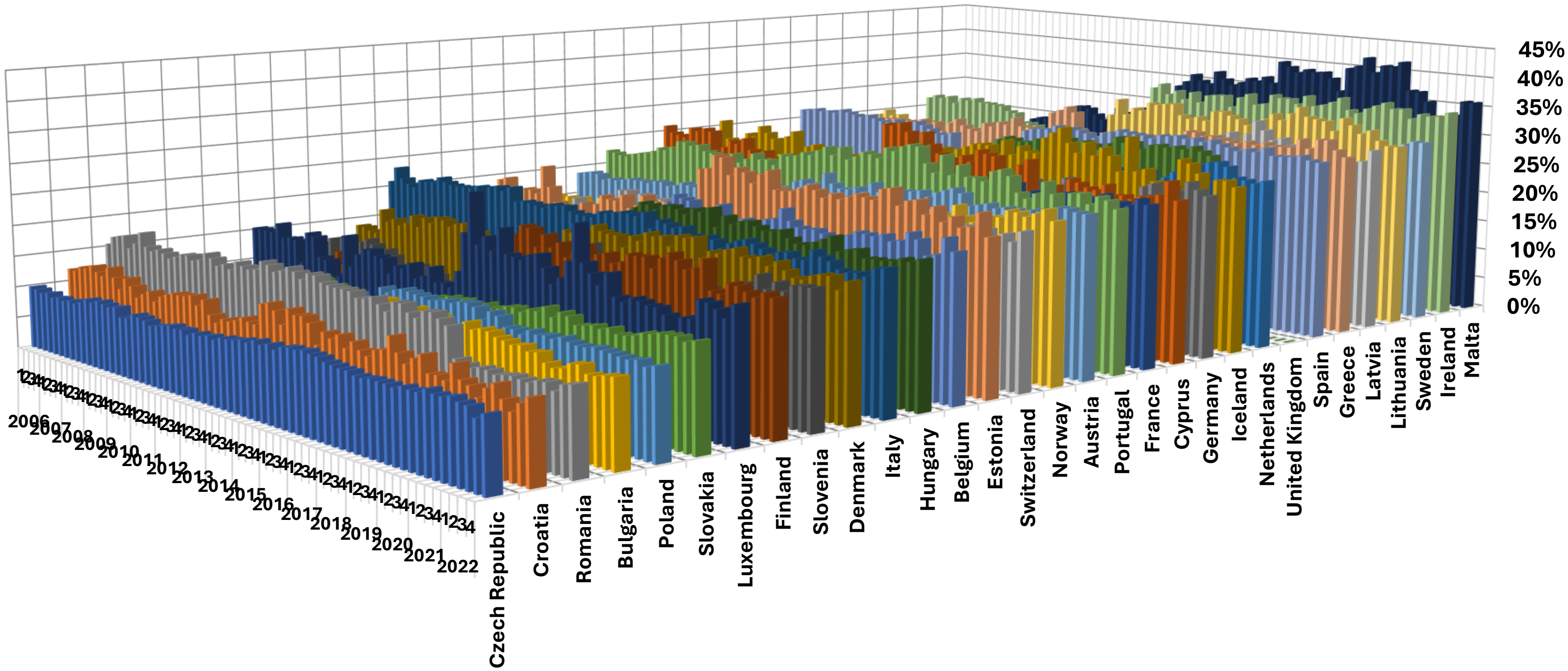


Figure 2-8: : EU-LFS$_{Quarterly}$ – %Overeducation by country and quarter

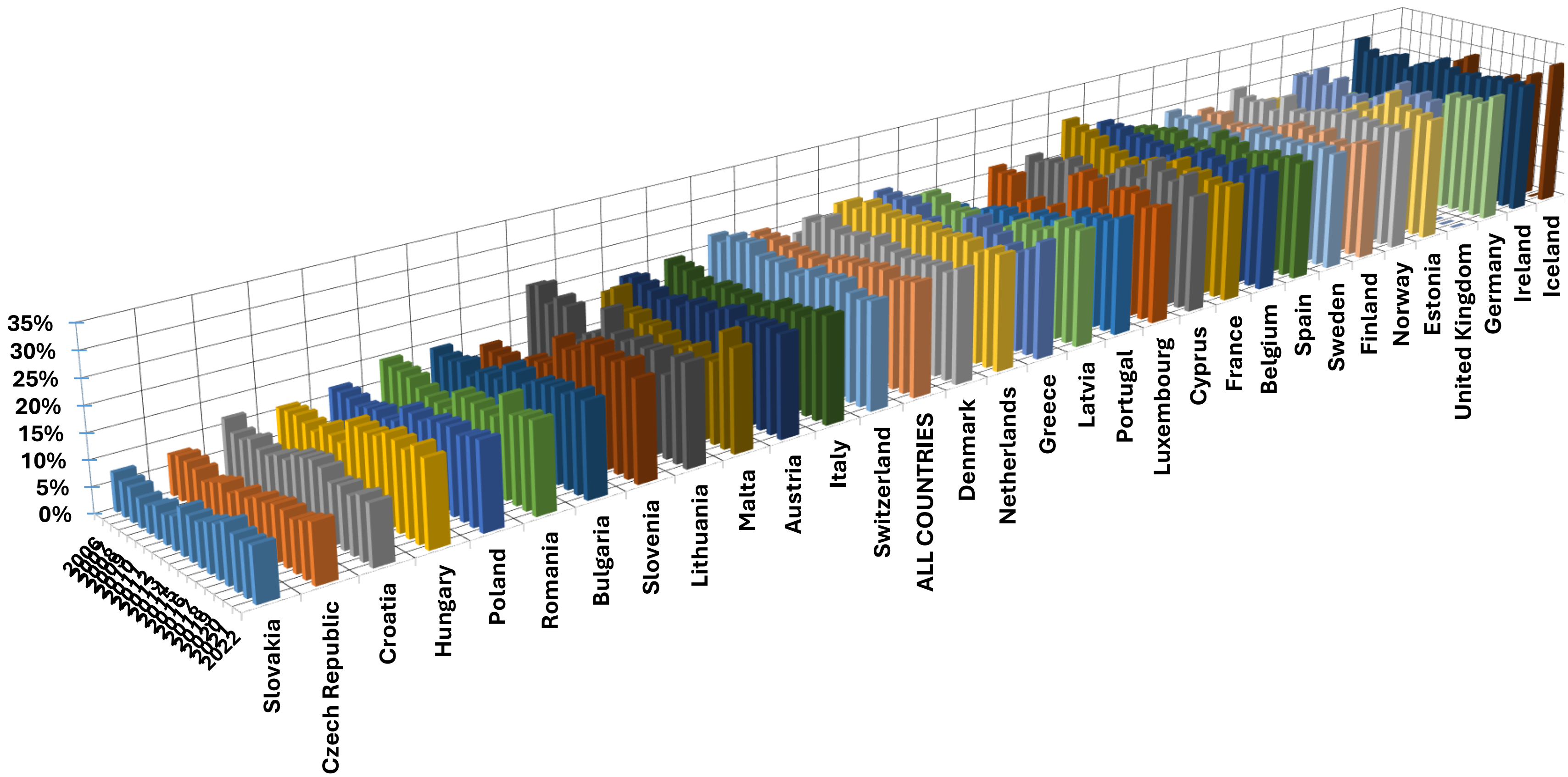


Figure 2-9: EU-LFS$_{Yearly}$ – %Undereducation by country and year

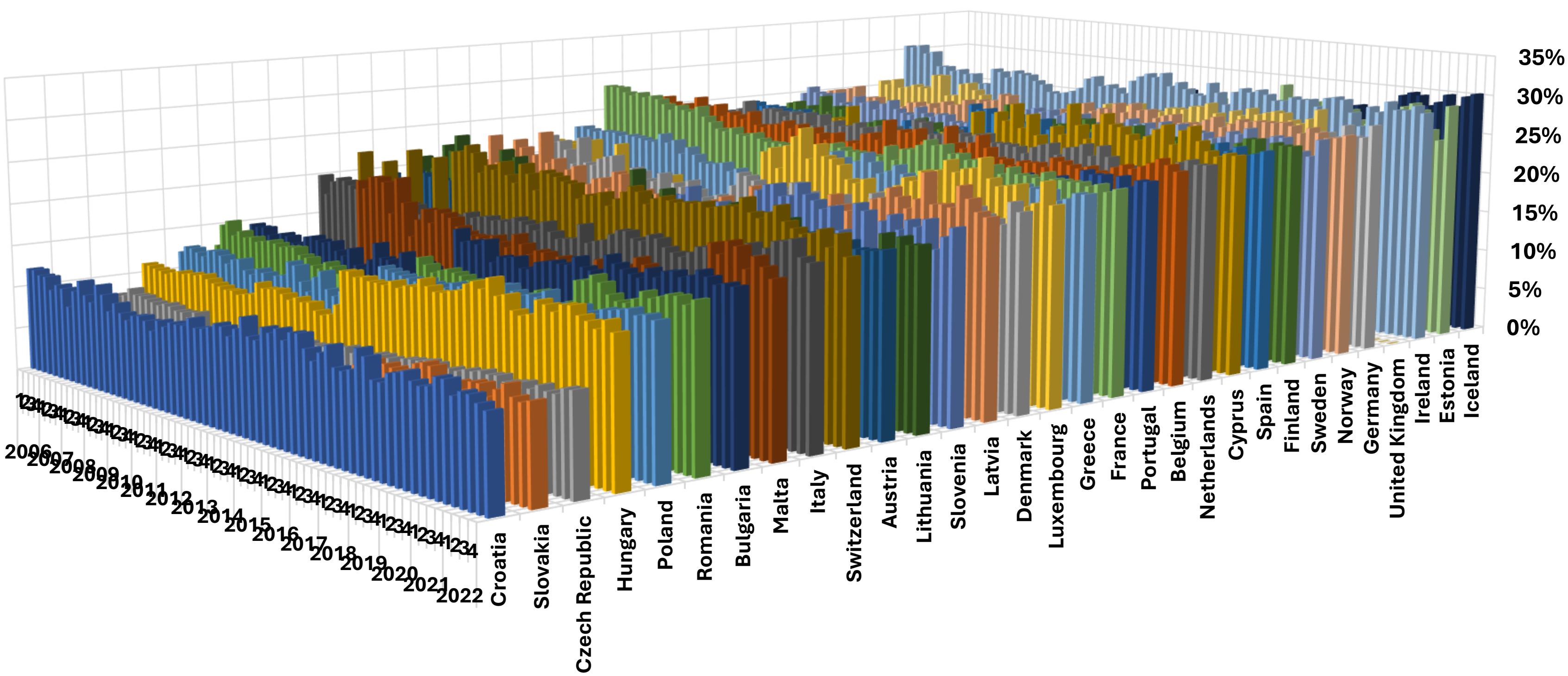


Figure 2-10: EU-LFS$_{Quarterly}$ – %Undereducation by country and quarter

Table 2-9: EU-LFS$_{Yearly}$– Differences in weighted averages of key variables my matching status

#OBSERVATIONS	MATCHED 16,377,575	MISMATCHED 11,016,780	OVEREDUC. 5,435,719	UNDEREDUC. 5,581,061	DIFF.	SIG.
EU country	97.0%	96.7%	96.9%	96.6%	0.29pp	***
Euro country	64.0%	71.9%	72.8%	71.1%	-7.95pp	***
Rural	28.3%	24.3%	22.4%	26.1%	3.96pp	***
Male	54.7%	53.9%	52.1%	55.6%	0.83pp	***
Years of schooling	12.41	12.21	14.81	9.67	0.2029	***
Age	41.72	41.89	40.35	43.39	-0.1698	***
Migrant	12.9%	17.1%	18.4%	15.8%	-4.17pp	***
Disabled	0.2%	0.3%	0.2%	0.4%	-0.03pp	***
Reference person	52.4%	52.5%	52.2%	52.7%	-0.03pp	
Reference couple	79.9%	79.8%	80.0%	79.6%	0.09pp	***
Financially dependent children	33.4%	32.1%	34.6%	29.8%	1.25pp	***
Spouse/ partner lives in same household	63.4%	61.3%	61.4%	61.3%	2.06pp	***
Father and mother live in same household	14.2%	13.5%	13.7%	13.4%	0.63pp	***
Child(ren) live(s) in same household	47.8%	45.0%	44.7%	45.3%	2.78pp	***
Registered at a public employment service	2.3%	3.1%	3.0%	3.2%	-0.76pp	***
Receives benefit or assistance	2.5%	3.8%	3.5%	4.0%	-1.23pp	***
Carer	2.9%	3.0%	3.5%	2.4%	-0.02pp	
Absentee	9.6%	9.6%	9.6%	9.6%	-0.03pp	
Number of jobs	1.11	1.11	1.13	1.10	0.0007	*
Income decile	5.59	5.40	5.86	4.93	0.1893	***
Number of children	0.68	0.67	0.68	0.65	0.0114	***
Moonlighter	4.0%	4.1%	4.6%	3.6%	-0.05pp	***
Full-time	82.6%	79.7%	80.6%	78.8%	2.83pp	***
Permanent job	86.7%	83.5%	84.5%	82.5%	3.25pp	***
Supervisor	20.5%	22.5%	25.5%	19.6%	-1.98pp	***
Home worker	14.6%	16.7%	19.5%	14.0%	-2.09pp	***
Internal migrant (nomad)	2.1%	2.1%	2.2%	2.1%	0.01pp	*
Wish to work more hours	9.0%	10.5%	10.7%	10.2%	-1.45pp	***
Not looking for another job	93.6%	92.5%	91.5%	93.5%	1.08pp	***
Hours of work (actual)	33.53	32.93	33.32	32.54	0.0108	***
Overtime hours of work	1.09	1.14	1.28	1.00	-0.0547	***
Labour market experience	21.75	21.81	17.22	26.73	-0.067	***
Time since started work (months)	127.97	121.55	106.34	136.47	6.3185	***
Education/training received in last 4 weeks	12.6%	14.7%	15.4%	14.1%	-2.16pp	***
Formal education/training in last 4 weeks	4.1%	5.9%	4.6%	7.2%	-1.88pp	***
Informal job-related training in last 4 weeks	9.1%	9.4%	11.3%	7.5%	-0.31pp	***
Inf. non-job-related training in last 4 weeks	0.2%	0.3%	0.4%	0.2%	-0.09pp	
Education/training received in last 12 months	29.3%	32.1%	35.5%	28.6%	-2.71pp	***
Formal education/training in last 12 months	4.9%	7.6%	6.5%	8.6%	-2.66pp	***
Informal job-related training in last 12 months	22.9%	22.8%	26.8%	18.9%	0.11pp	
Informal non-job-related training in last 12 months	3.1%	3.9%	4.5%	3.2%	-0.07pp	***
Self-employed in 2nd job	39.2%	37.6%	40.7%	33.7%	1.65pp	***
Paid employee in 2nd job	54.8%	58.8%	56.3%	62.0%	-4.03pp	***
Family worker in 2nd job	6.0%	3.6%	3.0%	4.4%	2.38pp	***

Table 2-10: EU-LFS$_{Quarterly}$ – Differences in weighted averages of key variables my matching status

#OBSERVATIONS	MATCHED *25,876,109*	UNMATCHED *18,798,232*	OVEREDUC. *9,118,753*	UNDEREDUC. *9,679,479*	Diff.	Sig.
EU country	96.8%	96.0%	96.2%	95.9%	0.76pp	***
Euro country	63.1%	71.1%	71.8%	70.3%	-7.92pp	***
Rural	28.0%	24.1%	22.3%	26.0%	3.81pp	***
Male	54.6%	53.8%	52.0%	55.6%	0.80pp	***
Years of schooling	12.39	12.19	14.80	9.64	0.1977	***
Age	41.68	41.81	40.33	43.26	-0.1287	***
Gen Z, iGen, or Centennials	2.5%	3.1%	1.9%	4.4%	-0.61pp	***
Millennials or Gen Y	34.6%	36.6%	43.6%	29.7%	-2.01pp	***
Generation X	32.8%	30.7%	31.9%	29.4%	2.18pp	***
Baby Boomers	29.1%	28.3%	21.9%	34.5%	0.80pp	***
Traditionalists or Silent Gen	1.0%	1.4%	0.8%	2.0%	-0.36pp	***
Migrant	12.5%	16.3%	17.5%	15.1%	-3.84pp	***
Disabled	0.1%	0.1%	0.0%	0.1%	-0.01pp	***
Registered at a public employment service	0.2%	0.4%	0.3%	0.4%	-0.13pp	***
Receives benefit or assistance	1.8%	2.8%	2.8%	2.8%	-0.97pp	***
Absentee	9.7%	9.8%	9.7%	9.8%	-0.09pp	***
Number of jobs	1.11	1.11	1.13	1.10	0.0000	
Moonlighter	4.0%	4.1%	4.5%	3.6%	-0.08pp	***
Full-timer worker	81.9%	78.9%	80.1%	77.7%	3.02pp	***
Permanent job	86.3%	82.8%	84.1%	81.6%	3.47pp	***
Internal migrant (nomad)	1.8%	1.9%	2.0%	1.8%	-0.04pp	***
Wish to work more hours	9.0%	10.4%	10.7%	10.2%	-1.45pp	***
Hours of work (actual)	33.29	32.60	33.09	32.11	0.6941	***
Overtime hours of work	1.0367	1.084	1.2226	0.9436	-0.0473	***
Time since person started to work (months)	127.54	121.00	106.03	135.77	6.536	***
Education/training received in last 4 weeks	12.9%	15.3%	15.7%	14.9%	-2.36pp	***
Formal job-related training in last 4 weeks	4.7%	6.7%	5.1%	8.3%	-2.03pp	***
Informal job-related training in last 4 weeks	8.9%	9.3%	11.3%	7.5%	-0.41pp	***
Inf. non-job-related training in last 4 weeks	0.2%	0.3%	0.4%	0.2%	-0.09pp	***
Self-employed in 2nd job	38.9%	36.8%	40.0%	33.0%	2.04pp	***
Paid employee in 2nd job	55.1%	59.5%	57.0%	62.7%	-4.40pp	***
Family worker in 2nd job	6.0%	3.6%	3.0%	4.4%	2.36pp	***
Industry: Agriculture, hunting and forestry	7.6%	17.5%	21.0%	14.3%	-9.89pp	***
"-": Fishing	0.1%	0.2%	0.2%	0.1%	-0.07pp	***
"-": Mining and quarrying	0.9%	0.5%	0.3%	0.6%	0.38pp	***
"-": Manufacturing	21.9%	17.1%	13.1%	20.7%	4.79pp	***
"-": Electricity, gas and water supply	1.6%	0.9%	1.2%	0.8%	0.64pp	***
"-": Construction	8.4%	7.6%	5.5%	9.4%	0.85pp	***
"-": Wholesale and retail trade; repairs	14.1%	13.1%	13.1%	13.1%	1.02pp	***
"-": Hotels and restaurants	3.6%	3.4%	3.1%	3.8%	0.17pp	***
"-": Transport, storage and communication	6.9%	5.9%	5.7%	6.0%	1.01pp	***
"-": Financial intermediation	1.9%	2.5%	4.1%	1.1%	-0.62pp	***
"-": Real estate, renting and business	6.9%	8.2%	9.4%	7.1%	-1.31pp	***
"-": Public administration and defence; CSS	6.0%	6.2%	7.4%	5.2%	-0.26pp	***
"-": Education	7.7%	4.5%	4.1%	4.8%	3.18pp	***
"-": Health and social work	8.6%	7.3%	6.9%	7.7%	1.25pp	***
"-": Other community, social & personal	3.8%	4.6%	4.3%	4.9%	-0.81pp	***
"-": Activities of households	0.2%	0.5%	0.5%	0.5%	-0.29pp	***

"-“: Extra-territorial organizations and bodies	0.0%	0.1%	0.1%	0.1%	-0.03pp	***

Having observed the basic for skills mismatching, Table 2-11 presents training weighted statistics for the employed sub-sample of the YLFS. On average for the years 1983-2022, 14.5% of the sample had training of any form during the last 4 weeks, 7.4% had formal, 7.8% had informal job-related training and an addition of 0.2% of the sample had informal not job-related training. The sub-sample for 2022 included additional questions regarding training during the last 12 months. Some 28.1% of the sample had training of any type during the last year, 7.2% had formal training, 19.4% had informal job-related training and an additional 3.5% had informal not job-related training during the last 12 months.

The countries with these highest figures for training during the recent past (4 weeks) are: Sweden (28.6%), Denmark (28.2%), Finland (25.3%), the Netherlands (21.3%) and Slovenia (16.8%). The countries at the bottom of the table are: Hungary (6.3%), Greece (6.1%), Croatia (5.1%), Slovakia (5%), and Romania (3.1%). In the most recent figures for 2022 regarding training during the last yar, the ranking at the top countries is identical. However, those at the bottom for any type of training become: Poland (17.4%), Romania (11.3%), Croatia (10.9%), Greece (7.3%), and Bulgaria (5%).

Figure 2-11 presents the evolution of the incidence of employee training overall between 1982-2022, i.e., for any type of training, both formal and informal, between the years 1983-2022. Evidently, there are some missing observations in some countries during earlier years in the sample. However, there is also a clear pattern of a reduction in the percentage of employees receiving training. The pattern is obvious for the years before the crisis in the countries with the lowest rates for training, i.e., Bulgaria and Greece. However, it is also present in Italy, Belgium and Ireland. The years after the Eurozone crisis show an increase in the amount of employees receiving training in Hungary, Ireland, Latvia and Malta. There is also a clear pattern of increase in training in the years post Covid-19 in Croatia, Romania, Hungary, Poland, Italy, the Czech Republic, Slovakia, Belgium, Ireland, Latvia, Malta, Spain, Portugal, France, Austria, Estonia, Norway, Slovenia, Iceland, Luxembourg,the Netherlands, and Denmark.

Figure 2-12 presents the evolution of formal employee training. At the left of the figure one can see that the countries with the lowest amounts of training are consistently low in all years post 2003, for which the variable distinguishing between formal and informal training is available at the YLFS. Slovakia, the Czech Republix, Romania, Hungary, Poland, Bulgaria, Lithuania and Croatia are the countries with the lowest rates for formal training. Interestingly, the low rates are getting even lower post 2014. The two countries with the largest reductions in the percentage of employees receiving formal training post 2014 are Germany, Norway and Iceland, which are among the top 10 countries in terms of formal training coverage in our sample. The Netherlands, the United Kingdom, Sweden, Iceland, and Finland are the top five countries for coverage in formal employee training in the YLFS.

Figure 2-13 presents the evolution of informal training, which is specific to the job. Bulgaria, Greece, Croatia, Germany and Ireland are the bottom five countries in terms of informal job-specific training, i.e., training that is specific to the job and is usually undertaken by the employee. The top five countries are Norway, Estonia, Sweden, Switzerland and Slovenia. However, it is worth noting that for Sweden and Switzerland, there are large reductions in the percentage of employees receiving informal job-specific training in the last 2-3 years of the sample, i.e., in the post-Covid19 period. A similar pattern emerges in Finland, Luxembourg, Denmark, France, and overall, for all the countries on average.

Figure 2-14 presents the evolution in formal employee training, which is general and not related to the job of an employee. The countries with the highest rates for generic training are Denmark, Sweden, France, Finland, and the Netherlands. The top four countries, excluding the Netherlands, show increases in the amounts of generic informal training between 2021 and 2022. The bottom five countries, limited to generic informal training among their employees are Croatia, Greece, Romania, Slovakia, and Bulgaria. It is worth noting that for the United Kingdom at the bottom, there is no data available for 2021-2022, i.e., post exit from the European Union.

Table 2-11: EU-LFS$_{Yearly}$ – Training statistics by country (weighted)

	DURING LAST 4 WEEKS				DURING LAST 12 MONTHS			
	TRAINING	FORMAL	INFORMAL JOB-RELATED	INFORMAL NON-JOB-RELATED	TRAINING	FORMAL	INFORMAL JOB-RELATED	INFORMAL NON-JOB-RELATED
All Countries	*14.5%*	*7.4%*	*7.8%*	*0.2%*	*28.1%*	*7.2%*	*19.4%*	*3.5%*
Sweden	28.6%	9.6%	20.9%	1.2%	60.0%	16.0%	39.4%	12.3%
Denmark	28.2%	9.9%	21.9%	1.3%	53.3%	15.1%	25.9%	20.2%
Finland	25.3%	11.2%	17.1%	0.5%	46.7%	18.4%	28.0%	9.2%
Netherlands	21.3%	8.8%	10.7%	0.5%	47.0%	13.7%	25.0%	9.0%
Slovenia	16.8%	8.6%	10.0%	0.4%	40.3%	7.8%	31.1%	4.9%
Austria	16.7%	7.5%	10.9%	0.3%	38.6%	9.6%	28.0%	4.9%
Germany	16.0%	11.3%	4.3%	0.1%	21.4%	9.2%	12.5%	1.2%
Spain	14.3%	7.4%	9.4%	0.1%	28.8%	6.9%	21.1%	2.7%
Luxembourg	13.9%	5.4%	12.0%	0.2%	39.3%	11.7%	29.7%	2.9%
France	13.6%	5.4%	11.2%	0.5%	39.6%	6.8%	28.0%	7.5%
Estonia	13.4%	7.1%	8.6%	0.2%	54.2%	10.4%	46.5%	3.5%
Ireland	11.5%	5.6%	4.4%	0.4%	25.1%	9.6%	11.6%	6.5%
Belgium	10.6%	3.8%	5.4%	0.1%	24.1%	5.8%	17.3%	1.9%
Malta	10.4%	4.4%	6.6%	0.5%	45.5%	9.0%	36.2%	7.5%
Latvia	9.8%	5.6%	4.3%	0.2%	22.3%	5.1%	16.3%	2.8%
Portugal	9.2%	4.7%	5.1%	0.2%	34.2%	7.6%	26.4%	3.0%
Italy	9.1%	3.8%	4.2%	0.1%	22.1%	4.5%	16.0%	2.5%
Czech Republic	9.0%	2.2%	7.0%	0.1%	25.8%	2.2%	24.5%	0.0%
Lithuania	8.5%	4.5%	3.7%	0.1%	21.9%	4.4%	17.3%	2.1%
Cyprus	8.1%	3.6%	5.3%	0.2%	27.1%	6.8%	19.2%	3.5%
Poland	7.9%	4.9%	2.6%	0.1%	17.4%	3.6%	13.2%	1.8%
Bulgaria	6.6%	5.8%	0.4%	0.0%	5.0%	3.7%	1.4%	0.2%
Hungary	6.3%	3.2%	3.0%	0.2%	24.9%	2.9%	20.8%	2.0%
Greece	6.1%	3.5%	1.6%	0.1%	7.3%	4.5%	2.9%	0.9%
Croatia	5.1%	3.7%	1.0%	0.1%	10.9%	4.2%	5.7%	1.6%
Slovakia	5.0%	1.8%	2.9%	0.0%	46.2%	2.0%	44.7%	0.3%
Romania	3.1%	2.4%	0.9%	0.0%	11.3%	1.8%	9.2%	0.6%
Non-EU								
Switzerland	33.1%	10.6%	23.5%	0.2%	44.3%	13.0%	33.9%	3.5%
Iceland	26.5%	14.4%	15.0%	0.2%	100.0%	18.8%	83.2%	16.8%

Norway	24.4%	12.8%	12.6%	0.1%	50.4%	14.7%	40.1%	2.5%
United Kingdom	23.2%	12.0%	14.3%					

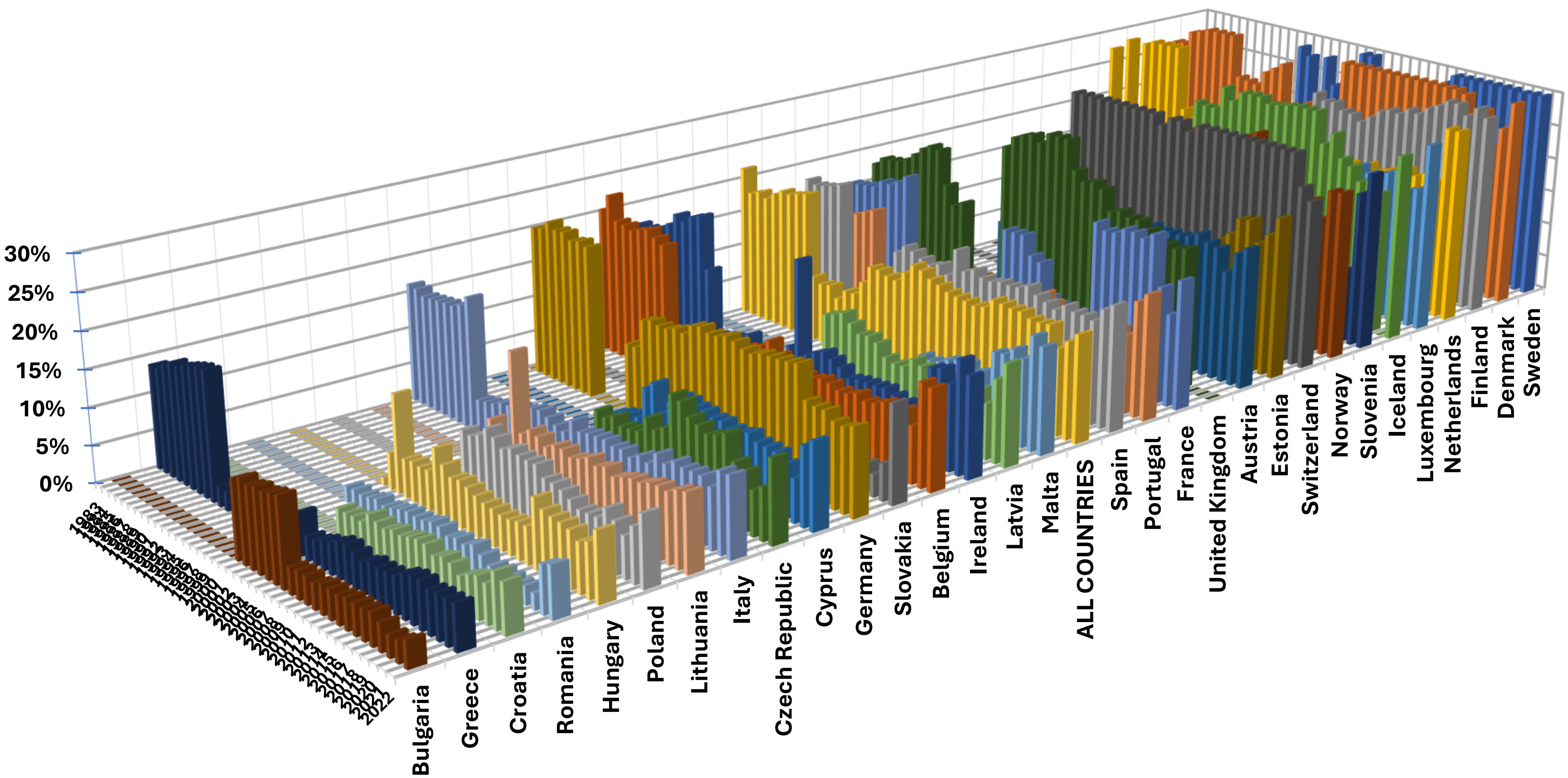

30%
25%
20%
15%
10%
5%
0%
Bulgaria
Greece
Croatia
Romania
Hungary
Poland
Lithuania
Italy
Czech Republic
Cyprus
Germany
Slovakia
Belgium
Ireland
Latvia
Malta
ALL COUNTRIES
Spain
Portugal
France
United Kingdom
Austria
Estonia
Switzerland
Norway
Slovenia
Iceland
Luxembourg
Netherlands
Finland
Denmark
Sweden

Figure 2-11: EU-LFS$_{Yearly}$ – % Training during the last 4 weeks by country and year

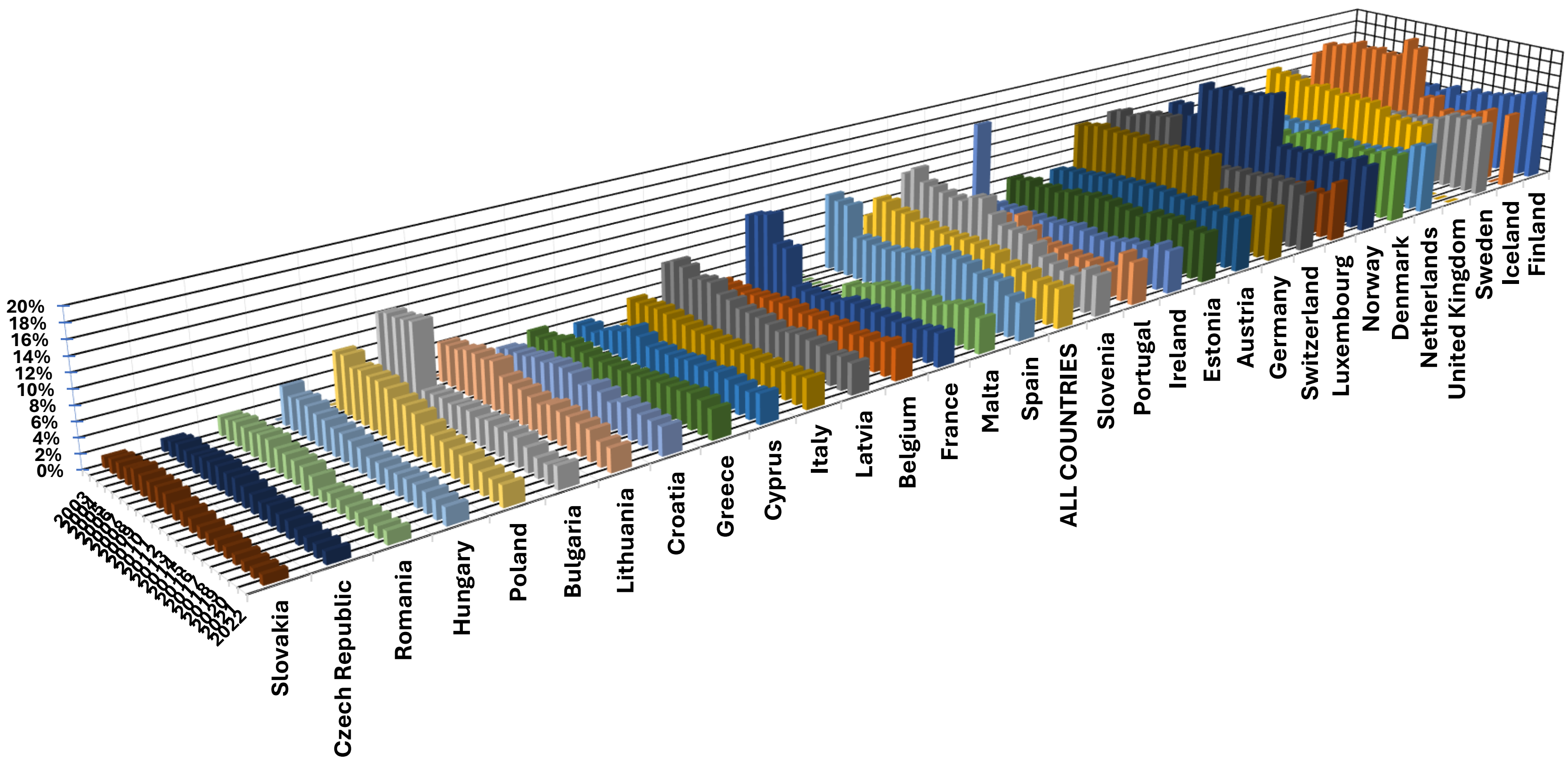


Figure 2-12: EU-LFS$_{Yearly}$ – %Formal training during the last 4 weeks

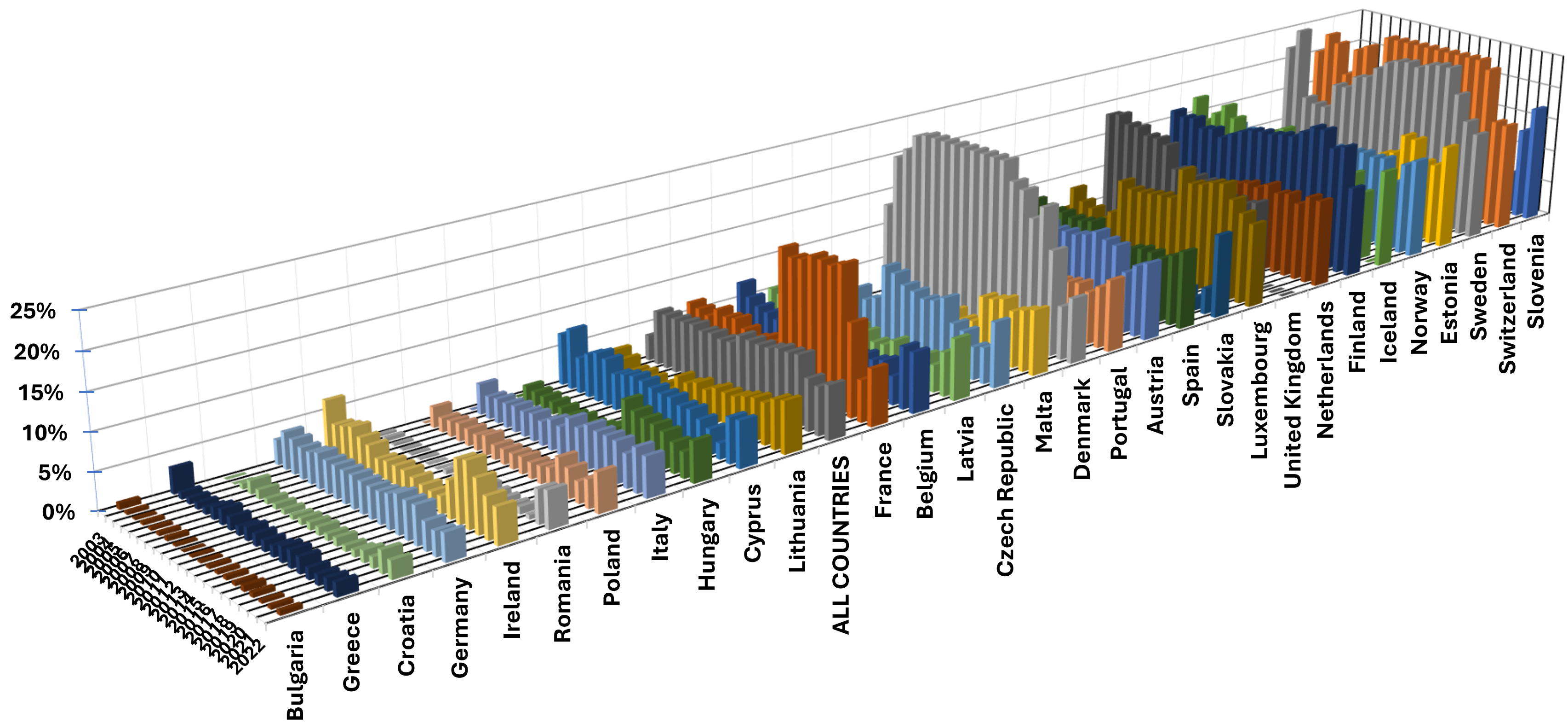


Figure 2-13: EU-LFS$_{Yearly}$ – %Informal job-related training during the last 4 weeks

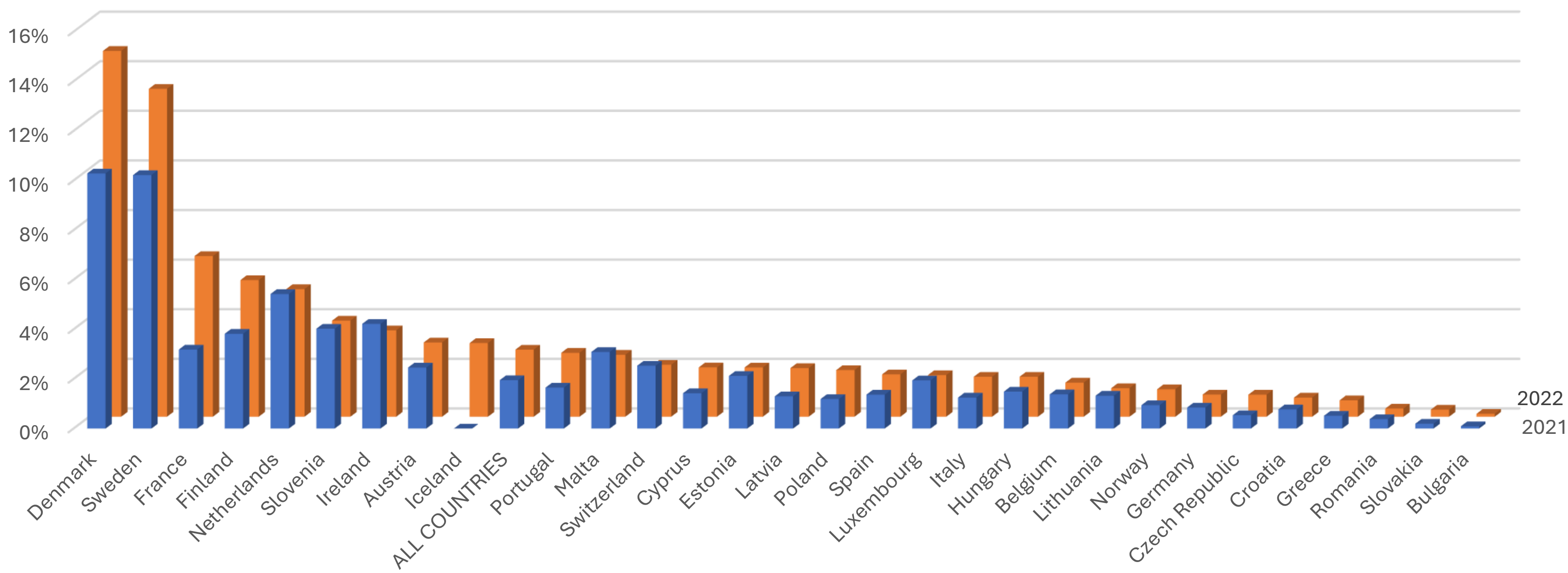


Figure 2-14: EU-LFS$_{Yearly}$ – %Informal not job-related training during the last 4 weeks

2.1.4 DIFFERENCES BY GENDER

This sub-section presents differences between males and females overall and in the 31 countries of the EU-LFS, in weighted averages related to employment, skills mismatching, overeducation and undereducation, as well as training.

Table 2-12 presents weighted averages overall and by country for the former employment outcomes. It is shown that there is 19.6 percentage point (pp) difference in employment among males and females overall in the pooled sample, with 77.2% of males being employed compared to 57.6% of females. The countries with the largest gender difference in employment are: Greece (36pp), Malta (34.9pp), Italy (34.3pp), Luxembourg (29.4pp), Spain (26.9pp) and Ireland (24.1pp). The countries with the lowest gender differences in employment are: Latvia (5.3), Sweden (5.2pp), Estonia (4.3pp), Finland (3.7pp) and Lithuania (0.8pp).

When it comes to skills mismatching, males are less likely to be mismatched, and there is a small negative difference of -0.8pp between males and females in the pooled sample of all countries. The top countries in which males are more likely to be mismatched are: Greece (3.6pp), Ireland (4pp), the Netherlands (4.9pp), Portugal (3.4pp), Denmark (6.3pp), and Norway (5pp). The bottom countries in which females are more likely to be mismatched are: Slovenia (-5.4pp), Slovakia (-5.3pp), Poland (-7.7pp), Hungary (-4.3pp), and Cyprus (-4.6pp).

The botom countries in which males are less likely to be overeducated than females are: Malta (-4.6pp), Cyprus (-7.1pp), France (-5.7pp), Poland (-5.7pp), Slovenia (-4.8pp), Latvia (-5.3pp), Estonia (-4.5pp). The top countries in which males are more likely to be undereducated than females are: Ireland (4.9pp), the Netherlands (5.3pp), Belgium (5.4pp), Denmark (5.7pp), Norway (4.4pp), France (3.9pp), Finland (4pp).

Figure 2-15 presents the ranking of countries in terms of gender differences in skills mismatching, along with the incidence of overeducation and undereducation. The previous findings are confirmed: Poland, Slovenia, Slovakia, the Czech Republic and Cyprus are the countries in which females are more likely to be mismatched. In these countries females are more likely to be both overeducated and undereducated, compared to males. Greece, Ireland, the Netherlands, Norway and Denmark are the countries in which the males are more likely to be mismatched. In Greece, Norway and Denmark, males are the ones more likely to be both overeducated and undereducated compared to females. In Ireland and the Netherlands, males are much more likely to be undereducated and less likely to be overeducated, compared to females.

Figure 2-16 presents the evolution of gender differences in employment (the difference in the weighted average between males and females) over time. It is shown that gender differences in employment have been declining throughout Europe and beyond between 1983-2022. The decline has been sharper for countries which had the biggest gender differences in employment in the past, i.e., Malta, Greece, and Spain. Romania is the exception here, in which gender differences are high and are also rising in the last decade.

Figure 2-17 presents the evolution of gender differences in skills mismatching (the difference in the weighted averages between males and females). In countries in which females are more likely to be mismatched, i.e., Slovakia, Slovenia, the Czech Republic, Poland, Bulgaria, Croatia, Romania, and

Hungary, the higher mismatching of females seems to be deteriorating further in the last decade. In contrast, in countries in which males are more likely to be mismatched, namely Denmark, Switzerland, Portugal, Norway, and the Netherlands, the patter seems to be a permanent one and even increasing over time.

Figure 2-18 presents the evolution of gender differences in overeducation (the difference in the weighted average between males and females). Here, we find persistent and increasing patterns of higher overeducation by females in France, Slovenia, Slovakia, Sweden and the United Kingdom. We find increasing patterns of higher overeducation by males in Switzerland, and Poland.

Figure 2-19 presents the evolution of gender differences in undereducation (the difference in the weighted average between males and females). We find persistent patterns of higher undereducation by females in the Czech Republic, Slovakia, Bulgaria, Romania and Poland. We find persistent and increasing patterns of higher undereducation by males in Denmark, Sweden, the Netherland, Norway and the United Kingdom.

Finally, Figure 2-20 presents gender differences in training and its types overall and by country. In its top panel, we notice, that in Sweden, Iceland, Finland, Denmark and Estonia, females are more likely to have received training of all types during the last 4 weeks, compared to males. In Switzerland, Luxembourg, the Netherlands, Germany and Greece, males are more likely to receive training compared to females. In Switzerland, Greece, and Luxembourg, males are more likely to receive formal training. In the bottom of the panel, we notice, that in Latvia, Sweden, Estonia, Finland, Hungary and Demark, females are more likely to have received training of all types during the last 12 months, compared to males. In Slovakia, Italy, the Czech Republic, Romania, and the Netherlands, males are more likely to receive training compared to females. However, in the majority of the countries, the differences are in favour of females. Moreover, in the countries in which males are more likely to have received training during the last year, they are less likely to receive formal training, and more likely to have received informal job-related training.

Table 2-12: EU-LFS$_{Yearly}$– Gender differences

	EMPLOYMENT			MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	MALE	FEMALE	DIFFERENCE	MALE	FEMALE	DIFFERENCE	MALE	FEMALE	DIFFERENCE	MALE	FEMALE	DIFFERENCE
ALL COUNTRIES	*77.2%*	*57.6%*	*19.6 pp*	*42.1%*	*42.9%*	*-0.8 pp*	*20.1%*	*22.0%*	*-1.9 pp*	*22.0%*	*20.9%*	*1.1 pp*
Greece	80.1%	44.1%	36.0 pp	51.4%	47.8%	3.6 pp	28.0%	27.6%	0.4 pp	23.4%	20.3%	3.2 pp
Malta	90.6%	55.7%	34.9 pp	51.4%	53.2%	-1.7 pp	32.1%	36.6%	-4.6 pp	19.4%	16.5%	2.8 pp
Italy	77.5%	43.2%	34.3 pp	41.6%	40.4%	1.2 pp	21.5%	22.5%	-1.0 pp	20.1%	17.9%	2.2 pp
Luxembourg	84.5%	55.1%	29.4 pp	39.3%	38.3%	1.0 pp	17.4%	16.1%	1.3 pp	21.9%	22.3%	-0.3 pp
Spain	70.7%	43.8%	26.9 pp	53.2%	51.3%	1.9 pp	28.3%	27.6%	0.7 pp	24.9%	23.7%	1.2 pp
Ireland	77.4%	53.2%	24.1 pp	60.2%	56.2%	4.0 pp	29.5%	30.5%	-0.9 pp	30.7%	25.7%	4.9 pp
Netherlands	82.1%	60.6%	21.5 pp	48.9%	44.0%	4.9 pp	22.5%	22.9%	-0.4 pp	26.4%	21.1%	5.3 pp
Belgium	77.3%	55.9%	21.4 pp	46.0%	43.1%	2.9 pp	18.6%	21.2%	-2.5 pp	27.4%	21.9%	5.4 pp
Cyprus	84.9%	66.9%	18.0 pp	47.2%	51.9%	-4.6 pp	21.4%	28.5%	-7.1 pp	25.8%	23.4%	2.4 pp
Portugal	82.7%	65.3%	17.4 pp	47.4%	44.1%	3.4 pp	26.9%	26.0%	0.8 pp	20.6%	18.0%	2.5 pp
Germany	74.9%	57.8%	17.1 pp	43.4%	45.8%	-2.4 pp	21.2%	22.1%	-0.9 pp	22.3%	23.7%	-1.5 pp
France	78.8%	62.2%	16.7 pp	45.4%	47.3%	-1.9 pp	18.4%	24.1%	-5.7 pp	27.0%	23.2%	3.9 pp
Croatia	79.7%	64.4%	15.3 pp	22.0%	24.1%	-2.1 pp	11.3%	12.2%	-0.9 pp	10.7%	11.9%	-1.2 pp
Switzerland	87.0%	72.1%	14.9 pp	45.1%	43.6%	1.5 pp	23.0%	20.7%	2.3 pp	22.1%	22.9%	-0.8 pp
Romania	84.8%	70.1%	14.6 pp	30.1%	31.8%	-1.6 pp	15.7%	16.3%	-0.6 pp	14.4%	15.5%	-1.1 pp
United Kingdom	73.8%	59.6%	14.2 pp	48.4%	47.9%	0.4 pp	20.7%	23.5%	-2.8 pp	27.6%	24.4%	3.2 pp
Czech Republic	89.1%	75.4%	13.7 pp	17.2%	22.2%	-5.0 pp	9.6%	11.6%	-2.0 pp	7.6%	10.6%	-3.1 pp
Austria	88.4%	75.0%	13.3 pp	41.1%	43.2%	-2.1 pp	22.0%	23.4%	-1.5 pp	19.2%	19.7%	-0.6 pp
Hungary	79.3%	66.7%	12.6 pp	30.8%	35.0%	-4.3 pp	17.4%	19.9%	-2.5 pp	13.3%	15.1%	-1.8 pp
Poland	77.9%	65.6%	12.4 pp	24.3%	32.0%	-7.7 pp	11.0%	16.8%	-5.7 pp	13.3%	15.2%	-1.9 pp
Slovakia	81.5%	71.0%	10.6 pp	18.1%	23.4%	-5.3 pp	11.1%	14.0%	-2.9 pp	7.0%	9.4%	-2.5 pp
Denmark	82.2%	72.5%	9.8 pp	41.2%	34.9%	6.3 pp	16.3%	15.8%	0.6 pp	24.9%	19.1%	5.7 pp
Iceland	89.7%	81.7%	8.0 pp	50.7%	48.9%	1.8 pp	26.7%	25.4%	1.2 pp	24.0%	23.4%	0.6 pp
Bulgaria	69.1%	61.2%	7.9 pp	28.9%	29.6%	-0.7 pp	12.8%	13.5%	-0.7 pp	16.1%	16.1%	0.0 pp
Norway	81.1%	74.2%	6.8 pp	47.3%	42.2%	5.0 pp	19.6%	19.0%	0.6 pp	27.7%	23.2%	4.4 pp
Slovenia	85.9%	79.5%	6.4 pp	29.1%	34.5%	-5.4 pp	12.1%	16.9%	-4.8 pp	17.0%	17.6%	-0.6 pp
Latvia	76.1%	70.8%	5.3 pp	42.9%	43.1%	-0.2 pp	19.5%	24.7%	-5.3 pp	23.5%	18.4%	5.1 pp
Sweden	82.9%	77.8%	5.2 pp	47.8%	44.7%	3.0 pp	20.8%	23.3%	-2.5 pp	27.0%	21.5%	5.5 pp
Estonia	81.2%	77.0%	4.3 pp	46.3%	48.2%	-1.8 pp	21.3%	25.8%	-4.5 pp	25.0%	22.4%	2.6 pp
Finland	79.1%	75.4%	3.7 pp	40.4%	38.7%	1.7 pp	15.1%	17.3%	-2.3 pp	25.3%	21.3%	4.0 pp

Lithuania	77.6%	76.8%	0.8 pp	46.6%	47.0%	-0.4 pp	27.7%	26.2%	1.5 pp	18.9%	20.8%	-1.9 pp

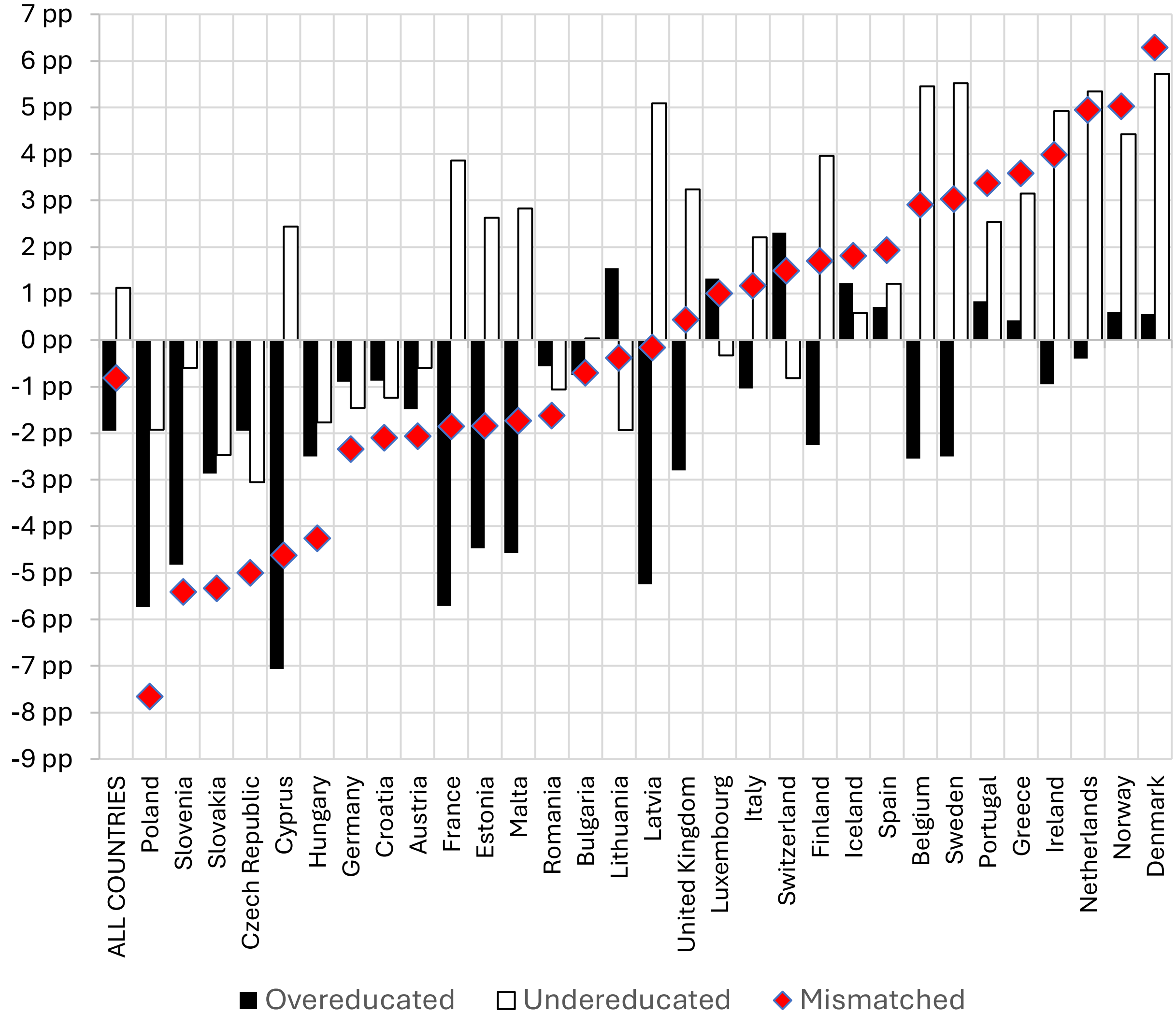


Figure 2-15: EU-LFS$_{Yearly}$ – Gender differences in skills mismatching by country

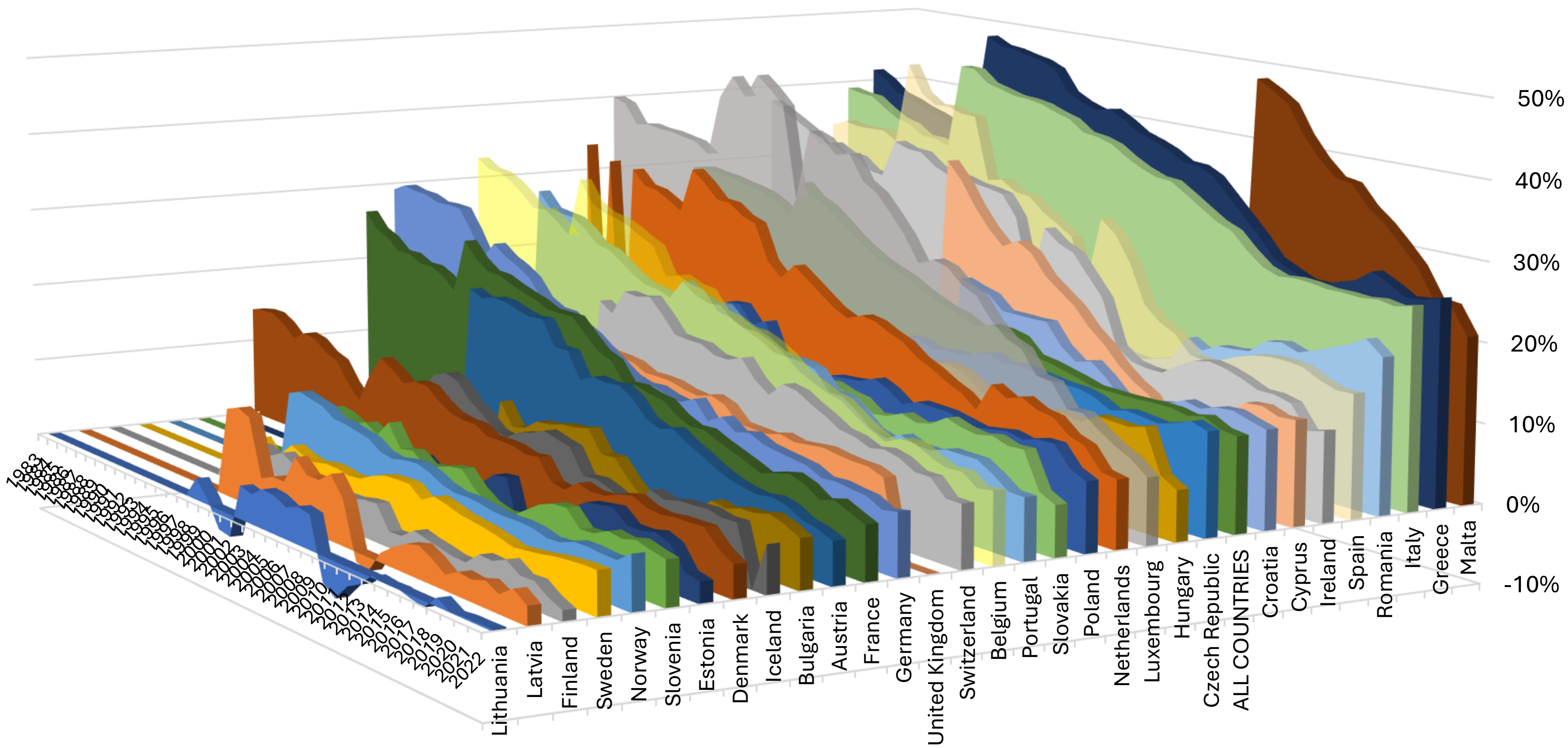

50%
40%
30%
20%
10%
0%
-10%
Lithuania
Latvia
Finland
Sweden
Norway
Slovenia
Estonia
Denmark
Iceland
Bulgaria
Austria
France
Germany
United Kingdom
Switzerland
Belgium
Portugal
Slovakia
Poland
Netherlands
Luxembourg
Hungary
Czech Republic
ALL COUNTRIES
Croatia
Cyprus
Ireland
Spain
Romania
Italy
Greece
Malta

Figure 2-16: EU-LFS$_{Yearly}$ – Gender differences in employment by country and year

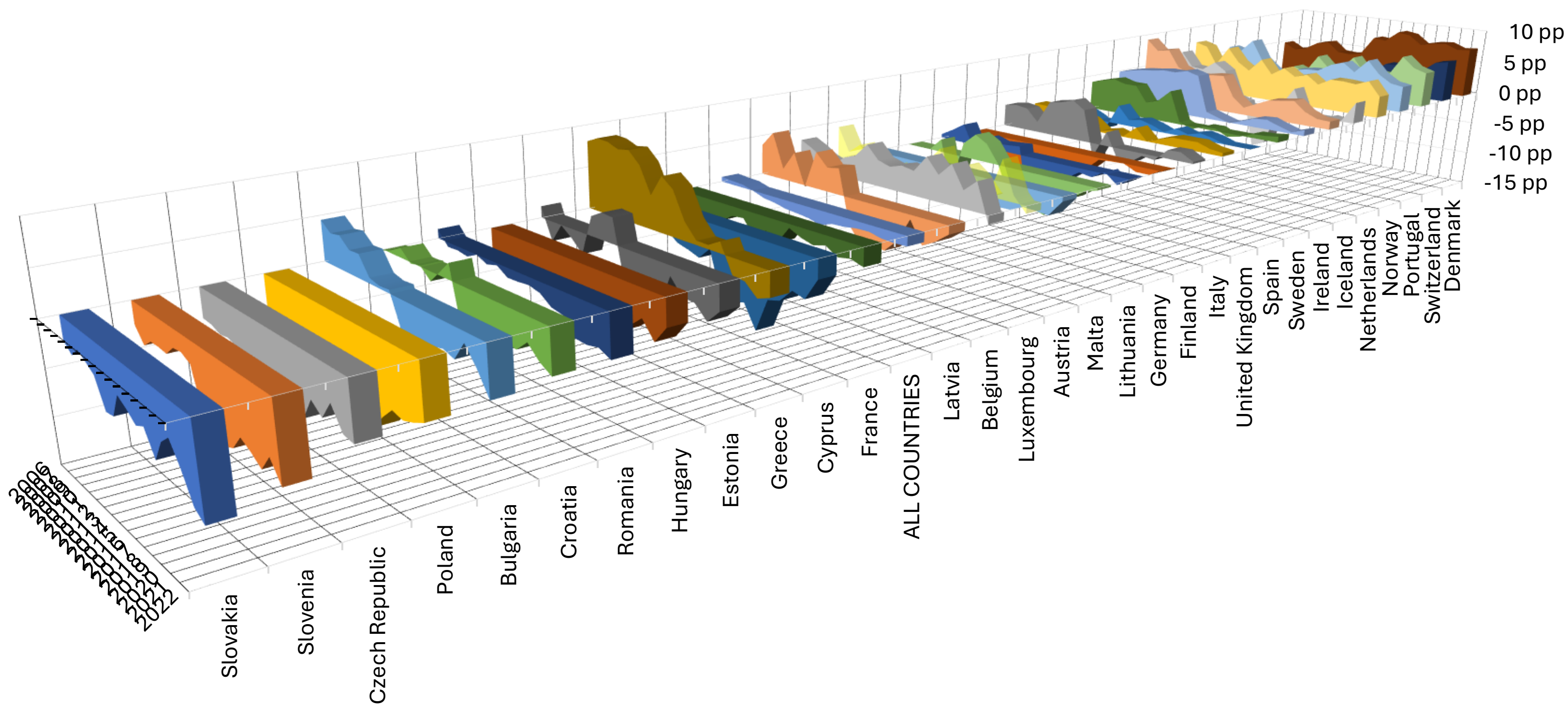


Figure 2-17: EU-LFS$_{Yearly}$ – Gender differences in skills mismatching by country and year

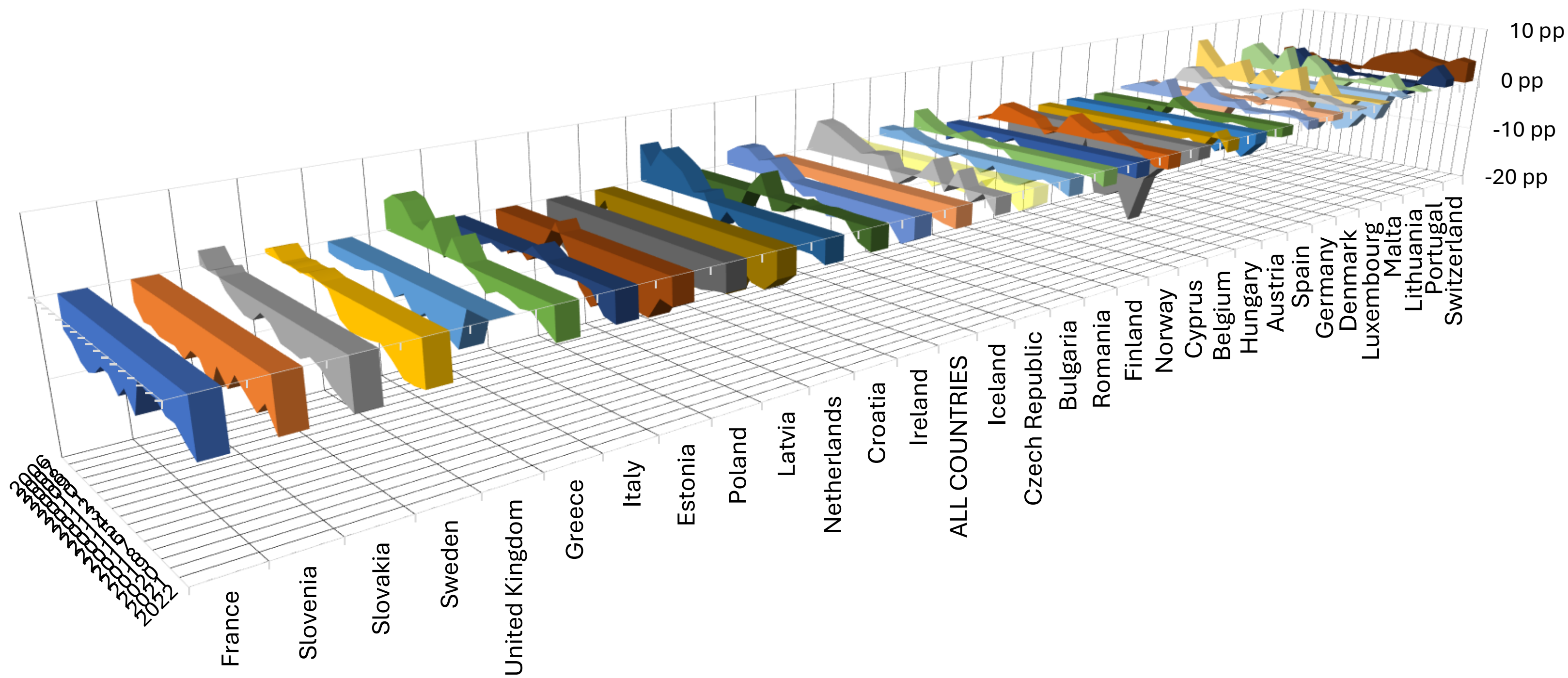


Figure 2-18: EU-LFS$_{Yearly}$ – Gender differences in overeducation by country and year

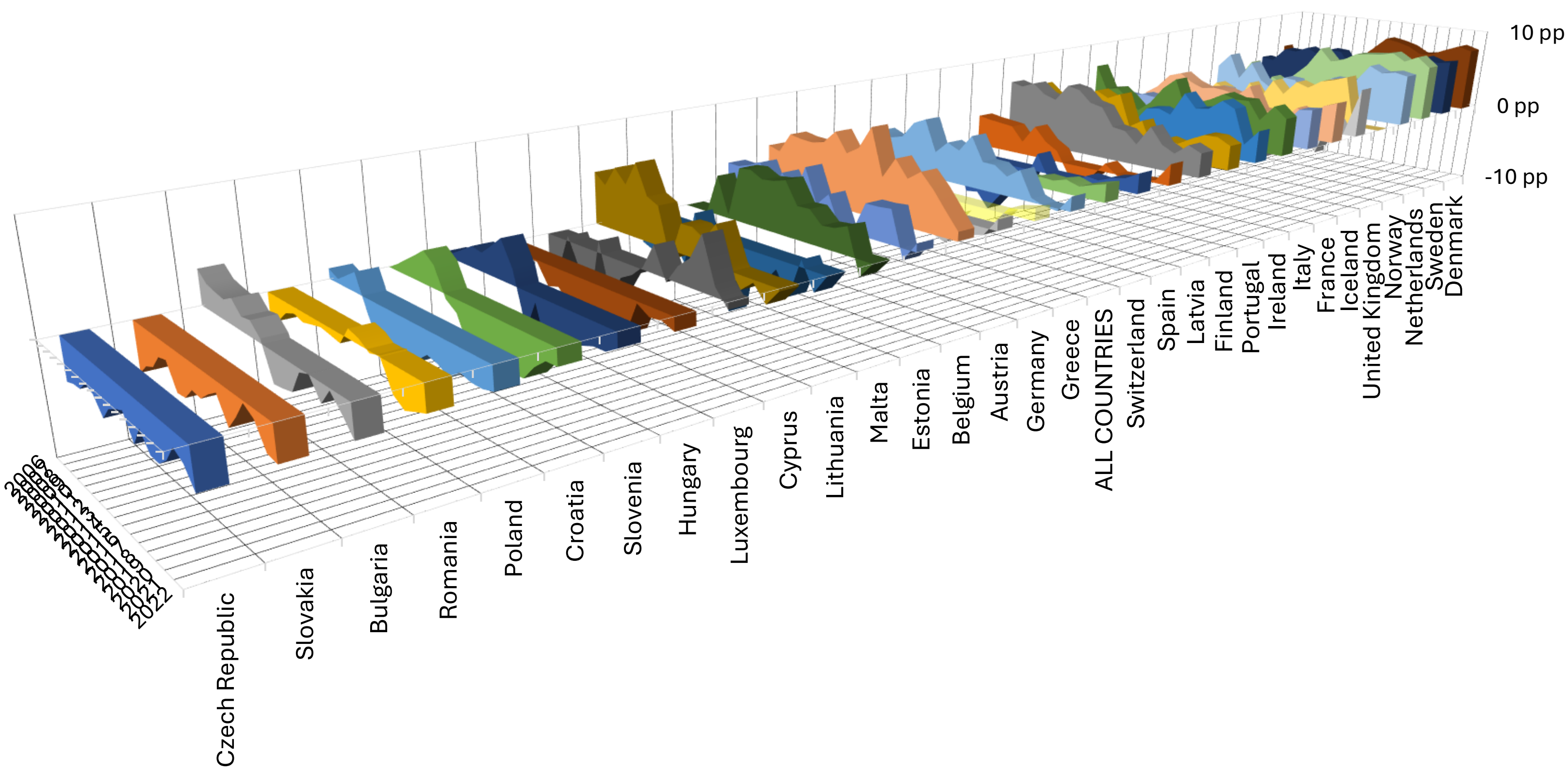
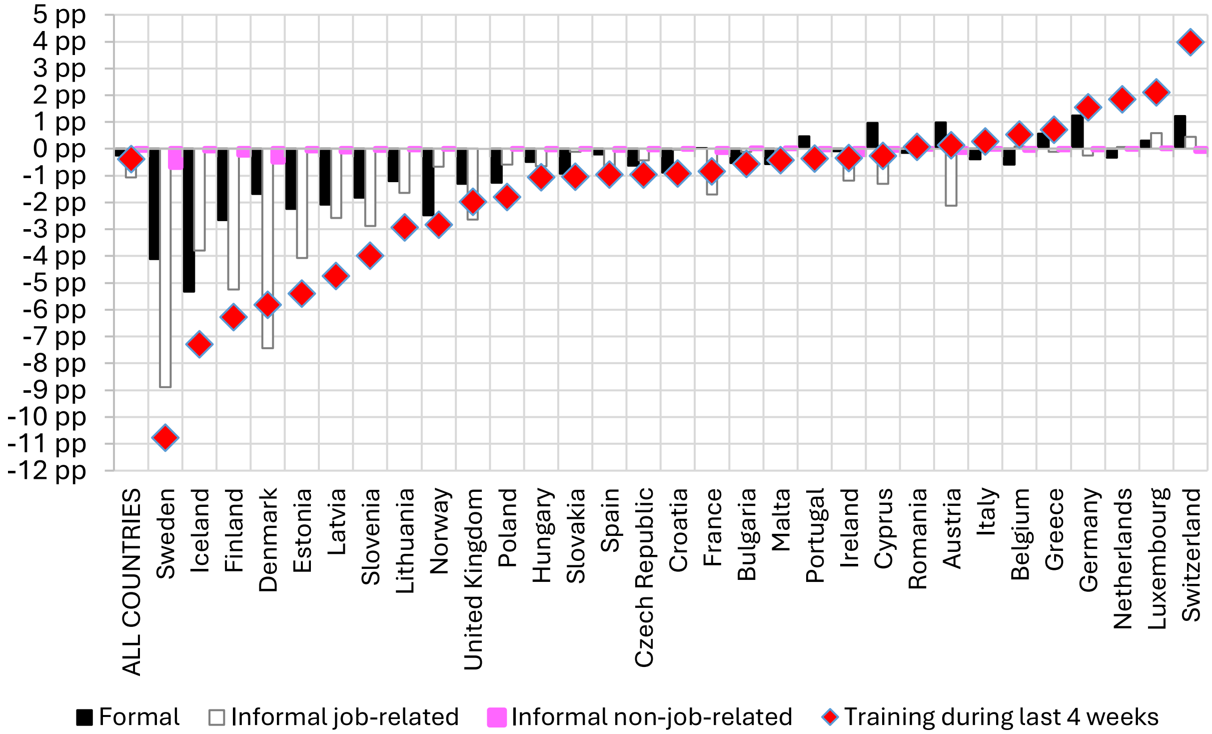


Figure 2-19: EU-LFS$_{Yearly}$ – Gender differences in undereducation by country and year


5 pp
4 pp
3 pp
2 pp
1 pp
0 pp
-1 pp
-2 pp
-3 pp
-4 pp
-5 pp
-6 pp
-7 pp
-8 pp
-9 pp
-10 pp
-11 pp
-12 pp
ALL COUNTRIES
Sweden
Iceland
Finland
Denmark
Estonia
Latvia
Slovenia
Lithuania
Norway
United Kingdom
Poland
Hungary
Slovakia
Spain
Czech Republic
Croatia
France
Bulgaria
Malta
Portugal
Ireland
Cyprus
Romania
Austria
Italy
Belgium
Greece
Germany
Netherlands
Luxembourg
Switzerland
Formal
Informal job-related
Informal non-job-related
Training during last 4 weeks

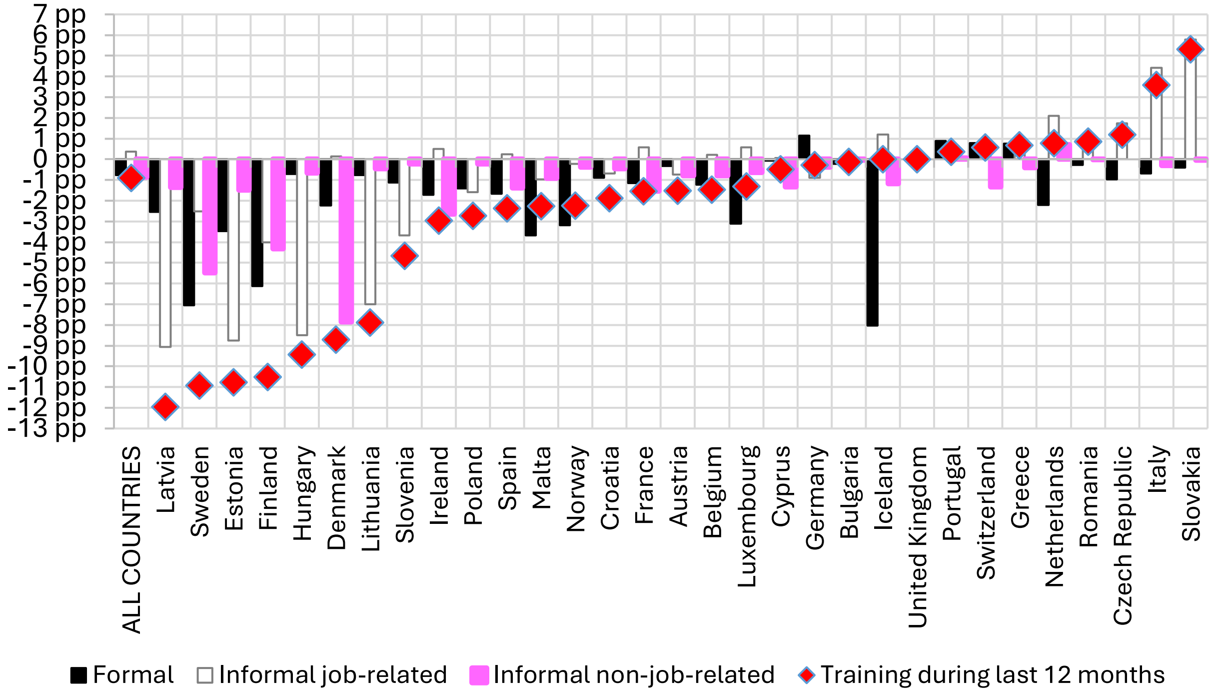


Figure 2-20: EU-LFS$_{Yearly}$ – Gender differences in training by country

2.1.5 DIFFERENCES BY AGE

This sub-section presents an overview of differences in employment, matching and training outcomes at the YLFS across age groups. We distinguish between 5 generational groups, namely Generation Z (iGen, or Centennials, born after 1995), Generation Y (or Millennials, born between 1977 and 1995), Generation X (born between 1965 and 1976), the Baby Boomers (born between 1946 and 1964), and the Traditionalists (or the Silent generation, born before 1945). Using these we define the young as generations Z and Y, and the old as generation X, the baby boomers and traditionalists.

Figure 2-21 presents an overview of the distribution of employment by generation overall and by country. While employment is balanced across the generations in the pooled sample of 31 countries, the countries at the top of the table have higher employment rates among the younger generations. The countries at the bottom of the table have relatively lower employment rates among the young compared to the old. The bottom five countries with lower relative employment rates among the young are Spain, the United Kingdom, Greece, Italy and Bulgaria. The top five countries, with higher relative employment rates among the young compared to the old are Malta, the Netherlands, Switzerland, Iceland and Austria.

Figure 2-22 replicates the same exercise overviewing relative rates of skills mismatching across the five generations. The bottom countries have higher rates of skills matching among the young compared to the old generations. These are: Croatia, Slovakia, the Czech Republic, Slovenia, Poland, Bulgaria, and Romania. In these countries the old are more likely to be mismatched in their occupation. The top countries have relatively higher rates of mismatching among the young, compared to the old. These are: Germany, Portugal, Austria, Norway, Spain, Ireland and Switzerland.

Figure 2-23 shows the generational distribution of overeducation at the YLFS. Countries in which the young are more likely to be overeducated compared to the old are at the top of the figure. These are: Portugal, Malta, Greece, Spain and Ireland. The bottom five countries in which the old are more likely to be overeducated compared to the young are: the Czech Republic, Finland, Switzerland, Croatia and Poland.

Figure 2-24 presents undereducation rates across generations in the countries of the YLFS. Germany, Switzerland, Norway, Austria, and Estonia are the top 5 countries in which the young are more undereducated compared to the old. Croatia, Malta, Slovakia, Portugal and Italy are the bottom 5 countries in which the old are the most undereducated compared to the young.

Table 2-13 presents weighted country averages for the outcomes of interest for the old and the young generations. In the pooled sample of all 31 countries, 66.8% of the older are employed, compared to 68.6% of the younger. 41.5% of the old are mismatched in the occupation, compared to 44.1% of the young. 18.5 of the old are overeducated, compared to 25% of the young. 23% of the old are undereducated, compared to 19.1% of the young. In most counties, the young are mismatched. In the 9 countries at the bottom of the table, it is the older generations that are more likely to be mismatched, namely in Cyprus, Iceland, the Netherlands, Finland, the United Kingdom, Luxembourg, Ireland, Belgium, and Croatia. In the majority of the countries, the young are overeducated compared to the older generations, with the only exceptions of Latvia, Switzerland and Lithuania. In the majority of countries, the older generations are undereducated, compared to the young.

Figure 2-25 summarises the previous findings by plotting differences in skills mismatching (in the scatterplot), along with differences in overeducation and undereducation (in the black and white bars, respectively) in the countries of the YLFS. All differences are calculated as the average difference of the old (traditionalists, baby boomers, and generation X) minus the average for the young (generations Y and Z) and they are presented in percentage points (not percentages). Overall, the old are less mismatched in their occupations compared to the young, and they are less overeducated and more undereducated. Portugal, Hungary, Latvia, Germany and Norway are the bottom five countries, in terms of the differences in skills mismatching between the old and the young, in disfavour of the younger generations which are more often mismatched in their occupations compared to the old. Croatia, Belgium, Ireland, Luxembourg, the United Kingdom, Finland, and Iceland are the 7 countries in which the old are more likely to be mismatched in their occupations compared to the young.

Figure 2-26 presents the evolution of the difference in employment rates between the old and the young between 1983 and 2002. For the countries at the right of the figure, there are persistent positive employment differences between in favour of the older generations, with the top five being the Czech Republic, the United Kingdom, Denmark, Bulgaria and Finland. For the countries at the left, there are persistent employment difference in favour of the younger generations, with the bottom five countries being Malta, Spain, the Netherlands, Cyprus, Lithuania, and Ireland.

Figure 2-27 presents the evolution of the difference in skills mismatching between the old and the young between 2006 and 2002. The top five countries at the right, in which the old are persistently more likely to be mismatched compared to the young, are Luxembourg, Finland, Bulgaria, Croatia, and the United Kingdom. The bottom five countries at the left, in which the young are persistently more likely to be mismatched compared to the old, are Hungary, Romania, Slovakia, Poland and Bulgaria.

Figure 2-28 presents the evolution of the difference in overeducation between the old and the young. The top five countries at the right, in which the old are persistently more often overeducated compared to the young, are Latvia, Estonia, Lithuania, Iceland, and Luxembourg. The bottom five countries at the left, in which the young are persistently more often overeducated compared to the old, are Portugal, Hungary, Cyprus, France, and Norway.

Then, Figure 2-29 presents the evolution of the difference in undereducation between the old and the young between 2006 and 2002. The top five countries at the right, in which the old are persistently more often undereducated compared to the young, are Greece, Ireland, Portugal, Malta, and France. The bottom five countries at the left, in which the young are persistently more often undereducated compared to the old, are Latvia, Estonia, Romania, Germany and Bulgaria.

Figure 2-30 presents an overview of differences in the incidence of training during the last month and during the last year between the young and the old. Differences are calculated for the pooled data on training during the last month (i.e., between 2003-2022) and for the year 2022 for training during the last year, i.e., the only available year in the YLFS. Both panels of the figure suggest that the old are less likely to receive training during the last month and during the last year. This holds for the pooled sample of all countries, but also for all 31 counties in the YLFS.

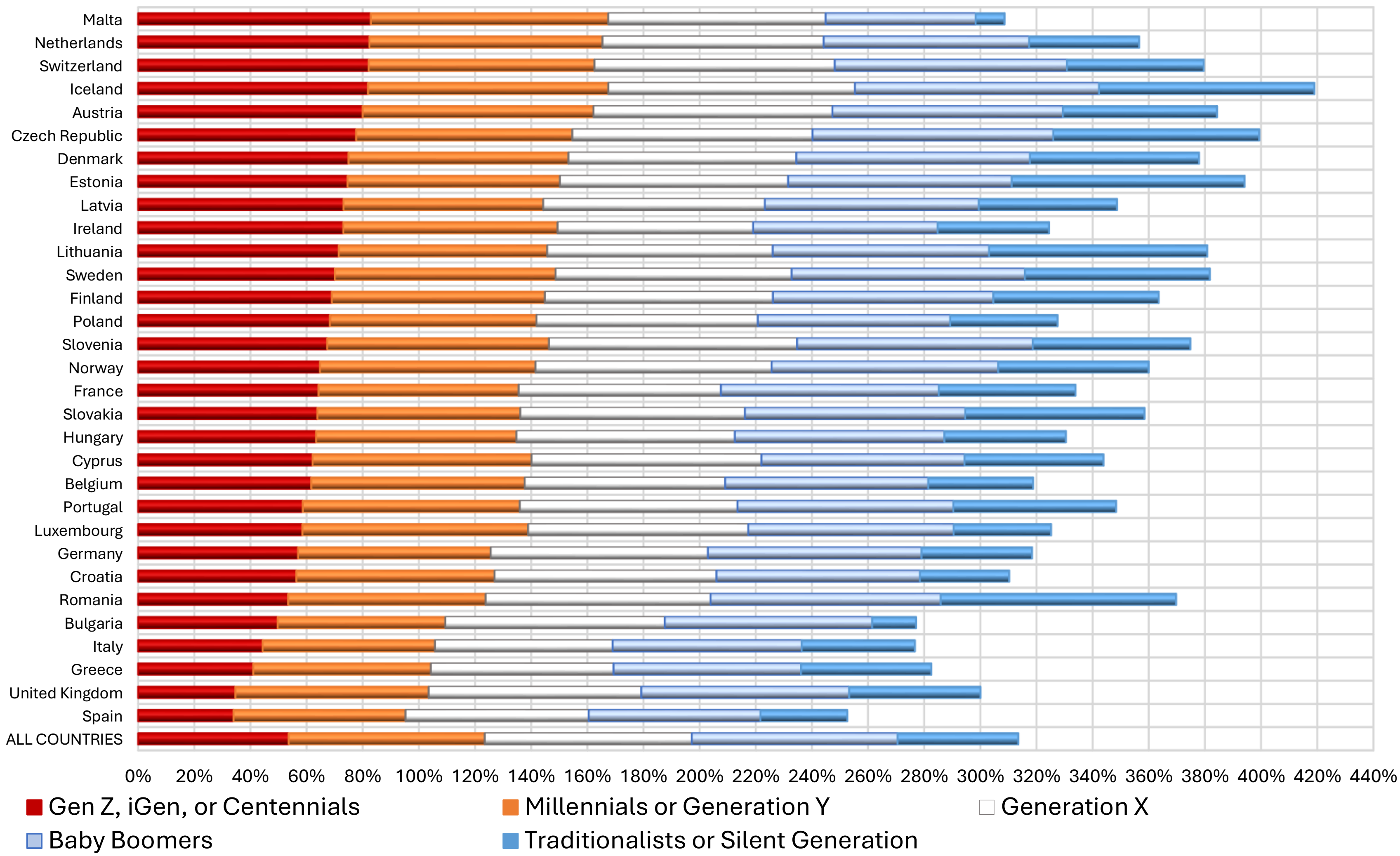

Malta
Netherlands
Switzerland
Iceland
Austria
Czech Republic
Denmark
Estonia
Latvia
Ireland
Lithuania
Sweden
Finland
Poland
Slovenia
Norway
France
Slovakia
Hungary
Cyprus
Belgium
Portugal
Luxembourg
Germany
Croatia
Romania
Bulgaria
Italy
Greece
United Kingdom
Spain
ALL COUNTRIES
0% 20% 40% 60% 80% 100% 120% 140% 160% 180% 200% 220% 240% 260% 280% 300% 320% 340% 360% 380% 400% 420% 440%
Gen Z, iGen, or Centennials
Millennials or Generation Y
Generation X
Baby Boomers
Traditionalists or Silent Generation

Figure 2-21: EU-LFS$_{Yearly}$ – Generational composition of employment by country

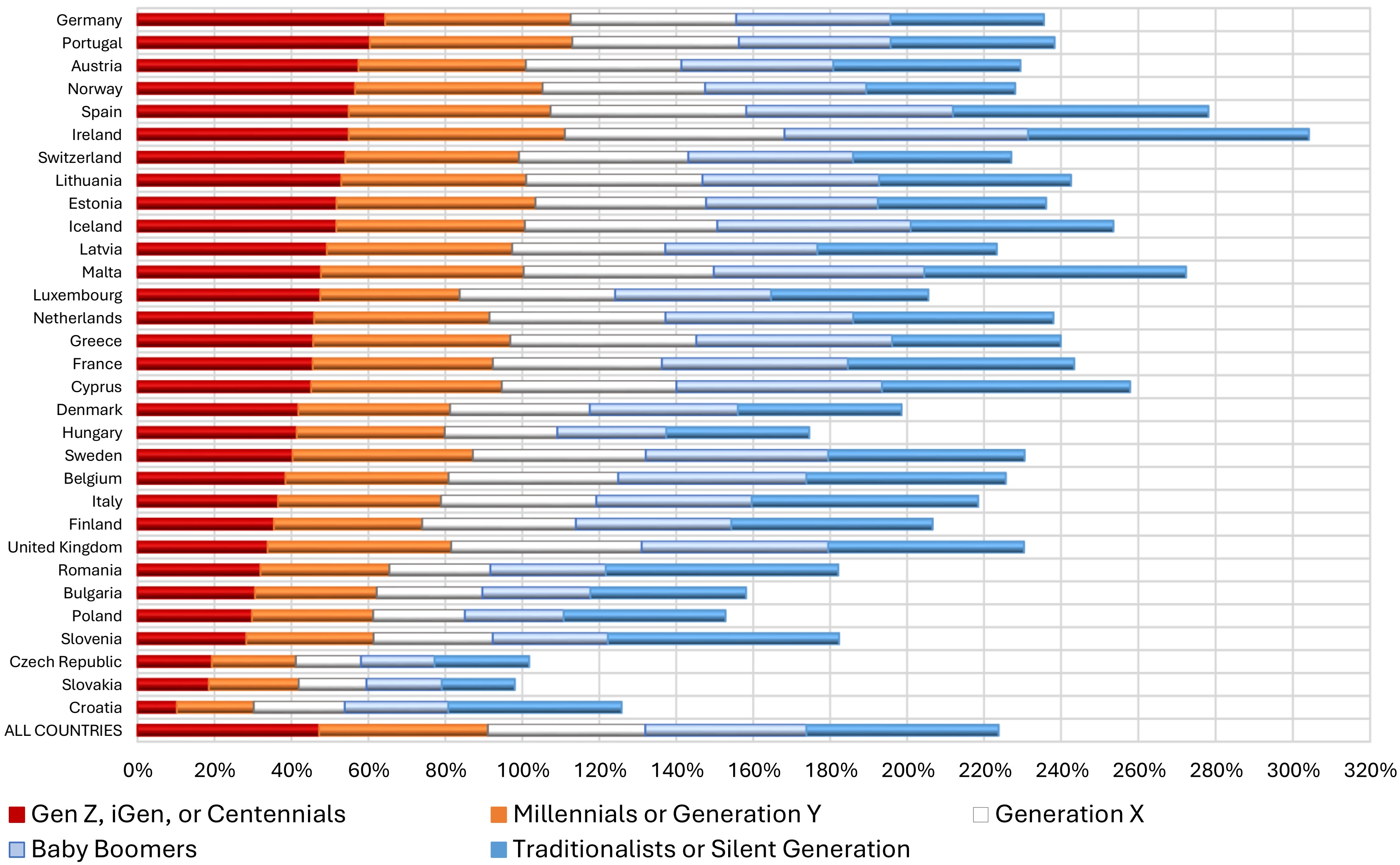


Figure 2-22: EU-LFS$_{Yearly}$ – Generational composition of mismatching by country

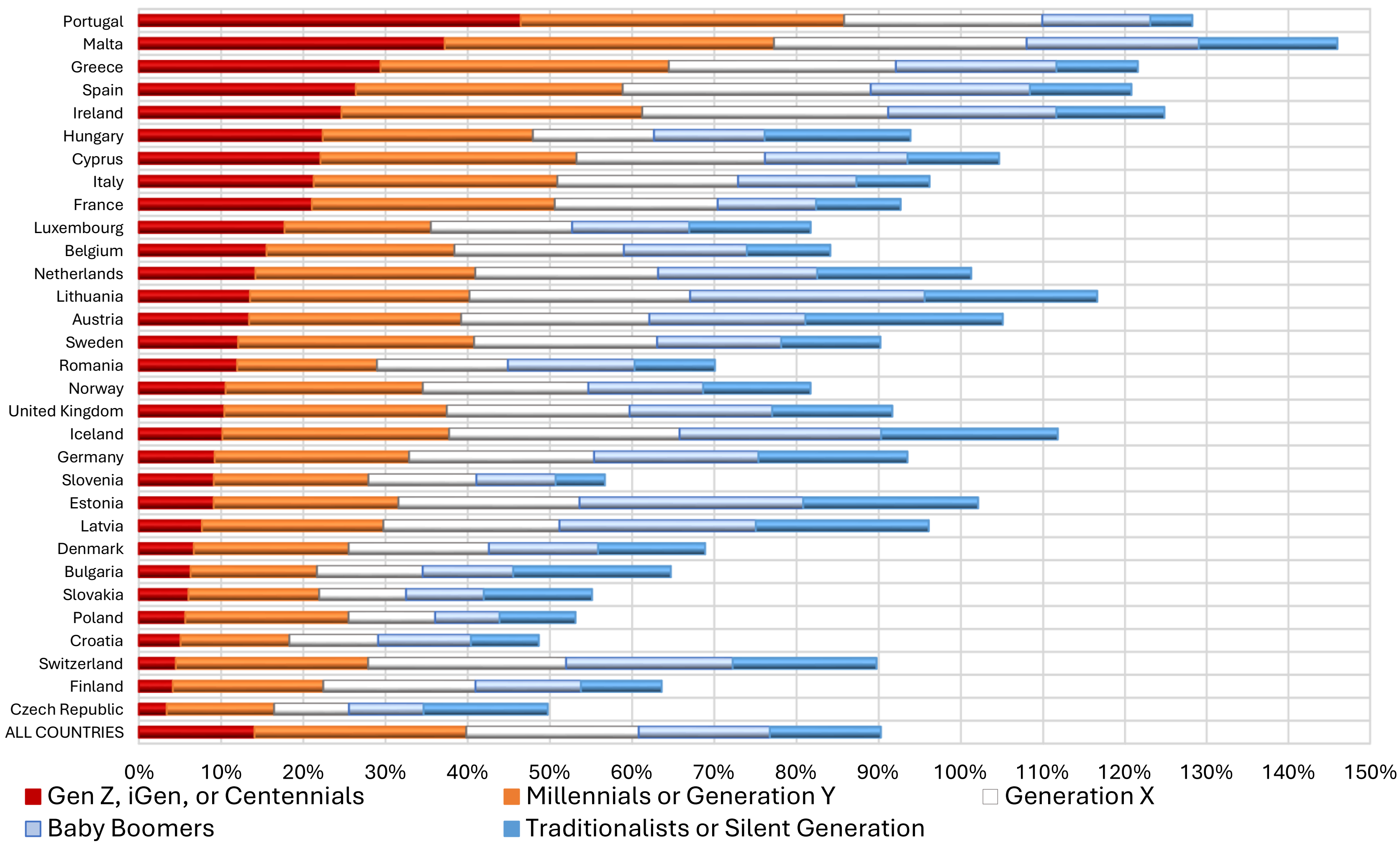


Figure 2-23: EU-LFS$_{Yearly}$ – Generational composition of overeducation by country

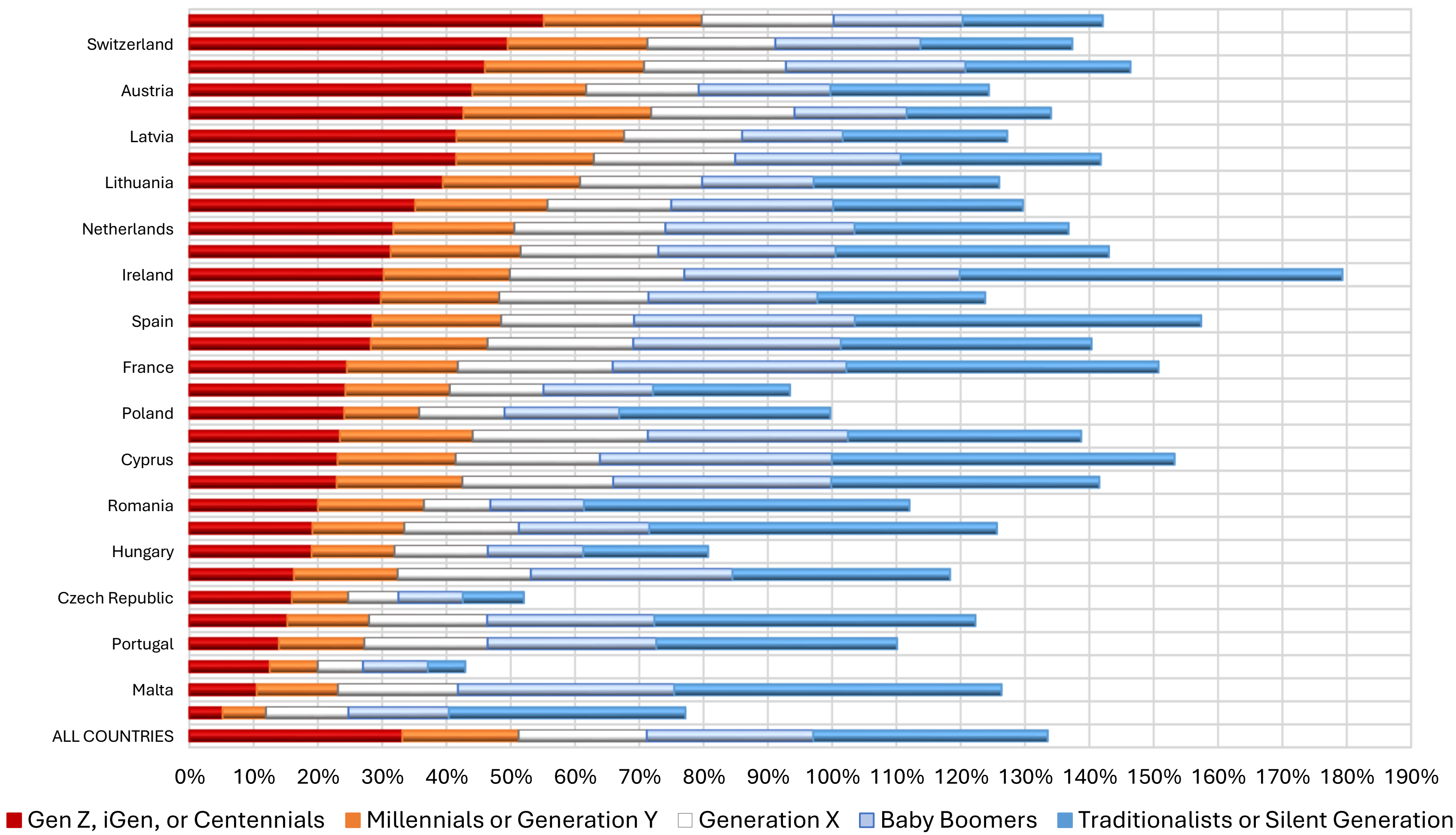


Figure 2-24: EU-LFS$_{Yearly}$ – Generational composition of undereducation by country

Table 2-13: EU-LFSYearly – Age differences

	EMPLOYMENT			MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE
ALL COUNTRIES	*66.8%*	*68.6%*	*-1.9 pp*	*41.5%*	*44.1%*	*-2.6 pp*	*18.5%*	*25.0%*	*-6.5 pp*	*23.0%*	*19.1%*	*3.9 pp*
Portugal	73.0%	76.2%	-3.1 pp	41.6%	53.0%	-11.5 pp	18.8%	39.7%	-20.9 pp	22.8%	13.3%	9.5 pp
Hungary	73.8%	70.9%	3.0 pp	28.9%	38.6%	-9.7 pp	14.2%	25.4%	-11.2 pp	14.7%	13.3%	1.4 pp
Latvia	74.3%	71.2%	3.0 pp	39.9%	48.2%	-8.3 pp	22.6%	21.3%	1.3 pp	17.3%	26.9%	-9.6 pp
Germany	66.0%	67.5%	-1.5 pp	41.5%	49.7%	-8.2 pp	21.2%	22.3%	-1.1 pp	20.3%	27.4%	-7.1 pp
Norway	78.6%	75.8%	2.8 pp	42.0%	49.4%	-7.4 pp	17.0%	22.9%	-5.9 pp	25.0%	26.5%	-1.5 pp
Estonia	80.6%	75.6%	5.0 pp	44.5%	51.7%	-7.2 pp	24.6%	21.7%	2.9 pp	19.9%	30.0%	-10.1 pp
Poland	71.1%	73.3%	-2.2 pp	24.9%	31.4%	-6.6 pp	9.3%	19.2%	-9.9 pp	15.6%	12.3%	3.3 pp
Austria	81.6%	82.0%	-0.4 pp	40.1%	44.9%	-4.8 pp	21.2%	24.6%	-3.3 pp	18.8%	20.3%	-1.5 pp
Slovakia	79.0%	71.9%	7.0 pp	18.5%	23.2%	-4.7 pp	10.1%	15.5%	-5.4 pp	8.4%	7.7%	0.7 pp
Romania	81.3%	69.4%	11.9 pp	29.2%	33.4%	-4.2 pp	15.5%	16.8%	-1.3 pp	13.7%	16.7%	-3.0 pp
Czech Republic	85.1%	77.0%	8.1 pp	18.0%	21.7%	-3.8 pp	9.1%	12.7%	-3.5 pp	8.8%	9.1%	-0.2 pp
Bulgaria	68.0%	59.3%	8.7 pp	27.9%	31.6%	-3.7 pp	12.1%	15.0%	-2.9 pp	15.8%	16.6%	-0.7 pp
Switzerland	79.1%	80.5%	-1.5 pp	43.4%	45.9%	-2.6 pp	22.1%	21.6%	0.5 pp	21.3%	24.3%	-3.1 pp
Lithuania	78.5%	74.1%	4.4 pp	45.9%	48.3%	-2.4 pp	27.6%	25.9%	1.7 pp	18.4%	22.4%	-4.1 pp
Slovenia	84.7%	78.5%	6.2 pp	30.7%	32.9%	-2.2 pp	11.6%	18.4%	-6.8 pp	19.1%	14.5%	4.6 pp
Denmark	77.3%	78.1%	-0.8 pp	37.5%	39.6%	-2.2 pp	15.2%	17.7%	-2.6 pp	22.3%	21.9%	0.4 pp
Greece	60.9%	62.2%	-1.3 pp	49.3%	51.0%	-1.7 pp	23.9%	34.9%	-10.9 pp	25.4%	16.1%	9.3 pp
Italy	59.4%	60.4%	-1.0 pp	40.6%	42.1%	-1.4 pp	18.5%	29.2%	-10.7 pp	22.1%	12.8%	9.3 pp
France	70.1%	70.8%	-0.7 pp	46.0%	46.7%	-0.7 pp	16.2%	28.9%	-12.7 pp	29.9%	17.8%	12.0 pp
Malta	62.2%	84.4%	-22.2 pp	51.9%	52.3%	-0.4 pp	26.4%	39.8%	-13.4 pp	25.5%	12.5%	13.0 pp
Spain	55.9%	59.3%	-3.4 pp	52.2%	52.6%	-0.4 pp	25.4%	32.2%	-6.7 pp	26.8%	20.4%	6.4 pp
Sweden	81.3%	78.0%	3.3 pp	46.3%	46.4%	-0.1 pp	18.5%	27.5%	-9.0 pp	27.8%	18.9%	8.9 pp
Cyprus	74.6%	77.0%	-2.3 pp	49.5%	49.3%	0.2 pp	20.1%	30.6%	-10.6 pp	29.5%	18.6%	10.8 pp
Iceland	86.0%	85.4%	0.6 pp	50.2%	49.2%	1.1 pp	26.0%	26.3%	-0.3 pp	24.3%	22.9%	1.4 pp
Netherlands	68.6%	83.0%	-14.3 pp	47.3%	45.6%	1.7 pp	20.8%	25.9%	-5.1 pp	26.5%	19.7%	6.8 pp
Finland	78.0%	75.4%	2.5 pp	40.3%	38.3%	2.0 pp	15.5%	17.3%	-1.8 pp	24.8%	21.0%	3.8 pp
United	66.9%	65.4%	1.5 pp	49.0%	46.8%	2.2 pp	19.6%	26.0%	-6.4 pp	29.5%	20.8%	8.6 pp
Luxembourg	66.6%	79.0%	-12.4 pp	40.5%	36.8%	3.7 pp	16.0%	17.8%	-1.7 pp	24.4%	19.0%	5.4 pp
Ireland	61.7%	76.2%	-14.5 pp	60.2%	56.1%	4.1 pp	25.4%	35.8%	-10.4 pp	34.8%	20.3%	14.5 pp
Belgium	64.5%	75.2%	-10.7 pp	46.3%	42.2%	4.1 pp	18.0%	22.5%	-4.4 pp	28.3%	19.7%	8.5 pp
Croatia	73.4%	69.6%	3.8 pp	25.4%	19.4%	6.0 pp	11.0%	12.7%	-1.7 pp	14.4%	6.7%	7.7 pp

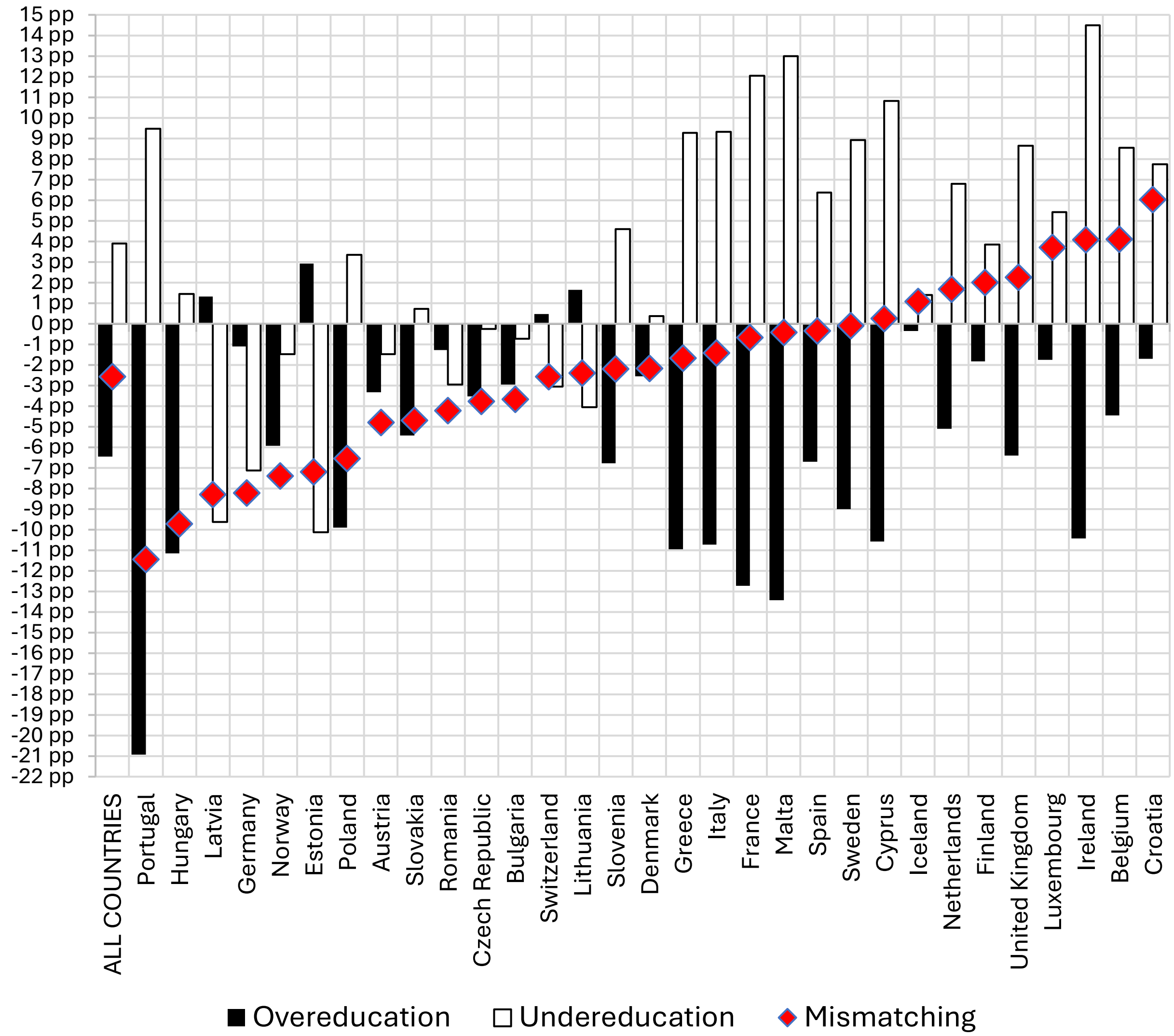


Figure 2-25: EU-LFS$_{Yearly}$ – Age differences by country (old vs. young)

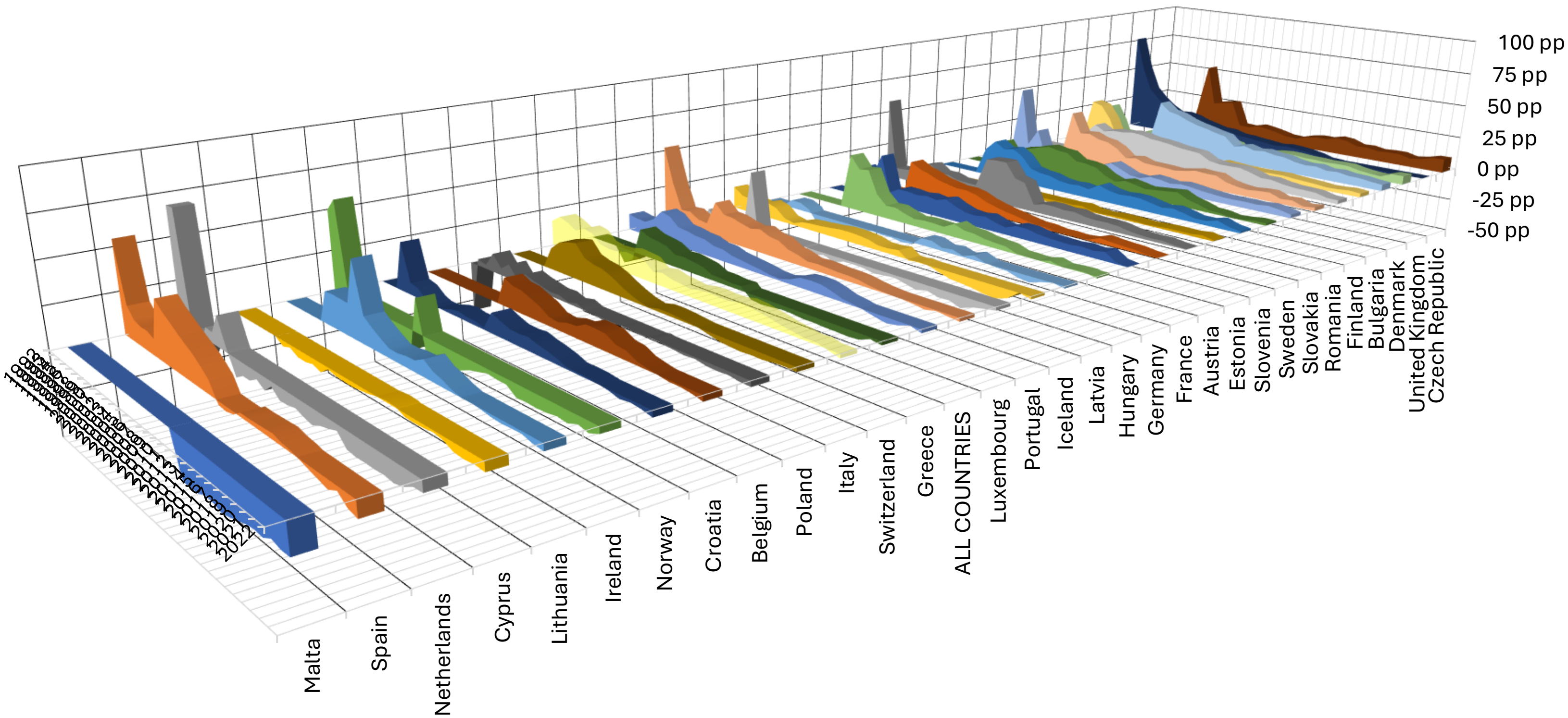

100 pp
75 pp
50 pp
25 pp
0 pp
-25 pp
-50 pp
Malta
Spain
Netherlands
Cyprus
Lithuania
Ireland
Norway
Croatia
Belgium
Poland
Italy
Switzerland
Greece
ALL COUNTRIES
Luxembourg
Portugal
Iceland
Latvia
Hungary
Germany
France
Austria
Estonia
Slovenia
Sweden
Slovakia
Romania
Finland
Bulgaria
Denmark
United Kingdom
Czech Republic

Figure 2-26: EU-LFS$_{Yearly}$ – Age differences in employment by country and year

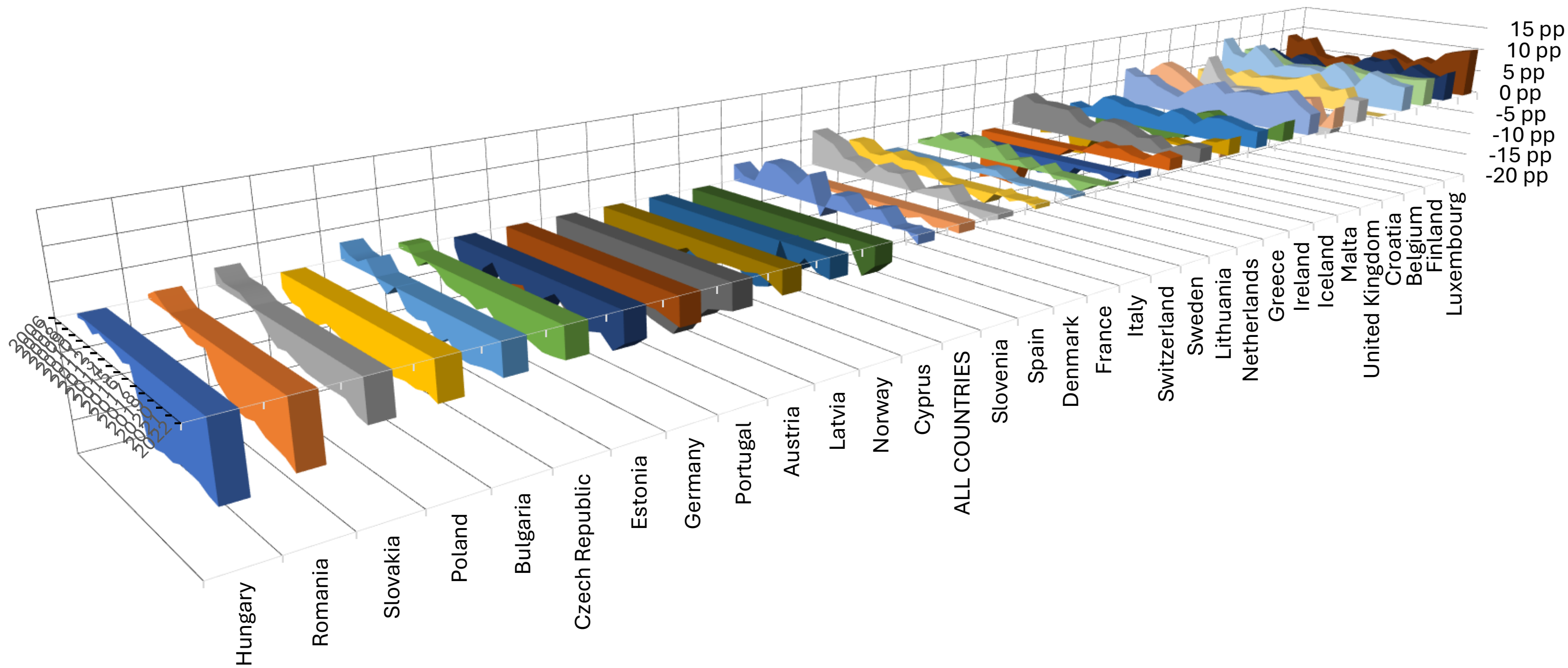


Figure 2-27: EU-LFS$_{Yearly}$ – Age differences in mismatching by country and year

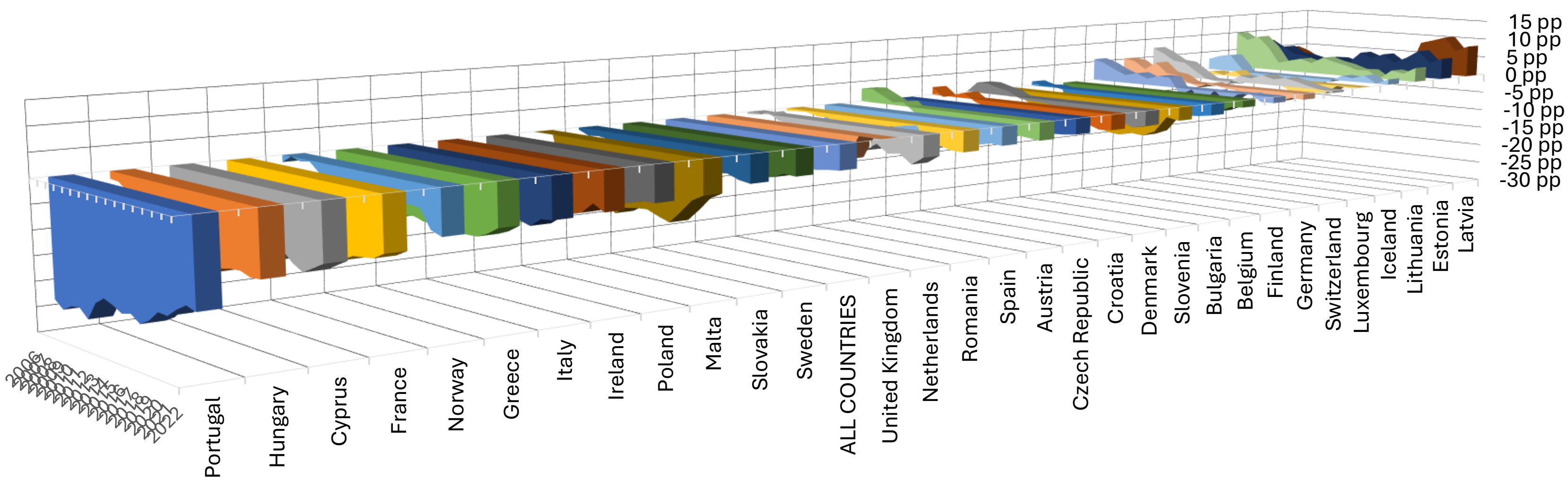


Figure 2-28: EU-LFS$_{Yearly}$ – Age differences in overeducation by country and year

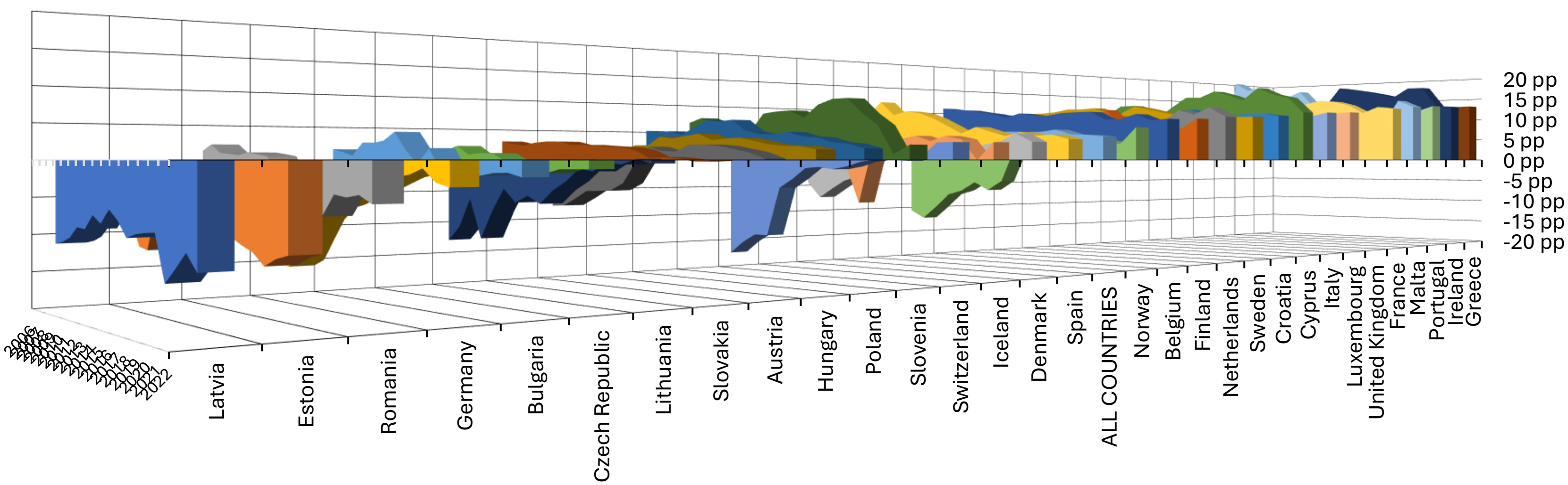
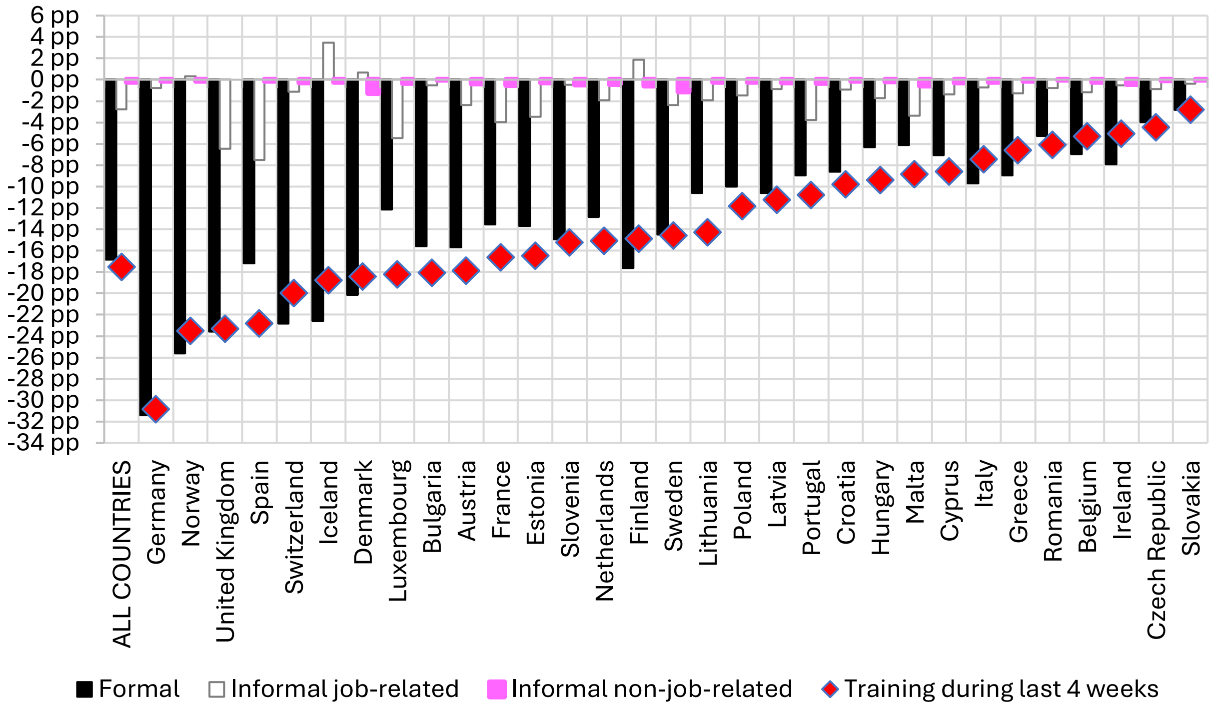


Figure 2-29: EU-LFS$_{Yearly}$ – Age differences in undereducation by country and year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ALL COUNTRIES
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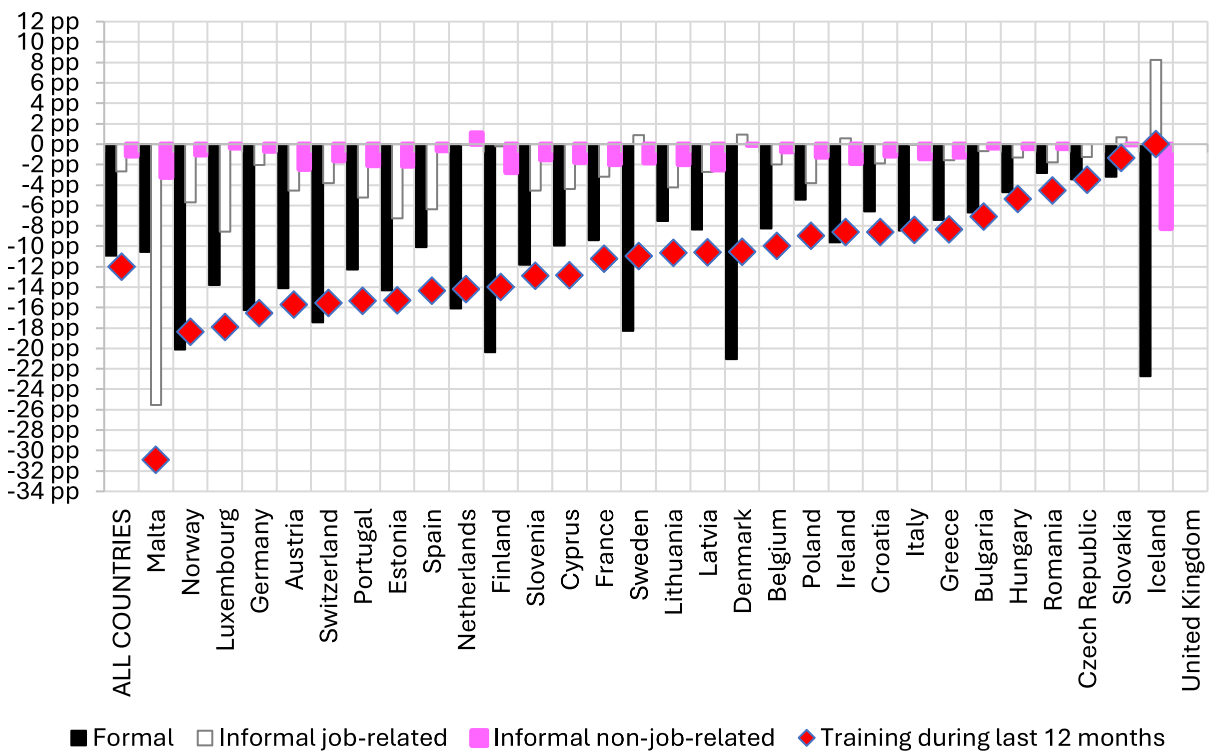
Norway
United Kingdom
Spain
Switzerland
Iceland
Denmark
Luxembourg
Bulgaria
Austria
France
Estonia
Slovenia
Netherlands
Finland
Sweden
Lithuania
Poland
Latvia
Portugal
Croatia
Hungary
Malta
Cyprus
Italy
Greece
Romania
Belgium
Ireland
Czech Republic
Slovakia
Formal
Informal job-related
Informal non-job-related
Training during last 4 weeks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ALL COUNTRIES
Malta
Norway
Luxembourg
Germany
Austria
Switzerland
Portugal
Estonia
Spain
Netherlands
Finland
Slovenia
Cyprus
France
Sweden
Lithuania
Latvia
Denmark
Belgium
Poland
Ireland
Croatia
Italy
Greece
Bulgaria
Hungary
Romania
Czech Republic
Slovakia
Iceland
United Kingdom
Formal
Informal job-related
Informal non-job-related
Training during last 12 months

Figure 2-30: EU-LFS$_{Yearly}$ – Age differences in training by country (old vs. young)

2.1.6 DIFFERENCES BY INCOME

In this sub-section we present an overview of differences in employment, skills mismatching and training by income decile. Income data is only available in the form of income decile for the employed sub-sample in the years 2009-2020 at the YLFS. Income is not available at all in the quarterly version of the dataset. We also distinguish between top 40% and bottom 60%.

Figure 2-31 presents the distinction of mismatching by income decile overall and by country. In countries at the top of the figure, skills (mis)matching seems to be more balanced across all income deciles. In countries at the bottom of the figure, mismatching is relatively more prevalent at top income deciles compared to the bottom ones. The countries at the top are Ireland, Switzerland, Cyprus, Spain and France. The countries at the bottom are the Czech Republic, Croatia, Romania, Slovakia, and Poland.

Figure 2-32 presents the distribution of overeducation by income decile. In the countries at the top there are either more overeducated among the lower income deciles, or there is a balanced distribution of overeducation among income deciles. The top five countries are Cyprus, Portugal, Spain, Greece, and Malta. In these countries, more overeducated exist among the bottom income deciles. For countries at the bottom of the table, there are relatively fewer overeducated among the bottom income deciles, compared to the higher ones. The bottom five countries, in which the overeducated earn relatively more are the Czech Republic, Bulgaria, Croatia, Romania, and Germany.

Figure 2-33 replicates the same exercise for the undereducated. At the top, there are countries in which there are relatively more undereducated among the lowest income deciles. The top five countries are Switzerland, France, Germany, Ireland, Luxembourg, At the bottom of table are countries in which there are relatively more undereducated among the top income deciles. The bottom five countries are the Czech Republic, Slovakia, Malta, Portugal, and Slovenia.

Table 2-14 presents differences in mismatching, overeducation and undereducation between individuals at the top 40% of the income distribution and those at the bottom 60%. In the pooled sample of 31 countries of the YLFS, 41.5% of the individuals at the top 40% are mismatched, 24.3% are overeducated and 17.2% are undereducated. The figures for those at the bottom 60% of the income distribution are 43.2%, 19.4%, and 23.7%, respectively. Hence, those earning more are less likely to be mismatched, more likely to be overeducated and less likely to be undereducated overall.

In the first half of the table, the richer individuals are less likely to be mismatched, i.e., in Luxembourg, Greece, Spain, Portugal, Cyprus, Ireland, Lithuania, Italy, Belgium, Estonia, France, Bulgaria, Poland, and Denmark. This is also the order of the magnitude of negative differences between those more and those less well off, from largest to smallest. In Croatia, Germany, Romania, Austria, Switzerland, Latvia, the Netherlands, Hungary, Finland, Slovenia, Slovakia, the Czech Republic, the United Kingdom, and Malta, there are more mismatched individuals among the top 40% of earners, compared to the bottom 60%. In these countries, there are also more overeducated and fewer undereducated among those at the top of the income distribution.

Figure 2-35 summarizes the previous analysis for the pooled sub-samples of all years for each country. The figure presents differences in mismatching (in the scatterplot), overeducation and undereducation (in the black and white bars, respectively) between the top 40% and the bottom 60% of the income distribution. All differences are presented in percentage points (not percentages). In half of the countries at the left, the richer are less likely to be mismatched in their occupation. In the remaining half at the right of the table, the richer are more likely to be mismatched. In most of the countries, they are more likely to be overeducated and less likely to be undereducated. In order of magnitude of the premium of overeducation, we observe Malta, the United Kingdom, the Czech Republic, Slovakia, Slovenia, Finland, Hungary, the Netherlands, Latvia, Switzerland, and Romania, and Germany.

Figure 2-36 illustrates the evolution of the difference in skills mismatching between the richer and the poorer over time, i.e., between 2009-2020, which are the years with income decile data available at the YLFS. For the countries at the left of the figure, the poorer are consistently more likely to be mismatched, although there seem to be reductions in Luxembourg, Spain, Greece, Ireland, and Cyprus. In Portugal and Italy, the poor are consistently the ones more likely to be mismatched. For the countries at the right of the table, it is the richer who are more likely to be mismatched in their occupation, and the trends are persistent and even increasing over time. The top 5 countries, in which the richer are mismatched the most in all years are Malta, Slovenia, Finland, the United Kingdom, and Switzerland.

Figure 2-37 illustrates the evolution of the difference in overeducation between the richer and the poorer over time. In Portugal, Luxembourg, Spain, Italy and Cyprus at the left, the rich are the ones that are more overeducated, although the trend is decreasing over time in all countries, except Portugal. For Greece, a bit further on the right, the trend seems to be completely reversed, and in the post-crisis years it is the poorer who are more overeducated. The top 5 countries at the right of the figure, for which the rich are the more overeducated are Switzerland, Germany, Belgium, Malta, and Slovenia. The trend is persistent over time and even increasing in most countries.

Figure 2-38 shows the evolution of the difference in undereducation between the richer and the poorer over time. It is evident that in most of the countries the poorer are more frequently undereducated and he differences presented are of large magnitudes. It is only in the Czech Republic, Malta, and Slovenia, at the right of the figure, that the top 40% of incomes have higher rates of undereducation, compared to the bottom 60%. The bottom five countries at the left are Ireland, Germany, Switzerland, Belgium, and Lithuania. In these countries, the rates of undereducation among the bottom 60% of incomes are the highest.

Finally, Figure 2-39 concludes the presentation of differences between the population groups of interest in the YLFS by presenting differences in the instance of training and its types between the top 40% and the bottom 60% of the income distribution. In most of the countries there is greater incidence of training, albeit informal job-related training, among the top 40% compared to the bottom 60%. It is only in Germany, Denmark, Austria, the United Kingdom, and the Netherlands that training is more common among the bottom 60% of the income distribution compared to the top 40%.

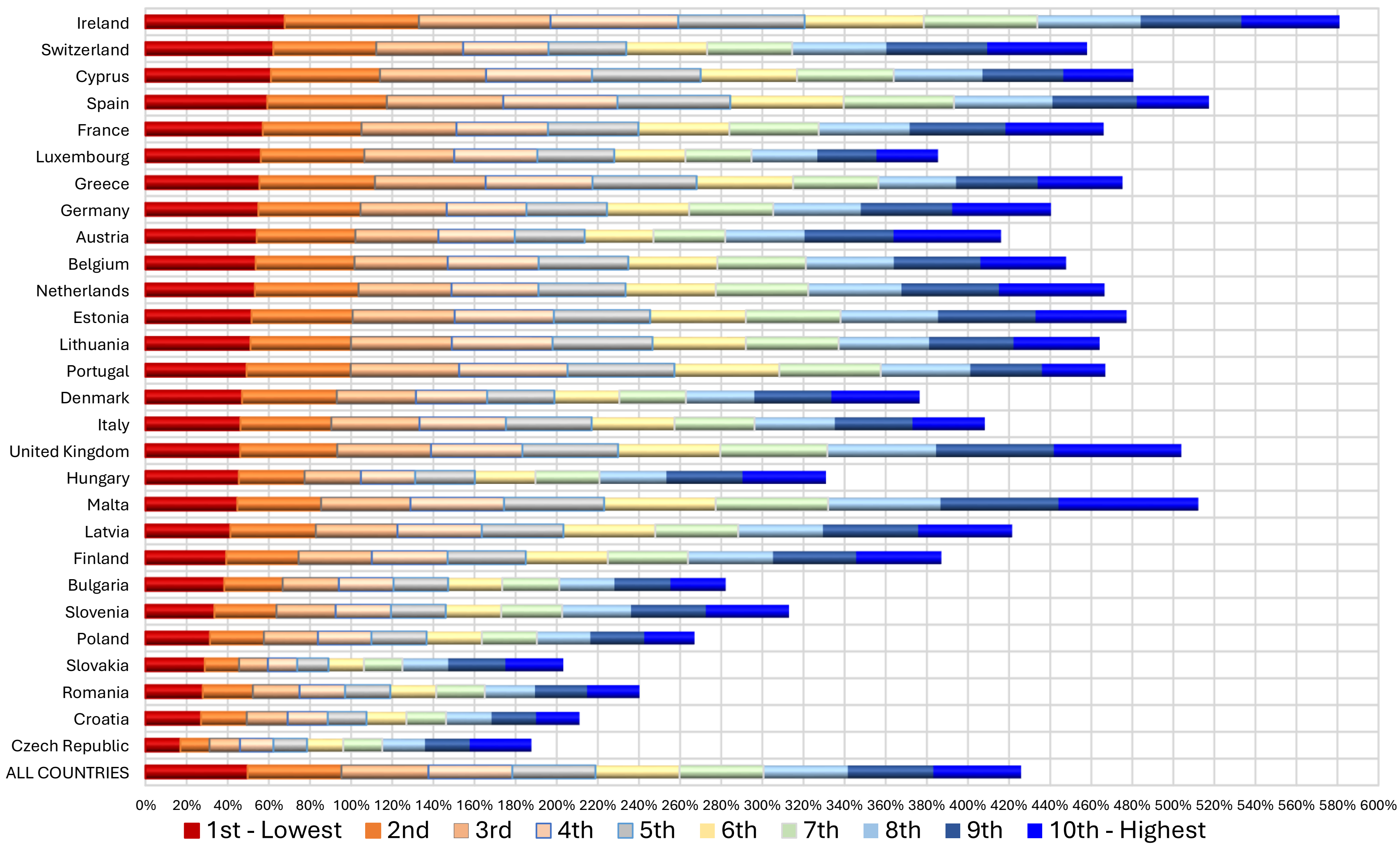

Ireland
Switzerland
Cyprus
Spain
France
Luxembourg
Greece
Germany
Austria
Belgium
Netherlands
Estonia
Lithuania
Portugal
Denmark
Italy
United Kingdom
Hungary
Malta
Latvia
Finland
Bulgaria
Slovenia
Poland
Slovakia
Romania
Croatia
Czech Republic
ALL COUNTRIES
0% 20% 40% 60% 80% 100% 120% 140% 160% 180% 200% 220% 240% 260% 280% 300% 320% 340% 360% 380% 400% 420% 440% 460% 480% 500% 520% 540% 560% 580% 600%
1st - Lowest
2nd
3rd
4th
5th
6th
7th
8th
9th
10th - Highest

Figure 2-31: EU-LFS$_{Yearly}$ – Income composition of skills mismatching by country

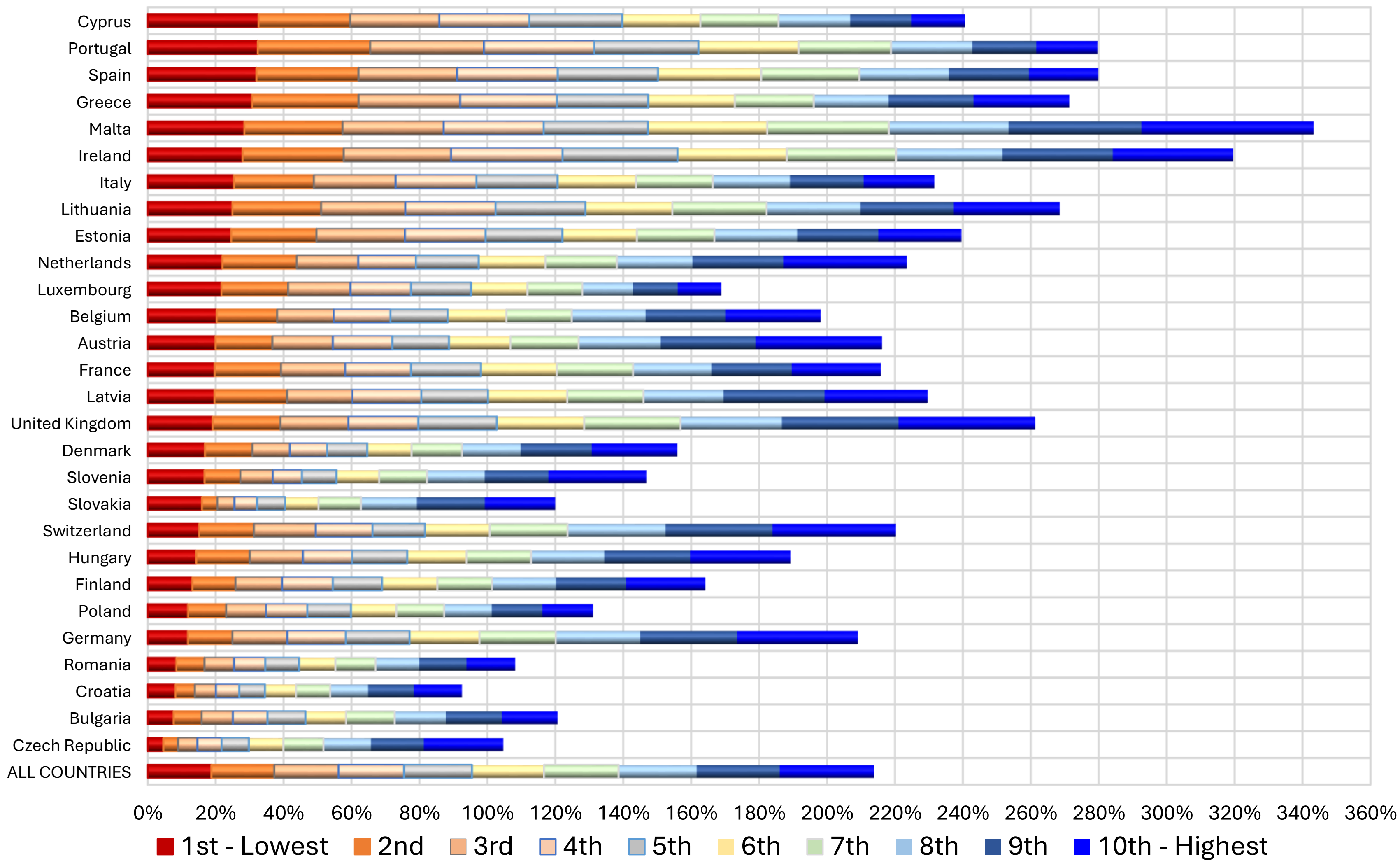


Figure 2-32: EU-LFS$_{Yearly}$ – Income composition of overeducation by country

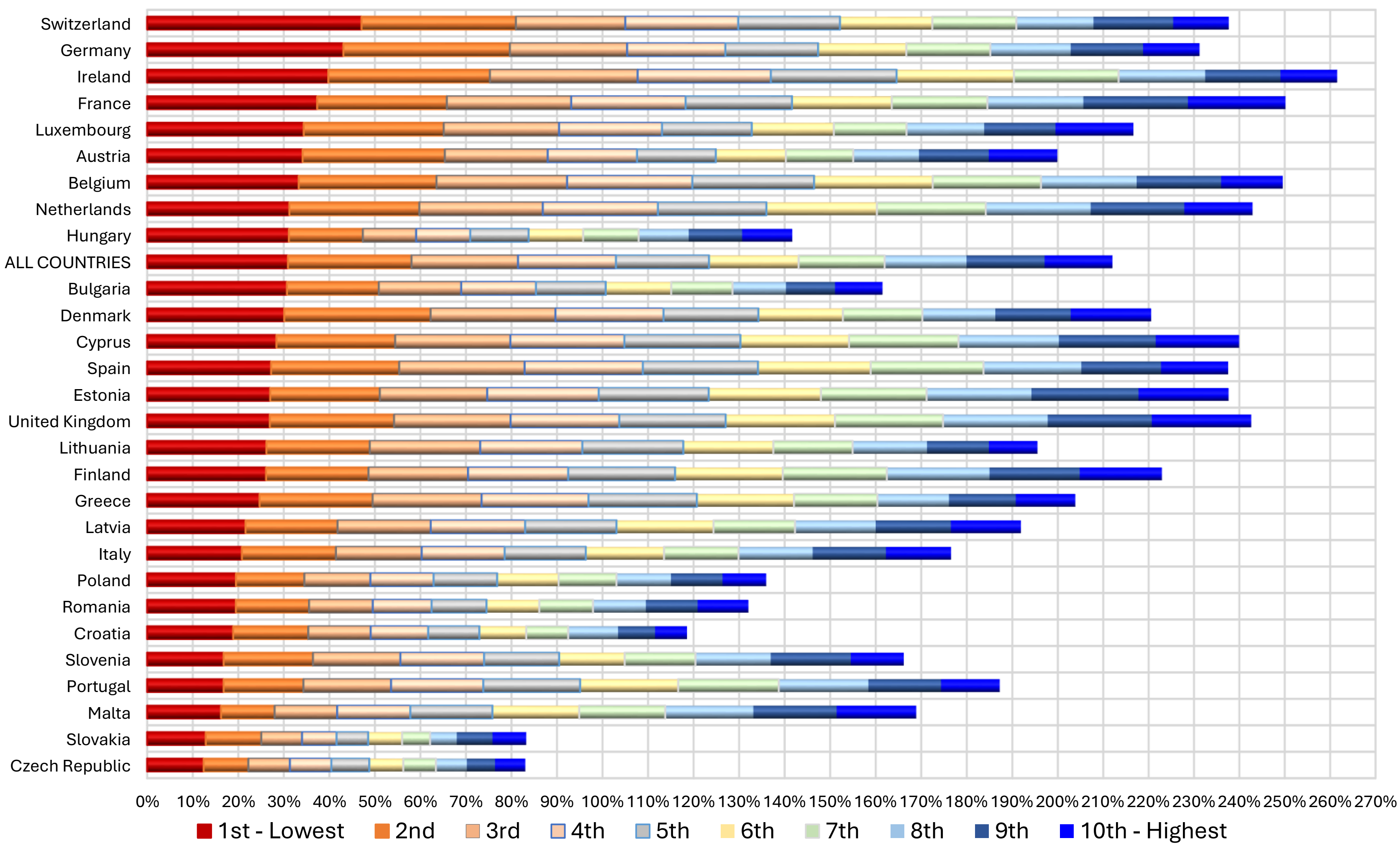


Figure 2-33: EU-LFS$_{Yearly}$ – Income composition of undereducation by country

Table 2-14: EU-LFS$_{Yearly}$ – Income differences (Top 40% vs. Bottom 60%)

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	T40%	B60&	DIFFERENCE	T40	B60	DIFFERENCE	T40%	B60%	DIFFERENCE
ALL COUNTRIES	41.5%	43.2%	-1.7 pp	24.3%	19.4%	4.8 pp	17.2%	23.7%	-6.5 pp
Luxembourg	30.7%	43.6%	-12.9 pp	14.3%	18.6%	-4.2 pp	16.4%	25.0%	-8.6 pp
Greece	40.1%	52.3%	-12.2 pp	24.3%	28.7%	-4.4 pp	15.9%	23.6%	-7.7 pp
Spain	44.5%	56.6%	-12.1 pp	24.8%	30.1%	-5.3 pp	19.7%	26.5%	-6.8 pp
Portugal	39.6%	51.4%	-11.7 pp	22.0%	31.9%	-9.9 pp	17.6%	19.5%	-1.8 pp
Cyprus	41.2%	52.9%	-11.7 pp	19.7%	27.2%	-7.5 pp	21.6%	25.7%	-4.2 pp
Ireland	51.1%	62.4%	-11.3 pp	32.6%	31.7%	0.9 pp	18.6%	30.7%	-12.2 pp
Lithuania	43.0%	48.6%	-5.7 pp	28.7%	25.7%	2.9 pp	14.3%	22.9%	-8.6 pp
Italy	37.7%	42.9%	-5.2 pp	22.0%	24.0%	-2.0 pp	15.8%	18.9%	-3.2 pp
Belgium	42.4%	46.2%	-3.8 pp	23.1%	17.6%	5.6 pp	19.3%	28.7%	-9.4 pp
Estonia	46.3%	48.6%	-2.3 pp	23.9%	24.0%	-0.1 pp	22.4%	24.6%	-2.2 pp
France	45.5%	47.2%	-1.7 pp	23.9%	20.1%	3.8 pp	21.7%	27.1%	-5.5 pp
Bulgaria	27.2%	28.9%	-1.7 pp	15.6%	9.7%	5.8 pp	11.6%	19.1%	-7.5 pp
Poland	25.8%	27.2%	-1.4 pp	14.5%	12.3%	2.2 pp	11.3%	14.9%	-3.6 pp
Denmark	36.5%	37.2%	-0.7 pp	19.6%	12.5%	7.1 pp	16.9%	24.7%	-7.8 pp
Croatia	21.0%	21.1%	0.0 pp	12.2%	7.3%	5.0 pp	8.8%	13.8%	-5.0 pp
Germany	44.0%	43.9%	0.1 pp	27.8%	16.4%	11.5 pp	16.1%	27.5%	-11.4 pp
Romania	24.7%	23.6%	1.1 pp	13.2%	9.2%	4.0 pp	11.5%	14.4%	-2.9 pp
Austria	42.3%	40.8%	1.5 pp	27.4%	17.7%	9.6 pp	14.9%	23.0%	-8.1 pp
Switzerland	46.2%	44.6%	1.6 pp	29.8%	16.9%	13.0 pp	16.3%	27.7%	-11.4 pp
Latvia	43.1%	41.2%	1.9 pp	26.2%	20.5%	5.7 pp	16.9%	20.8%	-3.8 pp
Netherlands	47.3%	45.2%	2.1 pp	26.6%	19.1%	7.5 pp	20.7%	26.1%	-5.4 pp
Hungary	35.3%	32.4%	2.9 pp	23.8%	15.6%	8.2 pp	11.5%	16.7%	-5.2 pp
Finland	40.6%	37.4%	3.2 pp	19.8%	14.3%	5.5 pp	20.8%	23.1%	-2.3 pp
Slovenia	35.0%	28.7%	6.3 pp	19.7%	11.2%	8.5 pp	15.3%	17.5%	-2.2 pp
Slovakia	23.1%	16.7%	6.5 pp	16.5%	8.1%	8.4 pp	6.6%	8.6%	-2.0 pp
Czech Republic	22.9%	16.0%	6.9 pp	16.2%	6.7%	9.5 pp	6.7%	9.3%	-2.6 pp
United Kingdom	56.2%	46.5%	9.8 pp	33.3%	21.1%	12.2 pp	22.9%	25.3%	-2.5 pp
Malta	58.8%	46.2%	12.6 pp	40.3%	30.4%	9.9 pp	18.5%	15.7%	2.7 pp

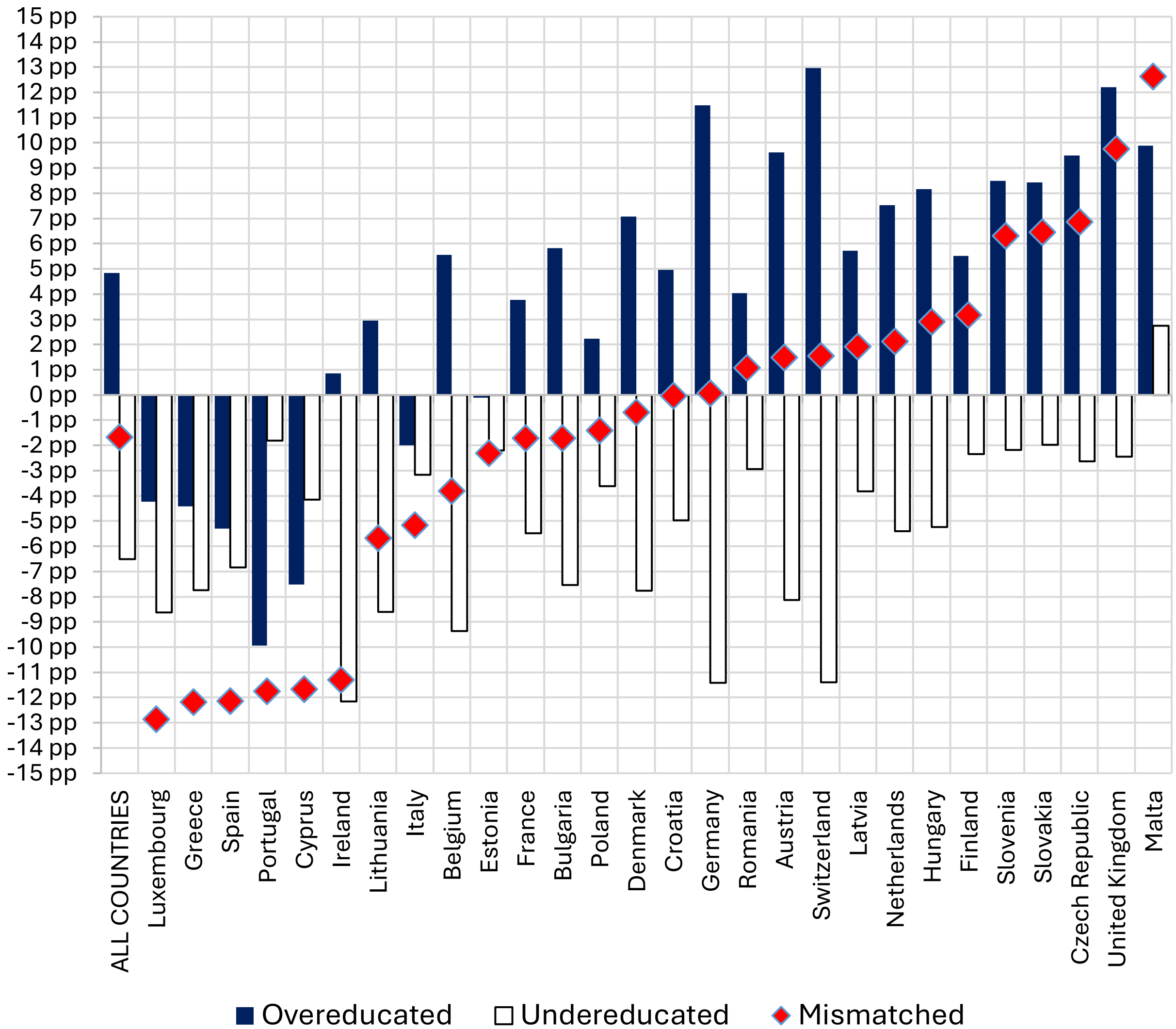
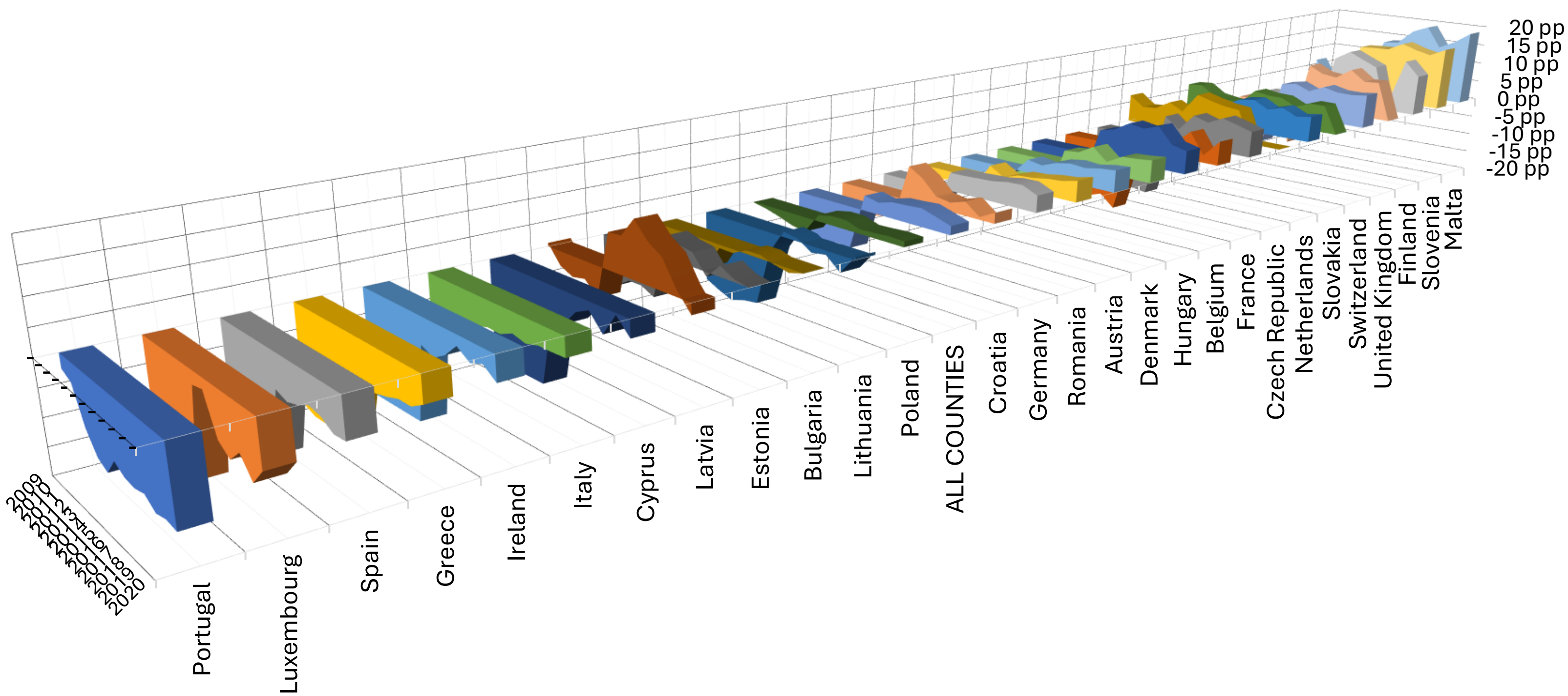


Figure 2-34: EU-LFS$_{Yearly}$ – Income differences by country (Top40 vs. Bottom60)



20 pp
15 pp
10 pp
5 pp
0 pp
-5 pp
-10 pp
-15 pp
-20 pp
Portugal
Luxembourg
Spain
Greece
Ireland
Italy
Cyprus
Latvia
Estonia
Bulgaria
Lithuania
Poland
ALL COUNTIES
Croatia
Germany
Romania
Austria
Denmark
Hungary
Belgium
France
Czech Republic
Netherlands
Slovakia
Switzerland
United Kingdom
Finland
Slovenia
Malta
2009
2020

Figure 2-35: EU-LFS$_{Yearly}$ – Income differences in skills mismatching by country and year

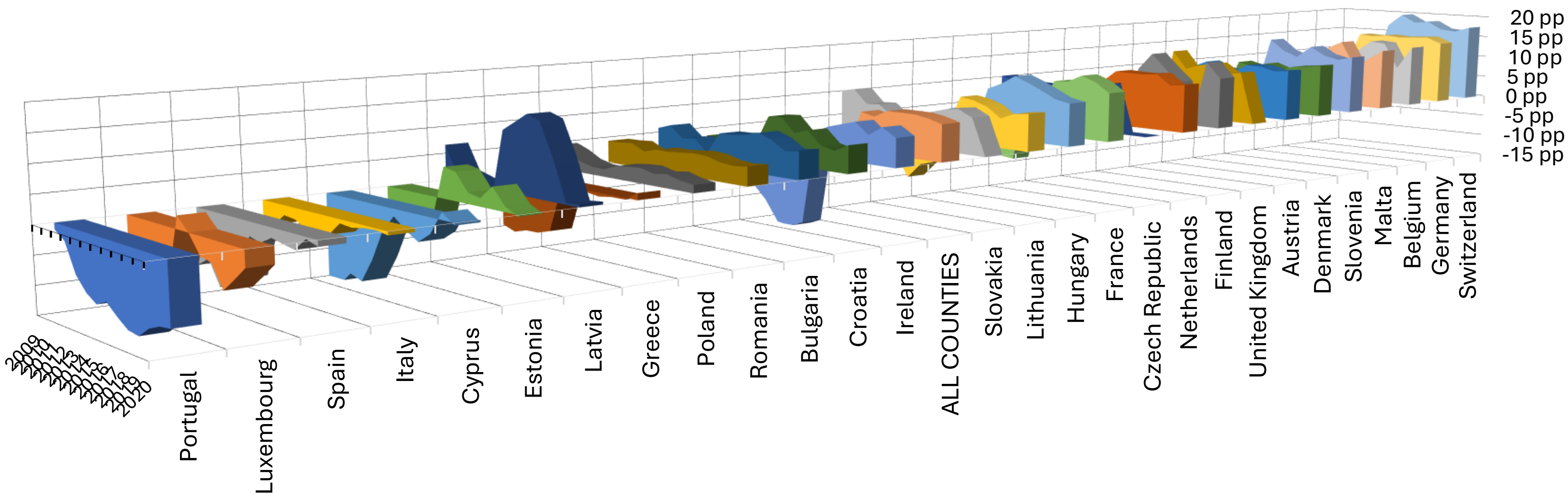


Figure 2-36: EU-LFS$_{Yearly}$ – Income differences in overeducation by country and year

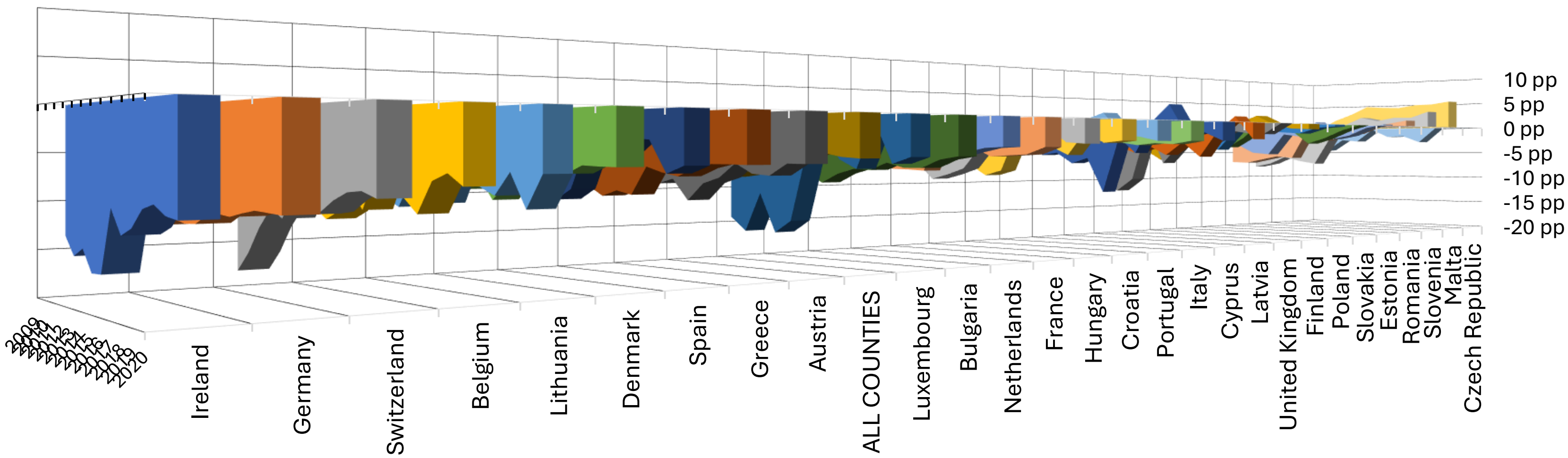


Figure 2-37: EU-LFS$_{Yearly}$ – Income differences in undereducation by country and year

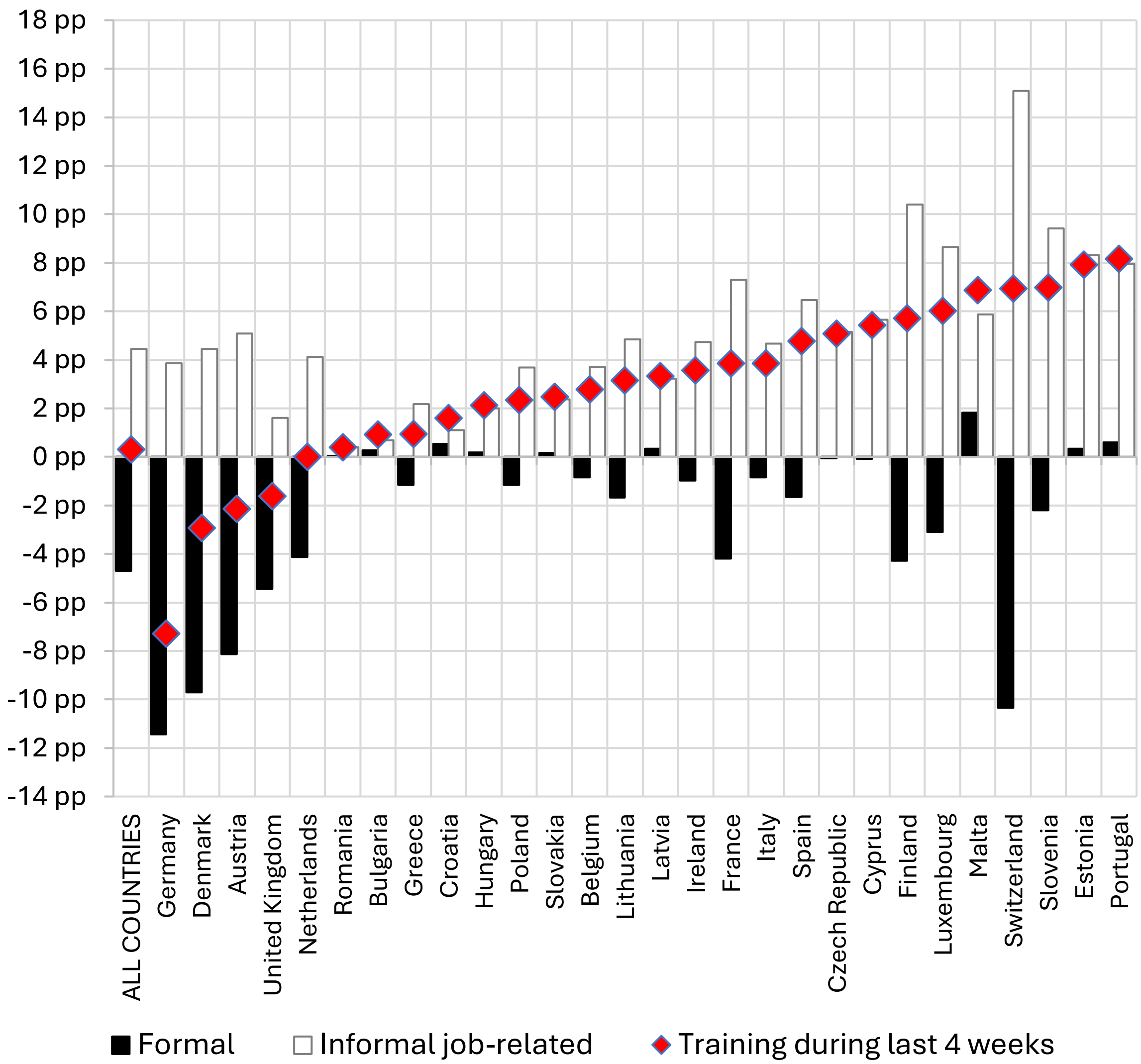


Figure 2-38: EU-LFS$_{Yearly}$ – Income differences in training by country

2.1.7 THE RELEVANT LITERATURE

An inquiry using the Scopus database suggests some 261 articles using the EU-LFS database. Out of these, 39 articles entail the word ‘Skill’. We conduct 2 relevant exercises using these 39 articles. In Figure 2-39 we present a word cloud of the most frequently appearing words in the index and author keywords of these articles. Then, in Table 2-15, we classify them into 5 key thematic categories, in terms of their content.

Figure 2-39: EU-LFS – Wordcloud of the keywords in the 39 articles on skills

The inspection of Figure 2-39 suggests that the most frequent words in the 39 articles are education, labour market, employment, human capital, skill, development Europe, and European Union, inter alia. The words cybersecurity, vocational, migration and immigrant, policies, numeracy, learning, training, automation, shortage, certification, social, regional, and women are also among the most frequently appearing words.

Table 2-15 shows 5 major thematic areas of research on skills using the EU-LFS. These are: (1) Automation, Digitalization and Cyberecurity; (2) Education, Vocational Training and Skills; (3) Migration; (4) Youth and Ageing; (5) Regional and Sectoral Analysis, with the most common themes being unemployment, productivity and inequality. Expectedly, research using the EU-LFS into automation, as well as youth and ageing appears in more recent years. Research in the remaining four thematic categories dates back to 2009 and covers all years until present.

Table 2-15: EU-LFS – Classification of the 39 articles on skills

Research domain	Cittions
Automation, Digitalization, and Cybersecurity	Lacová, et al. (2022), Josten & Lordan (2022), Blažič (2021; 2022), Polydoropoulou, et al. (2023)
Education, Vocational Training and Skills	Rodokanakis & Vlachos (2010), O'Mahony (2012), Tarman & Yigit (2013), Rodokanakis (2016), Daniele, et al. (2017), Protsch & Solga (2017), Daniele, et al. (2018), Katrňák & Doseděl (2019), Yue & Zhao (2020).
Migration	Dobson (2009), Manuguerra, et al. (2013), Cangiano (2014), Galgóczi, et al. (2016), Chletsos & Roupakias (2017), Kahanec & Guzi (2017), Ulceluse & Kahanec (2018), Barcevičius, et al. (2020), Leschke & Weiss (2020), Ulceluse (2020), Barcevičius, et al. (2020), Rosso (2021), Leschke & Weiss (2023).
Youth and Ageing	Bello & Galasso (2020), Lewis & Heyes (2020), Tåhlin & Westerman (2020).
Regional and Sectoral Analysis: Unemployment, Productivity and Inequality	Rodokanakis (2009), Rodríguez-Pose & Tselios (2009), Rodokanakis (2016), Rakowska (2014), Rakowska (2014), Pavolini & Kuhlmann (2016), Barzotto & De Propris (2019), Marois, Sabourin & Bélanger (2019), Roosmaa, Martma & Saar (2019).

2.2 EUROPEAN SKILLS AND JOBS SURVEY (ESJS)

The European Skills and Jobs Survey (ESJS) is a comprehensive survey conducted by the European Centre for the Development of Vocational Training (Cedefop). It aims to provide insights into the skills landscape across the European Union, focusing on the relationships between skills, education, and the labour market. The survey examines how skills are utilized at work, how they evolve, and how mismatches between workers' skills and job requirements impact productivity and career development.

The primary goal of the ESJS is to assess the skills that European workers possess, how these skills align with their job requirements, and the extent of skill mismatches (both over-skilling and under-skilling). The survey also looks at how jobs are changing due to technological advances, globalization, and other factors, and how workers adapt their skills over time.

The ESJS covers employees aged 24 to 65 across the EU member states. It includes a wide range of sectors and occupations, capturing a representative snapshot of the EU workforce. The survey caters to the following contents:

- Data collection and methodology: The ESJS employs a structured questionnaire, administered through interviews, to collect data from a sample of workers across EU countries. The survey is designed to ensure comparability of results across countries and sectors.
- Skills utilization: The survey investigates the types of skills used in the workplace, including cognitive, technical, interpersonal, and digital skills.
- Skill mismatches: It explores the extent of mismatches between the skills workers have and the skills required for their jobs. This includes situations where workers are either over-qualified (over-skilled) or under-qualified (under-skilled) for their roles.
- Skill development: The ESJS looks at opportunities for skills development, such as training and lifelong learning, and how these opportunities relate to job changes and career progression.
- Job changes and future skills: The survey also focuses on the evolving nature of jobs, particularly the impact of digitalization and automation on skill needs.

The results of the ESJS are used by policymakers, educators, and employers to design strategies for education and training systems, labour market policies, and workforce development. The data help in addressing skill gaps, improving the alignment of education and training with labour market needs, and fostering lifelong learning.

The ESJS provides valuable insights into the prevalence of skill mismatches in the EU, highlighting sectors and occupations where mismatches are most common. It sheds light on the relationship between skills and job quality, including job satisfaction, career advancement, and wage levels. The survey also identifies trends in skill demand, particularly in relation to technological change, helping policymakers understand future skills needs.

The ESJS is a crucial tool for understanding the dynamics of skills in the European labour market. It helps identify areas where the skills of the workforce need to be enhanced, where education and training systems may require adjustment, and how workers can be better prepared for the future of work. This is especially important in the context of rapid technological change and the growing emphasis on digital and green skills within the EU.

2.2.1 THE EMPLOYEE DATA AND SUMMARY STATISTICS

Table 2-16 presents the number of observations for each country and in each wave of the ESJS (2014 and 2021). Wave one records information for 48,676 respondents while there are 46,213 participants in wave 2. The United Kingdom is included in wave one (as this wave took place prior to Brexit), while Norway and Iceland appear in only the second wave of the survey.

Table 2-16: ESJS –Number of observations for each country and wave

COUNTRY	ACRONYM	OBSERVATIONS 2014	OBSERVATIONS 2021
ALL COUNTRIES	*POOLED*	*48,676*	*46,213*
Austria	AT	1,000	1,505
Belgium	BE	1,502	1,528
Bulgaria	BG	1,000	1,549
Croatia	HR	1,004	1,001
Cyprus	CY	500	1,001
Czechia	CZ	1,506	1,570
Denmark	DK	1,000	1,005
Estonia	EE	1,001	1,069
Finland	FI	2,004	1,307
France	FR	4,011	3,014
Germany	DE	4,013	3,051
Greece	GR	2,037	2,003
Hungary	HU	1,500	1,501
Ireland	IE	1,004	1,393
Italy	IT	3,016	3,000
Latvia	LV	1,004	1,004
Lithuania	LT	1,010	1,002
Luxembourg	LU	500	1,020
Malta	MT	500	1,003
Netherlands	NL	1,502	1,501
Poland	PL	4,017	3,068
Portugal	PT	1,503	1,525
Romania	RO	1,502	2,028
Slovakia	SK	1,019	1,003
Slovenia	SI	1,010	1,000
Spain	ES	4,009	3,010
Sweden	SE	1,001	1,506

United Kingdom	UK	4,001	0
Iceland	IS	0	1,022
Norway	NO	0	1,024

Table 2-17 presents descriptive statistics of key variables that are present in both survey waves. The number of observations for each variable in each wave is shown, along with their averages. A column is shown both for the raw survey data, and the data when (within-)country weights are applied. Variables included largely relate to individuals' education and employment characteristics.

Table 2-17: ESJS -Weighted and unweighted descriptive statistics

	2014				2021			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
VARIABLE	#OBS	MEAN	#OBS	MEAN	#OBS	MEAN	#OBS	MEAN
Male	48,676	56.0%	48,399	51.8%	46,096	51.4%	46,213	49.6%
Age	48,676	42.22	49,399	42.44	46,096	43.29	46,097	43.33
Tenure	48,306	10.21	48,056	10.29	45,537	9.82	45,538	10.08
Vocational	39,704	69.6%	39,534	69.1%	41,695	59.5%	41,696	58.7%
Contract type: Permanent	48,676	82.4%	48,399	82.1%	46,096	83.5%	46,213	84.2%
-"-: Temporary	48,676	12.7%	48,399	13.0%	46,096	13.4%	46,213	13.0%
-"-: No contract	48,676	3.1%	48,399	3.2%	46,096	2.9%	46,213	2.6%
-"-: Part-time	48,676	16.5%	48,399	17.1%	46,096	20.5%	46,213	20.9%
Firm size: 1 to 49	48,676	48.8%	48,399	49.6%	46,096	49.2%	46,213	47.8%
-"-: 50 to 249	48,676	25.1%	48,399	24.6%	46,096	25.5%	46,213	25.9%
-"-: 250 +	48,676	23.0%	48,399	22.7%	46,096	24.5%	46,213	25.5%
Sector: Private	48,676	63.3%	48,399	63.9%	46,096	63.3%	46,213	60.0%
-"-: Public	48,676	26.9%	48,399	26.2%	46,096	28.4%	46,213	31.8%
-"-: Not-for-profit	48,676	3.6%	48,399	5.2%	46,096	2.8%	46,213	3.0%
Occupation: Managers	48,676	7.4%	48,399	7.1%	46,096	9.2%	46,097	11.4%
-"-: Professionals	48,676	21.5%	48,399	19.2%	46,096	21.7%	46,097	28.0%
-"-: Technicicans	48,676	15.8%	48,399	16.2%	46,096	15.8%	46,097	15.2%
-"-: Clerical	48,676	21.4%	48,399	21.2%	46,096	11.6%	46,097	13.5%
-"-: Service and Sales	48,676	14.3%	48,399	14.9%	46,096	13.1%	46,097	13.0%
-"-: Skilled agriculture	48,676	0.8%	48,399	0.8%	46,096	1.2%	46,097	0.8%
-"-: Trades	48,676	7.3%	48,399	8.2%	46,096	11.0%	46,097	6.6%
-"-: Manufacturing	48,676	6.6%	48,399	7.1%	46,096	7.4%	46,097	4.6%
-"-: Elementary	48,676	4.5%	48,399	5.2%	46,096	7.7%	46,097	5.3%
Education Field: Education	28,008	7.3%	27,903	7.2%	27,369	6.6%	27,370	7.0%
-"-: Arts	28,008	8.3%	27,903	8.1%	27,369	8.3%	27,370	8.9%
-"-: Social Sciences	28,008	5.1%	27,903	5.1%	27,369	4.0%	27,370	4.6%
-"-: Business and law	28,008	21.4%	27,903	20.9%	27,369	18.4%	27,370	20.7%
-"-: Science and maths	28,008	7.4%	27,903	7.5%	27,369	8.4%	27,370	8.7%
-"-: ICT	28,008	8.3%	27,903	8.1%	27,369	8.1%	27,370	8.5%
-"-: Engineering	28,008	13.4%	27,903	13.4%	27,369	18.0%	27,370	15.4%
-"-: Agriculture and veterinary	28,008	1.7%	27,903	1.8%	27,369	2.7%	27,370	2.3%
-"-: Health and Welafre	28,008	8.4%	27,903	8.9%	27,369	8.3%	27,370	8.4%
-"-: Services	28,008	3.9%	27,903	4.0%	27,369	7.6%	27,370	7.3%
-"-: Other	28,008	11.9%	27,903	12.1%	27,369	9.7%	27,370	8.3%
Education: None	48,676	0.2%	48,399	0.4%	45,999	0.2%	46,213	0.2%
-"-: Primary	48,676	1.3%	48,399	1.8%	45,999	1.7%	46,213	1.0%
-"-: Lower Secondary	48,676	10.6%	48,399	11.0%	45,999	9.4%	46,213	8.1%
-"-: Upper Secondary	48,676	30.2%	48,399	36.9%	45,999	33.6%	46,213	25.8%

-“-: Post-Secondary non-	48,676	11.9%	48,399	13.0%	45,999	11.5%	46,213	10.2%
-“-: First level Tertiary	48,676	39.8%	48,399	32.0%	45,999	41.8%	46,213	52.2%
-“-: Advanced Level tertiary	48,676	5.9%	48,399	4.9%	45,999	1.8%	46,213	2.4%

2.2.2 SKILLS MATCHING AND TRAINING STATISTICS

Table 2-18 presents the incidence of educational mismatch at a country level in each wave of the ESJS. The (weighted) proportion of individuals in each country that are overeducated, undereducated or matched are reported in both waves, along with the country’s relative rank among other countries in each outcome. Overall, the incidence of both over- and undereducation has decreased between 2014 and 2021, meaning that more workers are matched.

Table 2-18: ESJS -Weighted educational mismatch statistics

	MATCHED				OVEREDUCATED				UNDEREDUCATED			
	2014	(RANK)	2021	(RANK)	2014	(RANK)	2021	(RANK)	2014	(RANK)	2021	(RANK)
ALL COUNTRIES	*52.9%*		*67.4%*		*28.0%*		20.7%		19.1%		11.9%	
Austria	48.7%	*(23)*	63.7%	*(23)*	34.9%	*(4)*	22.9%	*(10)*	16.3%	*(18)*	13.5%	*(9)*
Belgium	55.1%	*(14)*	70.8%	*(9)*	22.0%	*(22)*	17.1%	*(22)*	23.0%	*(6)*	12.1%	*(14)*
Bulgaria	63.3%	*(3)*	69.1%	*(11)*	25.9%	*(15)*	21.6%	*(13)*	10.7%	*(23)*	9.3%	*(22)*
Croatia	54.1%	*(16)*	73.5%	*(4)*	37.7%	*(3)*	16.3%	*(23)*	8.2%	*(27)*	10.2%	*(18)*
Cyprus	55.1%	*(13)*	71.6%	*(7)*	30.8%	*(10)*	20.8%	*(15)*	14.1%	*(21)*	7.6%	*(26)*
Czechia	53.1%	*(18)*	71.8%	*(6)*	38.6%	*(2)*	22.3%	*(11)*	8.3%	*(26)*	5.9%	*(29)*
Denmark	57.5%	*(10)*	64.2%	*(22)*	22.4%	*(21)*	25.2%	*(5)*	20.1%	*(12)*	10.6%	*(17)*
Estonia	48.0%	*(24)*	61.2%	*(28)*	34.0%	*(6)*	24.2%	*(7)*	18.0%	*(15)*	14.6%	*(7)*
Finland	58.6%	*(8)*	74.5%	*(2)*	20.9%	*(23)*	14.1%	*(26)*	20.5%	*(10)*	11.5%	*(15)*
France	37.5%	*(28)*	67.8%	*(13)*	34.1%	*(5)*	19.3%	*(18)*	28.4%	*(2)*	13.0%	*(10)*
Germany	56.1%	*(12)*	65.0%	*(20)*	25.8%	*(17)*	25.9%	*(2)*	18.1%	*(14)*	9.1%	*(24)*
Greece	59.2%	*(7)*	66.8%	*(18)*	24.3%	*(19)*	22.0%	*(12)*	16.5%	*(17)*	11.2%	*(16)*
Hungary	63.0%	*(4)*	61.6%	*(27)*	28.3%	*(13)*	28.7%	*(1)*	8.7%	*(25)*	9.7%	*(20)*
Iceland			65.9%	*(19)*			21.4%	*(14)*			12.7%	*(12)*
Ireland	46.0%	*(26)*	67.3%	*(15)*	32.5%	*(7)*	23.2%	*(8)*	21.6%	*(8)*	9.5%	*(21)*
Italy	52.3%	*(20)*	58.2%	*(29)*	19.1%	*(26)*	25.4%	*(4)*	28.5%	*(1)*	16.4%	*(4)*
Latvia	54.3%	*(15)*	67.6%	*(14)*	26.3%	*(14)*	19.8%	*(17)*	19.4%	*(13)*	12.6%	*(13)*
Lithuania	53.0%	*(19)*	67.0%	*(17)*	32.3%	*(9)*	24.5%	*(6)*	14.8%	*(19)*	8.5%	*(25)*
Luxembourg	79.0%	*(1)*	68.4%	*(12)*	13.6%	*(28)*	12.1%	*(28)*	7.4%	*(28)*	19.6%	*(3)*
Malta	58.2%	*(9)*	62.4%	*(26)*	19.5%	*(25)*	13.6%	*(27)*	22.4%	*(7)*	24.0%	*(1)*
Netherlands	60.4%	*(6)*	74.7%	*(1)*	14.1%	*(27)*	11.1%	*(29)*	25.6%	*(5)*	14.2%	*(8)*
Norway			63.7%	*(23)*			20.6%	*(16)*			15.8%	*(5)*
Poland	53.4%	*(17)*	74.3%	*(3)*	25.5%	*(18)*	18.3%	*(20)*	21.1%	*(9)*	7.4%	*(28)*
Portugal	39.3%	*(27)*	62.9%	*(25)*	32.4%	*(8)*	14.9%	*(25)*	28.4%	*(3)*	22.2%	*(2)*
Romania	65.6%	*(2)*	72.4%	*(5)*	19.8%	*(24)*	18.4%	*(19)*	14.6%	*(20)*	9.2%	*(23)*
Slovakia	61.4%	*(5)*	69.5%	*(10)*	29.4%	*(11)*	23.0%	*(9)*	9.3%	*(24)*	7.5%	*(27)*
Slovenia	56.3%	*(11)*	71.2%	*(8)*	25.9%	*(16)*	16.0%	*(24)*	17.8%	*(16)*	12.8%	*(11)*
Spain	50.7%	*(21)*	64.6%	*(21)*	28.8%	*(12)*	25.5%	*(3)*	20.5%	*(11)*	9.9%	*(19)*

Sweden	50.4%	*(22)*	67.1%	*(16)*	23.8%	*(20)*	17.6%	*(21)*	25.9%	*(4)*	15.2%	*(6)*
United Kingdom	46.6%	*(25)*			41.1%	*(1)*			12.4%	*(22)*		

Table 2-19 presents the mean outcomes (pooled over survey waves) for key variables among overeducated, undereducated and matched workers. An ANOVA F-test is carried out to compare the means of each variable for the three groups, and the corresponding F-statistic and p-value are shown in the right two columns. There is a significant difference between the groups across all variables besides the proportion of those working in agriculture, for which there is a notably small sample size (~1% of pooled sample).

Table 2-20 presents the mean outcomes (pooled over survey waves) for key variables among both matched and unmatched (people who are either overeducated or undereducated). A t-test is carried out and the significance of the related p-value is presented in the table, denoted by the asterisk (*). As was the case when over- and undereducated were treated separately, there is no significant difference in proportional of agricultural workers between matched and mismatched individuals. However, differences in means for public sector workers and graduates of either Education, ICT or Health related fields are also not significantly different between groups.

Table 2-21 presents the incidence of different forms of mismatch and the upskilling needs of workers across EU countries in the second wave of the ESJS (2021). It is not clear if vertical or horizontal mismatch is more prevalent, as it differs by country. However, underutilisation of skills (or 'Overskilling') seems to be more prevalent than both these forms of mismatch in nearly all countries, sometimes even being twice as high as either of them. In relation to upskilling requirements, social skills are most frequently reported as an area where employees need to improve, followed by job-specific skills, then numeracy skills. Digital skills are generally reported the least as an aspect of employees' jobs that they need to improve at.

Figure 2-40 presents the proportion of those in the ESJS whose highest education was Vocational in each country. The pale blue bars represent the proportion from the pooled sample over both waves, while the red (blue) dots represent the proportion in wave 1 (wave 2). In most countries, VET completion has fallen over time. Exceptions are Croatia, Finland and Romania. Countries that experienced the largest declines are Germany, Portugal, Belgium, Greece and Ireland.

Figure 2-41 presents the proportion of VET graduates by Industry and field of education. Across every industry and field of education, proportion of VET graduates have fallen, but the relative position of each group in relation to others has almost remained the same. In both waves, graduates of Health and Welfare and Engineering, and Construction programmes have the highest incidence of VET completion. As for industry, Education and Health, construction, and Utilities and Mining have the highest proportion of VET graduates.

Table 2-19: ESJS –Summary statistics of key variables by matching status

VARIABLE	OVEREDUCATED	MATCHED	UNDEREDUCATED	ANOVA F-STATISTIC	P-VALUE
Male	50.8%	54.1%	56.4%	2.33	0.10*
Age	41.82	43.01	44.95	446.46	0.00***
Tenure	8.81	10.31	12.46	685.8	0.00***
Hours of work	37.73	38.33	38.00	18.55	0.00***
Vocational training	59.6%	71.9%	64.4%	661.72	0.00***
Contract: Permanent	81.2%	83.8%	83.8%	25.49	0.00***
-“-: Temporary	14.6%	12.6%	11.2%	50.69	0.00***
-“-: None	3.2%	2.7%	3.4%	8.86	0.00***
Part-time	20.2%	17.9%	17.8%	25.8	0.00***
Firm size: 1 to 49	48.1%	50.5%	49.4%	30.93	0.00***
-“-: 50 to 249	25.7%	24.5%	25.0%	7.65	0.00***
-“-: 250+	24.6%	23.1%	22.3%	30.07	0.00***
Occupation: Manager	9.1%	7.1%	8.4%	81.97	0.00***
-“-: Professional	24.7%	19.2%	13.5%	562.81	0.00***
-“-: Technician	14.4%	16.2%	19.0%	72.31	0.00***
-“-: Clerical	14.4%	17.2%	19.6%	116.59	0.00***
-“-: Sales & services	14.1%	14.1%	13.6%	4.9	0.01***
-“-: Agriculture	1.0%	1.0%	1.0%	2.01	0.13
-“-: Trades	7.2%	11.2%	10.6%	235.97	0.00***
-“-: Manufacturing	6.7%	7.6%	7.5%	37.6	0.00***
-“-: Elementary	7.4%	5.8%	6.0%	20.16	0.00***
Sector: Private	63.0%	63.2%	66.2%	41.93	0.00***
-“-: Public	28.6%	27.2%	24.2%	92.82	0.00***
-“-: Not-for-profit	3.1%	3.2%	3.1%	2.89	0.06*
Field of Education:	4.6%	3.7%	1.4%	127.81	0.00***
-“-: Arts	6.4%	3.5%	2.0%	270.89	0.00***
-“-: Social Sciences	3.7%	2.0%	0.7%	202.39	0.00***
-“-: Business and law	12.9%	10.4%	5.3%	299.37	0.00***
-“-: Science and Maths	5.7%	4.0%	1.9%	169.5	0.00***
-“-: ICT	4.9%	4.4%	3.0%	31.57	0.00***
-“-: Engineering	9.0%	9.7%	3.9%	205.45	0.00***
-“-: Agriculture	1.4%	1.3%	0.6%	23.9	0.00***
-“-: Health	4.5%	5.5%	2.4%	140.93	0.00***
-“-: Services	3.3%	3.7%	1.4%	73.09	0.00***
-“-: Other	5.8%	6.6%	3.9%	61.43	0.00***
Education level: None	0.0%	0.3%	1.1%	124.75	0.00***
-“-: Primary	0.7%	1.3%	5.6%	624.13	0.00***
-“-: Lower secondary	4.4%	10.3%	24.2%	2545.46	0.00***
-“-: Upper secondary	18.7%	45.5%	46.5%	4588.51	0.00***
-“-: Post secondary non-	11.3%	12.0%	15.2%	260.58	0.00***
-“-: First-level tertiary	57.6%	29.3%	6.4%	8933.98	0.00***
-“-: Advanced-level	7.1%	1.2%	0.0%	1530.55	0.00***

Notes: *, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 2-20: ESJS -Differences in key variables between matched and unmatched employees

VARIABLE	MATCHED	MISMATCHED	DIFF.	SIGNIF.
Male	54.1%	52.4%	-0.016	
Age	43.01	42.72	-0.293	***
Tenure	10.31	9.85	-0.464	***
Vocational training	0.72	0.61	-0.112	***
Hours of work	38.33	37.81	-0.526	***
Contract: Permanent	83.8%	82.0%	-0.018	***
-“-: Temporary	12.6%	13.6%	0.010	***
-“-: None	2.7%	3.3%	0.006	***
Part-time	17.9%	19.5%	0.016	***
Firm size: 1 to 49	50.5%	48.5%	-0.020	***
-“-: 50 to 249	24.5%	25.5%	0.010	***
-“-: 250+	23.1%	23.9%	0.008	***
Occupation: Manager	7.1%	8.9%	0.018	***
-“-: Professional	19.2%	21.5%	0.022	***
-“-: Technician	16.2%	15.8%	-0.004	***
-“-: Clerical	17.2%	15.9%	-0.012	***
-“-: Sales & services	14.1%	13.9%	-0.001	***
-“-: Agriculture	1.0%	1.0%	0.000	
-“-: Trades	11.2%	8.2%	-0.030	***
-“-: Manufacturing	7.6%	6.9%	-0.007	***
-“-: Elementary	5.8%	7.0%	0.012	***
Sector: Private	63.2%	63.9%	0.007	**
-“-: Public	27.2%	27.3%	0.001	
-“-: Not-for-profit	3.2%	3.1%	-0.001	**
Field of Education: Education	3.7%	3.7%	0.000	
-“-: Arts	3.5%	5.2%	0.016	***
-“-: Social Sciences	2.0%	2.9%	0.009	***
-“-: Business and law	10.4%	10.7%	0.003	
-“-: Science and Maths	4.0%	4.6%	0.006	***
-“-: ICT	4.4%	4.3%	0.000	
-“-: Engineering	9.7%	7.6%	-0.021	***
-“-: Agriculture	1.3%	1.2%	-0.001	
-“-: Health	5.5%	3.9%	-0.016	***
-“-: Services	3.7%	2.7%	-0.010	***
-“-: Other	6.6%	5.3%	-0.014	***
Education level: None	0.3%	0.3%	0.000	***
-“-: Primary	1.3%	2.1%	0.008	***
-“-: Lower secondary	10.3%	10.1%	-0.002	***
-“-: Upper secondary	45.5%	26.7%	-0.188	***
-“-: Post secondary non-tertiary	12.0%	12.4%	0.004	***
-“-: First-level tertiary	29.3%	42.9%	0.136	***
-“-: Advanced-level Tertiary	1.2%	5.2%	0.040	***

Notes: Weighted t-test for differences in mean between matched VS mismatched (i.e. under- or overeducated). *, **, *** denote statistical significance at 10%, 5%, 1%.

Table 2-21: ESJS –Measurement of Skills Mismatching at the ESJS 2021 (CEDEFOP, 2024)

COUNTRY	MISMATCH			UPSKILLING NEEDS				
	VERTICAL: Qualification with job	HORIZONTAL: Field of study with job	UNDERUSE of skills at job	Overall	Digital skills	Technical or job-specific skills	Social skills	Numeracy skills
Austria	26%	26%	45%	22%	10%	32%	51%	27%
Belgium	23%	25%	39%	15%	12%	35%	47%	26%
Bulgaria	31%	32%	62%	18%	14%	44%	43%	29%
Croatia	19%	29%	63%	25%	20%	40%	63%	29%
Cyprus	35%	32%	–	16%	10%	–	–	–
Czech Republic	25%	21%	54%	24%	13%	46%	51%	26%
Denmark	28%	34%	48%	12%	7%	37%	38%	23%
Estonia	32%	34%	61%	15%	9%	52%	58%	38%
Finland	19%	41%	54%	9%	10%	50%	46%	31%
France	23%	29%	40%	18%	12%	41%	47%	26%
Germany	28%	26%	41%	10%	8%	33%	46%	28%
Greece	32%	23%	55%	21%	18%	39%	48%	26%
Hungary	34%	24%	47%	11%	11%	34%	45%	30%
Ireland	34%	22%	43%	12%	12%	44%	46%	29%
Italy	30%	33%	30%	8%	11%	38%	42%	25%
Latvia	33%	24%	55%	17%	12%	47%	51%	28%
Lithuania	38%	22%	54%	10%	9%	40%	43%	25%
Luxembourg	20%	29%	55%	26%	15%	38%	56%	28%
Malta	25%	36%	–	22%	12%	–	–	–
Netherlands	16%	22%	57%	13%	10%	29%	49%	21%
Poland	26%	21%	51%	25%	17%	47%	61%	36%
Portugal	22%	26%	53%	9%	14%	48%	46%	34%
Romania	25%	32%	66%	38%	26%	56%	62%	48%
Slovakia	27%	29%	52%	21%	15%	44%	55%	31%
Slovenia	24%	24%	48%	25%	15%	50%	56%	32%
Spain	37%	23%	42%	24%	18%	42%	58%	37%
Sweden	28%	23%	54%	12%	10%	43%	44%	27%

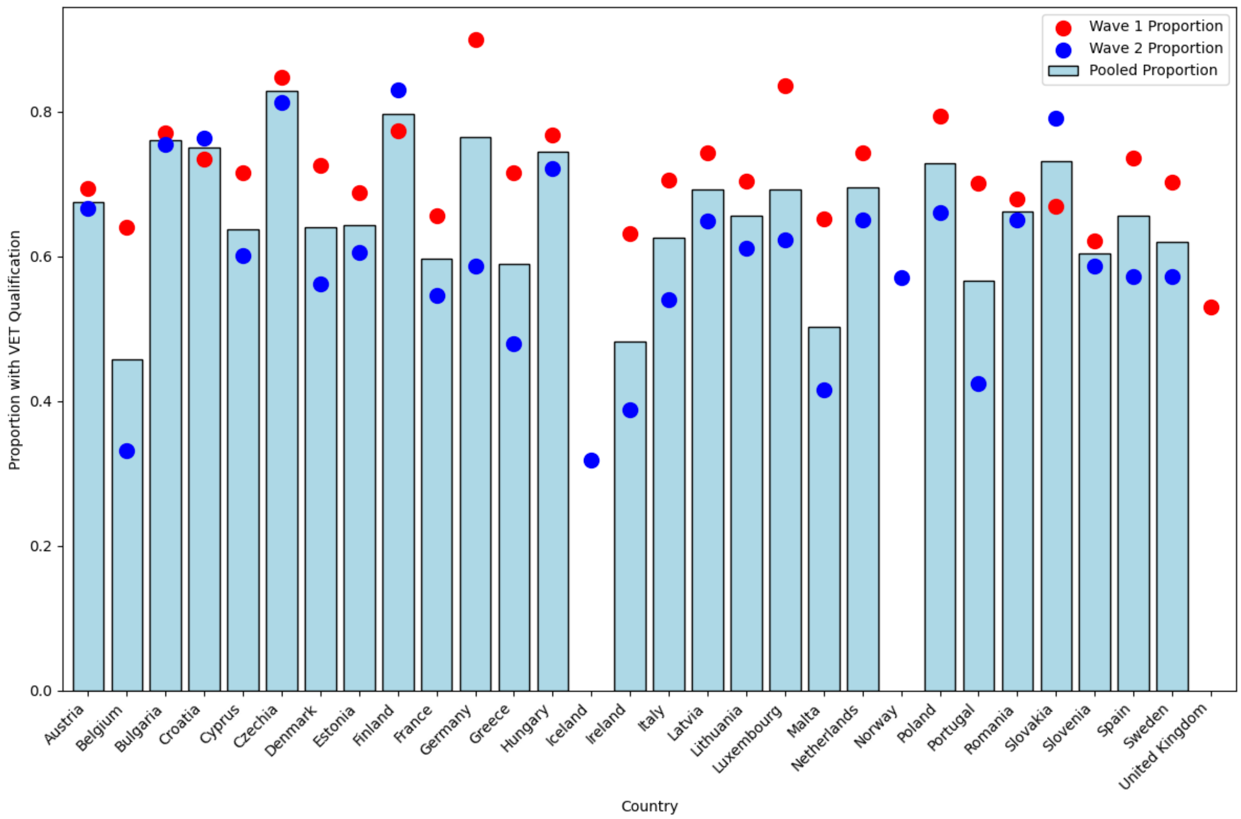
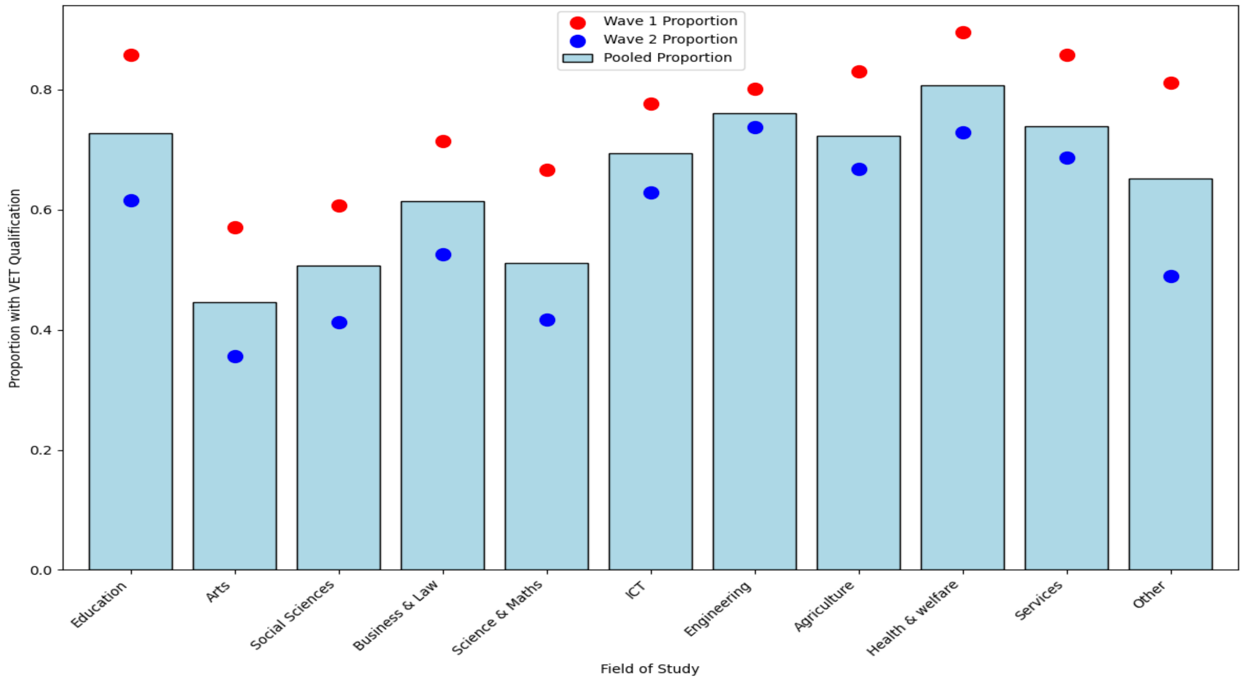


Figure 2-40: ESJS –Proportion with VET Qualification by Country (weighted)



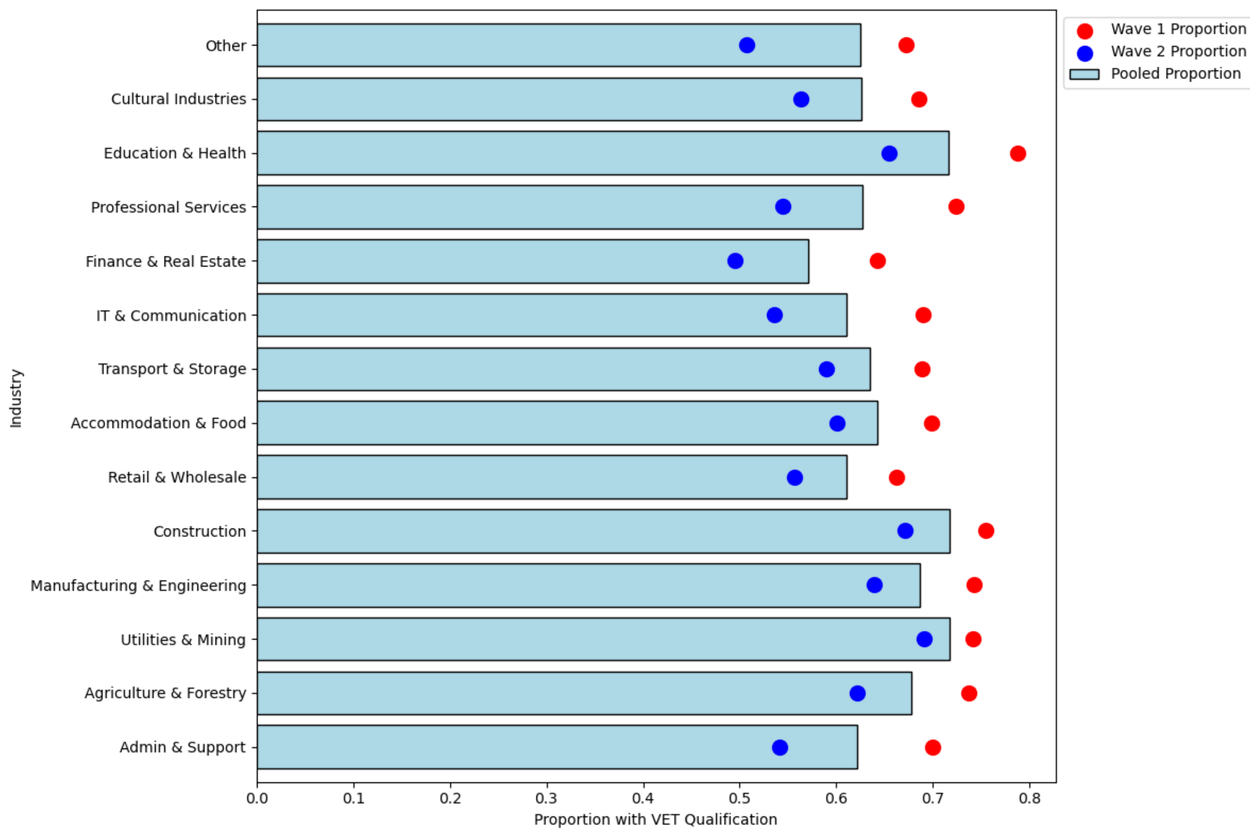


Figure 2-41: ESJS – Proportion with VET Qualification by country, field of education, and industry

2.2.3 DIFFERENCES BY GENDER

Figure 2-42 presents the educational mismatch by gender for wave 1 (2014) and wave 2 (2021) of the ESJS. Both over- and undereducation fell between survey waves, with the proportion of matched individuals obviously increasing as a result. In wave 1, overeducation is more prevalent for women than men, but this gap shrinks in wave 2 so that they are almost equally likely. In terms of undereducation, incidence is higher for men in both waves, however, the gender gap also shrinks between waves.

Then, Figure 2-43 shows the proportion with VET as the highest qualification completed by gender for wave 1 (2014) and wave 2 (2021) of the ESJS. Completion of VET has decreased slightly between waves. In both waves, a greater proportion of women have completed VET than men, but the gap is small in wave 1 and smaller again in wave 2.

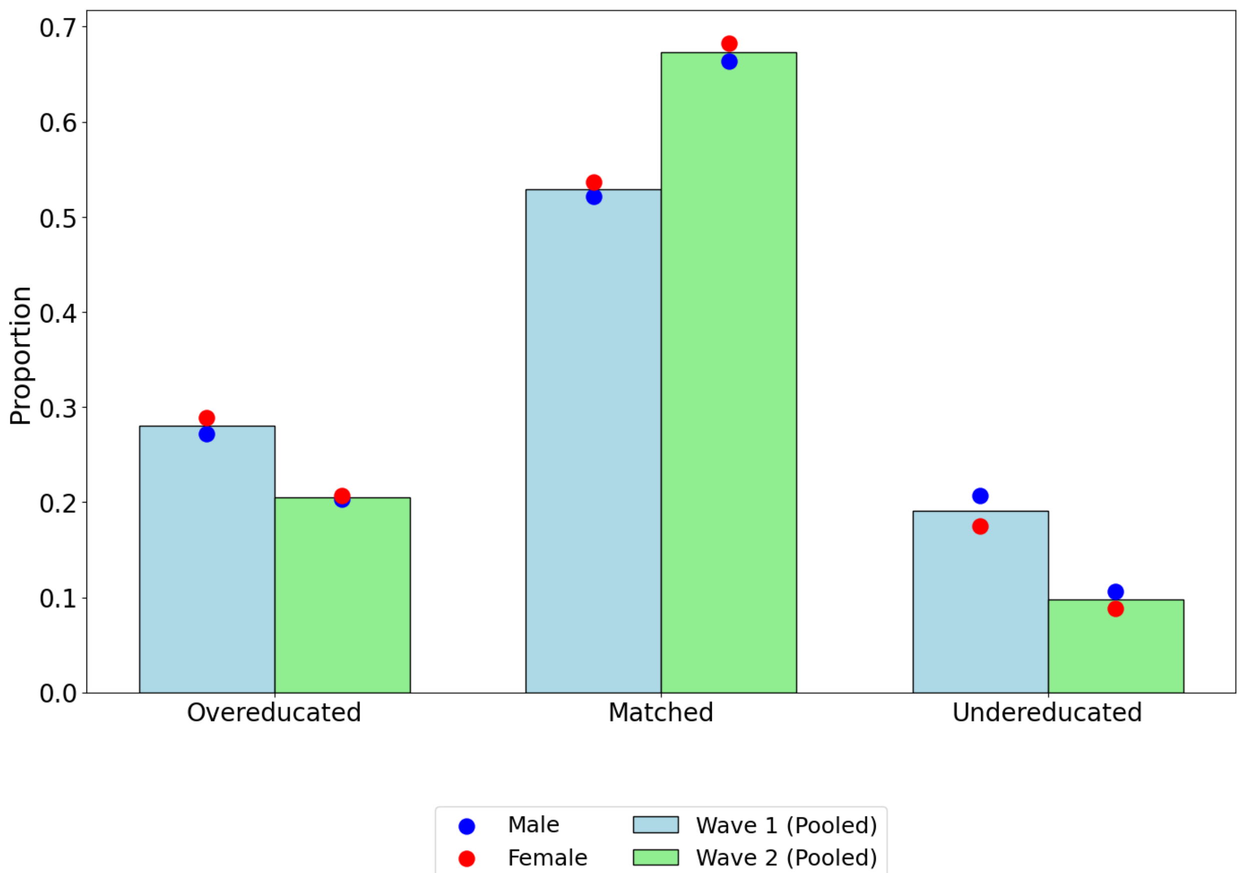


Figure 2-42: ESJS – Educational Mismatch by gender (weighted)

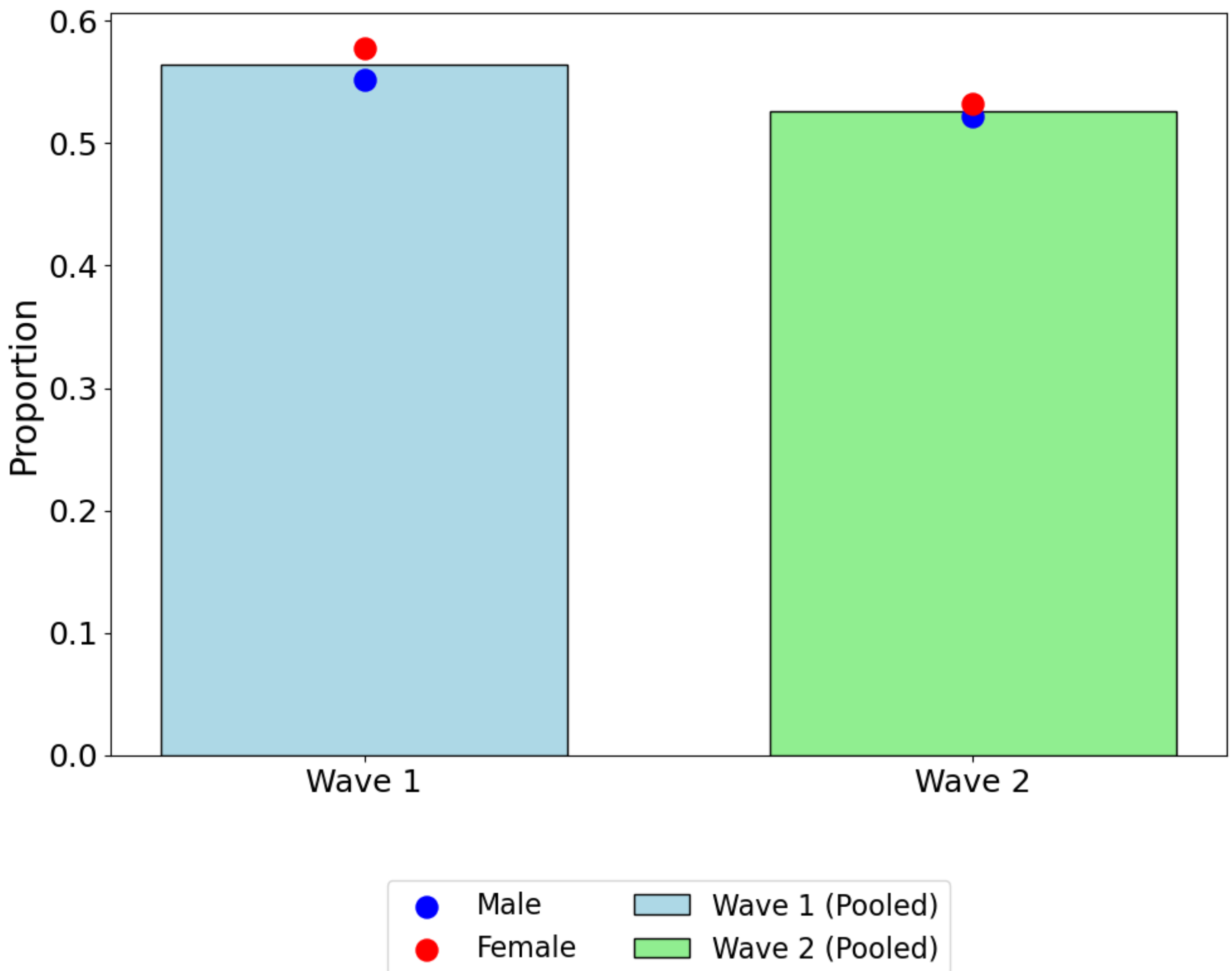


Figure 2-43: ESJS – VET completion by Gender (weighted)

2.2.4 DIFFERENCES BY AGE

Figure 2-44 presents the educational mismatch by age group for wave 1 (2014) and wave 2 (2021) of the ESJS. Overeducation is highest for the youngest age category, and follows a negative monotonic trend in both waves, with older participants recording lower incidences of this form of mismatch. As was the case with gender, the gap between categories is smaller in wave 2, but the same monotonic relationship holds. The opposite is true for undereducation, with its incidence being higher among older employees. Again, gaps are bigger in wave 1 than wave 2. It is likely that the human capital accumulated by more experienced workers can act as a substitute for formal education, explaining why undereducation is highest for the oldest individuals, and lowest for the youngest.

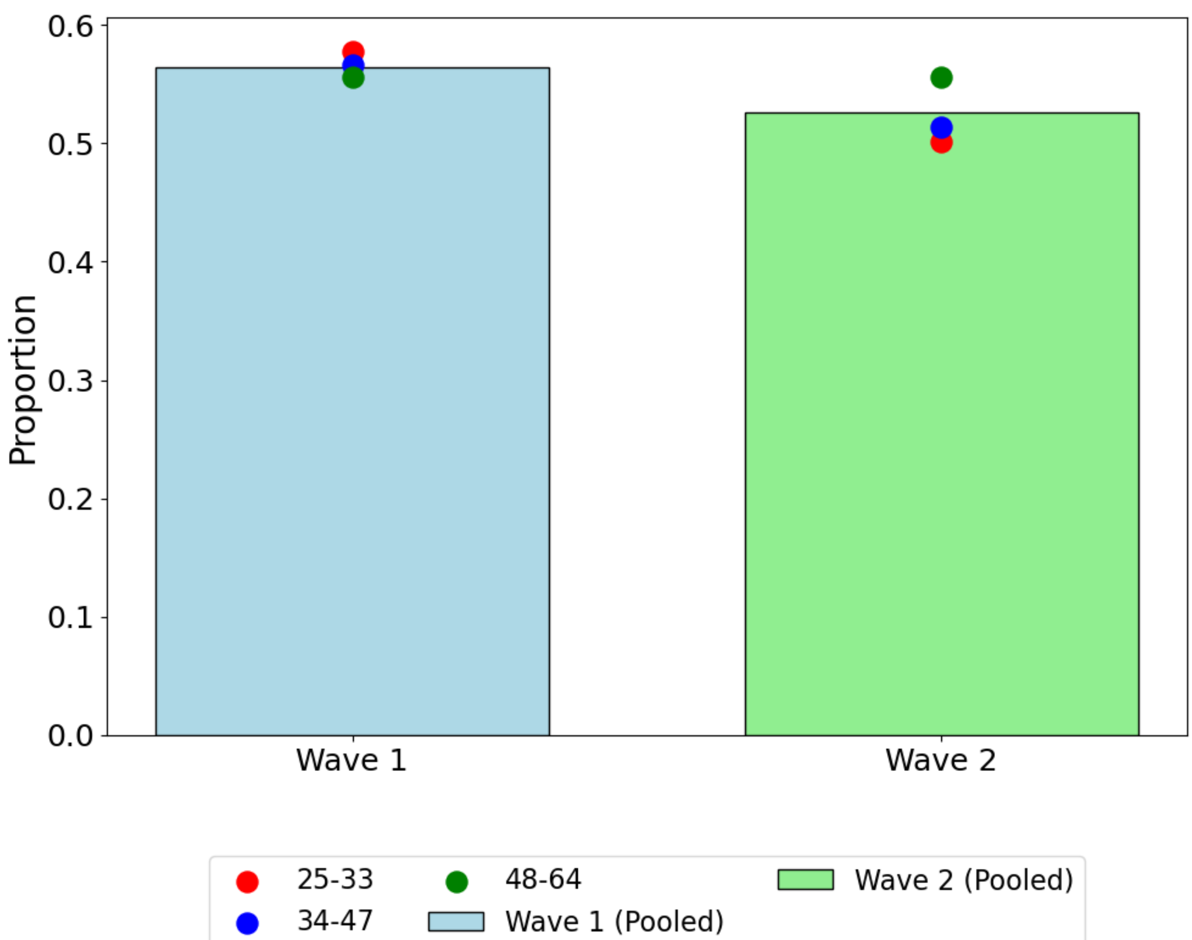


Figure 2-44: ESJS – Educational Mismatch by Age group (weighted)

Figure 2-45 presents the proportion with VET as the highest qualification completed by age group for wave 1 (2014) and wave 2 (2021) of the ESJS. Interestingly, the trends in VET completion by age group reverse over time. In wave 1, VET completion was highest for the youngest age group, and lowest for the oldest age group, but the gap is quite small. In wave 2, the oldest age group has the highest rate of VET completion, by a much larger margin than what is seen in wave 1, while the two younger age groups have lower incidence of VET completion and are bunched closer together.

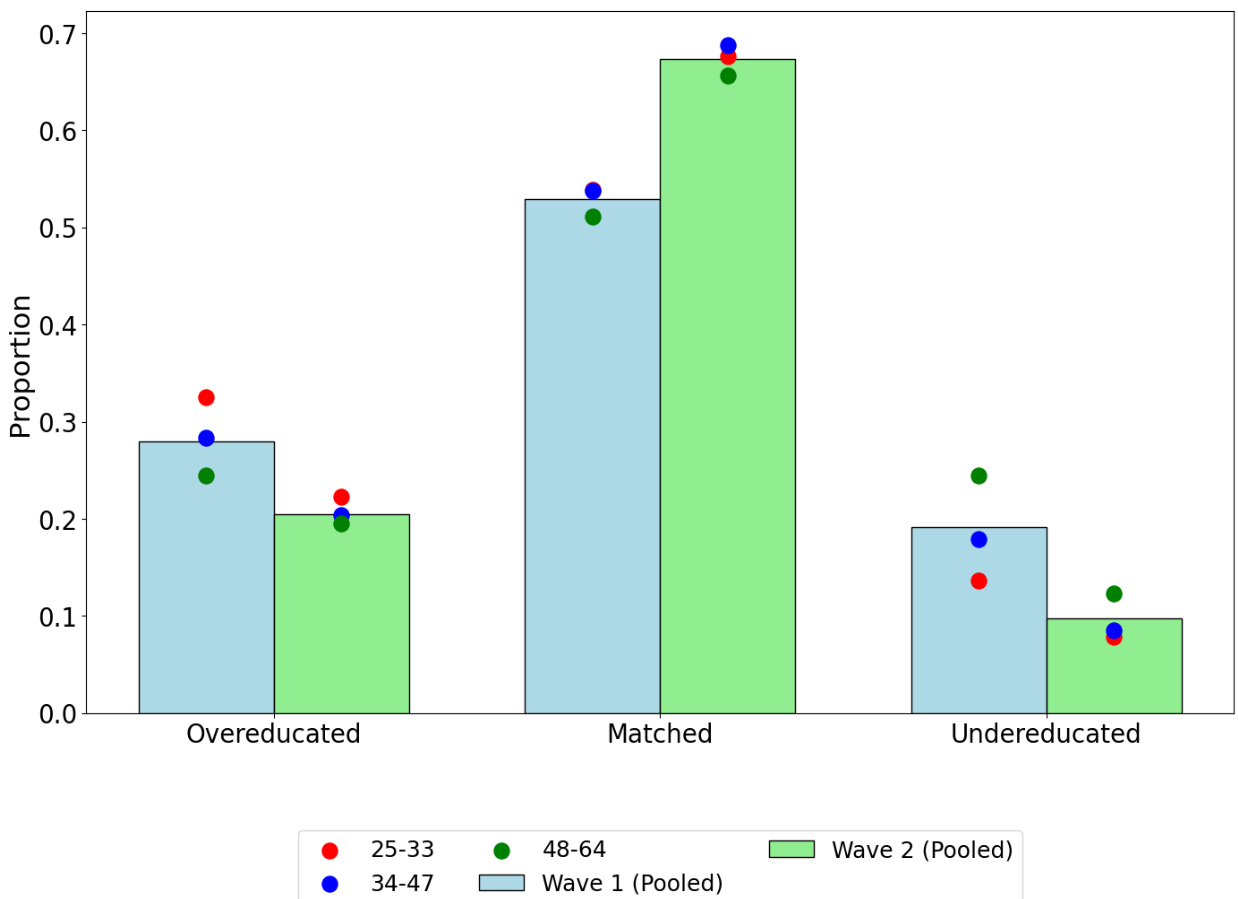


Figure 2-45: ESJS – VET completion by Age Group (weighted)

2.2.5 DIFFERENCES BY INCOME

Figure 2-46 presents the educational mismatch by income quartile for wave 1 (2014) and wave 2 (2021) of the ESJS. There is large variation in the incidence of overeducation across income quartiles. In both waves, the poorest quartile has the highest incidence of overeducation, by quite a substantial margin over the pooled sample. It follows an almost linear trend, as incidence decreases in income (incidence for the third quartile in wave 1 is marginally lower than for the fourth quartile). There is far less variation for undereducation, as quartiles are closely bunched. However, even though the difference in incidence is very similar between quartiles, a trend analogous to that for overeducation can still be observed, with undereducation being highest for the richer quartiles than the poorer quartiles. The richest quartile has the highest prevalence of matched instances in both waves.

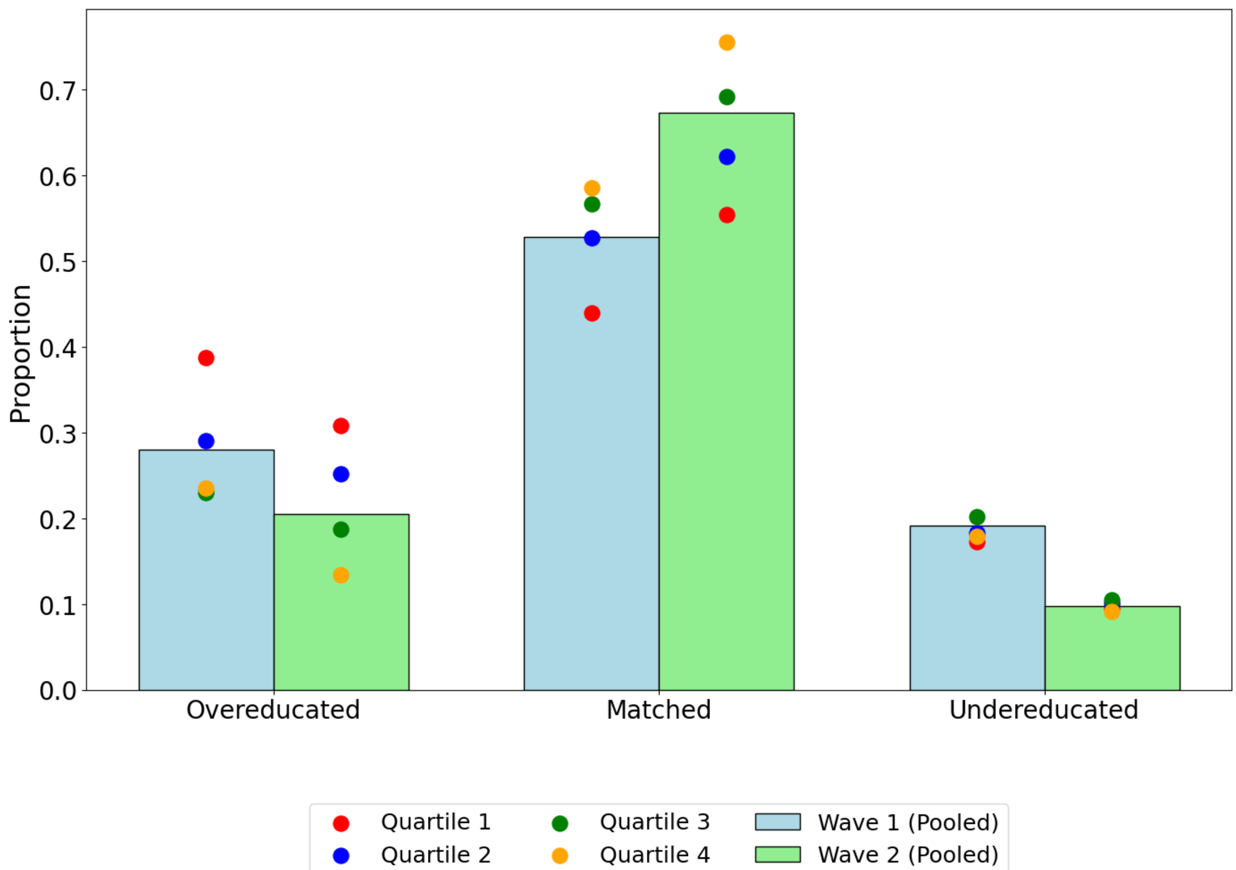


Figure 2-46: ESJS – Educational Mismatch by Income quartile (weighted)

Figure 2-47 presents the proportion with VET as the highest qualification completed by income quartile for wave 1 (2014) and wave 2 (2021) of the ESJS. Universally, the lowest income quartile has the lowest prevalence of VET completion. In wave 1 the rate of VET completion is very similar for the richest 3 quartiles, while in wave 2, There is a clearer linear relationship between VET completion and income.

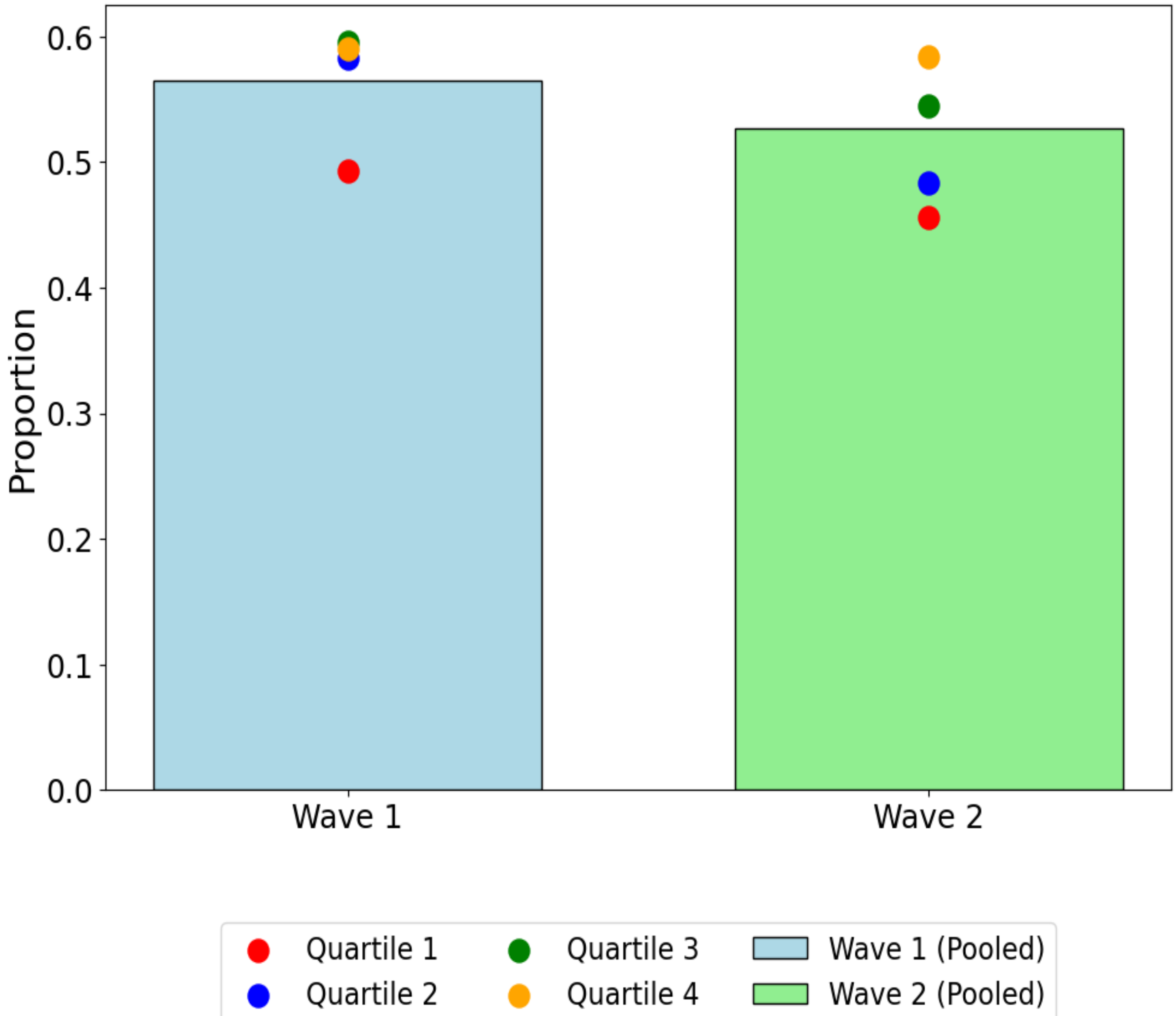


Figure 2-47: ESJS – VET completion by Income quartile (weighted)

2.2.6 THE RELEVANT LITERATURE

The inquiry using Scopus suggests some 293 relevant articles using the ESJS database. Out of these, 125 articles entail the word 'Skill' and are relevant. We replicate the two previous exercises using these articles. In Figure 2-48 we present a word cloud of the most frequently appearing words in the index and author keywords of these 125 articles. Then, in Table 2-21, we classify them into 10 key thematic categories, in terms of their content. The most frequent words in the 125 articles are education, learning, human capital, labour market, skill, mismatch, training, development, innovation, industry, science, policy, European, automation, and engineering.

Figure 2-48: ESJS – Word cloud of the keywords in the 125 articles on skills

Table 2-22 shows 10 major thematic areas of research using the EU-LFS. These are: (1) Skills and Competences; (2) Educational Mismatch; (3) Digitalization; (4) Career Progression; (5) VET; (6) Industry 4.0 and Automation; (7) Gender and Diversity; (8) Higher Education and Graduate Employment; (9) Workplace Innovation, and; (10) Non-formal Education and Adult Learning.

Table 2-22: ESJS – Classification of the 125 articles on skills

Research domain	Citations
Skills and Competences	Gábor, et al. (2018); Açıkgöz, et al. (2022); Filippi, et al. (2023); Cunha, et al. (2023); Suciu, et al. (2023); Tokarčíková, et al. (2020); Psifidou, & Grm (2022); Rodríguez, et al. (2024); Kononiuk (2022); Kargem, et al. (2022); Kalenda, et al. (2022)
Educational Mismatch	Karunaratne, & Mobini (2019); Rodríguez-Esteban, et al. (2019); Choi (2020); Sevilla, & Farías (2020); Battu, & Bender (2020); McGuinness, et al. (2018); Pereira, et al. (2023); Rodríguez-Esteban, & Vidal (2020); Drymiotou, et al. (2024); Summerfield (2022); Folea, & Folcut (2024)
Impact of Digitalization	Alasheev, et al. (2020); Nygren, et al. (2020); Tokarčíková, et al. (2020); Redmond (2022); Bouslama, et al. (2024); Edelsbrunner, et al. (2022); Marinas, et al. (2021); Varshavskaya (2021); Peruffo, & Fernández-Macías (2020); Giesecke, & Schartinger (2024); Alasheev, et al. (2020)
Career Development and Transition	Moso Díez, & Chacón Delgado (2018); Jandrić, & Ranđelović (2018); Parada (2021); Choi (2021); Drymiotou, et al. (2024); Redmond, & McGuinness (2020); Santiago-Vela, & Hall (2023); Okay-Somerville, & Scholarios (2022); Noppeney, et al. (2024); Lopes, et al. (2023); Okay-Somerville, & Scholarios (2022)
Vocational Education and Training (VET)	Bouslama, et al. (2024); Barbosa, et al. (2022); Kalenda, et al. (2022); Psifidou, & Grm (2022); Souto-Otero, et al. (2023); Tobback, et al. (2024); Cunha, et al. (2023); Kovacs (2022); Bampasidis, et al. (2021); Radovan (2024); Psifidou, & Grm (2022); Karger, et al. (2022)
Industry 4.0 and Automation	Moso Díez, & Chacón Delgado (2018); Ansari, et al. (2018); Perini, et al. (2022); Varshavskaya (2021); Kupka, & Černý (2024); Redmond (2022); Gábor, et al. (2018); Jona-Lasinio, & Venturini (2024); Totterdill (2020); Psifidou, & Grm (2022); Ansari, et al. (2018); Redmond (2022)
Gender and Diversity	Bouslama, et al. (2024); Giesecke, & Schartinger (2024); Hinterplattner (2023); Kargem, et al. (2022); Karunaratne, & Mobini (2019); Filippi, et al. (2023); Redmond, & McGuinness (2020); Stanković, et al. (2021); Stanković, et al. (2021); Sesen, et al. (2024)
Higher Education and Graduate Employment	Garcia-Esteban, & Jahnke (2020); van Wetten, et al. (2020); Nunes, et al. (2022); Redmond (2022); Cunha, et al. (2023); Rodríguez, et al. (2024); Hinterplattner (2023); Corrales-Herrero, & Rodríguez-Prado (2024); Bouslama, et al. (2024); Rodríguez, et al. (2024); Choi (2021)
Workplace Innovation	Totterdill (2017); Ansari, et al. (2018); Redmond (2022); Sesen, et al. (2024); Totterdill (2020); Tokarčíková, et al. (2020); Edelsbrunner, et al. (2022); Kononiuk (2022); Giesecke, & Schartinger (2024); Ansari, et al. (2018); Redmond, & McGuinness (2020); Ansari, et al. (2018)
Non-Formal Education and Adult Learning	Kalenda, et al. (2022); Karger, et al. (2022); Radovan (2024); Psifidou, & Grm (2022); Cunha, et al. (2023); Vaculíková, et al. (2024); Suciu, et al. (2023); Edelsbrunner, et al. (2022); Karger, et al. (2022); Kalenda, et al. (2022); Vaculíková, et al. (2024)

2.3 ADULT EDUCATION SURVEY (AES)

The Adult Education Survey (AES) is an integral component of the European Union's statistics on lifelong learning (LLL). It involves interviewing individuals aged 18 to 69 (25 to 64 up to 2016) about their involvement in various educational activities, including formal, non-formal, and informal learning. The survey captures data on participants' learning activities over the twelve months preceding the interview. Conducted every six years, the survey's findings are made publicly available on Eurostat's website.

The following information is available from the AES:

Participation in formal education, non-formal education and training and informal learning

- Volume of instruction hours
- Characteristics of the learning activities
- Reasons for participating
- Obstacles to participation
- Access to information on learning possibilities
- Employer financing and costs of learning
- Self-reported language skills

The initial phase of the survey, known as the 2007 AES or 'pilot survey,' was conducted between 2005 and 2008 in 29 countries, comprising member states of the European Union, candidate countries, and countries of the European Free Trade Association. This pilot initiative was established within a unified EU framework, utilizing a standard questionnaire and ensuring quality reporting.

The third AES data collection, referred to as the 2016 AES, was conducted in 2016 and 2017, with implementation details specified in Commission Regulation (EU) No 1175/2014.

The latest AES data collection occurred in 2022 and 2023, based on Framework Regulation (EU) No 1700/2019, with implementation details defined in Commission Implementing Regulation (EU) 2021/861.

Following the pilot phase, the AES became a mandatory European survey under the legal basis of Framework Regulation (EC) No 452/2008. The second AES data collection, known as the 2011 AES, occurred in 2011 and 2012, with implementation details outlined in Commission Regulation (EU) No 823/2010.

The Adult Education Survey (AES) has not been utilized much for research purposes, based on a related search in Scopus.

2.3.1 THE DATA AND FREQUENCIES

The pooled sample of the AES database used in the analysis consists of 930. 649 observations, collected from 27 EU countries and 6 non-EU countries. Table 2-22 below details each country's subsample in the AES, including the number of observations and the corresponding percentage of the total sample over the four pooled AES waves.

More specifically, the first wave of the survey (2007 AES pilot survey—referred to as 2007 in the following sections) covers data from 26 countries with a net sample size of 200. 895 individuals. Table 2-23 reveals that countries are not equally represented in the sample, with Italy, Poland, Spain, France, and Romania having a larger number of observations and Latvia, Norway, Croatia, Denmark, and the Netherlands being underrepresented. All the national subsamples include individuals aged between 25 and 64 years.

The 2011 AES wave (referred to as 2011 in the following sections) contains data from 30 countries, with the national samples totaling 225. 347 individuals. Poland, Spain, Portugal, France, and Romania rank among the countries with the largest representation, and Cyprus, Malta, Netherlands, Sweden, and Luxemburg rank among the countries with the fewer observations. Some countries include in their samples individuals aged less than 25 or more than 64, which are included in the following analysis.

The 2016 AES (referred to as 2016 in the following sections) is the third AES data collection, including data from 33 countries. The total net sample size is 239. 762, with Spain, Poland, Romania, France, and Italy having the largest number of observations and Malta, Norway, Croatia, Sweden, and Finland having the fewest. Individuals aged under 25 or more than 64 are also included in some national samples and the following analysis.

The most recent AES data collection, 2022 AES (2022 in the following sections), has the largest net sample size compared to the other waves. Data from 30 countries were collected, totaling 264. 645 individuals. Italy, Spain, Romania, France, and Switzerland are represented in the dataset with larger national subsamples, while Denmark, Bulgaria, Finland, Norway, and Croatia have smaller samples. The individuals included in the 2022 AES are aged more than 18 and less than 69 years.

Overall, the majority of EU countries have data coverage in all waves, while most non-EU countries (except Switzerland) do not. Turkey also participated in all AES waves, but its data could not be included in the pooled dataset due to national authorities' restrictions on data dissemination. Malta's AES, Switzerland's 2007 AES, and Albania's 2016 AES data were also not included due to restrictions by authorities.

Table 2-23: AES -Sample size

AES		2007		2011		2016		2022	
COUNTRY	ACRONYM	#Obs	(%)	#Obs	(%)	#Obs	(%)	#Obs	(%)
All Countries	***POOLED***	***200,895***	***(100.0%)***	***225,347***	***(100.0%)***	***239,762***	***(100.0%)***	***264,645***	***(100.0%)***
Austria	AT	4,675	(2.33%)	5,754	(2.55%)	5,620	(2.34%)	7,826	(2.96%)
Belgium	BE	4,850	(2.41%)	5,526	(2.46%)	5,150	(2.15%)	8,274	(3.13%)
Bulgaria	BG	5,263	(2.62%)	6,173	(2.74%)	6,530	(2.72%)	3,194	(1.21%)
Croatia	HR	3,089	(1.54%)	0	(0.00%)	2,936	(1.22%)	3,542	(1.34%)
Cyprus	CY	4,810	(2.39%)	2,404	(1.07%)	3,064	(1.28%)	6,891	(2.60%)
Czech Republic	CZ	9,543	(4.75%)	10,190	(4.52%)	12,272	(5.12%)	10,223	(3.86%)
Denmark	DK	3,099	(1.54%)	3,660	(1.62%)	3,435	(1.44%)	2,448	(0.93%)
Estonia	EE	3,585	(1.78%)	3,324	(1.48%)	3,838	(1.60%)	4,360	(1.65%)
Finland	FI	4,144	(2.06%)	3,605	(1.60%)	3,001	(1.25%)	3,202	(1.21%)
France	FR	15,350	(7.64%)	13,857	(6.15%)	14,953	(6.24%)	17,822	(6.73%)
Germany	DE	6,407	(3.19%)	6,213	(2.76%)	7,750	(3.23%)	9,818	(3.71%)
Greece	EL	6,510	(3.24%)	6,040	(2.68%)	5,469	(2.28%)	7,114	(2.69%)
Hungary	HU	7,494	(3.73%)	7,367	(3.27%)	8,300	(3.46%)	6,734	(2.54%)
Ireland	IE	0	(0.00%)	12,582	(5.58%)	4,863	(2.03%)	4,421	(1.67%)
Italy	IT	27,848	(1.86%)	11,593	(5.14%)	14,844	(6.19%)	33,790	(12.77%)
Latvia	LV	2,287	(1.14%)	5,048	(2.24%)	5,803	(2.42%)	5,492	(2.08%)
Lithuania	LT	3,696	(1.84%)	5,388	(2.39%)	3,445	(1.44%)	5,004	(1.89%)
Luxembourg	LU	0	(0.00%)	3,310	(1.47%)	4,072	(1.70%)	4,820	(1.82%)
Malta	MT	0	(0.00%)	2,882	(1.28%)	1,963	(0.82%)	4,236	(1.60%)
Netherlands	NL	3,326	(1.66%)	3,036	(1.35%)	3,092	(1.29%)	5,384	(2.03%)
Poland	PL	24,817	(12.35%)	27,633	(12.26%)	18,094	(7.55%)	14,749	(5.57%)
Portugal	PT	9,854	(4.91%)	14,189	(6.30%)	14,211	(5.93%)	14,064	(5.31%)
Romania	RO	13,909	(6.92%)	13,651	(6.06%)	15,257	(6.36%)	19,979	(7.55%)
Slovakia	SK	5,001	(2,49%)	5,000	(2.22%)	3,245	(1.35%)	4,380	(1.66%)
Slovenia	SI	4,192	(2.09%)	4,943	(2.19%)	5,517	(2.30%)	4,890	(1.85%)
Spain	ES	16,968	(8.45%)	17,829	(7.91%)	23,019	(9.60%)	22,162	(8.37%)
Sweden	SE	3,632	(1.81%)	3,096	(1.37%)	2,976	(1.24%)	4,595	(1.74%)
Non-EU									
Bosnia Herzegovina	BA	0	(0.00%)	0	(0.00%)	6,390	(2.67%)	0	(0.00%)
North Macedonia	MK	0	(0.00%)	0	(0.00%)	7,601	(3.17%)	0	(0.00%)
Norway	NO	3,018	(1.50%)	3,336	(1.48%)	2,723	(1.14%)	3,498	(1.32%)
Serbia	RS	0	(0.00%)	4,534	(2.01%)	4,993	(2.08%)	5,372	(2.03%)
Switzerland	CH	0	(0.00%)	9,660	(4.29%)	8,279	(3.45%)	16,361	(6.18%)
United Kingdom	UK	3,528	(1.76%)	3,524	(1.56%)	7,057	(2.94%)	0	(0.00%)

2.3.2 THE EMPLOYED SAMPLE AND SUMMARY STATISTICS

Table 2-24 illustrates how employment status is distributed within the sample, categorising individuals as employed full-time, employed part-time, self-employed full-time, self-employed part-time, family worker, unemployed, inactive, disabled, student and homemaker. The individuals who chose not to state their main activity status or whose data were not available were excluded from the economic activity analysis. Italy's data from Wave 2007 and 2016, Slovenia's from Wave 2007 and Hungary's from Wave 2011 were also excluded due to differences in the answers to their national AES questionnaires. The table outlines that most individuals, accounting for an unweighted percentage of 45.72% and a weighted percentage of 45.97% of the selected sample, are full-time employers, with economically inactive individuals following. A smaller percentage of the sample identified as unpaid family workers.

Table 2-24: AES – Economic activity

	ALL WAVES	
ECONOMIC ACTIVITY	UNWEIGHTED	WEIGHTED
Employed FT	**45.72%**	**45.97%**
	395,643	*395,643*
Employed PT	**6.88%**	**9.72%**
	59,507	*59,507*
Self-employed FT	**8.23%**	**8.26%**
	71,241	*71,241*
Self-employed PT	**1.13%**	**1.16%**
	9,784	*9,784*
Family worker (unpaid)	**0.81%**	**0.61%**
	7,020	*7,020*
Unemployed	**8.98%**	**8.42%**
	77,755	*77,755*
Inactive	**13.69%**	**11.73%**
	118,501	*118,501*
Disabled	**2.87%**	**2.72%**
	24,800	*24,800*
Student	**5.36%**	**4.98%**
	46,363	*46,363*
Homemaker	**6.33%**	**6.43%**
	54,777	*54,777*
Total	**100.00%**	**100.00%**
	865,391	*865,391*

Table 2-25 provides a more detailed analysis of the trends and shifts in employment status over time. Most categories show no significant changes, except for the "Inactive" group, whose sample representation increased from 9.78% in 2007 to 13.82% in 2022. Similarly, the "Students" category saw an increase in sample representation from 1.16% in 2007 to 7.31% in 2022.

Table 2-25: AES – Economic activity in the AES database by wave

ECONOMIC ACTIVITY	2007		2011		2016		2022	
	UNWEIGHTED	WEIGHTED	UNWEIGHTED	WEIGHTED	UNWEIGHTED	WEIGHTED	UNWEIGHTED	WEIGHTED
Employed FT	**50.49%**	**49.63%**	**42.89%**	**43.33%**	**45.34%**	**46.11%**	**45.25%**	**45.75%**
	84,824	*84,824*	*90,143*	*90,143*	*101,529*	*101,529*	*119,147*	*119,147*
Employed PT	**5.90%**	**9.78%**	**7.12%**	**9.94%**	**7.16%**	**10.46%**	**7.07%**	**8.77%**
	9,900	*9,900*	*14,970*	*14,970*	*16,029*	*16,029*	*18,608*	*18,608*
Self-employed FT	**9.78%**	**9.03%**	**8.18%**	**8.51%**	**8.15%**	**8.09%**	**7.35%**	**7.57%**
	16,424	*16,424*	*17,189*	*17,189*	*18,270*	*18,270*	*19,358*	*19,358*
Self-employed PT	**0.95%**	**1.09%**	**1.14%**	**1.22%**	**1.21%**	**1.26%**	**1.17%**	**1.08%**
	1,596	*1,596*	*2,387*	*2,387*	*2,708*	*2,708*	*3,093*	*3,093*
Family worker (unpaid)	**1.26%**	**0.83%**	**0.92%**	**0.73%**	**0.76%**	**0.56%**	**0.48%**	**0.39%**
	2,115	*2,115*	*1,942*	*1,942*	*1,694*	*1,694*	*1,269*	*1,269*
Unemployed	**6.85%**	**6.97%**	**10.73%**	**9.80%**	**10.84%**	**8.98%**	**7.38%**	**7.61%**
	11,513	*11,513*	*22,556*	*22,556*	*24,265*	*24,265*	*19,421*	*19,421*
Inactive	**11.90%**	**9.78%**	**13.97%**	**11.56%**	**13.82%**	**11.24%**	**14.51%**	**13.82%**
	19,995	*19,995*	*29,358*	*29,358*	*30,942*	*30,942*	*38,206*	*38,206*
Disabled	**4.09%**	**3.45%**	**3.13%**	**2.61%**	**2.77%**	**2.59%**	**1.96%**	**2.37%**
	6,863	*6,863*	*6,569*	*6,569*	*6,213*	*6,213*	*5,155*	*5,155*
Student	**0.89%**	**1.16%**	**4.76%**	**4.95%**	**4.10%**	**5.63%**	**9.75%**	**7.31%**
	1,503	*1,503*	*10,013*	*10,013*	*9,180*	*9,180*	*25,667*	*25,667*
Homemaker	**7.89%**	**8.28%**	**7.16%**	**7.35%**	**5.85%**	**5.08%**	**5.08%**	**5.33%**
	13,259	*13,259*	*15,045*	*15,045*	*13,106*	*13,106*	*13,367*	*13,367*
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
	167,992	*167,992*	*210,172*	*210,172*	*223,936*	*223,936*	*263,291*	*263,291*

Table 2-26 presents both unweighted and weighted summary statistics for key variables in both the pooled and employed samples. The chosen variables were selected for their comparability across waves and ability to provide a concise overview of central tendencies. Calculations were based on observations that reported valid values, with any instances of "not stated" or "not applicable" being excluded. The number of observations in the employed sample differs from those presented in previous economic activity analyses, as it includes people who did not state their professional status in their main job and whether they had full or part-time positions. The following analysis will focus on the weighted statistics as they are more representative of the population.

In the pooled sample, the weighted mean of males suggests a nearly balanced gender distribution, with slightly fewer males than females. The weighted mean age is 44, indicating a skew toward middle age in the population. Almost half of the population resides in urban areas, with a significant proportion living in intermediate or thinly-populated areas. The majority of individuals (88.81%) were born in the country where the survey was conducted, and the duration of their residence in the country was mostly over two years (96.73%).

A slightly larger proportion live without a legal or de facto partner, and 34.51% of the population are couples with children aged less than 25 years. Educational attainment is relatively high, with the average individual completing upper secondary education. However, parental educational levels are generally lower, with a larger proportion of fathers and mothers completing lower secondary education. In terms of employment status, 84.23% of the workforce are employees, and 83% hold full-time positions.

Table 2-26: AES – Summary statistics of key variables in AES

	POOLED SAMPLE				EMPLOYED SAMPLE			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean
Male	930,649	47.26%	930,649	49.74%	578,339	52.34%	578,339	54.86%
Age	930,649	44.69	930,649	43.87	578,339	43.13	578,339	42.57
Urbanisation: Densely-populated	920,242	38.82%	920,242	44.90%	572,130	39.48%	572,130	45.26%
"-"-: Intermediate area	920,242	28.62%	920,242	30.08%	572,130	28.76%	572,130	30.02%
"-"-:Thinly-populated area	920,242	32.56%	920,242	25.02%	572,130	31.76%	572,130	24.73%
Country of birth: Country of	876,556	90.53%	876,556	88.81%	544,616	90.49%	544,616	89.18%
-"-: EU	876,556	3.54%	876,556	3.55%	544,616	3.83%	544,616	3.77%
-"-: Non-EU	876,556	5.93%	876,556	7.64%	544,616	5.69%	544,616	7.05%
Duration of stay in the country: residence								
< 1 year	95,461	3.25%	95,461	3.27%	59,723	2.78%	59,723	2.48%
2-10 years	95,461	28.78%	95,461	30.87%	59,723	28.18%	59,723	29.22%
> 10 years	95,461	67.96%	95,461	65.86%	59,723	69.05%	59,723	68.30%
Cohabiting/married	702,736	46.49%	702,736	46.69%	432,358	49.99%	432,358	50.53%
Household type: One-person	722,683	13.72%	722,683	13.53%	437,526	12.98%	437,526	12.81%
Lone parent with child(ren)	722,683	5.90%	722,683	5.01%	437,526	5.79%	437,526	4.86%
Couple with child(ren)	722,683	33.35%	722,683	34.51%	437,526	38.58%	437,526	39.19%
Educational attainment level:								
≤Lower secondary	929,632	24.39%	929,632	24.28%	577,852	17.50%	577,852	17.59%
Upper secondary	929,632	48.57%	929,632	47.95%	577,852	48.60%	577,852	48.44%
Tertiary	929,632	27.04%	929,632	27.77%	577,852	33.91%	577,852	33.98%
Educational attainment level of the father:								
≤Lower secondary	783,397	52.43%	783,397	51.04%	484,268	47.52%	484,268	47.04%
Upper secondary	783,397	34.55%	783,397	34.41%	484,268	38.14%	484,268	37.24%
Tertiary	783,397	13.02%	783,397	14.55%	484,268	14.34%	484,268	15.72%
Educational attainment level of the mother:								
≤Lower secondary	799,274	58.02%	799,274	56.95%	493,984	53.21%	493,984	52.93%
Upper secondary	799,274	31.46%	799,274	32.27%	493,984	35.56%	493,984	35.75%
Tertiary	799,274	10.52%	799,274	10.77%	493,984	11.24%	493,984	11.32%
Status in employment in main								
Self-employed	582,639	15.31%	582,639	14.83%	576,281	15.29%	576,281	14.82%
Employee	582,639	83.45%	582,639	84.23%	576,281	83.46%	576,281	84.24%
Family worker	582,639	1.23%	582,639	0.94%	576,281	1.24%	576,281	0.94%
Full-time job	556,328	86.73%	556,328	83.00%	556,328	86.73%	556,328	83.00%

2.3.3 PARTICIPATION IN EDUCATION AND TRAINING STATISTICS

The AES survey provides information on two types of education and training: formal and non-formal. Specifically, participation in formal education and training is assumed for individuals who have been enrolled as students or apprentices in a formal education program in the last 12 months. Participation in non-formal education and training is assumed for individuals who have attended organized learning activities outside the formal education system in the last 12 months.

Table 2-27: AES – Participation rate in education and training by country (weighted)

AES COUNTRY	ACRONYM	EDUCATION & TRAINING	FORMAL EDUCATION & TRAINING	NON FORMAL EDUCATION & TRAINING
All Countries		***42.5%***	***9.6%***	***37.6%***
Austria	AT	52.8%	8.1%	49.3%
Belgium	BE	41.7%	10.3%	35.5%
Bulgaria	BG	28.9%	6.8%	24.0%
Croatia	HR	27.1%	5.7%	23.4%
Cyprus	CY	44.8%	6.0%	41.5%
Czech Republic	CZ	42.0%	8.0%	36.7%
Denmark	DK	51.9%	13.7%	44.7%
Estonia	EE	46.0%	7.3%	42.9%
Finland	FI	54.2%	14.3%	48.4%
France	FR	49.9%	9.1%	46.5%
Germany	DE	52.7%	8.8%	48.7%
Greece	EL	18.3%	6.8%	13.3%
Hungary	HU	42.4%	9.3%	37.5%
Ireland	IE	46.2%	11.5%	39.9%
Italy	IT	34.2%	6.3%	31.4%
Latvia	LV	40.8%	5.9%	38.0%
Lithuania	LT	32.4%	8.3%	26.8%
Luxembourg	LU	54.6%	11.5%	50.2%
Malta	MT	40.8%	8.4%	37.4%
Netherlands	NL	58.9%	12.0%	54.4%
Poland	PL	27.3%	10.2%	20.3%
Portugal	PT	41.8%	11.4%	36.4%
Romania	RO	14.5%	5.7%	10.0%
Slovakia	SK	48.7%	9.7%	42.6%
Slovenia	SI	42.6%	9.6%	36.8%
Spain	ES	43.2%	12.7%	37.0%
Sweden	SE	70.5%	17.0%	63.2%
Non-EU				
Bosnia Herzegovina	BA	8.9%	2.4%	7.0%
North Macedonia	MK	12.7%	4.0%	10.4%
Norway	NO	59.8%	15.2%	53.4%
Serbia	RS	20.5%	5.6%	16.9%
Switzerland	CH	62.3%	11.5%	57.9%
United Kingdom	UK	44.9%	13.8%	36.5%

Table 2-27 provides an overview of participation rates in education and training overall, including people who participated in formal or non-formal education and training, across different countries. According to the table, Sweden, Netherlands, Luxembourg, Finland, Austria, and Germany have the highest participation rates in all types of education and training among EU countries. At the same time, Romania, Greece, Croatia, Poland, and Bulgaria show lower participation levels. Among non-EU countries, Switzerland, Norway, and the United Kingdom demonstrate higher participation levels, while Serbia, North Macedonia, and Bosnia Herzegovina indicate reduced participation. In terms of the two types of education and training, individuals seem to engage more in non-formal programs rather than formal ones.

Figures 2-49, 2-50 and 2-51 illustrate the changes in participation rates across countries and waves for each type of education and training. Upon examining the figures, it is evident that most countries show increasing participation in both formal and non-formal education activities. Ireland, Sweden, Hungary, Netherlands, and Spain exhibit the most significant differences in participation between their first and last waves for formal education, while Hungary, Ireland, Romania, Portugal, and Spain show the largest differences for non-formal education.

However, some countries experienced significant decreases in participation, particularly in non-formal activities. Luxembourg recorded the largest decline, with its participation rate falling from 68% in the 2011 wave to just 42% in the 2022 wave.

Table 2-28 presents the weighted summary statistics of key variables for two different types of education and training, as well as the overall weighted summary statistics. The table shows that women are more likely to participate in formal education programs, while participation in non-formal education is more evenly distributed between genders. Those involved in formal education tend to be much younger than those in non-formal education, reflecting typical trends. Both types of education and training have a higher proportion of participants from urban areas than intermediate or thinly populated areas. However, non-formal education has more participation from individuals in intermediate and thinly populated areas.

Most education and training participants were born in the country where the survey was conducted. However, a higher proportion of individuals from other non-EU countries participated in formal education compared to non-formal education. Overall, 60.49% of education and training participants are long-term residents of the country where the survey was conducted.

In formal education and training, 25.47% of the participants are cohabiting or married, indicating that single persons tend to participate more in that program. This proportion is notably higher (48.37%) in non-formal education. In the overall education and training participation, 39.01% are part of a household with two people and children aged less than 25 years, while lone parents with child(ren) account for 5.65%.

Participants in formal education have higher rates of upper secondary education compared to those in non-formal education (50.34% vs 45.05%). However, non-formal education shows higher participation rates in tertiary education (42.28% vs 35.22%). Father's educational attainment shows a similar pattern across the two types, with those participating in formal education having slightly higher education levels. In non-formal education, mothers of participants exhibit lower educational attainment levels. Employees have higher rates among participants in both types of education, with 88.69% in overall education and training and 82.90% holding full-time positions.

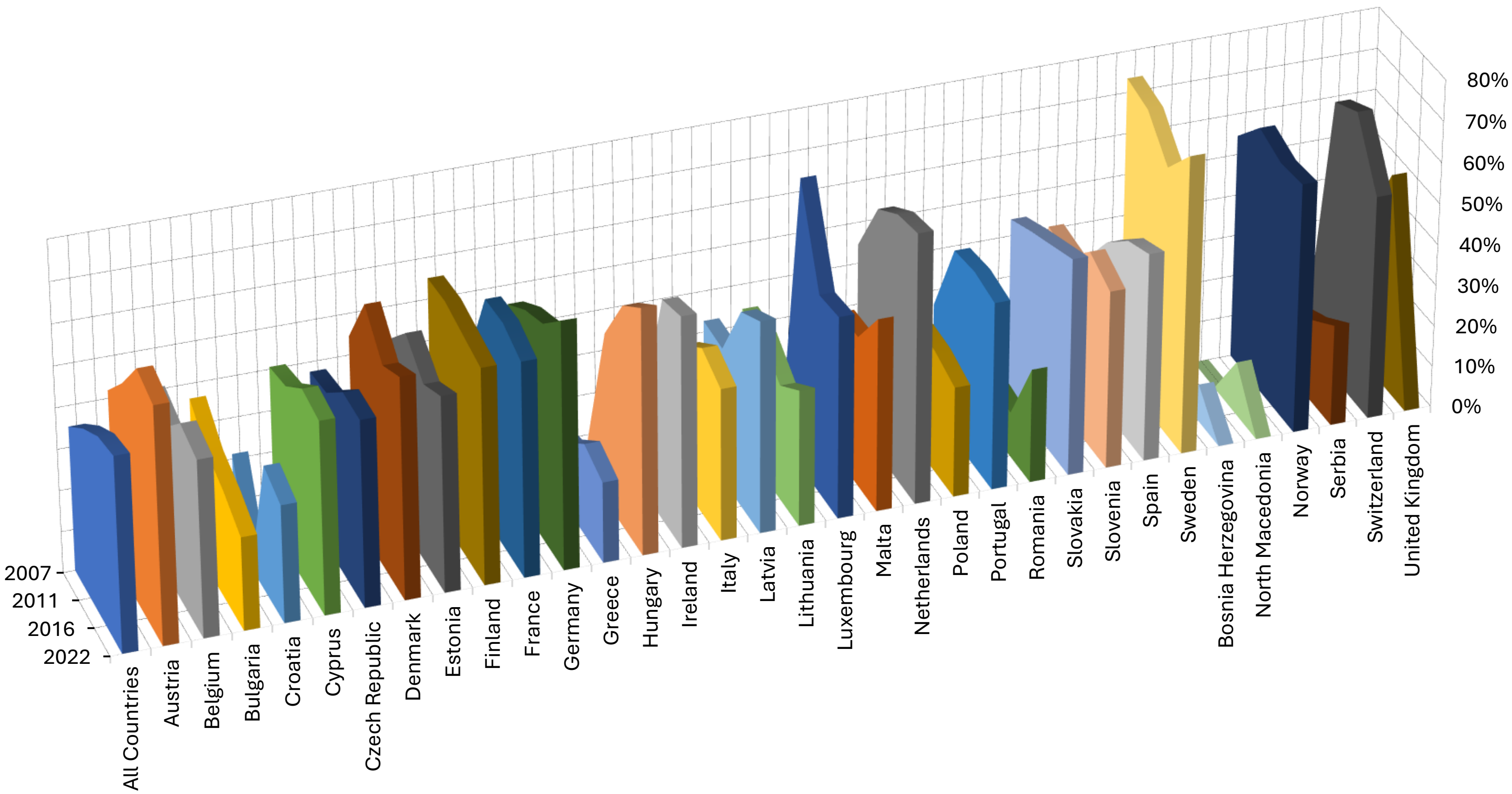


Figure 2-49: AES -Participation rate in education and training by country and wave (weighted)

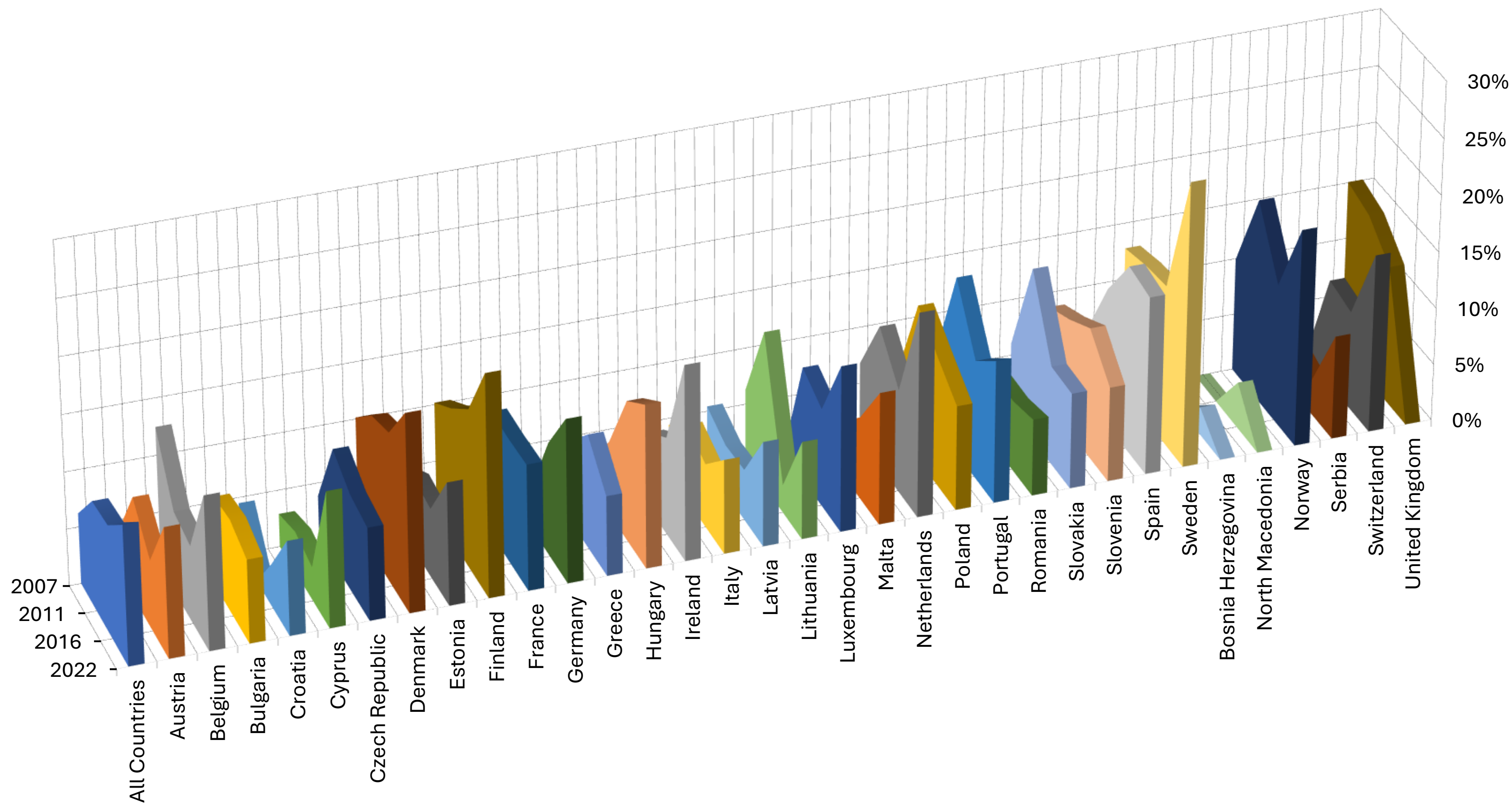


Figure 2-50: AES -Participation in formal education & training by country and wave (weighted)

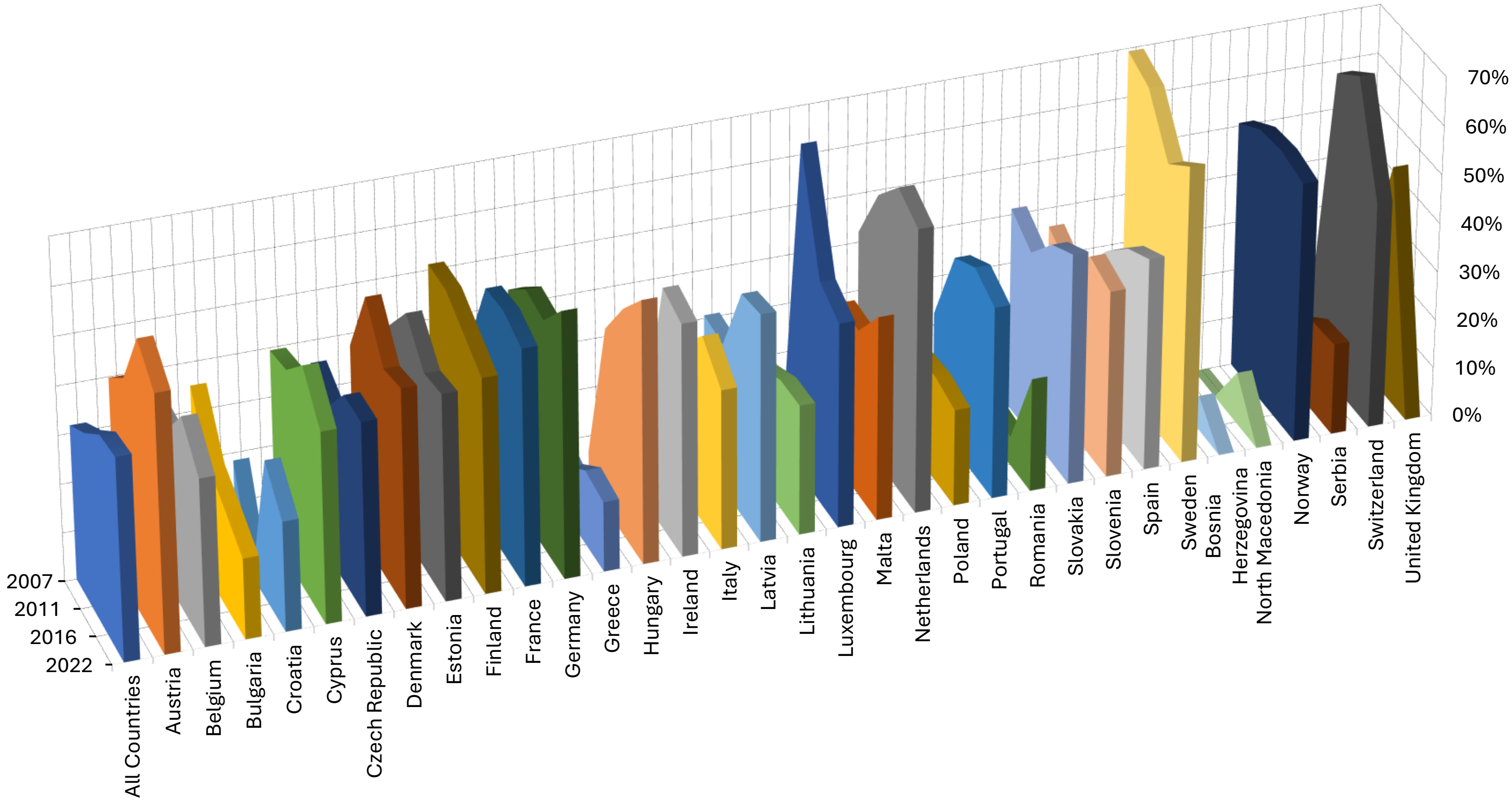


Figure 2-51: AES –Participation in non-formal education & training by country & wave (weighted)

Table 2-28: AES – Weighted summary statistics of key variables by education/training status

VARIABLE	EDUCATION & TRAINING		FORMAL EDUCATION & TRAINING (LAST 12 MONTHS)		NON-FORMAL EDUCATION & TRAINING (LAST 12 MONTHS)	
	#OBS.	MEAN	#OBS.	MEAN	#OBS.	MEAN
Male	365,492	49.67%	91,176	46.72%	317,698	50.00%
Age	365,492	40.03	91,176	29.31	317,698	41.49
Urbanisation: Densely-populated	359,954	48.19%	89,015	54.32%	313,457	47.43%
"-"-: Intermediate area	359,954	30.43%	89,015	26.88%	313,457	31.04%
"-"-:Thinly-populated area	359,954	21.39%	89,015	18.80%	313,457	21.53%
Country of birth: Country of survey	348,822	89.42%	86,135	88.83%	304,004	89.55%
-"-: EU	348,822	3.58%	86,135	2.95%	304,004	3.70%
-"-: Non-EU	348,822	7.00%	86,135	8.22%	304,004	6.76%
Duration of stay in the country:						
< 1 year	40,584	4.27%	10,122	6.42%	35,657	3.93%
2-10 years	40,584	35.24%	10,122	48.77%	35,657	33.39%
> 10 years	40,584	60.49%	10,122	44.81%	35,657	62.68%
Cohabiting/married	297,049	45.52%	78,305	25.47%	256,589	48.37%
Household type: One-person	302,597	13.93%	80,245	13.88%	260,660	14.12%
Lone parent with child(ren)	302,597	5.65%	80,245	8.35%	260,660	5.22%
Couple with child(ren) aged<25	302,597	39.01%	80,245	37.08%	260,660	39.19%
Educational attainment level:						
≤Lower secondary	365,069	13.13%	91,043	14.45%	317,337	12.66%
Upper secondary	365,069	45.98%	91,043	50.34%	317,337	45.05%
Tertiary	365,069	40.89%	91,043	35.22%	317,337	42.28%
Educational attainment level of the father:						
≤Lower secondary	316,463	38.74%	82,298	28.93%	273,336	39.90%
Upper secondary	316,463	39.07%	82,298	41.97%	273,336	38.28%
Tertiary	316,463	22.20%	82,298	29.09%	273,336	21.82%
Educational attainment level of the mother:						
≤Lower secondary	323,305	44.03%	84,039	29.87%	279,373	45.68%
Upper secondary	323,305	38.79%	84,039	42.42%	279,373	38.12%
Tertiary	323,305	17.18%	84,039	27.71%	279,373	16.20%
Status in employment in main job:						
Self-employed	273,972	10.96%	37,780	8.65%	258,110	11.04%
Employee	273,972	88.69%	37,780	90.91%	258,110	88.63%
Full- or part-time main job: Full-time	265,999	82.90%	36,639	78.55%	250,685	83.23%

2.3.4 DIFFERENCES BY GENDER

This section outlines the gender differences in participation rates in two types of education and training, as well as overall participation in formal or non-formal activities among individuals aged 25–64. Table 2-29 provides the participation rates of males and females in each education and training type by country, along with the gender differences. The weighted averages indicate that women aged 26 to 64 have higher participation rates than men in formal education and training. However, gender participation in non-formal and overall education and training appears to be relatively balanced.

Figure 2-52 depicts the gender difference, weighted averages male-female, (in percentage points) by country. The analysis of gender differences in education and training participation reveals diverse patterns across different countries. For instance, in Cyprus, the Czech Republic, Hungary, and the Netherlands, male participation significantly exceeds female participation. Conversely, in Finland, Estonia, Latvia, and Lithuania, male participation is notably lower than female participation.

For a more in-depth analysis, Figures 2-53, 2-54, and 2-55 present the differences in participation in education and training across gender groups by country and wave for overall education and training, formal education and training, and non-formal education and training, respectively.

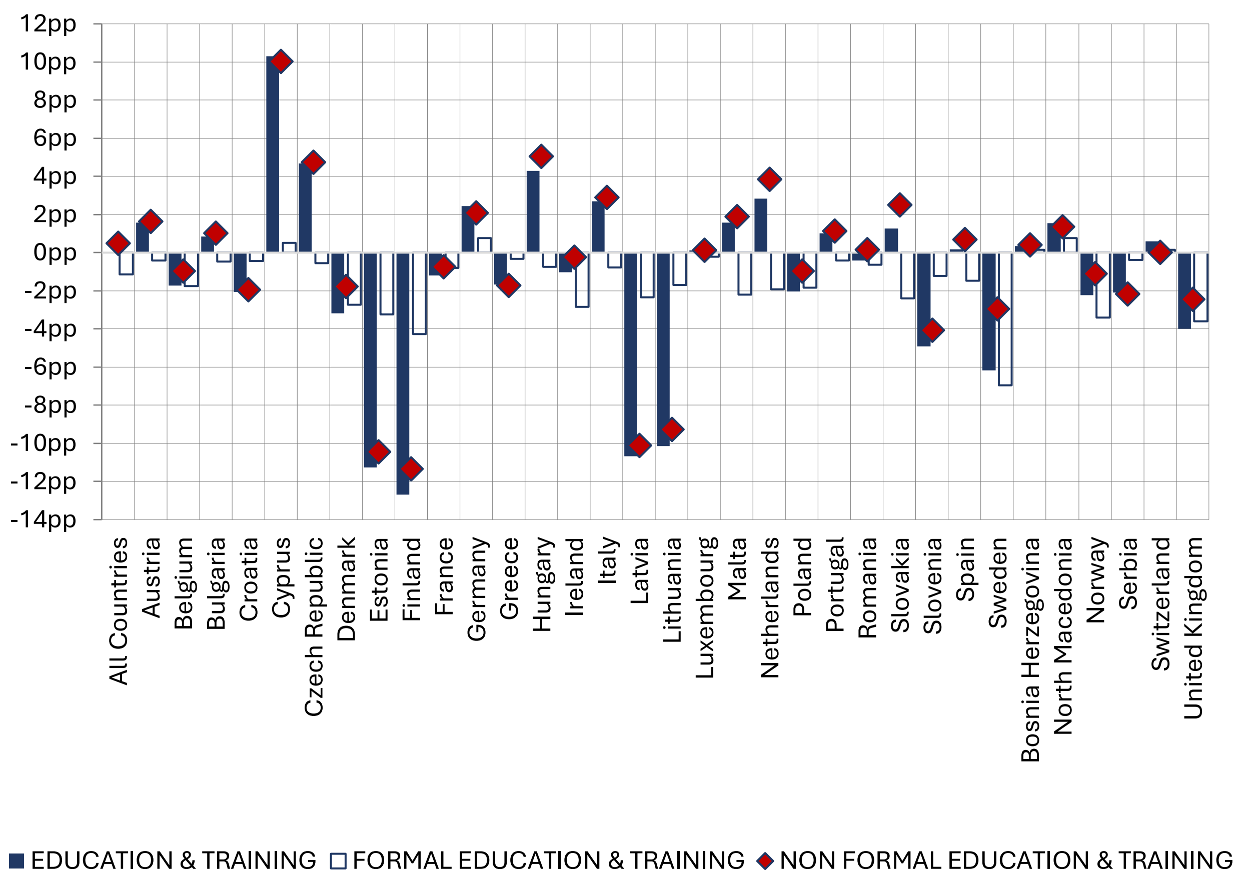


Figure 2-52: AES –Gender differences in participation in training by country

Table 2-29: AES – Participation rate in education and training by gender & country

AES	EDUCATION & TRAINING			FORMAL EDUCATION & TRAINING			NON FORMAL EDUCATION & TRAINING		
COUNTRY	MALE	FEMALE	DIFFERENCE (pp)	MALE	FEMALE	DIFFERENCE (pp)	MALE	FEMALE	DIFFERENCE (pp)
All Countries	***41.4%***	***41.4%***	***0.0***	***5.6%***	***6.7%***	***-1.1***	***38.6%***	***38.1%***	***0.5***
Austria	53.0%	51.4%	1.6	5.6%	6.0%	-0.4	50.9%	49.2%	1.6
Belgium	40.4%	42.2%	-1.7	7.6%	9.3%	-1.8	36.0%	37.0%	-1.0
Bulgaria	27.8%	26.9%	0.9	2.4%	2.8%	-0.5	26.2%	25.2%	1.0
Croatia	25.6%	27.7%	-2.0	3.8%	4.3%	-0.4	23.3%	25.2%	-1.9
Cyprus	49.4%	39.1%	10.3	3.9%	3.3%	0.5	47.8%	37.7%	10.0
Czech Republic	43.8%	39.1%	4.7	2.7%	3.3%	-0.5	42.1%	37.4%	4.7
Denmark	50.0%	53.1%	-3.2	10.8%	13.6%	-2.7	44.4%	46.2%	-1.8
Estonia	40.2%	51.5%	-11.3	4.5%	7.8%	-3.2	38.2%	48.7%	-10.4
Finland	48.2%	60.9%	-12.7	10.4%	14.7%	-4.3	44.0%	55.3%	-11.3
France	46.4%	47.6%	-1.2	2.7%	3.5%	-0.8	45.4%	46.2%	-0.8
Germany	53.2%	50.8%	2.5	5.4%	4.6%	0.8	50.9%	48.8%	2.1
Greece	14.0%	15.7%	-1.7	2.7%	3.0%	-0.3	11.8%	13.6%	-1.7
Hungary	43.7%	39.5%	4.3	6.1%	6.8%	-0.7	41.1%	36.0%	5.0
Ireland	44.4%	45.4%	-1.0	7.3%	10.2%	-2.8	40.0%	40.3%	-0.2
Italy	35.1%	32.4%	2.7	3.2%	3.9%	-0.8	33.7%	30.8%	2.9
Latvia	34.9%	45.6%	-10.7	3.4%	5.7%	-2.3	33.2%	43.3%	-10.1
Lithuania	25.2%	35.4%	-10.2	3.2%	4.9%	-1.7	23.4%	32.7%	-9.3
Luxembourg	55.5%	55.4%	0.1	9.9%	10.1%	-0.2	52.3%	52.2%	0.1
Malta	40.9%	39.3%	1.6	5.4%	7.6%	-2.2	38.5%	36.6%	1.9
Netherlands	59.7%	56.9%	2.8	8.9%	10.8%	-1.9	57.0%	53.1%	3.9
Poland	23.0%	25.0%	-2.0	3.9%	5.7%	-1.8	20.5%	21.5%	-1.0
Portugal	40.6%	39.6%	1.0	6.5%	6.9%	-0.4	37.5%	36.3%	1.1
Romania	11.4%	11.8%	-0.4	1.6%	2.3%	-0.6	10.2%	10.0%	0.2
Slovakia	47.2%	45.9%	1.3	2.9%	5.3%	-2.4	45.6%	43.1%	2.5
Slovenia	38.9%	43.8%	-4.9	4.2%	5.5%	-1.2	36.9%	41.0%	-4.1
Spain	40.5%	40.3%	0.2	7.4%	8.8%	-1.5	36.8%	36.1%	0.7
Sweden	67.7%	73.9%	-6.2	11.9%	18.9%	-6.9	62.8%	65.8%	-3.0
Non-EU									
Bosnia & Herzegovina	8.9%	8.5%	0.4	2.2%	2.1%	0.1	7.1%	6.7%	0.4
North Macedonia	13.5%	11.9%	1.6	4.4%	3.6%	0.8	11.0%	9.7%	1.3
Norway	57.6%	59.8%	-2.2	9.0%	12.4%	-3.4	54.0%	55.1%	-1.1
Serbia	18.3%	20.4%	-2.1	3.6%	3.9%	-0.4	15.8%	18.0%	-2.2
Switzerland	63.0%	62.4%	0.6	9.2%	9.0%	0.1	60.0%	60.0%	0.0
United Kingdom	43.6%	47.6%	-4.0	12.1%	15.7%	-3.6	36.0%	38.4%	-2.4

Notes: Weighted summary statistics for individuals aged 25-63

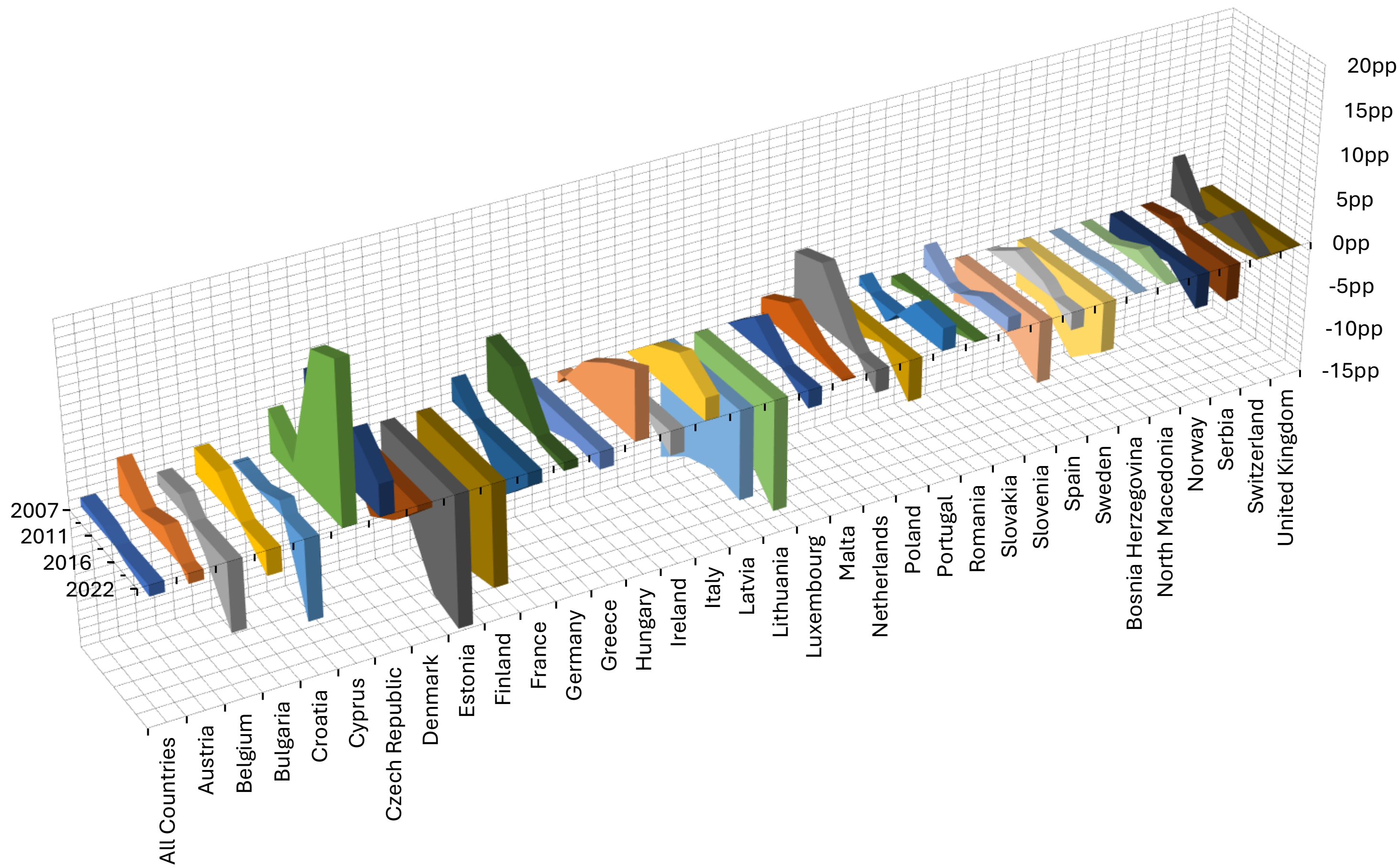


Figure 2-53: AES -Gender differences in participation in education & training by country and wave

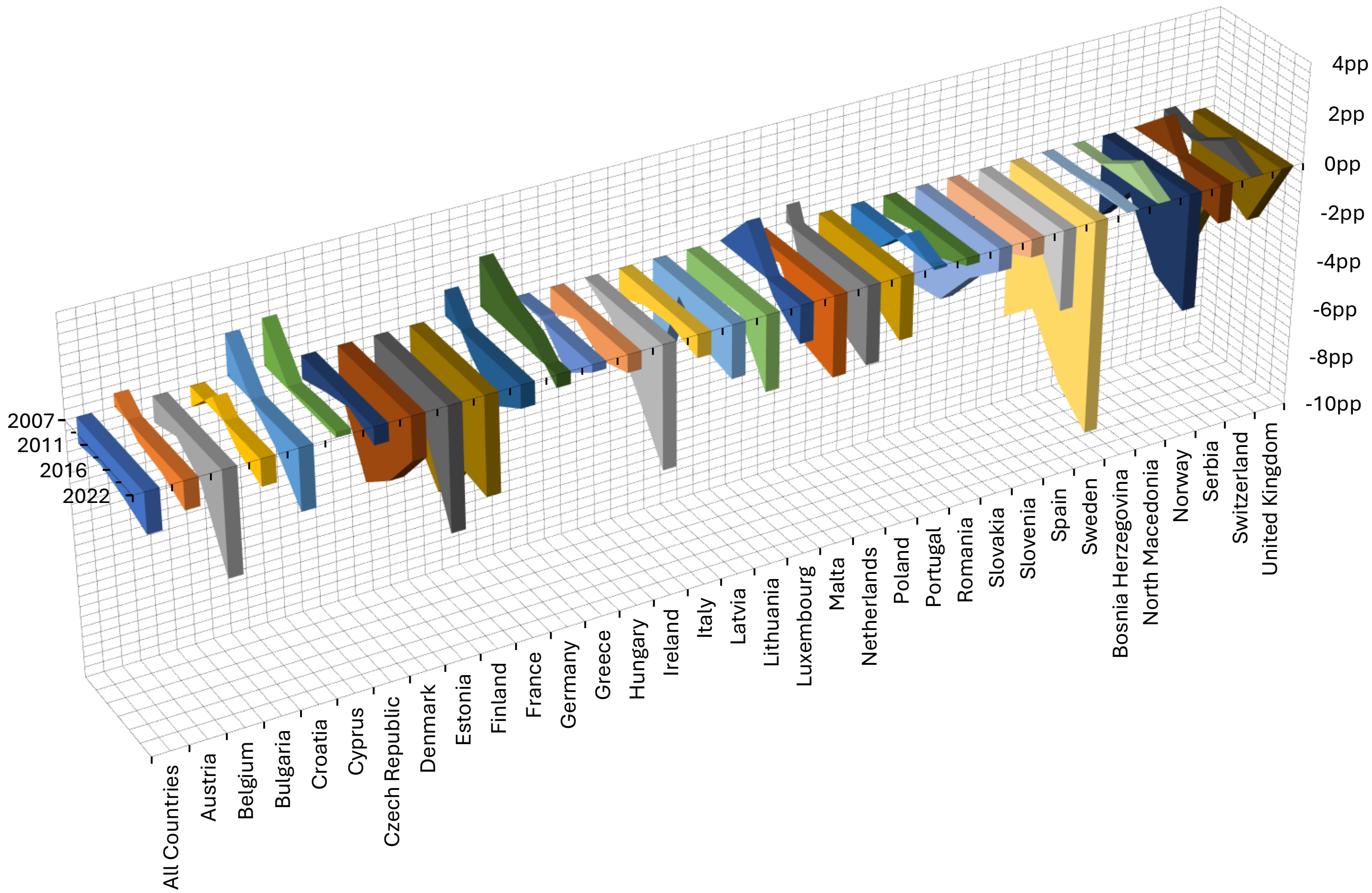


Figure 2-54: AES –Gender differences in participation in formal education and by country & wave

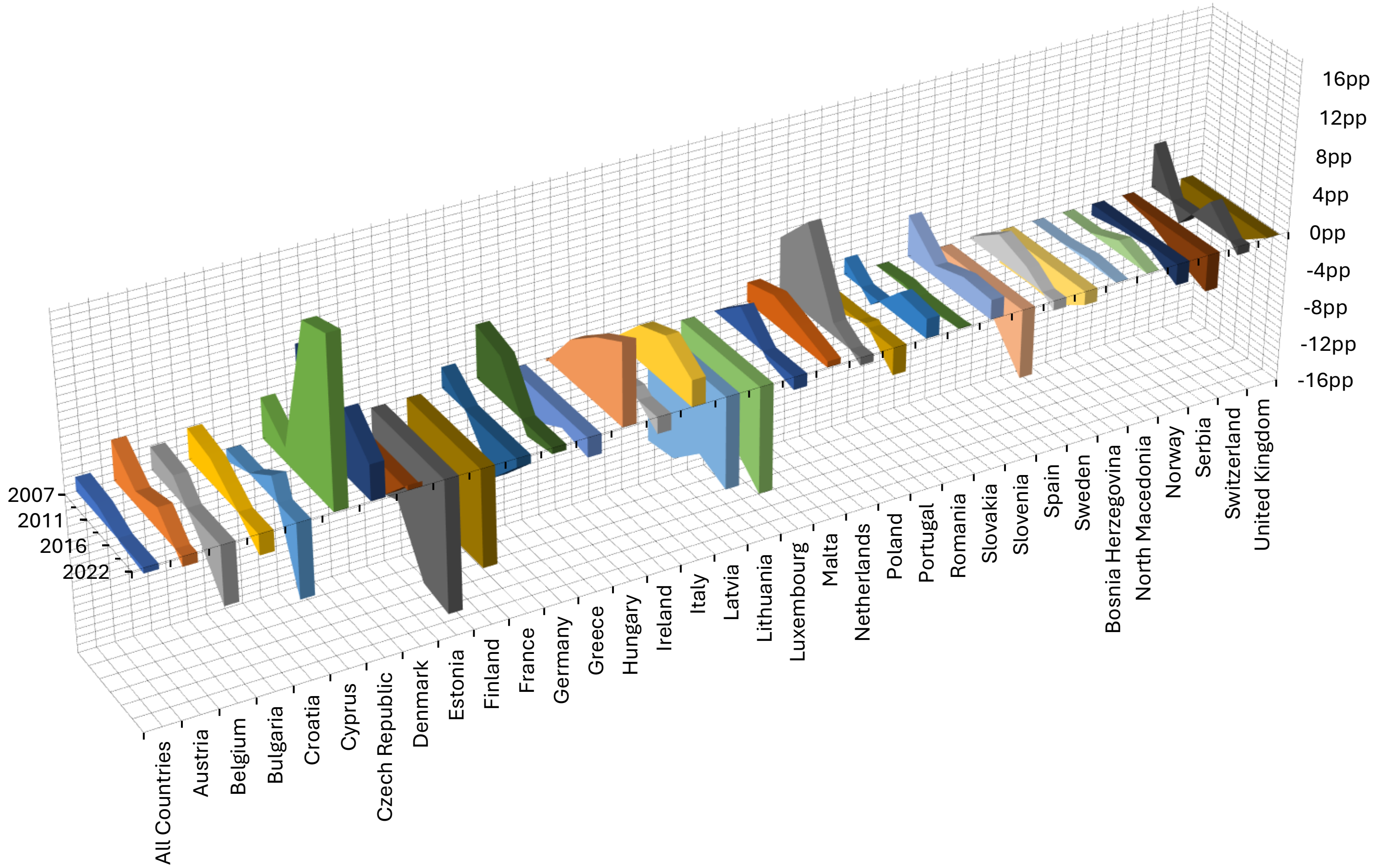


Figure 2-55: AES –Gender differences in non-formal education & training by country & wave

2.3.5 DIFFERENCES BY AGE

This section examines the disparities in participation in formal and non-formal education and training, as well as overall education and training, based on age. We utilise the same definition previously used for the YLFS, that distinguishes between the five generations. We then, classify then into an older and a younger group. The "old" group comprises individuals from the Baby Boomers generation (born between 1946 and 1964) and Generation X (born between 1965 and 1976). The "young" group includes participants from the Millennials (or Generation Y, born between 1977 and 1995) and Generation Z (iGen, or Centennials, born after 1995). It's important to note that the sample does not include individuals from the Silent Generation.

Figure 2-56 highlights that the Gen Z/iGen cohort is particularly engaged in education compared to other generations. However, Figures 2-57 and 2-58 reveal that the difference in participation rates is primarily due to formal training programs, as the millennials/Gen Y cohort shows greater involvement in non-formal training programs.

The averages in Table 2-30 indicate that younger individuals are more likely to participate in various forms of education and training compared to older age groups, a pattern observed across all countries. Figure 2-59 confirms this finding. In countries like Denmark, Sweden, Norway, and Bulgaria, formal education and training programs are the preferred choice for the younger population, whereas in countries such as Portugal, Malta, and Italy, non-formal education and training programs are predominantly favoured by the younger cohort.

Finally, Figures 2-60, 2-61, and 2-62 demonstrate that the gap in participation rates in education and training programs between older and younger cohorts is increasing over time. This trend is observed across all countries and all forms of education and training.

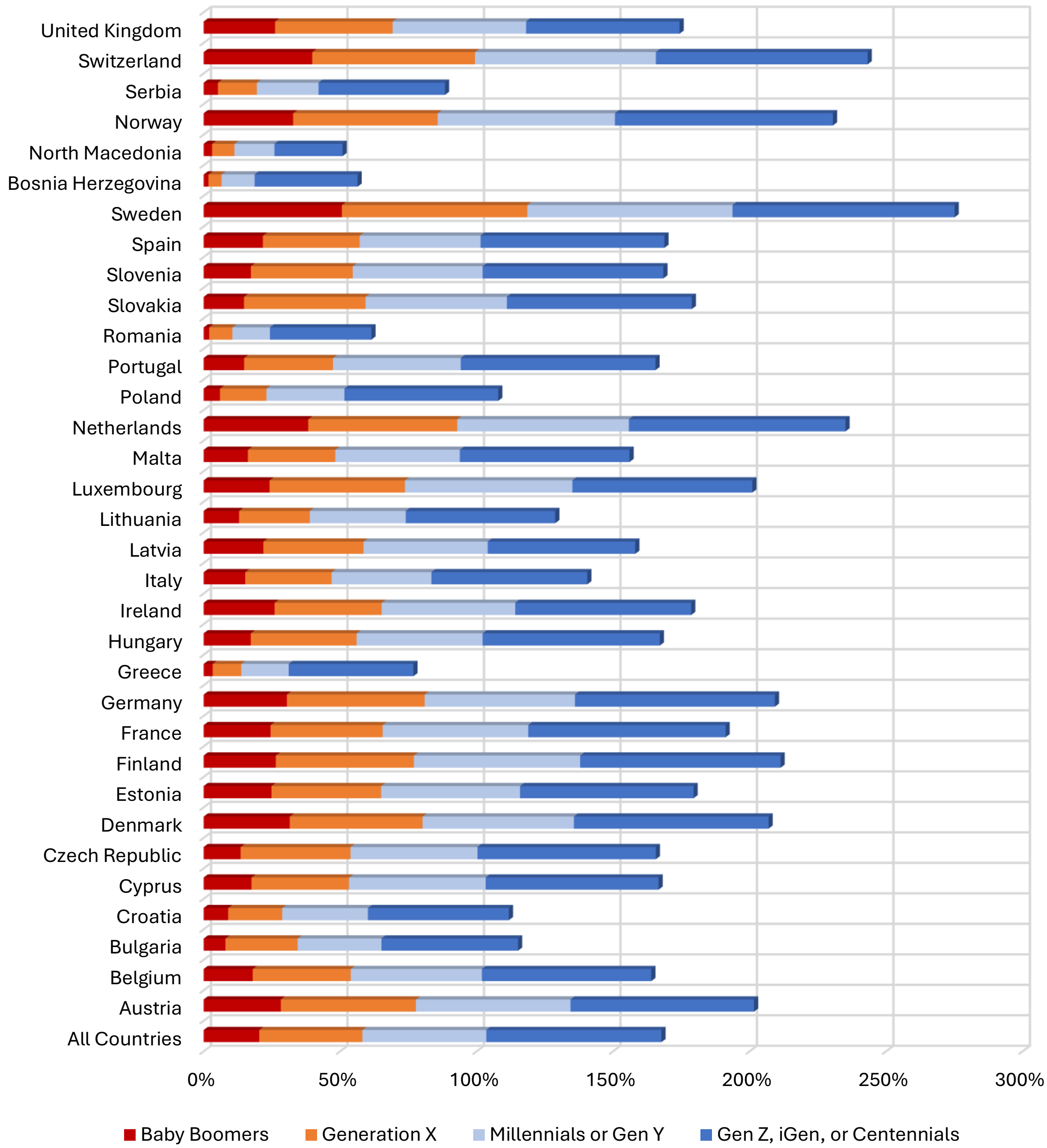


Figure 2-56: AES –Generational composition of participation in education and training

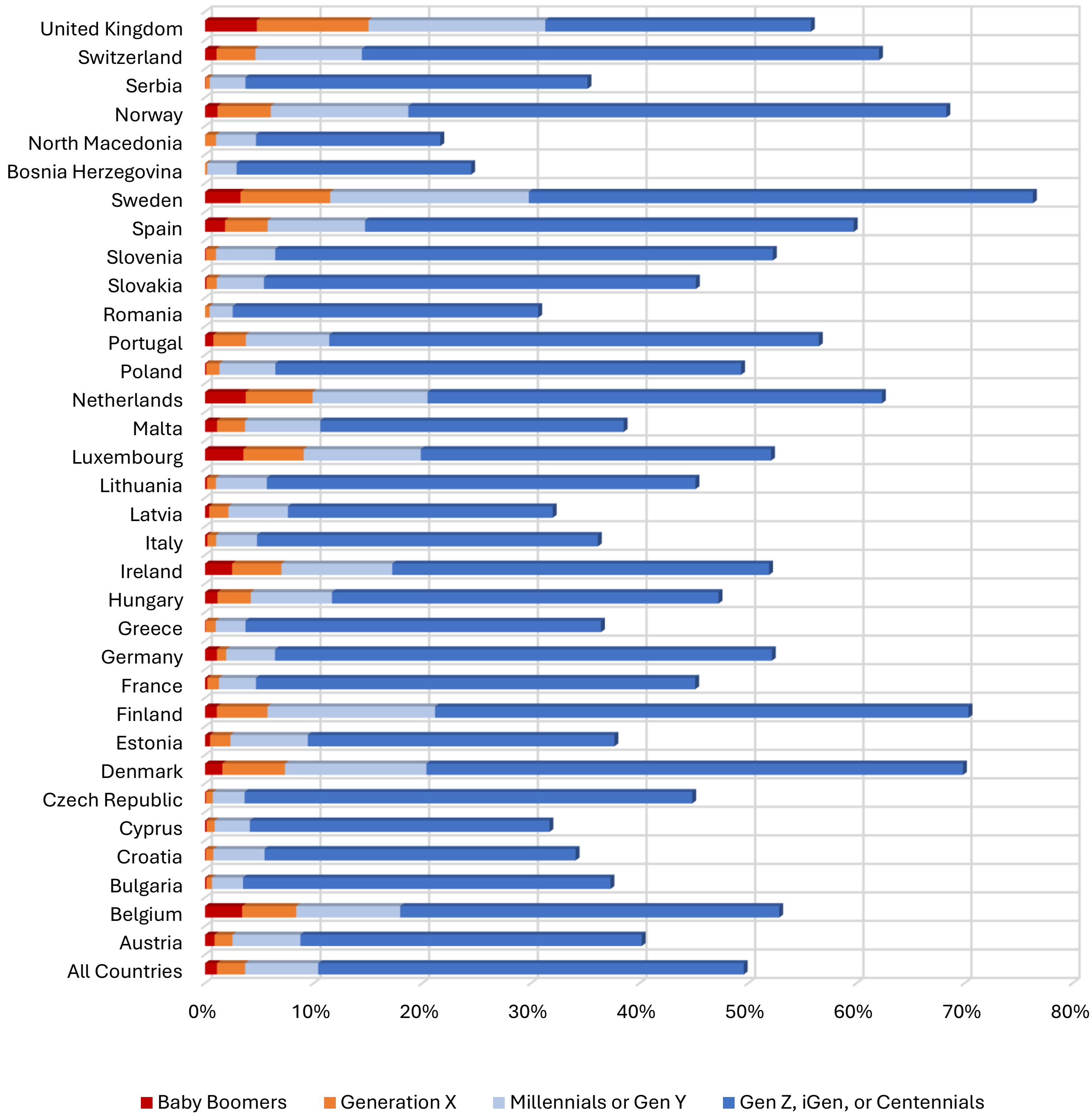


Figure 2-57: AES –Generational composition of participation in formal education and training

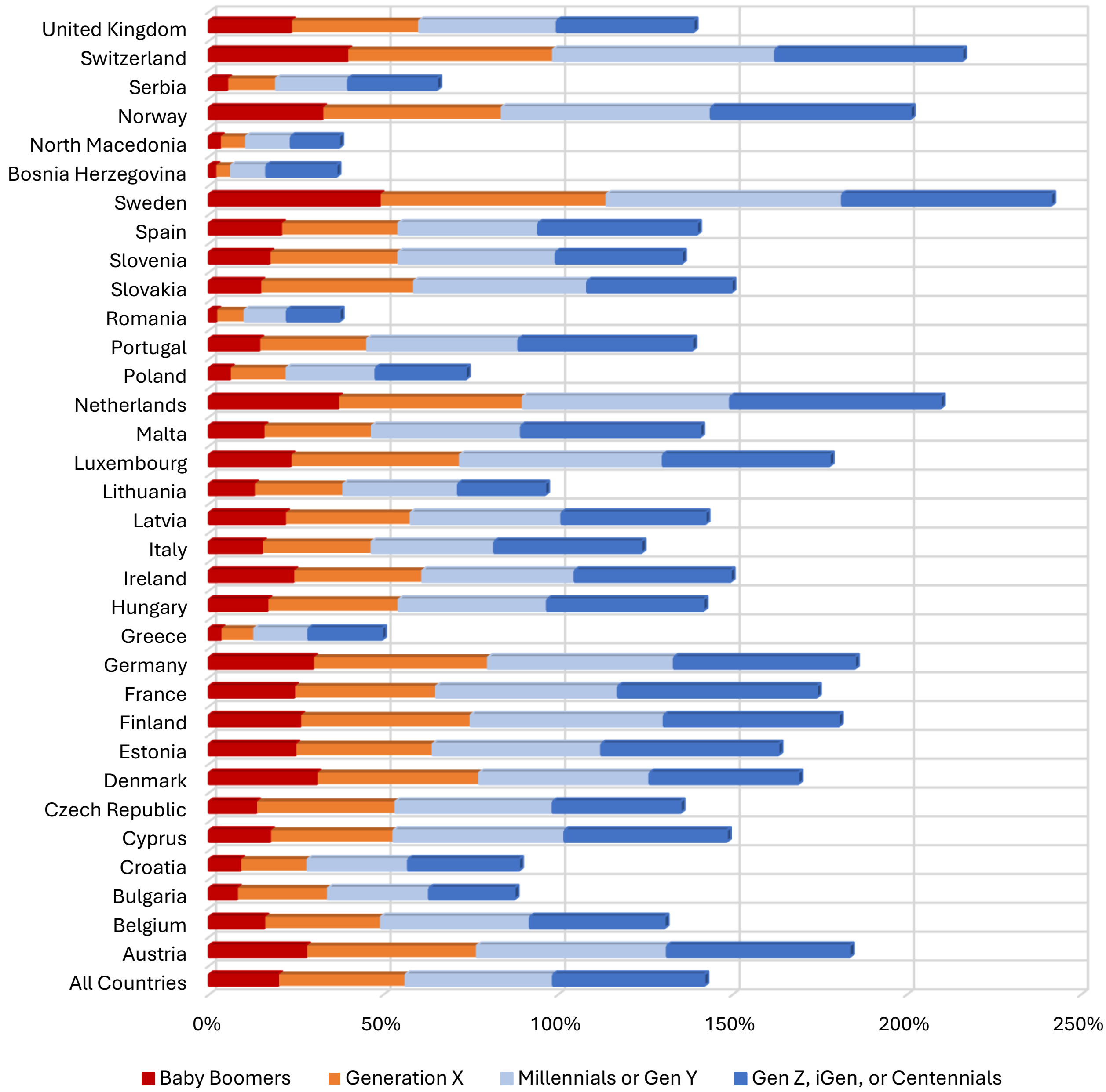


Figure 2-58: AES –Generational composition of participation in non formal education and training

Table 2-30: AES – Participation rate in education and training by age & country (old vs young)

AES	EDUCATION & TRAINING			FORMAL EDUCATION & TRAINING			NON FORMAL EDUCATION & TRAINING		
COUNTRY	OLD	YOUNG	DIFFERENCE (pp)	OLD	YOUNG	DIFFERENCE (pp)	OLD	YOUNG	DIFFERENCE (pp)
All Countries	***31.7%***	***50.2%***	***-18.5***	***2.1%***	***15.0%***	***-13.0***	***30.7%***	***42.5%***	***-11.8***
Austria	43.1%	59.3%	-16.2	1.4%	12.7%	-11.2	42.6%	53.9%	-11.3
Belgium	29.7%	50.9%	-21.2	4.4%	14.8%	-10.3	27.3%	41.8%	-14.4
Bulgaria	19.5%	36.2%	-16.7	0.4%	11.7%	-11.3	19.3%	27.6%	-8.4
Croatia	15.8%	35.6%	-19.7	0.5%	9.6%	-9.2	15.5%	29.4%	-13.8
Cyprus	30.2%	53.3%	-23.1	0.6%	9.3%	-8.7	29.9%	48.3%	-18.4
Czech Republic	28.5%	51.6%	-23.2	0.4%	13.4%	-13.0	28.3%	42.7%	-14.5
Denmark	42.9%	59.0%	-16.1	4.4%	21.1%	-16.7	41.3%	47.4%	-6.1
Estonia	35.3%	53.5%	-18.2	1.4%	11.5%	-10.1	34.7%	48.8%	-14.1
Finland	42.3%	63.7%	-21.4	3.4%	22.9%	-19.4	41.1%	54.2%	-13.1
France	36.0%	59.0%	-23.0	0.8%	14.5%	-13.7	35.6%	53.5%	-17.9
Germany	43.7%	59.6%	-15.9	0.9%	14.8%	-13.8	43.3%	52.9%	-9.6
Greece	8.2%	25.0%	-16.8	0.6%	10.8%	-10.2	7.6%	17.0%	-9.3
Hungary	30.6%	50.7%	-20.1	2.3%	14.3%	-11.9	29.6%	43.0%	-13.4
Ireland	34.8%	52.4%	-17.6	3.9%	15.7%	-11.9	32.7%	43.8%	-11.2
Italy	24.9%	42.1%	-17.3	0.6%	11.2%	-10.6	24.7%	37.0%	-12.3
Latvia	32.0%	47.2%	-15.2	1.3%	9.2%	-7.9	31.5%	42.8%	-11.4
Lithuania	21.5%	40.3%	-18.8	0.6%	13.8%	-13.2	21.3%	30.7%	-9.5
Luxembourg	42.2%	62.3%	-20.2	5.0%	15.6%	-10.6	41.2%	55.8%	-14.5
Malta	26.2%	49.9%	-23.7	2.0%	12.3%	-10.3	25.4%	44.9%	-19.5
Netherlands	49.1%	66.2%	-17.1	5.3%	17.0%	-11.7	47.6%	59.6%	-12.0
Poland	12.8%	37.0%	-24.1	0.8%	16.6%	-15.8	12.4%	25.6%	-13.2
Portugal	25.6%	53.7%	-28.1	2.1%	18.2%	-16.1	24.4%	45.2%	-20.7
Romania	6.0%	20.3%	-14.3	0.3%	9.4%	-9.1	5.8%	12.9%	-7.1
Slovakia	35.3%	56.6%	-21.2	0.7%	15.0%	-14.3	34.9%	47.1%	-12.2
Slovenia	29.1%	52.6%	-23.4	0.6%	16.3%	-15.7	28.9%	42.7%	-13.7
Spain	31.3%	50.3%	-19.0	3.3%	18.4%	-15.1	29.7%	41.4%	-11.7
Sweden	62.0%	76.5%	-14.5	6.5%	24.4%	-17.9	59.5%	65.8%	-6.3
Non-EU									
Bosnia Herzegovina	3.8%	15.9%	-12.0	0.1%	5.5%	-5.4	3.7%	11.5%	-7.8
North Macedonia	6.8%	16.5%	-9.7	0.7%	6.1%	-5.3	6.3%	13.0%	-6.7
Norway	45.8%	69.1%	-23.3	3.6%	22.9%	-19.4	44.7%	59.2%	-14.5
Serbia	11.1%	28.2%	-17.1	0.3%	9.9%	-9.6	10.9%	21.7%	-10.9
Switzerland	53.5%	68.7%	-15.1	2.8%	17.8%	-15.0	53.0%	61.5%	-8.5
United Kingdom	37.6%	50.0%	-12.4	8.5%	17.5%	-9.0	32.5%	39.4%	-6.9

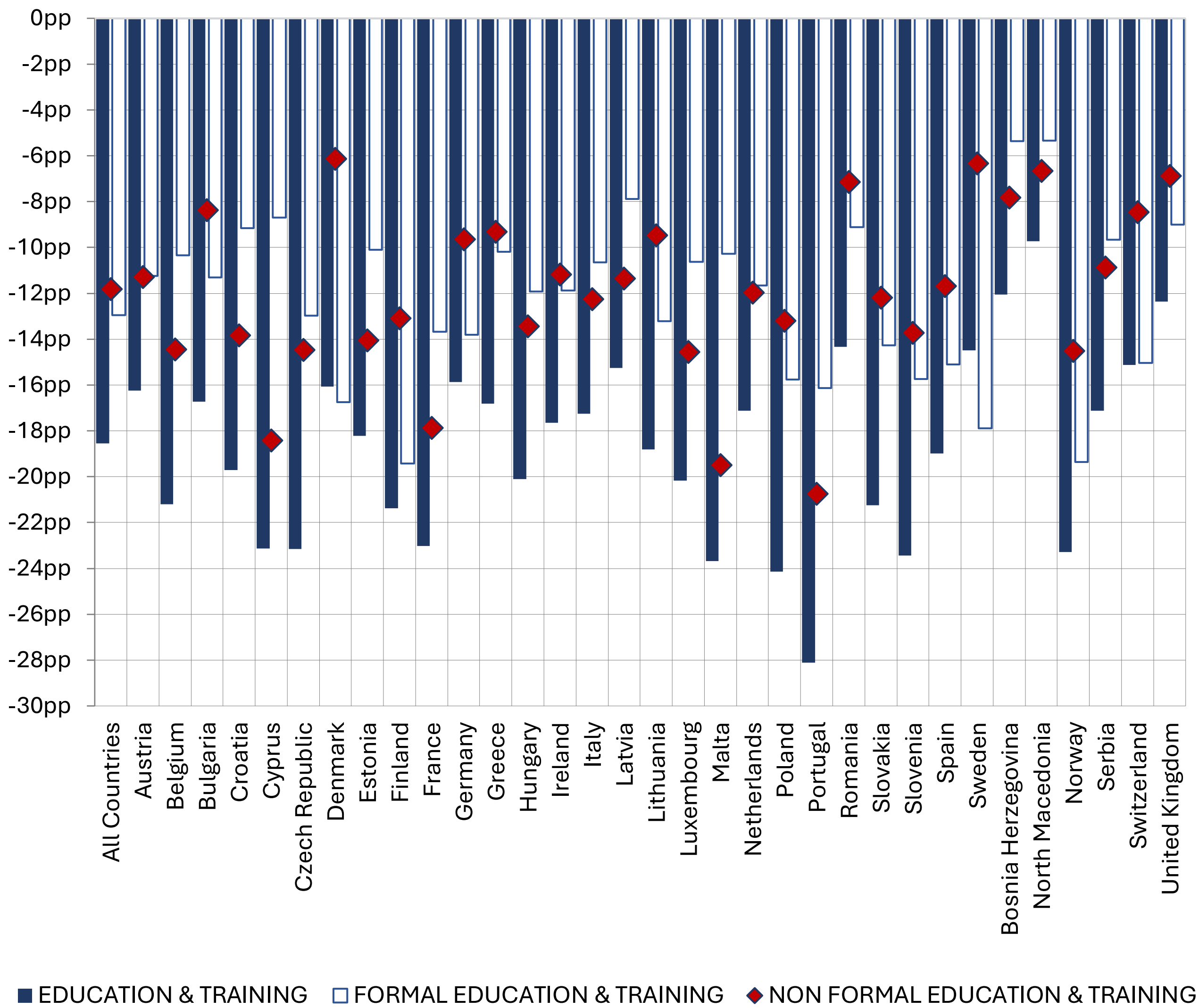


Figure 2-59: AES -Age differences in participation in training by country (old vs young, all waves)

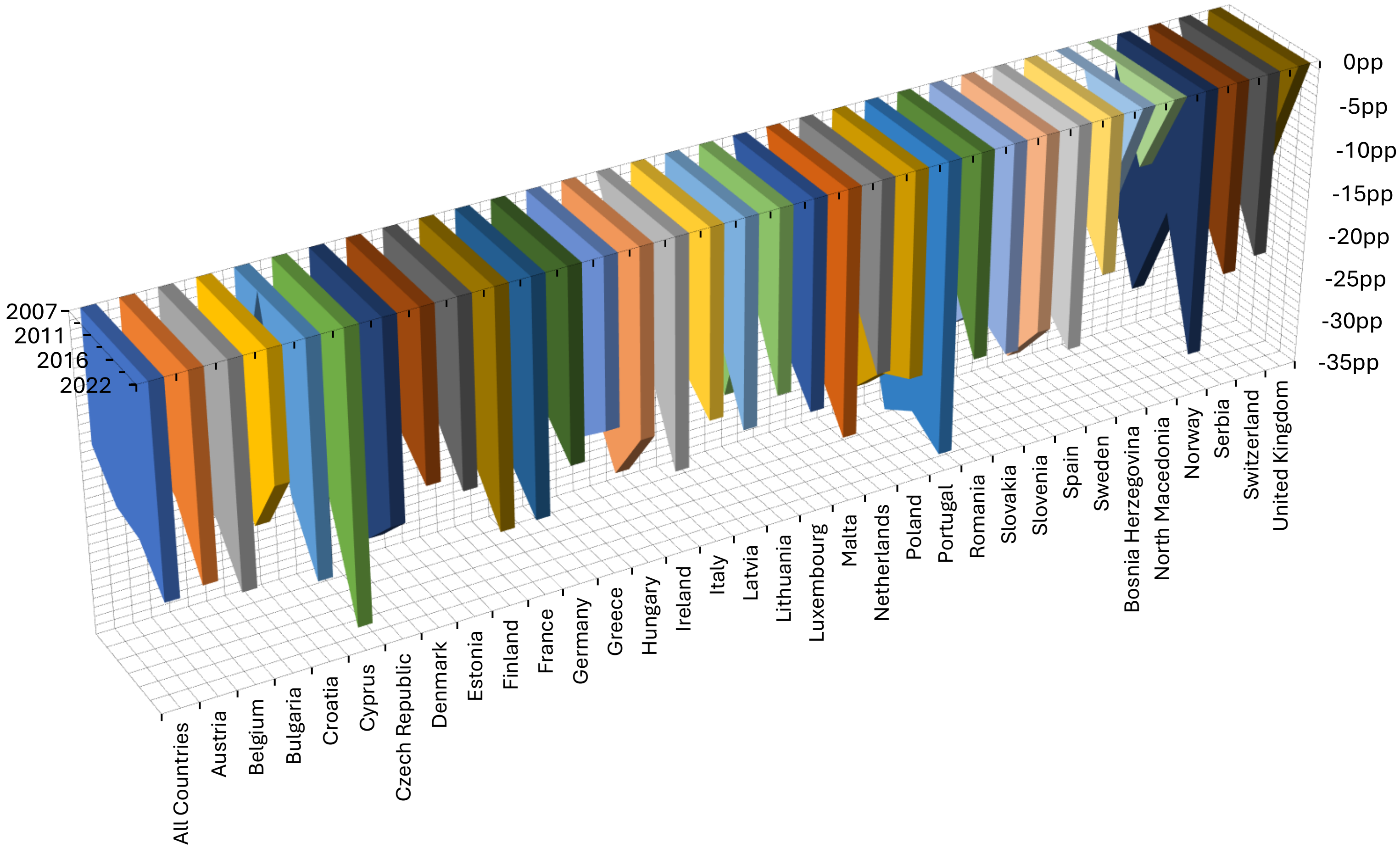


Figure 2-60: AES -Age differences in participation in education and training by country and wave

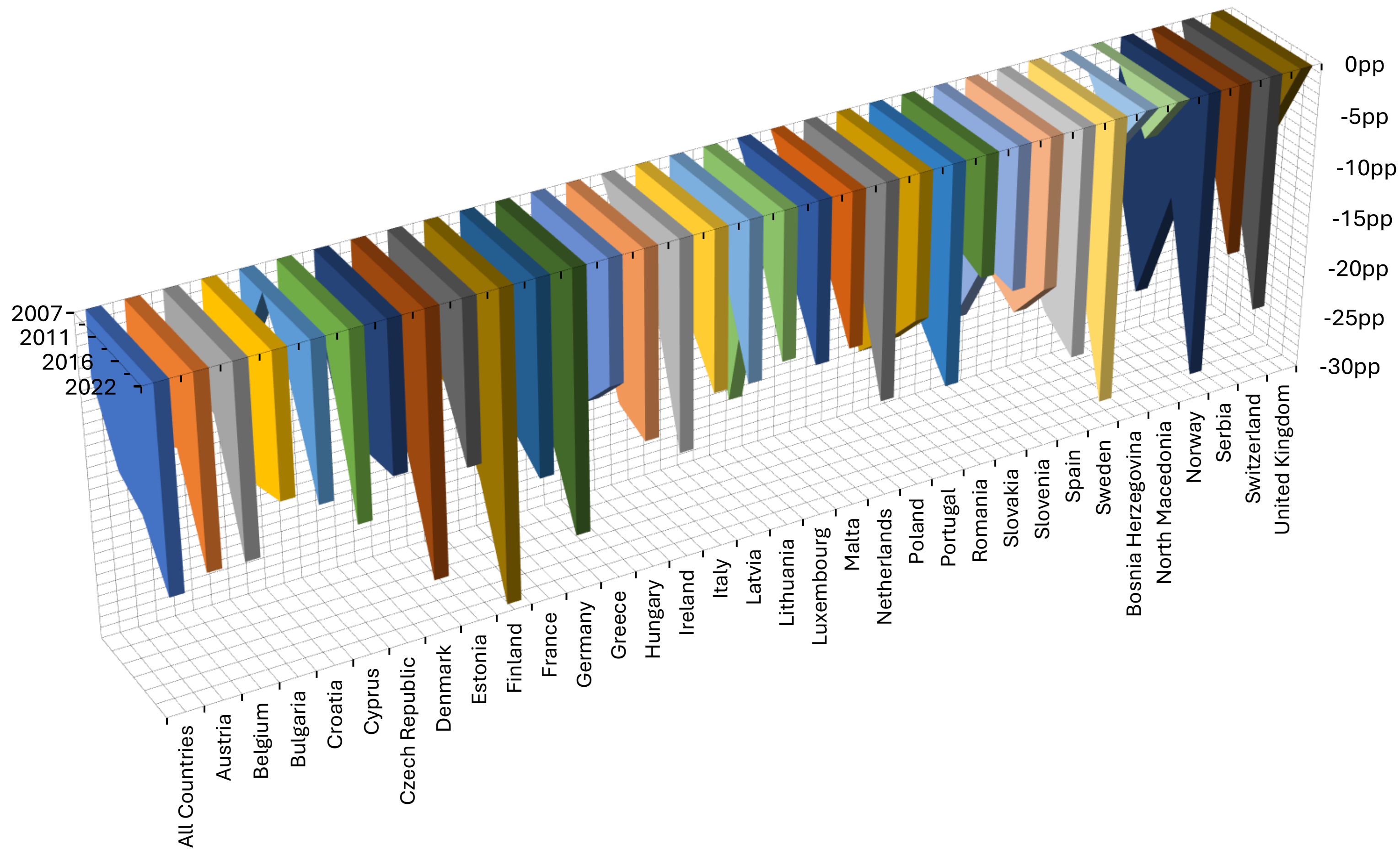


Figure 2-61: AES -Age differences in participation in formal education & training by country & wave

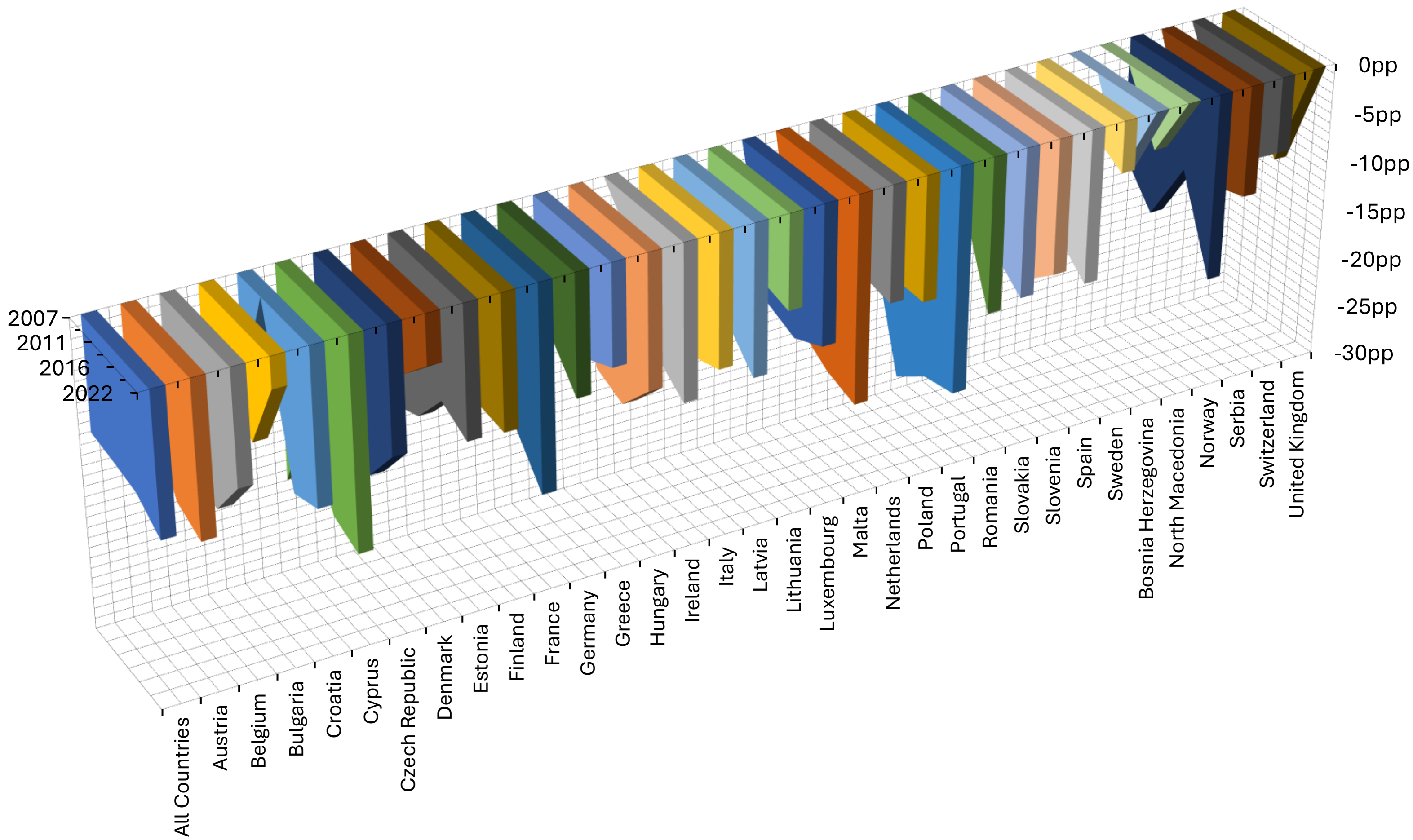


Figure 2-62: AES -Age differences in non-formal education & training by country & wave

2.3.6 DIFFERENCES BY INCOME

This section aims to highlight the differences in income level between individuals participating in different types of education and training. To analyse the data, we divided the sample based on the Top40% - Bottom60% distinction into richer and poorer subcategories. Data from the 2007 wave were excluded from the presentation due to incomparable income variables compared to other waves.

The weighted averages in Table 2-31 indicate that individuals in the top 40% cohort tend to participate more in education and training programs across all countries. However, upon further analysis of formal and non-formal activities, it becomes evident that in several countries such as Finland, France, Germany, and Italy, individuals in the bottom 60% cohort are more involved in formal education and training programmes. Conversely, in countries like Bulgaria, Croatia, Cyprus, and Lithuania, individuals in the top 40% cohort are more engaged in formal education and training programmes. This pattern is consistent across all countries in the survey when it comes to participation rates in non-formal education and training activities, as illustrated also in Figure 2-63.

The data presented in Figure 2-64 indicates a growing engagement in education and training programs among the top 40% income cohort across different countries over time. Notably, Figure 2-65 illustrates that the disparity in formal education and training between income groups remains relatively persistent in countries like Italy, Latvia, Hungary, Poland, and Cyprus. However, in other countries, this gap widens in line with each country's trend. Furthermore, Figure 2-66 demonstrates that the difference in participation rates in non-formal education and training programs between the richer and the poorer increases consistently across all countries.

Table 2-31: AES – Participation rate in education and training by income & country

COUNTRY	EDUCATION & TRAINING			FORMAL EDUCATION & TRAINING			NON-FORMAL EDUCATION & TRAINING		
	TOP 40%	BOTTOM 60%	DIFFERENCE (pp)	TOP 40%	BOTTOM 60%	DIFFERENCE (pp)	TOP 40%	BOTTOM 60%	DIFFERENCE (pp)
All Countries	***54.5%***	***39.0%***	***15.5***	***9.3%***	***11.0%***	***-1.6***	***50.4%***	***33.2%***	***17.2***
Austria	65.3%	50.1%	15.2	7.9%	10.0%	-2.1	62.3%	45.8%	16.5
Belgium	54.4%	34.7%	19.7	9.2%	10.8%	-1.6	49.7%	27.4%	22.3
Bulgaria	37.3%	20.6%	16.7	9.1%	7.0%	2.1	30.6%	15.2%	15.4
Croatia	42.7%	21.0%	21.7	7.7%	5.2%	2.5	38.3%	17.1%	21.2
Cyprus	64.0%	36.8%	27.2	10.8%	5.0%	5.8	58.1%	34.0%	24.1
Czech Republic	53.9%	36.5%	17.3	7.0%	10.3%	-3.4	49.6%	29.3%	20.3
Denmark	61.4%	49.6%	11.8	9.7%	17.9%	-8.3	57.4%	40.3%	17.1
Estonia	60.1%	38.5%	21.5	9.9%	6.8%	3.1	56.6%	35.2%	21.4
Finland	58.7%	50.0%	8.8	10.7%	19.5%	-8.8	55.8%	40.7%	15.1
France	63.7%	46.4%	17.3	8.3%	13.0%	-4.7	61.0%	41.3%	19.6
Germany	65.6%	48.8%	16.8	6.7%	11.4%	-4.7	63.4%	43.3%	20.1
Greece	25.1%	17.0%	8.2	8.7%	8.0%	0.7	19.2%	10.9%	8.3
Hungary	57.2%	44.2%	13.0	12.1%	8.8%	3.3	51.2%	40.0%	11.2
Ireland	58.6%	31.4%	27.1	12.1%	8.9%	3.2	53.7%	25.0%	28.7
Italy	45.8%	31.1%	14.7	6.1%	7.4%	-1.3	43.7%	27.4%	16.3
Latvia	56.9%	34.9%	22.0	7.9%	4.9%	2.9	53.7%	32.0%	21.7
Lithuania	45.0%	22.3%	22.7	10.4%	7.8%	2.5	38.2%	16.0%	22.2
Luxembourg	65.2%	47.6%	17.6	9.3%	12.2%	-2.8	62.9%	42.5%	20.4
Malta	52.8%	37.8%	15.0	9.7%	8.1%	1.6	49.7%	34.3%	15.4
Netherlands	70.7%	54.3%	16.4	13.0%	13.8%	-0.9	66.6%	48.1%	18.5
Poland	33.1%	20.3%	12.8	10.3%	9.3%	1.0	25.9%	13.5%	12.5
Portugal	57.1%	38.7%	18.4	14.7%	11.5%	3.2	51.3%	32.8%	18.5
Romania	21.4%	12.7%	8.7	6.8%	5.8%	1.0	16.2%	8.3%	7.9
Slovakia	60.3%	43.0%	17.3	10.0%	9.9%	0.1	54.3%	36.3%	17.9
Slovenia	57.2%	34.0%	23.2	11.2%	8.3%	2.9	50.9%	28.7%	22.3
Spain	58.8%	39.5%	19.2	14.9%	13.5%	1.4	53.1%	32.9%	20.2
Sweden	76.1%	65.8%	10.4	13.6%	21.5%	-8.0	71.5%	55.1%	16.4
Non-EU	14.1%	3.7%	10.4	3.2%	1.2%	2.0	11.4%	2.8%	8.5
Bosnia Herzegovina									
North Macedonia	22.6%	7.6%	15.0	6.4%	2.7%	3.6	18.9%	5.9%	13.0
Norway	65.8%	57.8%	8.0	10.9%	20.5%	-9.7	62.2%	48.5%	13.7
Serbia	31.9%	12.3%	19.6	8.3%	3.0%	5.3	26.1%	10.5%	15.7
Switzerland	80.4%	61.0%	19.4	10.6%	7.6%	3.0	78.6%	59.1%	19.5
United Kingdom	55.7%	40.0%	15.7	14.5%	13.4%	1.1	48.4%	31.5%	16.9

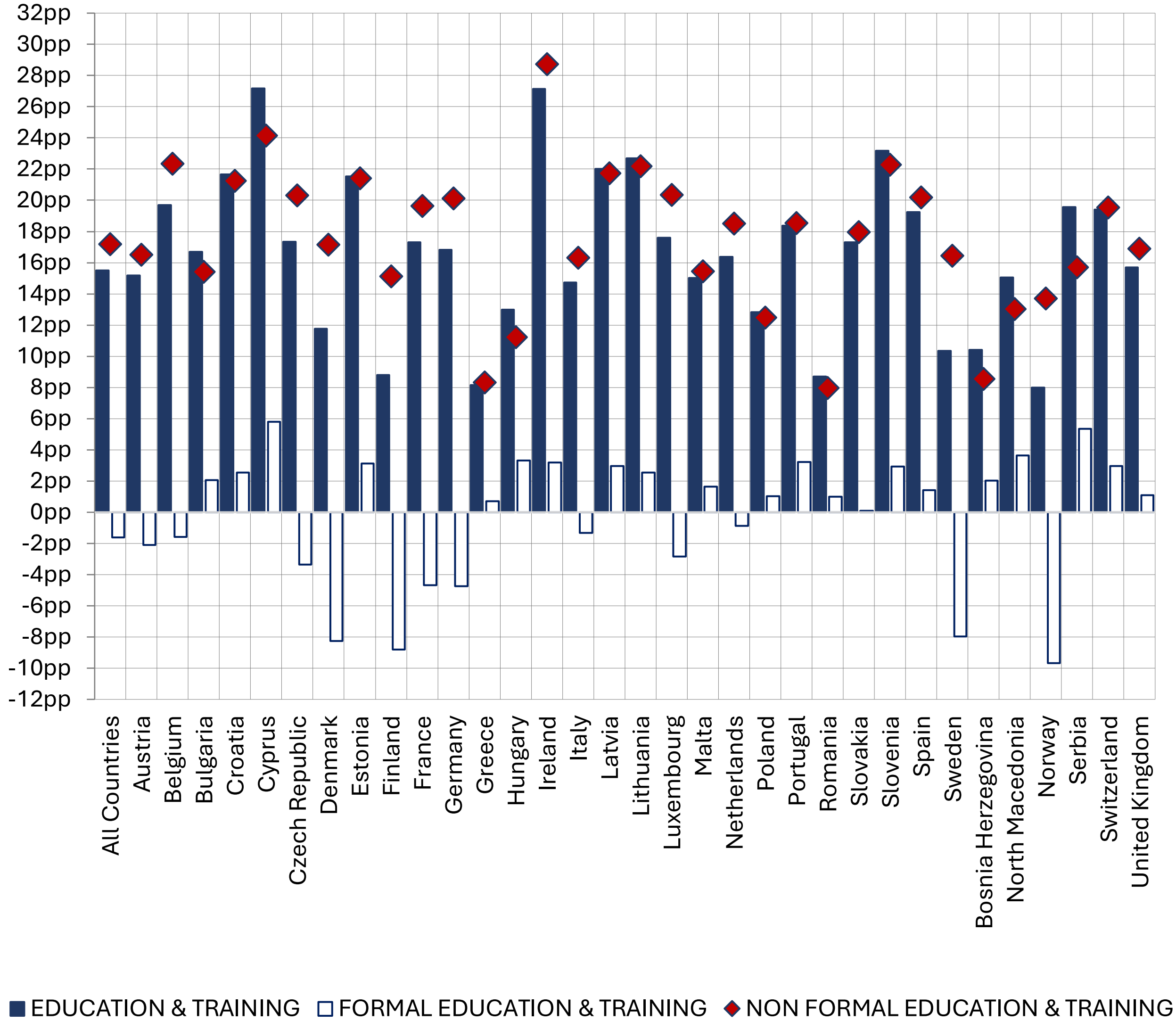


Figure 2-63: AES –Age differences in participation in training by country (Top 40% vs. Bottom 60%, all waves)

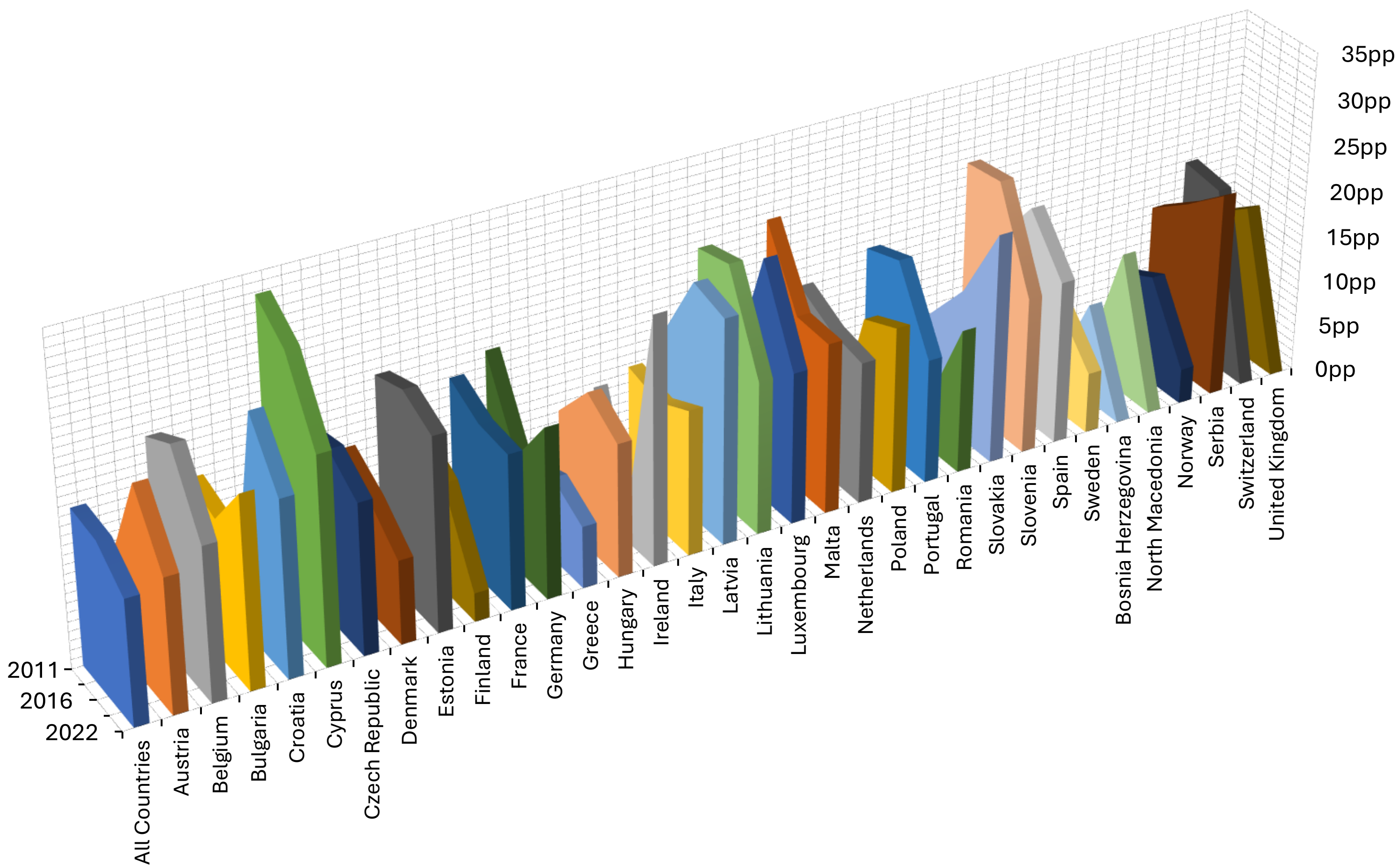


Figure 2-64: AES -Income differences in participation in education and training by country and wave

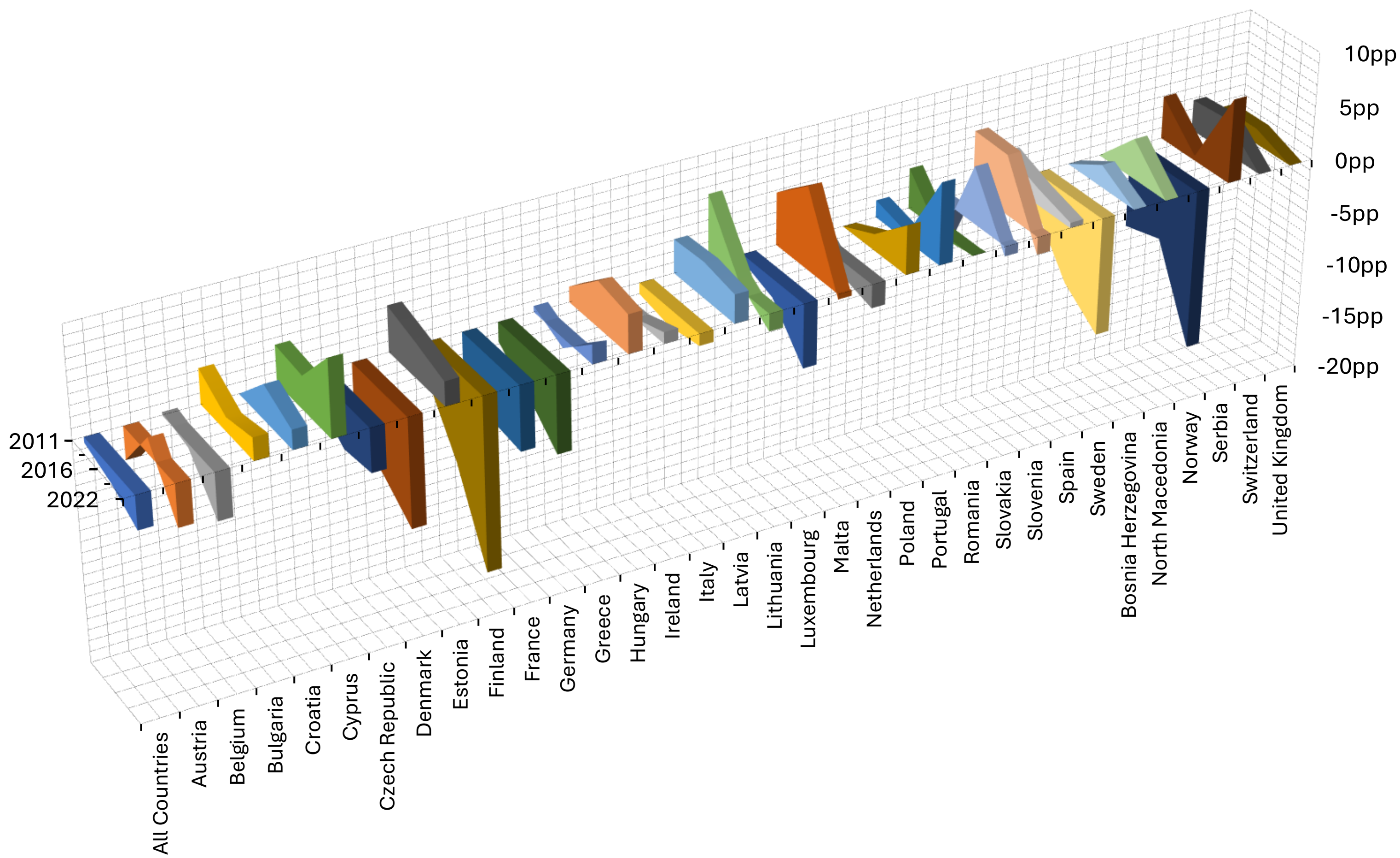


Figure 2-65: AES –Income differences in formal education & training by country & wave

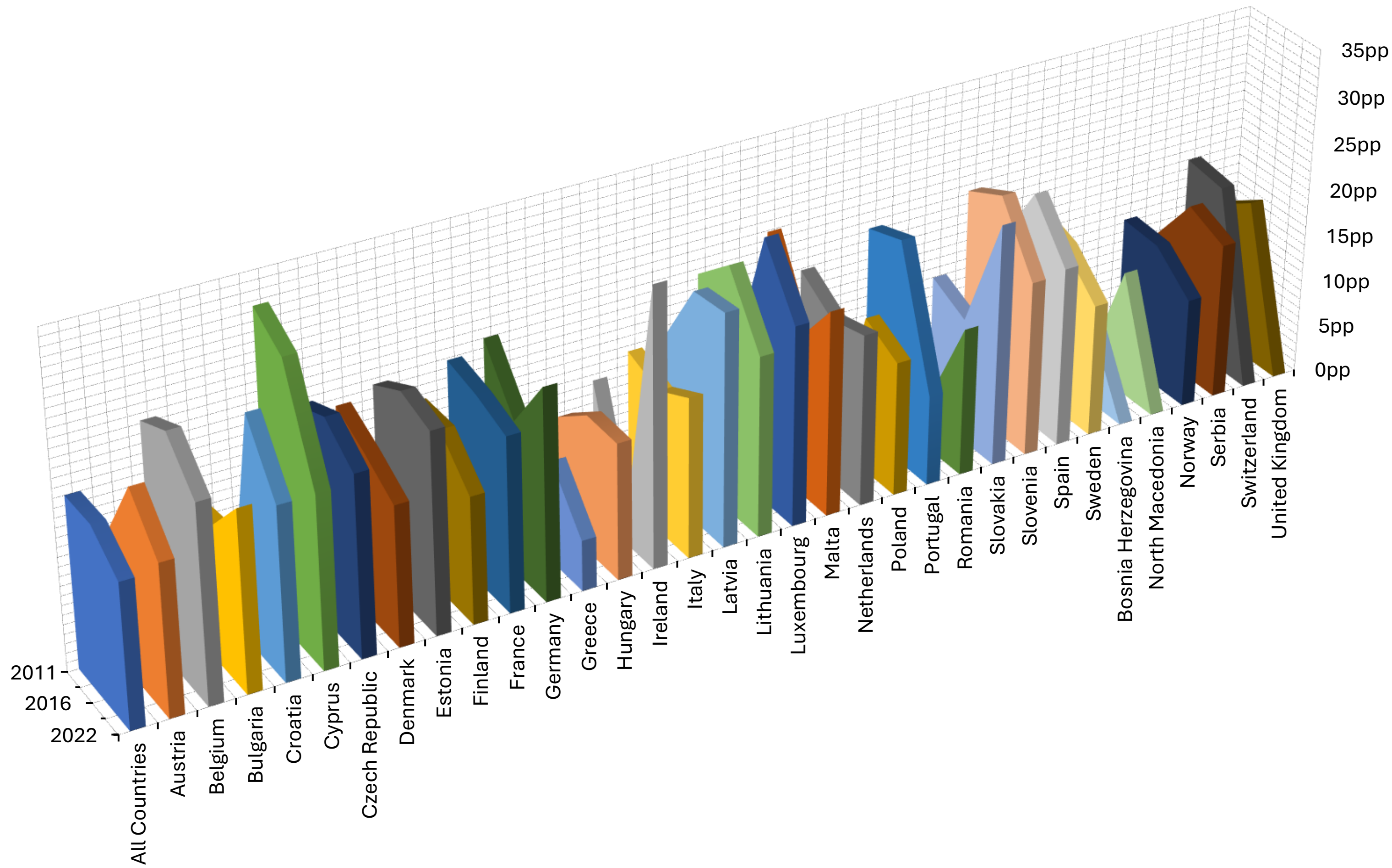


Figure 2-66: AES –Income differences in non-formal education & training by country & wave

3. HOUSEHOLD-LEVEL DATASETS

In this section, we present the two pan-European databases, which enable labour market analysis at both the individually and the household level, entailing richer information at the household level. These are the European Union Statistics on Income and Living Conditions (EU-SILC) and the European Central Bank's Household Finance and Consumption Survey (HFCS).

The EU-SILC covers a long timespan, between 2004-2021, and it is available in two variants. The first variant is the cross-sectional database (EU-SILC$_{Cross}$), which is used for a cross-section analysis entailing in the full sample of observations in every year. The second variant is the longitudinal database (EU-SILC$_{Panel}$), which is constructed as a rotating panel. It entails fewer observations than the previous variant, and most individuals and households are followed for four years. However, there are several individuals and households, which are present at the panel for more than four years. Both versions of the data entail sampling weights which enable the analysis to be representative at the country level.

The HFCS is a smaller database, which also provides sampling weights to render the data representative at the country level. The survey designers, i.e., ECB, have collected four waves of data, in 2010, 2014, 2017 and 2021. The survey is rich in terms of questions related to household finance and consumption. The data collectors provide the data in the form of a multiple-imputation dataset, in which 5 variants of responses are provided. This feature caters to variables than typically need imputation due to missing values, e.g., consumption, wealth, income, etc. This feature of the dataset requires special techniques of analysis.

Section 2 entails two major subsections, namely 3.1 presenting the EU-SILC and 3.2 presenting the HFCS. The contents of both sub-sections follow a similar structure. The begin with (1) presenting the data and frequencies, and (2) the employed sample and summary statistics. Then, (3) they present the most relevant statistics on skills (mis)matching, and differences in these statistics by (4) gender, (5) age, and (6) income. Each subsection concludes by (7) presenting a short systematic literature review of the literature using each of the two databases. It is worth noting that the two household level databases do not entail any questions on training.

3.1 STATISTICS ON INCOME AND LIVING CONDITIONS (SILC)

The Statistics on Income and Living Conditions (SILC) is a key instrument used by Eurostat and national statistical institutes across the European Union (EU) to collect and analyse data on income, poverty, social exclusion, and living conditions. This survey provides comprehensive, comparable statistics that are crucial for monitoring social inclusion and living standards in the EU.

The main objective of SILC is to gather data that helps understand the distribution of income, the extent of poverty and social exclusion, and the overall living conditions of individuals and households within the EU. The survey supports the development and evaluation of social and economic policies aimed at improving living standards and reducing inequality.

SILC covers all EU Member States, as well as some non-EU countries, including EFTA countries and candidate countries. It collects data from households and individuals aged 16 and over, with a particular focus on vulnerable groups such as low-income households, single-parent families, and the elderly. SILC is conducted annually, with each participating country responsible for collecting data according to harmonized guidelines set by Eurostat. The data collection involves household interviews, and sometimes the use of administrative records, to gather detailed information.

The survey caters to the following key domains, inter alia:

- Income: SILC provides detailed data on household income, including earnings from work, pensions, social benefits, and other sources. It also measures disposable income after taxes and transfers.
- Poverty and social exclusion: The survey includes indicators such as the at-risk-of-poverty rate, material deprivation, and the share of people living in households with very low work intensity.
- Living conditions: Data on housing conditions, access to essential services, and the quality of the living environment are also collected.
- Social Indicators: SILC measures inequality through indicators like the Gini coefficient and income quintile share ratio. It also looks at the intergenerational transmission of poverty and social mobility.
- At-risk-of-poverty rate: The percentage of the population living below the poverty threshold, which is set at 60% of the national median equivalized disposable income.
- Material deprivation Rate: The proportion of people who cannot afford a certain standard of living, such as being able to pay rent or utility bills, keep their home adequately warm, or afford a week's holiday away from home.
- Severe material deprivation Rate: A stricter measure, indicating those unable to afford at least four out of nine essential items.
- Low work intensity: The proportion of people living in households where adults work less than 20% of their total work potential during the past year.

SILC provides both cross-sectional data (data collected at a specific point in time) and longitudinal data (data collected over several years from the same households), allowing for the analysis of trends and changes in income and living conditions over time. The SILC survey is a vital tool for understanding the social fabric of Europe, providing insights into how income distribution, poverty, and living conditions affect different segments of the population. It plays a critical role in shaping social policy, targeting interventions to reduce poverty, and promoting social inclusion across the EU. The data was essential for monitoring progress towards the Europe 2020 strategy's poverty and social exclusion targets. It is also used to assess the impact of social and economic policies at both national and EU levels, particularly in the context of the European Pillar of Social Rights. It is designed to ensure that the data collected is comparable across countries and over time. Eurostat provides methodological guidelines and ensures that national surveys adhere to common standards, making the data robust for cross-country comparisons.

3.1.1 THE DATA AND FREQUENCIES

This section outlines the sample sizes across different countries and years, highlighting the structure of both cross-sectional and longitudinal (panel) datasets. These frequencies are essential for understanding the representativeness and scope of the data utilized in subsequent analysis focusing on skills mismatching.

Table 3-1 presents a breakdown of sample sizes across different countries for both cross-sectional and longitudinal dataset. Each dataset is divided into pre- and post-selection samples. The sample selection is based on certain criteria, which include: (i) individuals aged 15-74, (ii) those not living in institutions, (iii) individuals not in compulsory military service, (iv) non-retirees, and (v) individuals under the age of 23 whose reason for not searching for a job is not related to education. The total pooled sample size across all countries is provided at the top, with larger sample sizes in the pre-selection compared to the post-selection. The first column lists countries participating in the EU-SILC survey, including both EU and non-EU countries, such as Iceland, Norway, Serbia, Switzerland and the United Kingdom, which are listed in the lower section. Countries like Italy, Spain, and France exhibit some of the highest sample sizes in both cross-sectional and longitudinal versions, while Malta and Iceland have some of the smallest samples.

Table 3-2 presents the panel dimension of the longitudinal dataset, detailing the number of individuals and observations across different countries in both the pre- and post-selection phases. This detailed breakdown is crucial for understanding the structure of the data and for ensuring that the analysis based on this dataset is representative based on the population size of each country.

Table 3-3 provides an overview of the sample life in the longitudinal dataset, showing the duration (in years) that individuals remain in the sample. In both the pre- and post-selection datasets, most individuals are present for 4 years, indicating that the EU-SILC longitudinal survey typically follows individuals for this length of time. By contrast, relatively few individuals remain in the sample for longer durations, such as 10 years or more, where the number of individuals significantly decreases, along with their contribution to the overall dataset.

Figure 3-1 provides a visual representation of the EU-SILC cross-sectional dataset, illustrating the number of observations by country and year. This figure reveals clear variations in the volume of observations across different countries and time periods, which mainly occur due to disparities in population size between large and small countries. Larger countries, such as Italy, Spain, Germany and France consistently contribute the highest number of observations throughout the years. In contrast, smaller countries like Malta, Iceland, Croatia, and Cyprus have significantly fewer observations, with some fluctuation in participation over time.

Figure 3-2 presents a similar analysis for the EU-SILC panel dataset, showing the number of observations by country and year for the longitudinal component of the survey. As in the cross-sectional data, larger countries, such as Italy, Spain, and France exhibit the largest numbers of observations over time, particularly in recent years. However, in contrast to the cross-sectional data, the figure highlights sharper reductions in the number of observations for some countries in specific years, such as Malta, Switzerland, and Germany. This decline is because the longitudinal component has experienced a variation in participation and data collection consistency, due to dropout or other factors affecting continued participation by certain countries.

Table 3-1: EU-SILC – Sample size

EU-SILC		CROSS VERSION		LONG VERSION	
		SAMPLE SELECTION		SAMPLE SELECTION	
COUNTRY	ACRONYM	PRE	POST	PRE	POST
All Countries	***POOLED***	***9,406,534***	***6,295,784***	***7,814,979***	***4,706,680***
Austria	AT	207,795	137,133	194,395	117,231
Belgium	BE	221,986	151,199	201,412	116,597
Bulgaria	BG	214,554	131,836	202,132	104,633
Croatia	HR	196,646	110,632	167,092	78,845
Cyprus	CY	167,041	113,958	153,691	94,750
Czech Republic	CZ	297,112	182,256	277,108	155,208
Denmark	DK	218,412	153,126	140,665	88,956
Estonia	EE	222,416	151,631	208,142	127,467
Germany	DE	504,732	335,263	74,936	47,022
Greece	EL	423,022	263,033	355,798	229,411
Finland	FI	389,710	277,684	304,612	193,184
France	FR	407,685	265,706	361,950	215,797
Hungary	HU	314,790	199,324	290,073	171,701
Ireland	IE	185,954	136,510	134,523	88,066
Italy	IT	775,376	516,862	714,321	399,802
Latvia	LV	201,329	130,659	178,240	104,857
Lithuania	LT	187,393	118,475	171,005	96,883
Luxembourg	LU	161,293	120,929	154,179	107,195
Malta	MT	143,642	53,549	129,954	40,642
Netherlands	NL	384,430	291,847	348,581	225,348
Poland	PL	595,078	402,011	534,545	304,859
Portugal	PT	330,070	215,327	177,299	107,426
Romania	RO	253,636	147,327	229,785	119,360
Slovakia	SK	237,198	153,648	212,600	126,369
Slovenia	SI	413,930	258,307	387,709	219,395
Spain	ES	595,640	436,937	496,964	324,909
Sweden	SE	246,736	176,692	207,611	130,483
Non–EU					
Iceland	IS	100,656	83,098	97,941	80,074
Norway	NO	200,247	152,749	193,441	148,414
Serbia	RS	132,749	86,047	124,670	86,248
Switzerland	CH	213,066	160,261	131,223	80,151

United Kingdom	UK	262,210	181,768	258,382	175,397

Notes: Our sample selection strategy comprises of 5 stages, as follows: (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.

Table 3-2: EU-SILC – Panel dimension

	PRE-SAMPLE SELECTION				POST-SAMPLE SELECTION			
COUNTRY	#INDIVIDUALS	(%)	#OBSERVATIONS	(%)	#INDIVIDUALS	(%)	#OBSERVATIONS	(%)
All Countries	***2,510,441***	***(100.00)***	***7,814,979***	***(100.00)***	**1,730,676**	**(100.00)**	***4,706,680***	***(100.00)***
Austria	71,124	(2.83)	194,395	(2.49)	47,539	(2.75)	117,231	(0.02)
Belgium	69,807	(2.78)	201,412	(2.58)	48,947	(2.83)	116,597	(0.02)
Bulgaria	55,934	(2.23)	202,132	(2.59)	35,486	(2.05)	104,633	(0.02)
Croatia	59,779	(2.38)	167,092	(2.14)	33,371	(1.93)	78,845	(0.02)
Cyprus	49,718	(1.98)	153,691	(1.97)	35,183	(2.03)	94,750	(0.02)
Czech Republic	83,498	(3.33)	277,108	(3.55)	52,663	(3.04)	155,208	(0.03)
Denmark	44,600	(1.78)	140,665	(1.80)	32,663	(1.89)	88,956	(0.02)
Estonia	57,932	(2.31)	208,142	(2.66)	42,543	(2.46)	127,467	(0.03)
Germany	29,170	(1.16)	74,936	(0.96)	19,352	(1.12)	47,022	(0.01)
Greece	115,951	(4.62)	355,798	(4.55)	80,464	(4.65)	229,411	(0.05)
Finland	91,201	(3.63)	304,612	(3.90)	67,172	(3.88)	193,184	(0.04)
France	94,331	(3.76)	361,950	(4.63)	62,780	(3.63)	215,797	(0.05)
Hungary	99,542	(3.97)	290,073	(3.71)	65,150	(3.76)	171,701	(0.04)
Ireland	54,286	(2.16)	134,523	(1.72)	40,097	(2.32)	88,066	(0.02)
Italy	249,321	(9.93)	714,321	(9.14)	155,570	(8.99)	399,802	(0.08)
Latvia	62,642	(2.50)	178,240	(2.28)	41,317	(2.39)	104,857	(0.02)
Lithuania	39,168	(1.56)	171,005	(2.19)	27,915	(1.61)	96,883	(0.02)
Luxembourg	45,768	(1.82)	154,179	(1.97)	33,510	(1.94)	107,195	(0.02)
Malta	33,956	(1.35)	129,954	(1.66)	13,880	(0.80)	40,642	(0.01)
Netherlands	114,055	(4.54)	348,581	(4.46)	87,025	(5.03)	225,348	(0.05)
Poland	163,276	(6.50)	534,545	(6.84)	109,199	(6.31)	304,859	(0.06)
Portugal	36,195	(1.44)	177,299	(2.27)	27,588	(1.59)	107,426	(0.02)
Romania	62,554	(2.49)	229,785	(2.94)	38,529	(2.23)	119,360	(0.03)
Slovakia	33,239	(1.32)	212,600	(2.72)	27,129	(1.57)	126,369	(0.03)
Slovenia	144,822	(5.77)	387,709	(4.96)	90,254	(5.21)	219,395	(0.05)
Spain	153,577	(6.12)	496,964	(6.36)	117,177	(6.77)	324,909	(0.07)
Sweden	77,698	(3.09)	207,611	(2.66)	56,067	(3.24)	130,483	(0.03)
Non–EU								
Iceland	38,427	(1.53)	97,941	(1.25)	33,801	(1.95)	80,074	(0.02)
Norway	67,298	(2.68)	193,441	(2.48)	54,520	(3.15)	148,414	(0.03)
Serbia	43,274	(1.72)	124,670	(1.60)	31,900	(1.84)	86,248	(0.02)
Switzerland	48,902	(1.95)	131,223	(1.68)	34,555	(2.00)	80,151	(0.02)
United Kingdom	119,396	(4.76)	258,382	(3.31)	87,330	(5.05)	175,397	(0.04)

Notes: Our sample selection strategy comprises of 5 stages, as follows: (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.

Table 3-3: EU-SILC – The panel sample life

	PRE-SAMPLE SELECTION				POST-SAMPLE SELECTION			
# YEARS	# INDIVIDUALS	(%)	# OBSERVATIONS	(%)	# INDIVIDUALS	(%)	# OBSERVATIONS	(%)
Total	***2,510,441***	***(100.00)***	***7,814,979***	***(100.00)***	***1,730,676***	***(100.00)***	***4,706,680***	***(100.00)***
1	510,312	(20.33)	510,312	(6.53)	547,435	(31.63)	547,435	(11.63)
2	459,723	(18.31)	919,446	(11.77)	299,936	(17.33)	599,872	(12.75)
3	378,387	(15.07)	1,135,161	(14.53)	224,957	(13.00)	674,871	(14.34)
4	944,679	(37.63)	3,778,716	(48.35)	560,668	(32.40)	2,242,672	(47.65)
5	68,804	(2.74)	344,020	(4.40)	34,186	(1.98)	170,930	(3.63)
6	58,370	(2.33)	350,220	(4.48)	24,513	(1.42)	147,078	(3.12)
7	28,259	(1.13)	197,813	(2.53)	13,025	(0.75)	91,175	(1.94)
8	32,754	(1.30)	262,032	(3.35)	14,102	(0.81)	112,816	(2.40)
9	11,096	(0.44)	99,864	(1.28)	6,174	(0.36)	55,566	(1.18)
10	5,605	(0.22)	56,050	(0.72)	2,443	(0.14)	24,430	(0.52)
11	3,567	(0.14)	39,237	(0.50)	1,126	(0.07)	12,386	(0.26)
12	2,798	(0.11)	33,576	(0.43)	1,048	(0.06)	12,576	(0.27)
13	1,398	(0.06)	18,174	(0.23)	421	(0.02)	5,473	(0.12)
14	1,882	(0.07)	26,348	(0.34)	350	(0.02)	4,900	(0.10)
15	1,443	(0.06)	21,645	(0.28)	199	(0.01)	2,985	(0.06)
16	823	(0.03)	13,168	(0.17)	66	(0.00)	1,056	(0.02)
17	541	(0.02)	9,197	(0.12)	27	(0.00)	459	(0.01)

Notes: Our sample selection strategy comprises of 5 stages, as follows: (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.

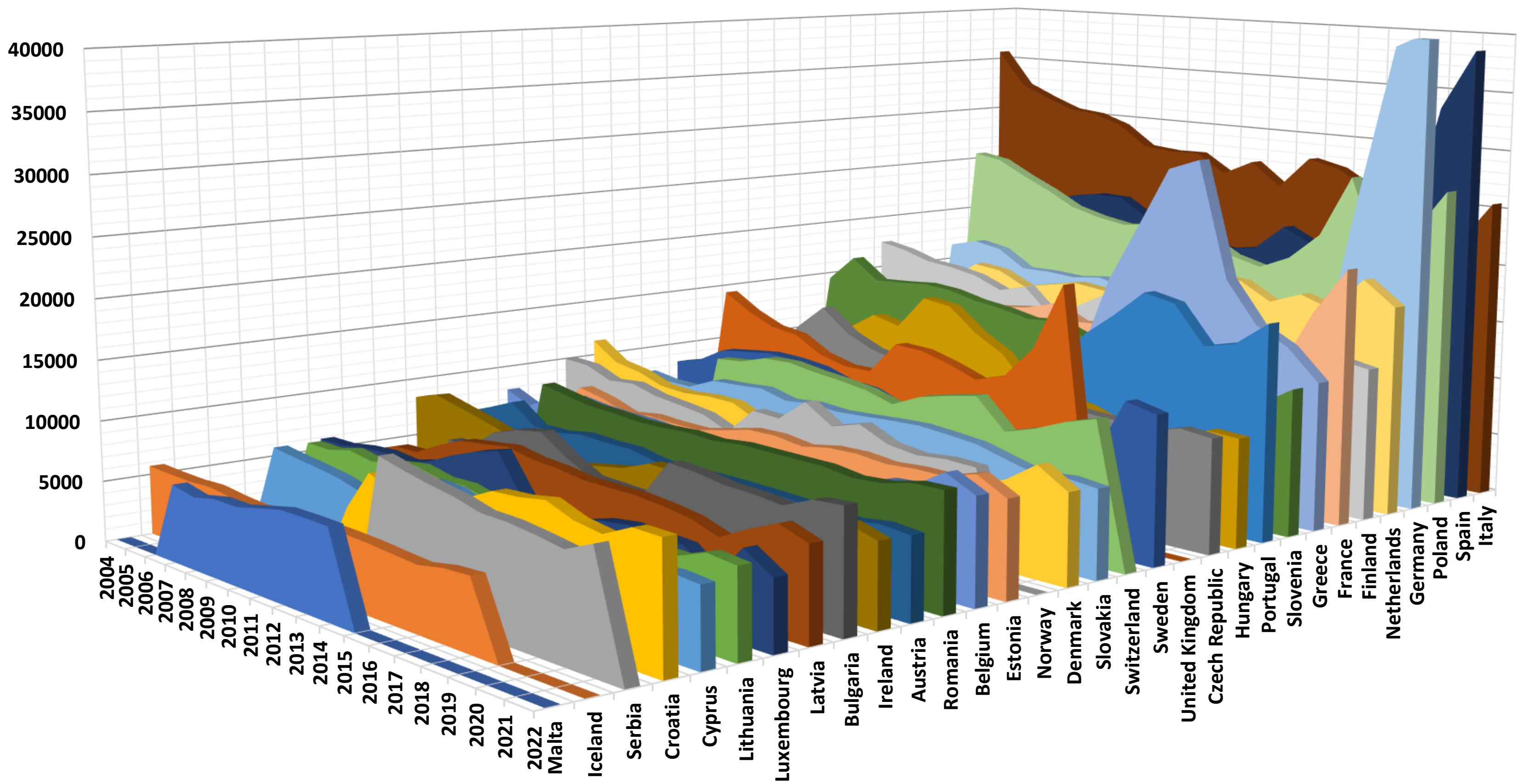


Figure 3-1: EU-SILC$_{Cross\text{-}sectional}$ – #Observations by country and year

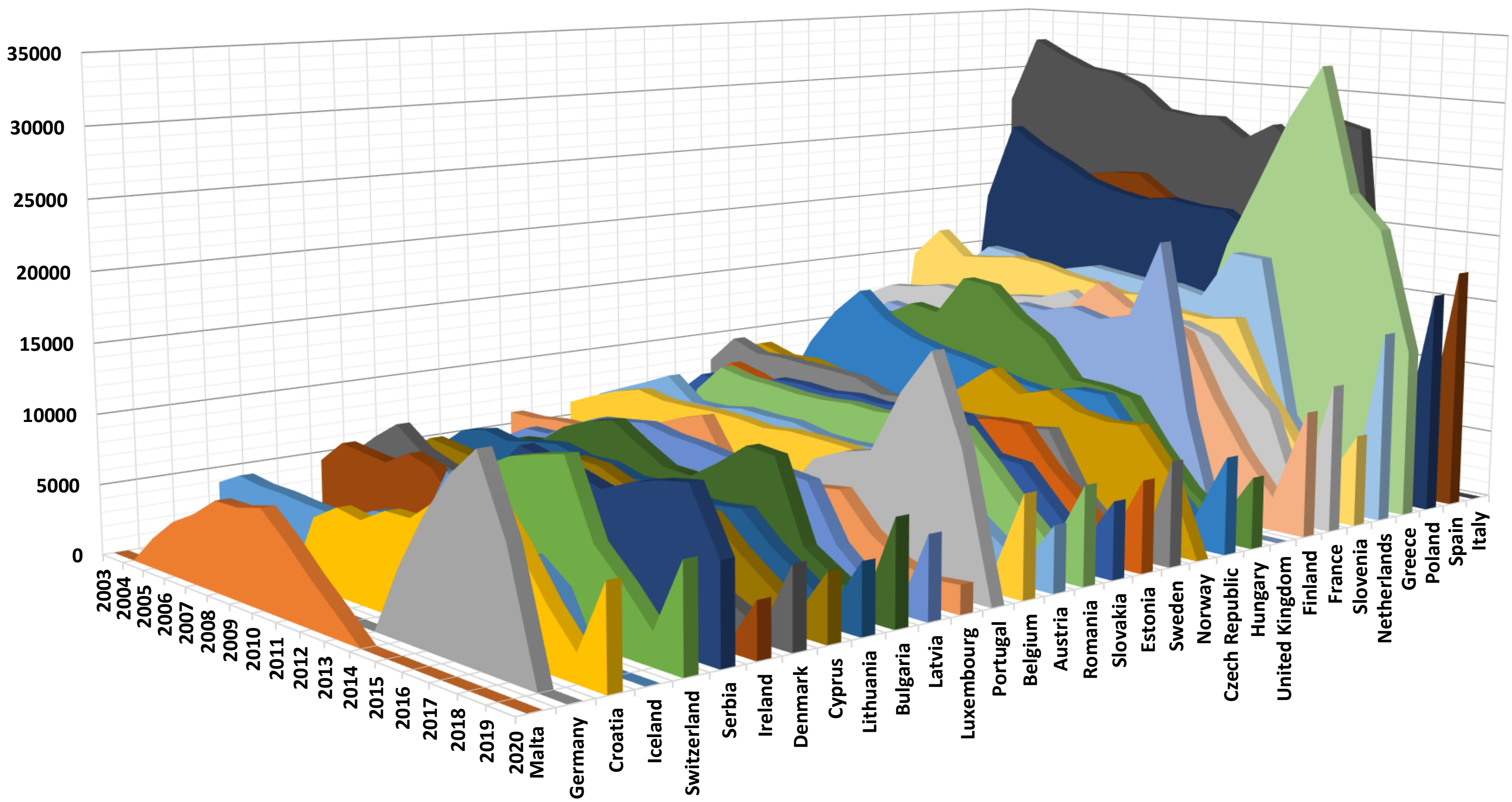


Figure 3-2: EU-SILC$_{Panel}$ – #Observations by country and year

3.1.2 THE EMPLOYED SAMPLE AND SUMMARY STATISTICS

This subsection provides an in-depth overview of the economic activity categories in the EU-SILC databases, distinguishing between the cross-sectional and the panel dataset. The tables present both unweighted and weighted descriptive statistics for a variety of economic activity groups across multiple countries, including some non-EU countries.

First, Table 3-4 provides a summary of economic activity categories for both the cross-sectional and panel dataset. It outlines the total number of observations (#OBS) for each category as unweighted and weighted averages as percentage. As it can be seen, employed full-time is the dominant category in both cross-sectional (51.45%) and panel data (52.35%), indicating that more than half of the respondents in both datasets are full-time workers. Employed part-time and self-employed full-time represent smaller groups, with employed part-time accounting for 11.07% (cross-sectional) and 10.82% (panel) of the total, while self-employed full-time makes up around 8.56% and 8.67%, of the samples respectively. The unemployed comprise 9% of the sample in both datasets. Students and disabled individuals account for approximately 3-4% of observations, while homemakers represent around 8% of the total.

Second, Table 3-5 breaks down the weighted economic activity statistics for each country in the cross-sectional dataset, enabling country-specific comparisons of employment trends. For example, Slovenia (67.60%), Slovakia (66.73%), Estonia (66.12%), Latvia (65.76%), Lithuania (64.93%) and Bulgaria (64.43%) shows a notably high percentage of full-time employed individuals significantly above the pooled sample average of 51.45%. In contrast, Greece and Spain present lower rates of full-time employment (39.04% and 46.46% respectively), which is partly offset by a higher rate of full-time self-employment (17.76% and 9.05% respectively) and a higher rate of unemployment (14.90% and 15.65% respectively) compared to the pooled sample averages. The Netherlands also exhibits a low rate of full-time employment (35.21%) but reports high rates of part-time employment (26.41%) relative to the average (11.07%) of the pooled sample, along with a very low rate of unemployment (3.20%).

Table 3-6 provides a similar breakdown of economic activity for the longitudinal dataset. As can be seen, the trends of economic activity status across countries remain consistent between cross-sectional and longitudinal datasets. In sum, both Tables 3-5 and Table 3-6 show that full-time employment is the most reported economic activity across the EU-SILC datasets, in both datasets, though there are notable differences between countries.

The following Tables 3-7 and 3-8 present the summary statistics of key variables in the EU-SILC dataset for both the cross-sectional and panel datasets, respectively. The tables provide both the unweighted and weighted averages for each variable for the pooled sample and for the employed subsample. The variables capture important demographic, socio-economic, and labour market characteristics.

In both tables, the gender composition is relatively balanced, with around 48-49% of observations being male in both the pooled and the employed sample. The urban-rural distinction shows that a significant proportion of respondents live in urban or semi-urban areas, with approximately 44-45% of the pooled sample residing in urban areas in both datasets. The proportion living in rural areas is

26% in the cross-sectional dataset and around 29% in the panel dataset. In terms of marital status, about 54-55% of the respondents are either married or in a civil partnership in both datasets. The percentage of individuals who are single is slightly higher in the cross-sectional dataset (36% vs 34% in the panel), indicating that longitudinal samples might capture more married individuals or those in stable relationships over time. The category of individuals who are separated, widowed, or divorced is consistent across both datasets, at around 10%.

As for years of schooling, the weighted mean for the pooled sample is about 11.5 years in both datasets. However, in the employed subsample, the weighted mean is slightly higher around 12 years in both datasets, reflecting a typical trend where individuals with higher educational attainment are more likely to be employed. In terms of educational attainment, about 43-44% of individuals in the employed subsample have an ISCED 3 (upper secondary education) level of education, while the corresponding percentage with a higher education (ISCED 5-8) is approximately 34%.

Regarding employment characteristics, in the cross-sectional dataset (Table 3-7), 70.5% of individuals reported having previous employment experience, and the average number of years of experience in paid work was around 19.8 years in the employed subsample. In the panel dataset (Table 3-8) there is only a question about the years of experience in paid work, where similar trends are observed, with an average of 19.9 years of work experience in the employed subsample. The question about the permanency of the main job is common in both datasets, with around 86% of employed individuals holding a contract without a fixed end in both datasets. The question about holding a managerial position is only asked in the cross-sectional survey, with about 25% in the employed subsample having a position in their main job with supervisory responsibilities.

Table 3-4: EU-SILC – Economic activity

	CROSS-SECTIONAL			PANEL		
ECONOMIC ACTIVITY	#OBS.	UNWEIGHTED	WEIGHTED	#OBS.	UNWEIGHTED	WEIGHTED
Pooled Sample	***6,170,735***	***100.00%***	***100.00%***	***4,568,293***	***100.00%***	***100.00%***
Employed full-time	3,271,201	53.01%	51.45%	2,429,006	53.17%	52.35%
Employed part-time	562,295	9.11%	11.07%	393,217	8.61%	10.82%
Self-employed full-time	558,311	9.05%	8.56%	419,274	9.18%	8.67%
Self-employed part-time	91,293	1.48%	1.54%	69,031	1.51%	1.58%
Unemployed	549,734	8.91%	8.87%	426,710	9.34%	8.93%
Student	250,360	4.06%	3.93%	160,113	3.50%	3.03%
Disabled	249,861	4.05%	3.82%	192,198	4.21%	4.23%
Homemaker	499,197	8.09%	8.29%	375,499	8.22%	7.98%
Other inactive	138,483	2.24%	2.49%	103,245	2.26%	2.41%

Notes: The sampling weights are provided by the data collectors and render the analysis representative at the country level and overall

Table 3-5: EU-SILC$_{Cross-sectional}$ – Economic activity by country (weighted statistics)

ACTIVITY	EMPLOYED FULL–TIME	EMPLOYED PART–TIME	SELF-EMPLOYED FULL–TIME	SELF-EMPLOYED PART–TIME	UNEMPLOYED	STUDENT	DISABLED	HOMEMAKER	OTHER INACTIVE
Pooled sample	***51.45%***	***11.07%***	***8.56%***	***1.54%***	***8.87%***	***3.93%***	***3.82%***	***8.29%***	***2.49%***
Austria	52.52%	15.96%	7.86%	1.32%	7.06%	3.87%	1.25%	8.97%	1.19%
Belgium	47.11%	17.17%	7.38%	0.76%	8.21%	3.49%	5.60%	7.33%	2.94%
Bulgaria	64.43%	2.58%	6.62%	0.55%	14.49%	2.43%	3.52%	3.50%	1.88%
Croatia	58.71%	1.29%	6.32%	0.54%	20.17%	4.44%	1.30%	6.47%	0.77%
Cyprus	61.26%	4.27%	6.19%	2.29%	9.87%	3.80%	1.78%	9.12%	1.41%
Czech Republic	63.32%	2.31%	12.57%	0.67%	7.46%	3.06%	4.66%	5.67%	0.29%
Denmark	58.04%	10.32%	6.09%	0.93%	5.81%	9.71%	6.17%	0.77%	2.16%
Estonia	66.12%	6.05%	5.70%	1.08%	7.19%	2.67%	5.46%	5.67%	0.06%
Germany	51.13%	19.08%	4.13%	1.24%	6.99%	4.91%	2.99%	6.90%	2.63%
Greece	39.04%	4.08%	17.76%	1.72%	14.90%	3.38%	1.95%	16.05%	1.12%
Finland	57.09%	6.53%	9.05%	0.92%	9.04%	6.84%	6.13%	3.55%	0.86%
France	56.66%	12.04%	7.43%	0.98%	9.36%	3.43%	3.71%	4.44%	1.95%
Hungary	61.12%	3.38%	7.99%	0.62%	8.76%	3.18%	7.87%	3.55%	3.54%
Ireland	42.18%	14.08%	7.41%	1.88%	9.15%	3.62%	6.24%	14.10%	1.34%
Italy	42.36%	7.38%	12.64%	1.35%	9.90%	4.29%	1.86%	16.95%	3.26%
Latvia	65.76%	4.14%	4.62%	1.00%	11.45%	2.16%	4.21%	4.86%	1.80%
Lithuania	64.93%	3.46%	6.52%	1.27%	10.53%	2.66%	6.26%	3.07%	1.30%
Luxembourg	56.60%	11.96%	3.85%	0.84%	4.86%	4.02%	3.38%	13.43%	1.05%
Malta	50.36%	4.77%	6.91%	0.73%	4.29%	0.83%	2.38%	28.13%	1.60%
Netherlands	35.21%	26.41%	7.08%	3.76%	3.20%	6.76%	5.13%	7.89%	4.54%
Poland	53.99%	3.68%	12.67%	1.50%	9.02%	2.49%	7.10%	4.08%	5.46%
Portugal	59.96%	3.25%	8.86%	1.71%	12.15%	3.17%	2.35%	7.02%	1.54%
Romania	58.29%	0.37%	13.09%	5.75%	3.30%	3.29%	1.17%	12.86%	1.88%
Slovakia	66.73%	2.26%	9.54%	0.32%	9.69%	3.33%	3.88%	0.66%	3.59%
Slovenia	67.60%	3.10%	7.23%	0.51%	12.59%	5.41%	0.85%	2.12%	0.60%
Spain	46.46%	7.04%	9.05%	0.63%	15.65%	3.66%	3.24%	11.92%	2.36%
Sweden	57.30%	14.70%	6.52%	1.24%	6.12%	8.54%	3.79%	1.13%	0.67%
Non–EU									
Iceland	57.63%	10.33%	8.44%	1.68%	2.83%	8.92%	4.72%	3.31%	2.14%
Norway	64.81%	9.15%	5.56%	0.68%	3.15%	5.67%	8.22%	1.20%	1.56%
Serbia	46.88%	0.77%	8.18%	1.04%	30.78%	3.97%	0.82%	6.30%	1.26%
Switzerland	52.46%	19.76%	6.12%	2.41%	3.06%	3.34%	2.35%	8.92%	1.59%
United Kingdom	53.03%	16.48%	7.34%	2.78%	4.24%	1.90%	5.89%	6.70%	1.64%

Notes: The sampling weights are provided by the data collectors and render the analysis representative at the country level and overall

Table 3-6: EU-SILC$_{Panel}$ – Economic activity by country (weighted statistics)

ACTIVITY	EMPLOYED FULL–TIME	EMPLOYED PART–TIME	SELF-EMPLOYED FULL–TIME	SELF-EMPLOYED PART–TIME	UNEMPLOYED	STUDENT	DISABLED	HOMEMAKER	OTHER INACTIVE
Pooled sample	***52.35%***	***10.82%***	***8.67%***	***1.58%***	***8.93%***	***3.03%***	***4.23%***	***7.98%***	***2.41%***
Austria	53.09%	16.00%	7.95%	1.36%	6.46%	3.47%	1.19%	9.51%	0.96%
Belgium	47.17%	17.40%	7.31%	0.78%	8.46%	3.02%	5.45%	7.58%	2.82%
Bulgaria	63.68%	2.55%	6.61%	0.56%	15.69%	2.18%	3.75%	3.21%	1.77%
Croatia	57.82%	1.29%	6.07%	0.62%	21.62%	3.91%	1.26%	6.59%	0.82%
Cyprus	60.34%	4.39%	6.40%	2.50%	9.89%	3.41%	1.77%	9.79%	1.51%
Czech Republic	64.41%	2.27%	12.33%	0.64%	6.90%	2.63%	4.95%	5.59%	0.27%
Denmark	62.20%	10.69%	5.80%	1.01%	4.74%	6.75%	6.34%	0.72%	1.75%
Estonia	66.77%	5.91%	5.38%	1.02%	7.45%	2.29%	5.67%	5.46%	0.04%
Germany	53.92%	21.03%	3.46%	1.31%	5.17%	4.37%	3.69%	5.32%	1.71%
Greece	36.73%	4.17%	17.94%	1.98%	17.49%	3.11%	1.96%	15.54%	1.07%
Finland	58.33%	6.44%	9.27%	0.93%	8.55%	5.82%	6.09%	3.79%	0.77%
France	57.20%	13.40%	6.62%	0.97%	8.68%	2.07%	4.29%	4.80%	1.98%
Hungary	61.45%	3.24%	7.29%	0.51%	8.31%	2.64%	8.33%	4.16%	4.06%
Ireland	39.57%	14.28%	7.52%	2.00%	9.61%	2.98%	6.62%	16.19%	1.22%
Italy	41.54%	6.71%	13.37%	1.49%	9.86%	3.77%	1.77%	17.83%	3.66%
Latvia	65.51%	4.17%	4.88%	1.04%	12.04%	1.80%	4.02%	4.59%	1.96%
Lithuania	65.47%	3.42%	6.32%	1.10%	10.40%	2.23%	6.70%	3.13%	1.24%
Luxembourg	55.61%	13.42%	4.07%	0.94%	4.95%	3.06%	3.39%	13.88%	0.67%
Malta	48.71%	4.76%	6.89%	0.73%	3.98%	0.82%	2.45%	30.25%	1.41%
Netherlands	35.80%	26.79%	6.61%	3.36%	2.87%	6.30%	4.83%	8.69%	4.76%
Poland	53.07%	3.76%	12.58%	1.60%	9.58%	2.17%	7.48%	3.99%	5.76%
Portugal	59.13%	3.54%	8.85%	1.81%	12.38%	2.68%	2.49%	7.38%	1.75%
Romania	57.81%	0.39%	13.37%	6.59%	3.76%	3.04%	1.42%	12.04%	1.60%
Slovakia	67.12%	2.26%	9.55%	0.32%	10.26%	2.67%	3.75%	0.57%	3.49%
Slovenia	67.89%	3.09%	6.91%	0.48%	12.90%	5.06%	0.82%	2.21%	0.64%
Spain	46.14%	6.83%	9.18%	0.62%	15.91%	3.38%	3.27%	12.26%	2.42%
Sweden	60.14%	16.23%	6.20%	1.25%	4.90%	6.62%	3.26%	0.85%	0.55%
Non–EU									
Iceland	57.80%	10.42%	8.78%	1.75%	2.67%	8.55%	4.56%	3.35%	2.12%
Norway	63.59%	8.27%	5.98%	0.53%	4.44%	6.20%	7.93%	1.52%	1.54%
Serbia	45.57%	0.80%	8.29%	1.09%	31.62%	3.99%	0.89%	6.43%	1.32%
Switzerland	51.84%	21.23%	5.50%	2.48%	2.94%	3.72%	2.56%	8.13%	1.61%
United Kingdom	52.00%	17.62%	7.03%	2.96%	4.02%	1.86%	6.20%	6.88%	1.44%

Notes: The sampling weights are provided by the data collectors and render the analysis representative at the country level and overall

Table 3-7: EU-SILC$_{\text{Cross-sectional}}$ – Summary statistics of key variables

	POOLED SAMPLE				EMPLOYED SAMPLE			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean
Gender (male=1)	6,295,744	48.50%	6,295,693	49.20%	4,526,696	53.20%	4,526,661	54.10%
Years of schooling	6,149,823	11.46	6,149,772	11.53	4,479,088	11.92	4,479,053	11.99
Urban: city	5,631,834	38.10%	5,631,785	44.90%	4,023,423	38.40%	4,023,390	44.90%
Semi-urban: town	5,631,834	26.30%	5,631,785	28.30%	4,023,423	26.40%	4,023,390	28.50%
Rural area	5,631,834	35.00%	5,631,834	26.00%	4,023,423	35.00%	4,023,390	26.60%
Single	6,236,525	32.60%	6,236,474	35.90%	4,520,034	30.00%	4,519,999	33.90%
Married or in civil union	6,236,525	57.00%	6,236,474	53.70%	4,520,034	60.00%	4,519,999	56.00%
Separated, widowed, or divorced	6,236,525	10.40%	6,236,474	10.50%	4,520,034	10.00%	4,519,999	10.10%
Age	6,295,784	43.05	6,295,733	41.9	4,526,707	43.33	4,526,672	42.03
Individual was born in the native country	6,235,680	90.20%	6,235,629	89.10%	4,517,915	90.80%	4,517,880	90.00%
Immigrant born in another EU country	6,235,680	3.40%	6,235,629	3.00%	4,517,915	3.40%	4,517,880	3.10%
Immigrant born outside EU	6,235,680	6.40%	6,235,629	7.90%	4,517,915	5.70%	4,517,880	7.00%
Limitation in activities due to health issues	5,327,627	18.7%	5,327,577	17.7%	3,847,934	13.9%	3,847,900	12.9%
Suffer from a chronic illness	5,330,829	25.0%	5,330,779	24.6%	3,849,959	20.7%	3,849,925	20.6%
Educational attainment level: ISCED 0	6,149,823	0.70%	6,149,772	0.80%	4,479,088	0.30%	4,479,053	0.30%
-“-: ISCED 1	6,149,823	7.20%	6,149,772	6.60%	4,479,088	4.80%	4,479,053	4.30%
-“-: ISCED 2	6,149,823	16.00%	6,149,772	16.80%	4,479,088	12.90%	4,479,053	13.70%
-“-: ISCED 3	6,149,823	44.10%	6,149,772	42.60%	4,479,088	45.00%	4,479,053	43.30%
-“-: ISCED 4	6,149,823	3.80%	6,149,772	3.90%	4,479,088	4.00%	4,479,053	4.20%
-“-: ISCED 5-8	6,149,823	28.20%	6,149,772	29.30%	4,479,088	33.10%	4,479,053	34.20%
Previous employment experience	1,636,466	69.30%	1,636,450	70.50%	22,158	100.00%	22,158	100.00%
Years of experience in paid work	4,359,769	20.0	4,359,728	18.87	3,446,003	21.0	3,445,971	19.82
Actively looking for a job	1,416,841	29.30%	1,416,831	29.10%	16,152	13.30%	16,152	14.60%
Hours worked per week in the main job	4,453,543	38.95	4,453,509	38.52	4,440,105	38.98	4,440,071	38.56
Permanent contract	4,032,690	83.50%	4,032,658	81.70%	3,305,608	87.20%	3,305,583	85.80%
Managerial position	4,096,582	20.50%	4,096,548	22.50%	3,326,055	22.80%	3,326,028	24.90%
Change of job since last year	3,142,501	8.00%	3,142,474	8.70%	3,132,011	7.90%	3,131,984	8.60%
NACE of main job: (a) Agriculture, forestry	4,112,132	5.80%	4,112,097	4.60%	4,099,009	5.80%	4,098,974	4.60%
-“-: (b-e) Mining and quarrying,	4,112,132	18.70%	4,112,097	18.20%	4,099,009	18.70%	4,098,974	18.20%
-“-: (f) Construction	4,112,132	7.30%	4,112,097	7.40%	4,099,009	7.30%	4,098,974	7.40%
-“-: (g) Wholesale and retail trade	4,112,132	13.10%	4,112,097	13.20%	4,099,009	13.10%	4,098,974	13.20%
-“-: (h) Transport and storage	4,112,132	5.50%	4,112,097	5.30%	4,099,009	5.50%	4,098,974	5.30%
-“-: (i) Accommodation and food services	4,112,132	4.10%	4,112,097	3.90%	4,099,009	4.10%	4,098,974	3.90%
-“-: (j) Information and communication	4,112,132	2.40%	4,112,097	2.80%	4,099,009	2.40%	4,098,974	2.80%
-“-: (k) Financial and insurance activities	4,112,132	3.10%	4,112,097	3.40%	4,099,009	3.10%	4,098,974	3.40%
-“-: (l-n) Real estate, Professional, scientific,	4,112,132	8.60%	4,112,097	9.20%	4,099,009	8.60%	4,098,974	9.20%
-“-: (o) Public administration and defence	4,112,132	8.00%	4,112,097	8.10%	4,099,009	8.00%	4,098,974	8.10%
-“-: (p) Education	4,112,132	8.50%	4,112,097	8.00%	4,099,009	8.50%	4,098,974	8.00%
-“-: (q) Human health and social work	4,112,132	9.90%	4,112,097	10.50%	4,099,009	9.90%	4,098,974	10.50%
-“-: (r-u) Arts entertainment & recreation,	4,112,132	5.00%	4,112,097	5.40%	4,099,009	5.00%	4,098,974	5.40%
Employee cash or near cash income (gross)	6,089,665	13,856.32	6,089,614	16,997.74	4,390,732	18,322.40	4,390,697	22,573.85
Cash or losses from self-employment (gross)	6,089,087	1,658.17	6,089,036	1,889.44	4,390,519	2,207.93	4,390,484	2,522.59
HH can face unexpected financial expenses	6,272,702	66.0%	6,272,651	64.9%	4,512,564	72.0%	4,512,529	71.3%
HH can make ends meet with difficulty	6,227,658	54.1%	6,227,607	52.0%	4,478,373	48.5%	4,478,338	45.8%
HH has a heavy financial burden	5,511,931	32.5%	5,511,891	33.2%	3,986,405	27.5%	3,986,376	28.1%

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year.

Table 3-8: EU-SILC$_{Panel}$– Summary statistics of key variables

	POOLED SAMPLE				EMPLOYED SAMPLE			
	UNWEIGHTED		WEIGHTED		UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean	#Obs.	Mean
Gender (male=1)	4,706,595	48.5%	4,436,485	48.8%	4,706,595	48.5%	3,135,190	53.6%
Years of schooling	4,544,375	11.35	4,285,178	11.49	4,544,375	11.35	3,107,333	11.96
Urban: city	4,211,276	37.5%	3,971,667	43.7%	4,211,276	37.5%	2,780,532	43.8%
Semi-urban: town	4,211,276	25.7%	3,971,667	27.4%	4,211,276	25.7%	2,780,532	27.5%
Rural area	4,211,276	36.8%	3,971,667	28.9%	4,211,276	36.8%	2,780,532	28.8%
Single	4,666,958	32.1%	4,399,332	34.7%	4,666,958	32.1%	3,130,729	32.9%
Married or in civil union	4,666,958	57.5%	4,399,332	55.2%	4,666,958	57.5%	3,130,729	57.4%
Separated, widowed, or divorced	4,666,958	10.4%	4,399,332	10.1%	4,666,958	10.4%	3,130,729	9.6%
Age at the date of interview	4,706,680	42.90	4,436,565	42.30	4,706,680	42.90	3,135,244	42.29
Country of birth	192,176	2.04	184,282	2.04	192,176	2.04	125,799	2.03
Country of birth of father	192,280	2.10	184,345	2.10	192,280	2.10	125,828	2.07
Country of birth of mother	192,280	2.09	184,345	2.09	192,280	2.09	125,828	2.06
Individual was born in the native country	192,176	90.6%	184,282	89.7%	192,176	90.6%	125,799	90.4%
Immigrant born in another EU country	192,176	2.9%	184,282	3.1%	192,176	2.9%	125,799	3.2%
Immigrant born outside EU	192,176	6.5%	184,282	7.2%	192,176	6.5%	125,799	6.4%
Limitation in activities due to health issues	4,009,392	18.4%	3,837,445	17.5%	4,009,392	18.4%	2,706,985	12.7%
Suffer from a chronic illness	4,008,972	24.4%	3,836,430	25.5%	4,008,972	24.4%	2,708,227	21.5%
Educational attainment: ISCED 0	4,544,375	0.7%	4,285,178	0.9%	4,544,375	0.7%	3,107,333	0.5%
-”-: ISCED 1	4,544,375	7.3%	4,285,178	6.9%	4,544,375	7.3%	3,107,333	4.3%
-”-: ISCED 2	4,544,375	16.3%	4,285,178	16.6%	4,544,375	16.3%	3,107,333	13.6%
-”-: ISCED 3	4,544,375	44.9%	4,285,178	43.1%	4,544,375	44.9%	3,107,333	44.2%
-”-: ISCED 4	4,544,375	3.6%	4,285,178	2.7%	4,544,375	3.6%	3,107,333	2.9%
-”-: ISCED 5-8	4,544,375	27.2%	4,285,178	29.7%	4,544,375	27.2%	3,107,333	34.5%
Years of experience in paid work	3,555,003	19.72	3,401,455	18.99	3,555,003	19.72	2,646,907	19.99
Employed	4,582,014	61.6%	4,320,086	63.0%	4,582,014	61.6%	3,135,244	85.6%
Self-employed	4,582,014	10.2%	4,320,086	9.8%	4,582,014	10.2%	3,135,244	13.3%
Family worker	4,582,014	0.8%	4,320,086	0.7%	4,582,014	0.8%	3,135,244	1.0%
Actively looking for a job	1,156,935	29.8%	1,097,131	29.2%	1,156,935	29.8%	6,899	16.3%
Hours worked per week in the main job	3,299,769	39.17	3,107,128	38.60	3,299,769	39.17	3,080,930	38.59
Permanent contract	2,737,301	84.6%	2,612,263	83.2%	2,737,301	84.6%	2,287,576	86.1%
Change of job since last year	2,694,465	8.4%	2,573,718	8.4%	2,694,465	8.4%	2,570,917	8.3%
Employee cash or near cash income (gross)	4,550,073	12,765.78	4,283,958	16,824.71	3,225,842	17,117.30	3,032,477	22,202.97
Cash or losses from self-employment (gross)	4,549,547	1,591.47	4,283,609	1,816.00	3,225,642	2,118.57	3,032,336	2,396.65
HH can face unexpected financial expenses	4,692,210	64.5%	4,426,321	65.1%	4,692,210	64.5%	3,128,635	71.5%
HH can make ends meet with difficulty	4,687,524	57.7%	4,421,252	56.8%	4,687,524	57.7%	3,124,395	50.8%
HH has a heavy financial burden	4,429,489	33.7%	4,173,117	33.9%	4,429,489	33.7%	2,994,806	28.6%

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country, and has been deflated using the GDP deflator specific to each country and year.

Finally, both datasets include variables related to the household's financial situation. In the cross-sectional dataset, about 65% of the households in the pooled sample report being able to cover unexpected financial expenses, while the corresponding percentage in the employed subsample is higher at 71%. However, in the pooled sample approximately 52% report having difficulty making ends meet, and 32% of households report facing a heavy financial burden. These figures are slightly lower in the panel dataset, at 46% and 28%, respectively.

3.1.3 STATISTICS ON SKILLS MATCHING

This section provides a detailed analysis of skills matching across countries using two constructed measures of skills mismatching. The data focuses on the alignment between individuals' educational attainment and the requirements of their occupations, which is captured through two distinct definitions. *Definition I* categorises skills mismatch based on the highest educational qualification attained relative to the median educational qualification within the same country, year, and occupation (2-digit ISCO code). Individuals are classified as matched if their education is equal to the median, overeducated if it is higher, and undereducated if it is lower.

In contrast, *Definition II* takes a different approach by focusing on the years of schooling. Under this definition, individuals are considered matched if their years of schooling fall within the range of the mean ± one standard error of the years of schooling by country, year, and occupation (2-digit ISCO code). The following tables, Table 3-9 and Table 3-10, present the distribution of matched, overeducated, and undereducated individuals for both definitions across various countries, providing a comprehensive overview of skills (mis)matching in the labour market across different European countries. As seen in the tables, there is generally consistency between the two definitions with some small exceptions in Estonia, Italy, Malta, Portugal and Switzerland.

Table 3-9 provides skills (mis)matching statistics for the cross-sectional dataset by country, reporting the weighted percentages of individuals classified as matched, overeducated, or undereducated based on two different definitions. The table is divided into three main categories: individuals whose educational qualifications match their job requirements (matched), those who have more education than required (overeducated), and those with less education than required (undereducated). On average, according to *Definition I*, about 58% of individuals are classified as matched, 18% as overeducated, and 21% as undereducated. The corresponding percentages according to *Definition II* are slightly higher: 60% matched, 22% overeducated and 21% undereducated.

The columns labelled "Rank" show the ranking for each measure. Countries with the highest matching according to Definition I are highlighted in blue, while those with the lowest matching in red. Central and Eastern European countries, such as Czech Republic, Slovakia, Croatia, Slovenia, Poland and Bulgaria, rank the highest for matched employees. In contrast, Ireland, Spain, France, Cyprus, Italy, Iceland and Finland rank the lowest rates of matched employees, reflecting higher levels of skills mismatches in these labour markets. Regarding overeducation, countries such as Portugal, France, Spain, Italy and Ireland report some of the highest levels of overeducated employees, while Czech Republic, Germany, Bulgaria, Denmark and Norway report some of the lowest levels. Finally, the highest levels of undereducation are reported in Ireland, Spain, Norway, Italy and Cyprus, while the lowest are reported in Slovakia, Czech Republic, Croatia, Slovenia, Serbia, Poland and Romania.

Then, Table 3-10 presents the weighted skills (mis)matching statistics for the panel dataset by country, using the same methodology and definitions as explained above. The table is divided into the three main categories: skills matching, overeducation, and undereducation. The panel dataset exhibits a similar pattern in the rates of matched employees across countries, with the same countries reporting the highest and lowest rates of matched employees. This trend also holds for overeducation and undereducation, where the countries with the highest and lowest rates remain consistent with those in the cross-sectional dataset.

Table 3-9: EU-SILC$_{Cross\text{-}sectional}$ – Skills matching statistics by country (weighted)

	EMPLOYED		MATCHED				OVEREDUCATED				UNDEREDUCATED			
			Definition I		Definition II		Definition I		Definition II		Definition I		Definition II	
All Countries	***61.27%***	*(Rank)*	***57.89%***	*(Rank)*	***60.30%***	*(Rank)*	***17.97%***	*(Rank)*	***21.61%***	*(Rank)*	***20.75%***	*(Rank)*	***21.49%***	*(Rank)*
Austria	68.4%	12	61.24%	17	55.92%	21	19.44%	12	21.26%	15	19.32%	22	22.82%	12
Belgium	64.3%	20	61.78%	16	56.30%	18	14.06%	20	21.22%	16	24.16%	4	22.48%	14
Bulgaria	66.9%	16	72.51%	7	70.37%	4	11.37%	30	15.46%	26	16.12%	23	14.17%	29
Croatia	60.0%	24	77.22%	3	69.90%	5	12.57%	24	14.02%	31	10.21%	30	16.08%	26
Cyprus	65.5%	18	55.04%	28	50.13%	29	21.28%	7	24.98%	5	23.68%	6	24.89%	7
Czech Republic	65.6%	17	81.07%	1	71.84%	2	9.14%	32	15.43%	27	9.79%	31	12.73%	31
Denmark	68.3%	13	67.35%	11	62.28%	13	11.77%	28	17.68%	20	20.88%	18	20.04%	19
Estonia	72.1%	3	59.85%	20	47.78%	30	19.31%	14	28.44%	1	20.83%	20	23.77%	9
Germany	63.6%	21	69.36%	10	63.31%	12	9.40%	31	16.08%	23	21.24%	16	20.61%	18
Greece	68.6%	9	63.92%	14	59.56%	16	13.38%	22	18.11%	19	22.69%	9	22.33%	15
Finland	70.1%	6	58.29%	23	50.89%	26	20.49%	10	23.47%	6	21.23%	17	25.63%	3
France	42.6%	32	51.91%	30	55.21%	23	25.64%	2	23.31%	7	22.45%	10	21.48%	17
Hungary	64.4%	19	70.31%	8	69.16%	6	15.55%	17	15.25%	28	14.15%	26	15.60%	27
Ireland	55.9%	27	51.41%	31	47.27%	31	21.69%	6	27.55%	2	26.90%	2	25.18%	6
Italy	49.4%	30	53.58%	29	63.52%	11	22.57%	4	19.78%	18	23.85%	5	16.70%	25
Latvia	69.1%	8	62.06%	15	56.10%	20	16.55%	16	22.17%	9	21.39%	14	21.73%	16
Lithuania	68.0%	14	57.23%	25	52.90%	25	20.62%	9	21.48%	14	22.15%	12	25.63%	4
Luxembourg	68.5%	10	58.25%	24	52.96%	24	20.87%	8	21.59%	13	20.87%	19	25.45%	5
Malta	55.1%	28	59.16%	22	67.33%	8	20.32%	11	15.10%	30	20.52%	21	17.57%	23
Netherlands	61.6%	23	60.22%	19	56.25%	19	17.08%	15	19.98%	17	22.70%	8	23.77%	10
Poland	57.3%	26	74.52%	4	68.62%	7	11.81%	27	15.92%	24	13.67%	27	15.47%	28
Portugal	63.0%	22	56.68%	26	60.04%	15	27.34%	1	21.65%	12	15.98%	24	18.31%	21
Romania	58.1%	25	69.59%	9	75.54%	1	15.24%	18	12.07%	32	15.17%	25	12.39%	32
Slovakia	68.5%	11	79.01%	2	66.07%	10	11.95%	26	16.48%	22	9.04%	32	17.45%	24
Slovenia	70.7%	5	74.37%	5	66.78%	9	12.88%	23	15.20%	29	12.75%	29	18.02%	22
Spain	53.4%	29	51.26%	32	50.46%	28	23.73%	3	25.04%	4	25.02%	3	24.50%	8
Sweden	72.0%	4	64.22%	13	60.09%	14	14.47%	19	17.30%	21	21.31%	15	22.61%	13
Non–EU														
Iceland	67.9%	15	55.69%	27	59.42%	17	21.97%	5	21.77%	10	22.34%	11	18.82%	20
Norway	73.9%	1	60.55%	18	55.27%	22	11.50%	29	21.67%	11	27.96%	1	23.06%	11
Serbia	47.6%	31	73.19%	6	70.48%	3	13.97%	21	15.61%	25	12.84%	28	13.92%	30
Switzerland	72.8%	2	64.92%	12	50.67%	27	12.15%	25	22.25%	8	22.93%	7	27.08%	1
United Kingdom	69.9%	7	59.19%	21	47.11%	32	19.33%	13	25.89%	3	21.48%	13	27.00%	2

Notes: Definition I is based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 2-digit ISCO code. Definition II is based on the years of schooling being equal to the mean ± one S.E. of the years of schooling by country, year and 2-digit ISCO code (matched). Countries with the highest matching are highlighted in blue, and those with the lowest matching in red.

Table 3-10: EU-SILC$_{Panel}$ – Skills matching statistics by country (weighted)

	EMPLOYED		MATCHED				OVEREDUCATED				UNDEREDUCATED			
			Definition I		Definition II		Definition I		Definition II		Definition I		Definition II	
All Countries	***63.04%***	*(Rank)*	***62.64%***	*(Rank)*	***59.46%***	*(Rank)*	***17.08%***	*(Rank)*	***19.73%***	*(Rank)*	***20.27%***	*(Rank)*	***20.79%***	*(Rank)*
Austria	69.00%	12	60.98%	17	56.39%	19	19.56%	13	20.84%	13	19.46%	21	22.77%	13
Belgium	64.54%	21	60.91%	18	55.19%	22	14.58%	20	21.71%	10	24.51%	4	23.10%	12
Bulgaria	66.08%	17	72.69%	6	71.53%	3	11.38%	29	14.63%	28	15.93%	24	13.85%	29
Croatia	59.10%	24	76.57%	3	69.86%	5	12.61%	24	13.74%	31	10.82%	30	16.40%	25
Cyprus	64.65%	19	54.08%	29	49.41%	29	21.91%	8	23.75%	6	24.01%	5	26.84%	1
Czech Republic	66.65%	16	81.67%	1	72.58%	2	8.66%	32	14.59%	29	9.67%	31	12.83%	31
Denmark	72.82%	4	67.74%	11	61.13%	14	11.61%	28	18.82%	19	20.65%	16	20.05%	17
Estonia	72.62%	5	59.97%	20	48.49%	30	19.59%	12	28.16%	1	20.44%	18	23.35%	10
Germany	64.73%	18	70.42%	8	64.25%	12	9.20%	31	16.19%	22	20.38%	19	19.56%	18
Greece	70.53%	8	64.98%	13	60.48%	15	13.70%	22	17.93%	21	21.32%	13	21.59%	16
Finland	74.94%	2	55.50%	26	50.17%	28	23.82%	4	24.69%	4	20.68%	15	25.14%	6
France	40.67%	32	52.61%	30	54.60%	24	25.98%	2	22.16%	9	21.41%	12	23.25%	11
Hungary	64.61%	20	70.02%	9	69.26%	6	15.85%	17	15.38%	25	14.13%	26	15.36%	28
Ireland	53.53%	27	50.10%	32	46.20%	32	22.00%	6	27.18%	2	27.90%	1	26.62%	2
Italy	47.94%	30	54.18%	28	65.46%	11	22.70%	5	18.57%	20	23.11%	8	15.97%	27
Latvia	69.22%	11	61.90%	15	55.66%	21	16.09%	16	22.41%	7	22.01%	10	21.93%	15
Lithuania	68.53%	14	56.08%	24	51.82%	26	22.00%	7	22.16%	8	21.92%	11	26.01%	4
Luxembourg	69.00%	13	58.43%	22	54.21%	25	21.70%	9	20.14%	17	19.87%	20	25.65%	5
Malta	53.45%	28	57.57%	23	68.29%	7	21.43%	10	14.22%	30	21.00%	14	17.49%	23
Netherlands	62.54%	22	59.79%	21	55.78%	20	17.62%	15	20.31%	15	22.59%	9	23.91%	9
Poland	56.50%	26	73.99%	5	68.21%	8	12.21%	27	15.81%	23	13.79%	27	15.99%	26
Portugal	62.50%	23	55.79%	25	59.72%	17	26.93%	1	21.24%	11	17.28%	23	19.04%	20
Romania	57.61%	25	69.83%	10	76.50%	1	15.24%	18	10.97%	32	14.92%	25	12.53%	32
Slovakia	69.38%	10	80.04%	2	67.15%	10	11.14%	30	15.74%	24	8.83%	32	17.12%	24
Slovenia	70.95%	7	74.38%	4	67.64%	9	12.37%	25	14.75%	27	13.25%	28	17.61%	22
Spain	52.90%	29	50.84%	31	50.90%	27	24.43%	3	24.33%	5	24.73%	3	24.77%	7
Sweden	76.35%	1	66.99%	12	61.75%	13	15.05%	19	18.88%	18	17.96%	22	19.37%	19
Non–EU														
Iceland	68.19%	15	54.82%	27	60.02%	16	21.26%	11	21.16%	12	23.93%	6	18.82%	21
Norway	71.77%	6	61.21%	16	56.91%	18	12.66%	23	20.71%	14	26.14%	2	22.37%	14
Serbia	46.28%	31	72.59%	7	71.15%	4	14.30%	21	15.21%	26	13.11%	29	13.65%	30
Switzerland	73.74%	3	64.48%	14	55.09%	23	12.26%	26	20.30%	16	23.27%	7	24.61%	8
United Kingdom	69.64%	9	60.45%	19	46.92%	31	19.09%	14	26.97%	3	20.46%	17	26.12%	3

Notes: Definition I is based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 2-digit ISCO code. Definition II is based on the years of schooling being equal to the mean ± one S.E. of the years of schooling by country, year and 2-digit ISCO code (matched). Countries with the highest matching are highlighted in blue, and those with the lowest matching in red.

In the remainder of this subsection, the evolution of skills matching statistics across countries and over time is presented. In each figure, the countries are ordered based on their overall weighted average (calculated across all years) Countries with the lowest overall average appear at the front of the figure, while those with the highest overall average are positioned toward the back. This ordering allows for an easy comparison of countries based on the extent of skills mismatching, helping to identify patterns and trends across different labour markets.

Figure 3-3 presents the weighted percentage of employed individuals by country and year for the cross-sectional dataset, showing notable differences across countries over time. Countries like Norway, Switzerland, Sweden, Estonia and Germany consistently display high rates of employment, reaching close to 80% in several years. In contrast, countries like Greece, Italy, Spain and Ireland exhibit lower rates, particularly in the aftermath of the 2008 financial crisis, where their percentages drop significantly. However, some of these countries show signs of recovery, with the share of employment gradually increasing in recent years (e.g., Ireland, Italy). Additionally, smaller countries such as Malta and Serbia demonstrate lower but relatively stable employment rates compared to larger economies.

Figure 3-4 depicts a similar analysis but for the panel dataset, again showing the weighted percentage of employment by country and year. The general trends observed in the cross-sectional dataset are mirrored in the panel data, with countries like Sweden, Estonia and Norway maintaining high rates of employment throughout the period. Switzerland and Germany have also high levels of employment but as noted in the Table 3-2 they do not have a continued participation in the longitudinal survey. Similar trends in Greece and Spain are also highlighted, where the financial crisis led to steep declines in employment, though recent years show improvements. Interestingly, countries such as Ireland and Italy, which exhibit more variability in the cross-sectional data, show relatively more stability in the panel dataset.

Figure 3-5 presents the weighted percentage of matched employment by country and year for the cross-sectional dataset. This figure illustrates the percentage of employees whose skills align with the requirements of their jobs across different countries and time periods. Countries like the Czech Republic, Slovakia, Croatia, Poland and Slovenia demonstrate consistently high levels of matched employment. This suggests that a significant portion of the workforce in these countries has qualifications that appropriately match the needs of the labour market. In contrast, countries such as Spain, Ireland, Greece, Italy and Cyprus show lower percentages of matched employment, ranging between 40 and 50%.

Figure 3-6 displays similar statistics for the panel dataset, again showing the weighted percentage of matched employment by country and year. The trends observed in the cross-sectional dataset are generally consistent in the panel data. Countries like the Czech Republic, Slovakia, Croatia, Poland and Slovenia still exhibit the highest levels of matched employment, often exceeding 70-80%, while countries such as Spain, Ireland, Greece, Italy and Cyprus report lower levels of matched employment.

Figure 3-7 presents the weighted percentage of overeducated individuals by country and year for the cross-sectional dataset. The figure illustrates significant variations in overeducation across countries and over time, with some countries consistently showing higher percentages of overeducated employment. For instance, Portugal, Greece, Spain, Italy, Iceland and Ireland report the highest overall percentages of overeducated employment, but with fluctuations over time. This suggests that a large portion of the workforce in these countries holds skills above what is required for their main jobs, highlighting a persistent issue of skills mismatching in the national labour markets. In contrast, countries like the Czech Republic, Finland, Bulgaria, Poland and Slovakia consistently show lower levels of overeducation, often below 10%. Other countries, such as Norway, Denmark and Switzerland, show some fluctuations but generally moderate levels of overeducation, ranging between 10-20%.

Figure 3-8 shows the weighted percentage of overeducated employment by country and year for the panel dataset, which tracks individuals over time. The trends seen in the cross-sectional dataset are generally consistent in the panel data. Countries like Portugal, Greece, and Spain still exhibit the highest levels of overeducation, often exceeding 25%, while countries such as the Czech Republic, Finland, Slovakia and Bulgaria report lower levels of overeducation.

Figure 3-9 presents the weighted percentage of undereducated employment by country and year for the cross-sectional dataset. The figure illustrates substantial variations in the levels of undereducation across countries. Countries like Spain, Ireland, Italy, Belgium, Norway and Cyprus consistently display high percentages of undereducated workforce, often exceeding 20-25% in several years. As in overeducation, the trends of undereducation also reveal some fluctuations over time. On the other hand, countries like the Czech Republic, Slovakia, Slovenia, and Croatia report much lower levels of undereducation, often below 10%. Other countries, such as Germany, Finland, Denmark and Sweden, show moderate levels of undereducation, typically fluctuating between 10-20%.

Figure 3-10 presents similar statistics for the panel dataset, focusing on the weighted percentage of undereducated employment by country and year. The trends observed in the cross-sectional data are generally consistent with those in the panel dataset. In general, countries with lower rates of matched employees tend to exhibit higher rates of overeducated and/or undereducated employment, indicating significant skills mismatching in their labour markets. Notable examples include Greece, Spain, Ireland, Italy, and Cyprus.

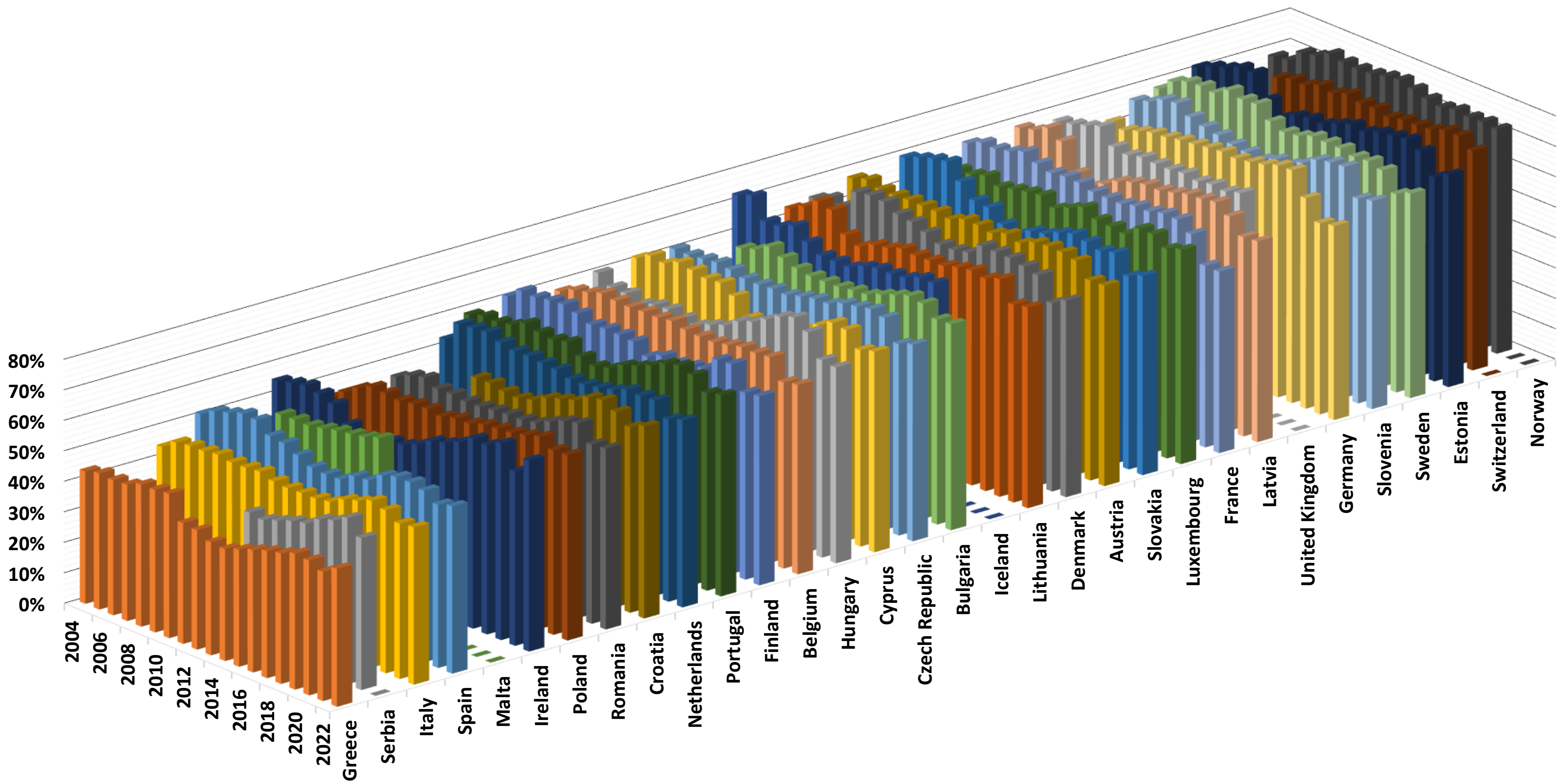


Figure 3-3: EU-SILC$_{Cross\text{-}sectional}$ – % Employed by country and year (weighted)

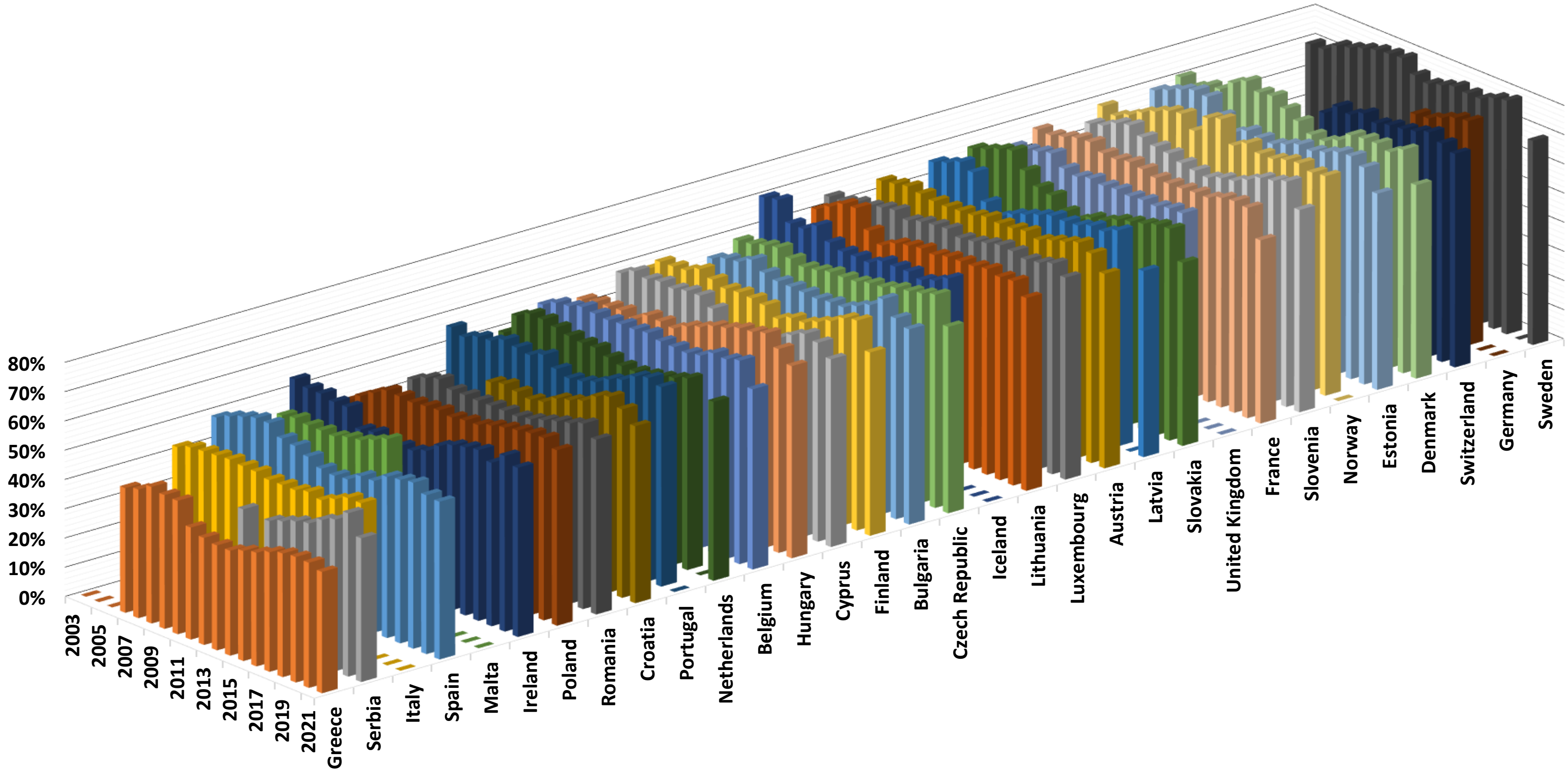


Figure 3-4: EU-SILC$_{Panel}$ – % Employed by country and year (weighted)

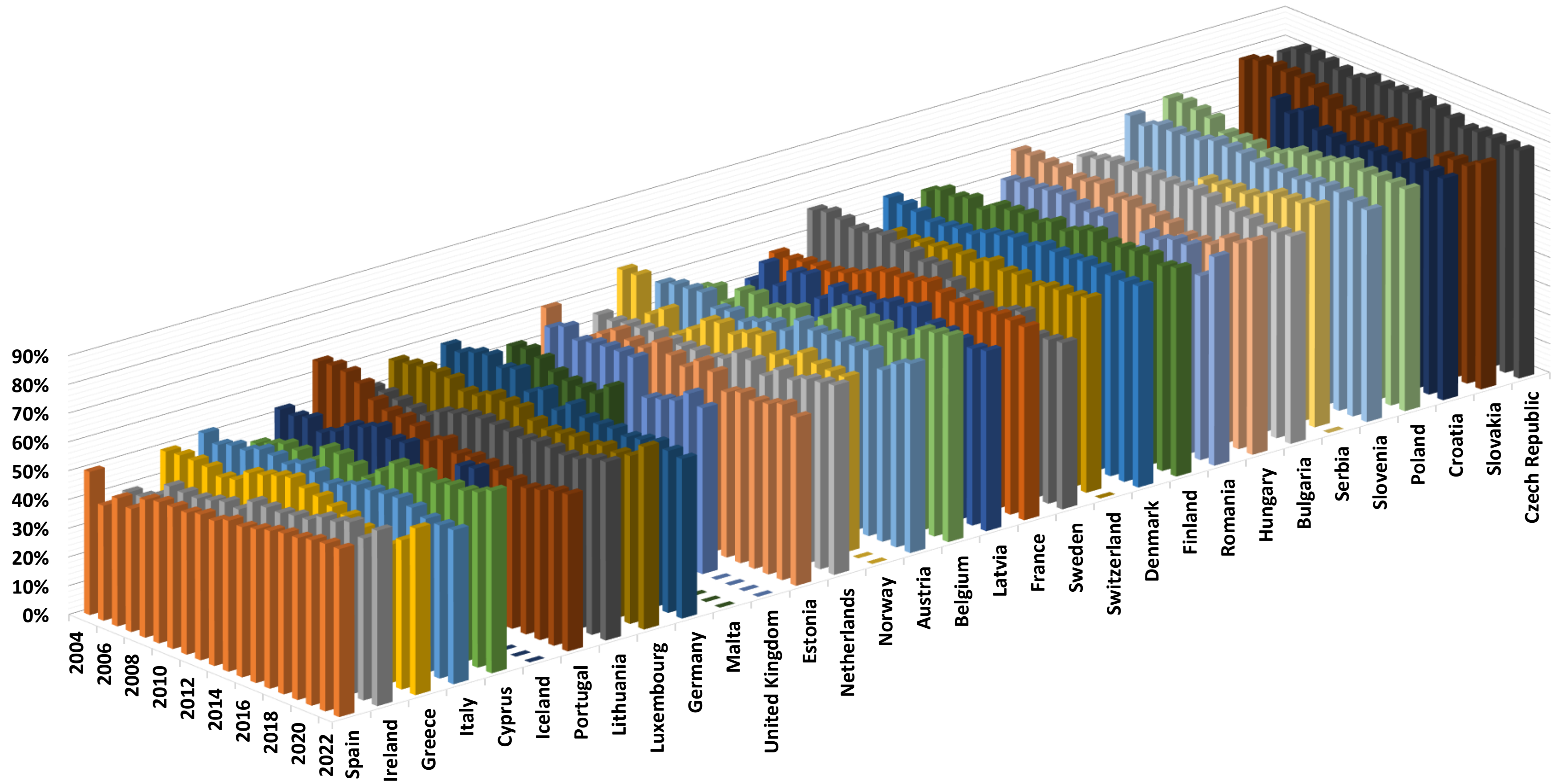


Figure 3-5: EU-SILC$_{Cross\text{-}sectional}$ – % Matched employees by country and year (weighted)

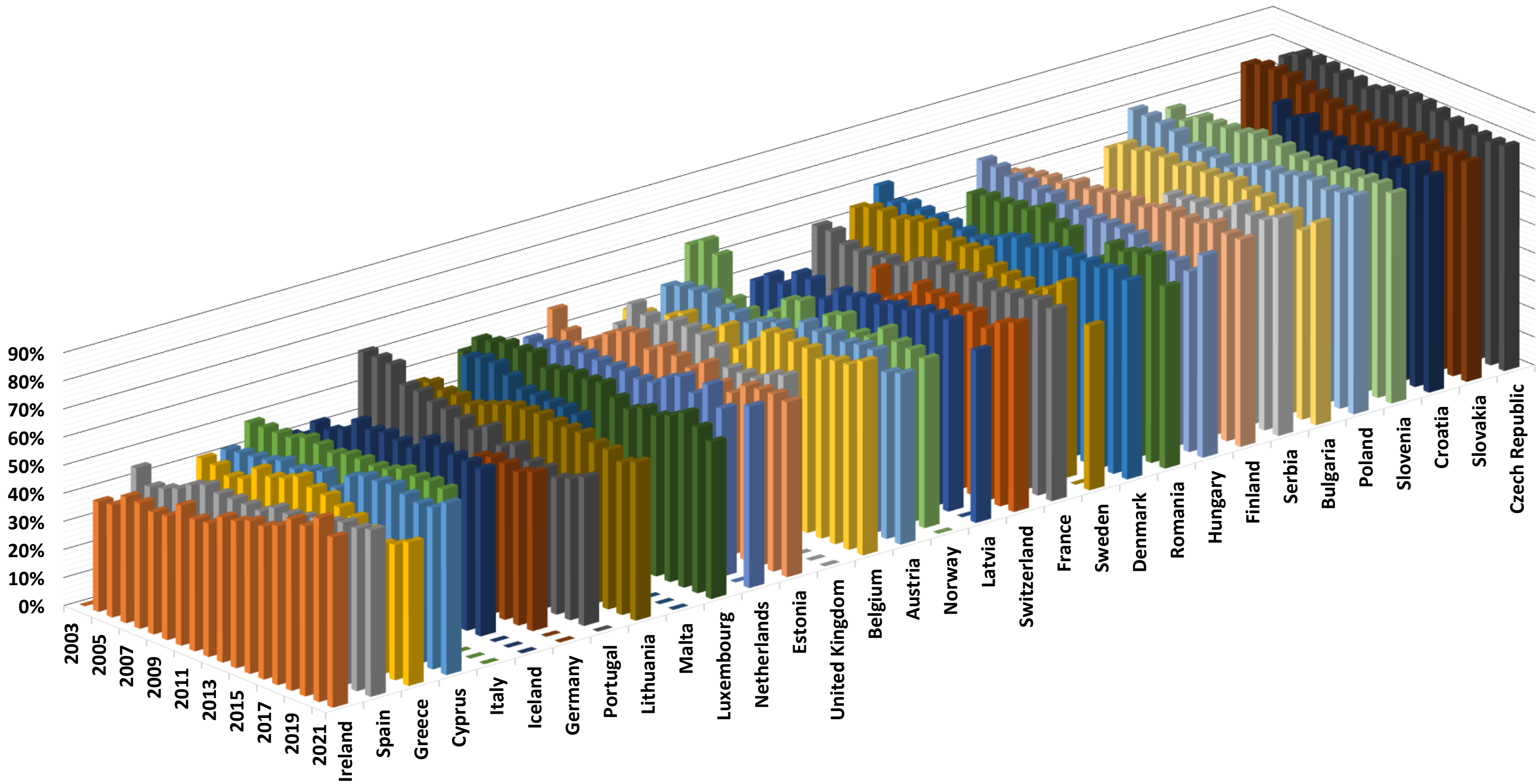


Figure 3-6: EU-SILC$_{Panel}$ – % Matched employees by country and year (weighted)

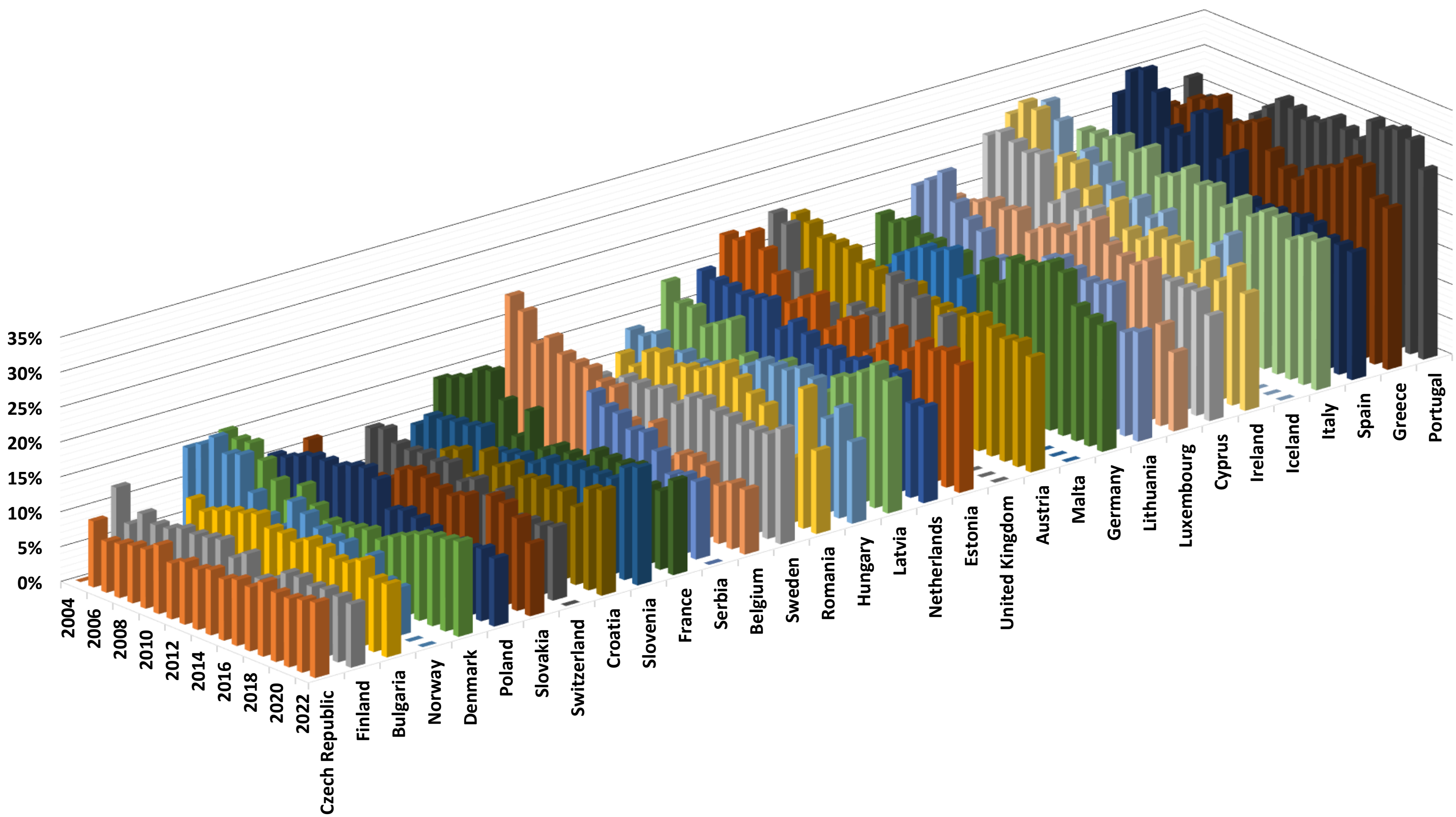


Figure 3-7: EU-SILC$_{Cross\text{-}sectional}$ – % Overeducated employees by country and year (weighted)

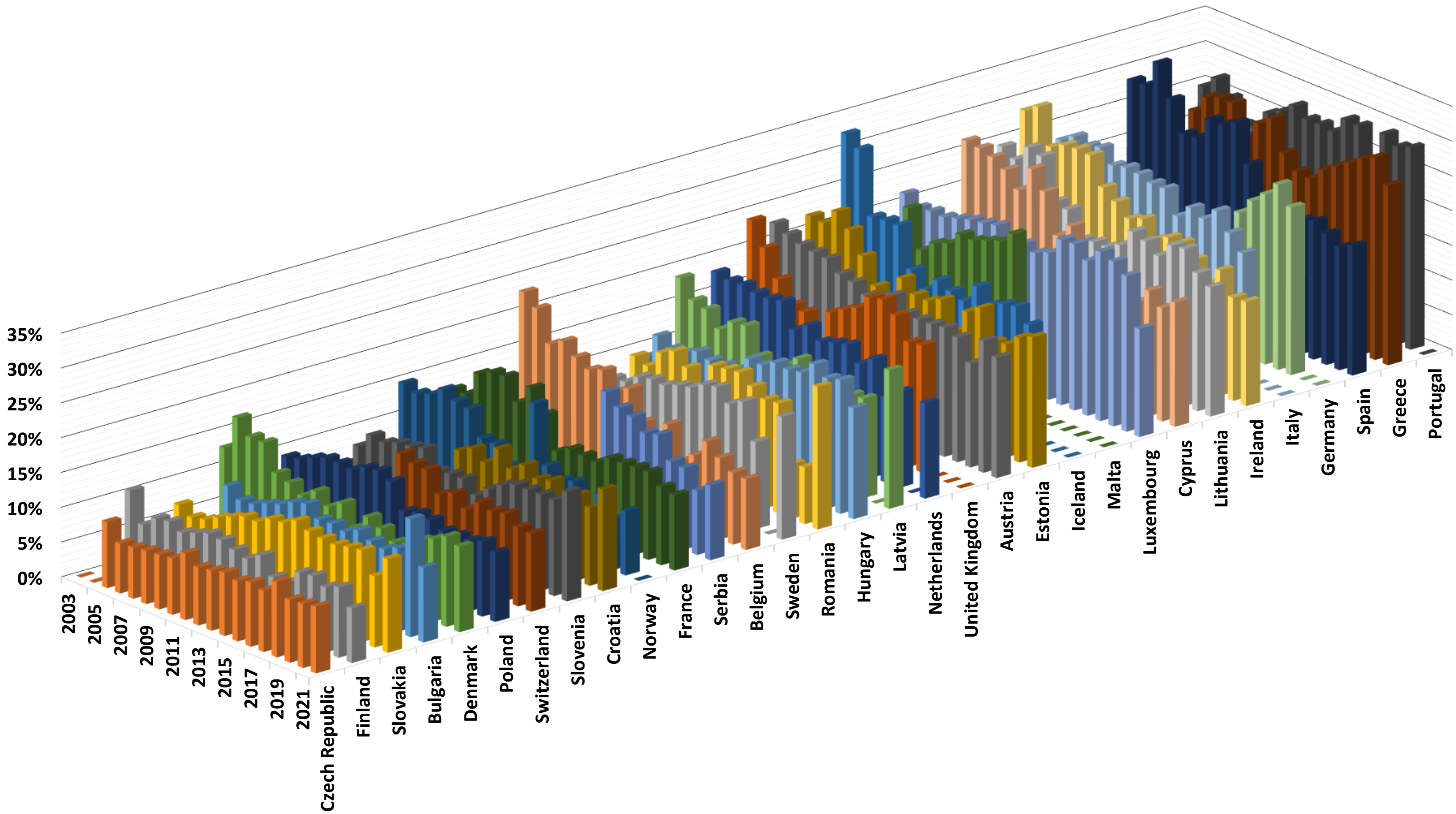


Figure 3-8: EU-SILC$_{Panel}$ – % Overeducated employees by country and year (weighted)

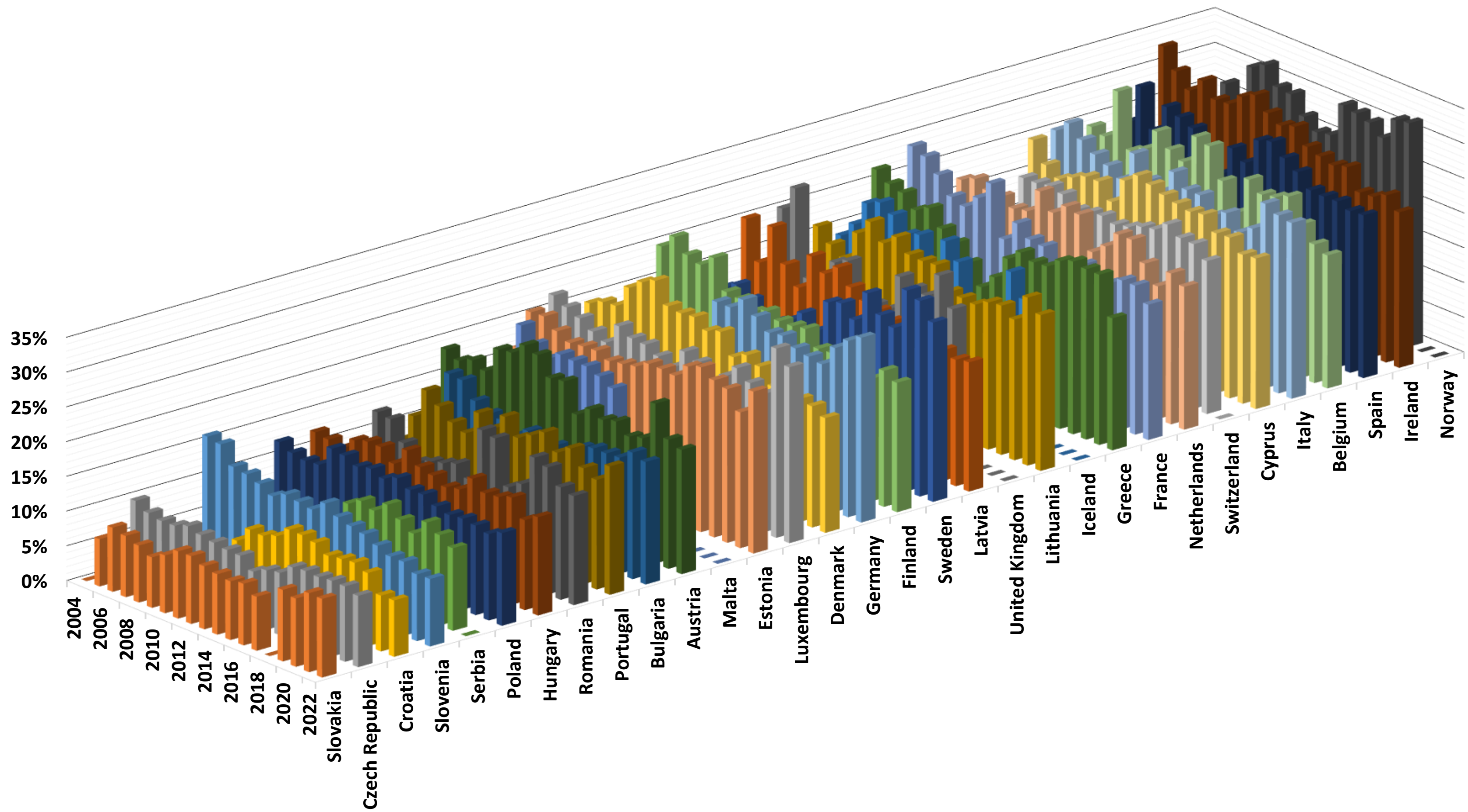


Figure 3-9 EU-SILC$_{Cross\text{-}sectional}$ – % Undereducated employees by country and year (weighted)

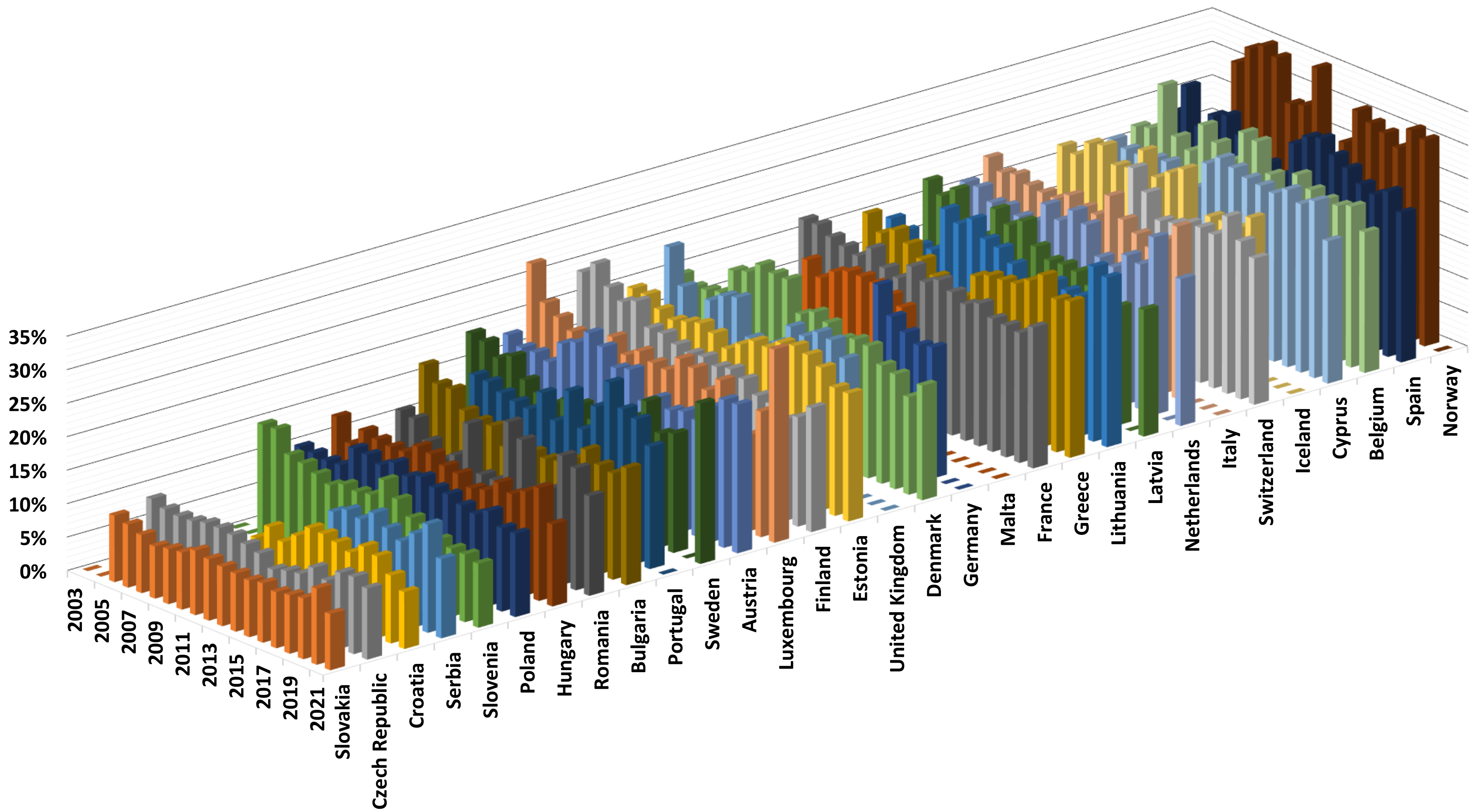


Figure 3-10: EU-SILC$_{Panel}$ – % Undereducated employees by country and year (weighted)

Finally, Table 3-11 and Table 3-12 present weighted statistics (matched, overeducated, and undereducated) and estimates on differences in means for key variables based on matching status for the cross-sectional and panel datasets, respectively. These tables help to compare characteristics across different categories of employees based on their skills matching to their jobs. The key variables include demographic, socioeconomic, and labour market characteristics. The columns labeled “DIFF” in both tables show the differences in means between matched and mismatched individuals (either overeducated or undereducated) for each key variable. These coefficients quantify how the average of a given variable differs between the two groups, with significant differences highlighted in the column labelled “SIGN”. The asterisks *, **, *** denote the levels of significance 1%, 5% and 10%, respectively.

The findings from Table 3-11, for the cross-sectional dataset, show some notable contrasts across key variables related to gender, education, age, and employment characteristics for matched, overeducated, and undereducated employed. While the percentage of male employed is similar across the three groups, the level of educational attainment varies significantly. Matched employees have an average of 12.26 years of schooling, while overeducated employees have a higher average of 14.55 years, and undereducated employees have only 8.76 years on average, indicating a strong relationship between overeducation and higher educational attainment, as well as undereducation and lower attainment.

In terms of age, matched employees tend to be older, with an average age of 41.9 years, compared to the overeducated (40.3) and undereducated (44.1). Additionally, immigrants born outside the EU are more likely to experience mismatching, with 9% of this group classified as mismatched compared to 5% in the matched group.

Employment characteristics also reveal interesting differences. Matched employees are more likely to hold permanent contracts (87%), compared to mismatched employees (84%). In addition, undereducated employees tend to have more years of paid work experience (22.3 years) compared to matched employees (19.7 years), suggesting that experience might compensate for lower educational levels in some sectors of the labour market. In terms of earned income, matched employees report higher personal cash or near cash earnings than mismatched employees.

At the household level, the financial situation of employees also varies by matching status. Around 73% of matched employees live in households that can cover unexpected financial expenses, compared to a lower rate of 64% for undereducated employees. Additionally, higher rates are observed among households of mismatched employees, who report having difficulty making ends meet and facing a heavy financial burden compared to households of matched employees.

The trends observed for the panel dataset in Table 3-12 are quite similar to those using cross-sectional analysis in Table 3-11.

Table 3-11: EU-SILC$_{\text{Cross-sectional}}$– Differences in means of key variables my matching status

#Observations	MATCHED 2,800,776	MISMATCHED 1,616,762	OVEREDUCATED 733,883	UNDEREDUCATED 882,879	DIFF.	SIGN.
Male	54.0%	54.0%	53.0%	55.0%	-0.003	***
Years of schooling	12.26	11.56	14.55	8.97	0.701	***
Urban: city	44.0%	45.0%	48.0%	43.0%	-0.008	***
Semi-urban: town	28.0%	29.0%	28.0%	30.0%	-0.007	***
Rural area	27.0%	26.0%	24.0%	28.0%	0.015	***
Single	34.0%	34.0%	38.0%	31.0%	-0.007	***
Married or in civil union	57.0%	55.0%	53.0%	57.0%	0.016	***
Separated, widowed, or divorced	10.0%	11.0%	9.0%	12.0%	-0.009	***
Age	41.90	42.32	40.29	44.08	-0.423	***
Year of immigration	1997	1999	2001	1997	-1.916	***
Individual was born in the native country	92.0%	87.0%	86.0%	88.0%	0.047	***
Immigrant born in another EU country	3.0%	4.0%	4.0%	3.0%	-0.010	***
Immigrant born outside EU	5.0%	9.0%	10.0%	9.0%	-0.037	***
Limitation in activities due to health issues	12.0%	14.0%	11.0%	16.0%	-0.014	***
Suffer from a chronic illness	20.0%	21.0%	19.0%	24.0%	-0.011	***
Education attainment level: ISCED 0	0.0%	1.0%	0.0%	2.0%	-0.009	***
Education attainment level: ISCED 1	1.0%	9.0%	0.0%	17.0%	-0.082	***
Education attainment level: ISCED 2	7.0%	25.0%	1.0%	45.0%	-0.179	***
Education attainment level: ISCED 3	55.0%	25.0%	17.0%	32.0%	0.299	***
Education attainment level: ISCED 4	2.0%	8.0%	14.0%	4.0%	-0.069	***
Education attainment level: ISCED 5-8	36.0%	32.0%	68.0%	0.0%	0.041	***
Previous employment experience	100.0%	100.0%	100.0%	100.0%	0.000	
Years of experience in paid work	19.70	20.02	17.42	22.34	-0.318	***
Actively looking for a job	17.0%	13.0%	23.0%	10.0%	0.035	***
Hours worked per week in the main job	10.97	10.93	10.75	11.12	0.041	
Permanent contract	87.0%	84.0%	85.0%	84.0%	0.024	***
Managerial position	25.0%	24.0%	26.0%	22.0%	0.016	***
Change of job since last year	8.0%	9.0%	10.0%	8.0%	-0.007	***
NACE: (a) Agriculture, forestry & fishing	4.0%	5.0%	6.0%	5.0%	-0.009	***
-“-: (b-e) Mining and quarrying,	19.0%	18.0%	18.0%	18.0%	0.007	***
-“-: (f) Construction	7.0%	7.0%	6.0%	8.0%	0.003	***
-“-: (g) Wholesale and retail trade	12.0%	14.0%	14.0%	15.0%	-0.019	***
-“-: (h) Transport and storage	5.0%	5.0%	6.0%	5.0%	-0.003	***
-“-: (i) Accommodation and food services	3.0%	5.0%	4.0%	5.0%	-0.016	***
-“-: (j) Information and communication	3.0%	2.0%	2.0%	3.0%	0.005	***
-“-: (k) Financial and insurance activities	3.0%	4.0%	5.0%	3.0%	-0.008	***
-“-: (l-n) Real estate, Professional, scientific,	9.0%	9.0%	10.0%	8.0%	0.002	***
-“-: (o) Public administration and defence	8.0%	9.0%	10.0%	8.0%	-0.012	***
-“-: (p) Education	10.0%	5.0%	4.0%	5.0%	0.056	***
-“-: (q) Human health and social work	11.0%	10.0%	9.0%	10.0%	0.009	***
-“-: (r-u) Arts entertainment and recreation,	5.0%	6.0%	7.0%	6.0%	-0.016	***
Employee cash or near cash income (gross)	22,880.3	21,686.3	23,225.7	20,366.0	1,200	***
Cash or losses from self-employment (gross)	2,446.5	2,561.2	2,699.4	2,442.6	-110	***
HH can face unexpected financial expenses	73.0%	69.0%	74.0%	64.0%	0.043	***
HH can make ends meet with difficulty	45.0%	48.0%	44.0%	51.0%	-0.033	***
HH has a heavy financial burden	27.0%	30.0%	28.0%	32.0%	-0.033	***

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year. *, **, *** denote statistical significance at 10%, 5%, 1%.

Table 3-12: EU-SILC$_{Panel}$– Differences in means of key variables my matching status

	MATCHED	MISMATCHED	OVEREDUCATED	UNDEREDUCATED	DIFF.	SIGN.
#Observations	*2,800,776*	*1,616,762*	*733,883*	*882,879*		
Gender (male=1)	53.0%	54.0%	52.0%	55.0%	-0.008	***
Years of schooling	12.26	11.43	14.59	8.76	0.833	***
Household living in a city	43.0%	44.0%	47.0%	42.0%	-0.008	***
Household living in a town	27.0%	28.0%	27.0%	28.0%	-0.007	***
Household living in a rural area	29.0%	28.0%	26.0%	30.0%	0.015	***
Single	33.0%	33.0%	38.0%	28.0%	0.002	*
Married or in civil union	58.0%	57.0%	54.0%	60.0%	0.008	***
Separated, widowed, or divorced	9.0%	10.0%	8.0%	12.0%	-0.010	***
Age at the date of interview	42.00	42.83	3988.0%	45.31	-0.830	***
Country of birth	2.02	2.06	2.05	2.06	-0.038	***
Country of birth of father	2.05	2.09	2.10	2.08	-0.042	***
Country of birth of mother	2.05	2.09	2.09	2.08	-0.040	***
Individual was born in the native country	92.0%	87.0%	87.0%	88.0%	0.048	***
Immigrant born in another EU country	3.0%	3.0%	4.0%	3.0%	-0.005	***
Immigrant born outside EU	5.0%	9.0%	9.0%	9.0%	-0.043	***
Limitation in activities due to health issues	12.0%	14.0%	11.0%	16.0%	-0.017	***
Suffer from a chronic illness	21.0%	22.0%	19.0%	25.0%	-0.015	***
Education attainment level: ISCED 0	0.0%	1.0%	0.0%	2.0%	-0.012	***
Education attainment level: ISCED 1	1.0%	11.0%	0.0%	20.0%	-0.101	***
Education attainment level: ISCED 2	7.0%	26.0%	1.0%	47.0%	-0.189	***
Education attainment level: ISCED 3	56.0%	24.0%	18.0%	29.0%	0.321	***
Education attainment level: ISCED 4	1.0%	6.0%	10.0%	2.0%	-0.051	***
Education attainment level: ISCED 5-8	36.0%	32.0%	71.0%	0.0%	0.032	***
Years of experience in paid work	19.73	20.34	16.73	23.41	-0.607	***
Employed	86.0%	84.0%	84.0%	84.0%	0.022	***
Self-employed	13.0%	15.0%	15.0%	15.0%	-0.018	***
Family worker	1.0%	1.0%	1.0%	1.0%	-0.004	***
Actively looking for a job	18.0%	15.0%	27.0%	11.0%	0.024	
Hours worked per week in the main job	38.87	38.22	38.50	37.98	0.657	***
Permanent contract	87.0%	85.0%	84.0%	85.0%	0.024	***
Change of job since last year	8.0%	9.0%	10.0%	7.0%	-0.008	***
Employee cash or near cash income (gross)	22,574.83	20,916.77	21,761.00	20,208.88	1,700	***
Cash or losses from self-employment (gross)	2,371.24	2,433.20	2,516.95	2,362.98	-61.96	***
HH can face unexpected financial expenses	73.0%	69.0%	74.0%	65.0%	0.044	***
HH can make ends meet with difficulty	50.0%	54.0%	50.0%	57.0%	-0.040	***
HH has a heavy financial burden	28.0%	31.0%	29.0%	33.0%	-0.037	***

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year. *, **, *** denote statistical significance at 10%, 5%, 1%.

3.1.4 DIFFERENCES BY GENDER

In the following three subsections, we analyse differences across key demographic groups (gender, age, income status). For this analysis, we proceed with the cross-sectional version of the EU-SILC to avoid repetition across datasets, given space considerations.

In this subsection we focus on gender differences in employment, skills mismatching, overeducation, and undereducation. Table 3-13 presents a breakdown of these categories for males and females. For each of the four categories the first two columns show the weighted percentage of individuals in that category by gender. The third column labeled "Difference" displays the percentage-point difference between males and females in each category.

On average across all countries, 80.6% of males are employed compared to 65.7% of females, resulting in a 14.8 percentage point (pp) gap in favor of males. This disparity is particularly stark in countries like Malta (44.3 pp), Italy (27.8 pp), Greece (27.4 pp), Luxembourg (22.1 pp), Romania (21.3 pp), and Spain (20.3 pp), where the gap significantly exceeds the average. This suggests that labour market participation among women in these countries is considerably lower than that of men. Conversely, countries like Lithuania, Estonia, Latvia, Finland, and Sweden report the smallest gender differences in employment, with gaps under 6 pp, indicating more balanced employment rates between genders.

In terms of skills mismatching, gender differences vary across countries. On average, there is only a 0.3 pp difference between males (38.9%) and females (38.6%), but this is because some countries show higher mismatching rates among female employees (e.g., Slovakia, Poland, Czech Republic, Germany, Slovenia, Italy) while in other countries mismatching is more pronounced among male employees (e.g., Norway, Sweden, Denmark, Ireland, Spain).

Countries also show notable disparities in gender differences in overeducation. For instance, in Slovenia, Estonia, Latvia, Cyprus and Poland, the percentage of overeducated female employees is higher than that of male employees. In contrast, fewer countries, such as Lithuania and Iceland, report higher rates of overeducated male employees compared to females. Countries like Italy and Denmark exhibit no gender gap in overeducation, with equal percentages of men and women experiencing overeducation. Finally, gender differences are more pronounced when it comes to undereducation, although disparities vary by country. For example, Norway, Sweden, Latvia, Finland, Ireland, the Netherlands and Belgium, there is a 5.9 pp or greater difference in undereducation among male employees compared to females.

Figure 3-11 provides a visual description of gender differences in skills mismatching by country. The bars represent the percentage point difference between males and females for overeducated (black bars) and undereducated (white bars) employees, while the red diamonds indicate overall mismatching rates. Countries on the left, such as Slovakia, Poland, and the Czech Republic, exhibit higher mismatching among female employees (negative differences), while countries like Norway, Sweden, Denmark, and Ireland on the right display higher mismatching among male employees (positive differences). Overall, the figure highlights that gender disparities in skills mismatching vary considerably across countries, with some showing pronounced differences in either overeducation or undereducation.

Table 3-13: EU-SILC$_{Cross-sectional}$– Gender differences by country (male vs. female)

	EMPLOYMENT			MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	Male	Female	Difference	Male	Female	Difference	Male	Female	Difference	Male	Female	Difference
All countries	80.6%	65.7%	14.8 pp	38.9%	38.6%	0.3 pp	17.6%	18.4%	-0.8 pp	21.3%	20.1%	1.1 pp
Malta	87.0%	42.7%	44.3 pp	42.2%	38.4%	3.9 pp	20.1%	20.8%	-0.7 pp	22.2%	17.6%	4.6 pp
Italy	78.9%	51.0%	27.8 pp	46.0%	47.0%	-1.0 pp	22.6%	22.6%	0.0 pp	23.5%	24.4%	-0.9 pp
Greece	78.4%	51.2%	27.2 pp	49.6%	46.0%	3.6 pp	25.8%	25.4%	0.4 pp	23.8%	20.6%	3.2 pp
Luxembourg	85.0%	62.9%	22.1 pp	42.8%	40.4%	2.5 pp	21.2%	20.4%	0.8 pp	21.6%	19.9%	1.7 pp
Romania	88.4%	67.1%	21.3 pp	29.9%	31.2%	-1.3 pp	15.1%	15.4%	-0.3 pp	14.7%	15.7%	-1.0 pp
Spain	74.3%	54.0%	20.3 pp	50.9%	46.0%	5.0 pp	24.7%	22.5%	2.2 pp	26.3%	23.5%	2.8 pp
Austria	86.1%	69.3%	16.7 pp	37.9%	39.8%	-1.9 pp	19.6%	19.3%	0.3 pp	18.4%	20.5%	-2.2 pp
Netherlands	80.7%	64.9%	15.7 pp	41.5%	37.7%	3.8 pp	16.3%	18.0%	-1.7 pp	25.2%	19.7%	5.5 pp
Ireland	73.8%	58.1%	15.7 pp	51.0%	45.8%	5.2 pp	21.4%	22.1%	-0.7 pp	29.6%	23.7%	5.9 pp
Switzerland	88.9%	74.6%	14.4 pp	34.7%	35.5%	-0.7 pp	12.7%	11.5%	1.1 pp	22.1%	24.0%	-1.9 pp
Cyprus	81.3%	67.8%	13.5 pp	44.3%	45.7%	-1.5 pp	19.0%	23.8%	-4.8 pp	25.2%	21.9%	3.3 pp
Czech Republic	85.3%	72.1%	13.3 pp	16.7%	21.7%	-5.0 pp	8.7%	9.7%	-1.0 pp	8.1%	12.0%	-4.0 pp
Belgium	79.1%	66.4%	12.7 pp	40.1%	36.1%	3.9 pp	13.3%	14.9%	-1.6 pp	26.8%	21.2%	5.6 pp
Croatia	73.4%	60.8%	12.6 pp	21.8%	23.9%	-2.1 pp	11.8%	13.5%	-1.6 pp	10.0%	10.5%	-0.5 pp
Poland	78.5%	66.9%	11.6 pp	22.8%	28.5%	-5.7 pp	9.8%	14.1%	-4.3 pp	13.0%	14.4%	-1.3 pp
Portugal	80.0%	68.6%	11.5 pp	44.7%	41.8%	3.0 pp	27.8%	26.8%	1.0 pp	16.9%	14.9%	2.0 pp
Germany	81.5%	70.3%	11.2 pp	40.0%	43.6%	-3.5 pp	19.9%	21.2%	-1.3 pp	20.2%	22.4%	-2.2 pp
France	82.9%	72.0%	10.9 pp	35.7%	36.4%	-0.7 pp	12.3%	14.6%	-2.3 pp	23.5%	21.8%	1.6 pp
Serbia	62.5%	52.0%	10.5 pp	27.4%	26.1%	1.3 pp	13.7%	14.3%	-0.6 pp	13.7%	11.8%	1.9 pp
Iceland	83.0%	73.5%	9.5 pp	45.0%	43.5%	1.5 pp	23.5%	20.2%	3.2 pp	21.5%	23.3%	-1.7 pp
Hungary	77.9%	68.5%	9.4 pp	27.8%	31.8%	-4.0 pp	14.3%	16.9%	-2.6 pp	13.5%	14.9%	-1.4 pp
United Kingdom	84.7%	75.5%	9.1 pp	42.7%	38.7%	4.0 pp	18.9%	19.8%	-0.9 pp	23.8%	18.9%	4.9 pp
Slovakia	82.9%	75.0%	7.9 pp	18.0%	24.5%	-6.5 pp	10.0%	14.2%	-4.1 pp	7.9%	10.3%	-2.4 pp
Norway	83.8%	76.7%	7.1 pp	43.9%	34.5%	9.4 pp	11.8%	11.2%	0.6 pp	32.1%	23.3%	8.7 pp
Denmark	78.9%	72.0%	6.9 pp	35.4%	29.5%	5.9 pp	11.8%	11.8%	0.0 pp	23.6%	17.8%	5.8 pp
Slovenia	81.7%	74.9%	6.7 pp	24.2%	27.3%	-3.1 pp	10.1%	16.1%	-6.0 pp	14.1%	11.2%	2.9 pp
Bulgaria	77.4%	71.0%	6.4 pp	28.8%	26.0%	2.8 pp	11.3%	11.5%	-0.2 pp	17.6%	14.5%	3.1 pp
Sweden	82.5%	76.9%	5.6 pp	39.3%	31.9%	7.4 pp	14.0%	15.0%	-0.9 pp	25.3%	16.9%	8.3 pp
Finland	75.5%	71.8%	3.7 pp	32.2%	29.0%	3.2 pp	7.9%	11.0%	-3.2 pp	24.3%	18.0%	6.3 pp
Latvia	77.6%	74.1%	3.5 pp	40.2%	35.8%	4.4 pp	14.2%	18.8%	-4.6 pp	26.0%	17.0%	9.0 pp
Estonia	80.6%	77.5%	3.1 pp	40.6%	39.7%	0.9 pp	16.4%	22.2%	-5.8 pp	24.2%	17.5%	6.6 pp
Lithuania	77.3%	75.6%	1.7 pp	44.5%	41.1%	3.4 pp	22.9%	18.3%	4.6 pp	21.5%	22.8%	-1.3 pp

Notes: Countries are ordered based on the percentage point difference between males and females in employment, from highest to lowest.

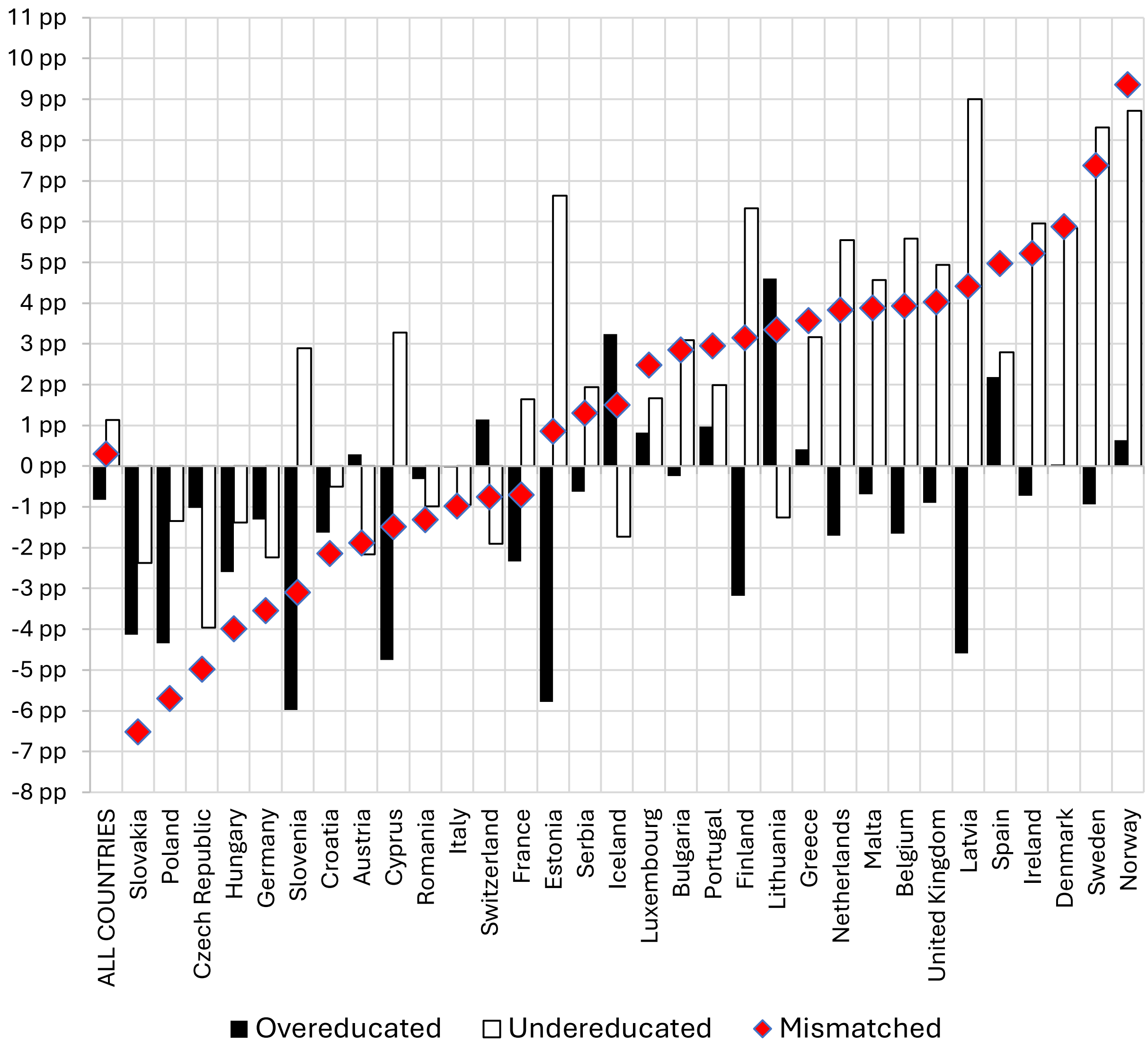


Figure 3-11: EU-SILC$_{Cross\text{-}sectional}$ – Gender differences in skills mismatching by country

The following figures provide a visual representation of gender differences in employment and skills mismatching by country and year, showing how these differences evolve across European countries and over time.

Figure 3-12 illustrates gender differences in employment by country and year. In countries such as Italy and Greece, although gender disparities in favor of males have decreased over the years, they remain high in recent years, around 20-30%. Evident decreases in gender differences are also observed in Spain, Luxembourg, Czech Republic and Switzerland. In contrast, Lithuania, Estonia and Latvia show relatively balanced employment rates between men and women, with minimal changes over time, especially around 2008-2009.

Figure 3-13 presents gender differences in mismatching. Countries like Sweden, Norway, Denmark, and Ireland consistently show a gap where male employees are more likely to be mismatched over time. In contrast, countries such as Slovakia, Poland, the Czech Republic, and Hungary display negative gender differences, indicating higher mismatching rates among female employees, particularly in the early part of the observed period. Interestingly, in Estonia, the patterns of mismatching have shifted over time. After 2012, mismatching became more pronounced among male employees, whereas before it was higher among female employees. A reverse trend is observed in Cyprus, where mismatching rates shifted from being higher among males before 2010 to being higher among females afterwards. Finally, countries such as Greece and Luxembourg have witnessed a decrease in gender differences in mismatching, while Lithuania and Latvia have experienced an increase.

Figure 3-14 highlights gender differences in overeducation, with most countries and years showing negative differences, indicating that female employees are consistently more overeducated than their male counterparts. Notable exceptions where male overeducation rates exceed those of females are observed in Lithuania and Spain (particularly in recent years), as well as in Portugal, Norway, and Switzerland during the earlier years of the observed period.

Finally, Figure 3-15 illustrates gender differences in undereducation, revealing distinct disparities across countries. In countries below the “ALL COUNTRIES” average, female employees consistently have higher undereducation rates compared to males, with a few exceptions in the most recent years where this trend reverses. Conversely, in countries above the average, males are consistently more undereducated than females.

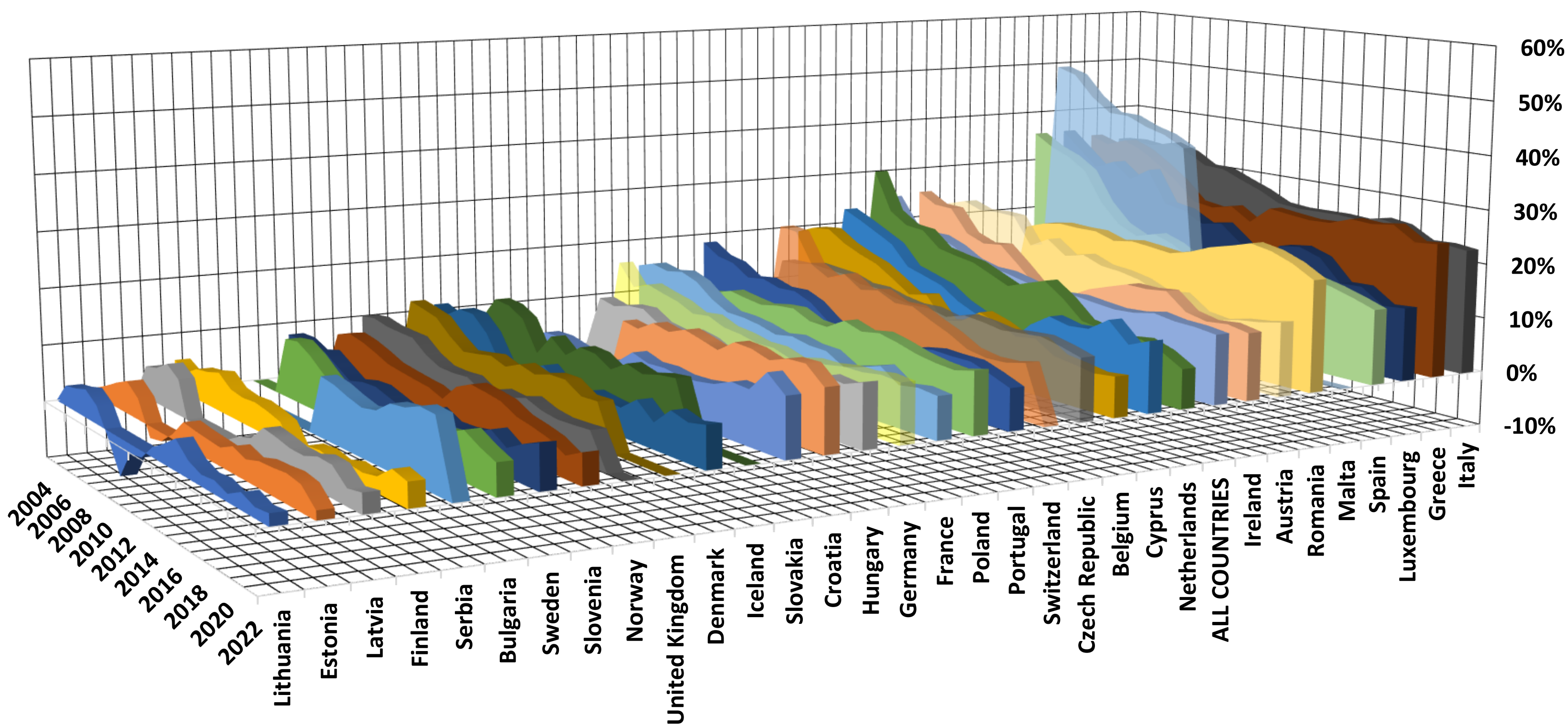


Figure 3-12: EU-SILC$_{Cross\text{-}sectional}$ – Gender differences in employment by country & year

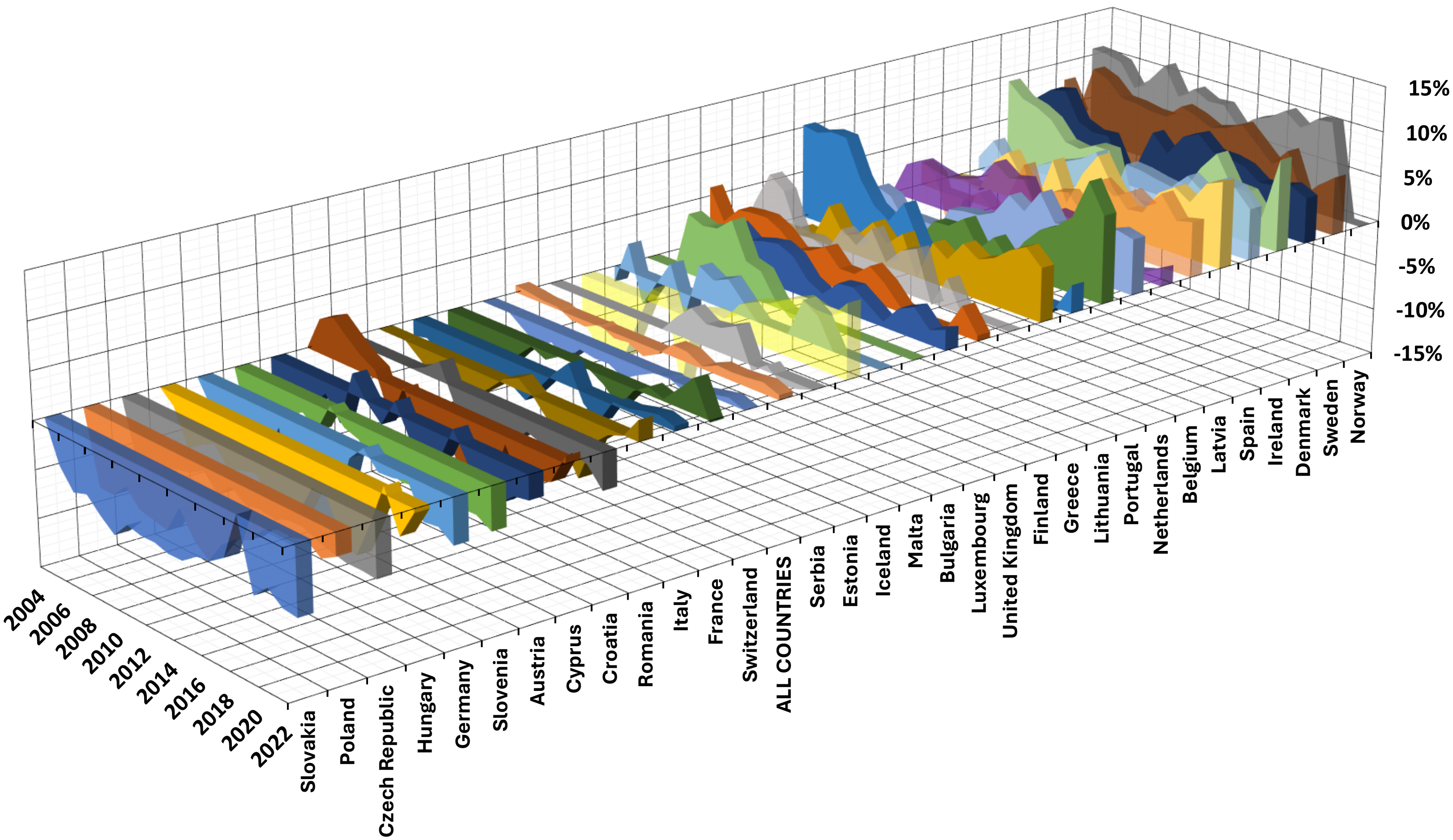


Figure 3-13: EU-SILC$_{Cross\text{-}sectional}$ – Gender differences in skills mismatching by country & year

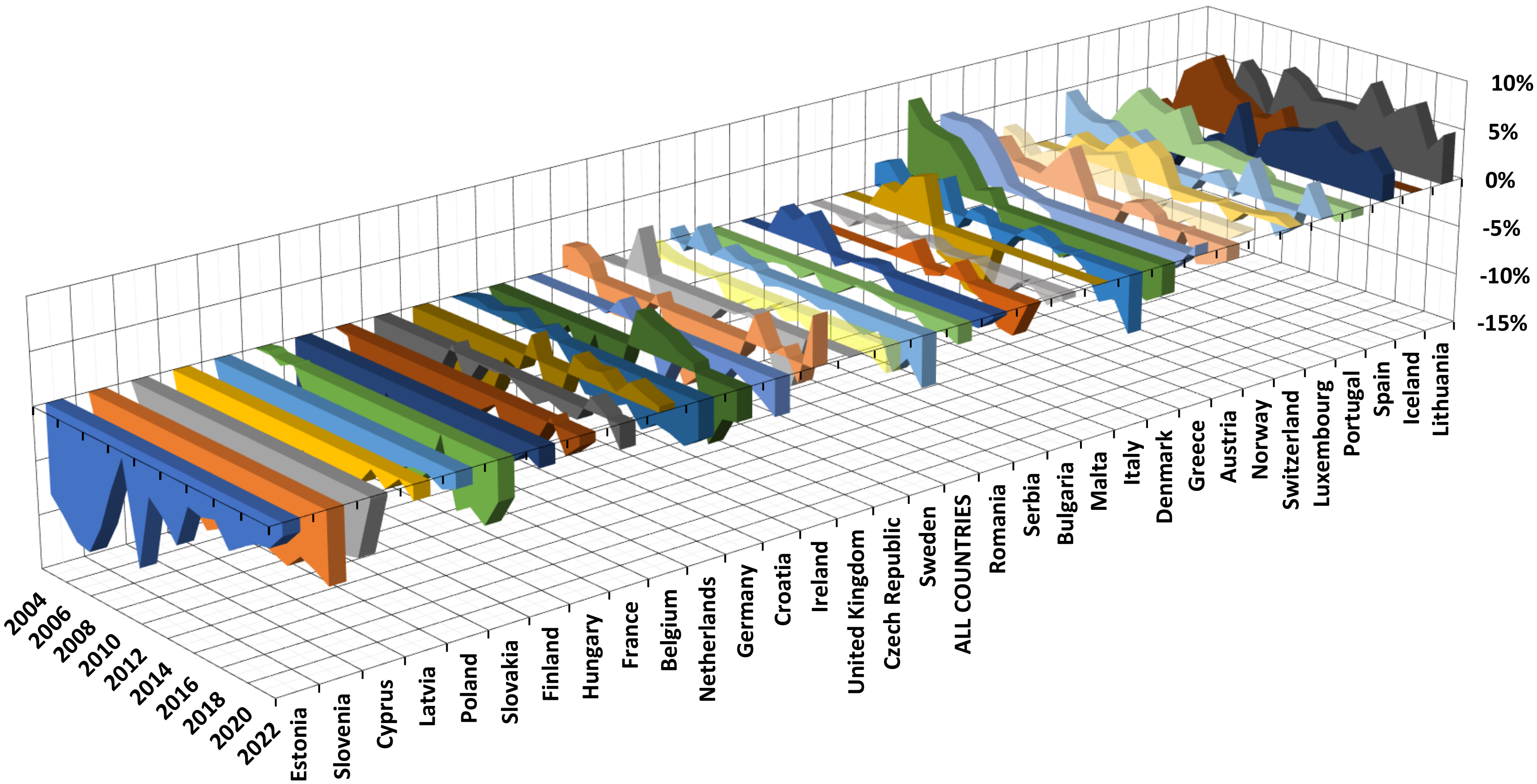


Figure 3-14: EU-SILC$_{Cross\text{-}sectional}$ – Gender differences in overeducation by country & year

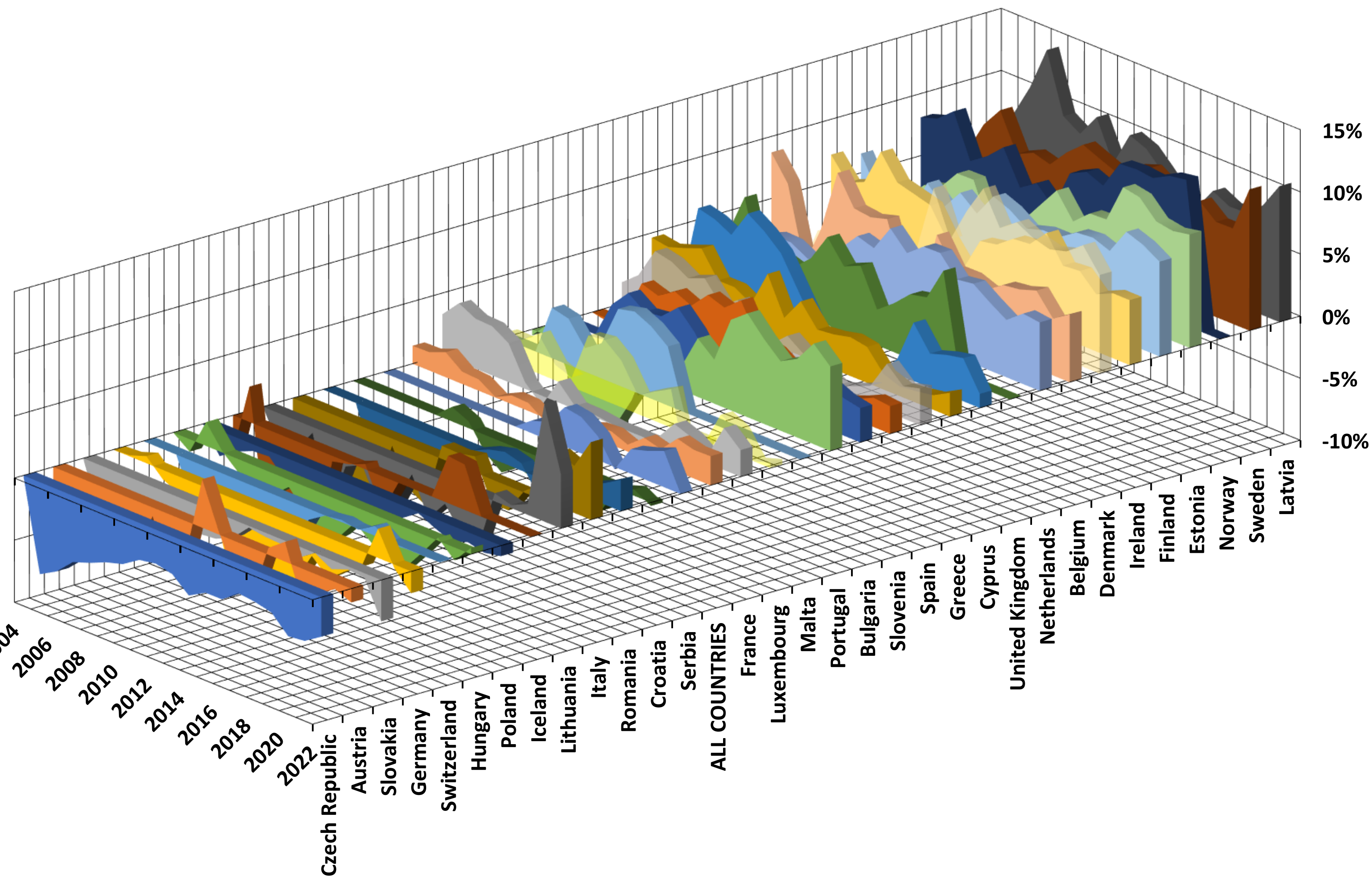


Figure 3-15: EU-SILC$_{Cross-sectional}$ – Gender differences in undereducation by country & year

3.1.5 DIFFERENCES BY AGE

This subsection analyses age-related differences in employment, skills mismatching, overeducation, and undereducation by comparing generational groups, as well as older and younger employees. Figures 3-16 to 3-19 display generational differences in employment, skills mismatching, overeducation, and undereducation across countries. Employment rates are generally higher among individuals born in the Silent Generation (or Traditionalists), though the differences are small when compared to other generations. In terms of skills mismatching, the figures reflect similar trends observed previously, with clear distinctions between overeducation and undereducation, though there are variations by country. Notably, Figure 3.18 reveals that employees born in Generation Y (or Millennials) tend to be more overeducated compared to other generations, while Baby Boomers and Traditionalists are more likely to be undereducated.

Table 3-14 provides a breakdown of these categories for older and younger employees across countries. Individuals born before 1977 are classified as ‘older’, while those born after 1977 are classified as ‘younger’. For each of the four categories the first two columns show the weighted percentage of individuals in that category by age group. The third column (*Difference*) displays the percentage point difference between old and young employees in each category.

On average, older individuals (74.9%) have higher employment rates than younger ones (69.5%), resulting in a 5.4 percentage point (pp) gap in favour of older workers across all countries. This trend is particularly pronounced in countries like Iceland (19.6 pp), Denmark (19 pp), Sweden (16.8 pp), and Slovenia (12.1 pp). In contrast, Malta (-26.1 pp) and Ireland (-4.1 pp) show an opposite trend, with employment differences favouring younger individuals. Countries like Belgium, the Netherlands, and Spain report very small age-related differences in employment, with gaps close to zero.

In terms of skills mismatching, age differences show opposing trends between overeducation and undereducation. Younger employees tend to be more overeducated than older ones, as evidenced by negative differences in most countries, such as Portugal, Greece, Italy, Malta, Poland, and Ireland). This reflects the challenges younger individuals face in finding jobs that align with their educational qualifications. On the other hand, older employees are more likely to be undereducated compared to younger ones, with significant positive differences in countries like Portugal, France, Greece, Italy, Cyprus, Malta, Ireland, and the UK, i.e., many of the same countries where younger employees are more overeducated.

Then, Figure 3-20 provides a visual representation of age differences in overeducation, undereducation, and mismatching by country. The red diamonds in the figure indicate mismatching differences between older and younger employees, while black and white bars represent overeducation and undereducation differences, respectively. Countries on the left, such as Portugal, Germany, Latvia, and Estonia, show higher rates of mismatching among younger employees (negative differences), whereas countries on the right, including Ireland, Belgium, Malta, and the Netherlands, exhibit higher mismatching rates among older employees (positive differences). Overall, the figure emphasizes that, in almost all countries, there are significant age-related differences in skills mismatching, with overeducation being more prevalent among younger employees and undereducation being more common among older employees.

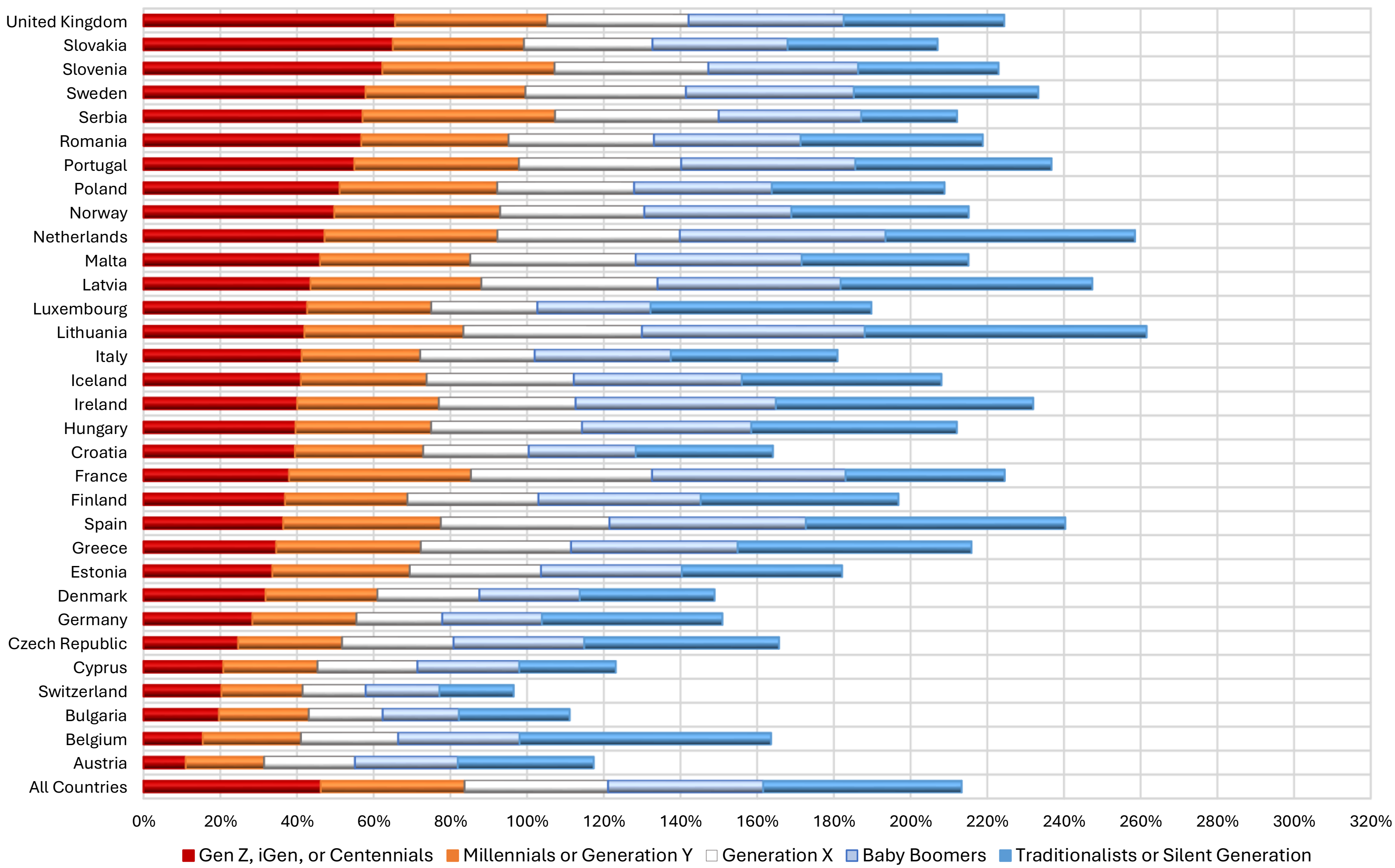


Figure 3-16: EU-SILC$_{Cross\text{-}sectional}$ – Generational composition of employment by country

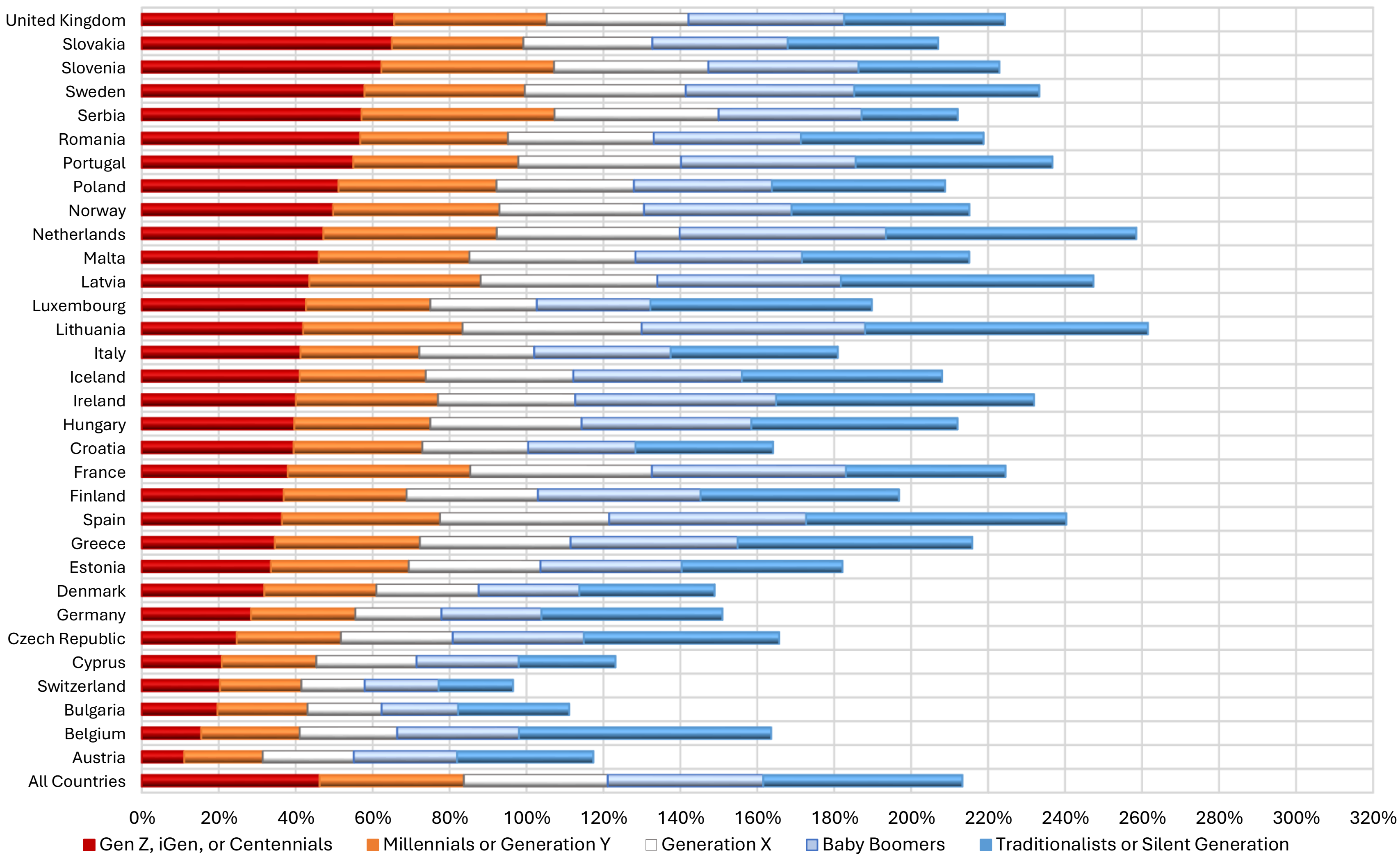


Figure 3-17: EU-SILC$_{Cross\text{-}sectional}$ – Generational composition of mismatching by country

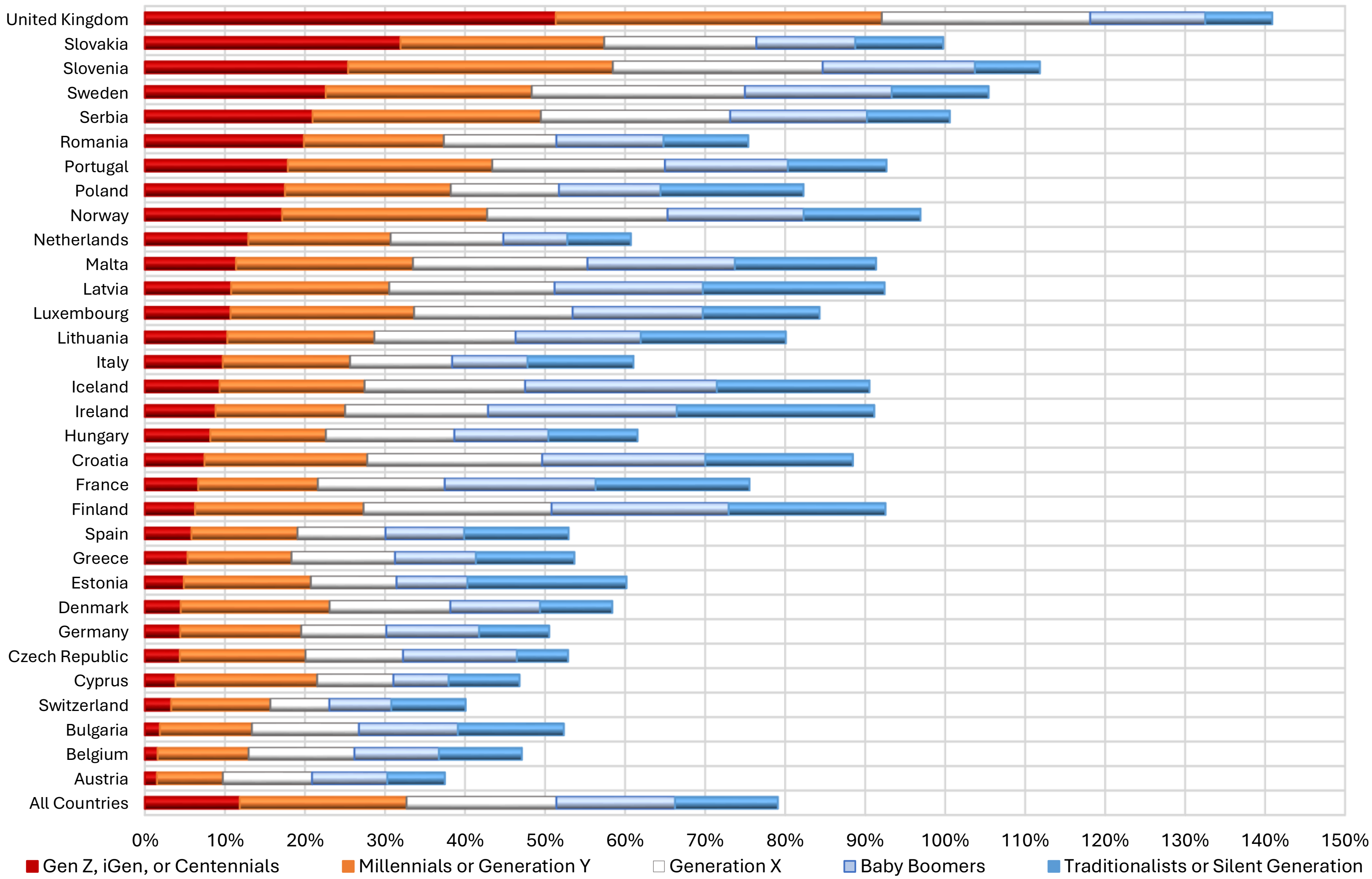


Figure 3-18: EU-SILC$_{Cross\text{-}sectional}$ – Generational composition of overeducation by country

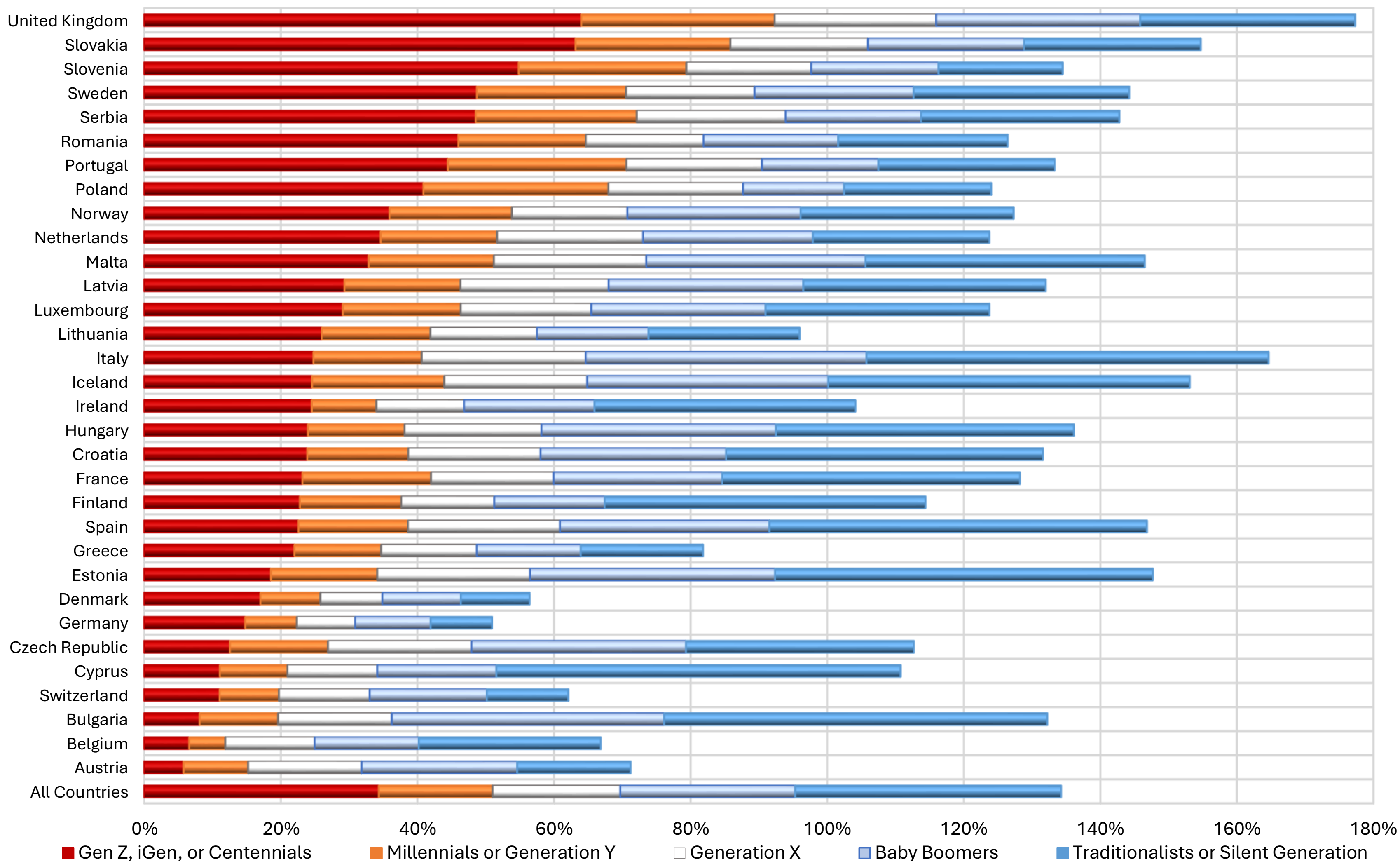


Figure 3-19: EU-SILC$_{Cross-sectional}$ – Generational composition of undereducation by country

Table 3-14: EU-SILC$_{Cross-sectional}$– Age differences (old vs. young) by country

	EMPLOYMENT			MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE	OLD	YOUNG	DIFFERENCE
All countries	74.9%	69.5%	5.4 pp	39.2%	37.9%	1.3 pp	16.7%	20.4%	-3.7 pp	22.4%	17.5%	4.9 pp
Portugal	75.2%	71.9%	3.3 pp	39.7%	50.5%	-10.8 pp	20.3%	41.2%	-20.9 pp	19.4%	9.3%	10.1 pp
Germany	78.3%	70.9%	7.4 pp	39.5%	46.3%	-6.7 pp	21.0%	19.3%	1.7 pp	18.5%	26.9%	-8.5 pp
Hungary	76.1%	68.0%	8.1 pp	27.8%	33.7%	-5.9 pp	13.2%	20.6%	-7.4 pp	14.6%	13.1%	1.5 pp
Latvia	78.5%	71.0%	7.5 pp	36.2%	41.4%	-5.3 pp	17.5%	14.7%	2.8 pp	18.7%	26.8%	-8.1 pp
Estonia	82.3%	73.5%	8.8 pp	38.4%	43.5%	-5.1 pp	21.1%	15.9%	5.2 pp	17.3%	27.6%	-10.4 pp
Romania	82.3%	72.1%	10.2 pp	28.9%	32.7%	-3.8 pp	13.7%	17.6%	-3.8 pp	15.2%	15.2%	0.0 pp
Slovakia	83.9%	72.1%	11.7 pp	19.6%	23.3%	-3.6 pp	9.9%	15.5%	-5.6 pp	9.8%	7.8%	2.0 pp
Czech Republic	83.2%	71.9%	11.2 pp	17.8%	21.1%	-3.3 pp	7.6%	12.1%	-4.5 pp	10.2%	9.0%	1.2 pp
Poland	72.0%	73.5%	-1.5 pp	24.4%	27.2%	-2.8 pp	8.3%	17.2%	-8.9 pp	16.1%	9.9%	6.2 pp
Bulgaria	78.9%	67.3%	11.6 pp	26.5%	29.3%	-2.8 pp	10.5%	13.0%	-2.5 pp	16.0%	16.3%	-0.2 pp
Norway	82.8%	74.9%	7.8 pp	38.9%	40.7%	-1.8 pp	11.7%	11.0%	0.7 pp	27.2%	29.8%	-2.5 pp
Austria	81.0%	72.5%	8.5 pp	38.2%	39.9%	-1.7 pp	19.7%	19.0%	0.6 pp	18.5%	20.8%	-2.3 pp
Switzerland	82.7%	80.0%	2.6 pp	34.5%	36.1%	-1.6 pp	12.9%	10.9%	2.0 pp	21.6%	25.2%	-3.5 pp
Sweden	86.1%	69.3%	16.8 pp	35.8%	35.7%	0.1 pp	12.9%	17.8%	-4.9 pp	22.9%	17.9%	5.0 pp
Lithuania	78.7%	72.2%	6.4 pp	43.0%	42.3%	0.7 pp	22.0%	17.8%	4.3 pp	21.0%	24.5%	-3.6 pp
Greece	66.6%	59.2%	7.3 pp	48.5%	47.1%	1.4 pp	22.5%	32.9%	-10.4 pp	26.0%	14.3%	11.7 pp
Iceland	84.9%	65.4%	19.6 pp	44.7%	43.3%	1.4 pp	22.4%	20.6%	1.8 pp	22.2%	22.7%	-0.4 pp
Denmark	82.1%	63.1%	19.0 pp	33.1%	31.5%	1.6 pp	11.5%	12.5%	-1.0 pp	21.6%	19.0%	2.6 pp
Slovenia	83.2%	71.1%	12.1 pp	26.3%	24.5%	1.8 pp	11.3%	15.7%	-4.4 pp	14.9%	8.7%	6.2 pp
Italy	66.9%	58.9%	8.0 pp	47.2%	44.5%	2.7 pp	20.3%	28.2%	-7.9 pp	26.8%	16.3%	10.6 pp
Serbia	59.4%	55.0%	4.4 pp	28.1%	25.1%	3.0 pp	13.0%	15.2%	-2.2 pp	15.1%	9.9%	5.2 pp
Luxembourg	72.1%	76.1%	-3.9 pp	43.2%	39.4%	3.8 pp	20.3%	21.7%	-1.4 pp	22.9%	17.7%	5.2 pp
United Kingdom	81.5%	77.5%	4.0 pp	42.3%	37.6%	4.7 pp	17.8%	22.6%	-4.8 pp	24.6%	15.0%	9.6 pp
Croatia	68.9%	64.8%	4.1 pp	25.1%	19.9%	5.2 pp	11.0%	14.5%	-3.5 pp	14.0%	5.4%	8.7 pp
Spain	63.9%	63.4%	0.5 pp	50.5%	45.2%	5.4 pp	22.8%	25.6%	-2.9 pp	27.7%	19.5%	8.2 pp
Finland	77.8%	66.2%	11.6 pp	32.4%	27.0%	5.4 pp	10.1%	7.9%	2.2 pp	22.3%	19.0%	3.3 pp
France	80.1%	72.5%	7.5 pp	38.2%	32.2%	6.0 pp	11.1%	17.6%	-6.4 pp	27.0%	14.6%	12.4 pp
Netherlands	72.8%	72.4%	0.4 pp	42.0%	35.6%	6.4 pp	16.6%	17.9%	-1.3 pp	25.3%	17.6%	7.7 pp
Cyprus	76.0%	72.1%	3.8 pp	47.9%	40.9%	7.0 pp	18.4%	25.2%	-6.8 pp	29.5%	15.7%	13.8 pp
Malta	53.4%	79.5%	-26.1 pp	44.3%	37.0%	7.3 pp	15.6%	25.6%	-10.0 pp	28.8%	11.4%	17.3 pp
Belgium	72.5%	72.8%	-0.2 pp	41.1%	33.0%	8.0 pp	14.0%	14.2%	-0.3 pp	27.1%	18.8%	8.3 pp
Ireland	64.1%	68.2%	-4.1 pp	53.2%	41.5%	11.7 pp	19.5%	25.0%	-5.5 pp	33.6%	16.5%	17.2 pp

Notes: Countries are ordered based on the percentage point difference between old and young employees in mismatching, from smaller to highest.

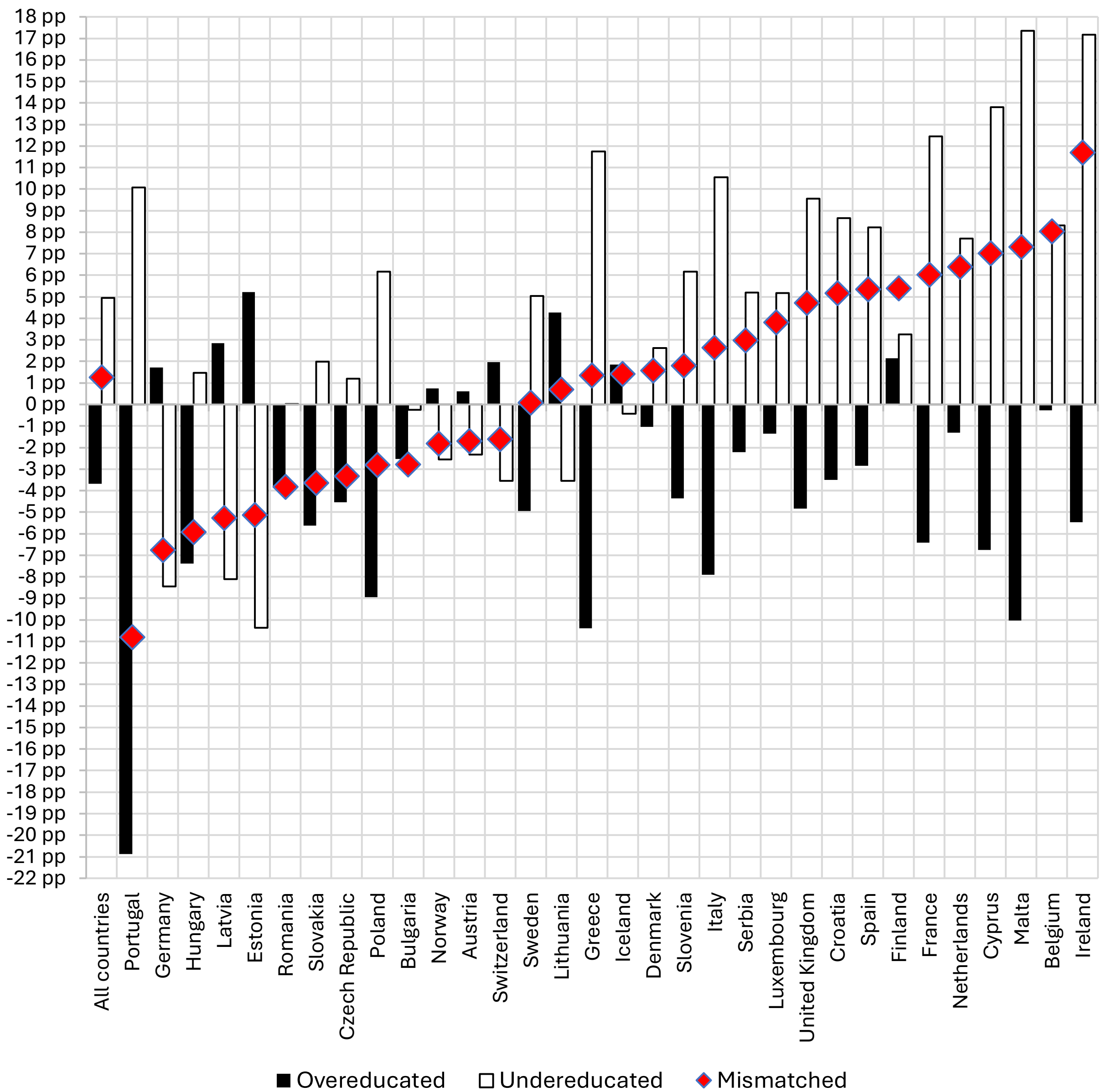


Figure 3-20: EU-SILC$_{Cross\text{-}sectional}$ – Age differences (old vs. young) by country

Figures 3-21 to 3-24 visually depict age-related differences in employment and skills mismatching by country and year, illustrating how these disparities evolve across European countries over time.

Figure 3-21 shows age differences in employment. As can be seen, in earlier years, older individuals tended to have significantly higher employment rates compared to younger individuals in many countries. However, this gap has narrowed over time, suggesting that younger individuals have increasingly gained access to the labour market in recent years, though differences remain in certain countries.

Figure 3.22 illustrates age differences in skills mismatching across countries. While in most European countries these age-related disparities have decreased over time, certain exceptions remain, particularly in Belgium, Cyprus, Luxembourg, Greece, and the Netherlands, where gaps, mainly against younger employees, have widened. However, a more nuanced picture emerges when examining overeducation and undereducation separately, as seen in Figures 3.23 and 3.24. These figures reveal that age differences are more pronounced when focusing on these specific dimensions of skills mismatching.

Specifically, Figure 3.23 shows that younger employees tend to consistently be more overeducated compared to older employees in most countries, with the exceptions being Germany, Finland, Latvia, Lithuania, Estonia – as well as in Norway, Austria, Denmark, and Iceland, particularly during the earlier years, up until 2011-2012. In contrast, Figure 3.24 demonstrates that older employees are generally more undereducated compared to younger employees across most countries, with exceptions in Estonia, Germany, Latvia, Lithuania, Switzerland, and Norway, Austria, Denmark, and Iceland for certain years.

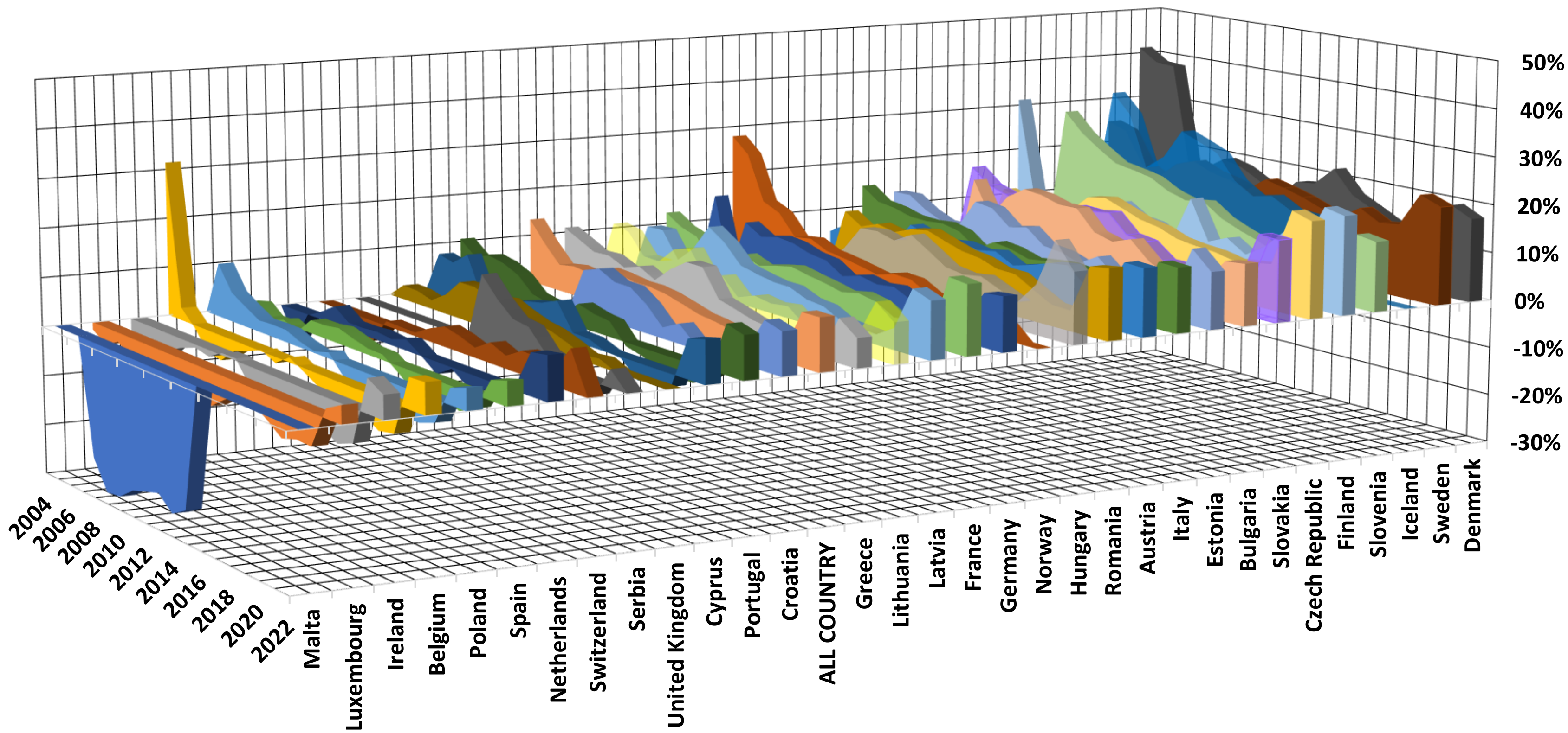


Figure 3-21: EU-SILC$_{Cross\text{-}sectional}$ – Age differences in employment by country and year (old vs. young)

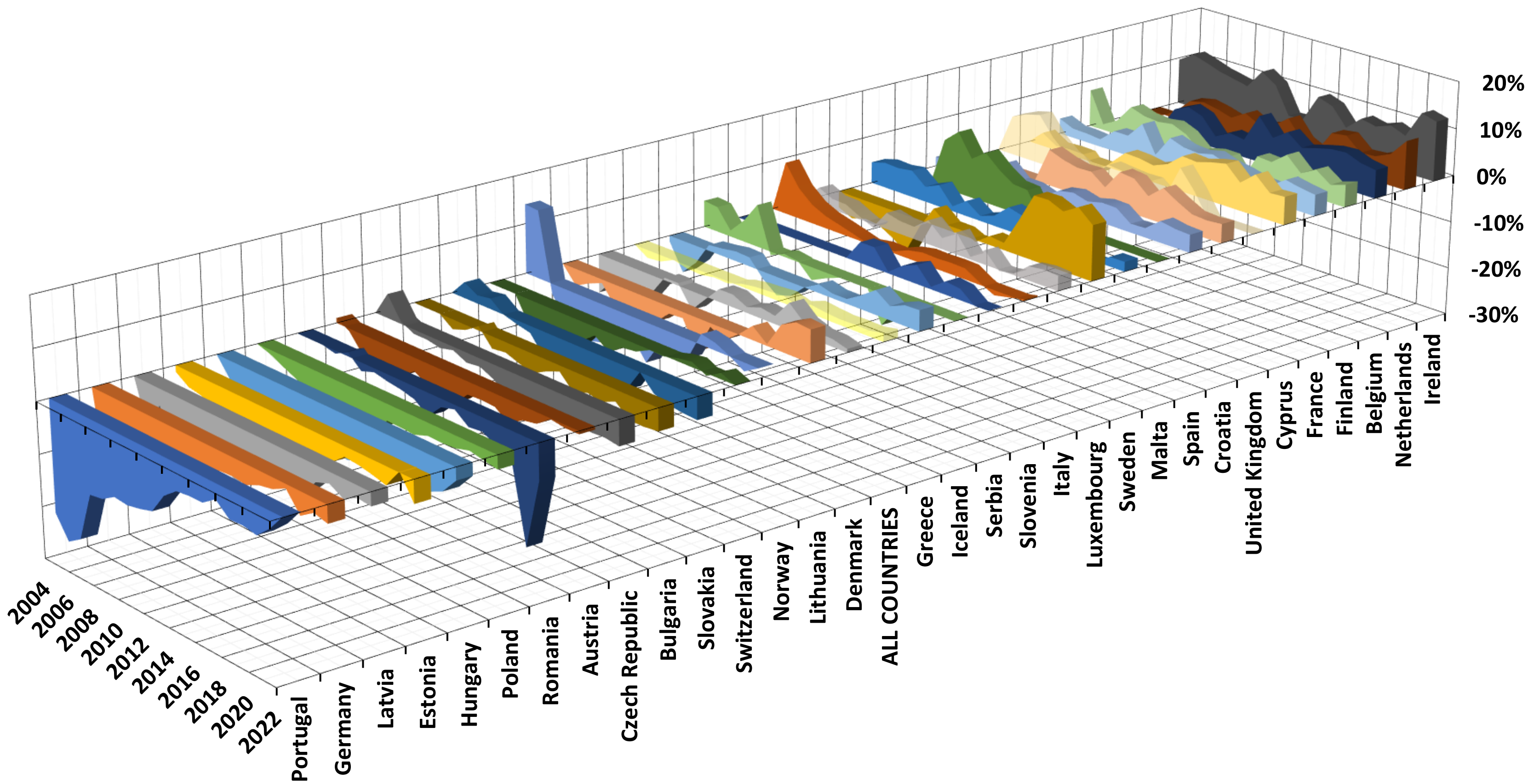


Figure 3-22: EU-SILC$_{Cross\text{-}sectional}$ – Age differences in skills mismatching by country and year (old vs. young)

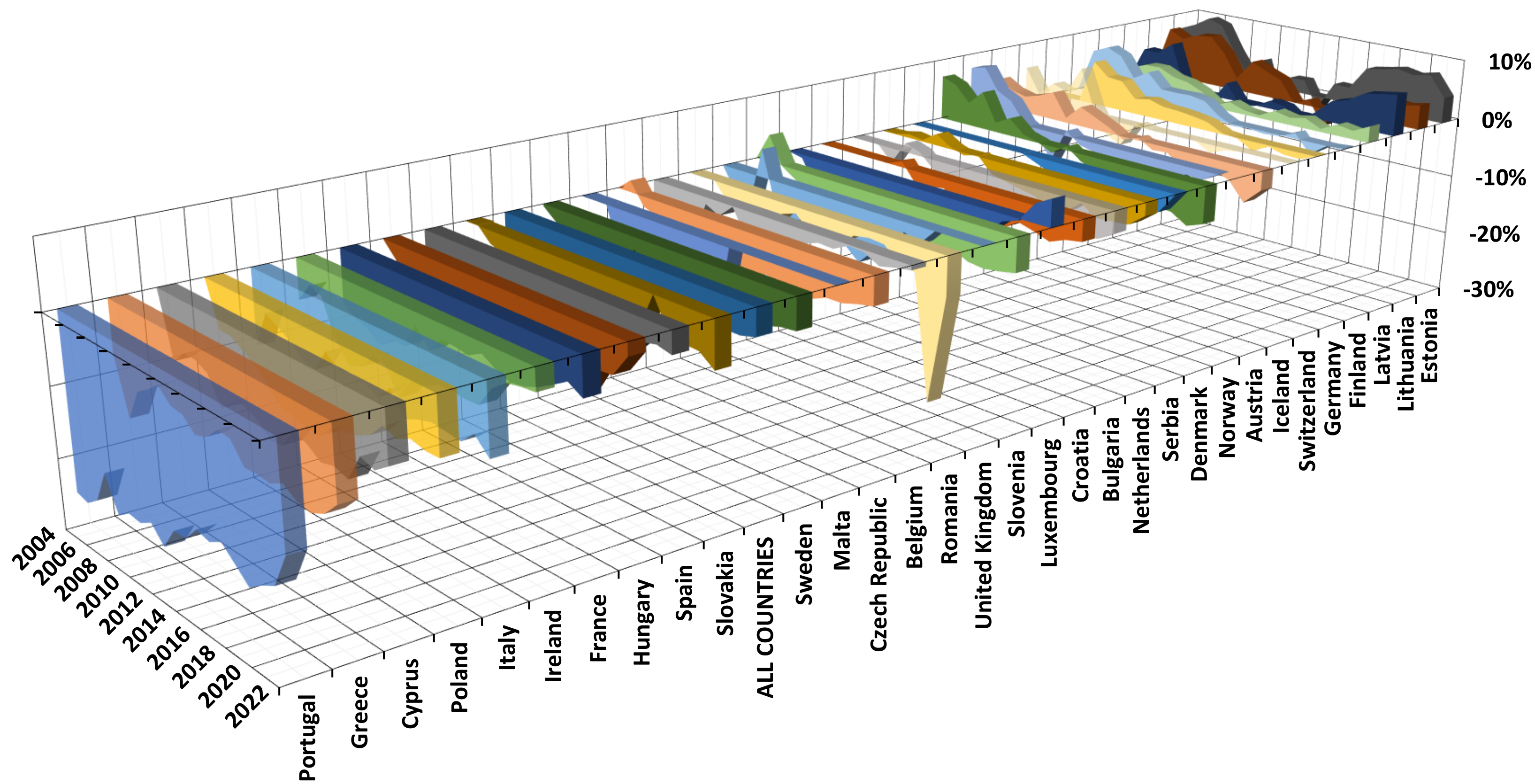


Figure 3-23: EU-SILC$_{Cross\text{-}sectional}$ – Age differences in overeducation by country and year (old vs. young)

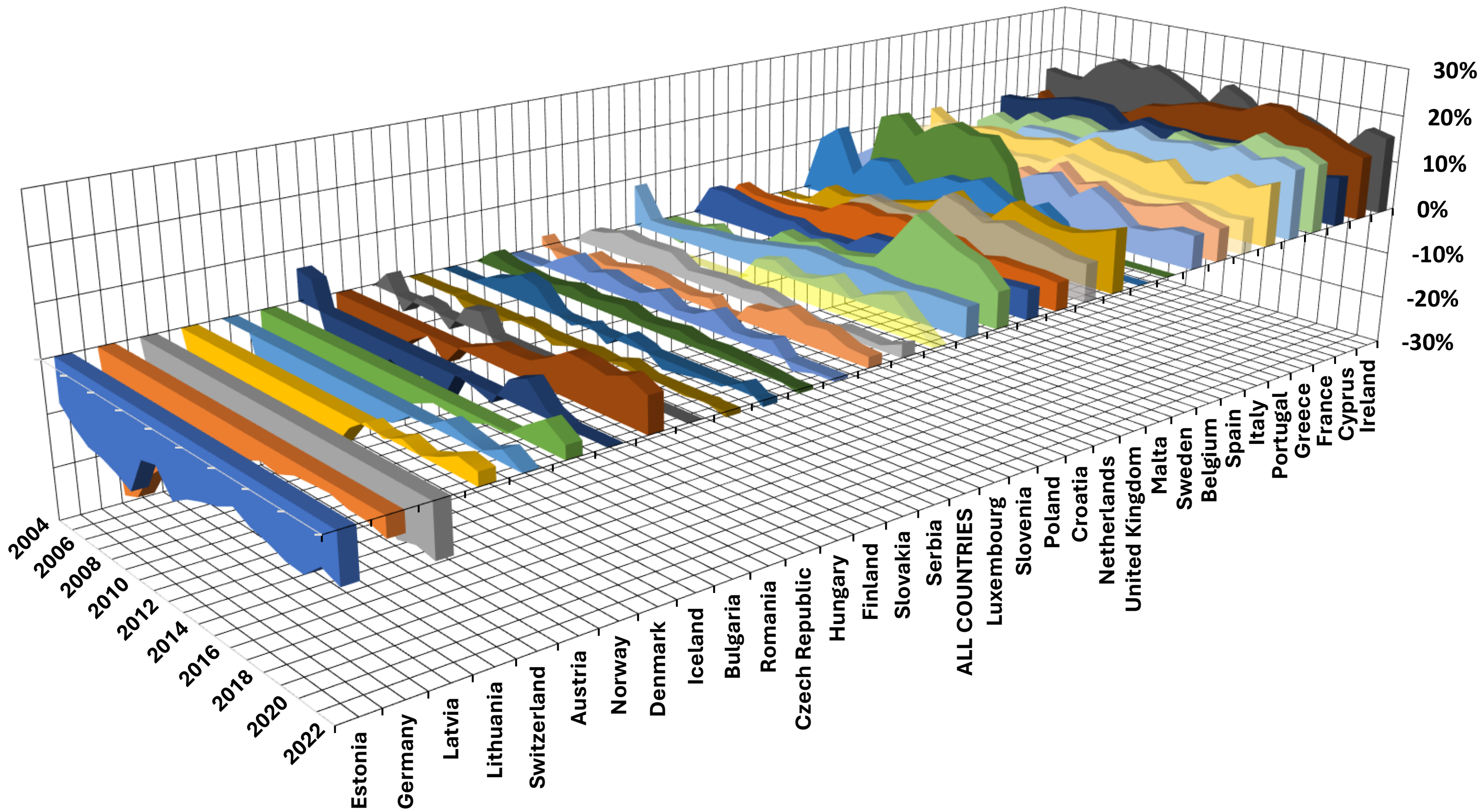


Figure 3-24: EU-SILC$_{Cross\text{-}sectional}$ – Age differences in undereducation by country & year

3.1.6 DIFFERENCES BY INCOME

This subsection analyses differences by income status in skills mismatching, overeducation, and undereducation.

Figures 3-25 to 3-27 present income composition (by income decile) differences in skills mismatching, overeducation, and undereducation across various countries, with income distribution divided into 10 deciles for more detailed insights. Figure 3-25 highlights that mismatching rates are generally more prevalent among individuals in the 1st and 2nd deciles (lowest income groups) across all countries. Figure 3-26 focuses on overeducation, showing that while overeducation is spread across all income deciles, it is more pronounced in higher income brackets, particularly after the 6th decile. Conversely, Figure 3-27 reveals the opposite pattern for undereducation, where the lowest income deciles – particularly the first three – exhibit significantly higher undereducation rates.

Table 3-15 shows the differences in these categories by comparing employees in the top 40% (T40) of the income distribution with those in the bottom 60% (B60). Income deciles have been constructed based on equivalized disposable income. In cases where national currencies were used, income data has been converted into euros using the average exchange rate for each year and country. Additionally, all income data has been deflated using the GDP deflator specific to each country and year to adjust for inflation.

In terms of overall mismatching, higher-income employees (T40) generally exhibit lower rates of mismatching compared to lower-income employees (B60). On average, the mismatch rate for T40 employees is 37.9%, while for B60 employees, it stands at 39.2%. This negative difference of -1.3 percentage points (pp) suggests that higher-income individuals experience fewer mismatches in the labour market. The largest gaps can be observed in countries like Ireland, Belgium, Malta, Cyprus, the Netherlands, France, Finland, Spain, and Croatia, where lower-income individuals face significantly higher rates of mismatching. In contrast, countries like Estonia, Latvia, Hungary, Germany, and Portugal display the opposite trend, where higher-income employees appear to experience higher rates of mismatching compared to lower-income employees.

However, to fully understand these discrepancies, it is essential to examine the specific types of mismatching – overeducation and undereducation. In most countries, higher-income employees tend to be less overeducated than lower-income employees. On average, 20.4% of T40 employees are overeducated compared to 16.7% of B60 employees, leading to a 3.7 pp gap in favor of T40 individuals. Countries like Portugal (20.9 pp), Greece (10.4 pp), Malta (10 pp), Poland (8.9 pp), Italy (7.9 pp), and France (6.4 pp) display such income-based disparities in overeducation. Smaller gaps are observed in countries like Belgium, Denmark, Austria, Norway, and Croatia. Interestingly, countries such as Estonia, Lithuania, Latvia, Finland, Switzerland, and Iceland show the reverse pattern, with higher overeducation rates among lower-income individuals (B60) than higher-income individuals (T40).

On the other hand, undereducation is more common among low-income employees. On average, 17.5% of T40 employees are undereducated compared to 22.4% of B60 employees, resulting in a gap of -4.9 percentage points (pp). The largest disparities are observed in countries such as Malta (-17.3 pp), Ireland (-17.2 pp), Cyprus (-13.8 pp), France (-12.4 pp), Greece (-11.7 pp), Italy (-10.6 pp), and Portugal (-10.1 pp), where lower-income individuals are significantly more undereducated than their higher-income counterparts. On the other hand, countries like Romania, Bulgaria, and Iceland exhibit nearly zero income-based gaps, while Estonia (10.4 pp), Germany (8.5 pp), and Latvia (8.1 pp) show positive differences in undereducation, indicating that T40 employees are more undereducated than B60 employees in those countries.

Figure 3-28 offers a visual representation of income-based differences in skills mismatching, overeducation, and undereducation, using the data from Table 3-15. The red diamonds indicate the differences in mismatching between T40 (higher-income) and B60 (lower-income) groups, while the black and white bars display the differences in overeducation and undereducation rates, respectively. Countries such as Ireland, Belgium, Malta, Cyprus, the Netherlands, France, Finland, Spain, and Croatia show significant mismatching rates, with absolute values exceeding 5pp, where lower-income individuals experience higher mismatching. Conversely, countries like Portugal, Germany, Hungary, Latvia, and Estonia exhibit mismatching rates in favor of higher-income individuals, with differences greater than +5 pp. Overall, the figure reinforces the findings from the table, highlighting that lower-income individuals tend to face higher rates of skills mismatching across most European countries.

Finally, Figures 3-29 to 3-31 visually depict income-related differences, between the top 40% and bottom 60% of employees, in skills mismatching, overeducation and undereducation by country and year, illustrating how these disparities evolve across European countries over time.

Figure 3-29 present income-based differences in skills mismatching. In most countries, the data show a consistent advantage for high-income (top 40%) employees with lower mismatching rates compared to lower-income (bottom 60%) employees over the years. However, notable exceptions exist in countries such as Poland, the Czech Republic, and Malta, where lower-income employees demonstrate lower mismatching rates than higher-income groups, indicating a reverse trend. Additionally, the figure shows no significant changes across years, underscoring the stability of these income-based mismatching patterns over time.

Figure 3-30 highlights income-based differences in overeducation. While the general trend in most countries indicates that higher-income (top 40%) employees tend to be more overeducated compared to lower-income (bottom 60%) employees, the magnitude and direction of these differences vary considerably across countries and over time. For countries above the “ALL COUNTRIES” average, high-income employees consistently show higher rates of overeducation, with the only exceptions in Switzerland and Norway where there is a slight reversal in the last three years. Conversely, in countries below the “ALL COUNTRIES” average, the trend initially aligns with the broader pattern where higher-income employees are more overeducated. However, after 2008-

2009, the pattern shifts, and lower-income employees increasingly display higher rates of overeducation, particularly in the wake of the financial crisis.

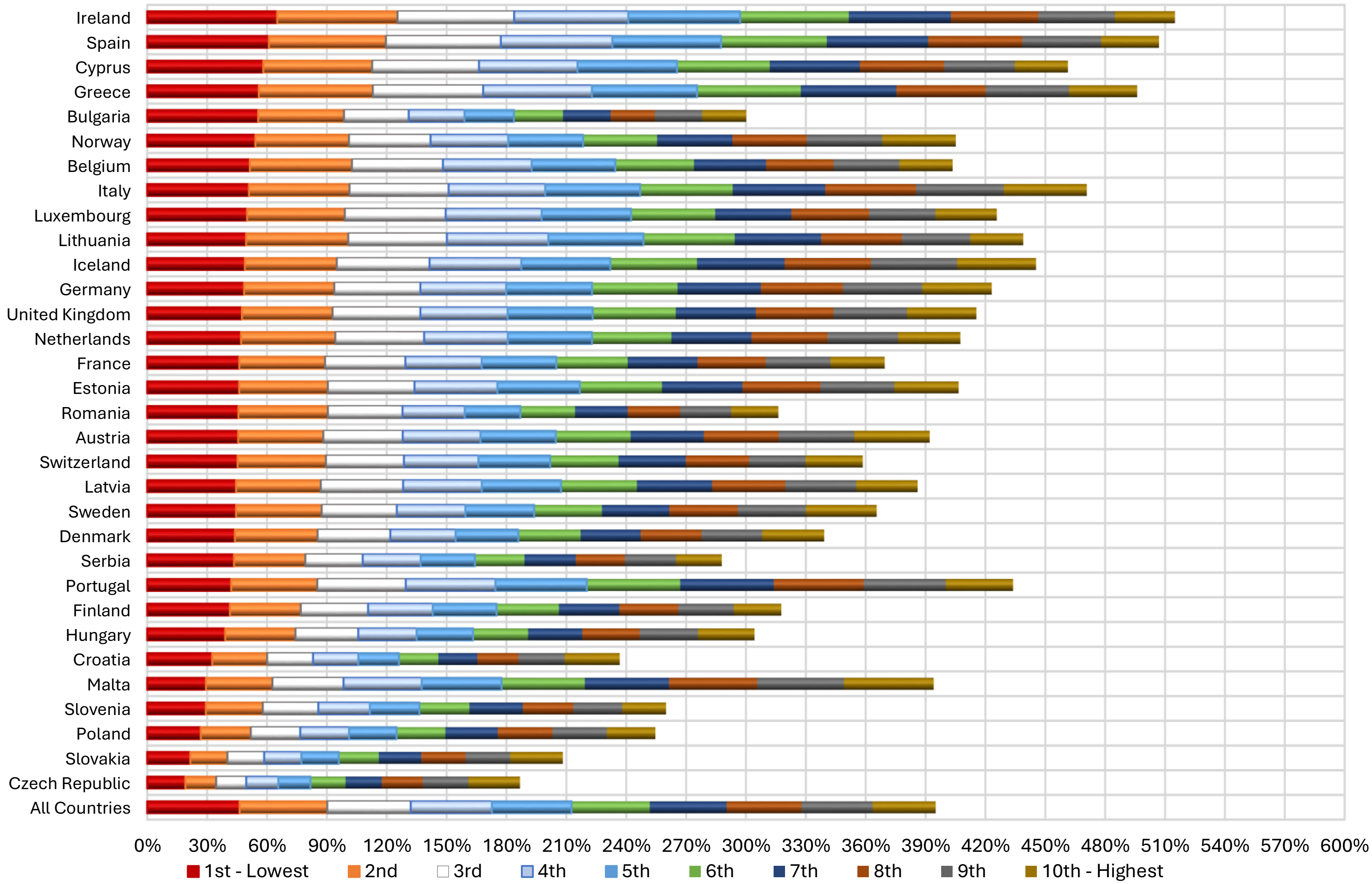


Figure 3-25: EU-SILC$_{Cross\text{-}sectional}$ – Income composition of skills mismatching by country

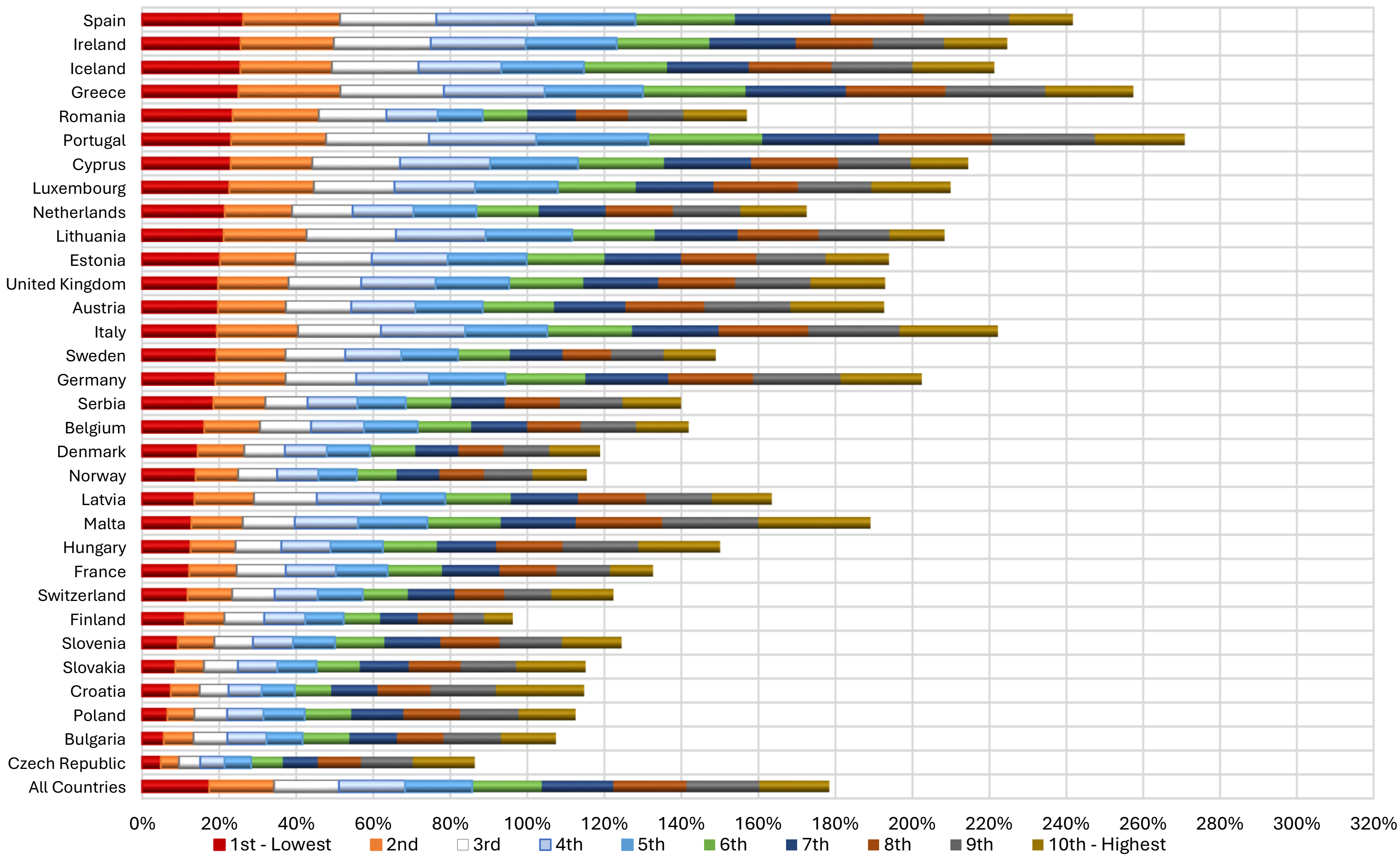


Figure 3-26 EU-SILC$_{Cross\text{-}sectional}$ – Income composition of overeducation by country

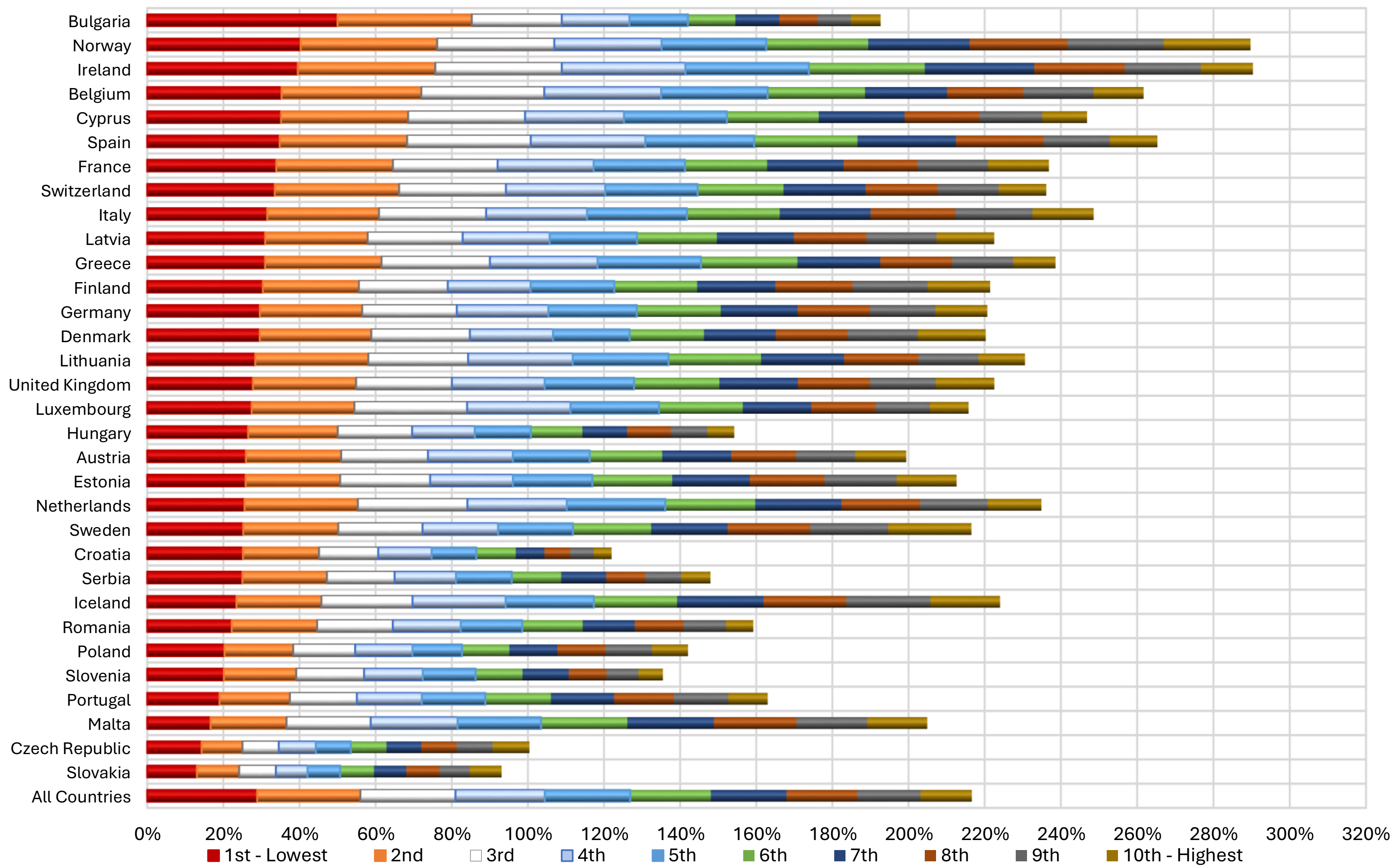


Figure 3-27: EU-SILC$_{\text{Cross-sectional}}$ – Income composition of undereducation by country

Table 3-15: EU-SILC$_{Cross\text{-}sectional}$ - Income differences (T40 vs. B60) by country

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	TOP40%	BOT.60%	DIFFERENCE	TOP40%	BOT.60%	DIFFERENCE	TOP40%	BOT.60%	DIFFERENCE
ALL COUNTRIES	37.9%	39.2%	-1.3 pp	20.4%	16.7%	3.7 pp	17.5%	22.4%	-4.9 pp
Ireland	41.5%	53.2%	-11.7 pp	25.0%	19.5%	5.5 pp	16.5%	33.6%	-17.2 pp
Belgium	33.0%	41.1%	-8.0 pp	14.2%	14.0%	0.3 pp	18.8%	27.1%	-8.3 pp
Malta	37.0%	44.3%	-7.3 pp	25.6%	15.6%	10.0 pp	11.4%	28.8%	-17.3 pp
Cyprus	40.9%	47.9%	-7.0 pp	25.2%	18.4%	6.8 pp	15.7%	29.5%	-13.8 pp
Netherlands	35.6%	42.0%	-6.4 pp	17.9%	16.6%	1.3 pp	17.6%	25.3%	-7.7 pp
France	32.2%	38.2%	-6.0 pp	17.6%	11.1%	6.4 pp	14.6%	27.0%	-12.4 pp
Finland	27.0%	32.4%	-5.4 pp	7.9%	10.1%	-2.2 pp	19.0%	22.3%	-3.3 pp
Spain	45.2%	50.5%	-5.4 pp	25.6%	22.8%	2.9 pp	19.5%	27.7%	-8.2 pp
Croatia	19.9%	25.1%	-5.2 pp	14.5%	11.0%	3.5 pp	5.4%	14.0%	-8.7 pp
United Kingdom	37.6%	42.3%	-4.7 pp	22.6%	17.8%	4.8 pp	15.0%	24.6%	-9.6 pp
Luxembourg	39.4%	43.2%	-3.8 pp	21.7%	20.3%	1.4 pp	17.7%	22.9%	-5.2 pp
Serbia	25.1%	28.1%	-3.0 pp	15.2%	13.0%	2.2 pp	9.9%	15.1%	-5.2 pp
Italy	44.5%	47.2%	-2.7 pp	28.2%	20.3%	7.9 pp	16.3%	26.8%	-10.6 pp
Slovenia	24.5%	26.3%	-1.8 pp	15.7%	11.3%	4.4 pp	8.7%	14.9%	-6.2 pp
Denmark	31.5%	33.1%	-1.6 pp	12.5%	11.5%	1.0 pp	19.0%	21.6%	-2.6 pp
Iceland	43.3%	44.7%	-1.4 pp	20.6%	22.4%	-1.8 pp	22.7%	22.2%	0.4 pp
Greece	47.1%	48.5%	-1.4 pp	32.9%	22.5%	10.4 pp	14.3%	26.0%	-11.7 pp
Lithuania	42.3%	43.0%	-0.7 pp	17.8%	22.0%	-4.3 pp	24.5%	21.0%	3.6 pp
Sweden	35.7%	35.8%	-0.1 pp	17.8%	12.9%	4.9 pp	17.9%	22.9%	-5.0 pp
Switzerland	36.1%	34.5%	1.6 pp	10.9%	12.9%	-2.0 pp	25.2%	21.6%	3.5 pp
Austria	39.9%	38.2%	1.7 pp	19.0%	19.7%	-0.6 pp	20.8%	18.5%	2.3 pp
Norway	40.7%	38.9%	1.8 pp	11.0%	11.7%	-0.7 pp	29.8%	27.2%	2.5 pp
Bulgaria	29.3%	26.5%	2.8 pp	13.0%	10.5%	2.5 pp	16.3%	16.0%	0.2 pp
Poland	27.2%	24.4%	2.8 pp	17.2%	8.3%	8.9 pp	9.9%	16.1%	-6.2 pp
Czech Republic	21.1%	17.8%	3.3 pp	12.1%	7.6%	4.5 pp	9.0%	10.2%	-1.2 pp
Slovakia	23.3%	19.6%	3.6 pp	15.5%	9.9%	5.6 pp	7.8%	9.8%	-2.0 pp
Romania	32.7%	28.9%	3.8 pp	17.6%	13.7%	3.8 pp	15.2%	15.2%	0.0 pp
Estonia	43.5%	38.4%	5.1 pp	15.9%	21.1%	-5.2 pp	27.6%	17.3%	10.4 pp
Latvia	41.4%	36.2%	5.3 pp	14.7%	17.5%	-2.8 pp	26.8%	18.7%	8.1 pp
Hungary	33.7%	27.8%	5.9 pp	20.6%	13.2%	7.4 pp	13.1%	14.6%	-1.5 pp
Germany	46.3%	39.5%	6.7 pp	19.3%	21.0%	-1.7 pp	26.9%	18.5%	8.5 pp
Portugal	50.5%	39.7%	10.8 pp	41.2%	20.3%	20.9 pp	9.3%	19.4%	-10.1 pp

Notes: Countries are ordered based on the percentage point difference between old and young employees in skills mismatching, from lower to highest.

Finally, Figure 3-31 illustrates income-based differences in undereducation. In most countries and across the years, negative percentage differences are observed, indicating that lower-income (bottom 60%) employees are consistently more undereducated than their higher-income (top 40%) counterparts. The only exceptions are seen in Sweden during the early years, up until 2013, and in the Czech Republic during the last three years after 2020. Overall, the pattern remains stable over time, with minimal year-to-year changes in the observed income-related differences in undereducation

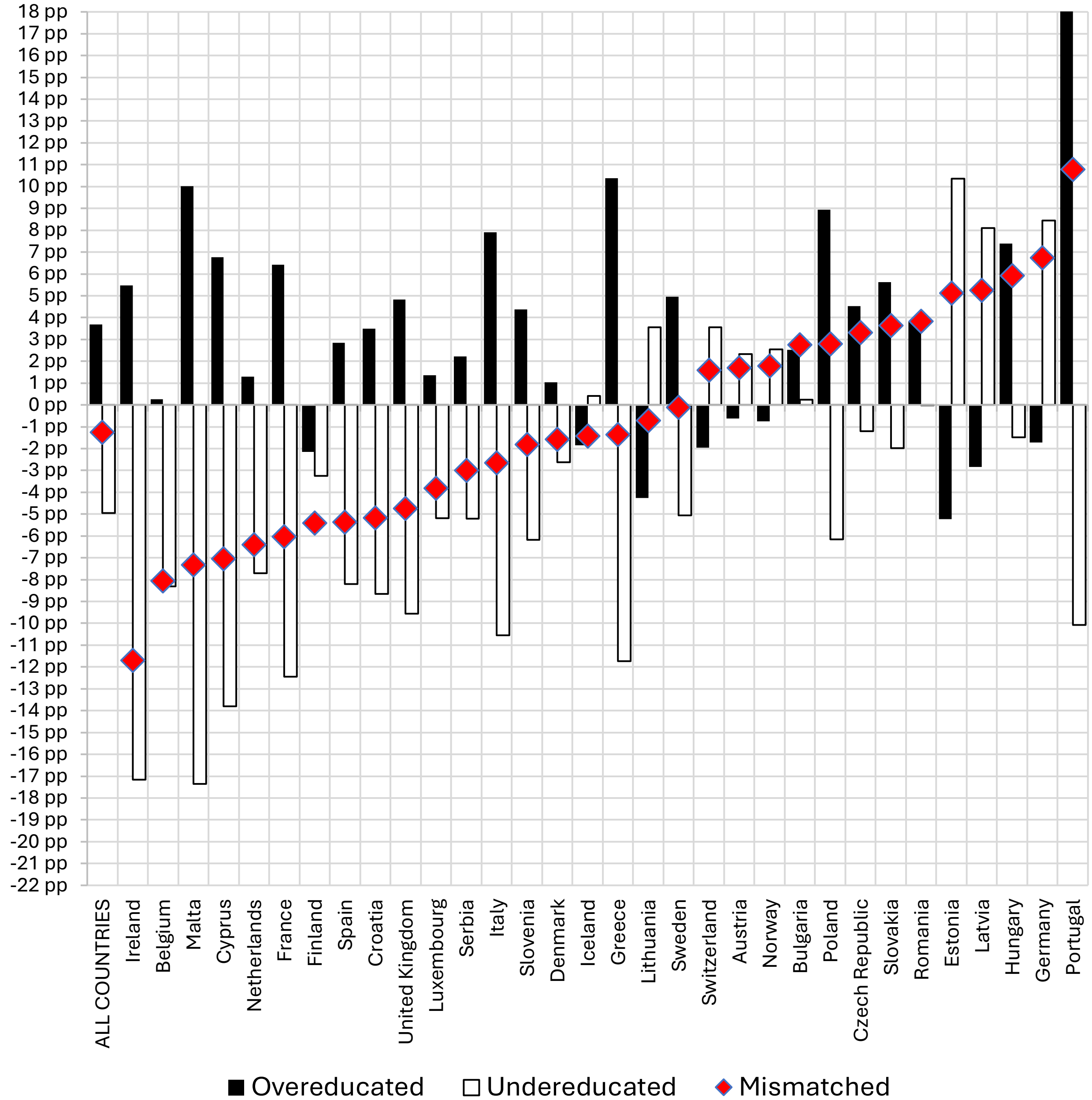


Figure 3-28: EU-SILC$_{Cross\text{-}sectional}$ – Income differences by country (Top40% vs. Bottom60%)

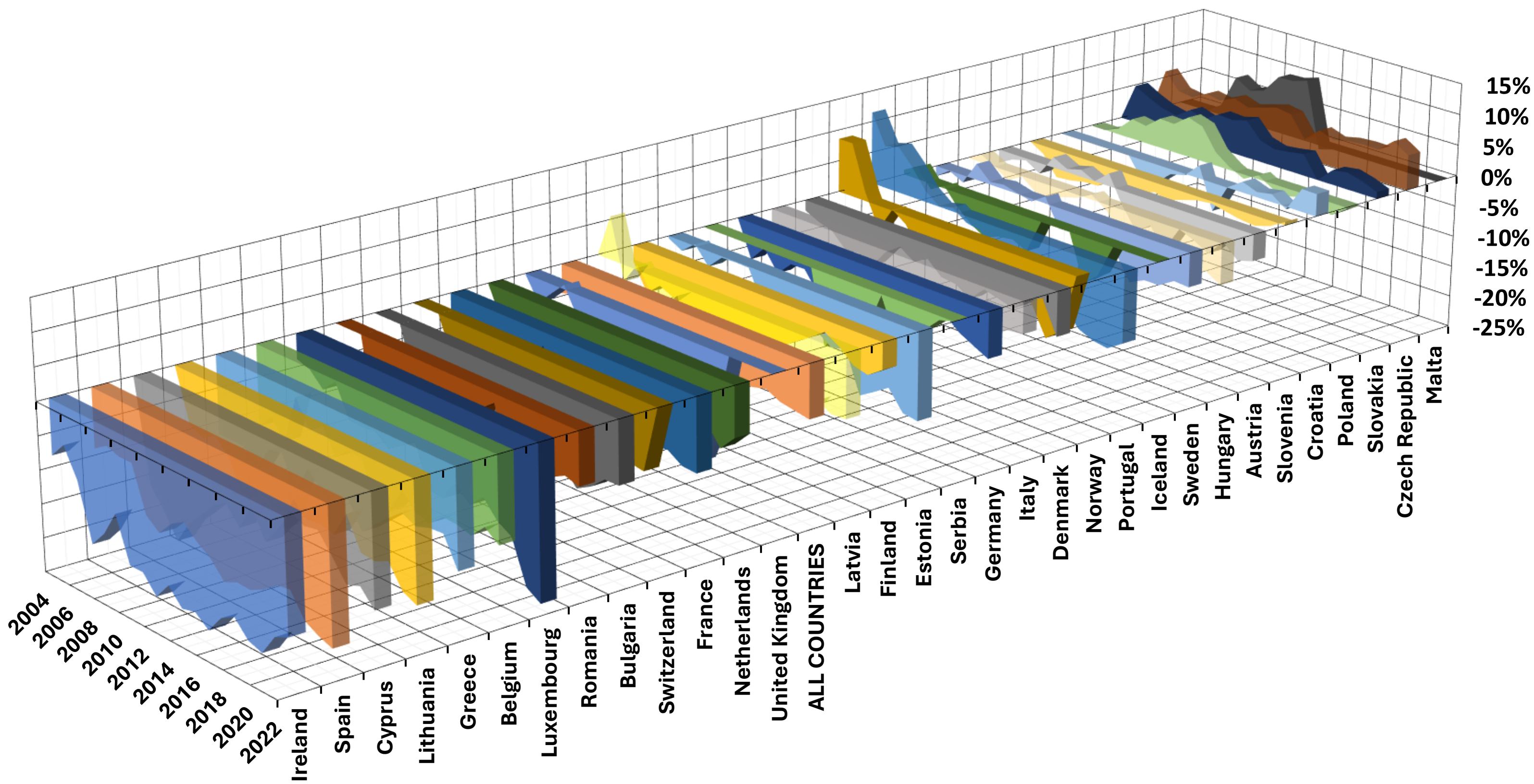


Figure 3-29: EU-SILC$_{Cross\text{-}sectional}$ – Income differences in skills mismatching by country & year

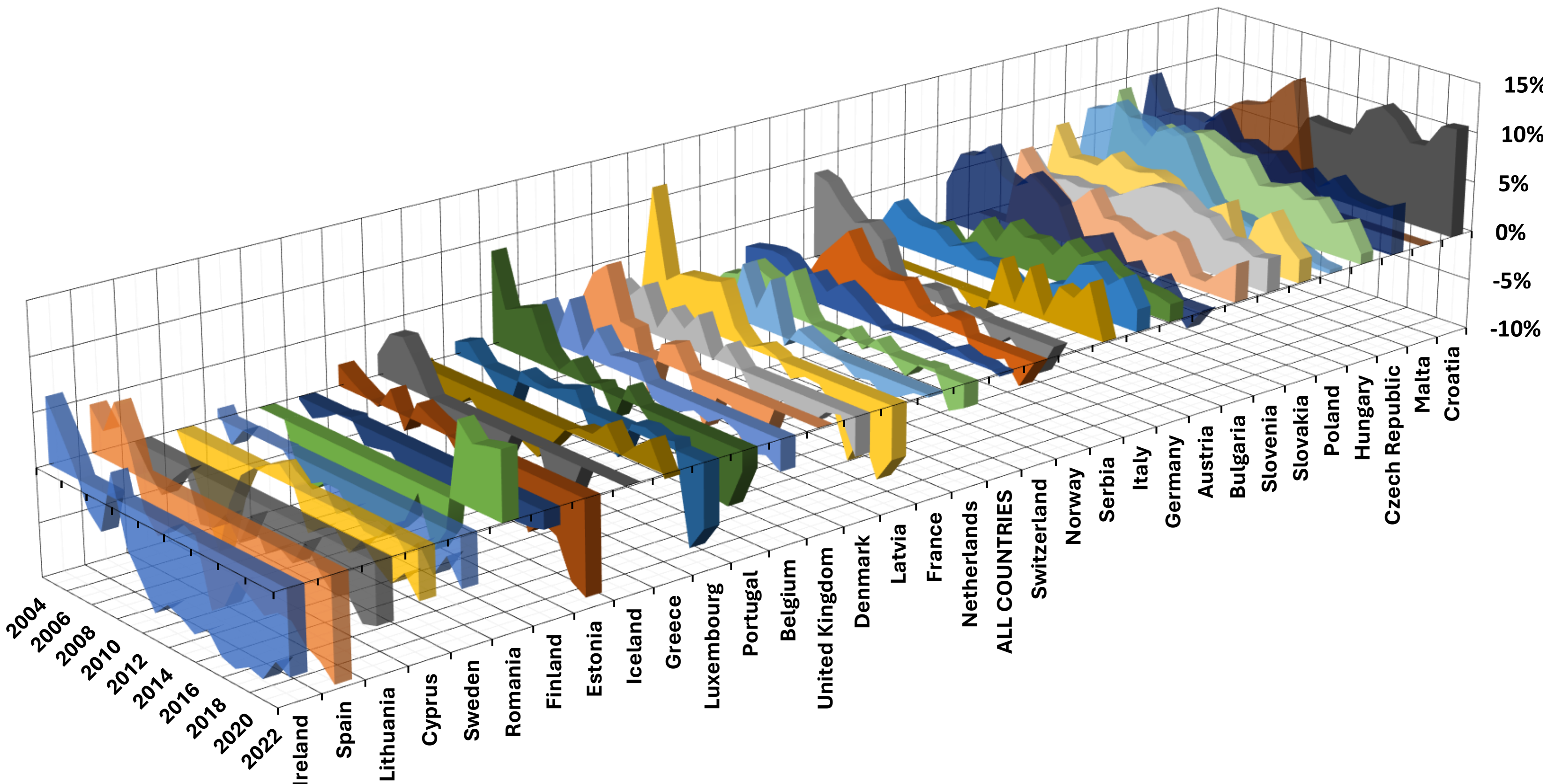


Figure 3-30: EU-SILC$_{Cross\text{-}sectional}$ – Income differences in overeducation by country & year

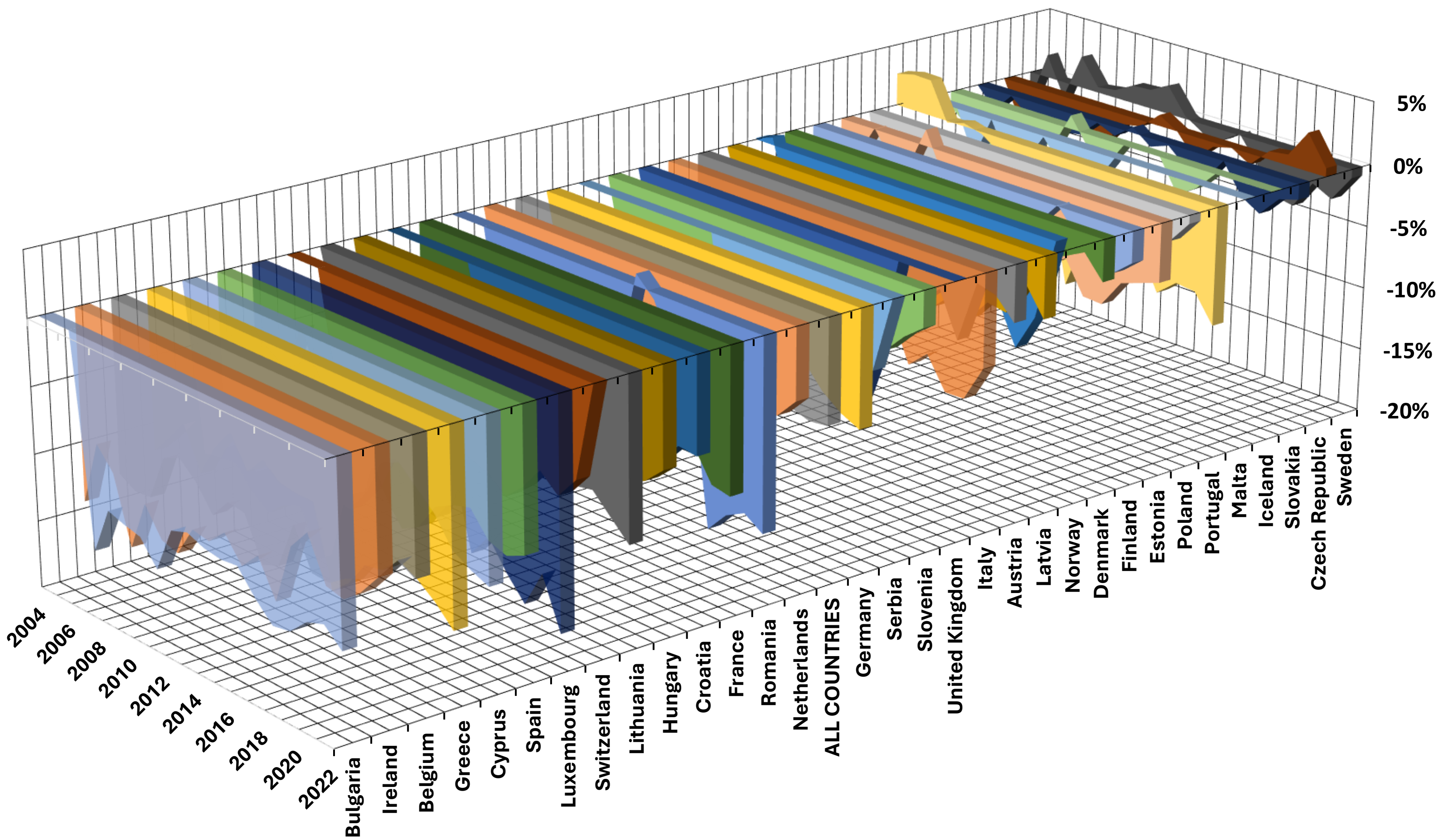


Figure 3-31: EU-SILC$_{Cross\text{-}sectional}$ – Income differences in undereducation by country and year

3.1.7 THE RELEVANT LITERATURE

This subsection presents an overview of the literature, focusing on skills-related research, that use the EU-SILC data. An inquiry using the Scopus database reveals that approximately 298 articles utilize the EU-SILC database in various research domains. Out of these, 21 articles use the EU-SILC for skills-related research. We perform two relevant exercises based on this subset of articles.

First, in Figure 3-32 we present a word cloud of the most frequently appearing words in the index and author keywords of these 21 articles. The word cloud visually emphasizes the central themes and concepts explored in this body of work, with prominent terms likely including "employment", "occupations", "job", "wage", "labour market", "decomposition", "inequality" and "education" among others. This visualization provides a clear, at-a-glance summary of the main research within the existing literature.

Second, in Table 3-16, we classify them into four key thematic categories based on their content and focus. This categorization allows for a more structured understanding of how the EU-SILC data has been leveraged in skills-related research. The four categories include the following themes: i) education, labour market and social exclusion, ii) employment, mobility and poverty, iii) inequality and labour marker structure, iv) job/life satisfaction and gender differences. By categorizing the literature into these key thematic areas, Table 3-16 illustrates the diverse ways in which the EU-SILC data is being leveraged to explore critical issues related to skills mismatch, employment, and inequality across Europe.

Table 3-16: EU-SILC – Classification of the 21 articles on skills

Research domain	Citations
Education, Labour Market, and Social Exclusion	Guzi, Kahanec & Kureková (2018), Guagnano & Santini (2020), Albertini, Ballarino & De Luca (2020), Skuciene & Markeviciute (2021), Plavgo (2023), Hansen (2024)
Employment, Mobility and Poverty	Ecchia, Gagliardi & Giannetti (2020), Angelini, Farina & Valentini (2020), Pohlig (2021), Tonutti, Garnero, Bertarelli & Pratesi (2024)
Inequality and Labour Market Structure	Biagetti & Scicchitano (2011), Nolan & Voitchovsky (2016), Castellano, Manna & Punzo (2016), Castellano, Musella & Punzo (2017), Garofalo, Castellano, Punzo & Musella (2018), Punzo, Ciommi, Musella & Castellano (2019), Ayllón & Nollenberger (2021), Consoli, Castellacci & Santoalha (2023), Dorjnyambuu & Galambosné Tiszberger (2024)
Job/Life Satisfaction and Gender Differences	Navarro & Salverda (2019), Vladisavljevic (2023)

Figure 3-32: EU-SILC - Word cloud of the keywords in the 39 articles on skills

3.2 HOUSEHOLD FINANCE AND CONSUMPTION SURVEY (HFCS)

The Household Finance and Consumption Survey (HFCS) is a comprehensive survey coordinated by the European Central Bank (ECB) that collects detailed data on the financial behaviour and conditions of households in the euro area and some additional European countries. The HFCS provides insights into household wealth, income, consumption, and indebtedness, making it a critical tool for understanding the economic well-being of households and for informing monetary policy and financial stability assessments.

The primary goal of the HFCS is to collect harmonized micro-level data on the financial situation of households, focusing on assets, liabilities, income, consumption, and intergenerational transfers. This data helps policymakers and researchers understand wealth distribution, household resilience to economic shocks, and the broader financial conditions in the euro area.

The HFCS is conducted in euro area countries as well as in some additional European Union (EU) and non-EU countries. The survey covers households, gathering information from all household members aged 16 and over. The survey is designed to represent the entire population, including both wealthy households and those with low incomes or assets.

The survey caters to the following key areas:

- Assets: The survey collects detailed data on both real assets (such as property and vehicles) and financial assets (such as bank accounts, stocks, bonds, and pension plans).
- Liabilities: Information is gathered on household debts, including mortgages, consumer loans, and other types of credit.
- Income: The HFCS records data on different sources of income, including wages, pensions, social benefits, and income from investments.
- Consumption and Expenditure: The survey examines household spending patterns, including regular expenses and large, infrequent expenditures.
- Intergenerational Transfers and Gifts: Data on inheritances, gifts, and other transfers between family members are also collected.
- Demographic and Socioeconomic Characteristics: The HFCS includes information on the composition of the household, education, employment status, and other relevant characteristics of household members.
- Net Wealth: The difference between total household assets and liabilities, providing a measure of financial security.
- Wealth Distribution: The survey provides detailed insights into how wealth is distributed across different households, including by income level, age, and other demographic factors.
- Debt-to-Income and Debt-to-Asset Ratios: These indicators help assess the sustainability of household debt and the potential risks to financial stability.
- Household Consumption and Savings: The HFCS measures how households allocate their income between consumption and savings, shedding light on economic behaviour and potential vulnerabilities.

The HFCS is conducted every three years, with each wave collecting data from a representative sample of households in each participating country. The survey employs a harmonized methodology across countries, ensuring comparability of data. This includes common definitions, questionnaires, and data processing procedures. Data collection is typically carried out through face-to-face interviews, supplemented by self-administered questionnaires for more sensitive topics.

The HFCS data is crucial for the European Central Bank and other policymakers in understanding how households might respond to changes in interest rates or other monetary policy measures. By analyzing the distribution of wealth and debt, the survey helps identify potential risks in the financial system, such as high levels of indebtedness among certain groups of households. The HFCS informs policies aimed at reducing wealth inequality, improving access to credit, and supporting household financial resilience.

Wealth data, particularly in terms of asset ownership and liabilities, provides a more complete picture of economic well-being than income data alone. The HFCS helps in understanding the role of housing, both as an asset and a source of debt, in the overall financial health of households. The survey also highlights differences in financial behaviour and risk exposure across countries, helping tailor national and EU-wide economic policies.

The Household Finance and Consumption Survey is essential for understanding the economic conditions of households in Europe. It provides valuable data for assessing the financial resilience of households, analysing the distribution of wealth, and understanding how households interact with the broader economy. This information is crucial for developing policies that promote financial stability, economic growth, and social equity in the euro area and beyond.

3.2.1 THE DATA AND FREQUENCIES

The HFCS is a rich household finance and consumption survey, whose particular characteristic is that it is designed as a multiple-imputation survey, entailing five imputations, i.e., approximations for aggregate variables on consumption, wealth, debt, etc. It has a panel element, which is rather limited to specific country-members. Tables 3-17 presents the list of countries and the respective sample sizes overall and by country, before and after sample selection. For sample selection, we apply the same criteria as in the previous surveys, i.e., we select (i) Individuals aged 15-74, (ii) not living in institutions, (iii) not in compulsory military service, (iv) not retirees, (v) whose reason for not searching for a job is not education if they are aged less than 23.

The full sample of HFCS in all countries comprises of 793, 994 observations from 666,094 individuals. In the narrower selected sample, there are 417,669 observations from 365,043 individuals. The countries with the larger samples are France, Finland, Italy, Spain, Portugal, and Ireland. Luxembourg, Latvia, Croatia, and the Czech Republic have sample sizes smaller than 10,000 observations in all waves in the full sample before sample selection.

Table 3-18 presents the panel element we identified in the HFCS. In the full sample, there are 528,132 individuals present in only one wave, 88,689 individuals present in two waves, 28,720 present in three waves, and 20,553 individuals present in all four waves of 2010, 2014, 2017, and 2021. The countries with a full panel element are Austria, Germany, Italy, Cyprus, Portugal, and Slovenia, and there are other countries with more limited panel elements. These are own computations, which should be interpreted with caution at the time of compilation of this deliverable task.

Table 3-17: HFCS – Frequencies in the pooled sample (4 waves)

		PRE SAMPLE SELECTION				POST SAMPLE SELECTION			
		# OBSERVATIONS (%)		# INDIVIDUALS (%)		# OBSERVATIONS (%)		# INDIVIDUALS (%)	
All Countries	POOLED	793,994	(100.00%)	666,094	(100.00%)	417,669	(100.00%)	365,043	(100.00%
Austria	AT	22,097	(2.78%)	15,811	(2.37%)	11,751	(2.81%)	9,500	(2.60%)
Belgium	BE	20,945	(2.64%)	20,945	(3.14%)	10,383	(2.49%)	10,383	(2.84%)
Croatia	HR	6,969	(0.88%)	6,969	(1.05%)	3,453	(0.83%)	3,453	(0.95%)
Cyprus	CY	16,596	(2.09%)	16,435	(2.47%)	9,474	(2.27%)	9,401	(2.58%)
Czech Republic	CZ	6,730	(0.85%)	6,730	(1.01%)	3,115	(0.75%)	3,115	(0.85%)
Estonia	EE	33,611	(4.23%)	33,562	(5.04%)	19,629	(4.70%)	19,608	(5.37%)
Finland	FI	101,670	(12.80%)	101,670	(15.26%)	57,164	(13.69%)	57,164	(15.66%)
France	FR	121,719	(15.33%)	106,369	(15.97%)	62,073	(14.86%)	56,419	(15.46%)
Germany	DE	38,462	(4.84%)	30,076	(4.52%)	21,172	(5.07%)	17,511	(4.80%)
Greece	GR	30,664	(3.86%)	30,416	(4.57%)	17,953	(4.30%)	17,842	(4.89%)
Hungary	HU	36,245	(4.56%)	36,245	(5.44%)	18,666	(4.47%)	18,666	(5.11%)
Ireland	IE	43,374	(5.46%)	32,862	(4.93%)	11,667	(2.79%)	8,906	(2.44%)
Italy	IT	70,862	(8.92%)	61,839	(9.28%)	39,189	(9.38%)	34,738	(9.52%)
Latvia	LV	5,598	(0.71%)	5,490	(0.82%)	3,406	(0.82%)	3,338	(0.91%)
Lithuania	LT	13,977	(1.76%)	13,469	(2.02%)	7,897	(1.89%)	7,670	(2.10%)
Luxembourg	LU	9,646	(1.21%)	9,646	(1.45%)	5,701	(1.36%)	5,701	(1.56%)
Malta	MT	13,048	(1.64%)	12,478	(1.87%)	3,993	(0.96%)	3,822	(1.05%)
Netherlands	NL	16,458	(2.07%)	15,679	(2.35%)	9,509	(2.28%)	9,249	(2.53%)
Poland	PL	24,052	(3.03%)	24,052	(3.61%)	13,145	(3.15%)	13,145	(3.60%)
Portugal	PT	57,795	(7.28%)	28,675	(4.30%)	31,432	(7.53%)	19,270	(5.28%)
Slovakia	SK	21,030	(2.65%)	17,322	(2.60%)	11,538	(2.76%)	10,239	(2.80%)
Slovenia	SI	18,636	(2.35%)	14,634	(2.20%)	9,812	(2.35%)	8,435	(2.31%)
Spain	ES	63,810	(8.04%)	24,720	(3.71%)	35,547	(8.51%)	17,468	(4.79%)

Notes: The calculations on unweighted multiple imputation data (5 imputations).

Table 3-18: HFCS – Panel sample life

	PRE SAMPLE SELECTION					POST SAMPLE SELECTION				
# YEARS	- 1 -	- 2 -	- 3 -	- 4 -	TOTAL	- 1 -	- 2 -	- 3 -	- 4 -	TOTAL
#Individuals	***528,132***	***88,689***	***28,720***	***20,553***	***666,094***	***269,668***	***57,906***	***20,747***	***16,722***	***365,043***
	(79.29%)	*(13.31%)*	*(4.31%)*	*(3.09%)*	*(100.00%)*	*(73.87%)*	*(15.86%)*	*(5.68%)*	*(4.58%)*	*(100.00%)*
#Observations	***529,813***	***136,796***	***63,621***	***63,764***	***793,994***	***270,131***	***72,888***	***36,134***	***38,516***	***417,669***
	(66.73%)	*(17.23%)*	*(8.01%)*	*(8.03%)*	*(100.00%)*	*(64.68%)*	*(17.45%)*	*(8.65%)*	*(9.22%)*	*(100.00%)*
Austria	13,248	6,684	2,121	44	22,097	6,633	3,832	1,260	26	11,751
Belgium	20,945	0	0	0	20,945	10,383	0	0	0	10,383
Croatia	6,969	0	0	0	6,969	3,453	0	0	0	3,453
Cyprus	5,238	11,170	108	80	16,596	2,934	6,418	70	52	9,474
Czech Republic	6,730	0	0	0	6,730	3,115	0	0	0	3,115
Estonia	27,171	6,440	0	0	33,611	15,773	3,856	0	0	19,629
Finland	101,670	0	0	0	101,670	57,164	0	0	0	57,164
France	91,019	30,700	0	0	121,719	43,943	18,130	0	0	62,073
Germany	9,336	9,780	10,818	8,528	38,462	5,466	5,376	5,775	4,555	21,172
Greece	30,168	496	0	0	30,664	17,627	326	0	0	17,953
Hungary	36,245	0	0	0	36,245	18,666	0	0	0	18,666
Ireland	23,703	15,612	4,059	0	43,374	4,450	5,299	1,918	0	11,667
Italy	35,415	13,782	11,817	9,848	70,862	19,772	7,564	6,414	5,439	39,189
Latvia	5,382	216	0	0	5,598	3,243	163	0	0	3,406
Lithuania	12,961	1,016	0	0	13,977	7,231	666	0	0	7,897
Luxembourg	9,646	0	0	0	9,646	5,701	0	0	0	5,701
Malta	13,048	0	0	0	13,048	3,993	0	0	0	3,993
Netherlands	13,248	3,210	0	0	16,458	7,665	1,844	0	0	9,509
Poland	24,052	0	0	0	24,052	13,145	0	0	0	13,145
Portugal	11,225	16,620	19,830	10,120	57,795	4,454	8,730	11,975	6,273	31,432
Slovakia	14,120	5,374	1,536	0	21,030	7,653	3,004	881	0	11,538
Slovenia	11,091	6,176	1,353	16	18,636	5,529	3,448	824	11	9,812
Spain	7,183	9,520	11,979	35,128	63,810	2,138	4,232	7,017	22,160	35,547

Notes: The calculations on unweighted multiple imputation data (5 imputations).

3.2.2 THE EMPLOYED SAMPLE AND SUMMARY STATISTICS

In this sub-section, we present unweighted statistics regarding employment status. Table 3-19 presents the distribution of our working-age individuals across 10 categories. In the pooled sample across all 4 waves, 54.6% of the sample are in full-time paid employment, 6.4% are in part-time employment, 11.9% are in full-time self-employment, 1.2% are in part-time self-employment, 0.4% identify as unpaid family workers, 10.2% are unemployed, 1.7% are inactive, 2.8% are disabled, another 2.8% are students looking for employment, and 8.2% are homemakers. One can observe an increase in full-time paid employment from 50.6% in 2010 to 58.8% in 2021. There is also a reduction in unemployment from 10.2% in 2010 to 8.5% in 2021, and a reduction in the number of homemakers from 9.2% in 2010 and 11.6% in 2014 into 6.1% in 2021. The increase in employment is justifiable noting that the 2010s were the decade of the Eurozone crisis and the post-crisis period.

Table 3-19: HFCS – Economic activity

	ALL WAVES	2010	2014	2017	2021
Paid employee full-time	**54.6%**	***50.6%***	**52.5%**	**56.1%**	**58.8%**
	(228,035)	*(46,814)*	*(56,485)*	*(65,229)*	*(59,507)*
Paid employee part-time	***6.4%***	**5.1%**	**6.9%**	**6.9%**	**6.8%**
	(26,913)	*(4,681)*	*(7,428)*	*(7,965)*	*(6,839)*
Self-employed full-time	**11.9%**	***13.4%***	**11.5%**	**11.3%**	**11.5%**
	(49,516)	*(12,400)*	*(12,351)*	*(13,138)*	*(11,627)*
Self-employed part-time	***1.2%***	**1.3%**	**1.1%**	**1.1%**	**1.3%**
	(4,989)	*(1,162)*	*(1,223)*	*(1,317)*	*(1,287)*
Unpaid family worker	**0.4%**	**0.3%**	**0.4%**	**0.5%**	**0.3%**
	(1,572)	*(316)*	*(429)*	*(518)*	*(309)*
Unemployed	***10.2%***	**10.6%**	**12.0%**	**9.7%**	**8.5%**
	(42,516)	*(9,766)*	*(12,937)*	*(11,259)*	*(8,554)*
Inactive	**1.7%**	**1.9%**	**1.7%**	**2.0%**	**1.1%**
	(7,038)	*(1,794)*	*(1,844)*	*(2,279)*	*(1,121)*
Disabled	***2.8%***	**2.3%**	**2.8%**	**2.8%**	**3.1%**
	(11,505)	*(2,138)*	*(3,022)*	*(3,253)*	*(3,092)*
Student	**2.8%**	**3.0%**	**2.9%**	**2.5%**	**2.7%**
	(11,556)	*(2,782)*	*(3,132)*	*(2,931)*	*(2,711)*
Homemaker	***8.2%***	**11.6%**	**8.2%**	**7.2%**	**6.1%**
	(34,029)	*(10,704)*	*(8,796)*	*(8,373)*	*(6,156)*
Pooled sample	***100.0%***	***100.0%***	***100.0%***	***100.0%***	***100.0%***
	(417,669)	*(92,557)*	*(107,647)*	*(116,262)*	*(101,203)*

Figure 3-33 documents this increase in employment in all countries between 2010 and 2021, with the sole exception of Slovakia between 2017 and 2021. We consider as employed the first 5 categories of Table 3.19. Countries with above-average employment are at the left of the figure, namely Austria (85.4%), and then the Czech Republic, Latvia, Germany, Hungary, Luxembourg, Lithuania, France, Slovakia, Finland, Slovenia and Malta (75.3%). Countries with below-average employment are Belgium (74.4%), Poland, Portugal, Ireland, Cyprus, Estonia, the Netherlands, Croatia, Greece, Spain, and Italy (62.8%).

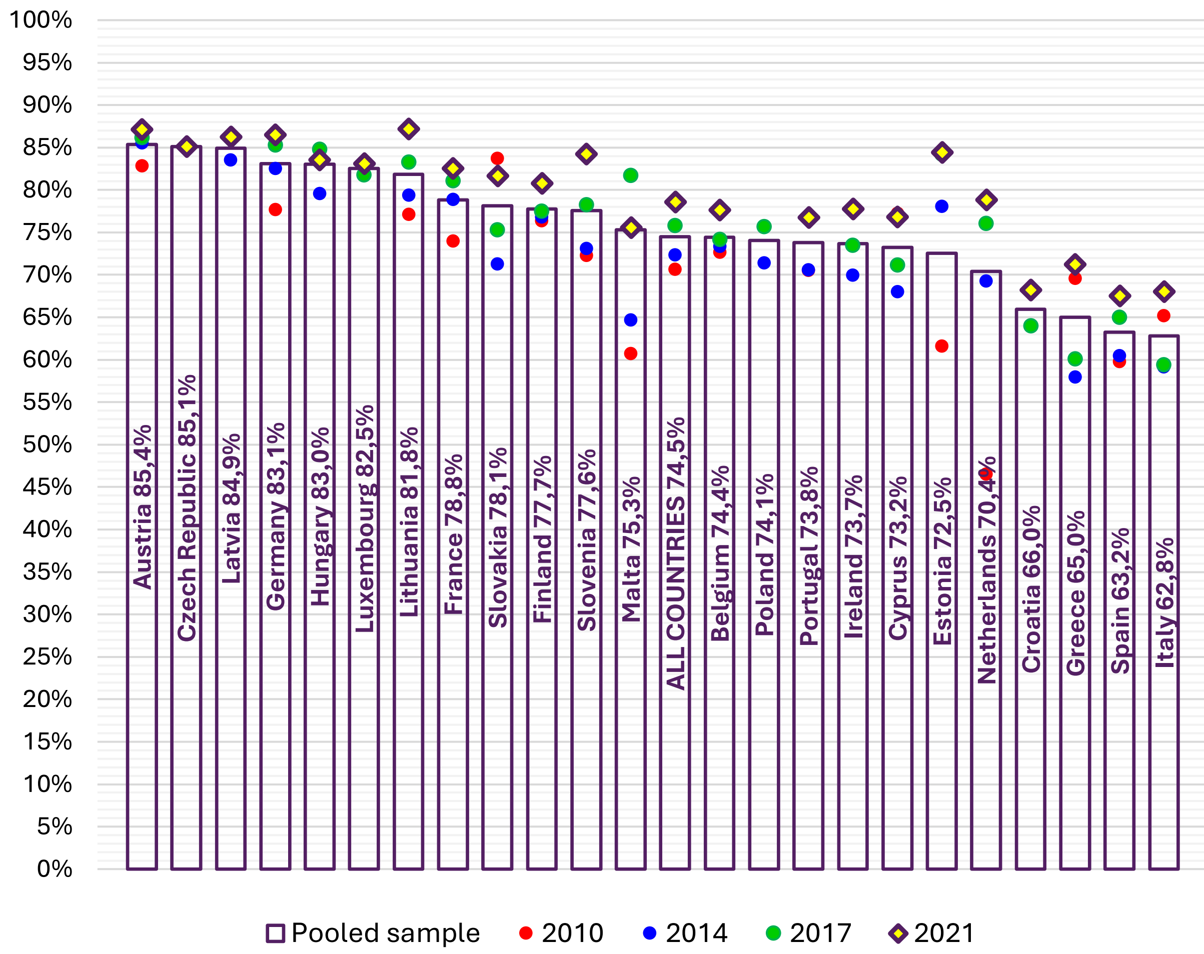


Figure 3-33: HFCS – % Employment by country and year

3.2.3 STATISTICS ON SKILLS MATCHING

In this section we present unweighted statistics related to skills mis(matching) and its constituents. It is worth noting that there are no questions related to training and work-based learning at the HFCS. We use the same primary definition for mismatching as in the previous datasets, i.e., an individual is considered matched to the skills required for his/her occupation if he/she has the same level of education as the median level by country and 2-digit ISCO code. Then, he/she is overeducated if the level of education is above that median, and undereducated if it is below.

The inverse bars in Figure 3-34 present the ranking of countries in terms of the instance of skills mismatching in the pooled sample of all 4 HFCS waves. The countries with higher instance of mismatching are Portugal (44.7%), Spain (42.5%), Cyprus (41.6%), the Netherlands (41.2%), and Italy (40.6%). The top 5 countries, which have lower instances of skills mismatching are Poland (19.6%), the Czech Republic (20.6%), Slovakia (21.1%), Austria (22.3%), and Croatia (22.6%). The coloured dots in the scatterplot of the right-hand axis present the rates of skills mismatching in each of the four years in the HFCS. There are notable increases in mismatching in 2021 in Luxembourg, Lithuania, Ireland, Italy, France, and Finland.

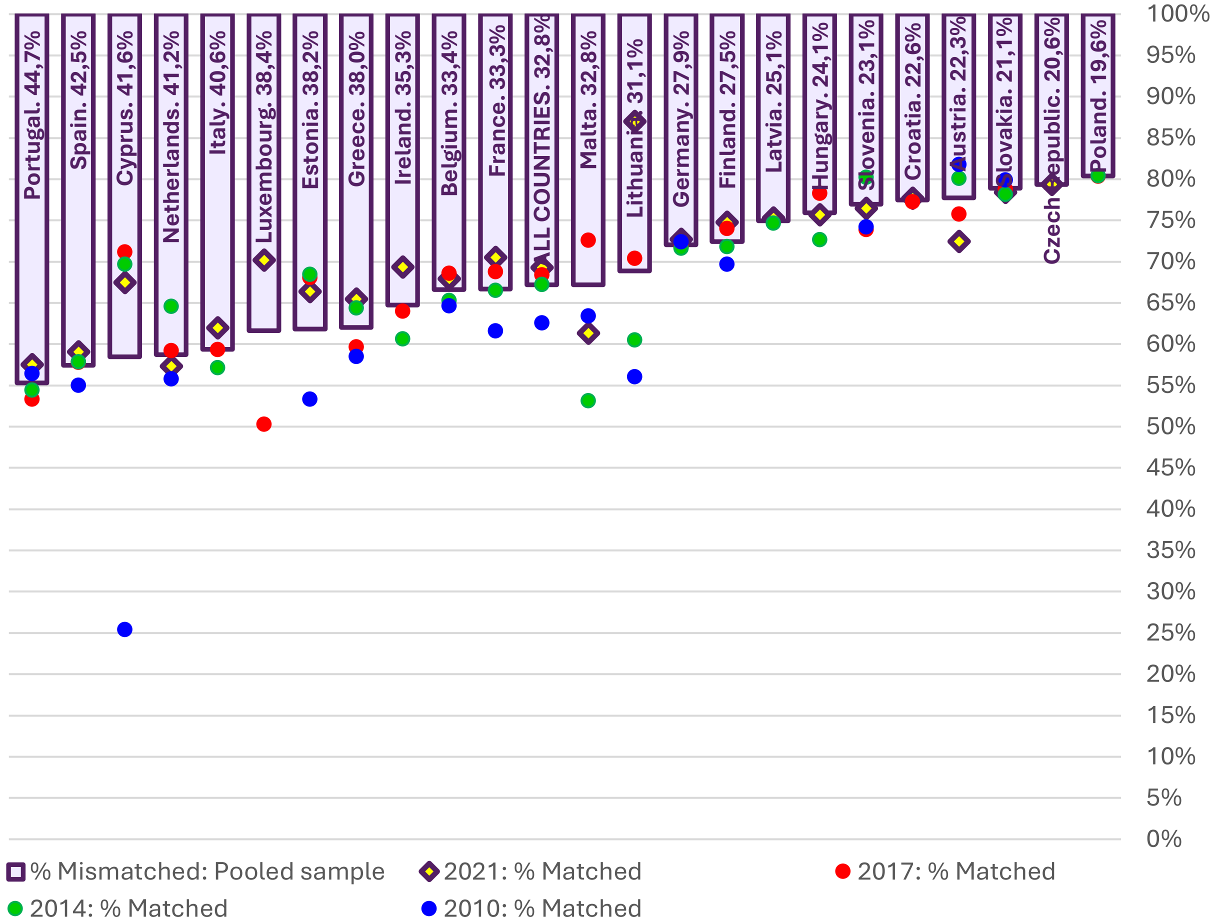


Figure 3-34: HFCS – % Mis(matched) by country and year

Figure 3.35 presents unweighted statistics for the pooled HFCS sample and the instance of overeducation by country. It also presents the yearly average in dots. The countries with the lower levels of overeducation are Poland, Latvia, Finland, the Czech Republic and Austria. The levels are below 10% in the first 4 out of the 5 countries. The countries with the higher instance of overeducation are Portugal (23.5%), Cyprus, Italy, Germany, and Greece (15.3%). By 2021, there appears to be a reduction in overeducation in all countries.

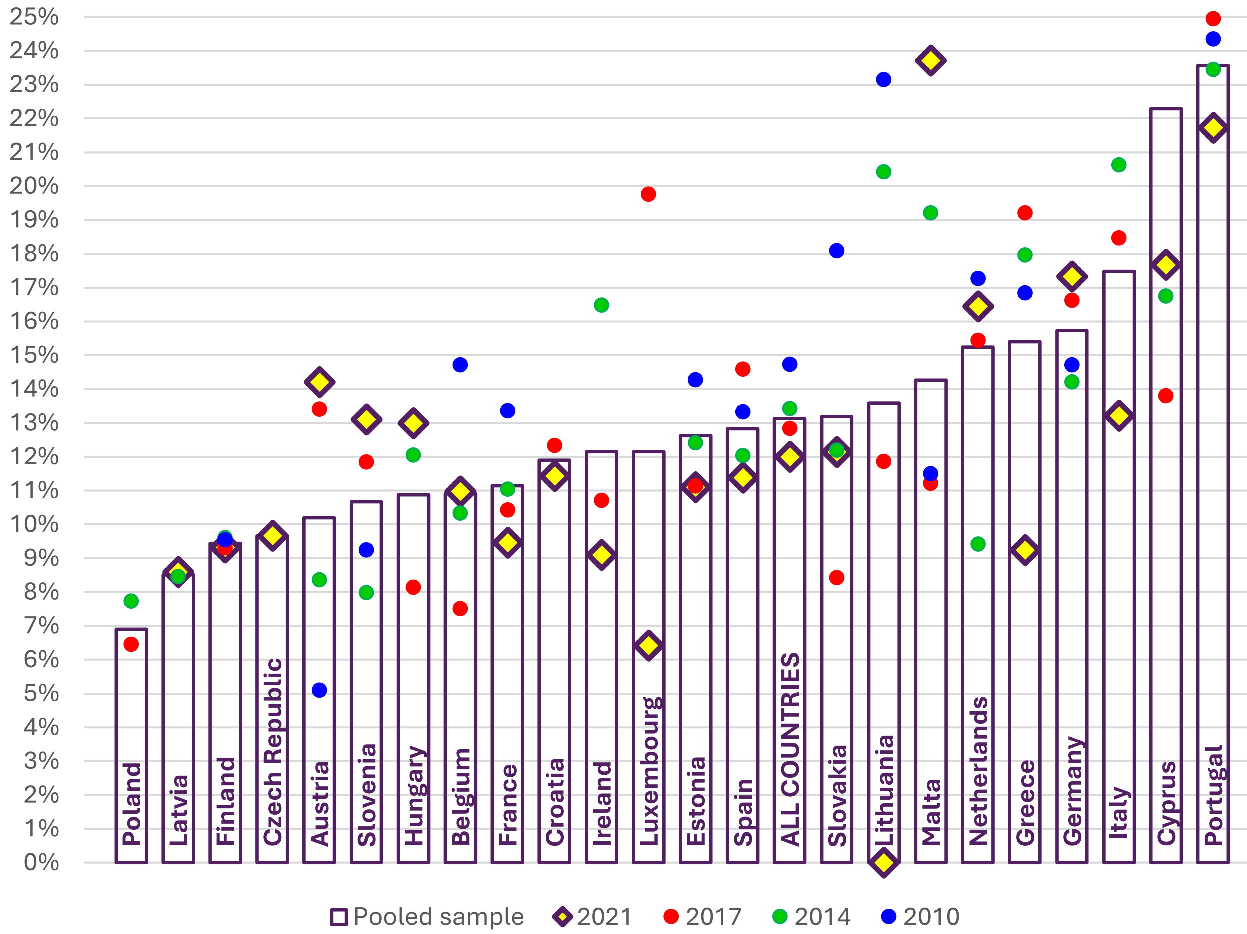


Figure 3-35: HFCS – % Overeducated by country and year

Figure 3.36 presents the respective figures for undereducation in the pooled sample and for each country by wave. The countries with the lowest rates of undereducation are Slovakia (8%), Croatia, the Czech Republic, Austria, and Germany (12.1%). The countries with the highest incidence of undereducation are Spain (29.3%), Luxembourg, the Netherlands, Estonia, and Ireland (23.1%). There is also a notable increase in undereducation in 2021, in all countries but Italy and Greece.

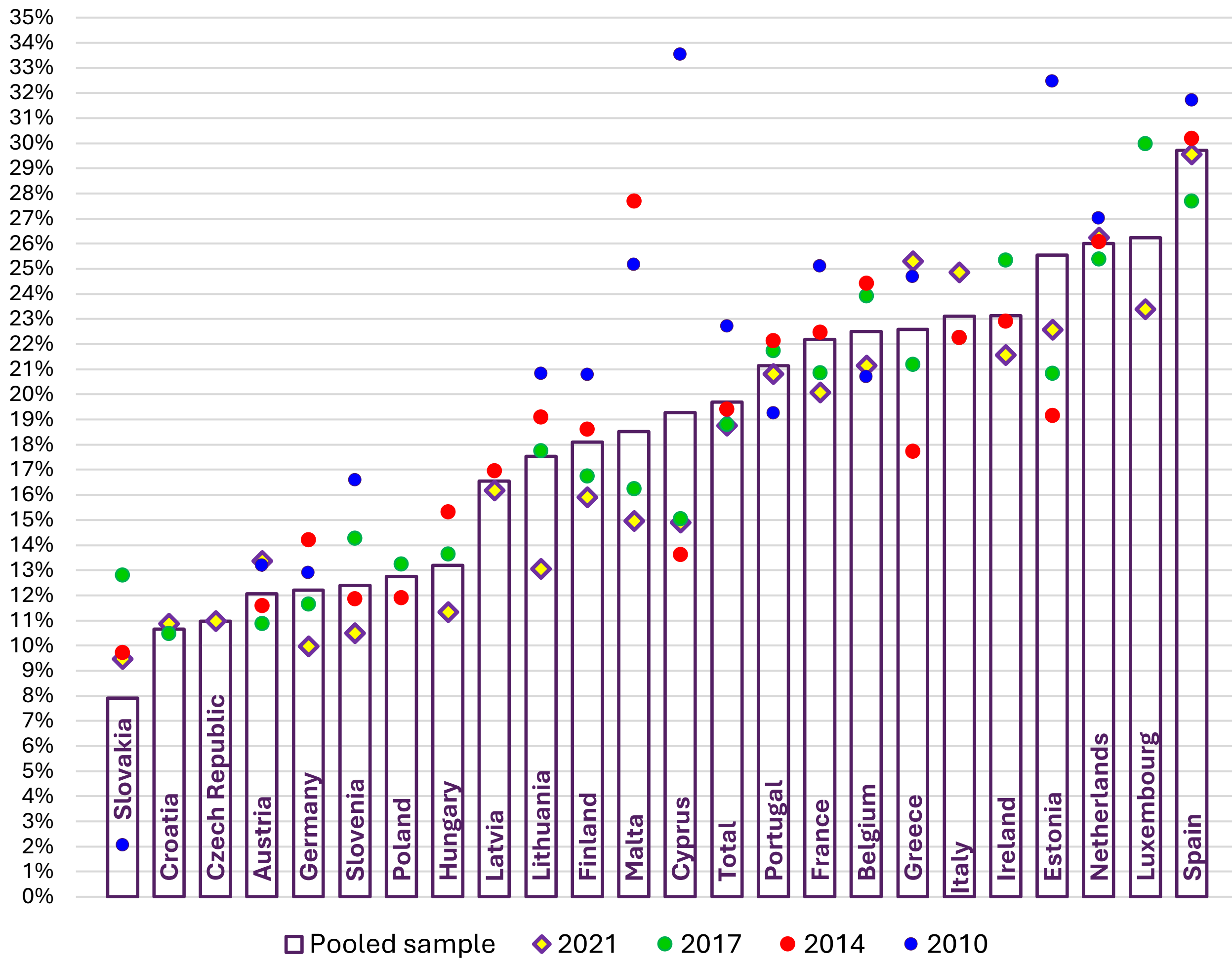


Figure 3-36: HFCS – % Undereducated by country and year

3.2.4 DIFFERENCES ACROSS KEY DEMOGRAPHIC GROUPS

In this sub-section, we present differences in skills mismatching, overeducation, and undereducation between 4 pairs of interest and policy relevance, namely (i) males-females; (ii) old-young; (iii) high-paid (Top 40%) – low-paid (Bottom 60%); (iv) wealth-rich (Top 40%) – wealth-poor (Botton 60%). For the former three pairs, we follow the definitions used in previous datasets, e.g., EU-LFS, EU-SILC, etc. The unique feature of the HFCS is that it has very detailed data on wealth and its constituents. For the distrinction between wealth-rich and wealth-poor we use net wealth, which accounts for the difference between gross wealth and total debt.

Figure 3-37 plots the difference in the average rate of mismatching between males and females. These are plotted in the red dots in percentage points (not percentages), overall and by coutnry. Then the black bars plot the difference in overeducation by gender, and the white bar plots the difference in undereducation by gender. On average, males are more likely to be mismatched and to be undereducated. In the countries at the left of the figure, it is females who are more likely to be mismatched. The bottom five countries are Croatia, the Czech Republic, Slovakia, Hungary, and Luxembourg. The top five countries, in which males are much more likely to be mismatched are Latvia, Malta, Spain, Estonia, and Portugal.

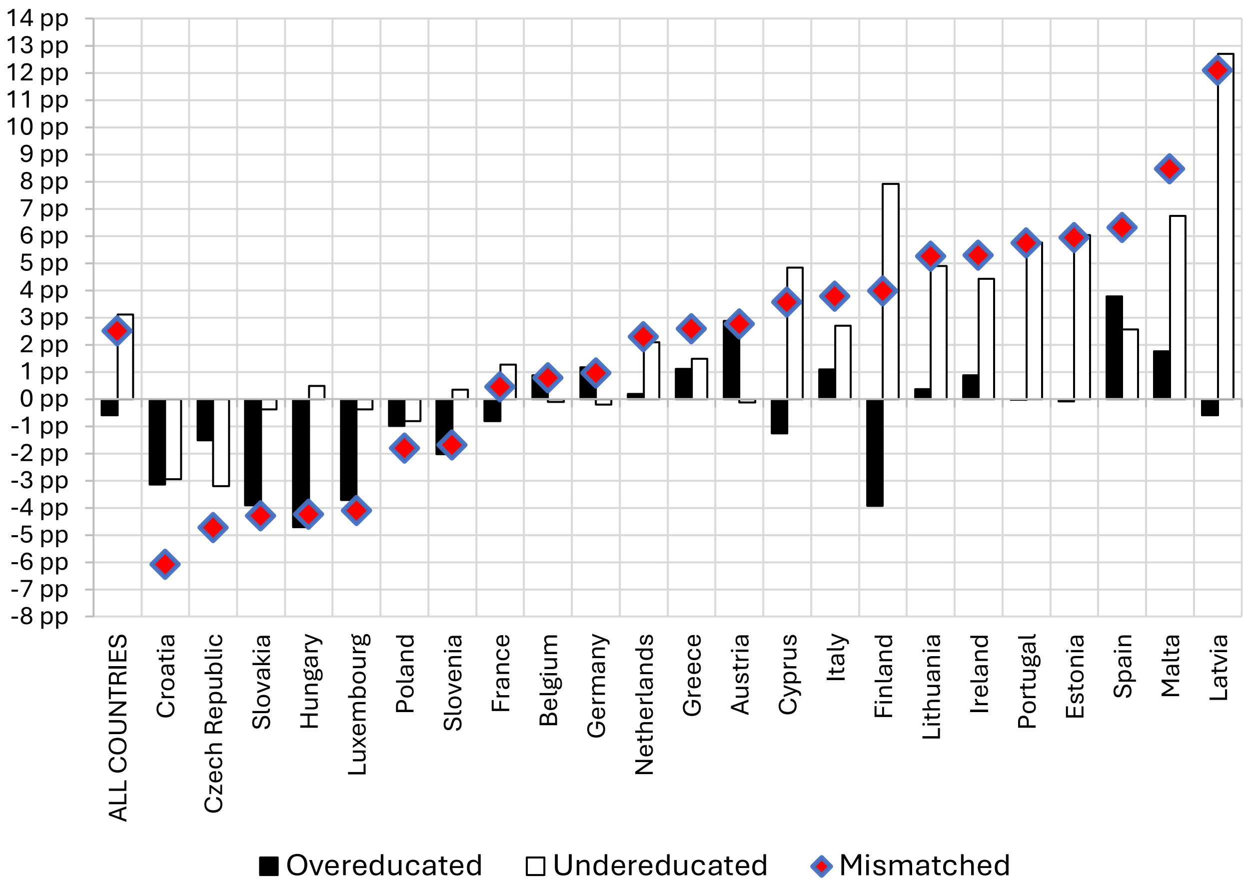


Figure 3-37: HFCS – Differences by gender (male-female)

Figure 3-38 plots the difference in the average rate of mismatching between the older and the younger generations, using the same definitions for age groups previously used for the EU-LFS, inter alia. In countries at the left, it is the young who are more likely to be mismatched, and in countryies at the right, it is the older generation. The bottom five countries, in which the young are much more likely to be mismatched are Latvia, the Czech Republic, Portugal, Hungary, and Germany. The top five countries in which the old are more likely to be mismatched are Ireland, Luxembourg, Greece, Cyprus and Finland.

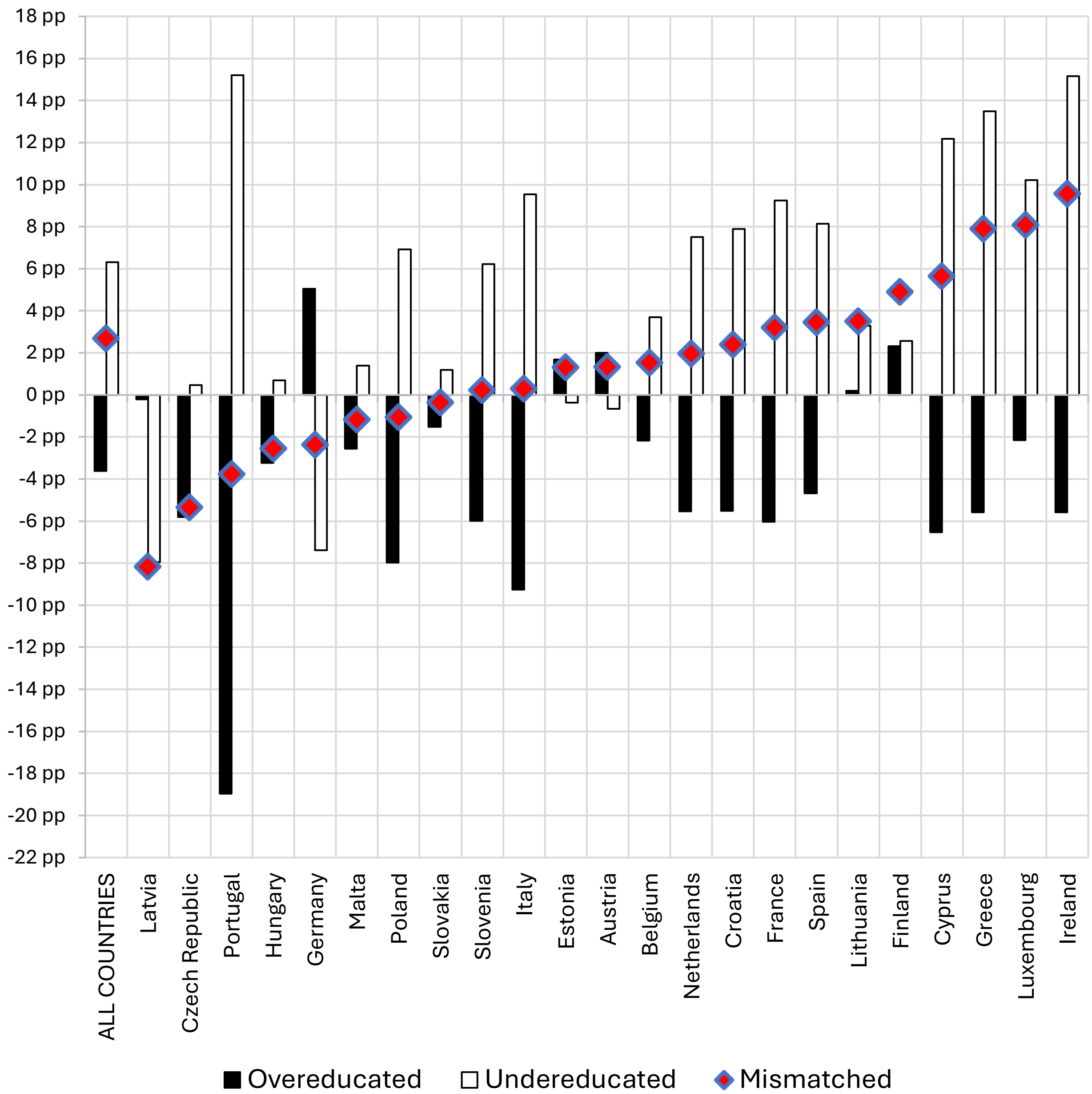


Figure 3-38: HFCS – Differences by age (old - young)

Figure 3-39 plots the difference in the average rate of mismatching between the highly-paid and the low-paid, i.e., the individuals in the top 4 deciles of the distribution for equivalised household income, versus those in the bottom 6 deciles. In countries at the left, it is the low-paid who are more likely to be mismatched, and in countryies at the right, it is the high-paid. The bottom five countries, in which the young are much more likely to be mismatched are Spain, Luxembourg, Ireland, Portugal, and Estonia. The top five countries in which the old are more likely to be mismatched are Slovakia, Lithuania, Croatia, Cyprus, and the Czech Republic. These are actually the only five countries in which the high-paid are more likely to be mismatched in terms of skills in their occupation.

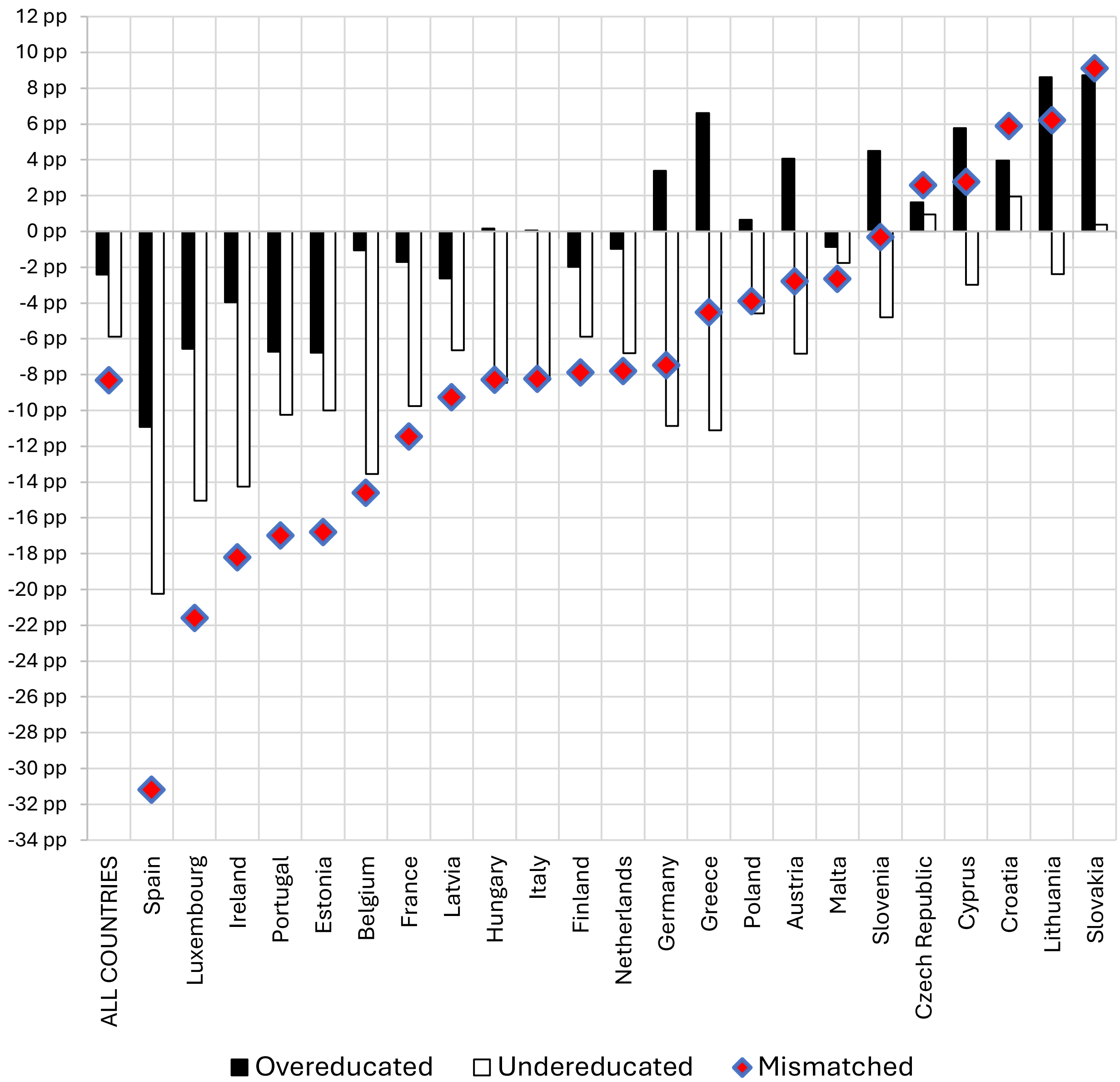


Figure 3-39: HFCS – Differences by income (high-paid – low-paid)

Figure 3-40 plots the difference in the average rate of mismatching between the wealth-rich and the wealth-poor, i.e., the individuals in the top 4 deciles of the distribution for net wealth, versus those in the bottom 6 deciles. In countries at the left, it is the relatively poor who are more likely to be mismatched, and in countryies at the right, it is the relatively rich. The bottom five countries, in which the less wealthy are much more likely to be mismatched are Spain, Belgium, Portugal, France, and Luxembourg. The countries in which the relatively rich are more likely to be mismatched in their occupation are Malta, Croatia, the Czech Republic, Slovakia and Lithuania. For most of the countries, it is the less wealthy who are more mismatched and typically more undereducated.

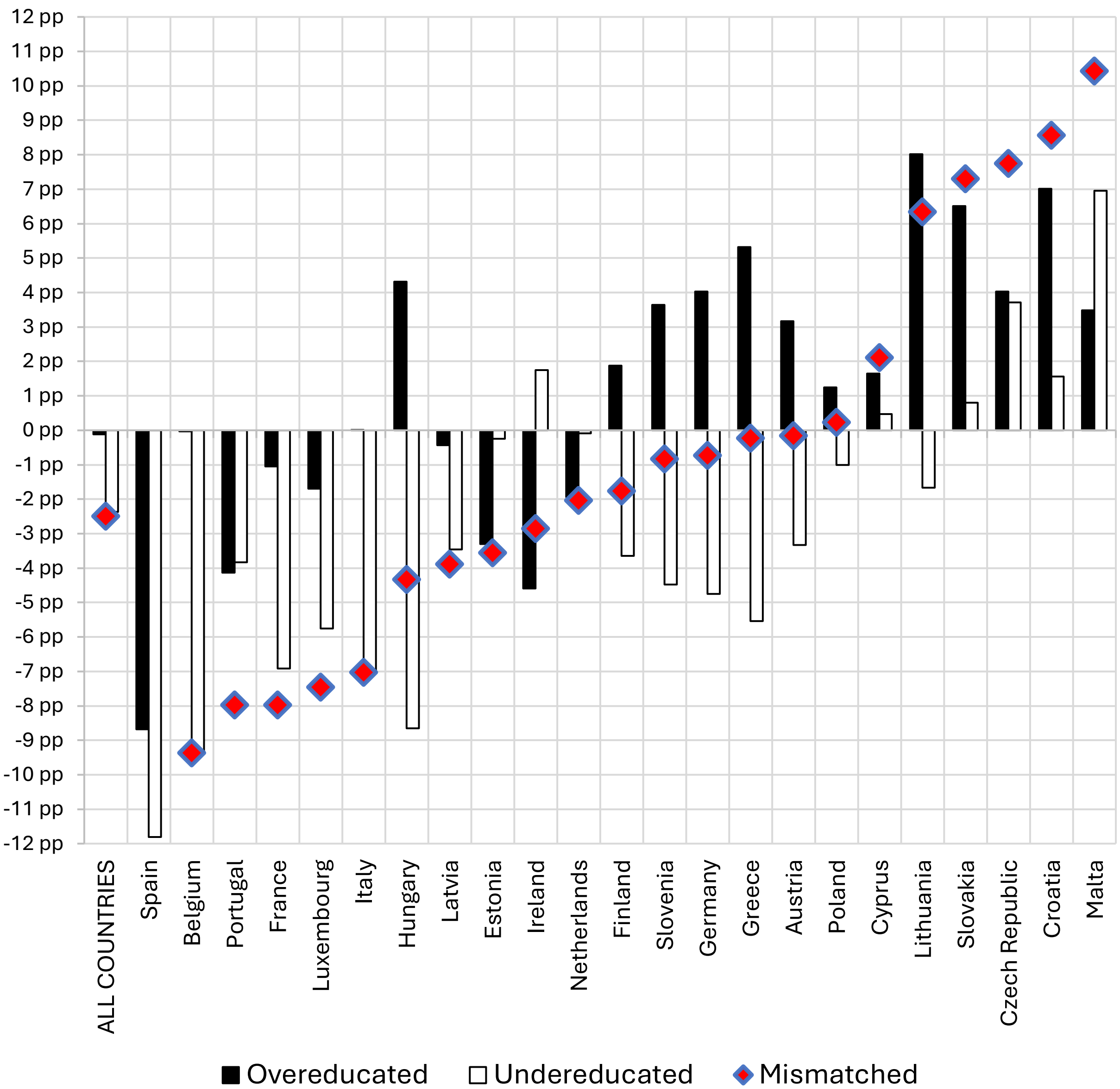


Figure 3-40: HFCS – Differences by net wealth (wealth-rich – wealth-poor)

3.2.5 THE RELEVANT LITERATURE

An inquiry using the Scopus database suggests some 436 articles using the HFCS database. Out of these, 46 articles use the EU-SILC for research that can somehow be conceptually linked to skills, although this link is only indirect. We conduct 2 relevant exercises using these 46 articles. In Figure

3-41 we present a wordcloud of the most frequently appearing words in the index and author keywords of these 21 articles. Then, in Table 3-20, we classify them into 4 key thematic categories, in terms of their content.

Table 3-20 shows 4 major thematic areas of research using the EU-SILC. These are: (1) Wealth Inequality and Distribution; (2) Data Quality and Methodology; (3) Policy and Reform; (4) Household Finance and Vulnerability.

Table 3-20: HFCS – Classification of the 46 relevant articles

Research Domain	Citations
Wealth Inequality and Distribution	Sipková & Sipko (2017); Brzeziński, Sałach & Wroński (2020); Kuypers & Marx (2021); Branten (2022); Mojsejová & Marcinová (2023); Bielskis (2023); Biewen, et al. (2024).
Data Quality and Methodology	Andreasch & Lindner (2016); Tiefensee & Grabka (2016); Kreutzmann, Marek, Runge, Salvati & Schmid (2022); Arrondel, Bartiloro, Fessler, Lindner, Mathä, Rampazzi, Savignac, Schmidt, Schürz & Vermeulen (2016); Bover, Schürz, Slacalek & Teppa (2016); Kolář (2024).
Policy and Reform	Adam & Tzamourani (2016); Fessler & Schürz (2018); Drescher, et al. (2020); Wind, et al. (2020); Bernardino (2020); Beznoska, et al. (2020); Kuypers, et al. (2020); Krenek & Schratzenstaller (2022); De Luigi, et al. (2023).
Household Finance and Vulnerability	Rehm & Schnetzer (2015); Kuypers, et al. (2016); Ampudia, et al. (2016); Gross & Población (2017); Müller (2017); Schnetzer (2018); Bach, et al. (2019); Chakraborty, et al. (2019); Massó & Abalde (2020); Wind, et al. (2020); Wind, et al. (2020); Kuypers, et al. (2020); Kuypers, et al. (2021); Branten (2022); Muckenhuber, et al. (2022); Midões & Seré (2022); Raviv & Hinz (2022); Buleca, et al. (2022); Muckenhuber, et al. (2022a); Muckenhuber, et al. (2022b); Du Caju, et al. (2023); Xidonas, et al. (2024); Xidonas, et al. (2024); Abalde, et al. (2024); Kolář (2024).

Figure 3-41: HFCS - Wordcloud of the keywords in the 46 articles

4. FIRM-LEVEL DATASETS

In this section, we present the five global and international microeconomic databases, which enable analysis at the European firm level. These are: (1) the World Bank Enterprise Surveys; (2) the Survey on the Access to Finance of Enterprises; (3) the Flash Eurobarometer 2023 - 529 on Skills and Qualifications; (4) the European Investment Bank Investment Climate Survey, and (5) the Continuing Vocational Education Survey. Section 4 entails five subsections. The three first sub-sections are more detailed, 4.1 presenting the World Bank Enterprise Surveys, 4.2 presenting the Survey on the Access to Finance of Enterprises, and 4.3 describing the Eurobarometer 81.3. The contents of these sub-sections follow a similar structure to the previous sub-sections. The begin with (1) presenting the data and frequencies, and (2) the employed sample and summary statistics. Then, (3) they present the most relevant statistics on skills (mis)matching and training, and differences in these statistics by (4) gender, (5) age, and (6) income. Each subsection concludes by (7) presenting a short systematic literature review of the literature using each of the two databases. Finally, subsections 4.4 and 4.5 present the basic descriptions of the two datasets, for the applications of which there are still pending approval, namely the European Investment Bank Investment Climate Survey and the Continuing Vocational Education Survey. The specifics of these datasets will be presented in detail at forthcoming deliverable tasks of the TRAILS project.

4.1 WORLD BANK ENTERPRISE SURVEYS (WBES)

The World Bank Enterprise Surveys are a set of comprehensive surveys conducted by the World Bank across various countries to assess the business environment and its impact on private sector firms. These surveys provide detailed insights into the experiences and challenges faced by firms in emerging and developing economies, focusing on areas such as access to finance, infrastructure, competition, and regulatory environment.

The primary aim of the World Bank Enterprise Surveys is to gather data that help policymakers, researchers, and development organizations understand the constraints to private sector growth and productivity. The surveys focus on identifying the key obstacles that businesses face and provide evidence-based insights to inform policy reforms aimed at improving the business environment.

The surveys are conducted in over 150 countries, with a focus on developing and transition economies. They cover a wide range of industries, including manufacturing, services, and retail sectors, and include businesses of different sizes, from small and medium-sized enterprises (SMEs) to large firms.

The survey covers the following themes:

- Firm Characteristics: Data on the size, age, and ownership structure of firms, as well as the gender of the top manager and other demographic information.

- Business Environment: The surveys assess various aspects of the business environment, including:
- Regulations and Taxation: The impact of business regulations, taxes, and the overall ease of doing business.
- Access to Finance: Information on firms' ability to access credit, collateral requirements, and the cost of financing.
- Infrastructure: The quality and reliability of infrastructure, including electricity, water, transportation, and telecommunications.
- Labour: The availability and cost of labour, as well as issues related to labour regulations and workforce skills.
- Trade: Barriers to trade, such as customs regulations and import/export procedures.
- Corruption and Governance: The prevalence of corruption, bribery, and the impact of governance issues on business operations.
- Innovation: The extent of innovation within firms, including research and development (R&D) activities, adoption of new technologies, and product innovation.
- Competition: The level of competition in the market, including the presence of informal firms and anticompetitive practices.
- Constraints to Business Growth: Identifying the most significant barriers to business growth, such as lack of access to finance, corruption, or inadequate infrastructure.
- Investment Climate: Measures of how conducive the local environment is to private investment, including regulatory and legal frameworks.
- Firm Dynamics: Insights into the factors that drive firm entry, exit, growth, and survival.

The surveys collect data on firm performance, such as sales growth, productivity, investment, and profitability. The surveys are typically conducted through face-to-face interviews with business owners or top managers. The sampling methodology ensures that the survey results are representative of the private sector in each country, allowing for cross-country comparisons and benchmarking. The surveys are updated periodically, typically every few years, to track changes in the business environment over time.

The data from Enterprise Surveys are used to inform economic policies that aim to enhance the business environment, promote private sector development, and foster economic growth. The surveys help identify areas where reforms are needed to improve the ease of doing business, reduce corruption, and enhance competitiveness. Policymakers and development agencies use the survey data to monitor the impact of reforms and development programs on the private sector.

The Enterprise Surveys allow for global comparisons, enabling countries to benchmark their business environment against others. This benchmarking helps identify best practices and lessons learned from other countries that have successfully improved their business climate. The World Bank Enterprise Surveys are a vital tool for understanding the challenges and opportunities facing the private sector in developing countries. By providing detailed, country-specific data on the business environment, these surveys support evidence-based policymaking and help drive reforms that can lead to economic growth, job creation, and poverty reduction. The insights gained from these surveys are essential for governments, international organizations, and businesses aiming to improve the competitiveness and sustainability of the private sector in emerging economies.

The sampling methodology for Enterprise Surveys is stratified random sampling with replacement. In a simple random sample, all members of the population have the same probability of being selected and no weighting of the observations is necessary. In a stratified random sample, all population units are grouped within homogeneous groups and simple random samples are selected within each group. This method allows computing estimates for each of the strata with a specified level of precision while population estimates can also be estimated by properly weighting individual observations. The sampling weights take care of the varying probabilities of selection across different strata. Under certain conditions, estimates' precision under stratified random sampling will be higher than under simple random sampling (lower standard errors may result from the estimation procedure).

The strata for Enterprise Surveys are firm size, business sector, and geographic region within a country. Firm size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large-sized firms). Since in most economies, most firms are small and medium-sized, Enterprise Surveys oversample large firms since larger firms tend to be engines of job creation. Sector breakdown is usually manufacturing, retail, and other services. For larger economies, specific manufacturing sub-sectors are selected as additional strata based on employment, value-added, and total number of establishments figures. Geographic regions within a country are selected based on which cities/regions collectively contain most of the economic activity.

4.1.1 THE DATA AND FREQUENCIES

World Bank Enterprise Surveys (WBES) are nationally representative firm-level surveys with top managers and owners of businesses in over 150 economies, reaching 180 in upcoming years, that provide insight into many business environment topics such as access to finance, workforce, corruption, infrastructure, and performance, among others. The information collected through the surveys is publicly available at the economy and firm level.

Workforce: A skilled labour force is essential for firms to thrive and compete. It fosters the ability to innovate and to adopt new technologies. Characteristics about the workforce such as a strong reliance on temporary workers may indicate regulatory inflexibilities regarding the hiring and firing of full-time workers. The indicators on the following figures measure labour issues in 159 economies. The results are based on surveys of more than 219,000 firms.

The manufacturing and services sectors are the primary business sectors of interest. This corresponds to firms classified with ISIC codes 15-37, 45, 50-52, 55, 60-64, and 72 (ISIC Rev.3.1). Formal (registered) companies with 5 or more employees are targeted for interview. Services firms include construction, retail, wholesale, hotels, restaurants, transport, storage, communications, and IT. Firms with 100% government/state ownership are not eligible for interview.

The Enterprise Survey covers a wide range of business environment topics including general business characteristics, infrastructure and services, sales and supplies, access to finance, degree of competition, land, crime, business-government relations, investment climate constraints, labour, and productivity. There are manufacturing-specific questions as well as a few retail-specific questions. In collaboration with economists in the regional departments of the World Bank, every Enterprise Survey is customized to include economy-specific questions (or region-specific questions). The questions are mostly objective questions aimed at measuring the quality of the business environment and the experience of firms. Less than 10% of the questions are subjective, that is asking the respondent for his/her opinion. The question answers are mostly the following types: yes/no, a percentage or monetary amount, days required to obtain a service, number of times a particular event has occurred, or a 5-point Likert scale.

4.1.2 THE SAMPLE AND SUMMARY STATISTICS

Table 4-1: WBES – Relevant EU microdata

COUNTRY	SURVEY YEAR	#SUB-NATIONAL REGIONS	TOTAL	SMALL (5-19)	MEDIUM (20-99)	LARGE (100+)	MANUFACTURING	RETAIL	OTHER SERVICES	NO SECTOR INFO
Belgium	2020	3	614	358	194	62	243	126	245	
Bulgaria	2019	6	772	335	245	192	428	138	206	
Bulgaria	2023	6	710	258	256	196				710
Croatia	2019	2	404	148	134	122	149	97	158	
Croatia	2023	4	474	213	154	107				474
Cyprus	2019	1	240	137	66	37	80	67	93	
Czech Republic	2019	4	502	234	154	114	291	62	149	
Estonia	2019	3	360	163	145	52	135	82	143	
Estonia	2023	3	351	153	121	77				351
Finland	2020	4	759	340	315	104	486	76	197	
France	2021	13	1566	695	612	259	821	146	599	
Germany	2021	16	1694	873	596	225	674	149	871	
Greece	2018	4	600	267	201	132	315	124	161	
Greece	2023	4	598	193	243	162				598
Hungary	2019	7	805	360	291	154	481	138	186	
Hungary	2023	8	831	373	300	158				831
Ireland	2020	3	606	351	214	41	178	137	291	
Italy	2019	5	760	342	232	186	461	127	172	
Latvia	2019	3	359	141	132	86	130	99	130	
Lithuania	2019	3	358	158	111	89	128	110	120	
Luxembourg	2020	1	170	85	60	25	37	18	115	
Malta	2019	1	242	112	99	31	83	53	106	
Netherlands	2020	4	808	450	275	83	347	137	324	
Poland	2019	6	1369	695	401	273	1004	110	255	
Portugal	2019	7	1062	478	357	227	775	121	166	
Portugal	2023	7	1007	461	325	221				1007
Romania	2019	8	814	342	270	202	518	128	168	
Romania	2023	8	947	398	312	237				947
Slovenia	2019	2	409	175	164	70	176	74	159	
Spain	2021	7	1051	369	444	238	744	97	210	
Sweden	2020	8	591	213	236	142	350	89	152	

Table 4-1 presents the relevant EU microdata from the World Bank Enterprise Survey from 2018 until 2023 for 26 European countries. The table illustrates the total number of companies participating in the survey and the breakdown of the number of companies from each sector per survey year (Manufacturing, Retail, Other Services and No Sector). In line with data availability, for some countries, the table includes the relevant figures for two years. For instance, data for Greece are available both for 2018 and 2023.

Table 4-2 presents the relevant ECA microdata from the World Bank Enterprise Survey from 2018 until 2023 for 15 counties. The table illustrates the total number of companies participating in the survey and the breakdown of the number of companies from each sector per survey year (Manufacturing, Retail, Other Services and No Sector). In line with data availability, for some countries, the table includes the relevant figures for two years. For instance, data for Montenegro are available both for 2018 and 2023.

Table 4-2: WBES – Relevant ECA microdata

COUNTRY	SURVEY YEAR	#SUB-NATIONAL REGIONS	TOTAL	SMALL (5-19)	MEDIUM (20-99)	LARGE (100+)	MANUFACTURING	RETAIL	OTHER SERVICES	NO SECTOR INFO
Albania	2019	3	377	166	115	96	146	77	154	
Belarus	2018	7	600	226	203	171	330	123	147	
Bosnia & Herzegovina	2019	5	362	133	140	89	134	93	135	
Bosnia & Herzegovina	2023	3	351	136	112	103				351
Georgia	2019	5	581	270	220	91	205	114	262	
Georgia	2023	4	592	269	212	111				592
Kazakhstan	2019	11	1446	717	499	230	926	180	340	
Kosovo	2019	7	271	132	113	26	148	28	95	
Moldova	2019	3	360	146	134	80	138	100	122	
Montenegro	2019	3	150	69	45	36	65	31	54	
Montenegro	2023	3	151	74	46	31				151
North Macedonia	2019	3	360	140	129	91	133	112	115	
North Macedonia	2023	3	354	138	125	91				354
Russian Federation	2019	7	1323	490	438	395	888	151	283	1
Serbia	2019	4	361	137	114	110	127	104	130	
Slovak Republic	2019	4	429	238	96	95	192	103	134	
Slovak Republic	2023	4	292	153	80	59	115	71	106	
Tajikistan	2019	4	352	170	122	60	160	73	119	
Türkiye	2019	12	1663	711	587	365	1065	222	376	
Ukraine	2019	8	1337	511	533	293	945	115	277	

4.1.3 STATISTICS ON SKILLS AND TRAINING

Figure 4-1 presents the World Bank Enterprise Survey global map of inadequately educated workforce as a constraint. Panel A illustrates the percentage of firms choosing inadequately educated workforce as their biggest obstacle while Panel B shows the percentage of firms identifying an inadequately educated workforce as a major or very severe constraint.

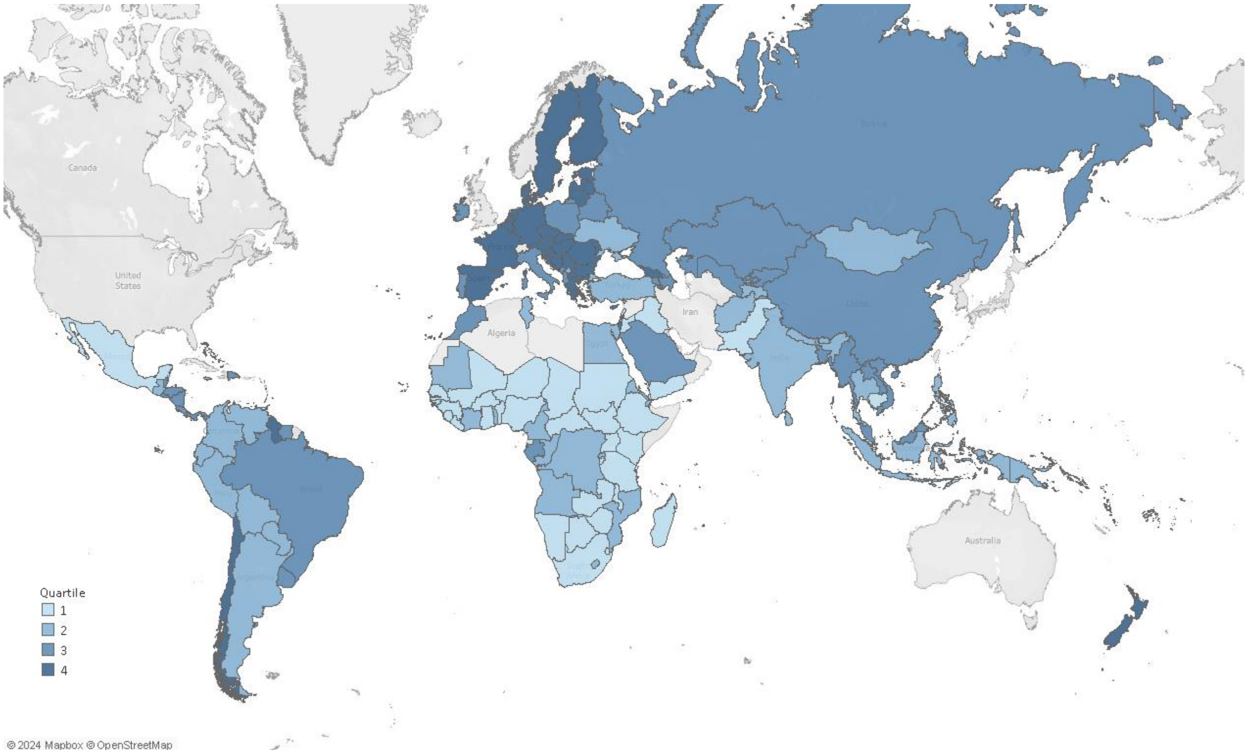
Figure 4-2 presents the World Bank Enterprise Survey global map of the percentage of skilled workers. Panel A illustrates the proportion of permanent full-time workers that completed high school while Panel B shows proportion of skilled workers, out of all permanent production workers for the countries that participated in the survey.

Figure 4-3 presents the World Bank Enterprise Survey global map of training in percentage. Panel A depicts the proportion of workers offered formal training over last fiscal year and interestingly we do not observe an increased percentage in most European countries, compared to China, India and counties of South America. Besides, Panel B shows the percentage of firms offering formal training over last fiscal year.

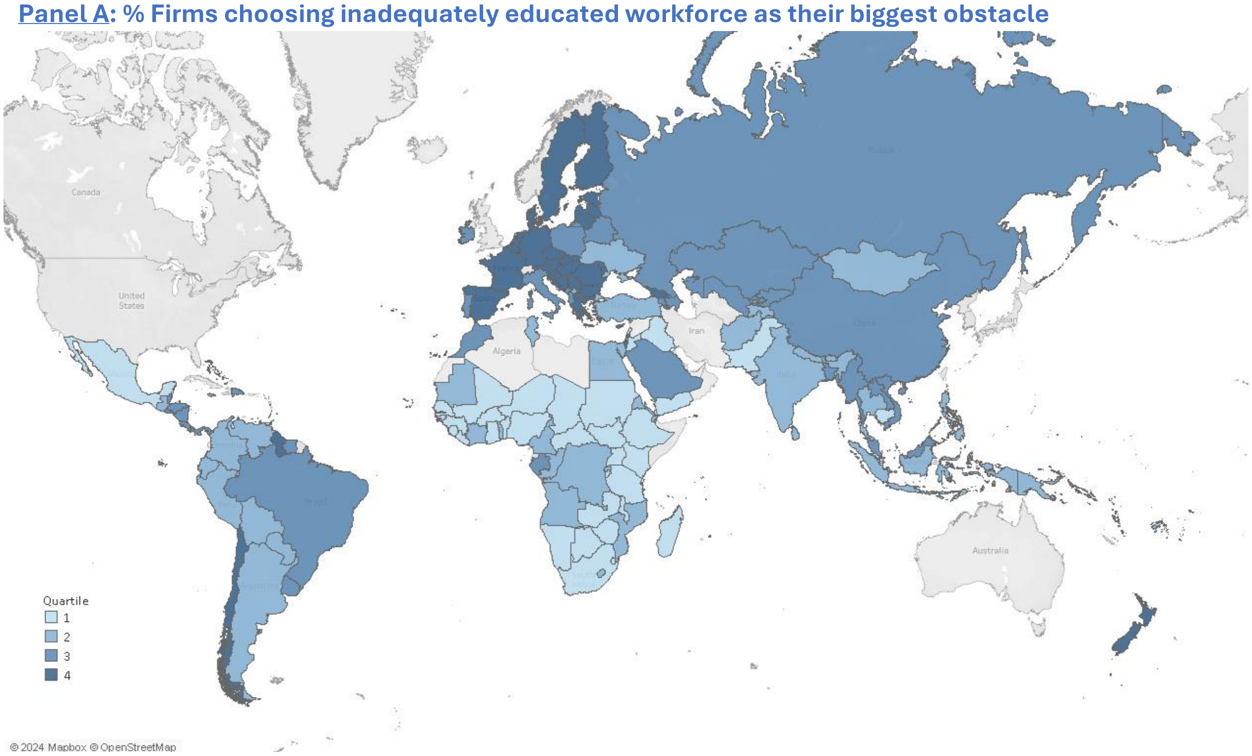
Table 4-3 presents the corresponding latest relevant data from World Bank Enterprise Survey of counties that identify as the biggest or major obstacle the inadequately educated workforce. For EU counties we observe Belgium (41%) and Greece (45.8) as the two counties with the highest figure facing those issues. Next, country with the lowest share of production workers in EU is Cyprus with 67.2% and Kosovo with 67.3% considering non-EU counties. The table also includes information per country in the percentage of workers and firms receiving formal training. Finally, a survey from the World Development Indicator (WDI) investigates the same topic (% of firms offering formal training, yet we observe recent data with greater availability on European counties. The top 3 ranking EU counties offering formal training are the following: France (67.8%), Luxembourg (66.1%) and Belgium (57.8%).

Figure 4-4 illustrates the percentage of firms stating inadequately educated workforce as their biggest obstacle. The survey from World Bank Enterprise Survey took place from 2007 until 2020, yet the data are not annual. Over the years we observe that more and more countries identify this particular issue, which reflects challenges in finding skilled labour that meets industry needs, impacting productivity and growth prospects for businesses across various sectors in Europe. For 2020, Belgium (41%), Luxembourg (39.9%) and Estonia (32.7%) are the countries suffering most from this obstacle.

Figure 4-5 shows the percentage of firms identifying an inadequately educated workforce as a major constraint. Again, the survey conducted from World Bank Enterprise Survey. The same pattern prevails also in this question, meaning that recently a growing number of countries identify this particular issue as important obstacle. This is a critical issue that requires attention from both the private sector and policymakers. Addressing this skills gap is essential for fostering economic growth, increasing innovation, and maintaining Europe's competitiveness in the global market. A collaborative approach involving education reform, vocational training, reskilling programs, and closer industry-education ties is needed to ensure that the workforce meets the evolving needs of businesses in the coming decades. According to latest available data, Greece (45.8%), Kosovo (44.2%) and Romania (43%) are the countries that have identified this obstacle as a major constrain for firms' operation.

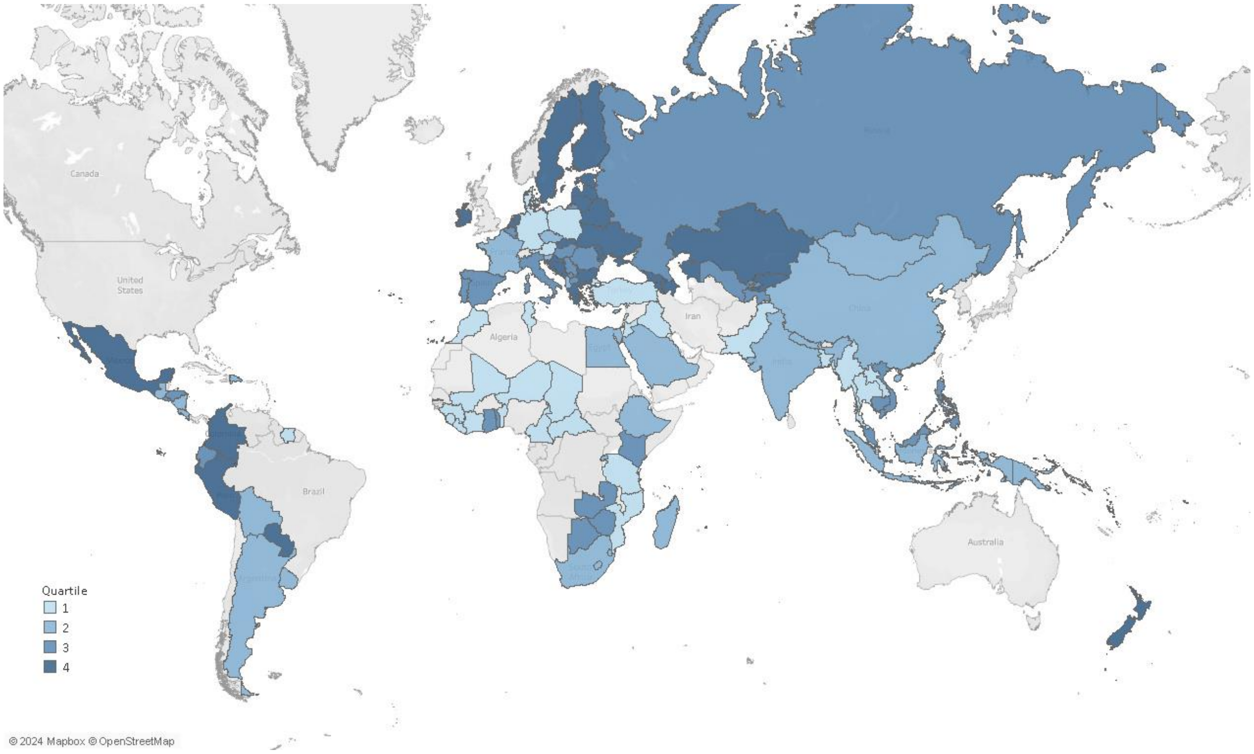


Panel A: % Firms choosing inadequately educated workforce as their biggest obstacle

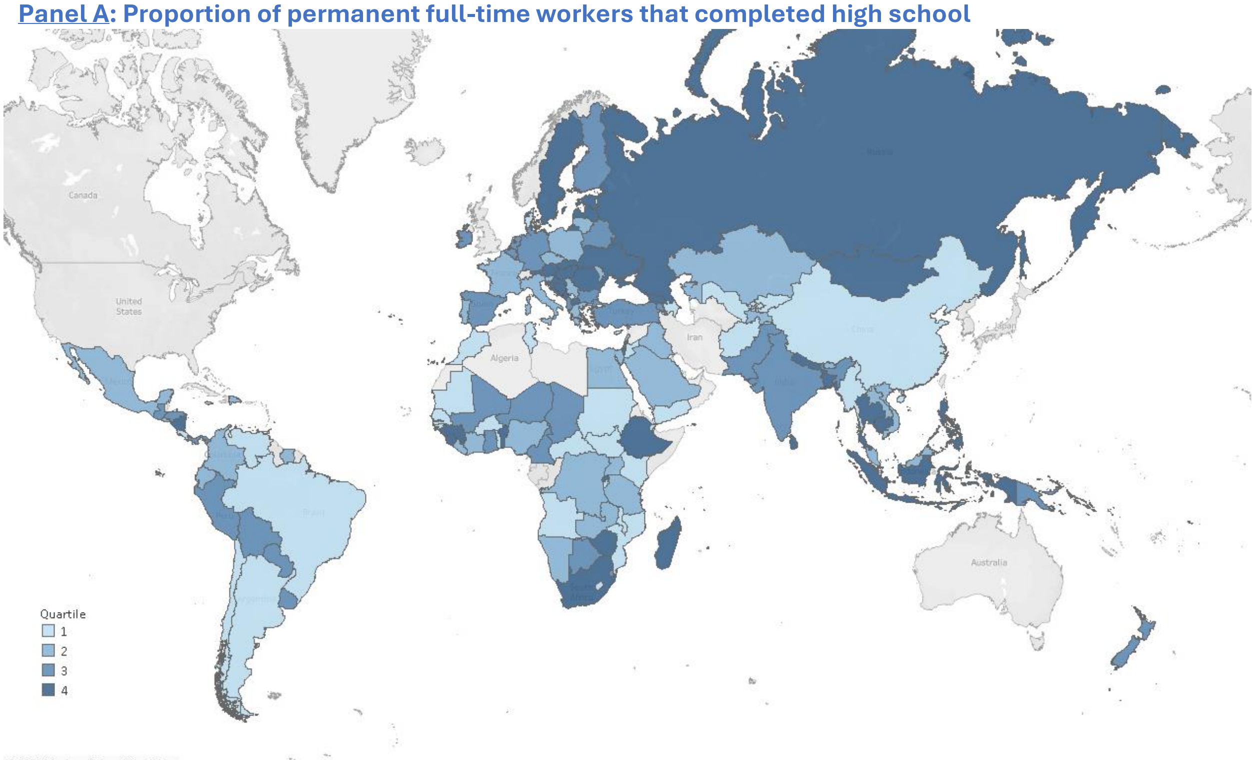


Panel B: % Firms identifying an inadequately educated workforce as a major or very severe constraint

Figure 4-1: WBES -Global map of inadequately educated workforce as a constraint

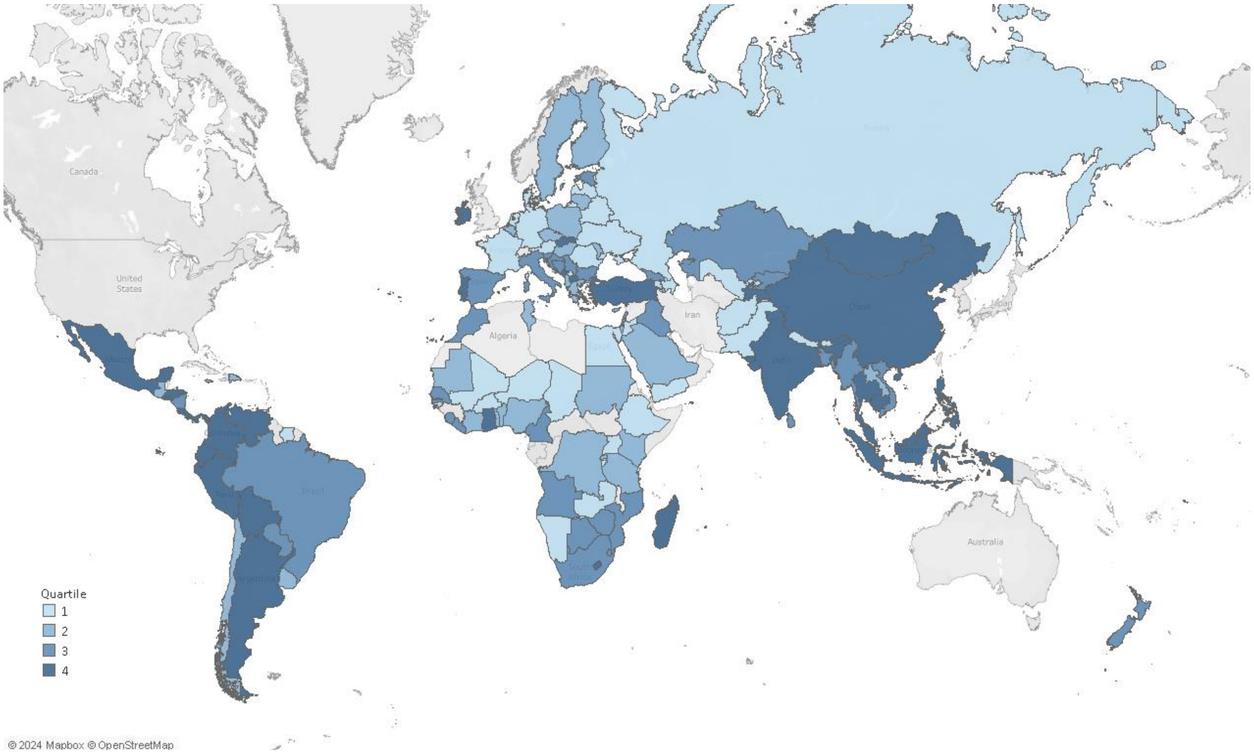


Panel A: Proportion of permanent full-time workers that completed high school

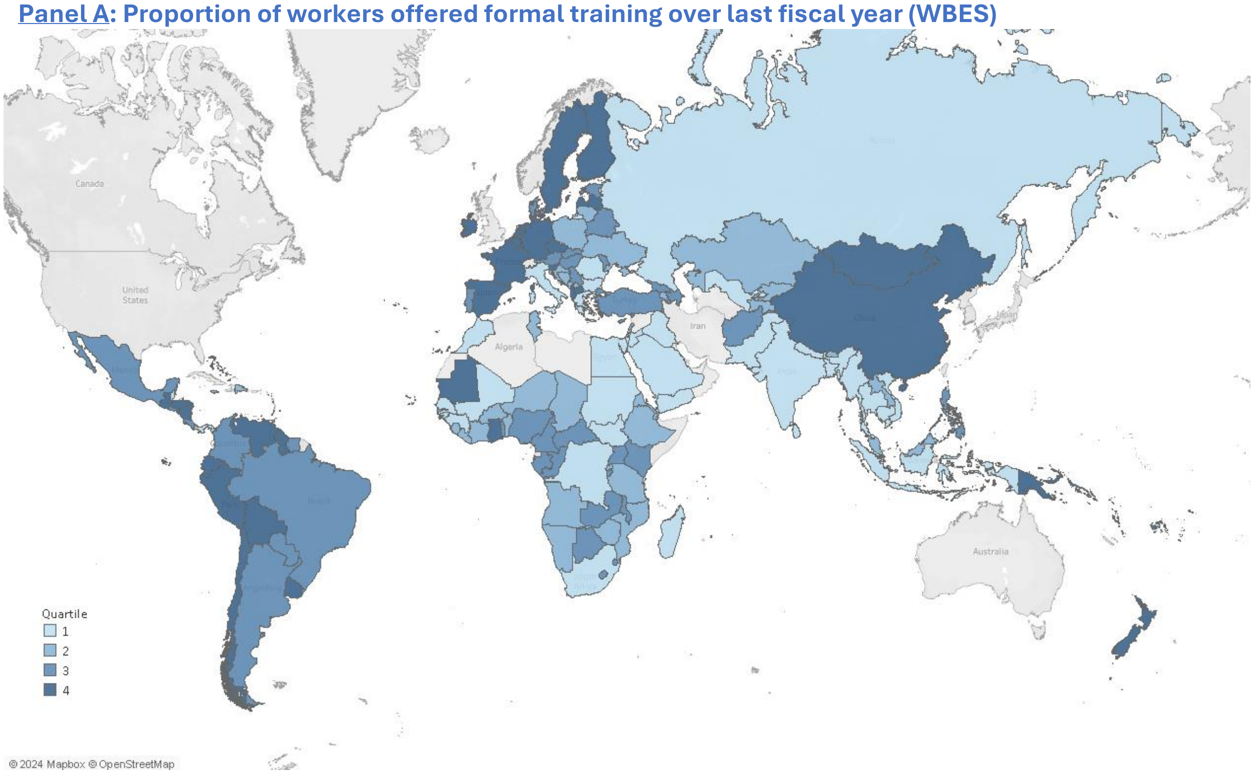


Panel B: Proportion of skilled workers, out of all permanent production workers (WBES)

Figure 4-2: WBES –Global map of %skilled workers



Panel A: Proportion of workers offered formal training over last fiscal year (WBES)



Panel B: Percentage of firms offering formal training over last fiscal year (WBES)

Figure 4-3: WBES -Global map of %training

Table 4-3: WBES –Latest relevant data

	INADEQUATELY EDUCATED WORKFORCE				SKILLED WORKERS (% production workers)		FORMAL TRAINING					
	Biggest obstacle		Major constraint				%Workers		%Firms (WBES)		%Firms (WDI)	
EU:												
Belgium	41.0%	(2020)	35.4%	(2020)	84.1%	(2020)	46.6%	(2020)	57.8%	(2020)	57.8%	(2020)
Bulgaria	22.1%	(2019)	30.3%	(2019)	71.5%	(2019)	62.9%	(2019)	20.0%	(2019)	15.5%	(2023)
Croatia	15.8%	(2019)	13.3%	(2019)	87.8%	(2019)	39.8%	(2019)	26.2%	(2019)	24.4%	(2023)
Cyprus	17.5%	(2019)	24.0%	(2019)	67.2%	(2019)	48.5%	(2019)	39.7%	(2019)	39.7%	(2019)
Estonia	32.7%	(2019)	15.9%	(2019)	94.4%	(2019)	37.3%	(2019)	40.7%	(2019)	42.2%	(2023)
Finland	-		-		-		-		-		50.2%	(2020)
France	-		-		-		-		-		67.9%	(2021)
Germany	-		-		-		-		-		44.1%	(2021)
Greece	5.0%	(2018)	45.8%	(2018)	77.7%	(2018)	47.2%	(2018)	21.6%	(2018)	13.7%	(2023)
Hungary	31.5%	(2019)	21.2%	(2019)	82.6%	(2019)	38.5%	(2019)	29.3%	(2019)	28.1%	(2023)
Italy	8.5%	(2019)	13.6%	(2019)	71.1%	(2019)	58.8%	(2019)	12.6%	(2019)	12.6%	(2019)
Latvia	24.5%	(2019)	37.3%	(2019)	88.0%	(2019)	35.9%	(2019)	52.9%	(2019)	52.9%	(2019)
Lithuania	17.6%	(2019)	23.1%	(2019)	77.3%	(2019)	50.1%	(2019)	27.5%	(2019)	27.5%	(2019)
Luxembourg	39.9%	(2020)	30.0%	(2020)	82.6%	(2020)	39.6%	(2020)	66.1%	(2020)	66.1%	(2020)
Poland	11.1%	(2019)	25.4%	(2019)	77.8%	(2019)	45.9%	(2019)	21.7%	(2019)	21.7%	(2019)
Portugal	4.4%	(2019)	11.1%	(2019)	78.3%	(2019)	65.0%	(2019)	29.0%	(2019)	39.5%	(2023)
Romania	22.3%	(2019)	43.0%	(2019)	70.2%	(2019)	59.9%	(2019)	20.5%	(2019)	17.6%	(2023)
Slovak Republic	16.4%	(2019)	11.1%	(2019)	73.1%	(2019)	73.5%	(2019)	43.3%	(2019)	40.3%	(2023)
Slovenia	20.3%	(2019)	19.4%	(2019)	74.1%	(2019)	58.9%	(2019)	44.0%	(2019)	44.0%	(2019)
Spain	-		-		-		-		-		55.2%	(2021)
Non-EU:												
Albania	9.0%	(2019)	24.8%	(2019)	82.2%	(2019)	42.2%	(2019)	46.2%	(2019)	46.2%	(2019)
Bosnia & Herzegovina	7.8%	(2019)	24.3%	(2019)	72.6%	(2019)	51.0%	(2019)	37.9%	(2019)	24.6%	(2023)
Georgia	14.9%	(2019)	42.5%	(2019)	78.6%	(2019)	44.0%	(2019)	32.0%	(2019)	31.4%	(2023)
Kosovo	3.3%	(2019)	44.2%	(2019)	67.3%	(2019)	26.4%	(2019)	20.4%	(2019)	20.4%	(2019)
Moldova	19.5%	(2019)	33.5%	(2019)	71.1%	(2019)	51.4%	(2019)	38.1%	(2019)	38.1%	(2019)
Montenegro	9.6%	(2019)	16.3%	(2019)	86.3%	(2019)	18.6%	(2019)	15.8%	(2019)	25.6%	(2023)
North Macedonia	13.0%	(2019)	19.0%	(2019)	80.6%	(2019)	55.8%	(2019)	39.0%	(2019)	44.3%	(2023)
Russian Federation	7.7%	(2019)	17.4%	(2019)	88.1%	(2019)	23.1%	(2019)	11.8%	(2019)	11.8%	(2019)
Serbia	18.0%	(2019)	20.3%	(2019)	76.2%	(2019)	56.2%	(2019)	38.3%	(2019)	38.3%	(2019)
Turkey	6.6%	(2019)	19.4%	(2019)	84.8%	(2019)	73.0%	(2019)	30.7%	(2019)	30.7%	(2019)
Ukraine	3.9%	(2019)	37.9%	(2019)	89.4%	(2019)	30.2%	(2019)	24.3%	(2019)	24.3%	(2019)

Figure 4-6 illustrates the percentage of skilled workers out of all production workers from the World Bank Enterprise Survey. The majority of countries that participated in this survey declare that around 80% is the share of skilled workers compared to all production workers. Notably, according to the most recent available data Greece (77.7%), Cyprus (67.2%) and Kosovo (67.3%) are the countries with the smallest share of skilled workers out of all production workers while Estonia (94.4%), Ukraine (89.4%) and Russia (88.1%) are the countries with the biggest share of skilled workers out of all production workers. Overall, lack of skilled labour can slow a company's growth and crucially affect a country's development.

Figure 4-7 shows the percentage of workers offered formal training from the World Bank Enterprise Survey. It is apparent that recently a growing number of countries invest in training their works compared to the data in 2007, 2008 and 2009. This statistic is often used to assess how companies invest in the development and skills enhancement of their workforce. Training is an important way of complementing and building upon academic and other qualifications so that workers can reskill and adapt to changes in labour market demand. According to latest available data, Montenegro (18.6%), Russia (23.1%) and Kosovo (26.4%) are the countries with the smallest share of workers offered formal training while Portugal (65%), Turkey (73%) and Slovak Republic (73.5%) are the countries with the biggest share of workers offered formal training.

Figure 4-8 is closely linked with the previous figure since it presents the percentage of firms offering workers formal training. The data source is again the World Bank Enterprise Survey from 2007 until 2020. Typically, a higher percentage of firms in high-income countries offer formal training programs. For example, countries like Luxembourg (66.1%) and Belgium (57.8%) tend to have an increased share of firms providing formal training. In middle-income economies like Serbia (38.3%), Portugal (29%) and Poland (21.7) the percentage of firms offering formal training is usually lower, often ranging between 20-40%. Finally, in low-income economies the proportion tends to be even lower, with less than 20% of firms offering formal training. For instance, in Greece the corresponding share is on 21.6% while in Montenegro is 15.8%. The size of the firm is also a key factor. Larger firms with global presence are more likely to offer formal training compared to small and medium-sized enterprises.

Finally, Figure 4-9 explores the same question, however the survey is available on World Development Indicators of World Bank. This indicator reflects the commitment of firms to skill development and workforce training, which is crucial for enhancing productivity and competitiveness. Typically, a higher percentage of firms in high-income countries offer formal training programs while low-income economies the proportion tends to be even lower. The figures are identical with those of Figure 4-8, yet this survey includes an earlier survey conducted in 2005. Two countries that are ranked at the bottom of this list is Italy with only 12.6% of firms offering workers formal training, while the corresponding share for Greece is 13.7%. Remarkably, France is ranked at the top share of this figure with 67.9% of firms offering formal training to workers.

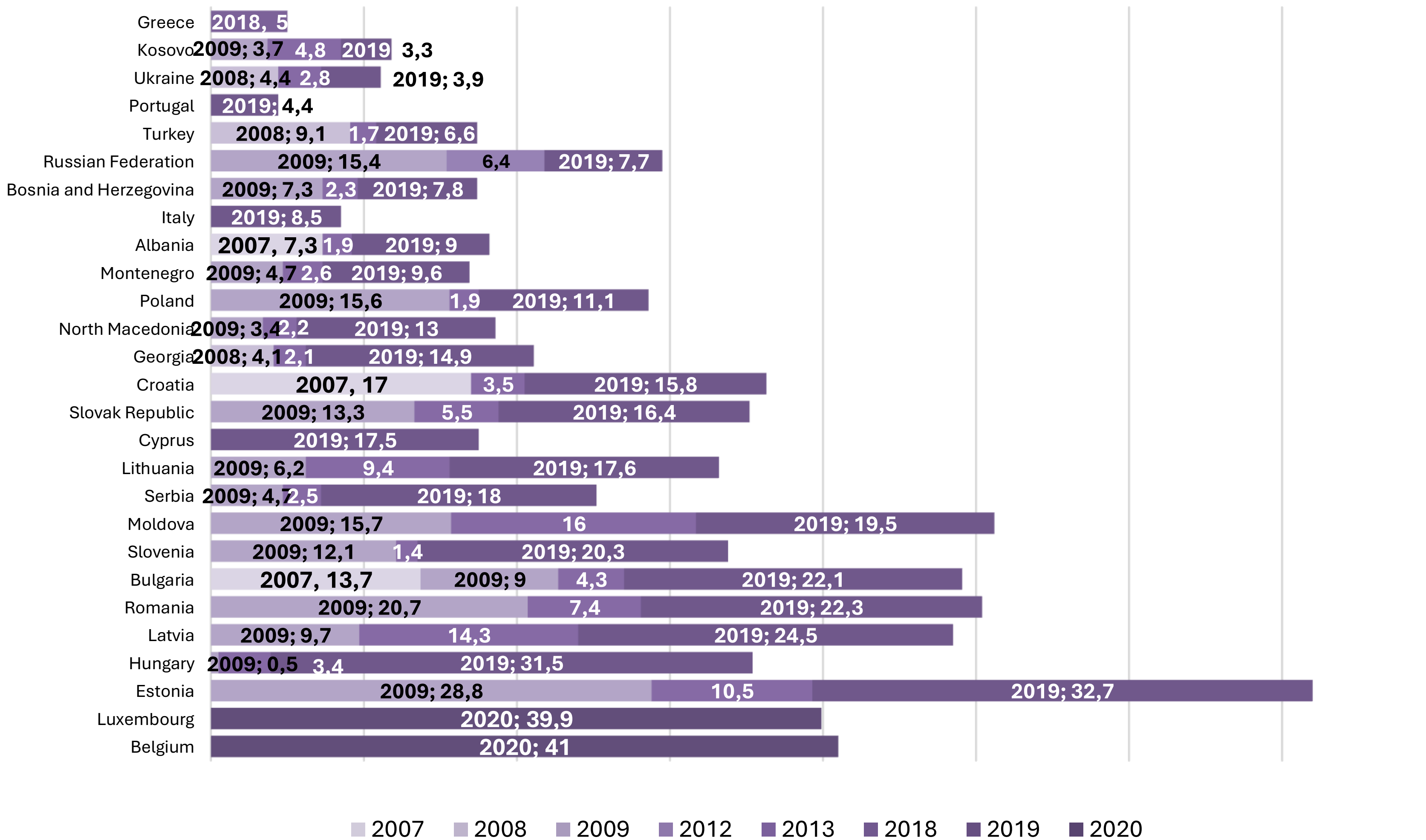


Figure 4-4: WBES -%Firms stating inadequately educated workforce as their biggest obstacle

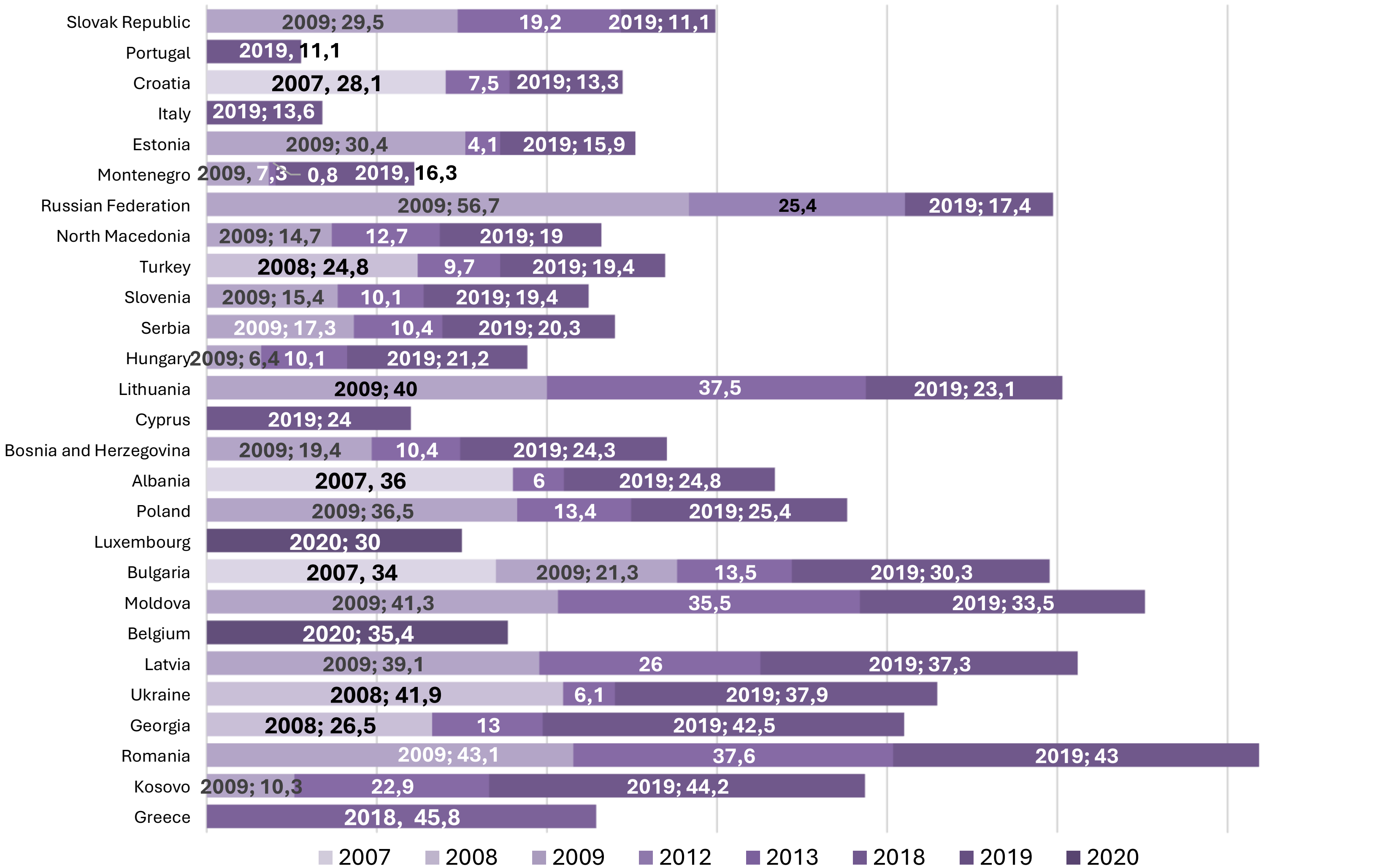


Figure 4-5: WBES -%Firms identifying an inadequately educated workforce as a major constraint

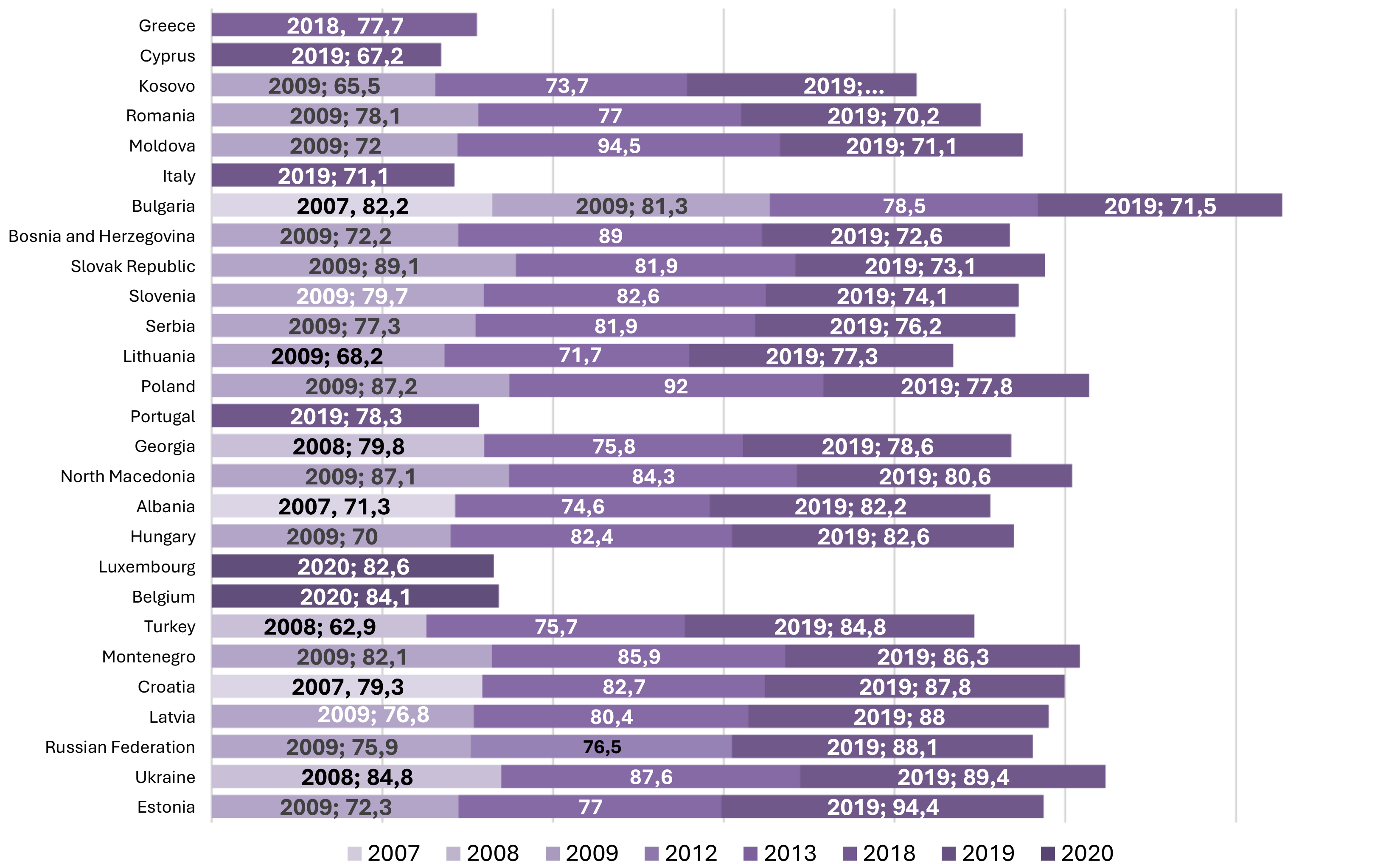


Figure 4-6: WBES -%Skilled workers out of all production workers

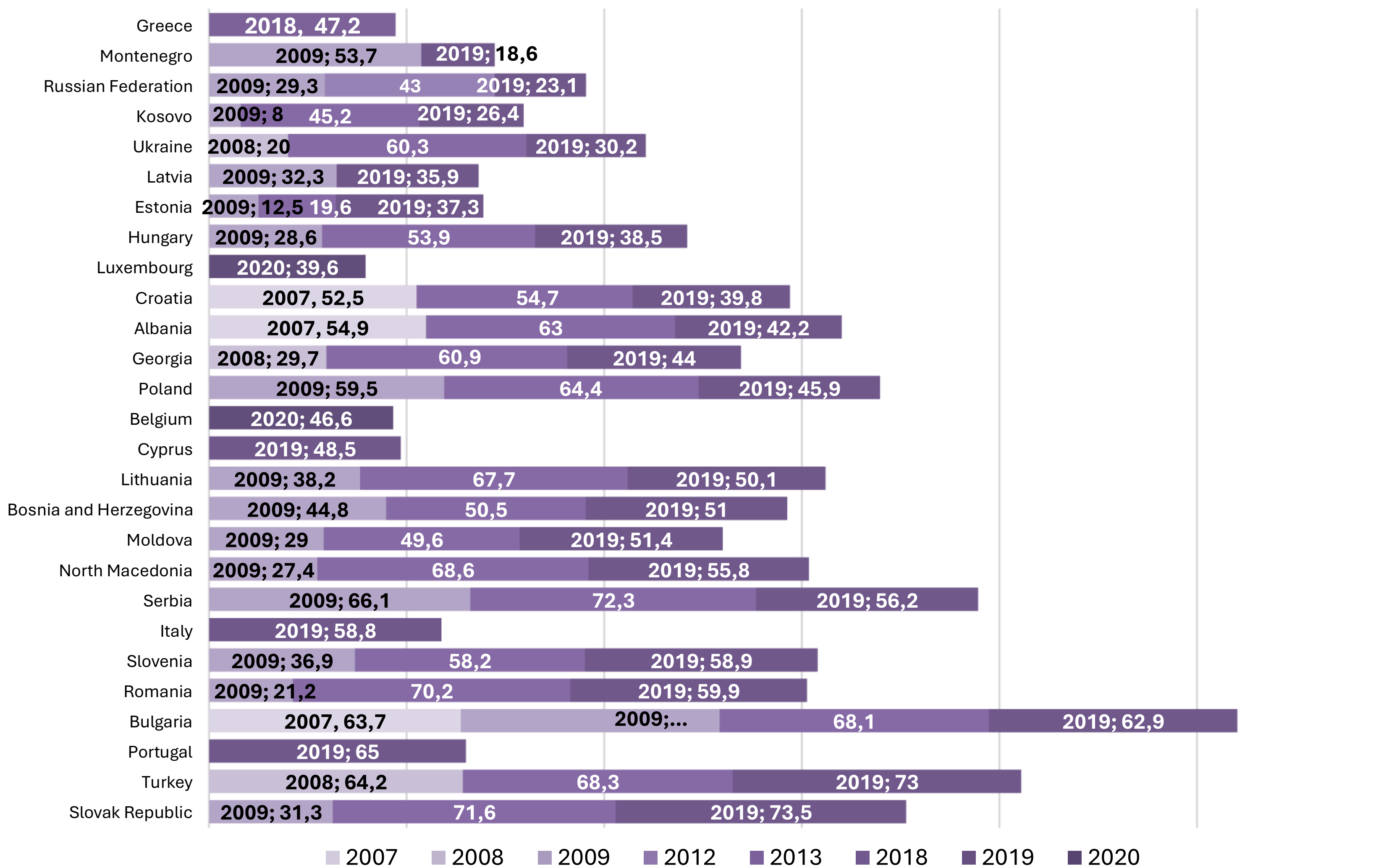


Figure 4-7: WBES – %Workers offered formal training

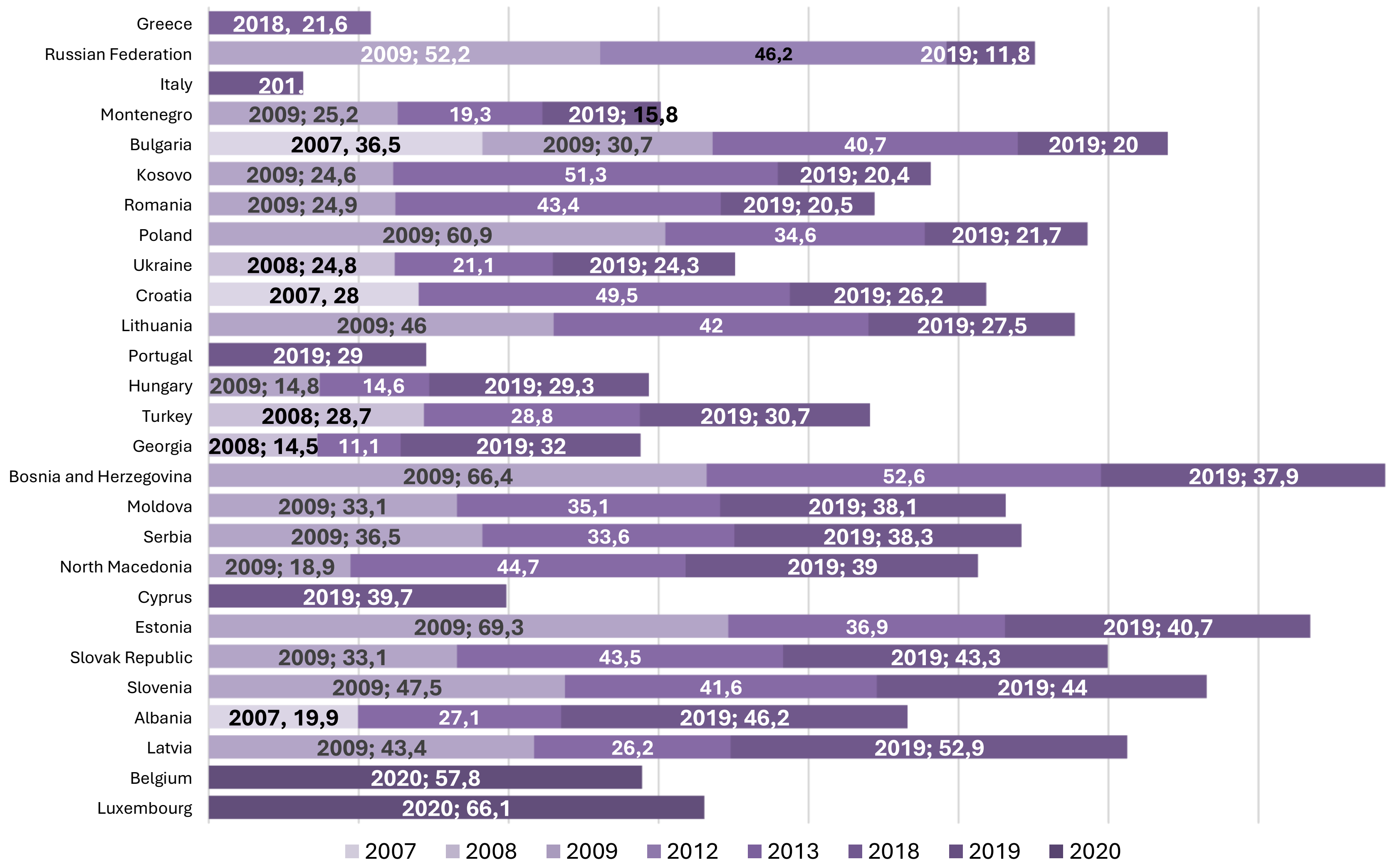


Figure 4-8: WBES –%Firms offering workers formal training

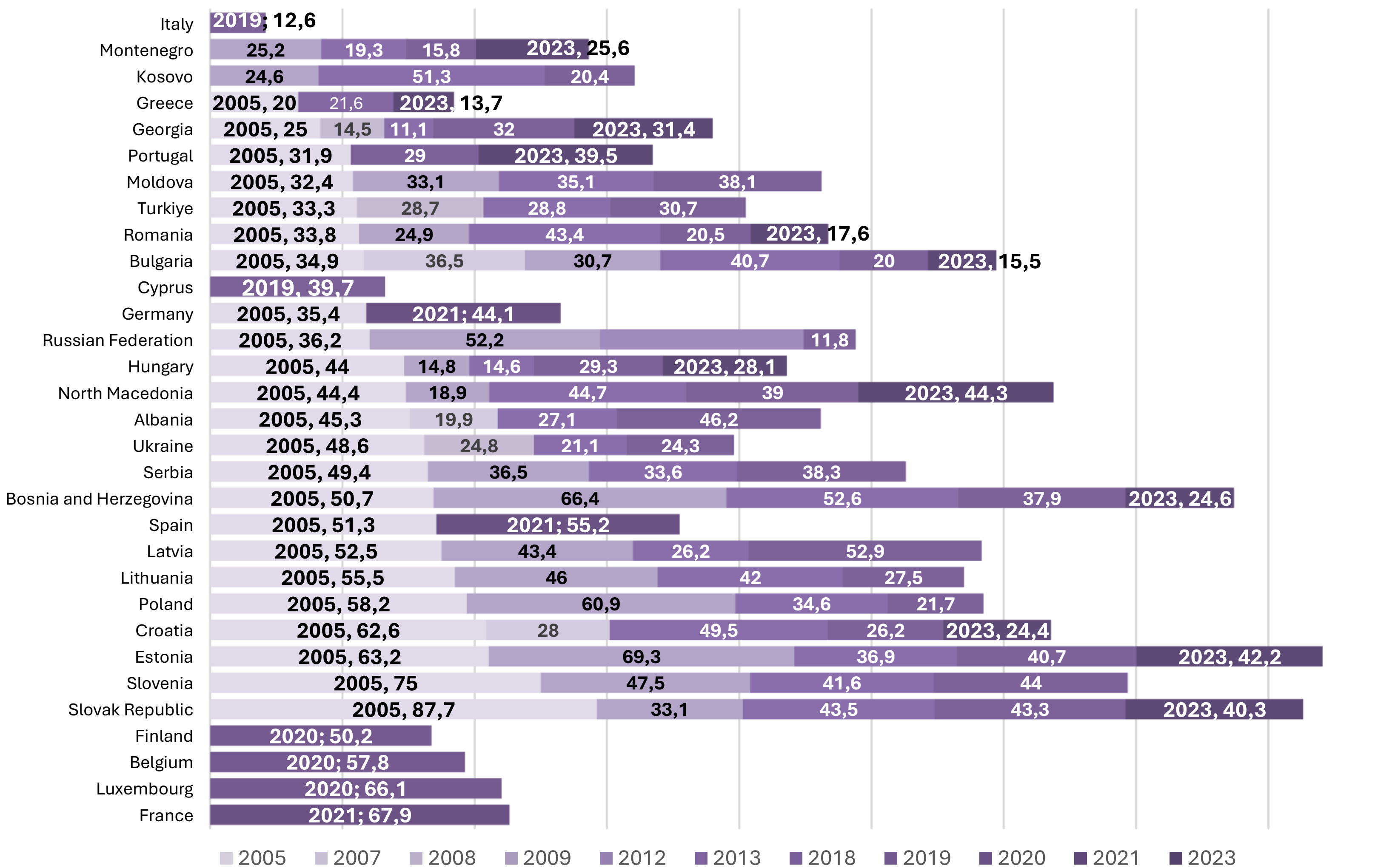


Figure 4-9: WBES/WDI – Firms offering workers formal training

4.1.4 THE RELEVANT LITERATURE

An inquiry using the Scopus database suggests some 949 articles using the WEBS database. Out of these, 45 articles use the WEBS for research that can linked to skills and training. We replicate the 2 relevant exercises using these 41 articles. In Figure 4-10 we present a word cloud of the most frequently appearing words in the index and author keywords of these 41 articles. Then, in Table 4-4, we classify them into 10 key thematic categories, in terms of their content.

Figure 4-10: WBES – Word cloud of the keywords in the 41 articles on skills

Table 4-4: WBES – Classification of the 41 articles on skills

Research domain	Cittions
Digital Transformation & Firm Performance	Paily (2018), Heredia, et al. (2022)
Informal Sector & Entrepreneurship	Joshi, et al. (2009), Pugalis, et al. (2014), Dutta, et al. (2023)
Sustainable Development & Efficiency	Amornkitvikai & Pholphirul (2023), Petreski, et al. (2024)
Innovation & Technology	Gashi & Adnett (2012), Grazzi & Jung (2016), Véganzonès-Varoudakis & Nguyen (2018), Sein & Vavra (2020), Aboushady & Zaki (2021), Botrić (2022), Vendrell-Herrero, et al. (2023), Medase & Savin (2024)
Labour Productivity & Human Capital	Mawejje & Okumu (2018), Okumu & Mawejje (2020), Ehab & Zaki (2021), Jibir, et al. (2023)
Business Environment & Constraints	Bhattacharya & Wolde (2012), Baklanoff (2008), Fakih & Ghazalian (2015), Beltran (2019), Mertzanis & Said (2019)
Foreign Investment & Ownership	Albogami (2017), Lv, et al. (2018), Orkoh & Viviers (2021)
Regional Focus	Brixiova (2010), Webster, et al. (2022), Orji, et al. (2022), Bakhadirov, et al. (2022), Chorito & Assefa (2024)
Employment & Skills Development	Totskaya (2020), Medase & Savin (2024), Abdin, et al. (2024)
Gender & Leadership	Beltran (2019), Orkoh & Viviers (2021)

The most frequent words in the 41 articles are firm, labour, innovation, productivity, Africa, manufacturing, world, model, human, constraints, technology, performance, property, digital, informal, intellectual, developing, decision, inter alia.

Table 4-4 shows four major thematic areas of research using the WBES. These are: (1) Digital Transformation and Firm Performance; (2) Informal Sector and Entrepreneurship; (3) Sustainable Development & Efficiency; (4) Innovation & Technology; (5) Labour Productivity and Human Capital; (6) Business Environment & Constraints; (7) Foreign Investment and Ownership; (8) Regional Studies; (9) Employment and Skills Development; (10) Gender and Leadership.

4.2 SURVEY ON THE ACCESS TO FINANCE OF ENTERPRISES (SAFE)

The Survey on the Access to Finance of Enterprises (SAFE) is a comprehensive survey conducted by the European Central Bank (ECB) and the European Commission. It aims to assess the financial conditions and financing needs of small and medium-sized enterprises (SMEs) across the European Union (EU) and some additional European countries. The survey provides valuable insights into how firms, particularly SMEs, access finance, the challenges they face in securing funding, and how these conditions impact their growth and operations.

The primary goal of the SAFE survey is to collect detailed information on the financial environment for enterprises, with a particular focus on SMEs. The survey examines the availability of external financing, the types of finance used by firms, and the obstacles that businesses encounter when seeking funding. The data is used to inform policy decisions aimed at improving access to finance for SMEs, which are critical drivers of economic growth and job creation in the EU.

The SAFE survey targets enterprises in the EU Member States, as well as in some additional countries such as Norway, Iceland, and the UK. While the survey covers firms of all sizes, it places a strong emphasis on SMEs due to their significant role in the European economy.

The survey covers the following themes:

- Access to Finance: The survey collects data on the different sources of external finance used by firms, including bank loans, credit lines, trade credit, equity, and other forms of financing.
- Financing Needs: Information is gathered on the financial needs of enterprises, including the purpose of financing (e.g., working capital, investment, debt refinancing) and the amount of funding required.
- Experience with Financial Institutions: The survey explores firms' relationships with banks and other financial institutions, including the ease or difficulty of obtaining credit, the terms and conditions of loans, and the role of public support schemes.
- Barriers to Accessing Finance: The survey identifies the main obstacles faced by firms when seeking external financing, such as high interest rates, insufficient collateral, complex application procedures, and rejection of loan applications.
- Economic and Financial Situation: SAFE also assesses the overall economic and financial situation of enterprises, including their revenue growth, profitability, and investment plans.
- Financial Constraints: Indicators of financial constraints, such as the proportion of firms that were unable to obtain the desired financing or had to settle for less favorable terms.
- Demand for External Finance: Measures of the demand for different types of external finance, and how this demand has changed over time.
- Rejection Rates: The percentage of firms whose loan applications were rejected, and the reasons for these rejections.
- Alternative Financing: The extent to which firms rely on alternative forms of financing, such as trade credit, equity financing, or peer-to-peer lending.

SAFE is conducted biannually (every six months), ensuring that the data reflects current market conditions and financing trends. The survey is carried out through structured interviews, usually by telephone, with senior managers or owners of the enterprises. A stratified random sampling approach is used to ensure that the survey results are representative of the broader population of firms in each country, with particular attention to SMEs.

The SAFE survey provides critical data that informs EU and national policies aimed at supporting SMEs, particularly in areas related to access to finance. The ECB and other financial authorities use SAFE data to understand the impact of monetary policy on SMEs and to design interventions that improve the functioning of financial markets. During economic crises, such as the COVID-19 pandemic, the SAFE survey has been instrumental in assessing the impact on SME financing and in guiding the development of targeted support measures.

Governments and EU institutions use the survey results to monitor the effectiveness of financial support programs for SMEs and to adjust policies as needed. Banks and other lenders use SAFE data to better understand the financing needs of SMEs and to tailor their products and services accordingly. The data is also used by researchers and analysts to study trends in SME financing, the effectiveness of public interventions, and the broader economic impact of access to finance.

The SAFE survey is a vital tool for understanding the financial landscape for enterprises, particularly SMEs, across Europe. By providing detailed and timely data on access to finance, the survey helps to identify bottlenecks in the financial system and informs policies that aim to improve the availability and conditions of financing for SMEs. This is crucial for fostering innovation, competitiveness, and economic growth in the European Union.

4.2.1 THE DATA AND FREQUENCIES

Table 4-5 presents the latest data of number of firms and observations from SAFE database. The database includes both EU and non-EU counties. The total number of firms is 172,994 including answers from 2009 until 2024, while the total number of observations is 378,886. As anticipated, the biggest countries in Europe accounted for the highest share of firms participating in the surveys. Precisely, Germany accounts for 9.5%, France for 9.3%, Italy 8.9% and Spain 8.7%. For non-EE counties, UK corresponds to 4.3% of the total answers and Turkey to 1.1%.

Figure 4-11 presents the sample size of SAFE database by wave. The counties that significantly participate over the years are the following: Germany, Italy, France, Spain, Poland and Netherlands. The numbers of firms per wave for those counties ranging between 1,300 to 1,500. The next group of counties includes Hungary, Greece, Austria, Sweden, Poland, Finland, Denmark and Belgium with the numbers of firms per wave for those counties ranging between 500 to 700. As expected, until 2020 the participation of United Kingdom was significantly higher than the recent years which is minor.

Next, Table 4-6 presents panel observations by wave. From the total number of observations (378,886) the 280,277 (74%) correspond to panel while 98,609 (26%) are non-panel observations. Until the first semester of 2011, the number of observations per wave floated around 7,000. However, in H1 of 2011 a significant increase in the number of observations observed (15,216). The following five semesters the average number of observations with 7,500, however in H1 of 2014 and H1 of 2015 we observed 17,075 and 17,979 corresponding observations. The record semester is H1 of 2018 with 18,257 observations. Following this point, we observe a gradual increase in the numbers of observations. The lower semester is H2 2009 with only 5,320 observations.

Table 4-5: SAFE – Number of firms and observations

COUNTRY	ACRONY	FIRMS	(%)	OBS	(%)	$YEAR_{MI}$	$YEAR_{MA}$
All Countries	***POOLED***	***172,99***	***(100.0%***	***378886***	***(100.0%***	***2009H1***	***2024Q2***
Austria	AT	6,977	(4.0%)	17,088	(4.5%)	2009H1	2024Q2
Belgium	BE	7,214	(4.2%)	17,347	(4.6%)	2009H1	2024Q2
Bulgaria	BG	3,910	(2.3%)	6,188	(1.6%)	2009H1	2023H1
Croatia	HR	2,047	(1.2%)	3,308	(0.9%)	2009H1	2023H1
Cyprus	CY	827	(0.5%)	1,318	(0.4%)	2009H1	2023H1
Czech Republic	CZ	3,500	(2.0%)	5,553	(1.5%)	2009H1	2023H1
Denmark	DK	3,759	(2.2%)	6,054	(1.6%)	2009H1	2023H1
Estonia	EE	910	(0.5%)	1,311	(0.4%)	2009H1	2023H1
Finland	FI	5,887	(3.4%)	14,039	(3.7%)	2009H1	2024Q2
France	FR	16,048	(9.3%)	40,310	(10.6%)	2009H1	2024Q2
Germany	DE	16,491	(9.5%)	39,307	(10.4%)	2009H1	2024Q2
Greece	GR	7,392	(4.3%)	17,437	(4.6%)	2009H1	2024Q2
Hungary	HU	3,789	(2.2%)	6,249	(1.7%)	2009H1	2023H1
Ireland	IE	5,079	(2.9%)	14,101	(3.7%)	2009H1	2024Q2
Italy	IT	15,357	(8.9%)	40,864	(10.8%)	2009H1	2024Q2
Latvia	LV	1,644	(1.0%)	2,492	(0.7%)	2009H1	2023H1
Lithuania	LT	2,266	(1.3%)	3,716	(1.0%)	2009H1	2023H1
Luxembourg	LU	790	(0.5%)	1,309	(0.4%)	2009H1	2023H1
Malta	MT	815	(0.5%)	1,304	(0.3%)	2009H1	2023H1
Montenegro	ME	603	(0.4%)	997	(0.3%)	2011H1	2021H1
Netherlands	NL	8,771	(5.1%)	22,520	(5.9%)	2009H1	2024Q2
Poland	PL	8,497	(4.9%)	14,621	(3.9%)	2009H1	2023H1
Portugal	PT	7,166	(4.1%)	17,794	(4.7%)	2009H1	2024Q2
Romania	RO	3,894	(2.3%)	6,277	(1.7%)	2009H1	2023H1
Slovakia	SK	5,019	(2.9%)	10,458	(2.8%)	2009H1	2024Q2
Slovenia	SI	1,351	(0.8%)	2,267	(0.6%)	2009H1	2023H1
Spain	ES	15,116	(8.7%)	38,375	(10.1%)	2009H1	2024Q2
Sweden	SE	3,776	(2.2%)	6,206	(1.6%)	2009H1	2023H1
Non-EU							
Albania	AL	650	(0.4%)	864	(0.2%)	2011H1	2021H1
Bosnia and Herzegovina	BA	305	(0.2%)	400	(0.1%)	2018H1	2021H1
Iceland	IS	777	(0.5%)	1,309	(0.4%)	2009H1	2023H1
Israel	IL	190	(0.1%)	190	(0.1%)	2011H1	2013H1
Kosovo	XK	319	(0.2%)	393	(0.1%)	2018H1	2021H1
Liechtenstein	LI	183	(0.1%)	193	(0.1%)	2011H1	2023H1
North Macedonia	MK	618	(0.4%)	896	(0.2%)	2011H1	2021H1
Norway	NO	738	(0.4%)	751	(0.2%)	2009H1	2023H1
Serbia	RS	963	(0.6%)	1,394	(0.4%)	2011H1	2021H1
Switzerland	CH	100	(0.1%)	100	(0.0%)	2011H1	2011H1
Turkey	TR	1,824	(1.1%)	2,657	(0.7%)	2011H1	2021H1
United Kingdom	UK	7,432	(4.3%)	10,929	(2.9%)	2009H1	2021H1

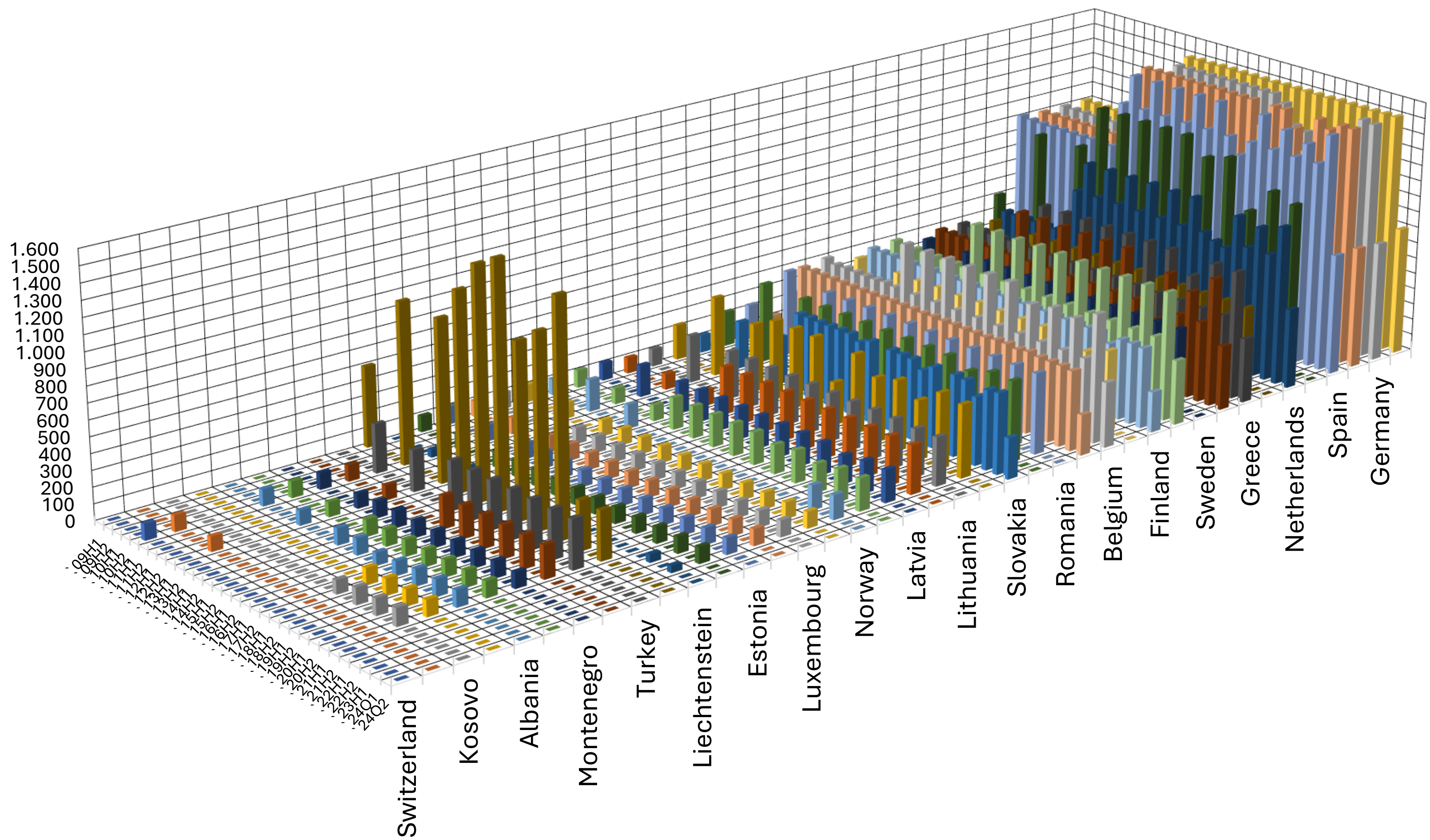


Figure 4-11: SAFE – Sample size by survey wave

Table 4-6: SAFE -Panel observations by wave

WAVE	TOTAL	NON-PANEL	PANEL	(%PANEL)
2009H1	9,063	8,097	966	(10.7%)
2009H2	5,320	2,700	2,620	(49.2%)
2010H1	5,312	2,497	2,815	(53.0%)
2010H2	7,532	3,034	4,498	(59.7%)
2011H1	15,216	10,724	4,492	(29.5%)
2011H2	7,511	2,257	5,254	(70.0%)
2012H1	7,514	2,480	5,034	(67.0%)
2012H2	7,510	1,969	5,541	(73.8%)
2013H1	14,859	8,166	6,693	(45.0%)
2013H2	7,520	1,734	5,786	(76.9%)
2014H1	17,075	4,602	12,473	(73.0%)
2014H2	11,720	1,815	9,905	(84.5%)
2015H1	17,979	3,909	14,070	(78.3%)
2015H2	11,725	1,796	9,929	(84.7%)
2016H1	18,257	3,821	14,436	(79.1%)
2016H2	11,724	1,348	10,376	(88.5%)
2017H1	17,534	3,120	14,414	(82.2%)
2017H2	11,733	1,615	10,118	(86.2%)
2018H1	17,848	2,782	15,066	(84.4%)
2018H2	11,722	1,705	10,017	(85.5%)
2019H1	18,159	3,278	14,881	(81.9%)
2019H2	11,236	2,294	8,942	(79.6%)
2020H1	16,918	2,424	14,494	(85.7%)
2020H2	11,007	1,770	9,237	(83.9%)
2021H1	15,840	3,030	12,810	(80.9%)
2021H2	10,950	1,671	9,279	(84.7%)
2022H1	15,625	4,152	11,473	(73.4%)
2022H2	10,983	1,733	9,250	(84.2%)
2023H1	15,855	3,986	11,869	(74.9%)
2024Q1	11,699	3,245	8,454	(72.3%)
2024Q2	5,940	855	5,085	(85.6%)
Total	***378,886***	***98,609***	***280,277***	***(74.0%)***

Table 4-7: SAFE -Panel sample life

#WAVES	#FIRMS	(%)	#OBSERVATIONS	(%)
1	98,609	(57.0%)	98,609	(26.0%)
2	28,804	(16.7%)	57,608	(15.2%)
3	15,836	(9.2%)	47,508	(12.5%)
4	9,617	(5.6%)	38,468	(10.2%)
5	6,954	(4.0%)	34,770	(9.2%)
6	4,426	(2.6%)	26,556	(7.0%)
7	3,200	(1.9%)	22,400	(5.9%)
8	2,105	(1.2%)	16,840	(4.4%)
9	1,425	(0.8%)	12,825	(3.4%)
10	835	(0.5%)	8,350	(2.2%)
11	445	(0.3%)	4,895	(1.3%)
12	256	(0.2%)	3,072	(0.8%)
13	177	(0.1%)	2,301	(0.6%)
14	124	(0.1%)	1,736	(0.5%)
15	78	(0.1%)	1,170	(0.3%)
16	40	(0.0%)	640	(0.2%)
17	26	(0.0%)	442	(0.1%)
18	21	(0.0%)	378	(0.1%)
19	9	(0.0%)	171	(0.1%)
20	3	(0.0%)	60	(0.0%)
21	2	(0.0%)	42	(0.0%)
22	1	(0.0%)	22	(0.0%)
23	1	(0.0%)	23	(0.0%)
Total	***172,994***	***(100.0%)***	***378,886***	***(100.0%)***

Table 4-7 depicts the panel sample life. Interestingly, we observe that 82.9% of the total numbers of firms come from only 3 waves: Wave 1 (98,609 firms, 57%), Wave 2 (28,804 firms, 16.7%), Wave 3 (15,836 firms, 9.2%). Considering their observations, Wave 1 (98,609 observations, 26%), Wave 2 (57,608 observations, 15.2%), Wave 3 (47,508 observations, 12.5%). The last four (4) of the total twenty-three (23) waves includes an almost zero amount of firms and observations.

4.2.2 THE SAMPLE AND SUMMARY STATISTICS

Table 4-8: — SAFE, Summary statistics of key variables

Variable Description	Obs	Mean	Std.dev.	Min	Max
Pressing problems: Costs of production or labour	286,126	6.20	(2.51)	1	10
“–”: Availability of skilled staff or experienced managers problems	281,103	6.07	(2.88)	1	10
“–”: Finding customers	293,190	6.02	(3.00)	1	10
“–”: Competition	293,077	5.80	(2.56)	1	10
“–”: Access to finance	290,987	4.41	(3.04)	1	10
“–”: Regulation	287,960	5.44	(2.75)	1	10
“–”: Finding customers	293,190	6.02	(3.00)	1	10
Purpose of financing: Hiring and training of employees	249,216	1.80	(0.40)	1	2
“–”: Developing and launching of new products or services	248,937	1.79	(0.41)	1	2
Use of internal and external financing: Equity	372,946	6.25	(1.84)	1	9
“–”: Debt securities issued	372,946	6.68	(1.38)	1	9
“–”: Factoring	285,589	6.59	(1.40)	3	9
“–”: Leasing or hire-purchase	272,992	4.31	(2.77)	1	7
“–”: Bank loan	134,156	1.62	(0.48)	1	2
“–”: Did not use external financing	33,393	2.18	(1.63)	1	9
Importance of factors for financing in the future: Business support	109,266	5.21	(2.77)	1	10
“–”: Guarantees for loans	107,293	5.29	(3.11)	1	10
“–”: Making existing public measures easier to obtain	106,311	6.35	(2.87)	1	10
“–”: Tax incentives	105,832	6.29	(3.02)	1	10
“–”: Measures to facilitate equity investments in the future	102,500	3.98	(2.88)	1	10
External financing availability over the past 6 months: Bank loan	234,226	2.65	(1.89)	1	9
“–”: Credit line, bank overdraft or credit cards overdraft	222,667	2.72	(1.94)	1	9
Income generation indicators: Labour cost (including social	367,183	1.58	(0.91)	1	9
Income generation indicators over the past 6 months: Fixed investmer	279,826	2.19	(1.63)	1	9
Access to finance: Willingness of banks to provide a loan	290,200	2.72	(2.04)	1	9
Application success in the past 6 months: Trade credit	47,652	2.54	(2.40)	1	9
Application to external finance in the past 6 months: Bank loan	258,097	2.76	(1.44)	1	9
External financing availability over the past 6 months: Trade credit	182,519	3.21	(2.28)	1	9
Willingness of investors to invest in equity or debt securities	180,916	5.13	(2.59)	1	9
Willingness of business partners to provide trade credit	152,907	2.88	(2.11)	1	9
Internal funds, e.g., from retained earnings and sale of assets	127,837	2.30	(1.61)	1	9
Percentage of exports in total turnover	267,463	17.04	(29.21)	0	100
Expected growth over the next two to three years	207,216	2.58	(1.50)	1	9
Expected inflation - five years, i.e. in 2029	11,557	5.78	(8.08)	-75	100
Interest rate charged for the credit line or bank overdraft - fixed rate	10,937	3.57	(3.54)	-1	100

Table 4-8 presents the summary statistics of key variables (variable description, total number of observations per variable, mean standard deviation, minimum and maximum. The first three rows of the Table illustrate information on the most relevant questions for our research. In details, the cost of production or labour corresponds to 286,126 observations as a pressing problem. The mean value of this question is 6.20 from the scale of 1 (minimum) to 10 (maximum) and a standard deviation of 2.51. Next, the 2nd relevant question is the availability of skilled staff or experienced managers as a pressing problem. This variable corresponds to 281,103 observations with mean value equal to 6.07 from the scale of 1 (minimum) to 10 (maximum) and a standard deviation of 2.88. Finally, the 3rd most relevant question is the hiring and training of employees as a purpose of financing. This variable corresponds to 249,216 observations with mean value equal to 1.8 from the scale of 1 (Yes) to 2 (No) and a standard deviation of 0.4. In summary, based on these findings the hiring and training of employees is not considered as a major purpose of financing.

4.2.3 THE QUESTIONS RELATED TO SKILLS AND TRAINING

Figure 4-12 presents the problem importance from (1 to10 scale) considering the costs of production or labour. We observed that for the majority of the countries under examination, the most common answer, around 20%, gives an 8 out 10 on this question. In other words, the labour costs which encompasses wages, salaries, benefits, and any other expenses associated with employing workers directly involved in production, is ranked at the top scale of the answers, since understanding these costs is crucial for businesses to effectively manage their finances and optimize production processes. It is apparent that that on average, the top 3 gradings account for 40% of the total answers [score 8 (20.4%), score 9 (7.9%) and score 10 (12.8%).

Figure 4-13 shows costs of production or labour as very important by wave. In the top ranking we identify Romania and Turkey and Hungary with an average answer throughout the years close to 70%. Interestingly, on the bottom ranking of this question we observe Switzerland, Sweden and Finland with an average answer throughout the years close to 20%. This means that, for the aforementioned countries the cost of labour or production is not considered to be that crucial. The cost of labour refers to the total expenses a business incurs to compensate its employees for their work. It includes both direct costs, like wages and salaries for workers directly involved in production, and indirect costs, like benefits, payroll taxes, and insurance. The two discrete components of the cost of labour are usually different from country to country.

Figure 4-14 presents the availability of skilled staff or experienced managers with problem importance ranking from 0-10. The figure is sorted to reflect the counties that identify this source of problem as a huge issue for their firms. The top five countries are: Bulgaria (37.3%), Albania (36.4%), Kosovo (33.2%), Austria (32.5%) and Turkey (31.6%). The bottom five countries that do not recognise the availability of skilled staff and experienced managers as a major problem are: Netherlands (9%) Spain (9%), United Kingdom (8.8%), Iceland (6.7%) Finland (4.5%)

Figure 4-15 shows the availability of skilled staff or experienced managers as very important by wave. In the top ranking we identify Austria, Romania, Bulgaria and Germany with an average answer throughout the years close to 65%. Interestingly, on the bottom ranking of this question we observe Switzerland, Iceland, Finland and Greece with an average answer throughout the years close to 35%

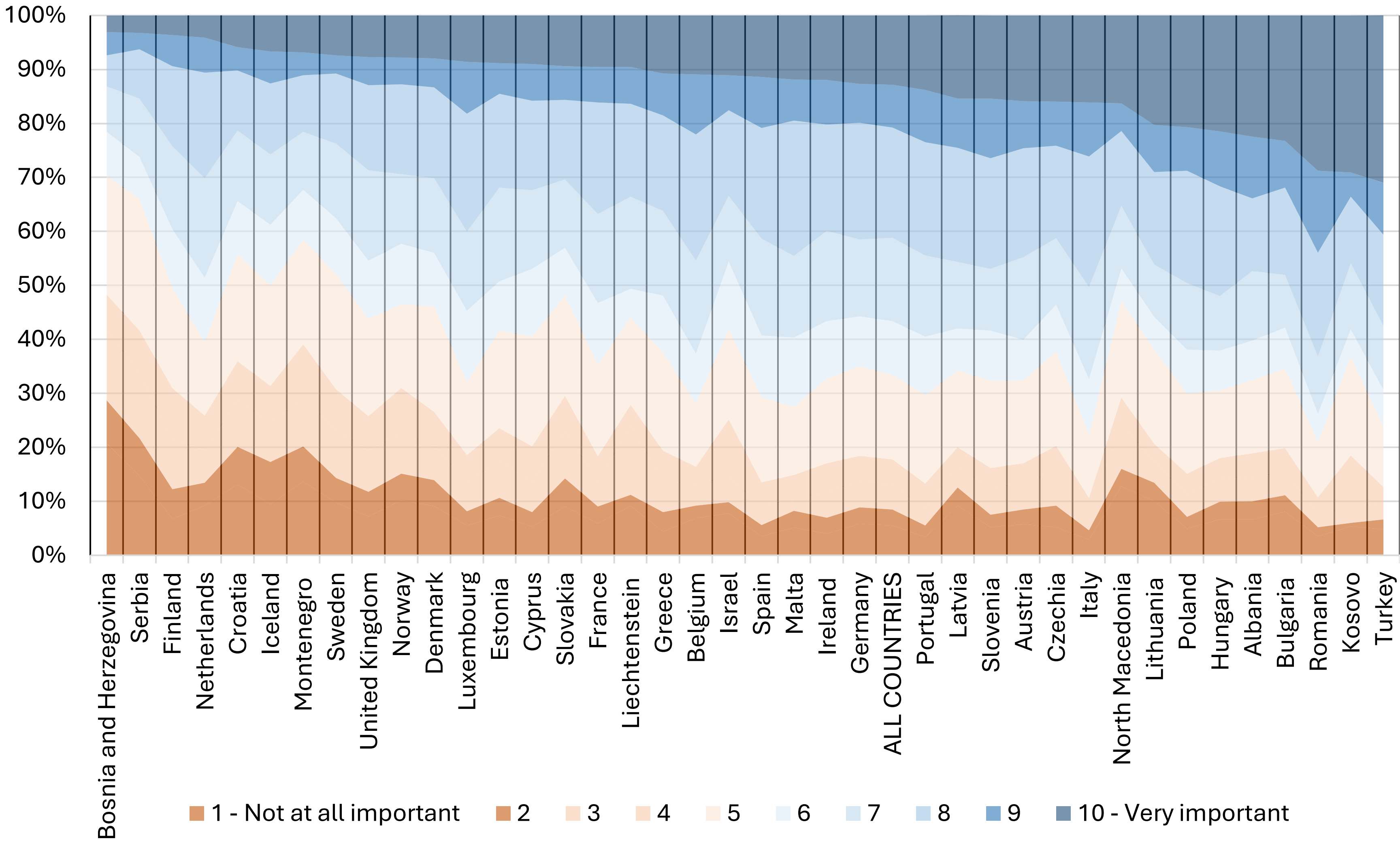


Figure 4-12: SAFE - Problem importance (1-10): Costs of production or labour

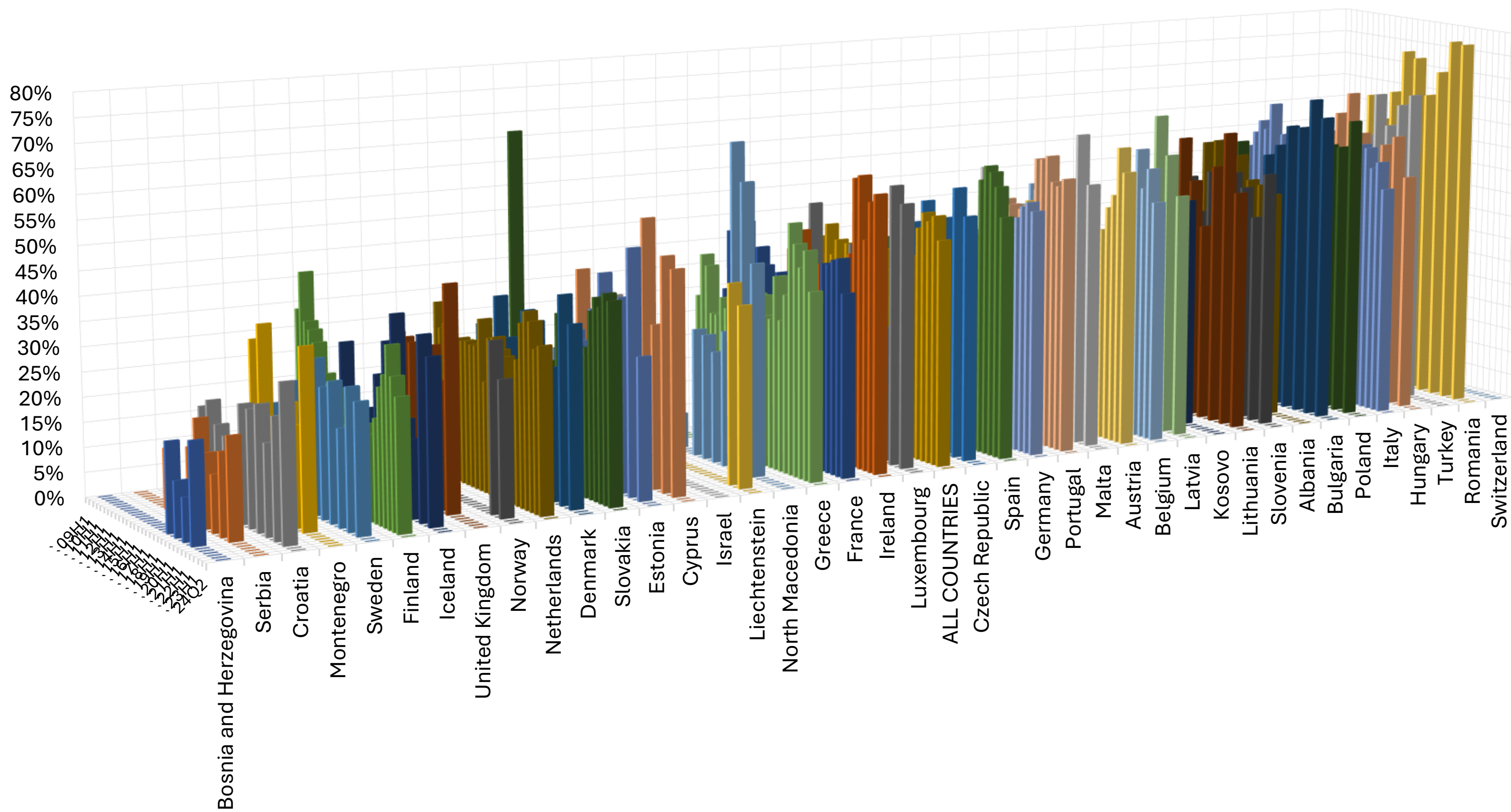


Figure 4-13: SAFE - Very important by year: Costs of production or labour

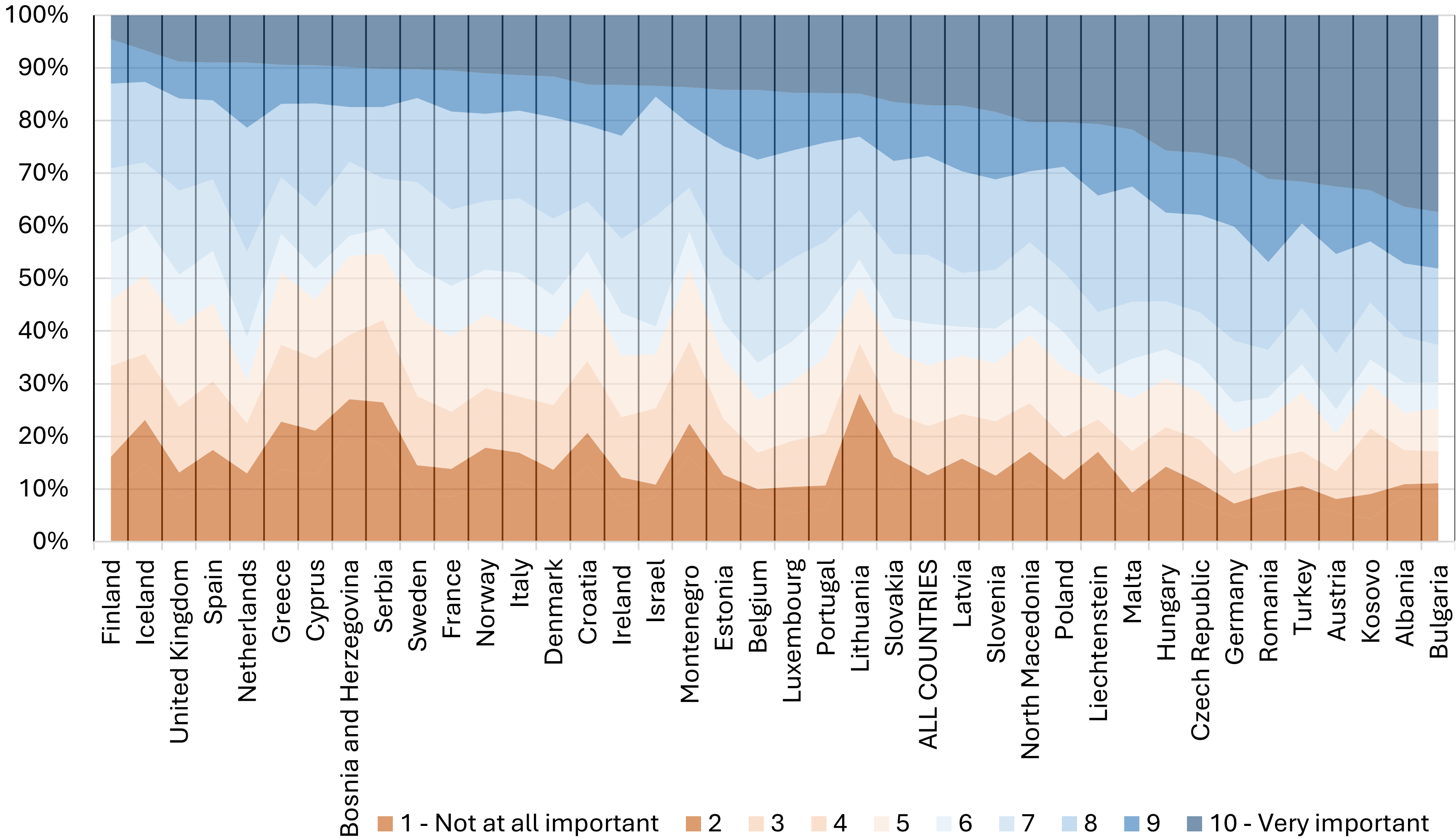


Figure 4-14: SAFE - Problem importance (0-10): Availability of skilled staff/exper. managers (Q0b4)

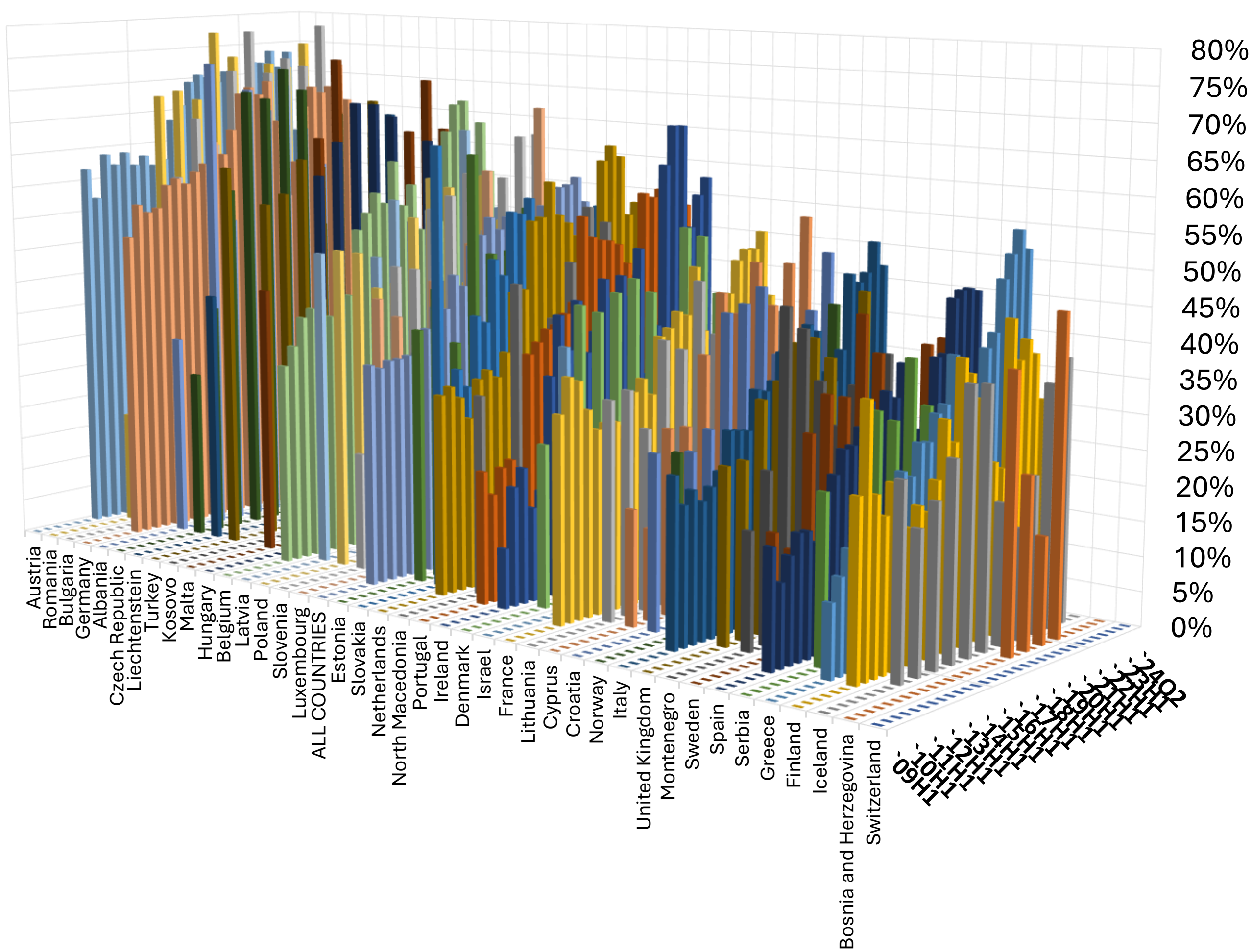


Figure 4-15: SAFE - Very important by year: Availability of skilled staff/experienced managers (Q0b4)

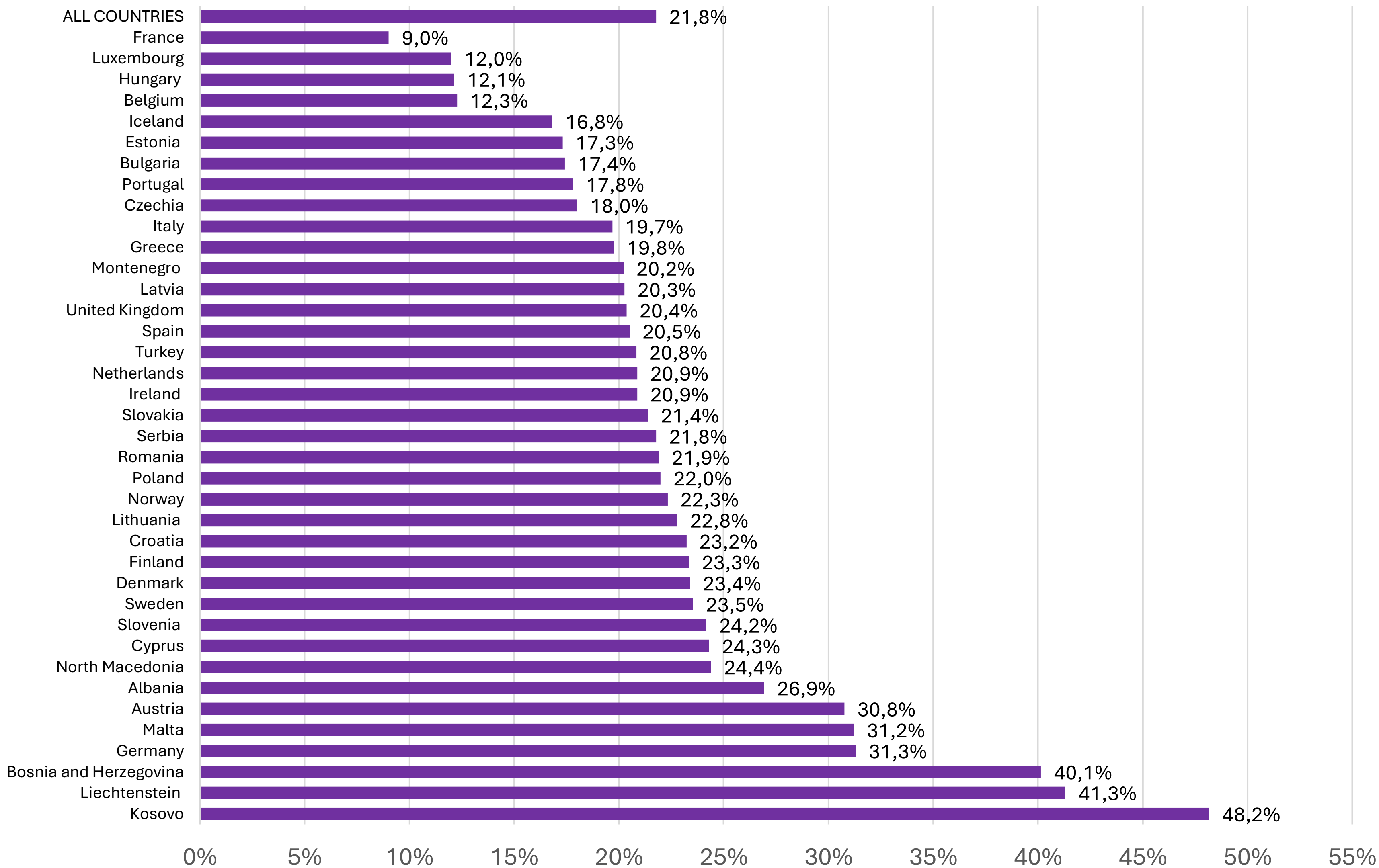


Figure 4-16: SAFE - Access to finance for: Hiring and training of employees (q6a3)

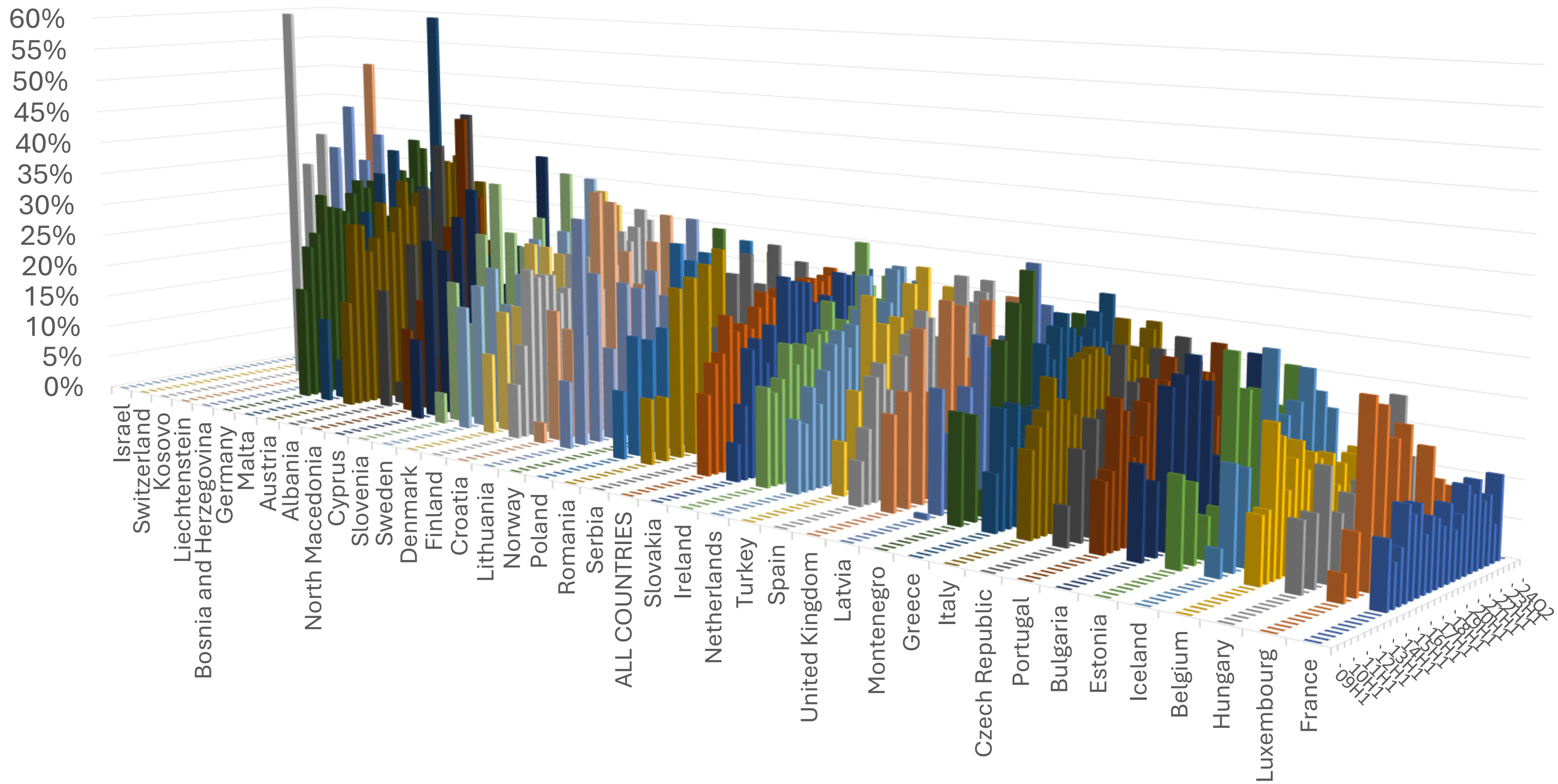


Figure 4-17: SAFE - Access to finance by year for: Hiring and training of employees (q6a3)

This means that, for the aforementioned countries the availability of skilled staff or experienced managers. The availability of skilled workers and experienced managers depends on a combination of factors, including education, labour market dynamics, demographic trends, and company strategies for attracting and retaining talent. The challenge for businesses is to navigate these factors to ensure they can access the necessary human resources for growth and success.

Figure 4-16 presents access to finance for hiring and training of employees with an overall score for the countries under examination at 21.8%. The countries with the lowest ranking are France (9%), Luxembourg (12%), Hungary (12.1%) and Belgium (12.3%). On the other hand, we identify Germany (31.3%), Bosnia Herzegovina (40.1%), Liechtenstein (41.3%) and Kosovo (48.2%) as the countries that face the difficulties with access to finance for hiring and training employees.

Finally, Figure 4-17 illustrates the question described above per wave. We observe that no data are available before 2015 for this question. Overall, access to finance plays a critical role in a company's ability to hire and train employees. Companies with better financial resources can invest in expanding their workforce and upskilling existing employees, which is essential for long-term growth and competitiveness.

4.2.4 THE RELEVANT LITERATURE

An inquiry using the Scopus database 16 articles use the SAFE database, although there is not much research related to skills and training directly. We replicate the 2 relevant exercises using these 16 articles. In Figure 4-18 we present a word cloud of the most frequently appearing words in the index and author keywords of these 16 articles. Then, in Table 4-8, we classify them into 4 key thematic categories, in terms of their content.

Table 4-9: SAFE A systematic classification of the 16 articles on skills using the SAFE into 4 themes

Research domain	Cittions
AI , Financial Innovation and Skills	Rybakovas & Zigiene (2021), Rybakovas & Zigiene (2022)
Access to Finance & Skills	Guercio, et al. (2020)
Access to Finance	Ferrando (2012), Wagner (2019), Calabrese, et al. (2021), Martínez, et al. (2022), Ferrando & Rariga (2024), Dumitru & Dumitru (2024)
Financing Preferences & Skills	Galli, et al. (2018), García-Posada Gómez (2019)
Financing Preferences	Bankowska, et al. (2015), Šeba (2016), Anastasiou & Giannoulakis (2022)
SME Growth	Moscalu, Girardone & Calabrese (2020), Rizk & Sassine (2023)

Figure 4-18: SAFE - Wordcloud of the keywords in 16 relevant articles

The most frequent words in the 16 articles are SAFE, financial, credit, constraints, finance, SME, access, European, bank, scoring, lending inter alia. Table 4-9 shows 4 major thematic areas of research using the SAFE. These are: (1) AI, Financial Innovation, and Skills; (2) Access to Finance and Skills; (3) Financing Preferences and Skills, and (4) SME Growth.

4.3 FLASH EUROBAROMETER 529 (2023)

The FLASH EUROBAROMETER 529 on Skills and Qualifications survey is part of the Eurobarometer series, which is a set of public opinion surveys conducted regularly on behalf of the European Commission. The Eurobarometer surveys aim to monitor the views and attitudes of firms and citizens across the European Union (EU) on various topics of interest, providing insights that help guide EU policies.

A previous version of the Eurobarometer 81.3, conducted in 2014, was on skills and qualifications, with an emphasis on understanding the perceptions, experiences, and needs of European citizens in these areas. The Eurobarometer 81.3 survey on skills and qualifications was a vital tool for understanding the perceptions and experiences of EU citizens regarding education, skills, and lifelong learning. Its findings played a crucial role in informing EU policies aimed at enhancing the skills base of the European workforce, promoting employability, and ensuring that education and training systems are responsive to the evolving needs of the economy. By highlighting areas where skills gaps exist and where barriers to education and training persist, the survey helped guide efforts to create a more inclusive and competitive European labour market.

The Flash Eurobarometer 529 is a survey focused on the skills needs and challenges faced by Small and Medium-sized Enterprises (SMEs) within the European Union. Conducted by the European Commission, it aims to assess how SMEs perceive the availability and adequacy of skills in the workforce, the impact of skill shortages on their operations, and how they respond to these challenges.

The survey explores the demand for skills among SMEs, looking at upskilling, reskilling, and the challenges faced due to the evolving job market. It also examines how SMEs approach talent acquisition, retention, and workforce development. The survey spans across the European Union Member States and looks at various sectors within SMEs. It provides insights on skill gaps across different industries and the steps businesses take to address them.

The data offers insights on perception by owners and managers of SMEs regarding the following domains:

- Skill shortages: Understanding the extent to which SMEs experience difficulties in finding workers with the right skills.
- Digital and green skills: Emphasis is placed on how SMEs adapt to the digital transition and the green economy, identifying the skills needed in these areas.
- Training and development: The survey explores how SMEs invest in employee training and the methods they use to develop the skills of their workforce, including formal and informal training.
- Recruitment strategies: Insights into how SMEs adjust their recruitment practices in response to skills shortages.
- Government support: It looks at how aware SMEs are of the support programs offered by governments, such as funding for training and upskilling, and their experiences in accessing these programs.

There is not much academic research using the Flash Eurobarometer 523, apart from the report by the European Commission (2023). Hence, the systematic literature review sub-section is omitted from this section. The report highlighted that SMEs often face difficulties finding workers with the right combination of technical and soft skills. There are particular challenges related to the adoption of digital tools, with a need for greater expertise in information technology and data management. Some SMEs struggle to keep pace with the rapid changes in skills demands, especially in sectors moving toward sustainability and green initiatives.

The shortage of necessary skills has a direct impact on productivity, innovation, and the ability to expand into new markets. SMEs particularly express concern over how skill shortages could affect their ability to embrace digital transformation and adapt to new environmental regulations. Overall, Flash Eurobarometer 529 offers a detailed snapshot of the evolving skills landscape in Europe, especially from the perspective of SMEs, and provides valuable data for policymakers to understand and support the needs of small businesses.

However, the report also suggested that many SMEs are investing in internal training or partnering with educational institutions to help develop needed skills. They are increasingly open to adopting flexible hiring strategies, like remote working, to attract skilled workers.

4.3.1 THE DATA AND FREQUENCIES

Table 4-11 presents the sample, sectors and firm size from Eurobarometer database. The dataset consists of 27 European countries, with total observations of 12,902 equally distributed among the countries (500 observation each country or 4% on average). Considering the different sectors under investigation, Eurobarometer survey includes Manufacturing (2,355 observations), Retail (3,540 observations) Services (4,791 observations) and Industry (2,236 observations). Again, the sample is proportionally divided among each country in the four sectors. Finally, in terms of the firm size, it is noted that 6,285 firms employ from 1 until 9 employees (48.7%). 4,211 firms (32.6%) employ from 10 until 49 employees and finally 2,406 (18.6%) employ from 50 until 249 employees.

4.3.2 THE SAMPLE AND SUMMARY STATISTICS

Table 4-12 presents the summary statistics of key variables (variable description, mean, standard deviation, both for unweighted and weighted sample along with the corresponding answer yes or no for the question as presented in the Table below and the corresponding significance level (*** at 1%, ** at 5%, and * at 10%). Regarding the importance of company's business model to have workers with right skills, 10,243 firms replied yes and only 2,659 no. The key variables include the number of employees, firm age, firm age, annual turnover and industry. We observe statistical significance of the difference between yes and no for the three categories of firm age. Next, positive and statistically significant difference corresponds to the annual turnover (>than 2 years ago, ***), (<than 2 years ago, ***) and turnover < €25,000, ***). Finaly, the difference is statistically significant in the following industries: Manufacturing (***), Electricity, gas stem and air conditioning (**), Water supply, waste management (**), Construction (**), wholesale and retail trade repair (***), Accommodation and food service activities (***), Information and communication (***), Financial and insurance activities (***), Real estate activities (**), Professional, scientific and technical (***), Other service activities (**), Education (***), Human health and social work activities (**).

Table 4-11: Flash Eurobarometer (2023) - The sample, sectors and firm size

COUNTRY	ACRONYM	#OBS.	(%)	SECTOR				EMPLOYMENT		
				Manufacturing	Retail	Services	Industry	1 - 9	10 - 49	50 - 249
All Countries	***POOLED***	***12,902***	***(100.0%)***	***2,355***	***3,520***	***4,791***	***2,236***	***6,285***	***4,211***	***2,406***
Austria	AT	507	(3.9%)	93	131	192	91	257	169	81
Belgium	BE	501	(3.9%)	81	150	188	82	235	168	98
Bulgaria	BG	500	(3.9%)	91	127	174	108	209	174	117
Croatia	HR	500	(3.9%)	112	129	195	64	198	181	121
Cyprus	CY	250	(1.9%)	40	90	95	25	150	67	33
Czech Republic	CZ	501	(3.9%)	99	119	192	91	216	171	114
Denmark	DK	507	(3.9%)	103	125	179	100	212	185	110
Estonia	EE	503	(3.9%)	95	138	190	80	260	165	78
Finland	FI	500	(3.9%)	101	146	151	102	208	193	99
France	FR	537	(4.2%)	94	159	181	103	271	163	103
Germany	DE	504	(3.9%)	101	102	200	101	237	172	95
Greece	GR	501	(3.9%)	88	147	189	77	250	164	87
Hungary	HU	504	(3.9%)	87	143	186	88	246	156	102
Ireland	IE	502	(3.9%)	90	156	179	77	252	155	95
Italy	IT	502	(3.9%)	85	150	183	84	251	151	100
Latvia	LV	506	(3.9%)	96	141	193	76	266	155	85
Lithuania	LT	502	(3.9%)	84	126	199	93	249	157	96
Luxembourg	LU	252	(2.0%)	14	75	134	29	136	88	28
Malta	MT	252	(2.0%)	52	73	110	17	179	57	16
Netherlands	NL	518	(4.0%)	92	148	186	92	248	167	103
Poland	PL	512	(4.0%)	85	126	192	109	223	173	116
Portugal	PT	504	(3.9%)	98	127	191	88	254	159	91
Romania	RO	503	(3.9%)	101	134	175	93	271	153	79
Slovakia	SK	537	(4.2%)	85	138	220	94	304	150	83
Slovenia	SI	503	(3.9%)	88	144	195	76	251	177	75
Spain	ES	500	(3.9%)	100	149	150	101	238	170	92
Sweden	SE	494	(3.8%)	100	127	172	95	214	171	109

Table 4-12: Flash Eurobarometer (2023) - Summary statistics of key variables

#Observations	*UNWEIGHTED (12,902)*		*WEIGHTED (12,902)*		*Very important for company's business model to have workers with right skills*			
	Mean	(S.D.)	Mean	(S.D.)	Yes (10,243)	No (2,659)	Difference	(Sig.)
#Employees: 1-10	48.7%	(0.50)	94.0%	(0.24)	94.0%	94.2%	-0.0019	
"-": 10-49	32.6%	(0.47)	5.1%	(0.22)	5.2%	4.9%	0.0024	
"-": 50-249	18.6%	(0.39)	0.9%	(0.09)	0.9%	0.9%	-0.0006	
Firm age: <1 year	0.9%	(0.10)	1.4%	(0.12)	1.4%	1.2%	0.0026	
"-": 1 - 5 years	9.7%	(0.30)	13.8%	(0.34)	13.2%	15.9%	-0.0268	**
"-":6 - 10 years	12.5%	(0.33)	15.2%	(0.36)	14.7%	17.1%	-0.0238	*
"-": >10 years	76.6%	(0.42)	69.5%	(0.46)	70.5%	65.8%	0.0470	***
Annual turnover: > than 2 years ago	46.5%	(0.50)	42.3%	(0.49)	43.3%	38.2%	0.0504	***
"-": Similar to 2 years ago	28.5%	(0.45)	31.1%	(0.46)	30.8%	32.4%	-0.0164	
"-": < than 2 years ago	17.6%	(0.38)	21.3%	(0.41)	20.4%	25.0%	-0.0463	***
"-": NA/DK/DA	7.5%	(0.26)	5.4%	(0.23)	5.6%	4.4%	-0.0164	
Turnover: <€25,000	23.7%	(0.43)	21.5%	(0.41)	22.2%	18.7%	0.0352	***
"-": €25,000 - €50,000	1.0%	(0.10)	0.1%	(0.04)	0.2%	0.1%	0.0005	
"-": €50 000 - €100 000	4.9%	(0.22)	1.1%	(0.11)	1.2%	0.9%	0.0035	
"-": €100,000 - €250,000	13.8%	(0.34)	5.4%	(0.23)	5.5%	4.7%	0.0086	
"-": €250 000 - €500,000	18.2%	(0.39)	15.4%	(0.36)	15.7%	14.1%	0.0154	
"-": €500 000 -€2 million	10.2%	(0.30)	13.4%	(0.34)	13.1%	14.5%	-0.0142	
"-": €2-10 million	10.2%	(0.30)	15.4%	(0.36)	15.1%	16.6%	-0.0155	
"-": €10-50 million	7.0%	(0.26)	10.7%	(0.31)	10.7%	11.0%	-0.0036	
"-": >€50 million	5.9%	(0.24)	9.2%	(0.29)	8.9%	10.5%	-0.0159	
"-": DK/DA	5.0%	(0.22)	7.8%	(0.27)	7.6%	9.0%	-0.0140	
Industry: Mining and Quarrying	0.3%	(0.05)	0.2%	(0.04)	0.2%	0.1%	0.0011	
"-": Manufacturing	18.3%	(0.39)	7.5%	(0.26)	7.1%	9.4%	-0.0233	***
"-": Electricity, gas, steam and air con	0.7%	(0.09)	0.4%	(0.06)	0.3%	0.8%	-0.0048	**
"-": Water supply, sewerage, waste management	1.2%	(0.11)	0.5%	(0.07)	0.4%	1.0%	-0.0056	**
"-": Construction	15.1%	(0.36)	11.8%	(0.32)	12.3%	10.1%	0.0211	**
"-": Wholesale and retail trade, repair	27.3%	(0.45)	19.4%	(0.40)	18.2%	23.8%	-0.0559	***
"-": Transportation and storage	3.8%	(0.19)	5.6%	(0.23)	5.4%	6.3%	-0.0091	
"-": Accommodation and food service activities	4.3%	(0.20)	7.2%	(0.26)	5.9%	12.6%	-0.0664	***
"-": Information and communication	3.0%	(0.17)	4.9%	(0.22)	5.4%	2.9%	0.0248	***
"-": Financial and insurance activities	1.9%	(0.14)	3.0%	(0.17)	3.4%	1.8%	0.0153	***
"-": Real estate activities	1.7%	(0.13)	3.4%	(0.18)	3.1%	4.6%	-0.0151	**
"-": Professional, scientific and technical	7.1%	(0.26)	13.8%	(0.34)	15.2%	7.9%	0.0729	***
"-": Administrative and support service	3.3%	(0.18)	5.2%	(0.22)	5.2%	5.5%	-0.0034	
"-": Arts, entertainment and recreation	1.4%	(0.12)	2.4%	(0.15)	2.4%	2.6%	-0.0027	
"-": Other service activities	4.1%	(0.20)	7.9%	(0.27)	8.3%	6.4%	0.0189	**
"-": Education	3.0%	(0.17)	2.7%	(0.16)	3.1%	1.2%	0.0189	***
"-": Human health and social work activities	3.5%	(0.18)	4.1%	(0.20)	4.3%	3.0%	0.0135	**

4.3.3 SKILLS MATCHING AND TRAINING STATISTICS

Figure 4-19 presents the findings from Eurobarometer database on the importance of having workers with the right skills. 80% of the total sample, replied very important with Austria (95.7%), Cyprus (92.7%) and Portugal (90.3%) ranked on the top level, while Belgium (69.2%), Lithuania (68.4%) and Slovakia (58.1%) ranked at the bottom of the particular list.

Figure 4-20 presents the importance of different skill types. The sample is divided into four categories: Soft Skills (48.5%), Green Skills (38.8%)), Digital Skills (30.3%) and Hard Skills (20.7%). The counties that consider Green Skills as most important are ranked first with Cyprus (70.6%), Greece (64.5%) and Croatia (51.7%) receiving higher rank, while Lithuania (27.6%), Estonia (22.1%) and Czech Republic (17.7%) ranked at the bottom of the particular list.

Figure 4-21 presents the difficulties with respect to skills and training. The sample is divided into six categories: Find workers with the right skills (50.4%), Retain skilled workers (20.7%), Find time for your staff to participate in training (20.5%), Finance staff training (13.4%), Identify appropriate training opportunities (9.1%) and assess training needs of the staff (5.9%). The counties are ranked based on the answer "*Find workers with the right skills"* with Slovakia (68.3%), Hungry (62.8%) and Belgium (61.9%) receiving higher rank, while Netherlands (39.4%), Ireland (34.4%) and Denmark (33.4%) ranked at the bottom of the particular list.

Figure 4-22 presents the difficulties in recruitment due to limited applications. The sample is divided into five categories: Managers (8.8%), Professionals and Technicians (21.7%), Administrative (10.6%), Machine operators (16.8%) and Manual labourers (17.2%). The counties are ranked based on the answer "*Managers"* with Croatia (18.8%), Poland (15%) and Netherlands (13.7%) receiving higher rank, while Estonia (4.5%), Portugal (4.3%) and Denmark (1.4%) ranked at the bottom of the particular list.

Figure 4-23 presents the difficulties in recruitment due to skills mismatch. The sample is divided into five categories: Managers (7.5%), Professionals and Technicians (15%), Administrative (9.1%), Machine operators (10.6%) and Manual labourers (10.9%). The counties are ranked based on the answer "*Managers"* with Luxemburg (18.2%), Ireland (13.4%) and Malta (13.3%) receiving higher rank, while Greece (4.1%), Austria(1.5%) and Cyprus (1.4%) ranked at the bottom of the particular list.

Figure 4-24 illustrates the limitations due to skills mismatch. The sample is divided into three categories: General business activity (26.2%), Greening business activity (12%) and Adopt (16.4%). The counties are ranked based on the answer "*General business activity"* with Hungry (45.2%), Bulgaria (42.4%) and Romania (40%) receiving higher rank, while Portugal (15.5%), Netherlands (14.5%) and Austria (13.3%) ranked at the bottom of the particular list.

Figure 4-25 shows the measures to tackle skill shortages. The two categories that account for the biggest share of the specific question is "*Invest more in training (33%)*" and "*Adjust hiring standards (31.8%)*". The counties are ranked based on the answer "*Invest more in training"* with Luxembourg (37.1%), Belgium (31.7%) and Czech Republic (30.7%) receiving higher rank, while Slovenia (12.7%), Denmark (11.2%) and Latvia (10.5%) ranked at the bottom of the particular list.

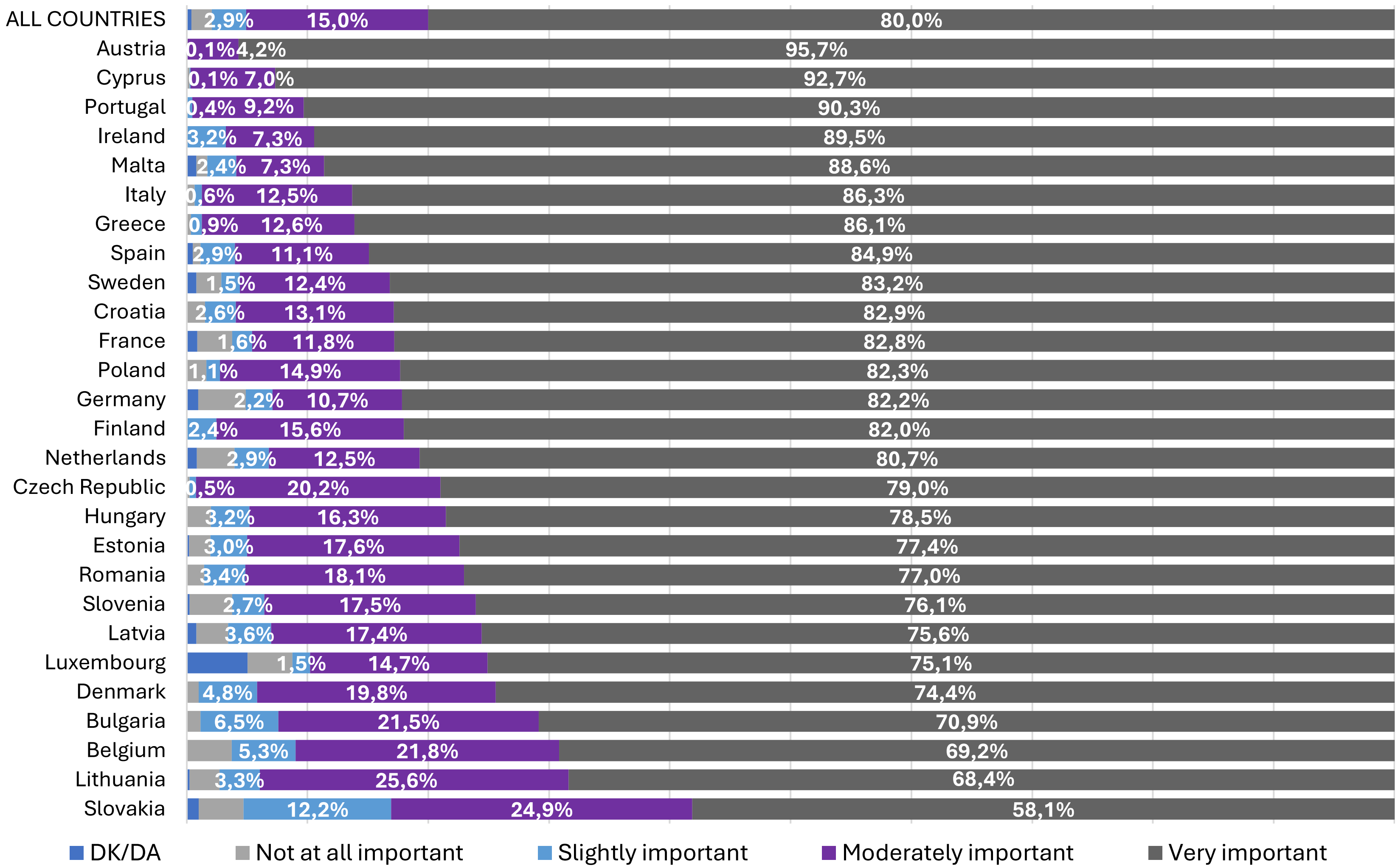


Figure 4-19: **Flash Eurobarometer (2023) -** ***Importance of having workers with the right skills (Q0)***

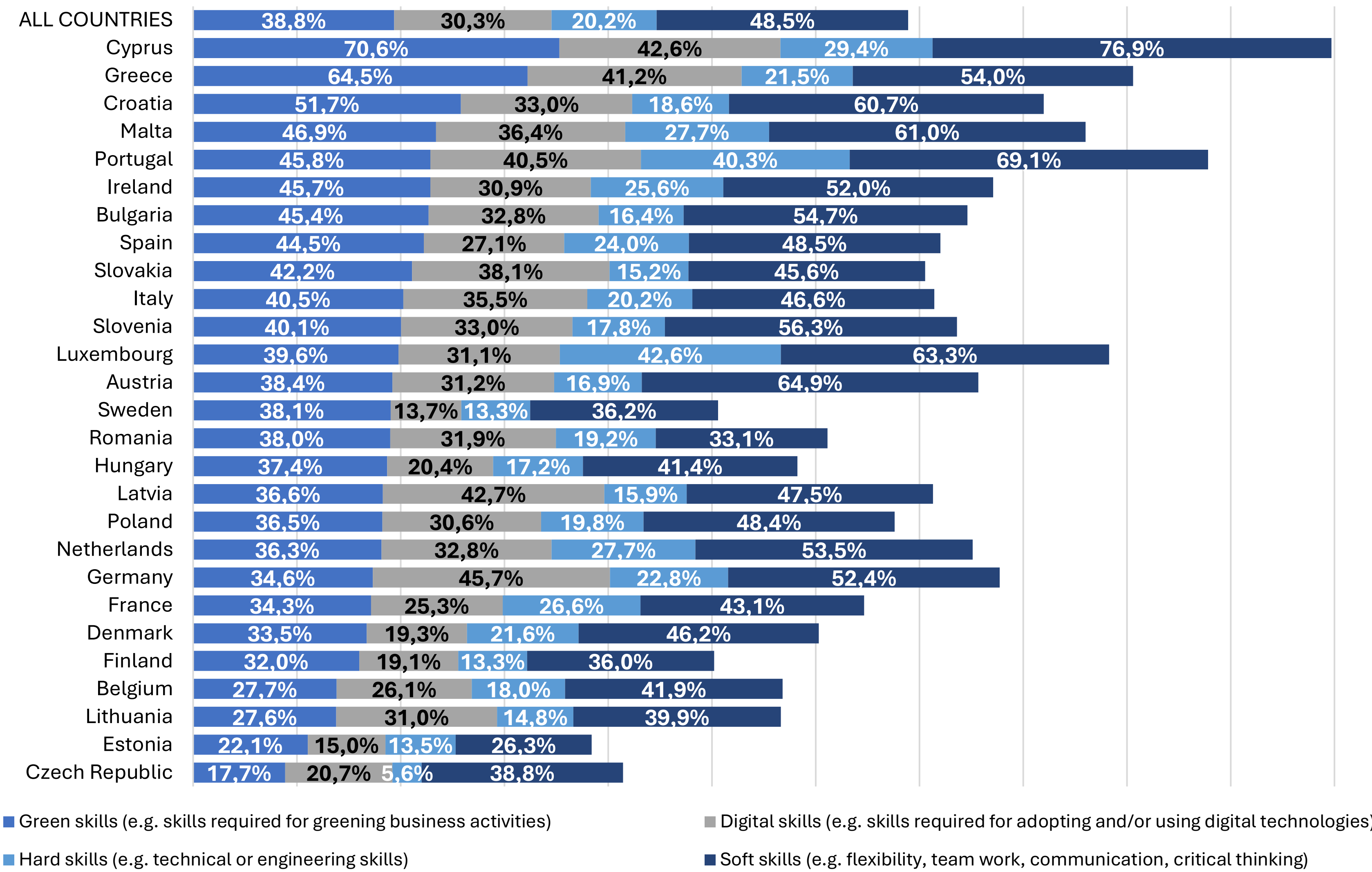


Figure 4-20: **Flash Eurobarometer (2023) -** ***Importance of different skill types (Q1)***

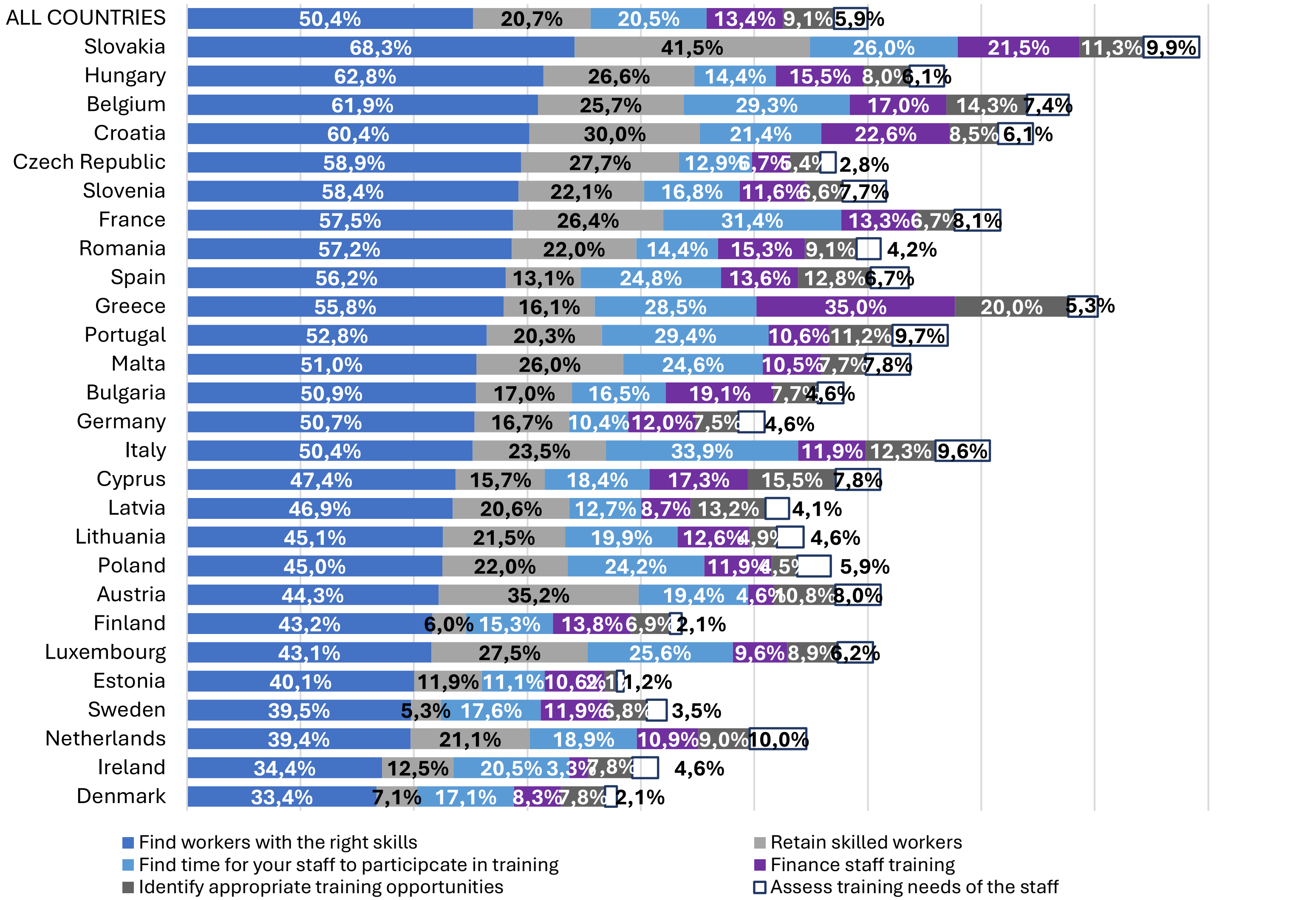


Figure 4-21: **Flash Eurobarometer (2023) -** ***Difficulties with respect to skills and training (Q2)***

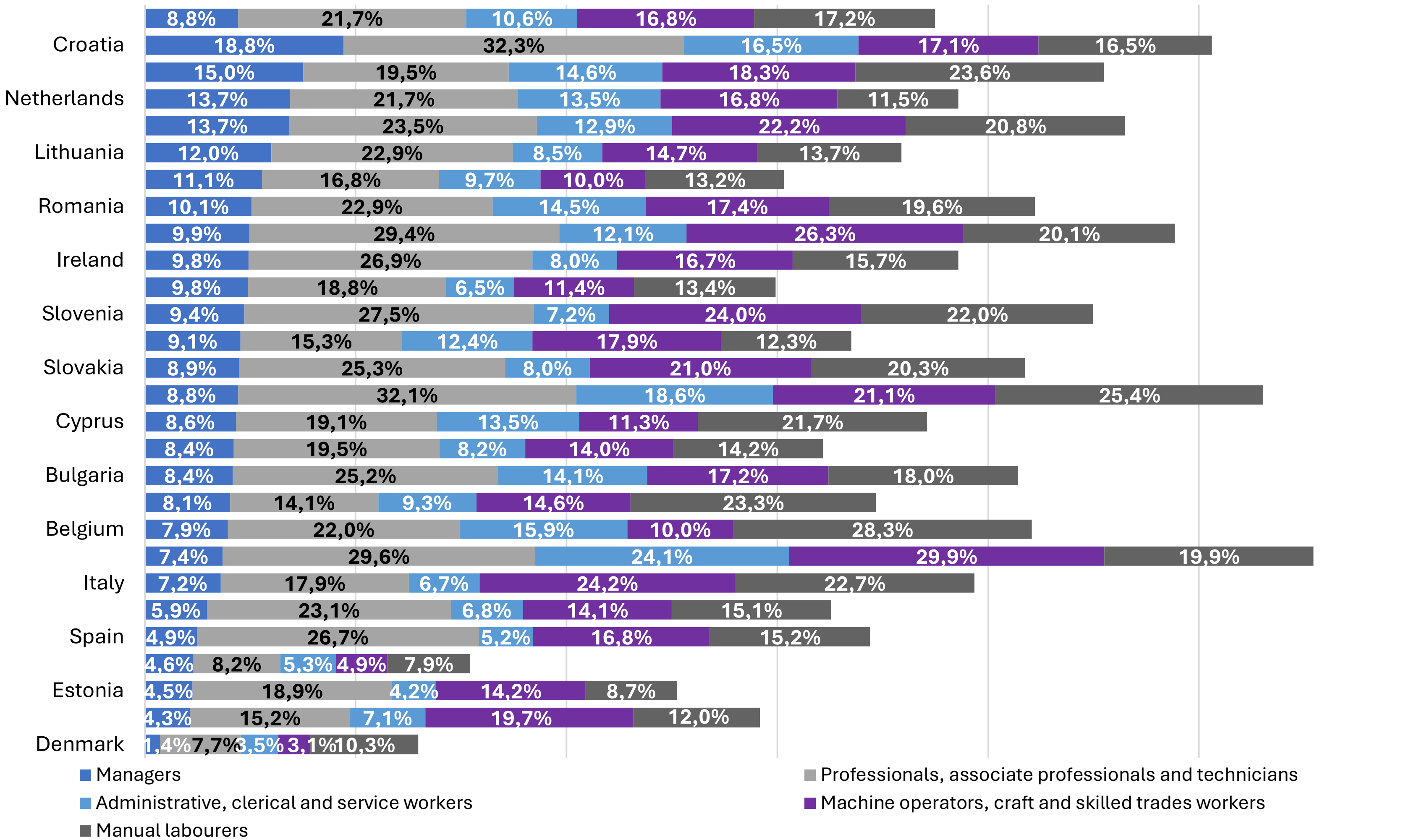


Figure 4-22: **Flash Eurobarometer (2023) -** ***Recruitment difficulties: limited applications (Q3.1)***

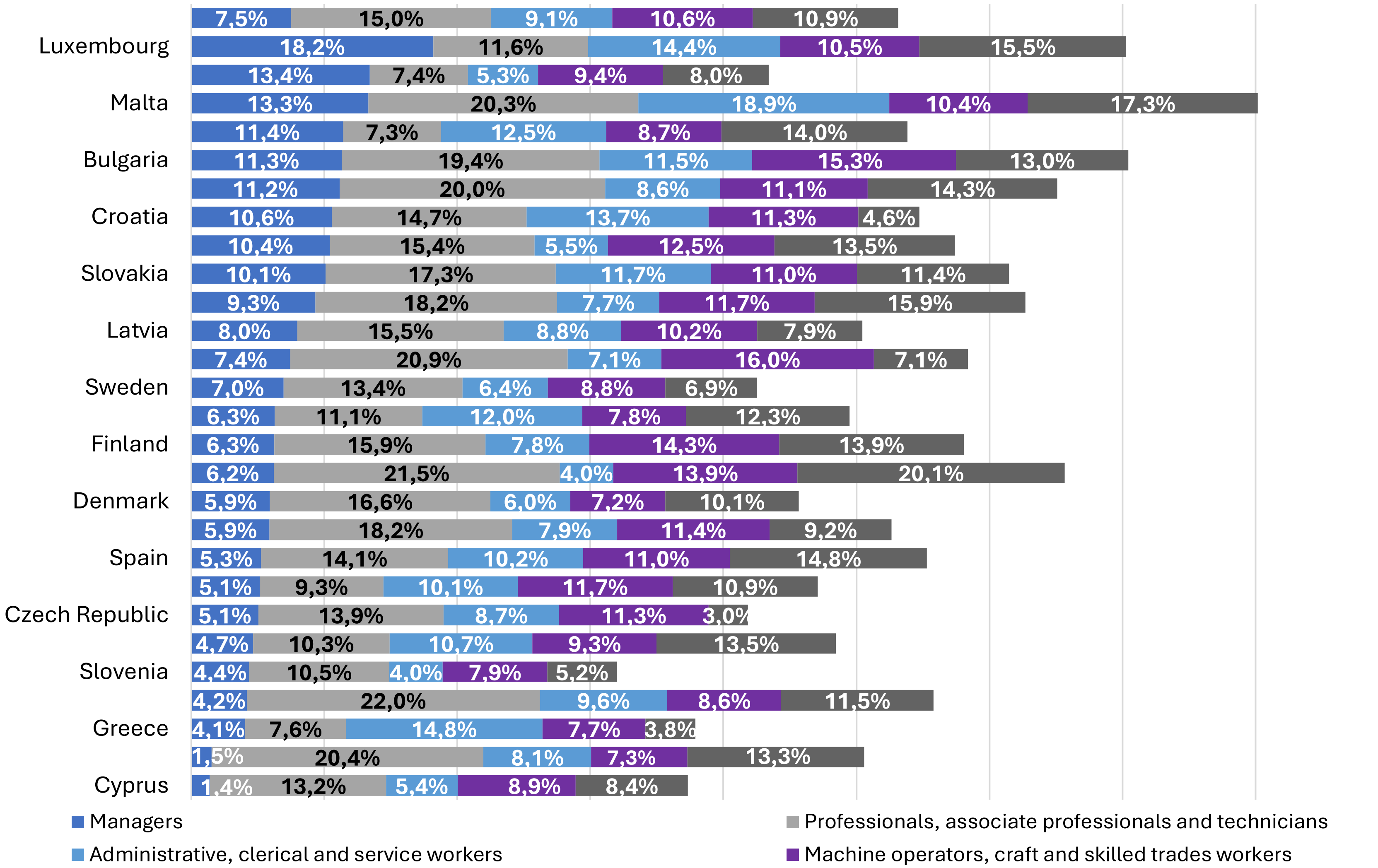


Figure 4-23: **Flash Eurobarometer (2023) -** ***Recruitment difficulties: skills mismatch (Q3.2)***

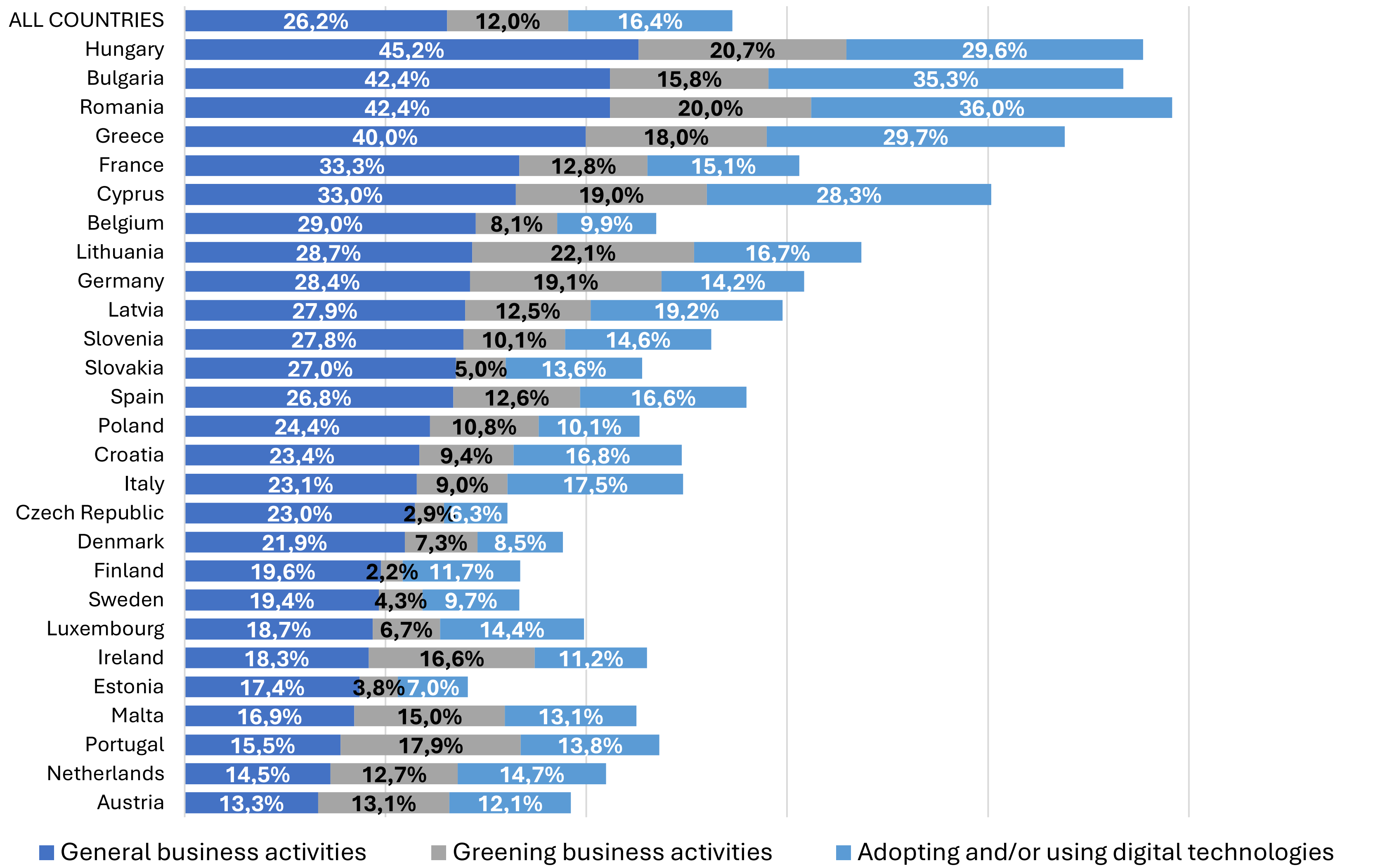


Figure 4-24: **Flash Eurobarometer (2023) -** ***Limitations due to skills mismatch (Q4)***

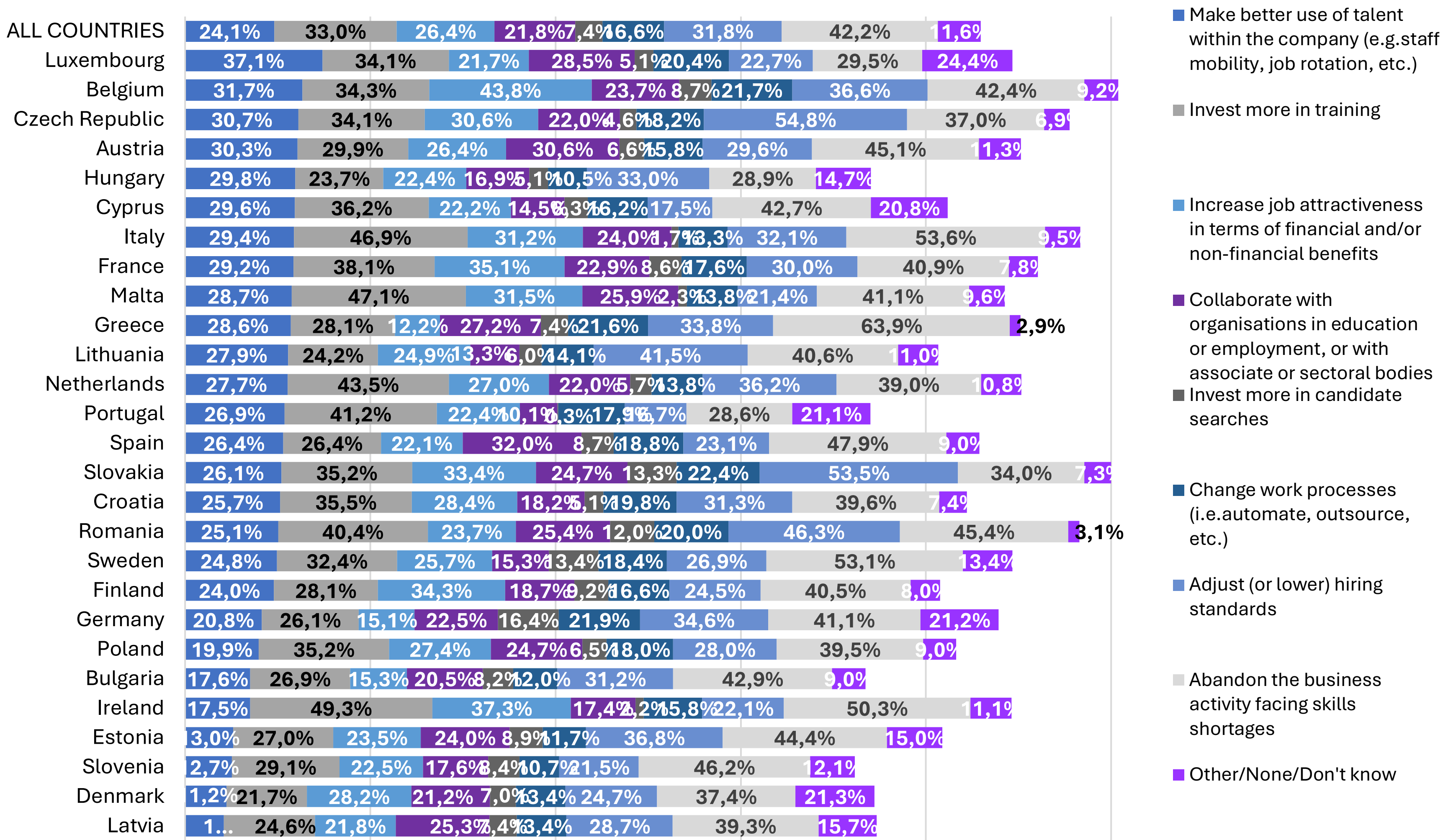


Figure 4-25: **Flash Eurobarometer (2023) -** ***Measures to tackle skill shortages (Q5)***

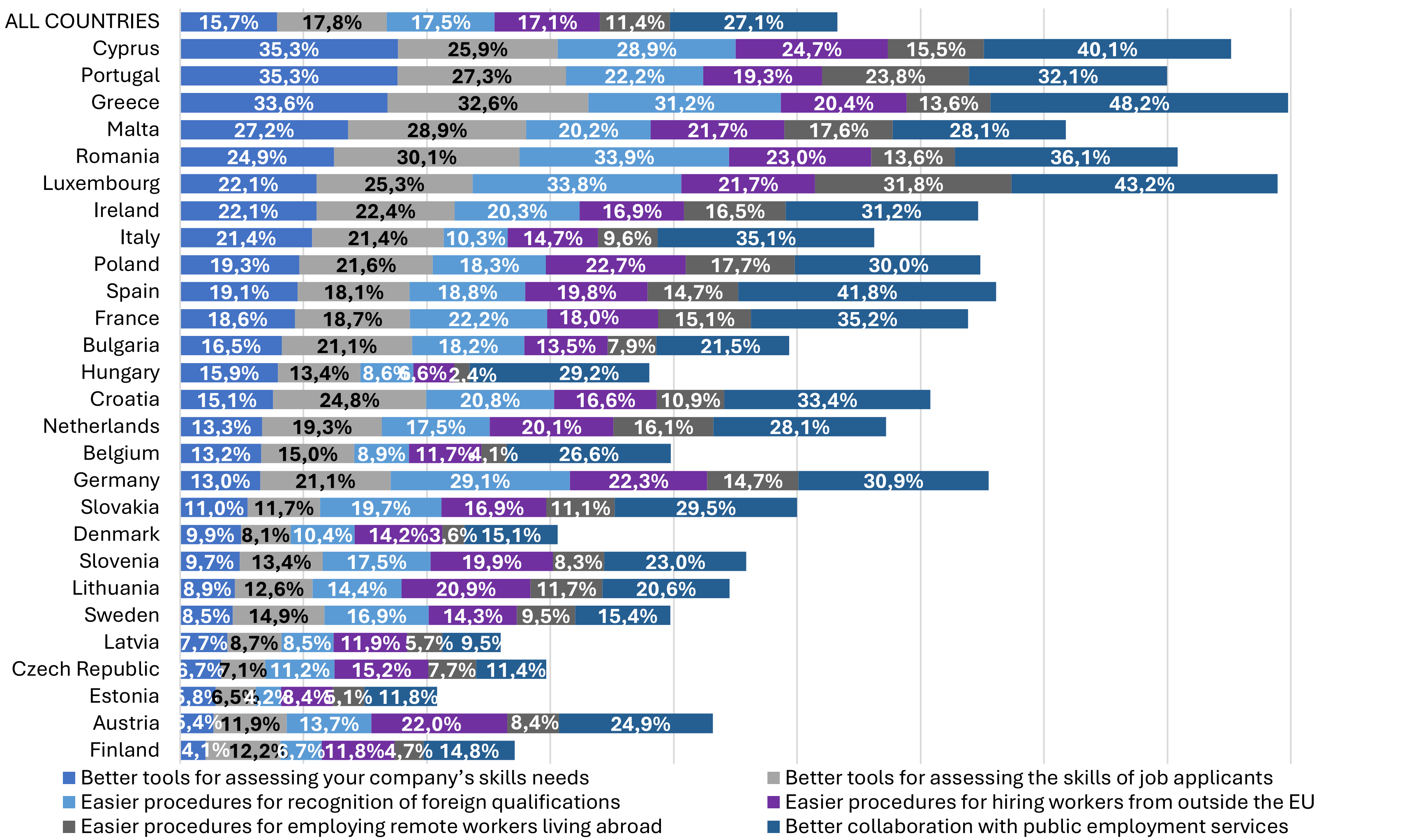


*Figure 4-26: **Flash Eurobarometer (2023) - Means of tackling skill shortages (Q8)***

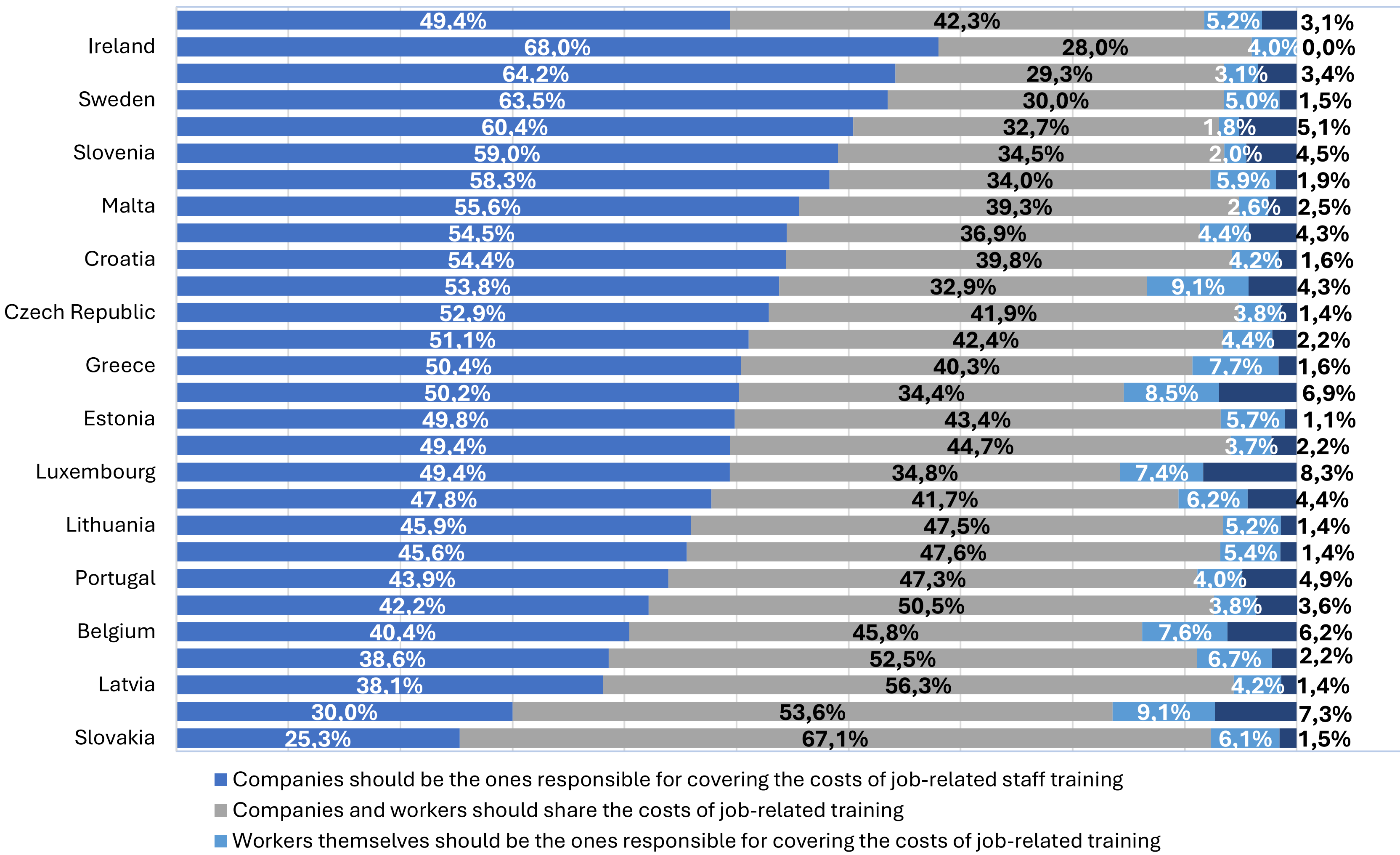


Figure 4-27: **Flash Eurobarometer (2023) -** ***Financing the cost of training (Q9)***

Figure 4-26 shows the means of tackling skill shortages. The two categories that account for the biggest share of the specific question is "*Better collaboration with public employment services (27%)*" and "*Better tools for assessing the skills of job applicants (17.8%)*". The counties are ranked based on the answer "*Better tools for assessing your company's skill needs*" with Cyprus (35.3%), Portugal (35.3%) and Greece (33.6%) receiving higher rank, while Estonia (5.8%), Austria (5.4%) and Finland (4.1%) ranked at the bottom of the particular list.

Figure 4-27 presents the financing the cost of training. The two categories that account for the biggest share of the specific question is "*Companies should be the ones responsible for covering the costs of job-related staff training (49.4%)*" and "*Companies and workers should share the costs of job-related training (42.3%)*".

4.3.4 DIFFERENCES ACROSS FIRM TYPES

Table 4-13 presents the summary statistics of skills-related variables in Eurobarometer 2023 (variable description, mean, standard deviation, both for unweighted and weighted sample along with the corresponding answer yes or no for the question as presented in the Table below and the corresponding significance level (*** at 1%, ** at 5%, and * at 10%). Regarding the importance of company's business model to have workers with right skills, 10,243 firms replied yes and only 2,659 no. We observe statistical significance of the difference between yes and no for the majority of the variables under consideration.

Table 4-13: Summary statistics of skills-related variables in Flash Eurobarometer (2023)

#Observations	UNWEIGHTED (*12,902*)		WEIGHTED (*12,902*)		Very important for company to have workers with right skills			
	Mean	(S.D.)	Mean	(S.D.)	Yes (10,243)	No (2,659)	Diff	(Sig.)
Very important for company: "Soft skills"	47.4%	(0.50)	48.5%	(0.50)	50.8%	39.3%	0.1153	***
"-": "Digital skills"	31.5%	(0.46)	30.3%	(0.46)	33.7%	16.8%	0.1689	***
"-": "Hard skills"	21.3%	(0.41)	20.2%	(0.40)	21.5%	15.2%	0.0628	***
"-": "Green skills"	36.7%	(0.48)	38.8%	(0.49)	41.8%	27.0%	0.1478	***
Difficulty in: Finding workers with the right skills	50.8%	(0.50)	50.4%	(0.50)	53.3%	38.9%	0.1437	***
"-": "Retaining skilled workers	20.3%	(0.40)	20.7%	(0.41)	21.1%	19.1%	0.0204	
"-": "Assessing training needs of the staff	5.7%	(0.23)	5.9%	(0.24)	6.0%	5.3%	0.0069	
"-": "Identifying appropriate training opportunities	8.4%	(0.28)	9.1%	(0.29)	9.6%	7.1%	0.0245	***
"-": "Financing staff training	11.2%	(0.31)	13.4%	(0.34)	13.2%	14.2%	-0.0109	
"-": "Finding time for staff to participate in training	19.7%	(0.40)	20.5%	(0.40)	21.2%	17.7%	0.0347	***
Difficulty in recruiting: Managers	9.9%	(0.30)	7.5%	(0.26)	7.7%	6.8%	0.0094	
"-": Professionals, assoc. professionals & technicians	16.3%	(0.37)	15.0%	(0.36)	16.3%	9.8%	0.0651	***
"-": Administrative, clerical and service workers	9.2%	(0.29)	9.1%	(0.29)	9.4%	7.8%	0.0161	*
"-": Machine operators, craft & skilled trades workers	13.7%	(0.34)	10.6%	(0.31)	11.0%	9.0%	0.0198	**
Strongly agree: Skill shortages hold your company back:								
... in general business activities	25.5%	(0.44)	26.2%	(0.44)	27.4%	21.2%	0.0615	***
... in greening business activities	11.8%	(0.32)	12.0%	(0.33)	12.7%	9.4%	0.0324	***
... in adopting and/or using digital technologies	15.5%	(0.36)	16.4%	(0.37)	17.1%	13.3%	0.0378	***
Treatment of skills challenges:								
Make better use of talent within the company	27.5%	(0.45)	24.1%	(0.43)	24.7%	21.9%	0.0284	**
Invest more in training	35.1%	(0.48)	33.0%	(0.47)	34.8%	25.7%	0.0908	***
Increase job attractiveness in terms of benefits	28.5%	(0.45)	26.4%	(0.44)	27.1%	23.8%	0.0325	**
Collabourate with organisations/bodies	21.7%	(0.41)	21.8%	(0.41)	21.4%	23.2%	-0.0174	
Invest more in candidate searches	6.3%	(0.24)	7.4%	(0.26)	7.4%	7.5%	-0.0015	
Change work processes	17.9%	(0.38)	16.6%	(0.37)	15.8%	19.8%	-0.0407	***
Adjust (or lower) hiring standards	33.5%	(0.47)	31.7%	(0.47)	31.0%	34.7%	-0.0363	**
Abandon business activity facing skills shortages	45.2%	(0.50)	42.2%	(0.49)	43.2%	38.5%	0.0466	***
Other/None/DK/DA	9.2%	(0.29)	11.6%	(0.32)	11.4%	12.1%	-0.0065	
Support for skills challenges:								
EU level organisations/authorities	3.4%	(0.18)	3.4%	(0.18)	3.4%	3.2%	0.0020	
National level organisations/authorities	4.9%	(0.22)	5.1%	(0.22)	5.2%	4.4%	0.0087	
Regional or local level organisations/authorities	6.0%	(0.24)	5.7%	(0.23)	5.8%	5.2%	0.0061	
Familiarity with:								
EU policy initiatives for skills	2.7%	(0.16)	2.5%	(0.16)	2.6%	2.4%	0.0016	
EU funding programmes for skills	6.5%	(0.25)	5.9%	(0.24)	6.2%	4.5%	0.0167	**
EU initiatives for hiring skilled workers from abroad	3.1%	(0.17)	2.6%	(0.16)	2.5%	3.0%	-0.0052	
Recruitment essentials:								
Better tools for assessing your company's skills needs	16.1%	(0.37)	15.7%	(0.36)	16.9%	11.2%	0.0566	***
Better tools for assessing the skills of job applicants	18.2%	(0.39)	17.8%	(0.38)	18.9%	13.4%	0.0549	***
Easier procedures for recognition of foreign qualifications	17.3%	(0.38)	17.5%	(0.38)	18.5%	13.4%	0.0511	***
Easier procedures for hiring workers from outside the EU	17.8%	(0.38)	17.1%	(0.38)	17.9%	13.7%	0.0423	***
Easier proced. for employing remote workers living	10.8%	(0.31)	11.4%	(0.32)	12.0%	8.7%	0.0327	***
Better collabouration with public employment services	28.0%	(0.45)	27.1%	(0.44)	27.8%	24.6%	0.0312	**
Cost of job-related staff training:								
Companies should be responsible for covering costs	52.2%	(0.50)	49.4%	(0.50)	50.2%	46.3%	0.0397	**
Companies and workers should share the costs	40.5%	(0.49)	42.3%	(0.49)	41.5%	45.2%	-0.0371	**
Workers should be responsible for covering costs	4.3%	(0.20)	5.2%	(0.22)	5.2%	5.2%	0.0002	
Don't know/No answer	3.0%	(0.17)	3.1%	(0.17)	3.1%	3.3%	-0.0028	
Ed. qualifications very important when recruiting workers	30.0%	(0.46)	30.3%	(0.46)	34.3%	14.3%	0.1996	***
Recruited from outside the European Union	15.9%	(0.37)	11.4%	(0.32)	11.6%	10.8%	0.0078	

4.4 EUROPEAN INVESTMENT BANK INVESTMENT CLIMATE SURVEY (EIBIS)

The European Investment Bank (EIB) Investment Survey (often referred to as the EIB Investment Climate Survey or EIBIS) is an annual survey conducted by the European Investment Bank. It aims to assess the investment activity, financing conditions, and challenges faced by companies across the European Union (EU) and some neighbouring countries. The survey provides critical insights into how firms are investing, the obstacles they encounter, and the overall economic and investment climate in Europe.

The EIB Investment Climate Survey is designed to gather comprehensive data on the investment patterns, needs, and challenges of businesses across Europe. It aims to understand how economic and financial conditions influence corporate investment decisions and how these decisions are shaping the broader economic landscape.

The survey covers all EU Member States as well as some additional European countries. It includes businesses of various sizes, sectors, and ownership types, though it has a particular focus on small and medium-sized enterprises (SMEs).

The survey covers the following themes:

- Investment Activity: The survey collects data on firms' investment activities over the past year, including the types of investments made (e.g., in machinery, buildings, research and development, digital technologies) and the overall level of investment.
- Investment Needs and Gaps: It assesses whether firms are meeting their investment needs or whether there are gaps, including under-investment in critical areas like infrastructure, skills, and innovation.
- Investment Outlook: Firms are asked about their future investment plans, including anticipated changes in investment levels and areas of focus.
- Financing Conditions: The survey explores how firms finance their investments, including the use of internal funds, bank loans, and other sources of external finance. It also examines the cost and availability of financing, credit conditions, and firms' perceptions of the financial market.
- Barriers to Investment: EIBIS identifies key obstacles to investment, such as regulatory uncertainty, taxation, labour market issues, and access to finance. The survey also considers broader macroeconomic factors that may impact investment, such as political instability or economic downturns.
- Innovation and Digitalization: The survey pays special attention to investment in innovation and digital technologies, assessing how firms are adopting new technologies and integrating them into their business models.
- Climate and Environmental Investment: Increasingly, EIBIS also looks at investment in energy efficiency, renewable energy, and other climate-related areas, reflecting the EU's green transition priorities.
- Investment Intensity: Measures the level of investment relative to the size of the firm, providing insights into how aggressively firms are investing.

- Investment Gaps: Identifies areas where firms report that they are investing less than they need to, signalling potential future growth bottlenecks.
- Financing Constraints: Tracks the proportion of firms reporting difficulties in obtaining external finance, along with the reasons for these difficulties.
- Investment in Innovation: Measures the extent to which firms are investing in new products, processes, and technologies.

The EIBIS is conducted annually through structured interviews, typically with senior decision-makers within firms. The sample is designed to be representative of the business population in each country, ensuring that the results reflect the experiences of a wide range of firms. The survey includes both qualitative and quantitative questions, allowing for a nuanced understanding of investment behaviours and challenges.

EIBIS data is used by the European Investment Bank, European Commission, and national governments to shape policies that support business investment, particularly in innovation, infrastructure, and green technologies. The survey informs policy measures aimed at improving access to finance for businesses, especially SMEs, which are often more constrained in their financing options. EIBIS contributes to understanding how businesses are responding to strategic EU priorities, such as the digital transition and the Green Deal, by tracking investment in relevant sectors.

The survey's findings are used to design and refine investment support programs, address barriers to investment, and ensure that public policy effectively encourages private sector investment. Firms can use EIBIS data to benchmark their own investment activity against that of their peers and to identify potential opportunities or risks in the investment climate. The data provides a rich source of information for analysing investment trends, the impact of economic policies, and the broader economic environment.

The EIB Investment Climate Survey is a crucial tool for understanding the investment behaviour and financing conditions of businesses across Europe. By providing detailed and timely data on how firms are investing, the survey helps to identify challenges and opportunities in the European investment landscape. This, in turn, supports the development of policies and initiatives that foster a more conducive environment for business investment, driving economic growth, innovation, and the transition to a more sustainable economy in Europe.

At the time of compilation of D2.1, there is still a pending application to the EIB for access to the EIBIS database. Hence, its presentation and analysis is left for one of the forthcoming deliverable tasks of the TRAILS project.

4.5 CONTINUING VOCATIONAL EDUCATION SURVEY (CVTS)

The CVTS provides comparable data on vocational training within the EU enterprises with at least 10 or more employed persons and belonging to a certain group of economic activities. The CVTS along with the following two other data collections, the adult education survey (AES) and the EU labour force survey (EU-LFS) provide EU statistics on lifelong learning. Lifelong learning is defined as an intentional search for knowledge throughout life (after the end of initial education in particular). It is aimed at improving a person's skills and competences for personal or professional reasons.

The CVTS is an EU-wide data collection on continuing vocational training carried out in enterprises. It refers to education and training activities financed totally or partially by the enterprise for their persons employed. The use of work-time and the acquisition of training equipment is also considered as financing.

The following topics are covered in the CVTS data:

- provision of CVT courses and other forms of CVT (training/non-training enterprises);
- CVT strategies;
- participants in CVT courses;
- costs of CVT courses;
- time spent in CVT courses;
- characteristics of CVT courses;
- assessment of CVT activities.

On top of these topics, some information on initial vocational training is also collected through the CVTS.

At the time of compilation of D2.1, access to the CVTS database was just acquired. Hence, its presentation and analysis is left for one of the forthcoming deliverable tasks of the TRAILS project.

5. MATCHED EMPLOYER-EMPLOYEE DATASETS

5.1 EUROPEAN UNION STRUCTURE OF EARNINGS SURVEY (EU-SES)

The European Union Structure of Earnings Survey (EU-SES) is a large-scale, detailed survey conducted by the national statistical offices of the EU Member States under the coordination of Eurostat, the statistical office of the European Union. The survey provides comprehensive and comparable data on the distribution and structure of earnings in the EU, which is crucial for analysing wage disparities, gender pay gaps, and the overall dynamics of the labour market.

The main goal of the SES is to collect detailed information on the level, distribution, and composition of earnings across different sectors, occupations, and worker characteristics in the EU. The survey aims to support the development of EU policies related to employment, social inclusion, and gender equality by providing reliable data on wage structures and disparities.

The SES is conducted every four years and covers enterprises across all EU Member States, as well as some additional European countries (such as Norway and Switzerland). It focuses on enterprises with at least 10 employees in various sectors, including industry, construction, services, and the public sector.

The survey collects data on employees, typically covering both full-time and part-time workers. The survey covers the following themes:

- Gross Earnings: The SES collects data on gross monthly and annual earnings, including basic pay, overtime, bonuses, and other allowances.
- Hourly Earnings: Information on hourly earnings, which allows for the analysis of earnings in relation to working hours.
- Working Hours: Data on the number of hours worked, including regular and overtime hours.
- Employee Characteristics: The survey gathers detailed information about employees, such as age, gender, educational level, occupation, type of employment contract (e.g., permanent vs. temporary), and full-time or part-time status.
- Enterprise Characteristics: The SES includes data on enterprise size, economic sector, and location, providing context for understanding wage structures within different types of organizations.
- Pay Components: The survey breaks down earnings into various components, such as regular wages, irregular bonuses, and in-kind benefits, allowing for a more detailed analysis of how compensation is structured.

- Earnings Distribution: The survey provides insights into the distribution of earnings across different groups of workers, enabling analysis of wage inequality, the gender pay gap, and other disparities.
- Average Earnings: The survey provides average earnings data for different groups of workers, broken down by factors such as gender, occupation, industry, and educational level.
- Earnings Dispersion: Measures of earnings dispersion, such as the Gini coefficient or earnings percentiles, which help to assess the level of wage inequality within and across countries.
- Gender Pay Gap: One of the most important indicators derived from the SES is the gender pay gap, which measures the difference in average earnings between male and female workers.
- Occupational Earnings: Detailed data on earnings by occupation, allowing for analysis of pay levels in specific job categories.
- Sectoral Earnings: Information on earnings by sector, providing insights into how wages vary across different industries.
- Wage and Employment Policies: The SES data is crucial for shaping EU and national policies related to wages, employment, and social protection. It helps policymakers understand wage structures and address issues such as wage inequality and low pay.
- Gender Equality: The survey provides key data for monitoring progress towards gender equality in the labour market, particularly in terms of reducing the gender pay gap.
- Labour Market Analysis: SES data is used to analyse labour market trends, including the impact of economic cycles on wage distribution, and to identify groups that may be at risk of low pay or wage discrimination.

The SES is conducted through a combination of administrative data sources and enterprise surveys. Enterprises are typically required to provide detailed earnings data for a sample of their employees. The data is anonymized and aggregated to ensure the confidentiality of individual employees and enterprises. The survey follows a standardized methodology across countries, allowing for the comparability of data between Member States and over time.

Governments and EU institutions use SES data to develop and evaluate policies aimed at promoting fair wages, reducing wage disparities, and ensuring equal pay for equal work. The data helps labour unions and employer organizations negotiate wages and working conditions, as well as advocate for policies that support fair compensation. The SES provides a valuable resource for studying wage structures, labour market dynamics, and issues related to income inequality and social mobility.

The European Union Structure of Earnings Survey (SES) is a vital tool for understanding wage dynamics within the EU. By providing detailed, comparable data on earnings and their distribution across different sectors, occupations, and demographic groups, the survey helps to identify and address key challenges in the labour market. The insights gained from the SES are essential for informing policies that promote fair wages, reduce gender and income inequalities, and support the overall economic and social well-being of workers across Europe.

An inquiry into Scopus regarding the literature using the EU-SES identifies 20 articles, with only two having a content that is related to skills, namely Castellano, et al. (2017) and Riva, et al. (2022).

5.1.1 THE DATA AND FREQUENCIES

This subsection outlines the sample sizes across different countries, detailing the number of firms and employees covered by the European Union Structure of Earnings Surveys (EU-SES). The EU-SES data is collected every four years and provides harmonized information on a wide range of factors, including firm size, sector of economic activity, employee characteristics (such as gender, age, education, and occupation), and earnings across EU member states and some non-EU countries.

Table 5-1 provides a detailed breakdown of the sample size by country, highlighting the number of firms and employees covered in each country. The pooled dataset includes over 2 million firms and 43 million employees across all countries. The proportion of firms and employees represented varies significantly by country, with Czech Republic, Norway, Denmark, Hungary, Slovakia accounting for some of the largest shares in the dataset. While countries such as Cyprus, Malta, Croatia, Luxembourg, Greece, Lithuania and Iceland have relatively lower shares of firms and employees. This distribution highlights both the comprehensiveness of the EU-SES dataset and the diversity of labour markets across the participating countries, providing a solid foundation for examining cross-country labour market dynamics, including skills mismatching and wage disparities.

Figure 5-1 illustrates the number of firms participating in the EU-SES survey across countries and survey years (2002, 2006, 2010, 2014, and 2018). The data show a significant increase in the number of firms surveyed over time in most countries. Notably, Norway exhibits the highest number of firms participating in the 2018 survey, with 187,998 firms, while the United Kingdom, which does not participate in the 2018 survey covers 107,774 firm in the 2014 survey. These countries, alongside the Netherlands, Italy, France and Spain, show consistently high participation across survey years. Smaller countries, such as Luxembourg, Malta, Cyprus, and Iceland, report lower firm participation.

Figure 5-2 highlights the number of employees covered in the EU-SES survey across countries and years. Similar to the trend in firm participation, the number of employees surveyed has grown substantially across most countries. Countries like the Czech Republic, Denmark, and Norway lead with the highest number of employees surveyed in 2014 and 2018, each exceeding 2 million employees in these survey waves. In contrast, smaller countries such as Malta, Cyprus, and Luxembourg have much lower employee participation.

Table 5-1: EU-SES – Sample size

EU-SES		4-YEARLY DATASET			
COUNTRY	**ACRONYM**	**#Firms**	**(%)**	**#Employees**	**(%)**
All Countries	***POOLED***	***2,170,244***	***(100.00%)***	***43,126,009***	***(100.00%)***
Belgium	BE	37,944	(1.75%)	740,360	(1.72%)
Bulgaria	BG	63,202	(2.91%)	811,502	(1.88%)
Cyprus	CY	5,517	(0.25%)	133,233	(0.31%)
Czech Republic	CZ	76,276	(3.51%)	9,632,214	(22.34%)
Denmark	DK	105,303	(4.85%)	3,383,320	(7.85%)
Estonia	EE	26,519	(1.22%)	601,441	(1.39%)
Greece	EL	31,954	(1.47%)	215,079	(0.50%)
Spain	ES	125,148	(5.77%)	1,097,590	(2.55%)
Finland	FI	-	-	1,380,255	(3.20%)
France	FR	138,870	(6.40%)	979,171	(2.27%)
Croatia	HR	5,984	(0.28%)	202,956	(0.47%)
Hungary	HU	122,189	(5.63%)	3,854,256	(8.94%)
Italy	IT	133,418	(6.15%)	939,737	(2.18%)
Lithuania	LT	30,317	(1.40%)	403,234	(0.94%)
Luxembourg	LU	2,461	(0.11%)	159,357	(0.37%)
Latvia	LV	52,243	(2.41%)	1,076,818	(2.50%)
Malta	MT	2,818	(0.13%)	85,649	(0.20%)
Netherlands	NL	209,135	(9.64%)	738,677	(1.71%)
Poland	PL	37,104	(1.71%)	727,739	(1.69%)
Portugal	PT	50,137	(2.31%)	469,462	(1.09%)
Romania	RO	80,019	(3.69%)	1,384,911	(3.21%)
Sweden	SE	27,098	(1.25%)	2,108,936	(4.89%)
Slovenia	SI	-	-	580,493	(1.35%)
Slovakia	SK	26,134	(1.20%)	3,719,377	(8.62%)
Non-EU					
Iceland	IS	-	-	64,836	(0.15%)
Norway	NO	386,405	(17.80%)	7,002,795	(16.24%)
United Kingdom	UK	394,049	(18.16%)	632,611	(1.47%)

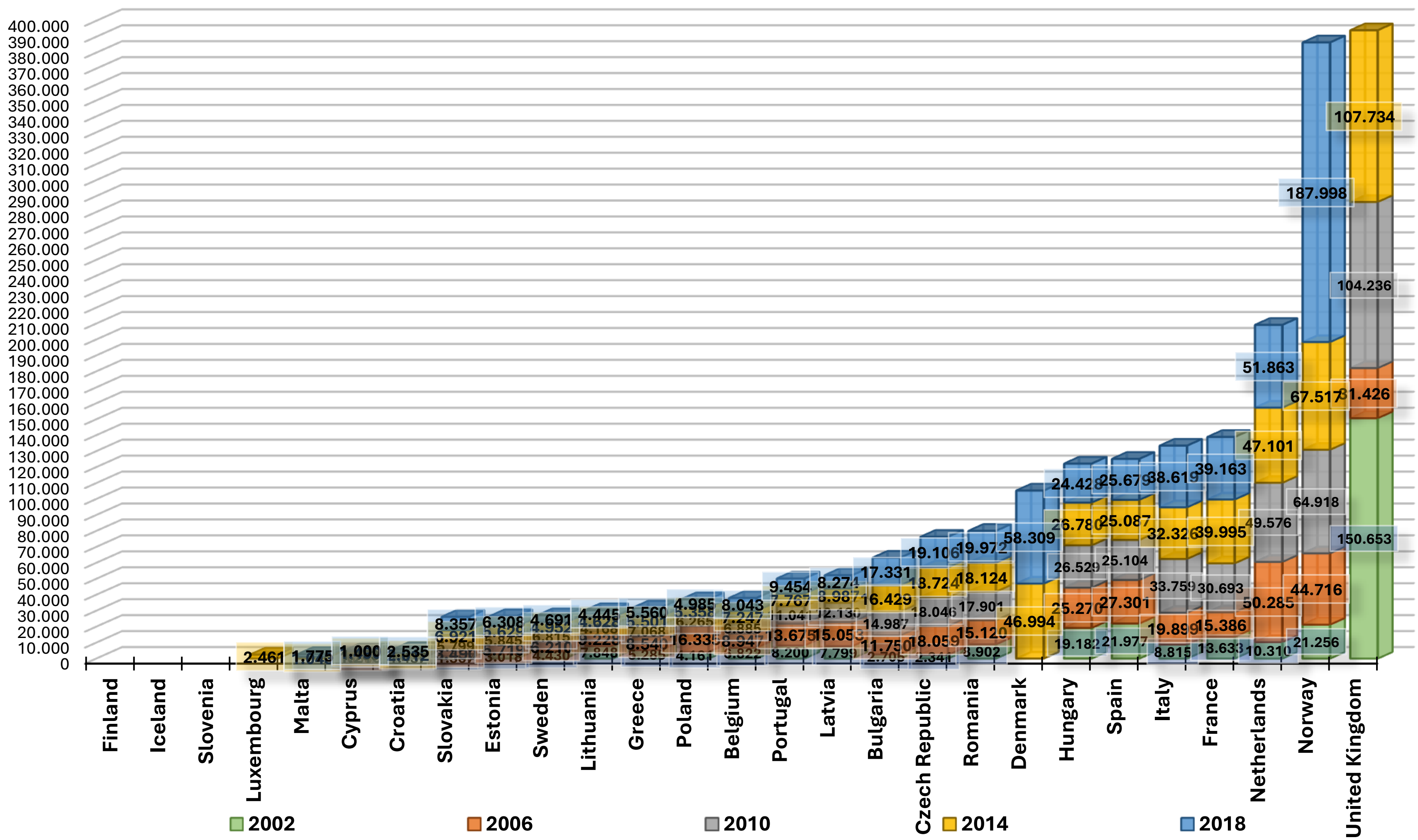


Figure 5-1: EU-SES – Number of firms by country and survey year

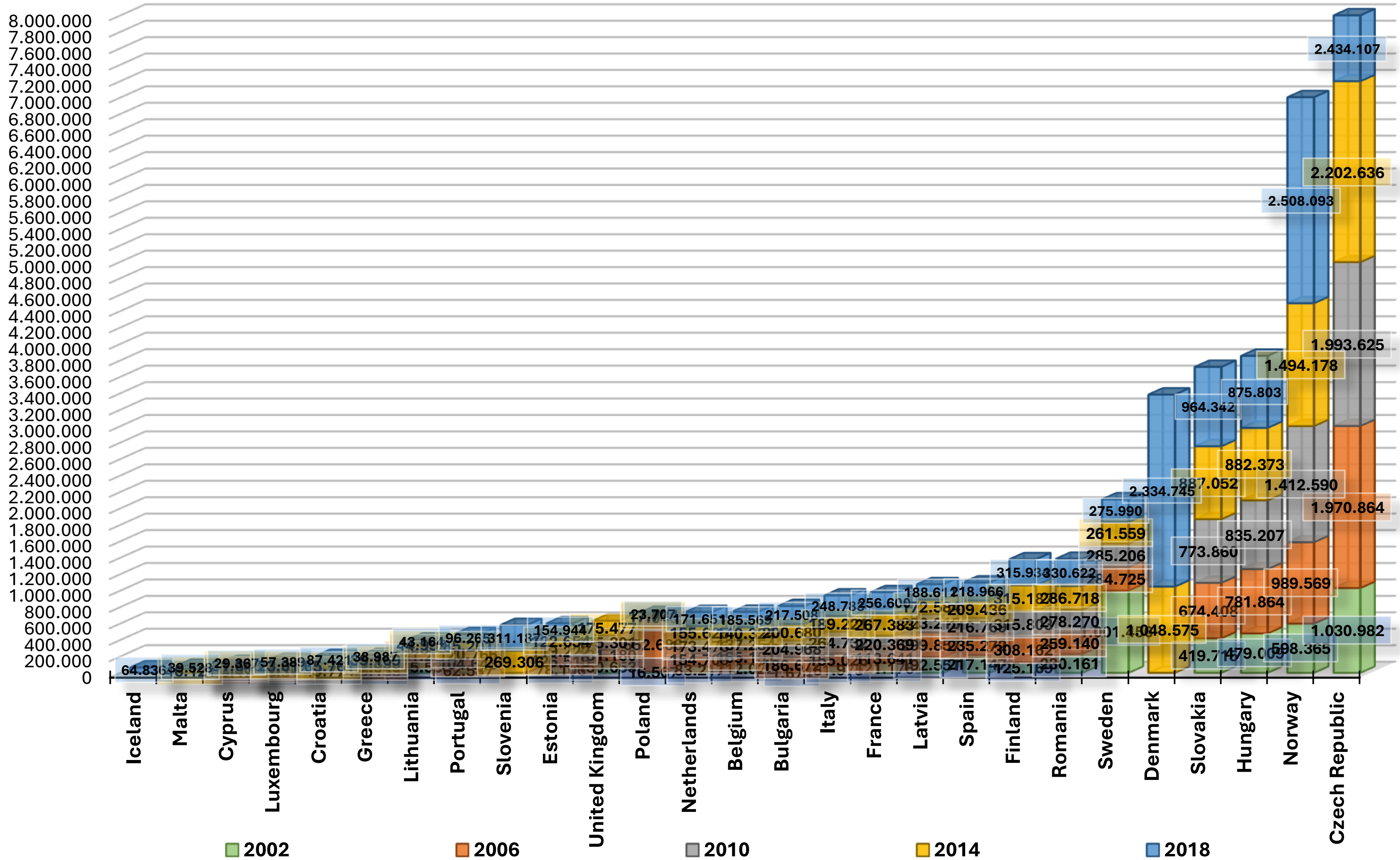


Figure 5-2: EU-SES – Number of employees by country and survey year

5.1.2 THE SAMPLE AND SUMMARY STATISTICS

This subsection gives a more comprehensive overview of the dataset, presenting the summary statistics of key variables from the EU-SES pooled sample with both unweighted and weighted data. The weight used is the grossing-up factor for employees, which is calculated as the ratio of the number of employees in the population to the number of employees in the sample, as provided by the EU-SES. Specifically, Table 5-2 presents an overview of firm-level and employee-level variables, outlining the distribution and key characteristics of the firms and employees included in the survey. The variables captured reflect various dimensions of economic activity, firm size, control structure, employee demographics, and job characteristics.

At the firm level, the NACE classification is used to categorize industries, with manufacturing accounting for 21.2% of the sample in the unweighted. Other notable sectors include health and social work (13.8%), education (11.4%), wholesale and retail trade (10.5%), public administration and defense (9.4%), transport storage and communication (8.9%) and real estate and renting business (8.8%). Firm size is also varied, with smaller firms (1-49 employees) making up 17.6% of the sample and medium-sized firms (50-249 employees) accounting for 21.2%. Firms with 250-499 employees represent the majority of the sample at 58.8%, while the largest firms (500+ employees) represent a smaller portion of the sample at just 2.6%. Regarding firm financial control, most firms have private financial control (58.7%) while those under public financial control account for 41.2%.

At the employee level, the gender distribution is relatively balanced, with male employees comprising 49.7% of the sample. In terms of educational attainment, most employees (51.2%) have completed ISCED levels 3-4, which corresponds to upper secondary and post-secondary education. In contrast, higher education qualifications, such as ISCED levels 7-8 (master’s, PhD, or equivalent), are less prevalent, accounting for only 10.5% of the workforce.

Other key variables include contract types and job roles. Full-time employment is the dominant job type, with 84.7% of employees working full-time. A similar pattern is observed in contract types, where 87.4% of employees hold indefinite contracts, while only 12.3% are on fixed-term contracts. Finally, income data, including gross monthly earnings, has been adjusted using the GDP deflator and converted into euros (where the national currency differs) based on the average exchange rate for each year.

Table 5-2: EU-SES – Summary statistics of key variables

	POOLED SAMPLE			
	UNWEIGHTED		WEIGHTED	
Variable	#Obs.	Mean	#Obs.	Mean
Firm-level variables				
NACE of local unit: (c) Mining and quarrying and	45,682,634	1.3%	45,682,427	1.1%
-“-: (d) Manufacturing	45,682,634	21.2%	45,682,427	54.3%
-“-: (e) Electricity, gas and water supply	45,682,634	2.2%	45,682,427	2.4%
-“-: (f) Construction	45,682,634	4.1%	45,682,427	2.7%
-“-: (g) Wholesale and retail trade, repair of	45,682,634	10.5%	45,682,427	10.0%
-“-: (h) Hotels and restaurants	45,682,634	2.1%	45,682,427	2.3%
-“-: (i) Transport, storage and communication	45,682,634	8.9%	45,682,427	8.1%
-“-: (j) Financial intermediation	45,682,634	3.3%	45,682,427	8.2%
-“-: (k) Real estate, renting and business	45,682,634	8.8%	45,682,427	10.9%
-“-: (l) Public administration and defence,	45,682,634	9.4%	45,682,427	0.0%
-“-: (m) Education	45,682,634	11.4%	45,682,427	0.0%
-“-: (n) Health and social work	45,682,634	13.8%	45,682,427	0.0%
-“-: (o) Other community, social and personal	45,682,634	2.9%	45,682,427	0.0%
Size class category of firm: 1-49 employees	45,459,544	17.6%	45,459,337	29.6%
Size class category of firm: 50-249 employees	45,459,544	21.2%	45,459,337	19.3%
Size class category of firm: 250-499 employees	45,459,544	58.8%	45,459,337	4.7%
Size class category of firm: 500-999 employees	45,459,544	0.9%	45,459,337	0.1%
Size class category of firm: 1000 or more	45,459,544	1.5%	45,459,337	46.2%
Firm has a form of public financial control	45,847,497	41.2%	45,847,290	5.9%
Firm has a form of private financial control	45,847,497	58.7%	45,847,290	92.0%
Firm has a form of shared (private/public)	45,847,497	0.1%	45,847,290	2.1%
Principal market of firm: local or regional	46,123,442	0.5%	46,123,235	0.0%
Principal market of firm: national market	46,123,442	0.5%	46,123,235	0.0%
Principal market of firm: European Union	46,123,442	0.5%	46,123,235	0.0%
Principal market of firm: world market	46,123,442	0.1%	46,123,235	0.0%
Employee-level variables				
Gender (male=1)	46,123,441	49.7%	46,123,234	68.1%
Age class of the employee (six age groups)	45,858,710	3.70	45,858,503	3.46
Educational attainment level: ISCED 0-2	44,013,680	15.4%	44,013,473	48.2%
-“-: ISCED 3-4	44,013,680	51.2%	44,013,473	42.8%
-“-: ISCED 5-6	44,013,680	22.9%	44,013,473	8.4%
-“-: ISCED 7-8	44,013,680	10.5%	44,013,473	0.6%
Managerial position	8,832,073	11.4%	8,832,073	13.4%
Full time job	46,123,442	84.7%	46,123,235	88.6%
Indefinite duration of contract	43,554,077	87.4%	43,553,870	95.4%
Fixed/temporary duration of contract	43,554,077	12.3%	43,553,870	3.6%
Apprentice/trainee contract)	43,554,077	0.4%	43,553,870	1.0%
Gross monthly earnings	46,123,442	25,844.62	46,123,235	117.68

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year. The sampling weights are provided by the data collectors and represent the grossing-up factor for employees.

5.1.3 SKILLS MATCHING STATISTICS

This subsection focuses on skill-matching statistics. Skills mismatch is defined based on the highest educational qualification attained relative to the median educational qualification within the same country, year, and occupation (3-digit ISCO code). Individuals are classified as matched if their education is equal to the median, overeducated if it is higher, and undereducated if it is lower.

Table 5-3 provides statistics on skills (mis)matching by country, reporting the weighted percentages of employees classified as matched, overeducated, or undereducated. The table is divided into three main categories: employees whose educational qualifications match their job requirements (matched), those who have more education than required (overeducated), and those with less education than required (undereducated). On average about 62% of employees are classified as matched, 23.2% as overeducated, and 14.2% as undereducated.

The columns labelled "Rank" show the ranking for each measure. Countries with the highest matching are highlighted in blue, while those with the lowest in red. Central and Eastern European countries, such as Bulgaria, Croatia, Czech Republic, Romania and Slovakia rank the highest for matched employees. In contrast, France, the Netherlands, Spain, Norway and the United Kingdom rank the lowest rates of matched employees, reflecting higher levels of skills mismatches in these labour markets. Regarding overeducation, countries such as Portugal, Spain, Italy, Iceland and the United Kingdom report some of the highest levels of overeducated employees, while Bulgaria, Czech Republic, Romania, Slovakia and Slovenia y report some of the lowest levels. Finally, the highest levels of undereducation are reported in France, Finland, the Netherlands, Norway and the United Kingdom, while the lowest are reported in Czech Republic, Hungary, Romania, Slovakia and Iceland.

The next tables show the evolution of skills (mis)match across countries and over survey years. Table 5-4 specifically presents the weighted percentages of matched employees – those whose skills align with the requirements of their jobs – by country and survey year. In most countries, there is a general upward trend in the share of matched employees over time, indicating improvements in the alignment between employee qualifications and job requirements. However, exceptions to this trend are observed in Italy, Norway, and Slovakia, where there is a slight decrease in the percentage of matched employees. Additionally, Portugal experienced a decline in matching rates in 2010, followed by a subsequent increase in the later years.

Table 5-5 presents statistics on overeducated employees by country and survey year, highlighting significant variations across countries and over time. Some countries consistently report higher levels of overeducation, while others show fluctuating trends with both increases and decreases throughout the survey periods. For example, countries like Cyprus, Estonia, Greece, Spain, Italy, and Portugal consistently show some of the highest percentages of overeducated employees, though their figures fluctuate over time. Notably, Belgium exhibited a significant decline in overeducation, dropping from 29.7% in 2002 to just 8.8% in 2018. Similarly, Latvia and Lithuania have seen a steady decrease in overeducation rates over time.

Finally, Table 5-6 presents the weighted percentage of undereducated employees by country and survey year, showing substantial variations in undereducation levels across different countries. While the majority of countries demonstrate a general decline in the share of undereducated employees over time, some exceptions are observed, such as the Czech Republic, Italy, the Netherlands, and Slovakia, where slight increases in undereducation rates are noted.

Table 5-3: EU-SES – Skills matching statistics by country (weighted)

	MATCHED		OVEREDUCATED		UNDEREDUCATED	
All Countries	***62.6%***	*(Rank)*	***23.2%***	*(Rank)*	***14.2%***	*(Rank)*
Belgium	64.7%	11	15.3%	18	20.1%	14
Bulgaria	73.0%	4	11.9%	22	15.2%	19
Croatia	72.8%	5	12.2%	21	15.0%	20
Cyprus	58.9%	19	20.5%	9	20.7%	11
Czech Republic	75.6%	3	10.2%	24	14.2%	23
Denmark	59.9%	16	17.8%	13	22.3%	9
Estonia	58.5%	21	21.3%	6	20.2%	12
Finland	59.7%	17	14.8%	19	25.5%	4
France	54.8%	23	18.0%	12	27.2%	2
Greece	62.5%	13	20.2%	10	17.3%	16
Hungary	69.0%	6	17.4%	14	13.6%	24
Italy	62.6%	12	23.2%	4	14.2%	22
Latvia	61.9%	15	16.9%	16	21.2%	10
Lithuania	67.5%	7	15.7%	17	16.7%	17
Luxembourg	58.8%	20	18.5%	11	22.7%	7
Malta	59.3%	18	20.6%	8	20.1%	13
Netherlands	53.9%	24	20.7%	7	25.4%	5
Poland	65.9%	9	14.6%	20	19.4%	15
Portugal	62.0%	14	22.2%	5	15.8%	18
Romania	79.5%	1	8.9%	26	11.6%	25
Slovakia	75.9%	2	9.7%	25	14.4%	21
Slovenia	66.4%	8	11.0%	23	22.6%	8
Spain	50.5%	25	24.4%	3	25.2%	6
Sweden	-	-	-	-	-	-
Non–EU						
Iceland	65.0%	10	26.1%	1	8.9%	26
Norway	55.2%	22	17.0%	15	27.8%	1
United Kingdom	47.9%	26	25.7%	2	26.5%	3

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal o higher/lower than the median educational qualification by country, year and 3-digit ISCO code. Countries wit the highest matching are highlighted in blue, and those with the lowest matching in red. In Sweden n information on ISCO codes is available.

Table 5-4: EU-SES – The evolution of skills matching over time by country (weighted averages)

Country	2002	2006	2010	2014	2018
Belgium	44.9%	52.6%	55.5%	66.7%	79.5%
Bulgaria	70.2%	74.6%	75.4%	72.0%	71.8%
Croatia	-	-	71.4%	73.2%	73.6%
Cyprus	44.0%	56.5%	61.6%	63.6%	60.6%
Czech Republic	77.7%	77.0%	75.3%	76.2%	72.6%
Denmark	-	-	-	57.7%	61.0%
Estonia	37.2%	72.5%	69.1%	56.0%	57.2%
Finland	51.8%	57.3%	58.1%	63.6%	64.1%
France	51.2%	53.9%	56.0%	55.3%	55.5%
Greece	53.1%	58.3%	63.1%	69.6%	64.6%
Hungary	52.0%	78.3%	77.8%	68.1%	64.2%
Iceland	-	-	-	-	65.0%
Italy	62.6%	59.4%	60.3%	57.5%	58.5%
Latvia	40.4%	68.7%	67.2%	62.0%	62.1%
Lithuania	59.2%	68.8%	71.9%	67.1%	69.4%
Luxembourg	56.5%	55.5%	58.6%	60.5%	60.8%
Malta	-	-	-	55.7%	62.0%
Netherlands	51.3%	55.8%	58.7%	51.3%	52.6%
Norway	59.9%	57.7%	56.0%	51.0%	54.4%
Poland	55.3%	53.4%	75.6%	71.9%	70.6%
Portugal	63.0%	61.3%	54.6%	68.1%	63.9%
Romania	79.7%	76.4%	83.9%	79.0%	79.2%
Slovakia	79.2%	78.1%	77.6%	74.1%	71.2%
Slovenia	-	-	-	66.0%	66.7%
Spain	41.7%	43.0%	49.3%	57.4%	57.7%
Sweden	-	-	-	-	-
United Kingdom	36.0%	58.8%	45.6%	51.4%	-

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 3-digit ISCO code. In Sweden no information on ISCO codes is available.

Table 5-5: EU-SES – The evolution of overeducation over time by country (weighted averages)

Country	2002	2006	2010	2014	2018
Belgium	29.7%	20.6%	17.7%	14.8%	8.8%
Bulgaria	11.6%	10.5%	11.6%	13.3%	12.3%
Croatia	–	–	13.2%	11.4%	12.2%
Cyprus	29.9%	20.2%	17.5%	19.5%	20.0%
Czech Republic	7.6%	9.5%	10.7%	10.3%	12.2%
Denmark	–	–	–	18.6%	17.3%
Estonia	34.2%	13.5%	16.3%	21.9%	21.4%
Finland	14.5%	16.0%	16.8%	12.7%	14.1%
France	18.9%	17.4%	15.8%	17.8%	20.4%
Greece	25.0%	18.8%	18.1%	17.0%	22.7%
Hungary	18.8%	9.1%	11.6%	24.1%	23.7%
Iceland	–	–	–	–	26.1%
Italy	23.2%	20.7%	19.3%	21.9%	22.6%
Latvia	31.4%	10.2%	13.0%	19.0%	17.3%
Lithuania	22.7%	11.4%	10.8%	17.8%	16.8%
Luxembourg	20.2%	18.8%	14.4%	18.8%	20.2%
Malta	–	–	–	20.4%	20.8%
Netherlands	22.2%	19.6%	15.3%	27.5%	18.8%
Norway	15.8%	13.0%	12.9%	19.2%	21.6%
Poland	21.7%	24.1%	9.4%	10.8%	9.4%
Portugal	19.2%	24.5%	24.3%	18.9%	22.9%
Romania	5.2%	8.7%	5.1%	11.8%	13.0%
Slovakia	7.8%	9.0%	10.4%	10.7%	10.3%
Slovenia	–	–	–	11.2%	10.7%
Spain	26.6%	28.4%	24.8%	22.7%	20.2%
Sweden	-	-	-	-	-
United Kingdom	29.0%	20.5%	29.8%	23.3%	-

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 3-digit ISCO code. In Sweden no information on ISCO codes is available.

Table 5-6: EU-SES – The evolution of undereducation over time by country (weighted averages)

Country	2002	2006	2010	2014	2018
Belgium	25.4%	26.7%	26.8%	18.5%	11.7%
Bulgaria	18.2%	14.9%	13.0%	14.7%	15.8%
Croatia	–	–	15.5%	15.4%	14.2%
Cyprus	26.0%	23.3%	20.8%	16.9%	19.4%
Czech Republic	14.7%	13.5%	14.0%	13.5%	15.1%
Denmark	–	–	–	23.7%	21.6%
Estonia	28.7%	14.0%	14.6%	22.0%	21.4%
Finland	33.7%	26.7%	25.1%	23.7%	21.8%
France	29.9%	28.8%	28.1%	26.9%	24.1%
Greece	21.9%	22.9%	18.8%	13.4%	12.7%
Hungary	29.2%	12.5%	10.5%	7.8%	12.2%
Iceland	–	–	–	–	8.9%
Italy	14.2%	19.9%	20.4%	20.6%	18.9%
Latvia	28.3%	21.1%	19.8%	18.9%	20.6%
Lithuania	18.1%	19.7%	17.3%	15.1%	13.8%
Luxembourg	23.3%	25.7%	27.0%	20.7%	18.9%
Malta	–	–	–	23.9%	17.2%
Netherlands	26.5%	24.7%	26.0%	21.1%	28.6%
Norway	24.3%	29.3%	31.1%	29.8%	24.0%
Poland	23.0%	22.5%	15.0%	17.3%	20.0%
Portugal	17.8%	14.2%	21.1%	13.0%	13.2%
Romania	15.2%	14.9%	11.0%	9.3%	7.8%
Slovakia	13.1%	12.9%	12.0%	15.1%	18.5%
Slovenia	–	–	–	22.8%	22.5%
Spain	31.8%	28.6%	25.9%	19.8%	22.1%
Sweden	–	–	–	–	–
United Kingdom	34.9%	20.7%	24.6%	25.3%	–

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 3-digit ISCO code. In Sweden no information on ISCO codes is available.

5.1.4 DIFFERENCES ACROSS FIRM TYPES

In this subsection, we analyse differences in skills mismatching, overeducation, and undereducation across firm types.

First, we focus on differences across firm size (expressed by the number of employees) and type of firm's financial control. Table 5-7 provides an insightful breakdown of skills mismatching, overeducation, and undereducation across different firm sizes in various countries, categorized into microenterprises and small firms (1-49 employees), medium-sized firms (50-249 employees), and large firms (250+ employees). Large firms generally exhibit higher rates of mismatching across most countries, with an average of 40.7%, compared to 35.0% in medium-sized firms and 33.1% in small firms. However, there are notable disparities across countries. When it comes to overeducation, larger firms tend to have a higher percentage of overeducated employees (25.9% on average) across most countries, with France being an exception, where the share of overeducated employees remains almost equal across small, medium, and large firms. Undereducation follows a similar but more pronounced trend, with significantly higher rates observed in larger firms (33.1% overall) across all countries. Finally, it's worth noting that in Luxembourg, Malta, and Cyprus, the surveys cover only small firms, which may limit the scope of comparison for those countries.

Then, Figures 5-3 to 5-5 offer a visual representation of the data presented in Table 5-7, highlighting firm size differences in skills mismatching, overeducation, and undereducation across countries. These figures provide a clearer depiction of how skills mismatch varies depending on firm size, making it easier to identify patterns and trends by country.

Table 5-8 provides a comparison of skills mismatching, overeducation, and undereducation across firms with different types of financial control (public, private, and shared). However, the focus here is on the comparison between public and private financial control, as the number of firms with shared control (a combination of public and private) is minimal or non-existent in many countries. On average, mismatching rates are relatively similar between public (39.3%) and private (37.2%) firms. However, several countries exhibit notable variations. For instance, Denmark, Greece, the Netherlands, Norway, and Spain report significantly higher mismatching rates in private-controlled firms. Iceland stands out with the largest disparity, where 44.1% of employees in public-controlled firms experience mismatching, compared to just 29.2% in private-controlled firms. Overeducation is more prevalent in private-sector firms, averaging 23.3%, compared to 20.2% in public-sector firms, while undereducation is more common in public-sector firms, where 19% of employees are undereducated, compared to 13.9% in private-sector firms.

Figure 5-6 visually represents the above-mentioned differences. The red diamonds indicate the overall mismatch rate percentage point difference, while the black and white bars represent differences in overeducation and undereducation, respectively. Countries like Denmark, Norway, and Greece show significant mismatching rates in private-controlled firms. Conversely, countries like Iceland, Romania, Czech Republic and Belgium display substantial differences with higher mismatched rates in public-controlled firms, particularly in overeducation. Overall, the figure highlights significant disparities across countries in terms of how firm financial control influences skills mismatching.

Table 5-7: EU-SES – Firm-size differences by country (#employees)

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	Microenterprises and small firms (1-49 employees)	Medium-sized firms (50-249 employees)	Large firms (250+ employees)	Microenterprises and small firms (1-49 employees)	Medium-sized firms (50-249 employees)	Large firms (250+ employees)	Microenterprises and small firms (1-49 employees)	Medium-sized firms (50-249 employees)	Large firms (250+ employees)
All countries	33.1%	35.0%	40.7%	19.7%	21.3%	25.9%	13.4%	13.7%	33.1%
Belgium	30.0%	35.1%	37.0%	9.9%	15.4%	16.9%	20.1%	19.7%	30.0%
Bulgaria	24.9%	27.2%	29.4%	11.8%	10.2%	13.5%	13.1%	17.0%	24.9%
Croatia	28.8%	29.0%	24.1%	13.3%	12.2%	11.3%	15.5%	16.8%	28.8%
Cyprus	41.1%			20.5%			20.7%		41.1%
Czech Republic	24.8%	23.6%	24.5%	10.7%	8.6%	10.7%	14.1%	15.0%	24.8%
Denmark	44.9%	46.2%	36.3%	18.0%	21.9%	16.3%	27.0%	24.2%	44.9%
Estonia	46.0%	38.2%		22.7%	20.3%		23.4%	17.9%	46.0%
Finland	43.6%	42.8%	38.5%	13.9%	15.0%	15.0%	29.7%	27.8%	43.6%
France	46.3%	45.8%	44.6%	18.0%	18.9%	17.8%	28.4%	26.9%	46.3%
Greece	33.8%	42.3%	37.3%	18.0%	23.0%	20.1%	15.8%	19.3%	33.8%
Hungary	29.4%	29.6%	33.0%	17.2%	16.4%	18.1%	12.3%	13.2%	29.4%
Iceland	35.0%			26.1%			8.9%		35.0%
Italy	33.1%	35.0%	40.7%	19.7%	21.3%	25.9%	13.4%	13.7%	33.1%
Latvia	40.5%	34.4%	38.2%	16.9%	15.1%	18.3%	23.5%	19.3%	40.5%
Lithuania	33.8%	30.1%	33.2%	14.8%	14.6%	17.9%	19.0%	15.4%	33.8%
Luxembourg	41.2%			18.5%			22.7%		41.2%
Malta	40.7%			20.6%			20.1%		40.7%
Netherlands	47.7%	46.1%	45.1%	18.9%	20.3%	21.8%	28.8%	25.9%	47.7%
Norway	48.5%	46.4%	41.4%	15.8%	17.5%	17.5%	32.7%	28.9%	48.5%
Poland	31.8%	33.3%	36.3%	12.6%	14.1%	16.6%	19.2%	19.2%	31.8%
Portugal	38.2%	34.4%	40.7%	20.7%	20.4%	24.8%	17.4%	14.0%	38.2%
Romania	19.7%	19.7%	21.1%	8.3%	8.4%	9.3%	11.4%	11.2%	19.7%
Slovakia	27.7%	23.7%	22.0%	10.4%	8.9%	9.7%	17.3%	14.8%	27.7%
Slovenia	36.1%	34.0%	30.8%	11.2%	9.8%	11.7%	25.0%	24.2%	36.1%
Spain	52.8%	52.4%	50.5%	23.1%	25.3%	28.1%	29.7%	27.2%	52.8%
Sweden	-	-	-	-	-	-	-	-	-
United Kingdom	50.9%	50.7%	51.7%	22.6%	23.3%	25.1%	28.4%	27.3%	50.9%

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 3-digit ISCO code. In Sweden no information on ISCO codes is available.

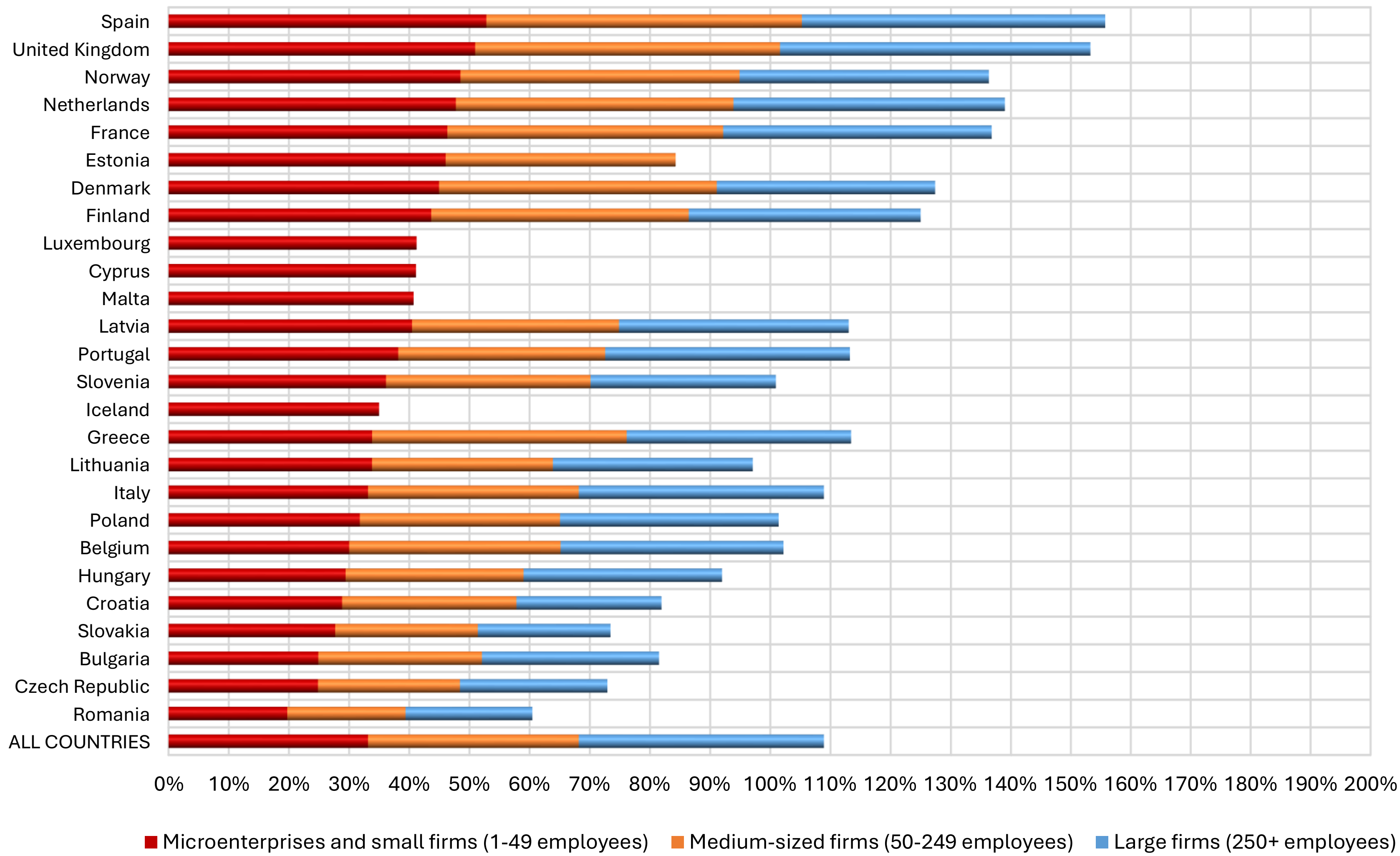


Figure 5-3: EU-SES – Firm-size composition of skills mismatching by country (#employees)

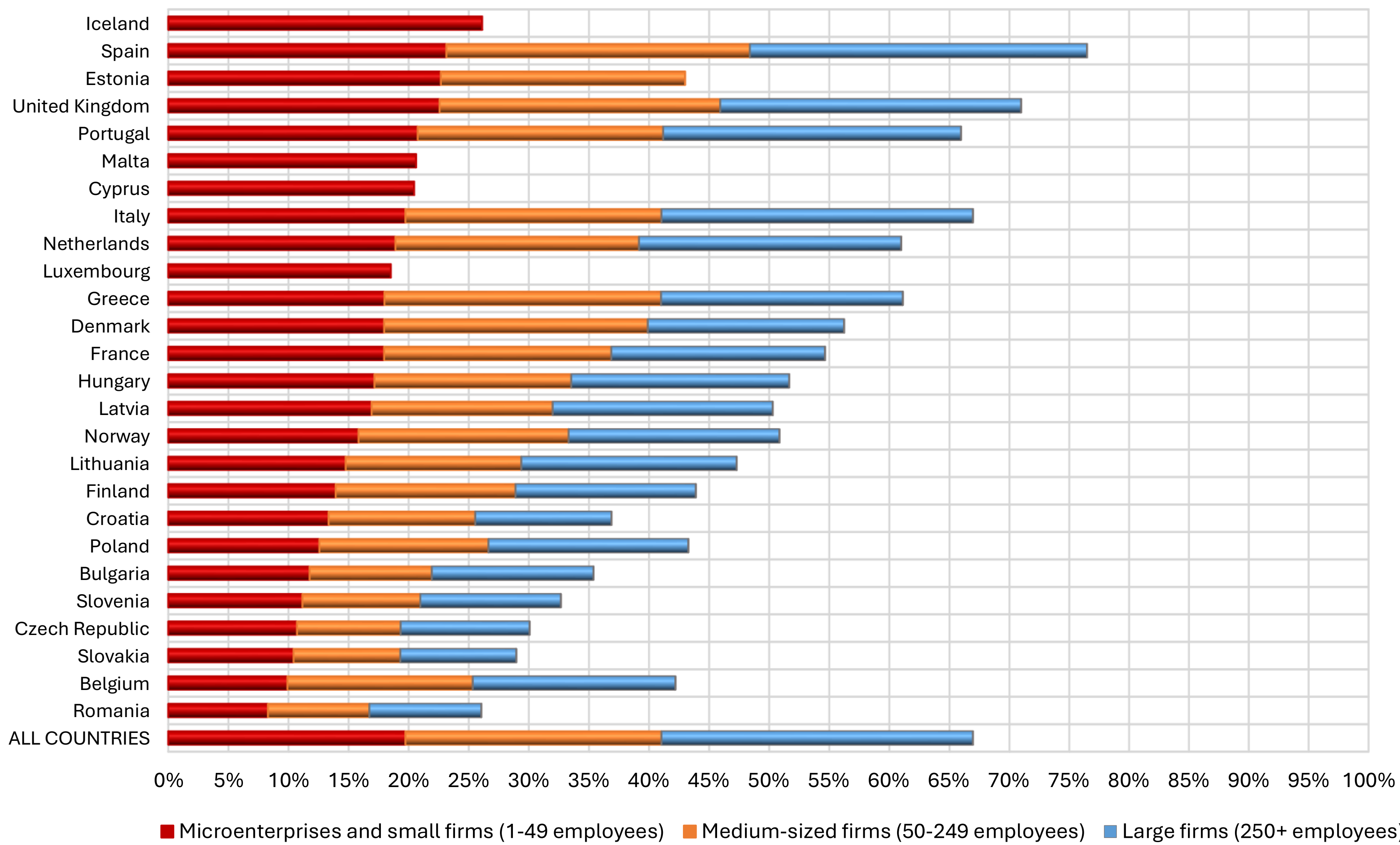


Figure 5-4: EU-SES – Firm-size composition of overeducation by country (#employees)

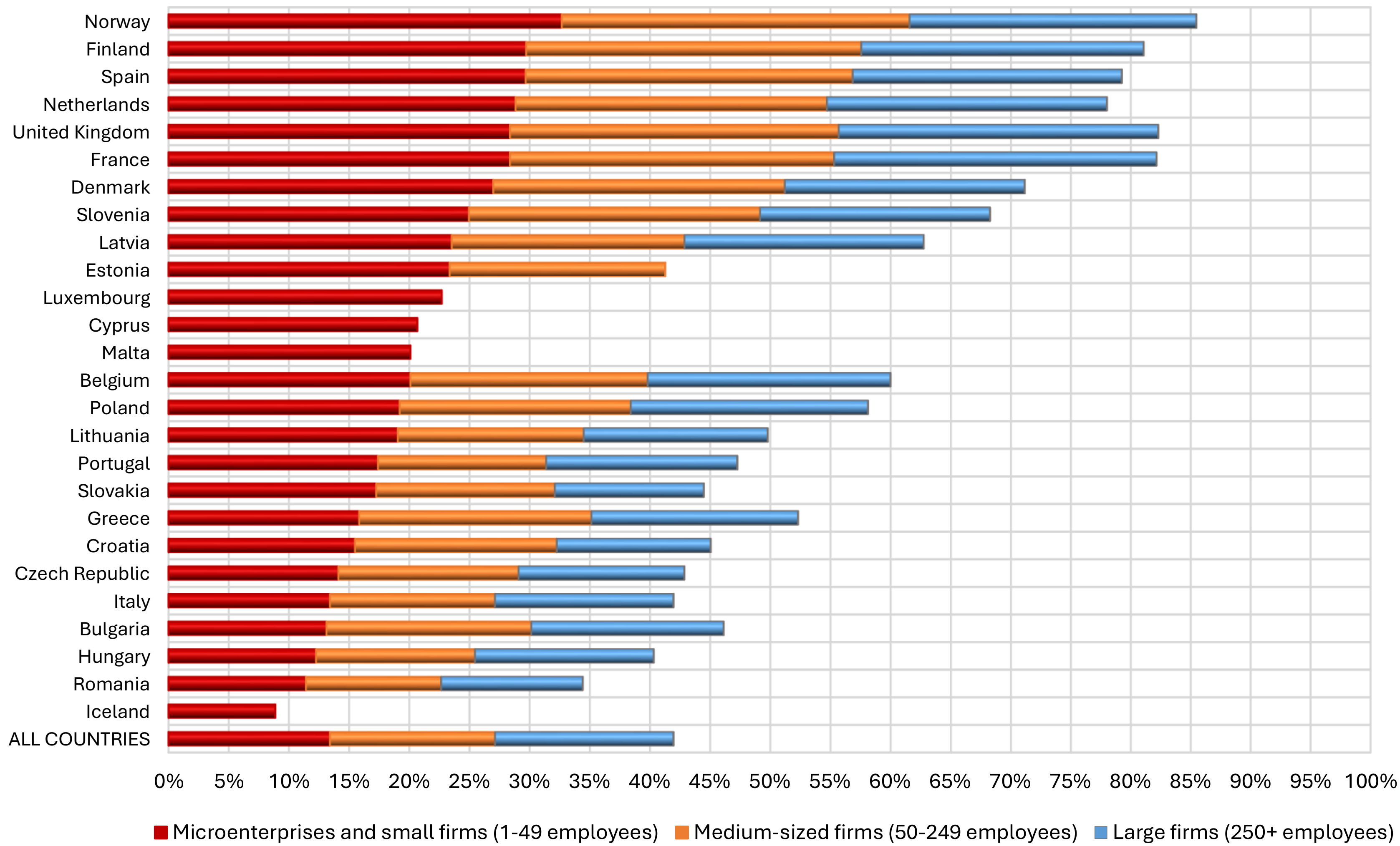


Figure 5-5: EU-SES – Firm-size composition of overeducation by country (#employees)

Table 5-8: EU-SES – Firm-type differences by country (public vs. private)

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	Public control	Private control	Shared control	Public control	Private control	Shared control	Public control	Private control	Shared control
All countries	39.3%	37.2%	41.4%	20.2%	23.3%	27.4%	19.0%	13.9%	14.0%
Belgium	39.1%	35.1%	–	25.9%	14.2%	–	13.3%	21.0%	–
Bulgaria	28.4%	26.4%	31.4%	10.5%	12.2%	6.5%	17.9%	14.2%	24.9%
Croatia	28.5%	26.3%	–	13.4%	11.4%	–	15.0%	14.9%	–
Cyprus	35.0%	42.6%	–	18.8%	20.9%	–	16.2%	21.8%	–
Czech Republic	27.3%	23.3%	–	13.7%	8.9%	–	13.6%	14.4%	–
Denmark	28.8%	47.1%	–	11.0%	22.0%	–	17.8%	25.1%	–
Estonia	36.9%	43.2%	–	18.9%	22.2%	–	18.1%	21.0%	–
Finland	35.1%	43.2%	45.4%	13.2%	15.7%	18.0%	21.9%	27.5%	27.4%
France	40.2%	47.1%	–	16.3%	18.7%	–	23.9%	28.4%	–
Greece	28.1%	40.2%	48.7%	14.2%	22.0%	24.3%	13.9%	18.3%	24.4%
Hungary	28.6%	32.1%	47.4%	17.7%	17.3%	15.8%	10.9%	14.8%	31.6%
Iceland	44.1%	29.2%	–	35.8%	19.9%	–	8.3%	9.2%	–
Italy	39.3%	37.2%	41.4%	20.2%	23.3%	27.4%	19.0%	13.9%	14.0%
Latvia	37.2%	38.5%	48.1%	18.0%	16.4%	33.6%	19.2%	22.2%	14.5%
Lithuania	31.7%	33.7%	–	15.4%	15.5%	–	16.3%	18.3%	–
Luxembourg	38.8%	42.6%	–	12.8%	20.0%	–	26.0%	22.6%	–
Malta	41.6%	40.3%	–	23.5%	19.5%	–	18.1%	20.9%	–
Netherlands	39.7%	49.0%	–	21.1%	20.5%	–	18.6%	28.5%	–
Norway	34.5%	48.9%	–	16.6%	17.1%	–	17.9%	31.7%	–
Poland	33.6%	34.3%	–	14.7%	14.6%	–	18.9%	19.7%	–
Portugal	30.0%	39.5%	–	18.7%	22.9%	–	11.3%	16.7%	–
Romania	24.0%	18.7%	–	11.0%	7.9%	–	13.0%	10.8%	–
Slovakia	25.3%	23.6%	–	9.9%	9.6%	–	15.4%	14.0%	–
Slovenia	32.9%	34.0%	–	11.9%	10.5%	–	20.9%	23.4%	–
Spain	44.5%	50.4%	43.6%	21.8%	24.8%	24.0%	22.7%	25.6%	19.6%
Sweden	–	–	–	–	–	–	–	–	–
United Kingdom	53.4%	51.6%	54.4%	29.1%	24.3%	29.1%	24.2%	27.3%	25.3%

Notes: Skills mismatch is defined based on the highest educational qualification attained being equal or higher/lower than the median educational qualification by country, year and 3-digit ISCO code. In Sweden no information on ISCO codes is available

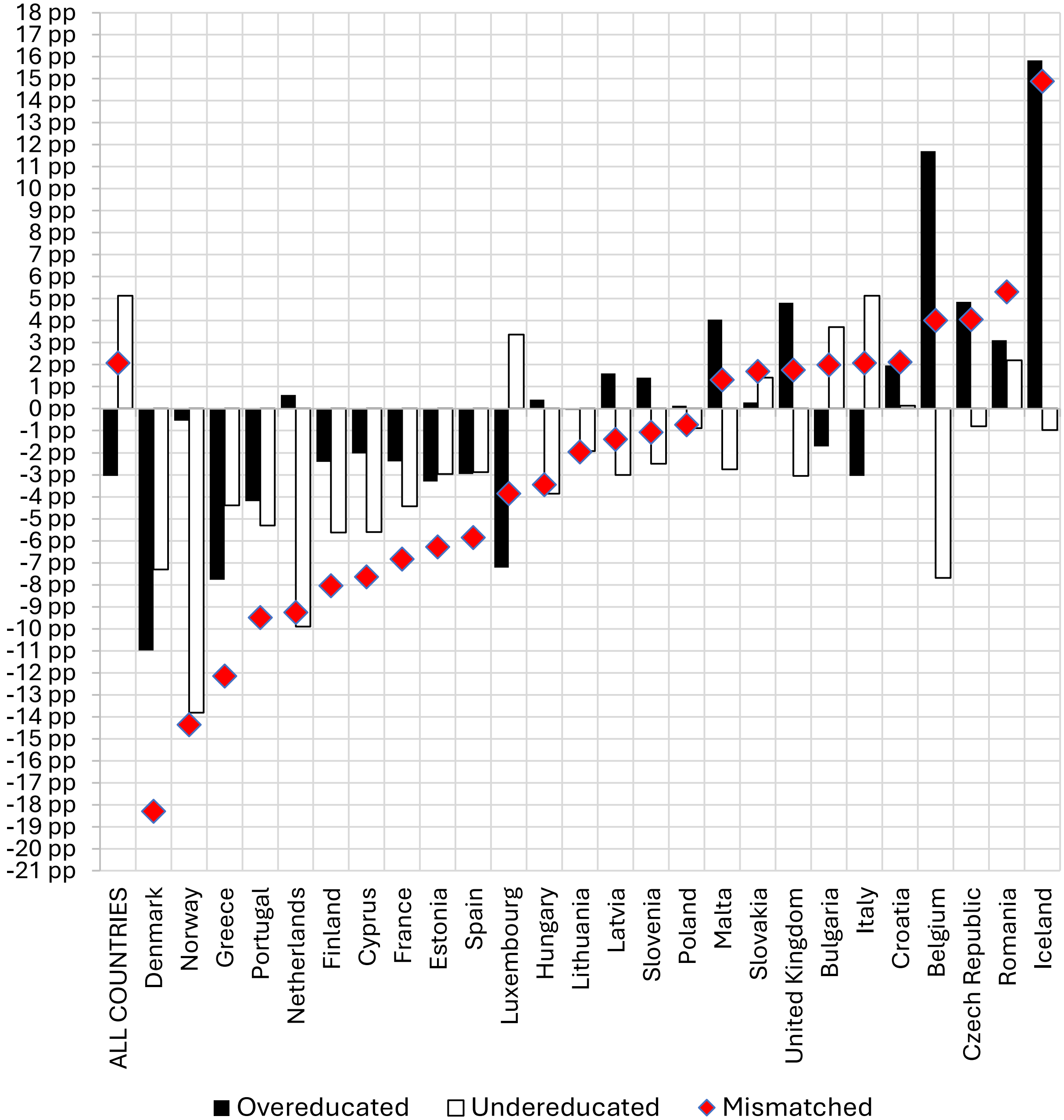


Figure 5-6: EU-SES – Firm-type differences in skills mismatching by country (public vs. private)

5.1.5 DIFFERENCES ACROSS KEY DEMOGRAPHIC GROUPS OF EMPLOYEES

In this subsection we analyse differences between key demographic groups of employees (age, gender and income status).

First, Table 5-9 presents the gender differences in skills mismatching, overeducation, and undereducation. For each of the three categories the first two columns show the weighted percentage of individuals in that category by gender. The third column labeled “Difference” displays the percentage point difference between males and females in each category. On average across all countries, 38.8% of male employees are mismatched compared to 34.5% of female employees, resulting in a 4.3 percentage point (pp) difference. This positive difference, indicating that mismatching is more pronounced among male employees, is particularly evident in Greece and Portugal. Conversely, in several Central and Eastern European countries – such as Slovakia, Slovenia, Croatia, Romania, the Czech Republic, Poland, and Lithuania – mismatching tends to be higher among female employees.

Countries show smaller disparities in gender differences in overeducation. In most countries such as Slovenia, Croatia, Latvia, Iceland, Romania France and Belgium, the percentage of overeducated female employees is higher than that of male employees. In contrast, fewer countries, such as Italy, the Netherlands, Denmark, Luxembourg and Greece, report higher rates of overeducated male employees compared to females. Regarding undereducation, the overall average difference between male and female employees seems to be very small (0.4pp). However, this average covers significant disparities between countries, with some showing higher undereducation rates among male employees, while in others, undereducation is more prevalent among female employees.

Figure 5-7 provides a visual representation of the gender differences by country, as outlined in Table 5-9. The black bars represent the percentage point difference between males and females for overeducated employees, and the white bars represent undereducated employees. The red diamonds indicate the overall gender difference in mismatching rates. Countries on the left side of the figure, from Slovakia to the United Kingdom, show higher mismatching rates among female employees (indicated by negative differences), whereas the countries on the right demonstrate higher mismatching rates among male employees (indicated by positive differences).

Second, Table 5-10 provides a detailed breakdown of skills mismatching, overeducation, and undereducation among older and younger employees across various countries. In this context, employees aged 40 and above are classified as ‘old’, while those under 40 are considered ‘young’. For each category of mismatching, the first two columns present the weighted percentage of individuals in that category, divided by age group. The third column (Difference) shows the percentage point difference between older and younger employees in each category.

On average, older individuals (37.9%) have higher mismatching rates than younger ones (36.9%), resulting in a just 1 percentage point (pp) gap. However, age differences show opposing trends between overeducation and undereducation. Younger employees tend to be more overeducated than older ones, as evidenced by negative differences in all countries, except Iceland. On the other hand, older employees are more undereducated compared to younger ones, with positive differences in all countries, except Denmark, Norway, Latvia, Estonia.

Table 5-9: EU-SES – Gender differences by country (male vs. female)

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	Male	Female	Difference	Male	Female	Difference	Male	Female	Difference
ALL	*38.8%*	*34.5%*	*4.3 pp*	*24.4%*	*20.5%*	*3.9 pp*	*14.3%*	*13.9%*	*0.4 pp*
Slovakia	20.8%	27.4%	-6.5 pp	9.1%	10.2%	-1.2 pp	11.7%	17.1%	-5.4 pp
Slovenia	30.8%	36.9%	-6.1 pp	9.0%	13.3%	-4.3 pp	21.8%	23.6%	-1.8 pp
Croatia	24.7%	29.9%	-5.2 pp	9.9%	14.7%	-4.8 pp	14.8%	15.2%	-0.4 pp
Romania	18.6%	22.5%	-3.9 pp	7.5%	10.5%	-3.0 pp	11.1%	12.1%	-1.0 pp
Czech	22.7%	26.4%	-3.7 pp	9.9%	10.5%	-0.5 pp	12.7%	15.9%	-3.2 pp
Poland	32.4%	35.7%	-3.3 pp	14.0%	15.3%	-1.3 pp	18.4%	20.4%	-2.0 pp
Lithuania	31.3%	33.5%	-2.2 pp	15.4%	16.1%	-0.7 pp	15.9%	17.4%	-1.5 pp
Iceland	33.9%	35.9%	-2.0 pp	24.3%	27.7%	-3.3 pp	9.6%	8.2%	1.4 pp
Bulgaria	26.3%	27.8%	-1.5 pp	11.3%	12.4%	-1.1 pp	15.0%	15.4%	-0.4 pp
Hungary	30.4%	31.6%	-1.2 pp	16.5%	18.3%	-1.8 pp	13.8%	13.3%	0.5 pp
United	51.5%	52.8%	-1.2 pp	25.2%	26.2%	-1.0 pp	26.4%	26.6%	-0.2 pp
Latvia	38.6%	37.7%	0.9 pp	15.2%	18.3%	-3.1 pp	23.3%	19.3%	4.0 pp
France	45.7%	44.7%	0.9 pp	16.0%	20.4%	-4.4 pp	29.7%	24.3%	5.4 pp
Finland	41.1%	39.5%	1.6 pp	13.3%	16.2%	-3.0 pp	27.8%	23.3%	4.6 pp
Luxembourg	41.8%	40.1%	1.7 pp	18.8%	18.0%	0.8 pp	23.0%	22.1%	0.9 pp
Estonia	42.6%	40.5%	2.2 pp	20.4%	22.0%	-1.6 pp	22.2%	18.4%	3.8 pp
Cyprus	42.2%	39.9%	2.4 pp	19.6%	21.4%	-1.8 pp	22.6%	18.5%	4.2 pp
Belgium	36.5%	33.9%	2.6 pp	13.9%	16.9%	-3.1 pp	22.6%	17.0%	5.6 pp
Spain	51.0%	47.8%	3.2 pp	23.1%	26.0%	-2.9 pp	27.9%	21.8%	6.1 pp
Portugal	39.7%	36.1%	3.6 pp	22.3%	22.0%	0.3 pp	17.4%	14.0%	3.4 pp
Italy	38.8%	34.5%	4.3 pp	24.4%	20.5%	3.9 pp	14.3%	13.9%	0.4 pp
Malta	42.7%	38.0%	4.8 pp	20.7%	20.5%	0.2 pp	22.0%	17.4%	4.6 pp
Netherlands	48.7%	43.1%	5.6 pp	21.3%	20.0%	1.3 pp	27.5%	23.1%	4.3 pp
Denmark	43.9%	36.7%	7.2 pp	18.1%	17.4%	0.7 pp	25.8%	19.3%	6.4 pp
Norway	48.1%	40.7%	7.4 pp	17.0%	17.0%	0.0 pp	31.1%	23.7%	7.4 pp
Greece	40.9%	33.4%	7.5 pp	20.4%	20.0%	0.4 pp	20.5%	13.4%	7.1 pp

Figures 5-8 to 5-10 display age classes differences in skills mismatching, overeducation, and undereducation across countries. Although skills mismatching rates are distributed relatively evenly across all age groups, the figures reveal distinct patterns when it comes to overeducation and undereducation. Specifically, Figure 5-9 highlights that employees in the younger age groups (10-19 and 20-29) are generally more overeducated compared to their older counterparts, reflecting potential challenges in finding jobs that match their qualifications early in their careers. On the other hand, Figure 5-10 shows that undereducation tends to be more prevalent among employees in the youngest (10-19) and oldest (60+) age groups.

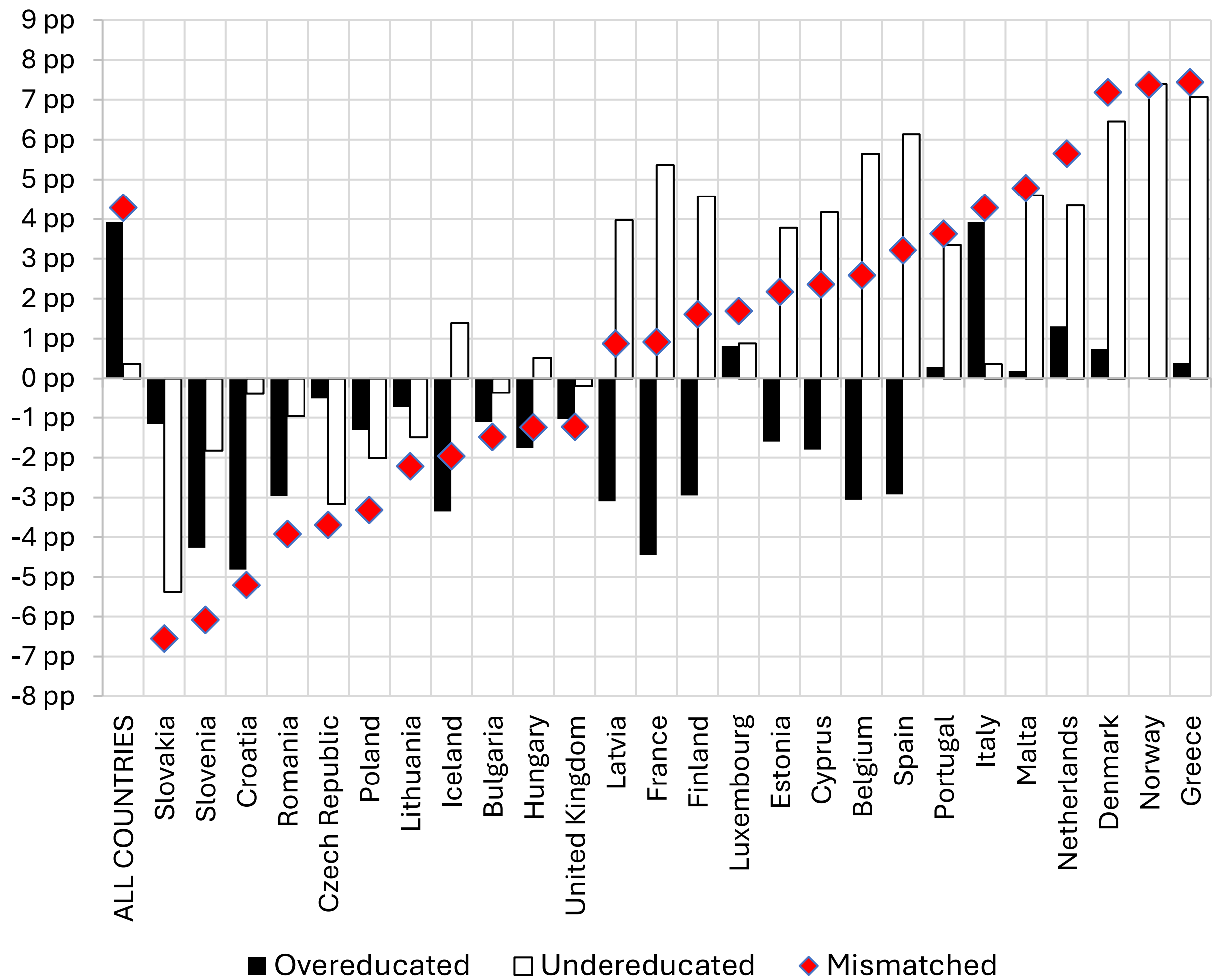


Figure 5-7: EU-SES – Gender (male vs. female) differences in skills mismatching by country

Then Figure 5-11 provides a visual representation of age differences in overeducation, undereducation, and mismatching by country, as outlined in Table 5-10. The red diamonds in the figure indicate mismatching differences between older and younger employees, while black and white bars represent overeducation and undereducation differences, respectively. Countries on the left, such as Portugal, Poland, Denmark, Norway, Sapin, Latvia and Estonia, show higher rates of mismatching among younger employees (negative differences), whereas countries on the right, including Iceland, Belgium, Croatia, the United Kingdom, Cyprus, France and Slovenia, exhibit higher mismatching rates among older employees (positive differences). Overall, the figure emphasizes that, in almost all countries, there are significant age-related differences in skills mismatching, with overeducation being more prevalent among younger employees and undereducation being more common among older employees.

Table 5-10: EU-SES – Age (old vs. young) differences by country

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	Old (40+)	Young (14-39)	Difference	Old (40+)	Young (14-39)	Difference	Old (40+)	Young (14-39)	Difference
ALL COUNTRIES	37.9%	36.9%	1.0 pp	16.7%	28.8%	-12.1 pp	21.2%	8.1%	13.1 pp
Portugal	32.5%	43.3%	-10.7 pp	13.5%	30.7%	-17.1 pp	19.0%	12.6%	6.4 pp
Poland	31.2%	37.2%	-6.0 pp	10.5%	19.3%	-8.8 pp	20.7%	18.0%	2.8 pp
Denmark	37.6%	42.6%	-5.0 pp	16.1%	19.4%	-3.4 pp	21.5%	23.1%	-1.6 pp
Norway	42.6%	47.2%	-4.6 pp	16.1%	17.9%	-1.8 pp	26.5%	29.3%	-2.8 pp
Spain	47.8%	51.3%	-3.5 pp	19.8%	29.0%	-9.2 pp	28.0%	22.3%	5.7 pp
Latvia	37.3%	39.2%	-1.9 pp	16.5%	17.5%	-1.1 pp	20.8%	21.6%	-0.8 pp
Estonia	40.7%	42.6%	-1.8 pp	23.0%	18.9%	4.1 pp	17.7%	23.7%	-5.9 pp
Hungary	30.3%	31.8%	-1.5 pp	15.7%	19.6%	-3.9 pp	14.6%	12.2%	2.4 pp
Lithuania	32.1%	33.0%	-0.9 pp	15.1%	16.6%	-1.5 pp	17.0%	16.4%	0.6 pp
Bulgaria	26.9%	27.3%	-0.5 pp	10.3%	14.2%	-3.9 pp	16.6%	13.2%	3.4 pp
Slovakia	24.2%	24.0%	0.1 pp	7.8%	12.2%	-4.3 pp	16.4%	11.9%	4.5 pp
Czech Republic	24.5%	24.2%	0.4 pp	9.2%	11.4%	-2.2 pp	15.3%	12.8%	2.6 pp
Greece	37.8%	37.1%	0.7 pp	16.7%	23.9%	-7.2 pp	21.1%	13.2%	7.9 pp
Romania	20.8%	20.1%	0.7 pp	8.2%	9.8%	-1.6 pp	12.6%	10.3%	2.4 pp
Italy	37.9%	36.9%	1.0 pp	16.7%	28.8%	-12.1 pp	21.2%	8.1%	13.1 pp
Finland	41.0%	39.2%	1.8 pp	12.5%	18.1%	-5.7 pp	28.6%	21.0%	7.5 pp
Luxembourg	42.3%	40.3%	2.0 pp	15.2%	21.4%	-6.2 pp	27.1%	18.8%	8.3 pp
Malta	42.1%	39.6%	2.5 pp	20.5%	20.7%	-0.2 pp	21.6%	18.9%	2.7 pp
Netherlands	47.4%	44.8%	2.6 pp	18.6%	22.7%	-4.0 pp	28.8%	22.1%	6.7 pp
Slovenia	34.8%	32.0%	2.9 pp	9.4%	13.2%	-3.8 pp	25.5%	18.8%	6.7 pp
France	46.7%	43.3%	3.4 pp	13.6%	23.8%	-10.2 pp	33.1%	19.5%	13.6 pp
Cyprus	42.9%	39.2%	3.7 pp	15.8%	25.3%	-9.5 pp	27.2%	13.9%	13.2 pp
United Kingdom	53.9%	50.2%	3.7 pp	25.0%	26.4%	-1.3 pp	28.9%	23.9%	5.0 pp
Croatia	29.2%	24.5%	4.7 pp	11.1%	13.7%	-2.5 pp	18.1%	10.9%	7.2 pp
Belgium	38.6%	31.5%	7.1 pp	13.4%	17.4%	-4.1 pp	25.3%	14.1%	11.2 pp
Iceland	42.5%	27.4%	15.1 pp	32.4%	19.8%	12.6 pp	10.1%	7.7%	2.4 pp

Third, Table 5-11 presents income status differences in skills mismatching, overeducation, and undereducation by comparing employees in the top 40% (T40) of the income distribution with those in the bottom 60% (B60). Income deciles have been constructed based on gross monthly earnings of the employees. In cases where national currencies were used, income data has been converted into euros using the average exchange rate for each year and country. Additionally, all income data has been deflated using the GDP deflator specific to each country and year to adjust for inflation. Countries are ordered by their percentage point difference in mismatching, from lowest to highest.

Overall, higher-income individuals (T40) exhibit slightly lower rates of skills mismatching compared to lower-income individuals (B60). On average, the mismatching rate for T40 employees is 37.0%, while for B60 employees, it stands at 37.7%. However, to fully understand skills mismatch discrepancies, it is essential to examine the specific types of mismatching – overeducation and undereducation. Overeducation seems to be more pronounced among higher-income employees compared to the lower-income employees across all countries, except Greece, Italy and Portugal. On the other hand, undereducation is more common among lower-income employees in most countries, with the exceptions of Iceland, Luxembourg, France, the United Kingdom, Bulgaria and Malta.

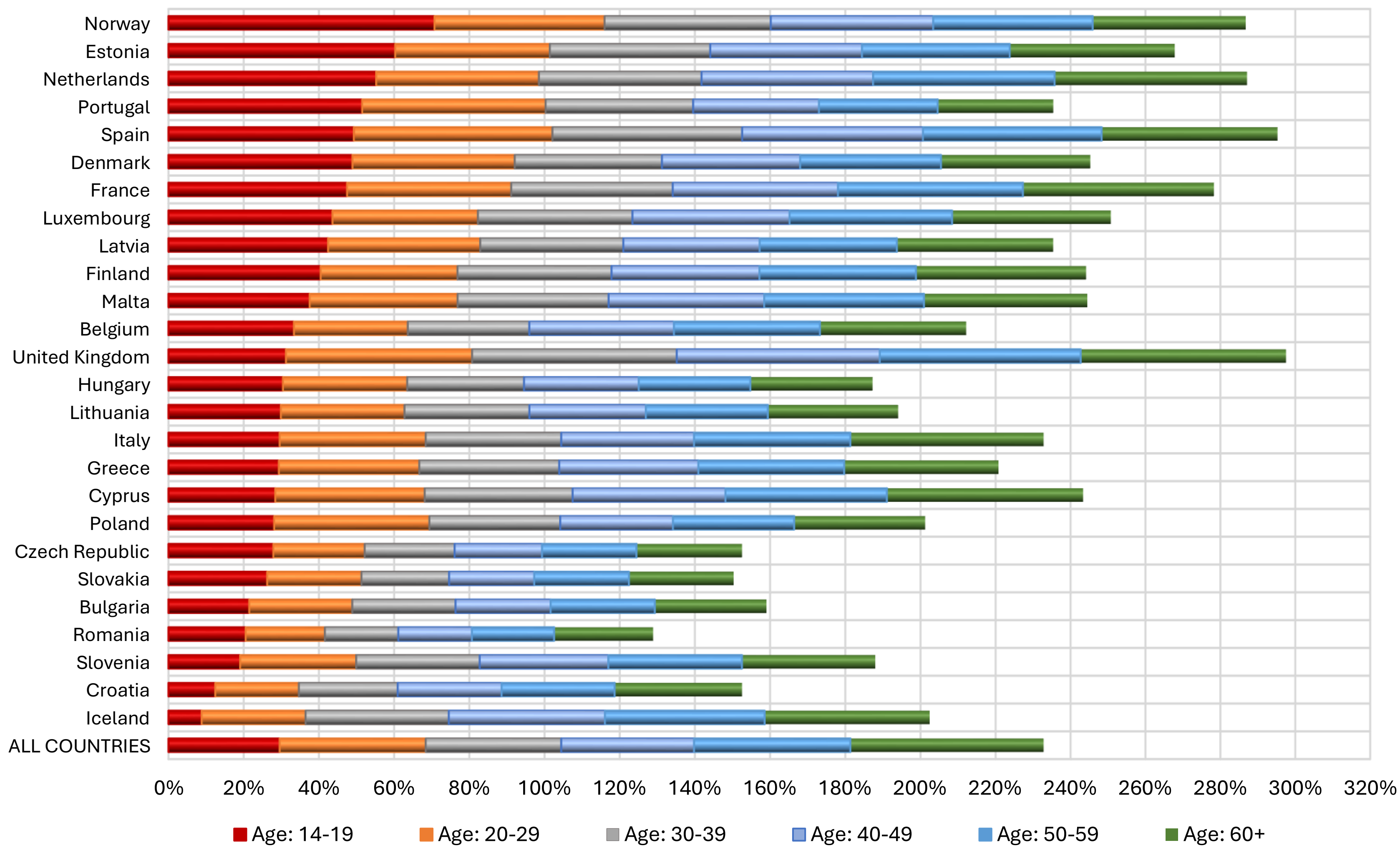


Figure 5-8: EU-SES – Age composition of skills mismatching by country

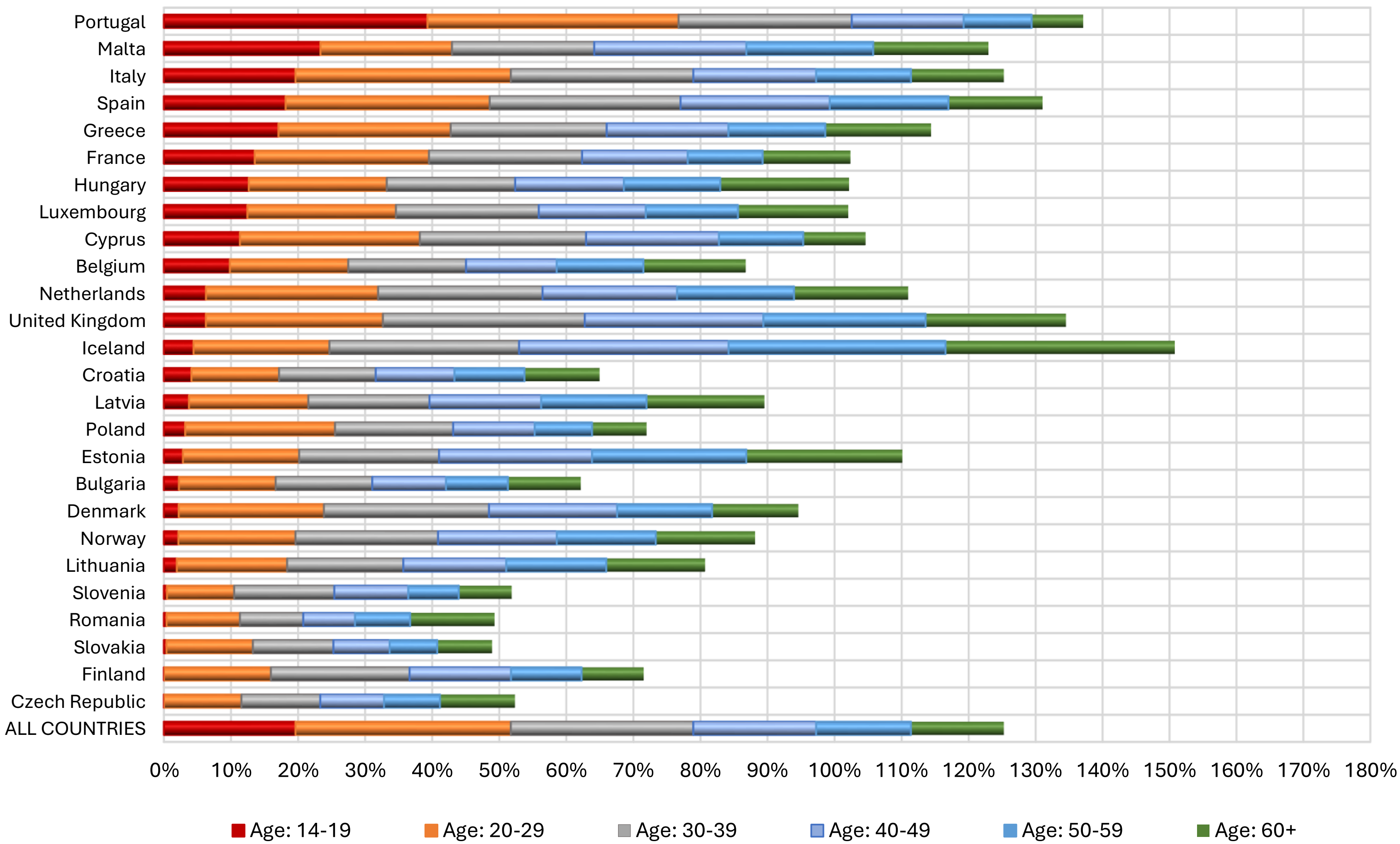


Figure 5-9: EU-SES – Age composition of overeducation by country

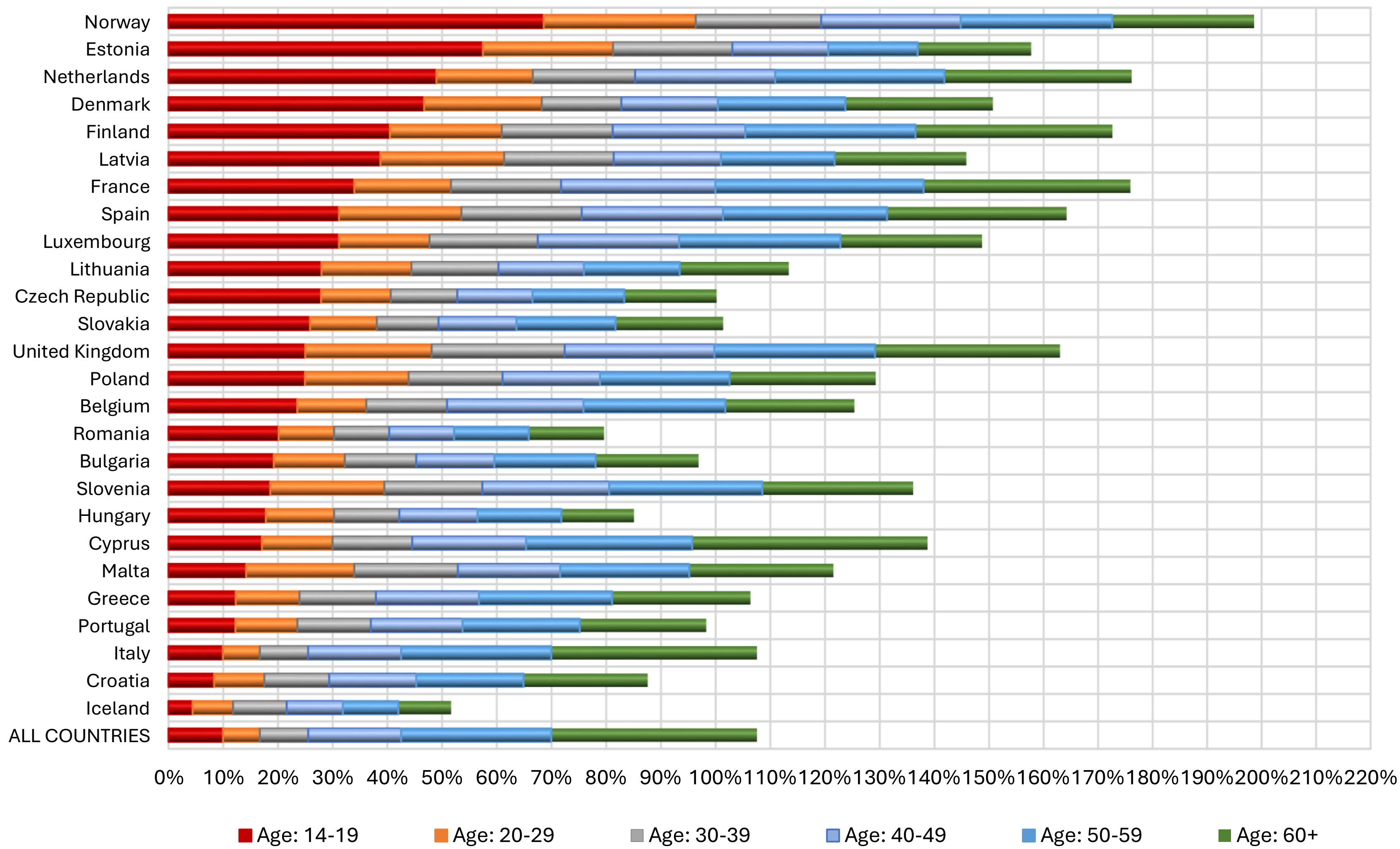


Figure 5-10: EU-SES – Age composition of undereducation by country

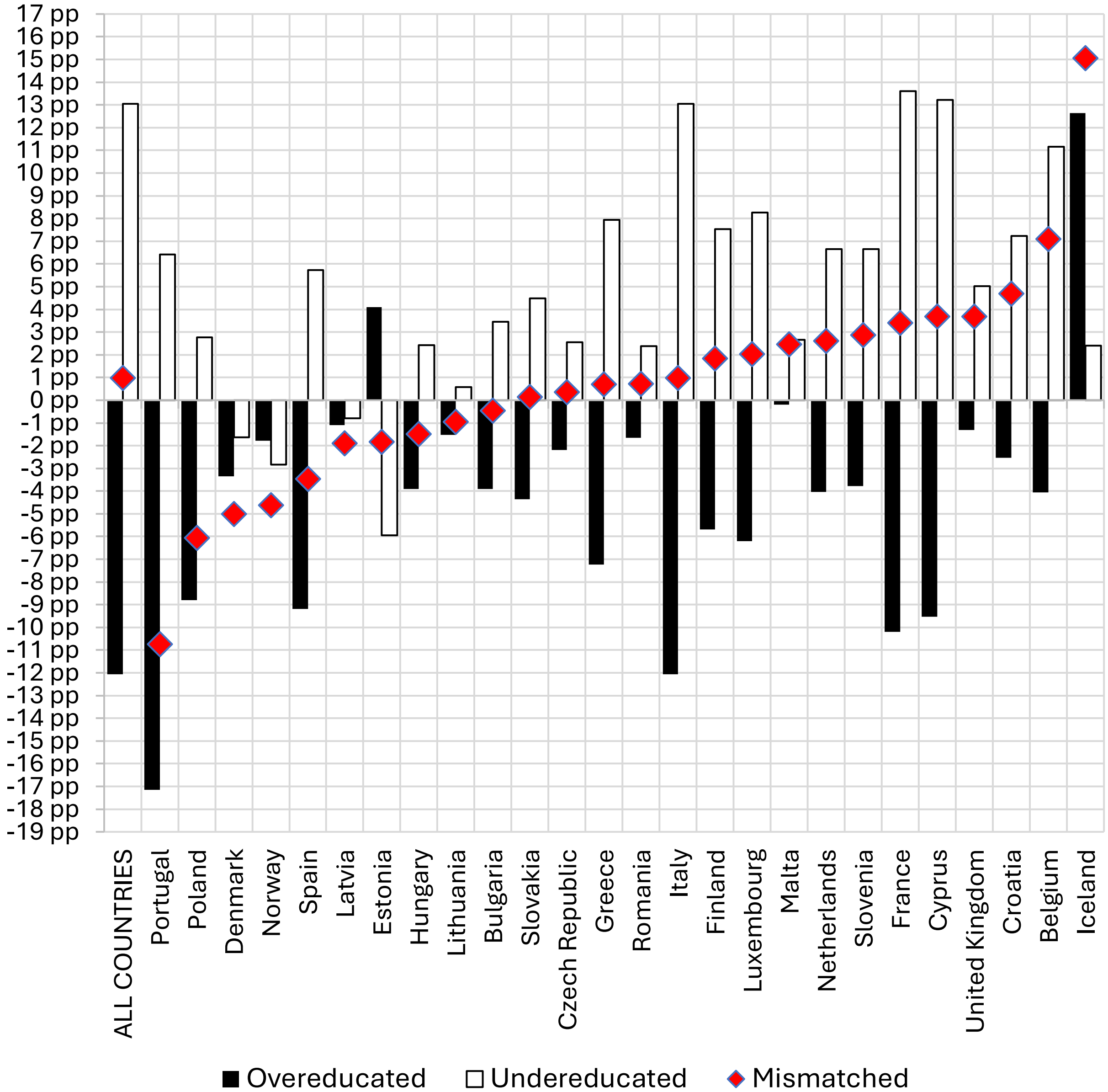


Figure 5-11: EU-SES – Age (old vs. young) differences in skills mismatching by country

Table 5-11: EU-SES – Income (Top40% vs. Bottom60%) differences by country

	MISMATCHING			OVEREDUCATION			UNDEREDUCATION		
	T40	B60	Difference	T40	B60	Difference	T40	B60	Difference
ALL COUNTRIES	*37.0%*	*37.7%*	*-0.7 pp*	*22.8%*	*23.5%*	*-0.7 pp*	*14.2%*	*14.2%*	*0.0 pp*
Cyprus	37.7%	42.3%	-4.7 pp	20.6%	20.4%	0.2 pp	17.1%	21.9%	-4.9 pp
Greece	35.4%	38.9%	-3.5 pp	20.0%	20.3%	-0.3 pp	15.4%	18.5%	-3.2 pp
Belgium	34.1%	36.1%	-2.0 pp	16.2%	14.6%	1.6 pp	17.9%	21.5%	-3.6 pp
Denmark	39.2%	40.6%	-1.4 pp	21.9%	15.2%	6.6 pp	17.3%	25.4%	-8.0 pp
Lithuania	31.8%	32.8%	-1.0 pp	17.3%	14.9%	2.5 pp	14.5%	18.0%	-3.5 pp
Estonia	41.0%	41.8%	-0.8 pp	22.3%	20.8%	1.5 pp	18.7%	21.0%	-2.3 pp
Italy	37.0%	37.7%	-0.7 pp	22.8%	23.5%	-0.7 pp	14.2%	14.2%	0.0 pp
Norway	44.6%	44.9%	-0.3 pp	22.3%	13.6%	8.7 pp	22.3%	31.3%	-9.0 pp
Romania	21.0%	20.1%	0.9 pp	13.3%	5.8%	7.5 pp	7.7%	14.4%	-6.7 pp
Slovakia	25.0%	23.7%	1.3 pp	15.7%	6.5%	9.2 pp	9.3%	17.2%	-7.9 pp
Spain	50.4%	49.1%	1.3 pp	25.2%	23.9%	1.3 pp	25.2%	25.1%	0.1 pp
Netherlands	46.9%	45.6%	1.4 pp	25.4%	17.9%	7.6 pp	21.5%	27.7%	-6.2 pp
Poland	34.9%	33.5%	1.4 pp	16.3%	13.7%	2.6 pp	18.6%	19.9%	-1.2 pp
Latvia	39.0%	37.6%	1.4 pp	20.7%	14.7%	5.9 pp	18.3%	22.8%	-4.5 pp
Hungary	32.0%	30.4%	1.6 pp	20.7%	15.6%	5.1 pp	11.3%	14.8%	-3.5 pp
Portugal	39.0%	37.4%	1.6 pp	20.8%	22.9%	-2.0 pp	18.2%	14.5%	3.6 pp
Finland	41.7%	39.4%	2.3 pp	18.0%	12.8%	5.2 pp	23.7%	26.6%	-2.9 pp
Croatia	29.5%	25.7%	3.8 pp	14.6%	10.7%	3.9 pp	14.9%	15.0%	-0.1 pp
France	48.3%	44.3%	3.9 pp	20.7%	17.3%	3.4 pp	27.6%	27.1%	0.5 pp
Bulgaria	30.1%	25.4%	4.7 pp	14.6%	10.3%	4.3 pp	15.4%	15.0%	0.4 pp
Malta	44.0%	39.2%	4.9 pp	23.6%	19.2%	4.4 pp	20.4%	20.0%	0.5 pp
Luxembourg	44.6%	39.4%	5.2 pp	20.4%	17.5%	2.9 pp	24.2%	21.9%	2.3 pp
Slovenia	37.3%	31.8%	5.4 pp	14.6%	9.2%	5.3 pp	22.7%	22.6%	0.1 pp
United Kingdom	56.5%	48.9%	7.7 pp	29.9%	22.6%	7.3 pp	26.7%	26.3%	0.4 pp
Czech Republic	29.9%	21.6%	8.4 pp	18.6%	6.0%	12.7 pp	11.3%	15.6%	-4.3 pp
Iceland	43.2%	30.4%	12.7 pp	31.5%	23.1%	8.4 pp	11.6%	7.3%	4.3 pp

Figures 5-12 to 5-14 present income composition differences in skills mismatching, overeducation, and undereducation across countries, with income distribution divided into 10 deciles for more detailed insights. Figure 5-12 highlights that mismatching rates are distributed relatively evenly across all income deciles in all countries. Figure 5-13 focuses on overeducation, showing that it is more pronounced in higher income brackets, particularly after the 7th decile. In contrast, Figure5-14 reveals the opposite pattern for undereducation, where the lowest income deciles – particularly the first three – exhibit significantly higher undereducation rates.

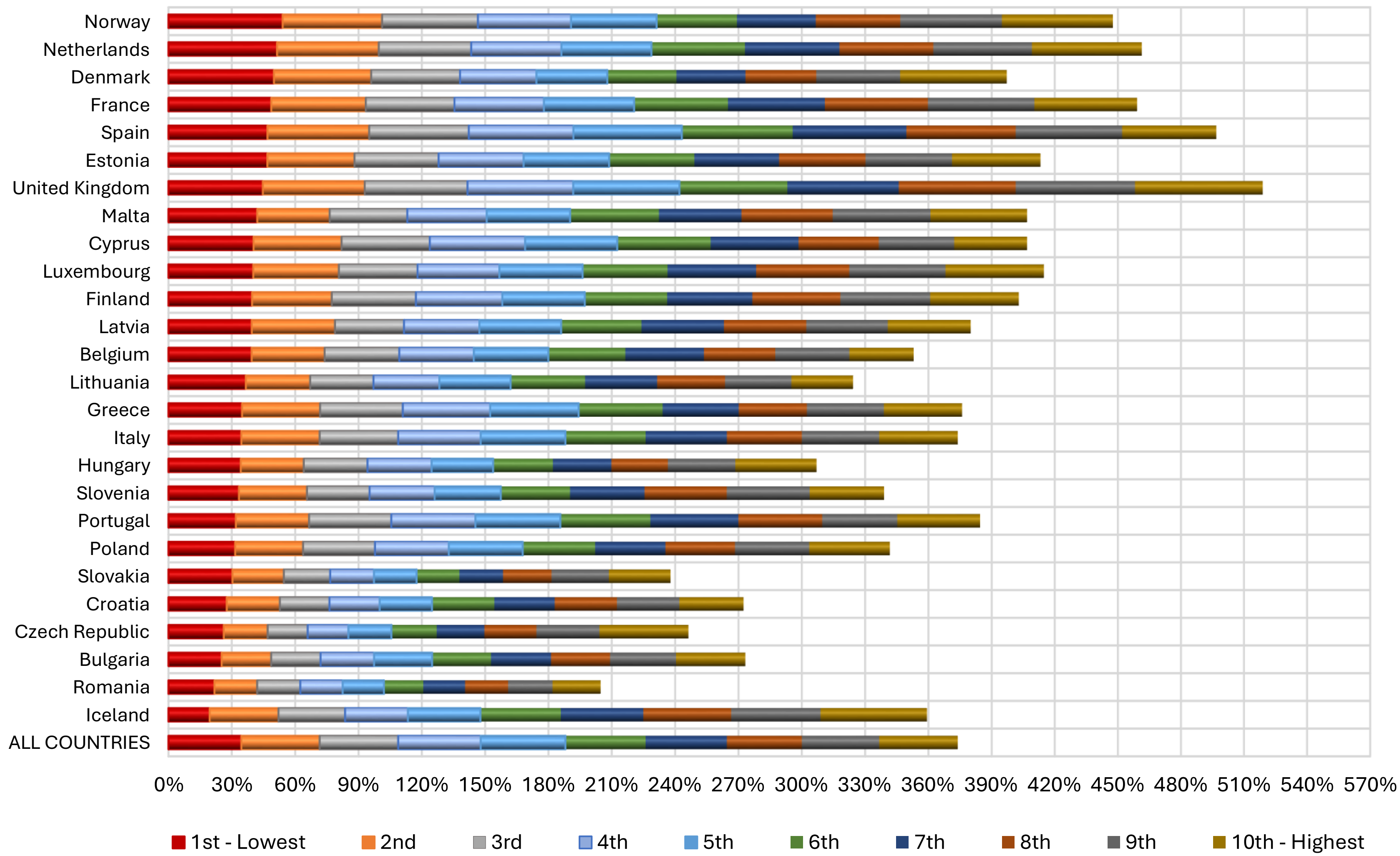


Figure 5-12: EU-SES – Income composition of skills mismatching by country

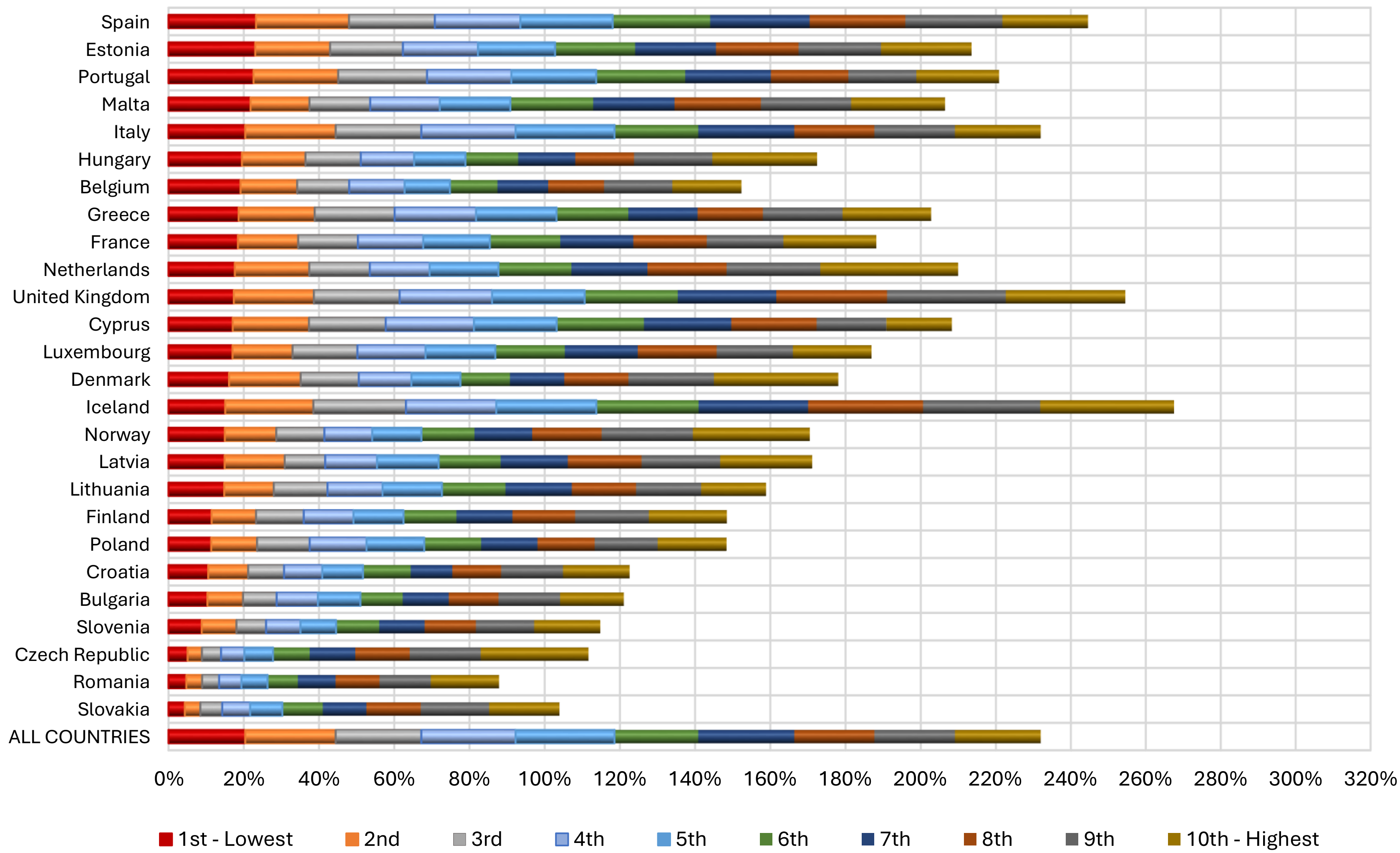


Figure 5-13: EU-SES – Income composition of overeducation by country

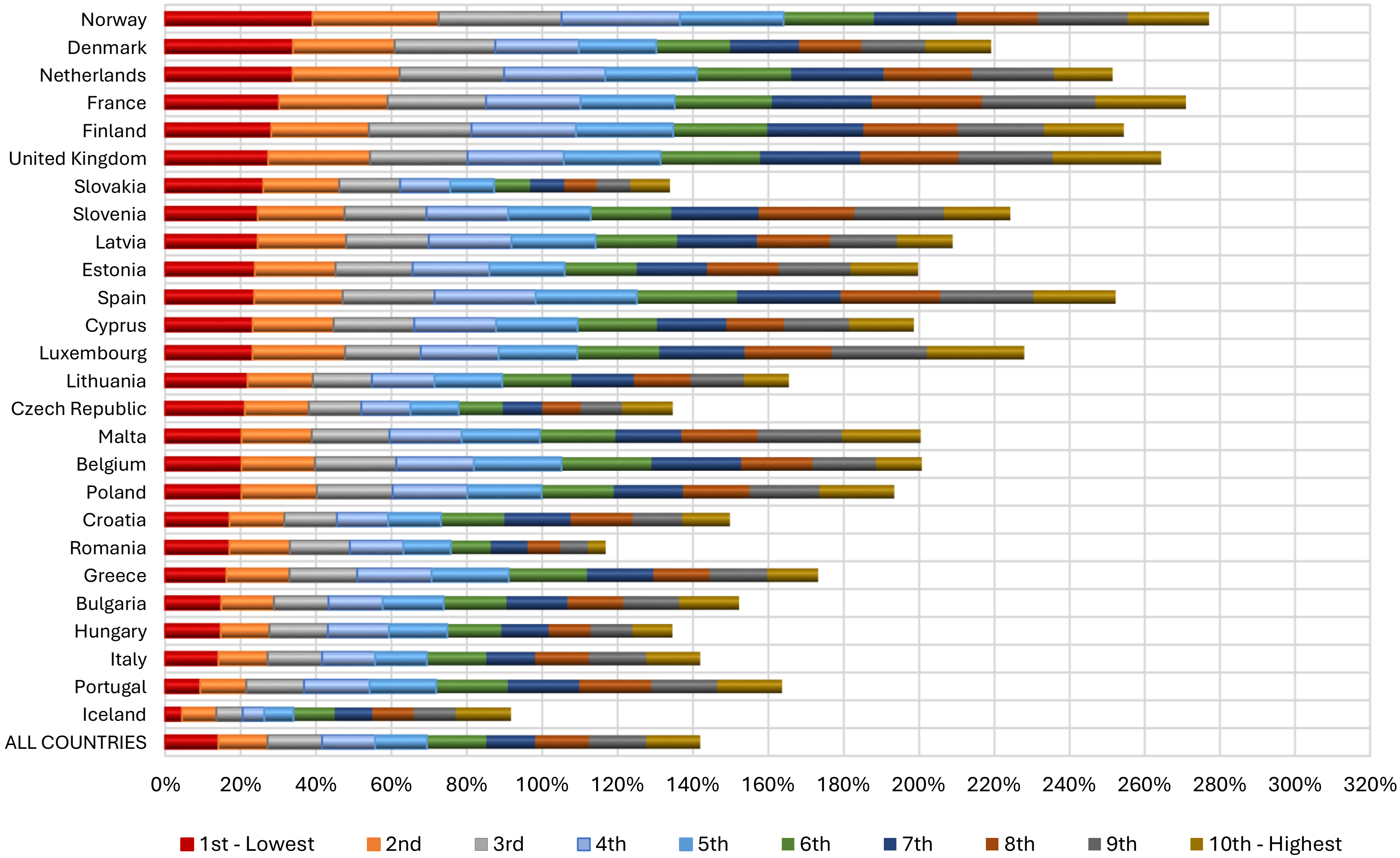


Figure 5-14: EU-SES – Income composition of undereducation by country

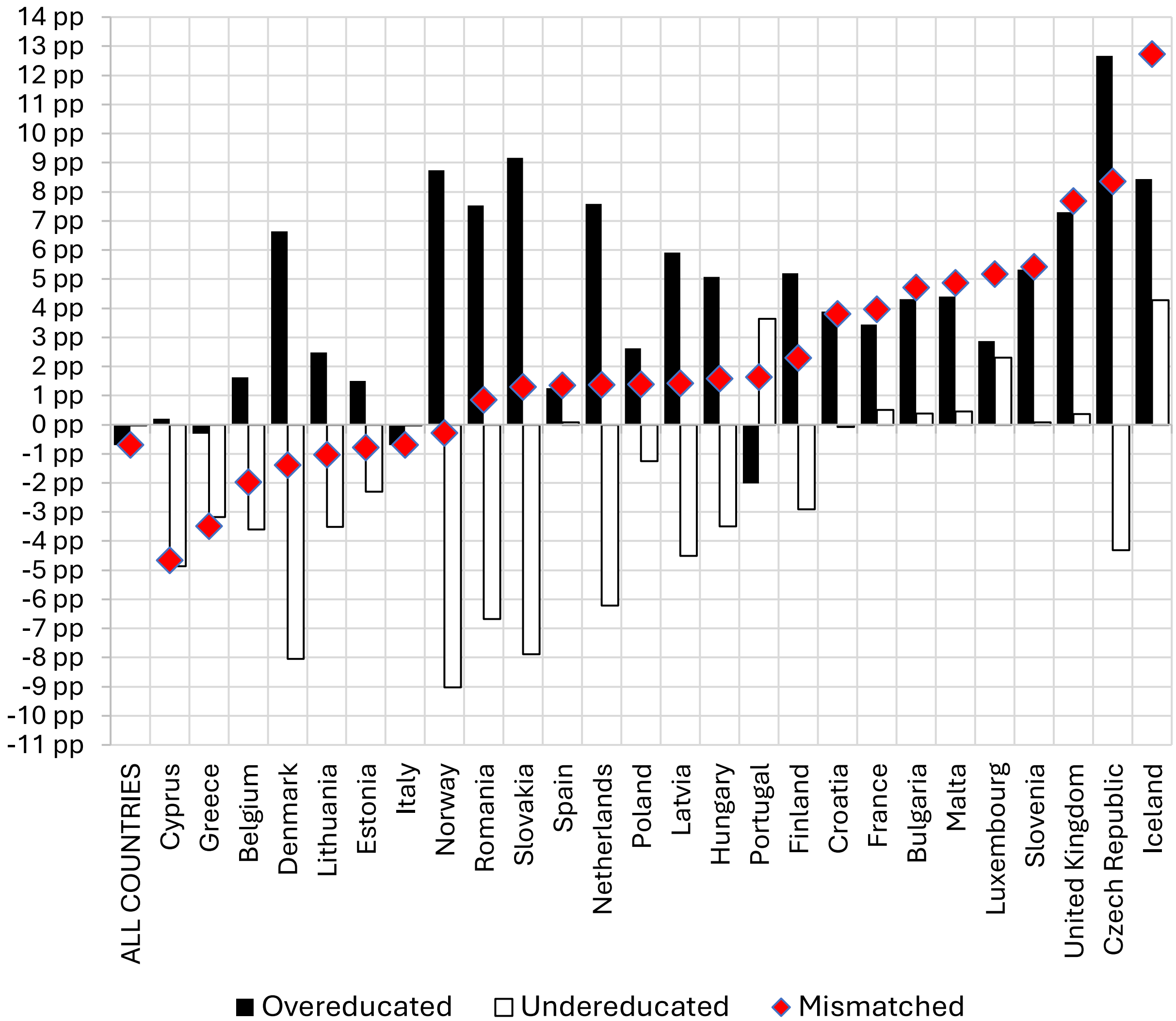


Figure 5-15: EU-SES – Income differences (Top40% – Bottom60%) in skills mismatching by country

Finally, Figure 5-15 provides a visual representation of disparities in skills mismatching, overeducation, and undereducation, based on gross monthly earnings data from Table 5-11. The red diamonds illustrate the mismatching rate differences between the top 40% (T40) higher-income group and the bottom 60% (B60) lower-income group, while the black and white bars represent the differences in overeducation and undereducation rates, respectively. The figure highlights clear income-related patterns, with noticeable disparities in both overeducation and undereducation across income groups, as reported in the table. Overeducation is more pronounced among higher-income employees, a trend that remains consistent across most countries. In contrast, undereducation tends to be more prevalent among lower-income employees, particularly in lower-income countries, reinforcing the socioeconomic divides in skills mismatching.

5.2 STATISTICS SWEDEN (LISA/FEC)

LISA (Longitudinal Integration Database for Health Insurance and Labour Market Studies) and FEC (Swedish Register of Education) are two important databases managed by Statistics Sweden, the country's national statistical agency. These databases provide comprehensive and detailed longitudinal data on various aspects of the Swedish population, particularly focusing on the labour market, health insurance, and education. These datasets are essential for research and policy analysis in Sweden.

LISA is designed to offer a broad and detailed view of the Swedish population's labour market participation, income, and health insurance status. The database integrates data from various registers, creating a longitudinal dataset that allows for in-depth analysis over time.

LISA includes all individuals aged 16 and over who are registered in Sweden, providing nearly complete coverage of the population. The database spans from 1990 onwards, with data being updated annually.

The data covers the following themes:

- Labour market data: LISA contains detailed information on employment status, income from work, unemployment, participation in labour market programs, and other employment-related variables.
- Income and benefits: The database includes comprehensive data on different sources of income, including wages, pensions, social benefits, and unemployment insurance.
- Health insurance: LISA integrates data on health insurance coverage and utilization, allowing for analysis of the relationship between labour market status and health outcomes.
- Demographic variables: Information on age, gender, marital status, place of residence, and migration history is included, enabling demographic analysis in conjunction with labour market data.
- Longitudinal aspect: The ability to track individuals over time is a key strength of LISA, making it possible to study changes in employment, income, and health insurance status across different periods of life.

The FEC database (Swedish Register of Education) provides detailed information on the educational attainment and qualifications of individuals in Sweden. It is used to monitor and analyse educational trends, assess the impact of education on labour market outcomes, and support educational planning and policy making. The FEC covers the entire population of Sweden, with data available from the early 1990s. It includes information on all levels of formal education attained by individuals. The data provides the following information and functions:

- Educational attainment: FEC includes detailed data on the highest level of education completed by individuals, categorized by type of education (e.g., primary, secondary, tertiary) and field of study.
- Qualifications and degrees: The database records specific qualifications and degrees obtained, such as diplomas, bachelor's, master's, and doctoral degrees, as well as vocational qualifications.

- Educational Institutions: Information about the institutions where qualifications were obtained is included, enabling analysis of educational paths and outcomes associated with different types of schools or universities.
- Linkage to other registers: Like LISA, the FEC can be linked with other registers, such as income and employment data, allowing for comprehensive analyses of the relationship between education and labour market outcomes.

LISA and FEC are extensively used by researchers studying labour economics, social policy, public health, and education. The longitudinal nature of LISA is particularly valuable for understanding life-course dynamics and the long-term effects of policy interventions. These databases are critical for policymakers in Sweden, providing the empirical basis for decisions related to labour market policies, social welfare programs, education reform, and public health initiatives. The integration of labour market data with health and education information enables complex analyses of social inequalities, the impact of education on economic mobility, and the effectiveness of the welfare state.

The longitudinal data provided by LISA allows for tracking individual life trajectories over time, offering insights into how education, employment, and health interact throughout different stages of life. The breadth and depth of information in LISA and FEC make them invaluable resources for understanding the social and economic structure of Sweden. The data from these registers directly inform evidence-based policymaking in Sweden, ensuring that decisions are grounded in robust empirical evidence.

Access to LISA and FEC is generally available to researchers under strict confidentiality agreements, given the sensitive nature of the data. Swedish public institutions use these databases for planning, monitoring, and evaluating public policies and programs. These databases, LISA and FEC, play a crucial role in understanding and addressing the social and economic challenges in Sweden, supporting a wide range of research and policy initiatives aimed at improving the well-being of the Swedish population.

5.2.1 THE DATA, THE SAMPLE AND FREQUENCIES

In Figures 5-16, 5-17, 5-18, and 5-19 we describe the data and the sample. Panel A of the four figures below shows the distribution of the sample of firms in the LISA database used to build the skill match quality measure: by (i) size, (ii) industry, (iii) age, and (iv) firm structure. The sample includes 9,023 firms operating in three different sectors, collectively employing over 6 million workers. Panel B of the four figures below analogously describes the sub-sample of firms active in 2010, which was used to gather descriptive statistics on the skill match quality measures reported in the following subsection. The graphs show that the 2010 subsample of firms closely resembles the full sample.

For consistency in the match quality measurement procedure, the distribution of sampled firms by size is slightly skewed towards larger firms: more than half employ between 30 and 80 workers, while only 7.3% have a workforce of fewer than 30 employees (Figure 5-16).

The firms are nearly evenly distributed across the three sectors, with a slight concentration in manufacturing (Figure 5-17). 12.2% are family-owned, while only 1.2% are publicly listed (Figure 5-18). Additionally, the vast majority have been active for more than 10 years (Figure 5-19).

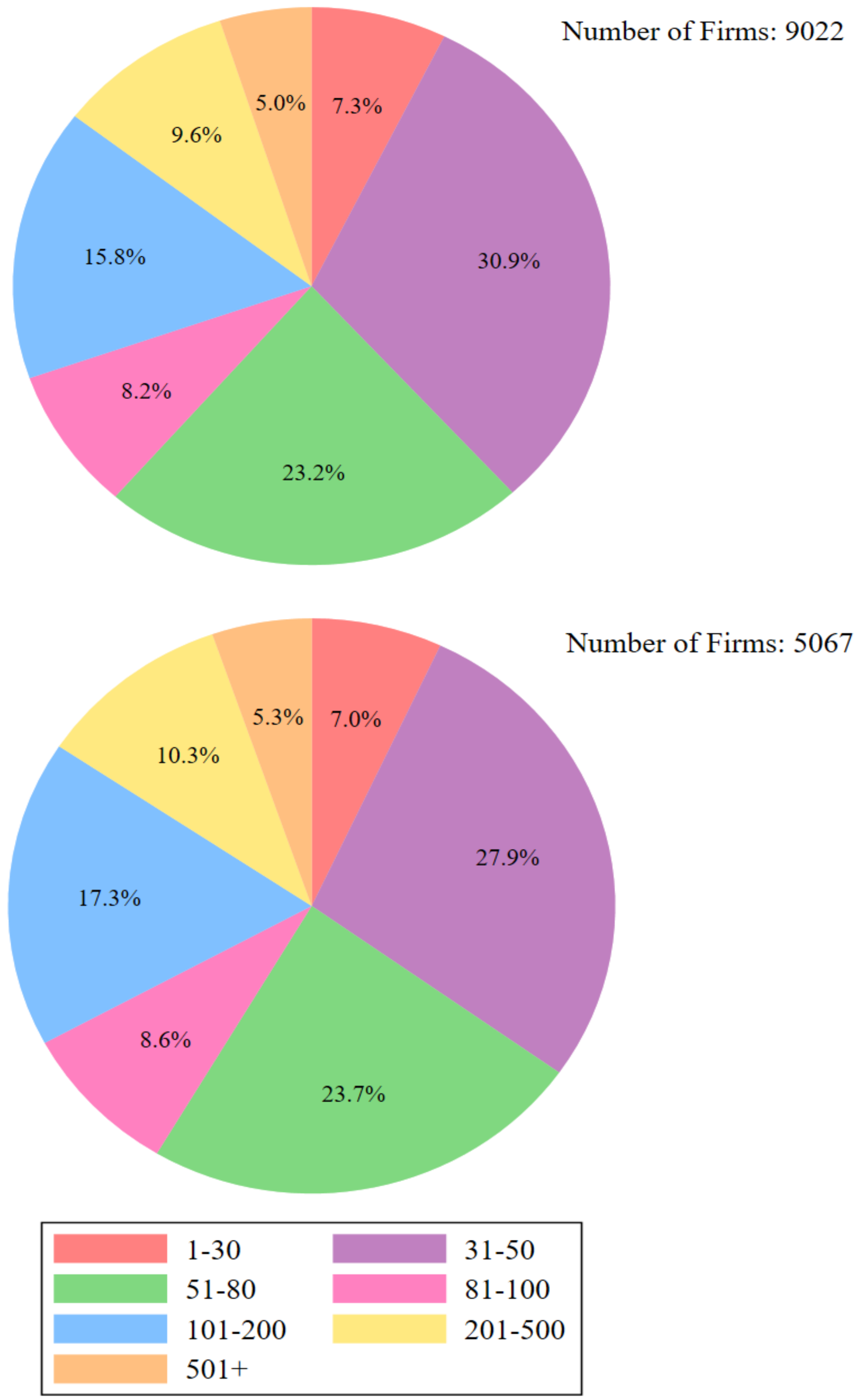


Figure 5-16: LISA/FEC –Distribution of firms by size pre- and post-sample selection

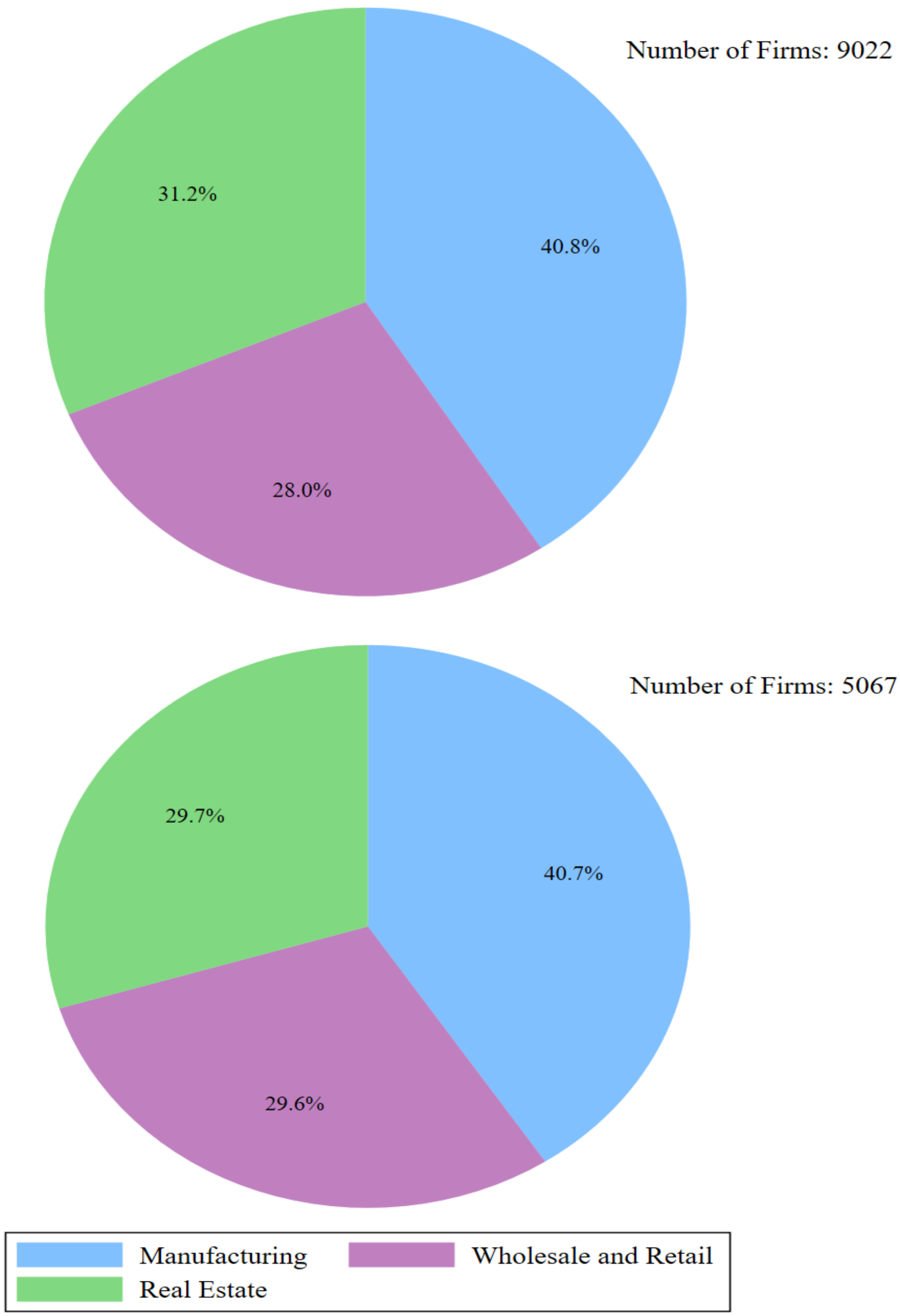


Figure 5-17: LISA/FEC – Distribution of firms by sector pre- and post-sample selection

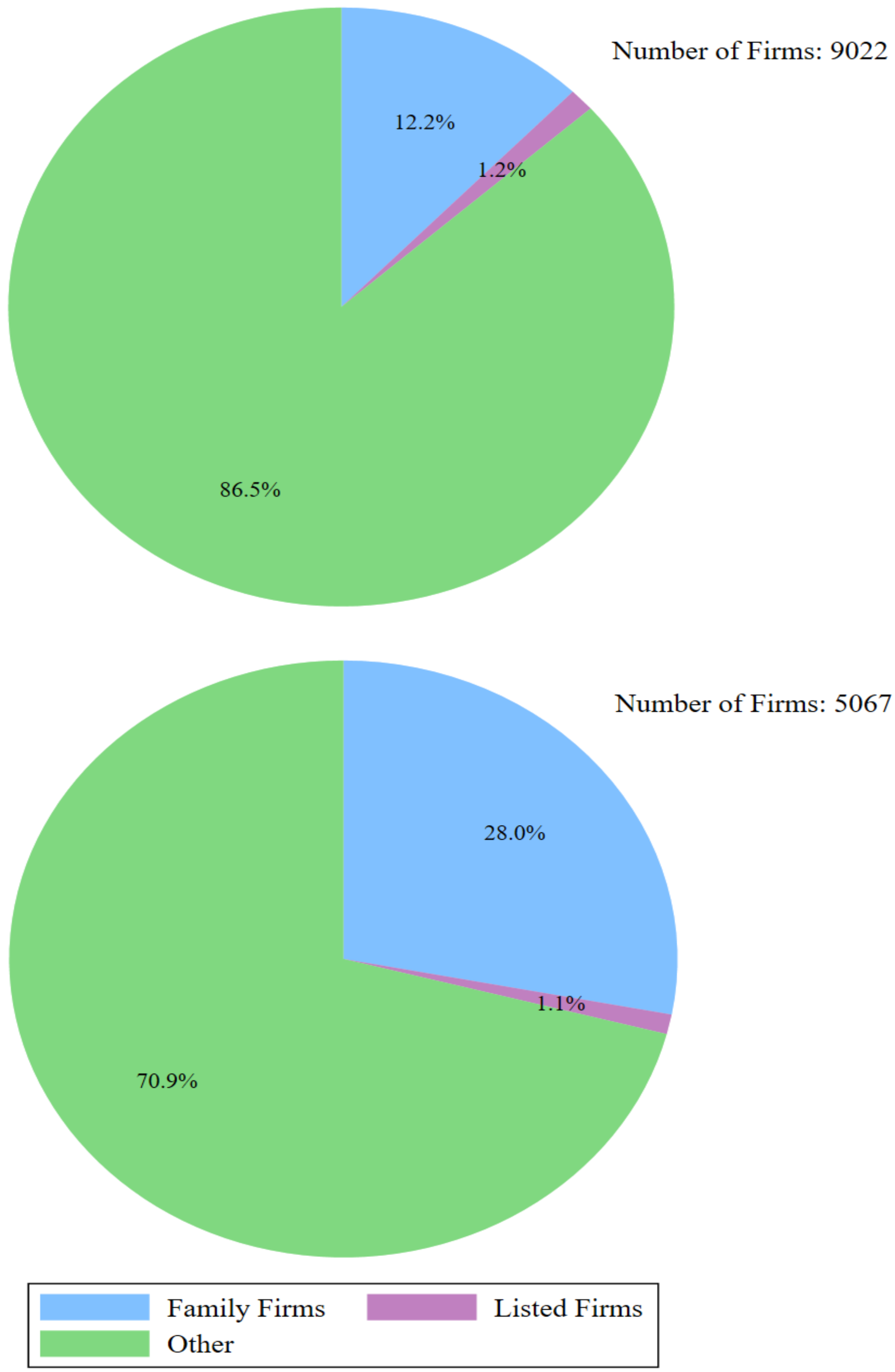


Figure 5-18: LISA/FEC – Distribution of firms by structure pre- and post-sample selection

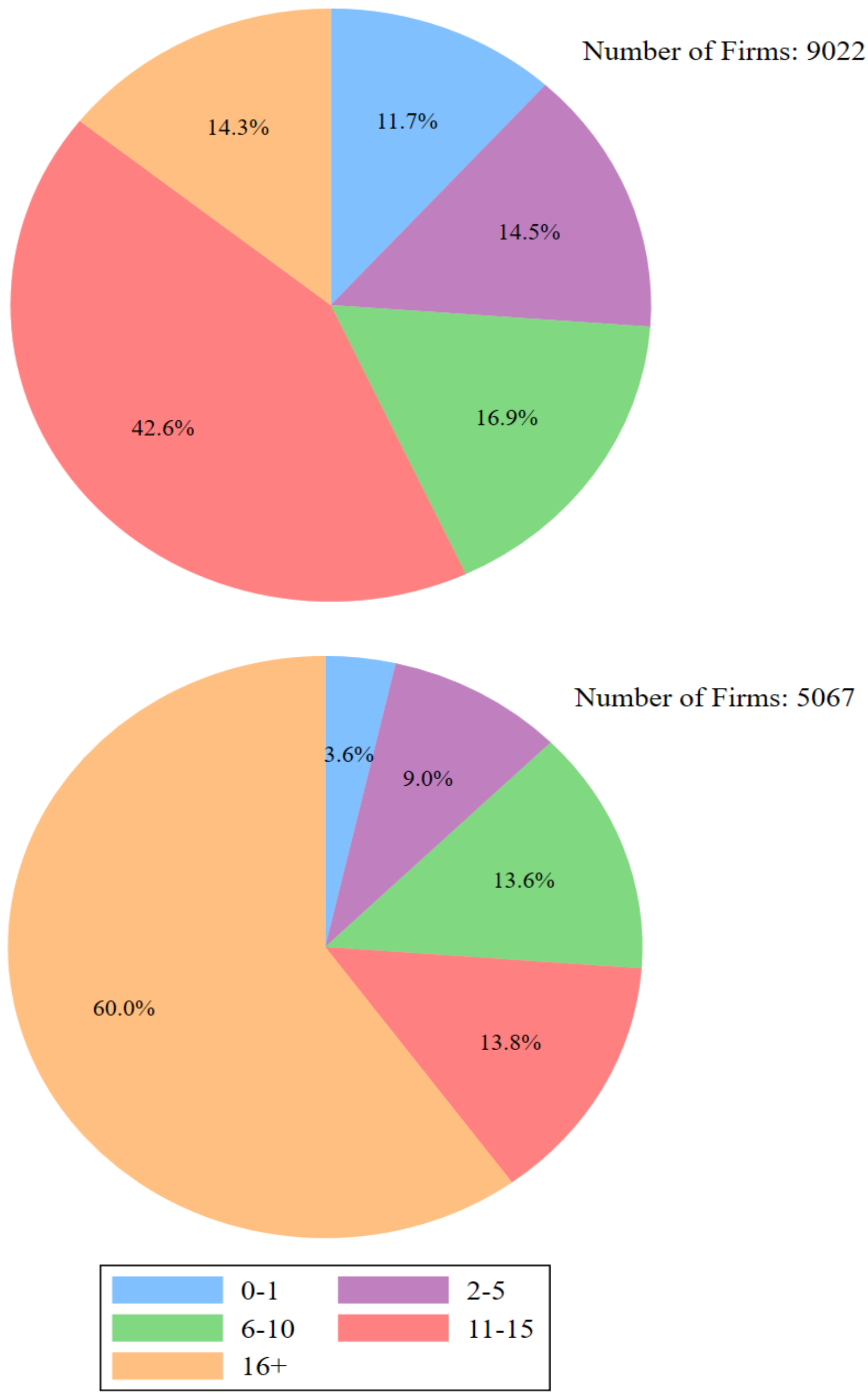


Figure 5-19: LISA/FEC – Distribution of firms by age pre- and post-sample selection

5.2.2 SKILLS MATCHING AND/OR TRAINING STATISTICS

Measures of occupational skill mismatch that rely on administrative data typically use the objective method, i.e., they define match quality based on comparisons between individual job assignments and moments of the distribution of realized matches.

The measures of occupational skill match quality reported in the following figures instead are built using the methodology developed in ongoing work for Workpackage 4 of the TRAILS project.

1. start by using the observed distribution of workers across jobs in firms in the top productivity decile to estimate, via machine learning methods, a function mapping observable worker characteristics and detailed job history into jobs.
2. In the second step, the model estimated for firms in the top productivity decile is used to produce out-of-sample predictions of the counterfactual job assignment of a given worker, had she been in a top productivity decile firm.
3. Under the assumption that workers in firms in the top productivity decile hold their most suitable job based on observable characteristics and job histories, the out-of-sample predicted probabilities of being in each job provide a measure of the worker suitability for that job. The predicted worker suitability measures can then be used to build an employee-level metric, which measures the congruence between the job to which the worker is assigned and the job to which he/she would be assigned in top-decile firms.

The only recent study that uses the LISA database to address questions related to multidimensional skill mismatch is by Fredriksson et al. (2018). They combine LISA data with military draft test scores which include four measures of cognitive skills and four measures of noncognitive skills. To measure skill mismatch, they compare the talents (as reported by test scores) of new hires with those of tenured workers in the same jobs, assuming that tenured workers have the right talents for their roles.

According to the measure, as shown in Figure 5-20, managers and elementary-occupation workers are the most likely to be mismatched. In contrast, professionals are the best matched, with roughly two-thirds of them working in the most suitable jobs.

Figure 5-21 shows that at the earlier stages of their careers, workers are more likely to be mismatched. However, as they gain labour market experience, their job matches improve significantly. After 9 years of experience, nearly 70% of workers are matched with their most suitable job.

Figure 5-22 illustrates that workers with higher levels of education are more easily placed in their ideal job positions.

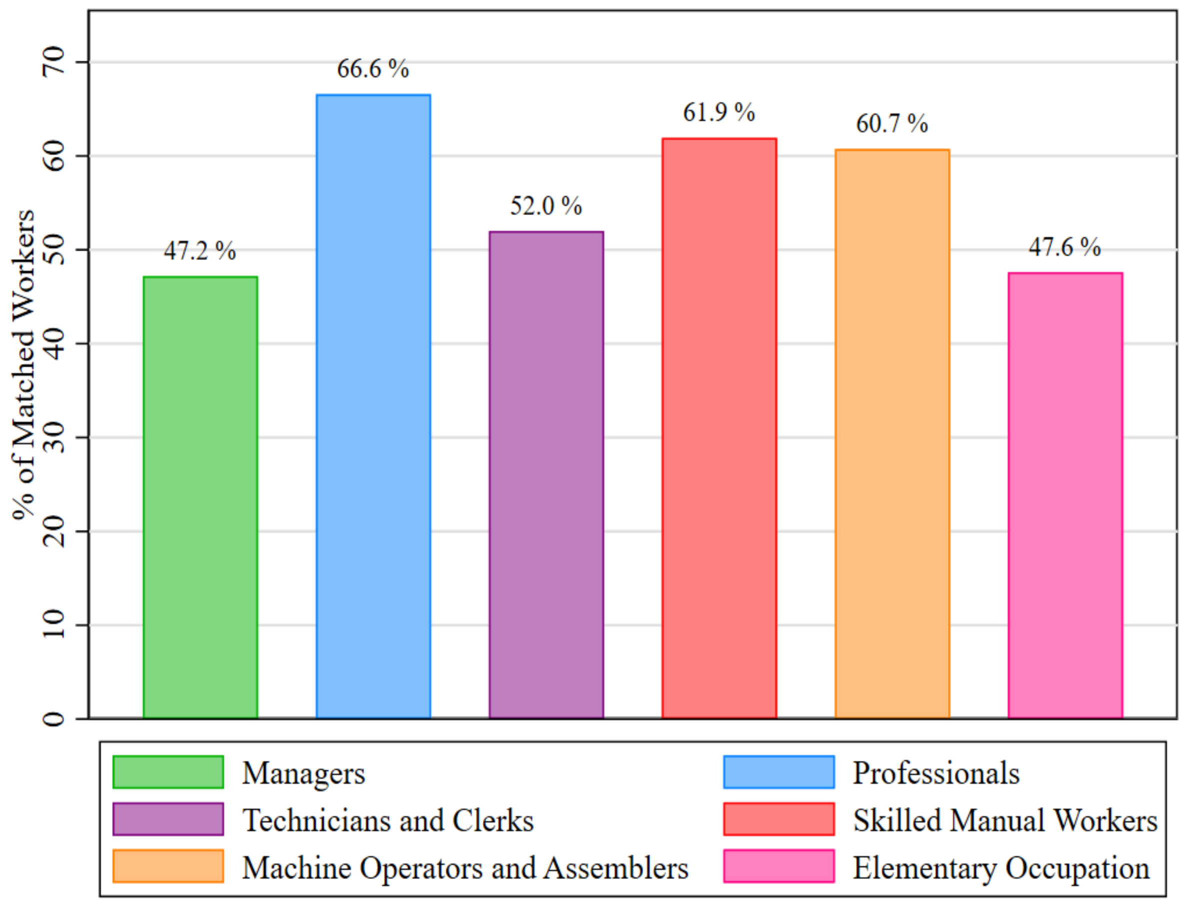


Figure 5-20: LISA/FEC – Percentage of matched workers by occupation

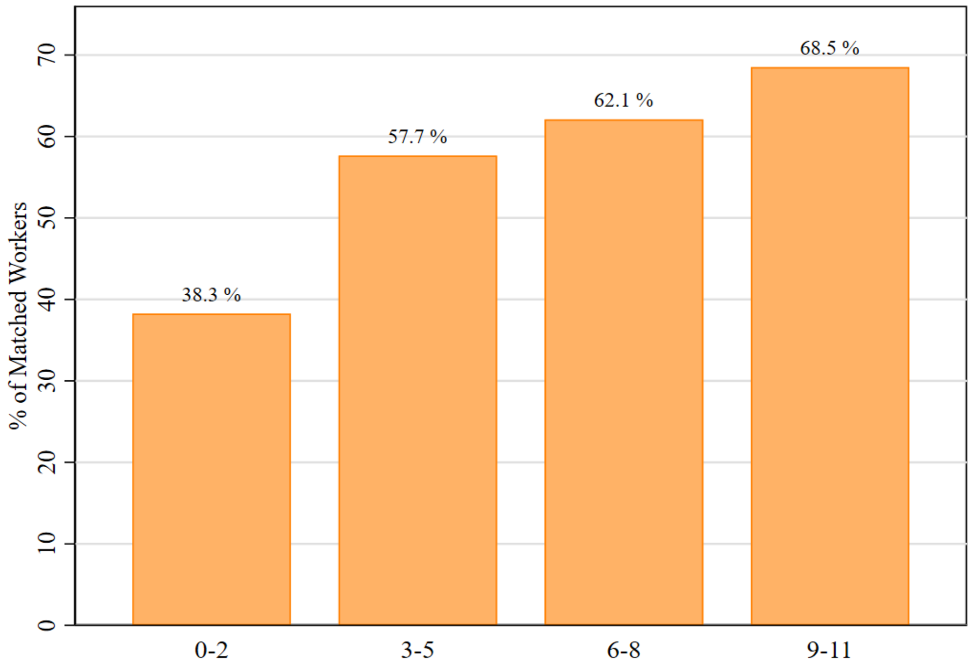


Figure 5-21: LISA/FEC – Percentage of matched workers by years of experience

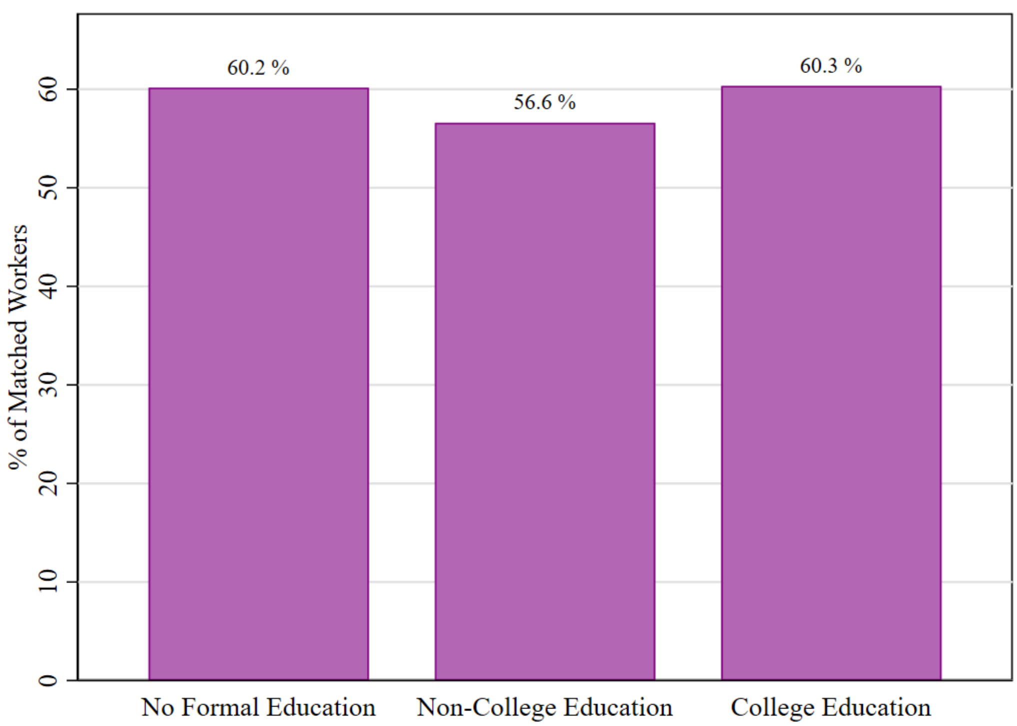


Figure 5-22: LISA/FEC – Percentage of matched workers by level of education

5.2.3 DIFFERENCES ACROSS FIRM TYPES AND KEY DEMOGRAPHIC GROUPS

Figure 5-23 shows that firms in the wholesale and retail sectors achieve the best employee-job matches, although the differences compared to manufacturing are not substantial. Firms in real estate, renting, and business activities, instead register a lower, close to half, fraction of matched workers.

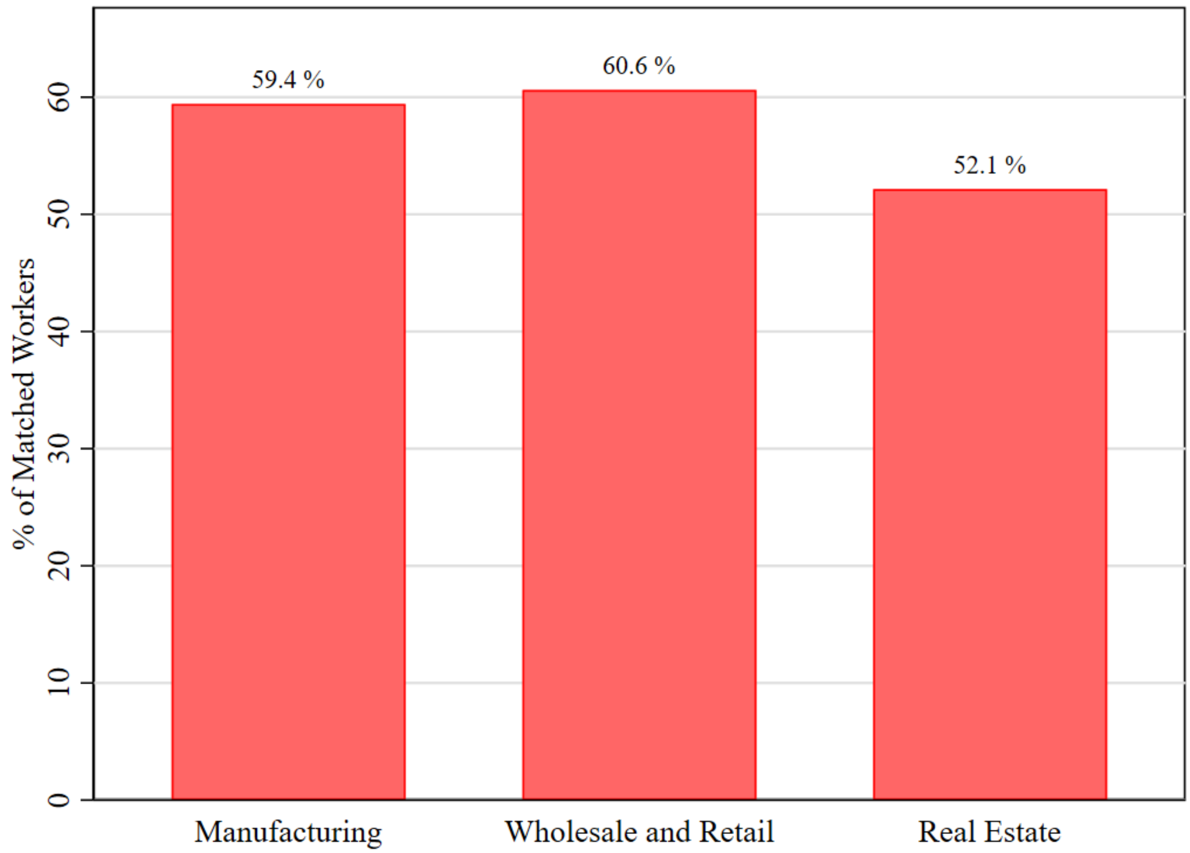


Figure 5-23: LISA/FEC – Percentage of matched workers by industry

Regarding workers' demographic characteristics, Figure 5-24 shows no substantial difference in the percentage of well-matched female and male workers. However, when workers are categorized by age, Figure 5-25 reveals a clear positive relationship between the proportion of well-matched workers and their age. This trend is likely correlated with increased experience.

The positive trend characterizing the relationship between the fraction of matched workers and labour income earned is evident in Figure 5-26. This is likely to be correlated with career progression, experience, and occupation type.

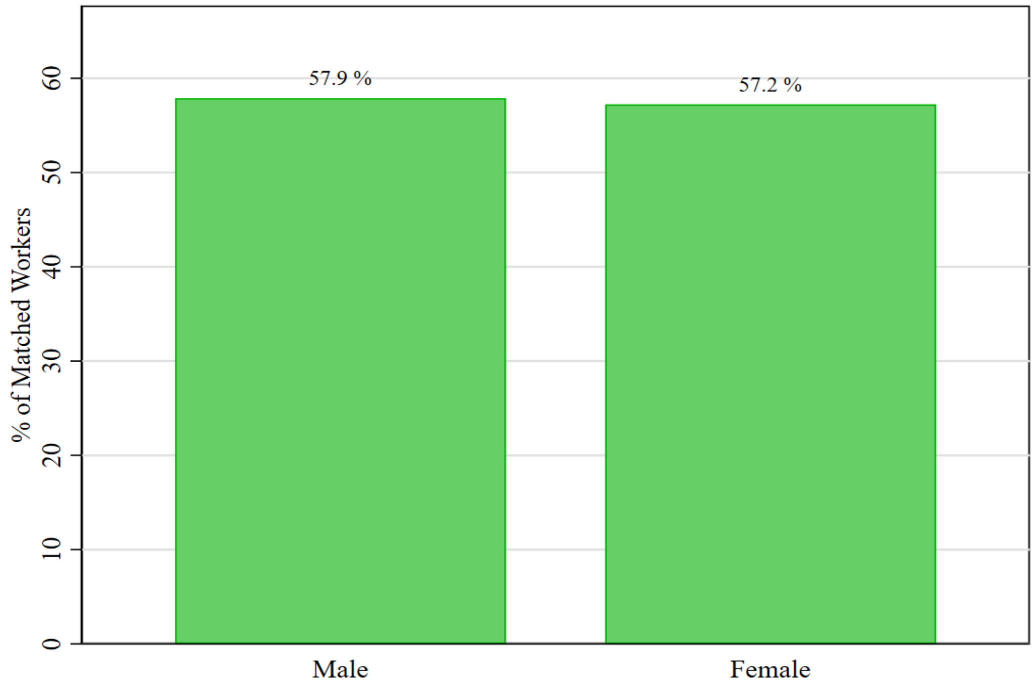


Figure 5-24: LISA/FEC – Percentage of matched workers by gender

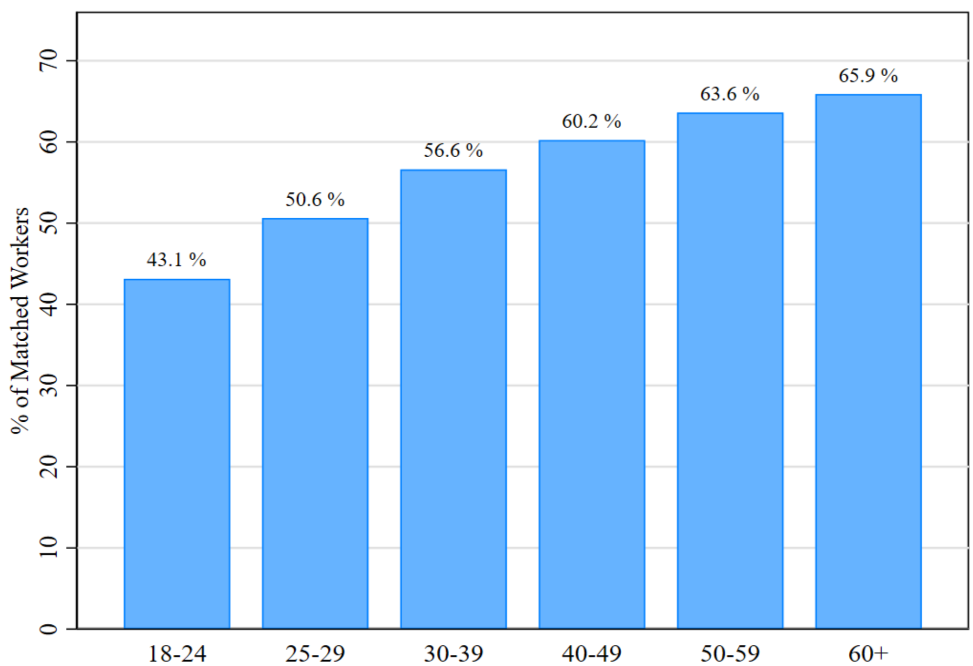


Figure 5-25: LISA/FEC – Percentage of matched workers by age group

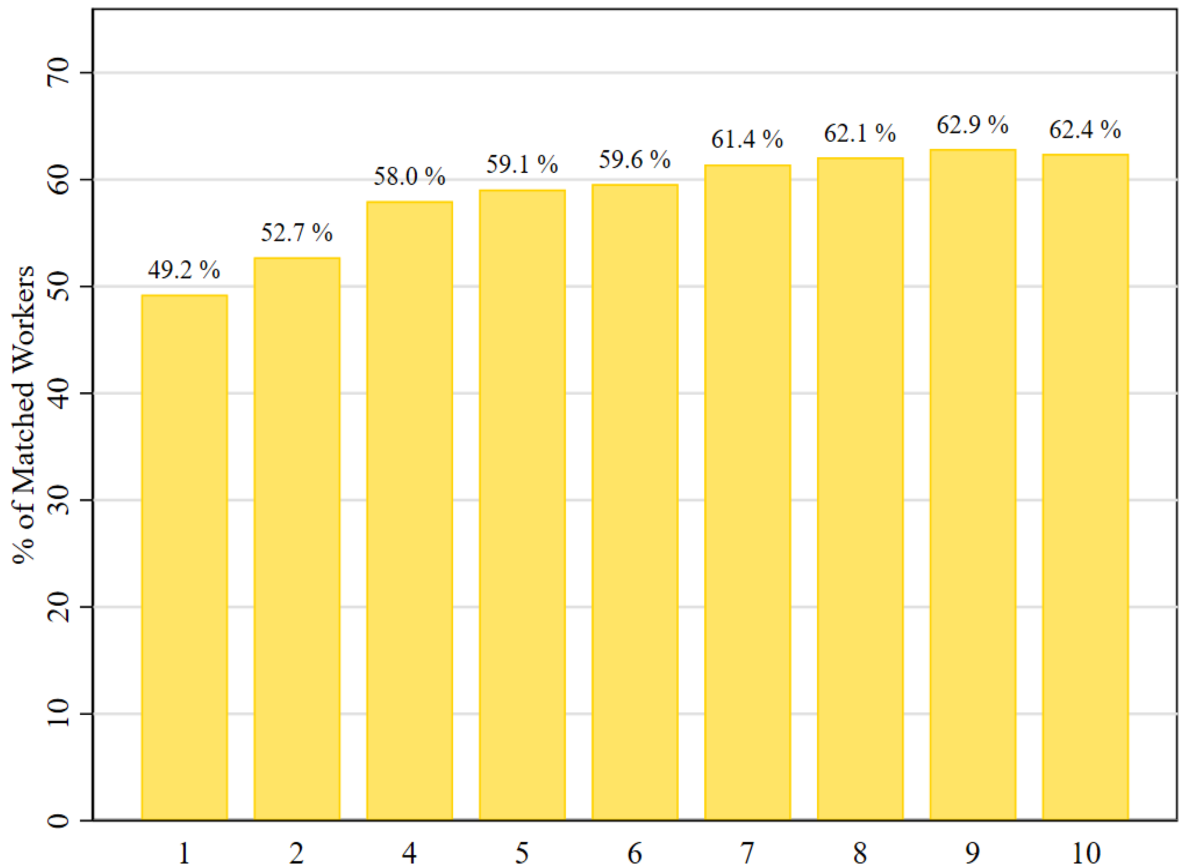


Figure 5-26: LISA/FEC – Percentage of matched workers by income distribution decile

5.3 OTHER COUNTRY-LEVEL MATCHED DATASETS

This sub-section presents a set of 5 administrative matched employer-employee databases that are of interest to the TRAILS project. At the time of this deliverable there are pending applications for access to these databases. Hence, their full description will be presented in follow-up deliverable tasks.

5.3.1 INSEE DATABASE (FRANCE)

The INSEE database refers to a collection of statistical data managed by the Institut National de la Statistique et des Études Économiques (INSEE), which is the National Institute of Statistics and Economic Studies in France. INSEE is responsible for producing and disseminating official statistics related to the French economy and society. The database encompasses a broad range of datasets and statistical products that are essential for economic analysis, policy-making, and research in France.

The primary goal of the INSEE database is to provide accurate, comprehensive, and timely statistical information about various aspects of French society and the economy. This data supports policy-making, economic analysis, and academic research.

The data provides the following information and functions:

- Economic Statistics: Includes data on national accounts, industrial production, trade, investment, and business cycles.
- Labour Market: Provides information on employment, unemployment, wages, labour force participation, and working conditions.
- Demographic Data: Contains data on population size, structure, migration, and demographic changes.
- Household Surveys: Covers income, consumption, and living conditions of households, including detailed survey results from sources like the Household Budget Survey (Enquête Budget de Famille) and the Labour Force Survey (Enquête Emploi).
- Regional and Local Data: Offers detailed statistical data at regional and local levels, including economic, demographic, and social indicators.
- National Accounts: Includes data on GDP, GNP, and other macroeconomic indicators, providing a comprehensive overview of the French economy.
- Labour Force Survey (Enquête Emploi): Provides data on employment, unemployment, job types, and working conditions, allowing for detailed analysis of labour market trends.
- Household Budget Survey (Enquête Budget de Famille): Offers insights into household income, expenditure patterns, and living conditions.
- Census Data: Includes detailed demographic and housing data from the French population census, which is conducted every 5 years.

- Business Statistics: Provides data on business activities, including information on enterprise demographics, financial performance, and sector-specific statistics.

INSEE collects data through various surveys, including regular household surveys, business surveys, and national censuses. INSEE also utilizes data from administrative sources, such as tax records and social security data, to complement survey data and enhance accuracy. INSEE integrates data from multiple sources to provide a comprehensive view of economic and social phenomena.

INSEE provides access to a wide range of statistical data through its website, where users can access datasets, publications, and reports. The data is available in various formats, including tables, charts, and downloadable files. Users can create customized queries and access specific data subsets using online tools provided by INSEE. INSEE publishes regular reports, analytical studies, and statistical bulletins that interpret and contextualize the data.

The data from INSEE is crucial for economic planning and policy formulation, providing insights into economic performance, labour market dynamics, and demographic trends. The information helps in designing and evaluating social policies related to income distribution, housing, and living standards. Regional data supports local development initiatives and helps in addressing regional disparities.

French government agencies and local authorities use INSEE data to inform policy decisions and assess the impact of various programs. Scholars and researchers use the data for economic, social, and demographic research, contributing to a deeper understanding of French society and its dynamics. Companies use INSEE data for market research, business planning, and economic forecasting.

The INSEE database is a vital resource for understanding the economic and social landscape of France. It provides comprehensive, reliable, and up-to-date statistical information that supports informed decision-making and policy development. By offering detailed insights into various aspects of French life, the INSEE database plays a crucial role in shaping economic and social research, guiding public policy, and enhancing public knowledge.

5.3.2 LIAB – LINKED EMPLOYER-EMPLOYEE DATA OF THE IAB (GERMANY)

The LIAB (Linked Employer-Employee Data) is a comprehensive dataset managed by the Institute for Employment Research (IAB) in Germany. LIAB provides detailed linked data on both employers and employees, making it a valuable resource for analyzing labour market dynamics, wage structures, and employment trends in Germany. The dataset integrates information from various sources to offer a nuanced view of employment relationships and economic conditions.

The main goal of LIAB is to provide an extensive and detailed dataset that links information about employees with data about their employers. This linkage enables in-depth analysis of labour market issues, including wage determination, employment stability, and the impact of workplace characteristics on employee outcomes.

The data provides the following information and functions:

- Employee Data: LIAB includes information on individual employees, such as wages, working hours, job tenure, occupation, and demographic characteristics.
- Employer Data: The dataset also contains information on employers, including firm size, industry, location, and business performance.
- Time Period: LIAB covers a significant historical period, typically from the late 1990s to the present, allowing for longitudinal analysis of employment and wage data.
- Social Security Data: LIAB integrates data from the German social security system, which provides detailed records on employees' earnings, contributions, and employment history.
- Firm-Level Data: Information on firms comes from administrative sources, including data on business activities, financial performance, and employment practices.
- Linked Data: The unique aspect of LIAB is the linkage of individual employee records with firm-level data, enabling the analysis of how firm characteristics influence employee outcomes and vice versa.

The key variables include:

- Wages and Salaries: Detailed information on gross and net earnings, bonuses, and other forms of compensation.
- Employment Characteristics: Data on job types, working hours, contract types, and job stability.
- Firm Attributes: Information on firm size, industry sector, regional location, and financial performance indicators.
- Employee Demographics: Age, gender, education level, and other personal characteristics.

LIAB is based on administrative data collected from various sources, including social security institutions and business registries. This ensures high data quality and coverage. The dataset uses sophisticated techniques to link employee records with their respective employers, creating a rich dataset that combines individual and firm-level information.

Researchers use LIAB to study various labour market phenomena, including wage inequality, employment trends, job mobility, and the effects of firm characteristics on employee outcomes. The dataset provides insights into the effects of economic policies on employment and wages, helping policymakers design and evaluate labour market interventions. LIAB supports research on social inequalities, labour market integration, and the impact of labour market policies on different demographic groups.

The dataset helps analyse how wages are influenced by firm characteristics, economic conditions, and employee demographics. LIAB provides insights into job stability and turnover, which are important for understanding employment dynamics and job security. By linking regional data with employment outcomes, LIAB helps to study regional differences in labour market performance and economic development.

LIAB is accessible to researchers and institutions with appropriate permissions, typically through secure data centers or research data services. The dataset is subject to strict confidentiality rules to protect personal and business information. Access is granted under specific conditions to ensure that data privacy is maintained.

The LIAB dataset is a crucial tool for understanding the complex interactions between employers and employees in Germany. By linking individual employee data with firm-level information, LIAB enables detailed and comprehensive analysis of labour market dynamics, wage structures, and employment trends. The insights derived from this dataset are invaluable for researchers, policymakers, and economists working to address labour market challenges and improve economic and social outcomes in Germany.

5.3.3 CBS – CENTRAL BUREAU VOOR DE STATISTIEK DATA (CBS - NETHERLANDS)

The CBS (Centraal Bureau voor de Statistiek), also known as Statistics Netherlands, is the national statistical office of the Netherlands. The CBS provides a wide range of data on various aspects of Dutch society, including the economy, population, and environment. The data collected and disseminated by CBS is crucial for policy-making, economic planning, and research.

In the Netherlands, matched employer-employee data is primarily managed through the Dutch Employee-Employer Database, known as the "Employee-Employer Data (BEST)". This database is a key resource for understanding labour market dynamics, wage structures, and employment patterns in the Netherlands. It integrates detailed information about employees with data about their employers, providing a comprehensive view of employment relationships and firm characteristics.

The primary goal of the Dutch Employee-Employer Database is to provide a detailed, integrated dataset that links information about individual employees with their respective employers. This allows for in-depth analysis of various aspects of the labour market, including wage determination, job stability, and the effects of firm characteristics on employee outcomes.

The data provides the following information and functions:

- Employee Data: Includes detailed records on individual employees such as wages, job titles, employment history, working hours, and demographic information.
- Firm Data: Contains information about firms, including firm size, industry sector, location, financial performance, and other relevant characteristics.
- Employee-Employer Data: Combines administrative records from various sources, including social security and tax data, to link individual worker data with firm-level data.

Data is primarily collected from administrative records maintained by institutions such as the Dutch Social Security Agency (UWV), the Dutch Tax Authority (Belastingdienst), and other governmental bodies. Employees and firms are linked using unique identifiers to integrate individual records with firm-level information. This process allows for detailed longitudinal analysis of employment and wage data.

The key variables include:

- Employee Information: Includes details on gross and net wages, job positions, contract types, job tenure, working hours, and personal demographics (e.g., age, gender, education level).
- Firm Characteristics: Data on firm size (number of employees), industry sector, geographic location, financial status, and organizational structure.
- Employment Relationships: Tracks employment transitions, changes in job roles, and contract types over time.

Researchers use the data to study employment trends, wage disparities, job mobility, and the impact of firm characteristics on worker outcomes. The database supports the evaluation of labour market policies, wage regulation, and employment interventions, helping policymakers understand the effects of various policy measures. The dataset enables insights into how firm attributes influence employment conditions and wage levels, aiding in business planning and economic forecasting.

The dataset helps in designing and assessing policies aimed at improving wage structures, job quality, and overall labour market efficiency. By analyzing firm-level and employment data, insights are gained into regional economic development and addressing economic disparities. Integration of employment data with social security information helps in understanding the impact of social protection programs on the labour market.

Access to the matched employer-employee data is typically available to researchers, academic institutions, and policymakers under strict confidentiality agreements. Data is often accessed through secure data centers or research facilities. The data is anonymized and aggregated to protect the privacy of individual workers and firms. Access is controlled to ensure data security and confidentiality.

The matched employer-employee data for the Netherlands is an invaluable resource for understanding the intricate relationships between employees and employers. By linking detailed individual and firm-level data, it enables comprehensive analysis of labour market dynamics, wage structures, and employment patterns. This rich dataset supports evidence-based policy-making, provides insights into economic and social issues, and contributes to a better understanding of the Dutch labour market and its challenges.

5.3.4 INPS/CERVED – MATCHED WORKER-FIRM DATABASE (ITALY)

The INPS/CERVED Matched Worker-Firm Database is a comprehensive dataset from Italy that combines individual worker data with firm-level information. Managed by the National Institute of Social Security (INPS) in collaboration with CERVED, this database provides a detailed view of the interactions between employees and employers in Italy, enabling rich analyses of labour market dynamics, employment patterns, and economic performance. The primary objective of this database is to integrate detailed worker and firm data to facilitate an in-depth analysis of labour market trends, wage dynamics, employment stability, and the impact of firm characteristics on employee outcomes. The data provides the following information and functions:

- Worker Data: Includes detailed records on employees, such as wages, employment history, job tenure, job types, and demographic information.
- Firm Data: Provides information about firms, including size, industry, financial performance, and other business characteristics.
- Integration: The database links individual employee records with their respective employers, creating a rich dataset for analysis.

The INPS (Istituto Nazionale della Previdenza Sociale) provides detailed records on social security contributions, which include data on wages, employment periods, and other relevant worker information. CERVED provides comprehensive business information, including firm size, economic sector, financial performance indicators, and other organizational attributes.

The database uses administrative records from INPS and business information from CERVED. This includes data on social security contributions and detailed firm characteristics. Data from INPS and CERVED are linked using sophisticated matching techniques, enabling the integration of individual worker data with firm-level data. The key variables include:

- Employee Information: Gross and net earnings, job type, working hours, job stability, education level, and demographic characteristics (e.g., age, gender).
- Firm Characteristics: Firm size, industry classification, financial performance, and regional location.
- Employment Relationships: Job tenure, employment transitions, and changes in job conditions.

Researchers use the database to study wage determinants, employment stability, job mobility, and the effects of firm characteristics on worker outcomes. The dataset supports policy analysis by providing insights into how different types of firms and industries impact employment and wages. The data helps in analysing the relationship between firm performance and employee outcomes, including how economic conditions affect job security and wage levels.

The database provides evidence for evaluating the effectiveness of labour market policies and interventions aimed at improving employment conditions and wage structures. Insights into how firm characteristics influence employment and wages can inform strategies for regional development and business support. The linkage of employment data with social security records allows for better understanding of the impact of social protection programs on worker outcomes.

Access to the INPS/CERVED Matched Worker-Firm Database is generally restricted to researchers and institutions with appropriate permissions, typically through secure data centres. The database is subject to strict confidentiality rules to protect personal and business information. Data is anonymized and aggregated to ensure privacy.

The INPS/CERVED Matched Worker-Firm Database is a crucial tool for analysing the interplay between individual workers and firms in Italy. By linking detailed worker and firm data, it enables comprehensive studies on labour market dynamics, wage distribution, and employment patterns. This rich dataset supports evidence-based policy-making, provides insights into economic and social issues, and contributes to a deeper understanding of the Italian labour market.

5.3.5 Quadros de Pessoal (QdP) dataset (INE: STATISTICS PORTUGAL)

In Portugal, matched employer-employee data is managed and utilized primarily through the Quadros de Pessoal (QdP) dataset, which is a comprehensive administrative database provided by Statistics Portugal (INE). This dataset links individual worker information with firm-level characteristics, allowing for in-depth analysis of labour market dynamics, wage structures, and employment patterns within the country.

The primary goal of the matched employer-employee data is to provide a detailed, integrated view of both employee and employer characteristics. This enables extensive analysis of the interactions between workers and firms, including studies on wage determination, employment stability, and the impact of firm characteristics on employee outcomes.

The data provides the following information and functions:

- Employee Data: The dataset includes detailed information on individual employees, such as job positions, wages, employment history, working hours, and demographic attributes.
- Firm Data: It encompasses information on firms, including size, sector, location, financial performance, and other relevant organizational characteristics.
- Linked Employer-Employee Data: Individual records are linked with firm-level data using unique identifiers, allowing for detailed analyses of employment relationships and firm characteristics.

This is the main source of matched employer-employee data in Portugal. The QdP is an administrative dataset collected by INE, which integrates data from the tax and social security systems. The QdP dataset is derived from various administrative sources, including social security records and tax filings. This ensures a comprehensive and accurate collection of data.

The key variables include:

- Employee Information: Includes details on salaries, job titles, types of contracts, job tenure, working hours, educational background, and personal demographics (e.g., age, gender).
- Firm Characteristics: Provides data on firm size (number of employees), industry sector, geographic location, financial status, and organizational structure.
- Employment Relationships: Tracks job transitions, contract types, changes in job roles, and tenure within firms.

Researchers use this data to study employment trends, wage disparities, job mobility, and the impact of firm characteristics on employment outcomes. The data supports the analysis of labour market policies, wage regulation, and employment interventions, providing insights into the effectiveness of various policy measures. Businesses and policymakers can analyse how different types of firms and industries affect employment conditions and wage levels.

The dataset provides valuable information for designing and assessing policies aimed at improving wage structures, job quality, and labour market flexibility. Insights into firm-level data and employment patterns help in regional development planning and in addressing economic disparities. By linking employee data with social security records, the dataset aids in understanding the impact of social protection programs on labour market outcomes.

Access to the matched employer-employee data is typically granted to researchers, academic institutions, and policy analysts under strict confidentiality agreements. Data is accessed through INE or designated research data centres. The data is anonymized and aggregated to ensure the privacy of individual workers and firms. Access is controlled to protect sensitive information.

The matched employer-employee data in Portugal, particularly through the Quadros de Pessoal (QdP), is a critical resource for understanding the complex interactions between workers and firms. It enables detailed analysis of labour market dynamics, wage structures, and employment patterns, providing essential insights for policymakers, researchers, and businesses. The data supports evidence-based policy-making, economic planning, and social research, contributing to a better understanding of the Portuguese labour market and its challenges.

6. VACANCY DATASETS

This section describes the vacancy datasets that will be used in the TRAILS project, namely SKILLSOVATE and Lightcast. The following two sub-sections present a preliminary inquiry into the specifics of the two datasets.

6.1 SKILLSOVATE

Skillsovate is a comprehensive platform designed to help organizations and individuals understand, manage, and develop skills. It aims to bridge the gap between educational qualifications, job requirements, and skill development by providing data-driven insights and tools. The primary goal of Skillsovate is to enhance skills management by providing a clear understanding of the skills needed in various roles and industries, thereby facilitating skill development, career planning, and workforce management.

The data provides the following information and functions:

- Skills Mapping: Skillsovate offers tools to map skills required for specific job roles, industries, and professions. This includes identifying key competencies and qualifications needed for various positions.
- Skill Assessment: The platform provides tools for assessing current skill levels of individuals or teams, allowing organizations to identify skills gaps and development needs.
- Skill Development: Skillsovate offers resources and recommendations for skill development, including training programs, courses, and educational opportunities tailored to the identified needs.
- Career Pathways: It provides insights into potential career pathways and progression based on existing skills and career goals.

The functions of the data can help organizations manage and develop their workforce by identifying skill gaps and planning training and development initiatives. It can also assist in creating job descriptions and recruitment strategies by defining the skills and qualifications required for various roles. It can support strategic workforce planning by aligning skills with organizational goals and future needs. For Individuals, Skillsovate can aid in understanding the skills required for different career paths and provides guidance on how to acquire these skills. It offers resources and recommendations for skill improvement and continuing education. It can support individuals to find job opportunities that align with their skills and career aspirations.

Skillsovate integrates data from various sources, including job market trends, educational institutions, and industry standards, to provide a comprehensive view of skills and qualifications. It provides customizable dashboards for organizations and individuals to track skills, assess gaps, and monitor progress. It offers advanced analytics and reporting tools to provide insights into skill trends, gaps, and development needs. It suggests relevant training programs, courses, and certifications based on identified skill gaps and career goals.

Skillsovate often uses artificial intelligence and machine learning algorithms to analyse skill data, predict trends, and provide personalized recommendations. It is designed to be intuitive and user-friendly, enabling easy navigation and interaction with the platform. It provides a structured approach to managing and developing skills, leading to improved workforce capabilities and performance. It can facilitate informed decision-making in recruitment, career development, and training by providing accurate and up-to-date skills information. It may support individuals in achieving career advancement by identifying skill gaps and providing resources for improvement.

Skillsovate aspires to play a crucial role in the modern workforce by addressing the increasing need for effective skills management and development. By offering detailed insights into skills and competencies, the platform helps organizations and individuals align their skills with job market demands, improve career prospects, and enhance overall productivity and performance. It is a valuable tool for bridging the gap between current skills and future needs, making it an essential resource for both workforce development and career planning.

6.1.1 THE DATA, THE SAMPLE AND FREQUENCIES

Table 6-1 presents the number of job ads for each EU27 country in 2023. In just 2023, the dataset accounts for over 17 million job advertisements. As is expected, there is a correlation between the number of job ads and the population of each country as just Germany and France together make up over half of the sample, while countries like Malta and Cyprus make up less than 0.1% combined.

Table 6-2 presents the proportion of total job ads that come from each country, over time. Most advertisements come from more populated countries like France and Germany, and the United Kingdom, while smaller countries make up a very small part of the sample.

Figure 6-1 presents the top skills demanded from 2019 to 2023, measured by proportion of total job ads they appear in, in each year. Skills are divided into three categories according to ESCO classification: ‘Skills’, ‘Knowledge’ and ‘Transversal skills and competences’. ‘Demonstrating willingness to learn’ is the top skill in each year and consistently appears in 20 to 40 percent of online job adverts. The structure of the top five skills remains mostly the same over time, with the only key difference being that ‘personal skills and development’ drops out in 2021 and stays out for the remainder of the study period, and is replaced by ‘working efficiently’.

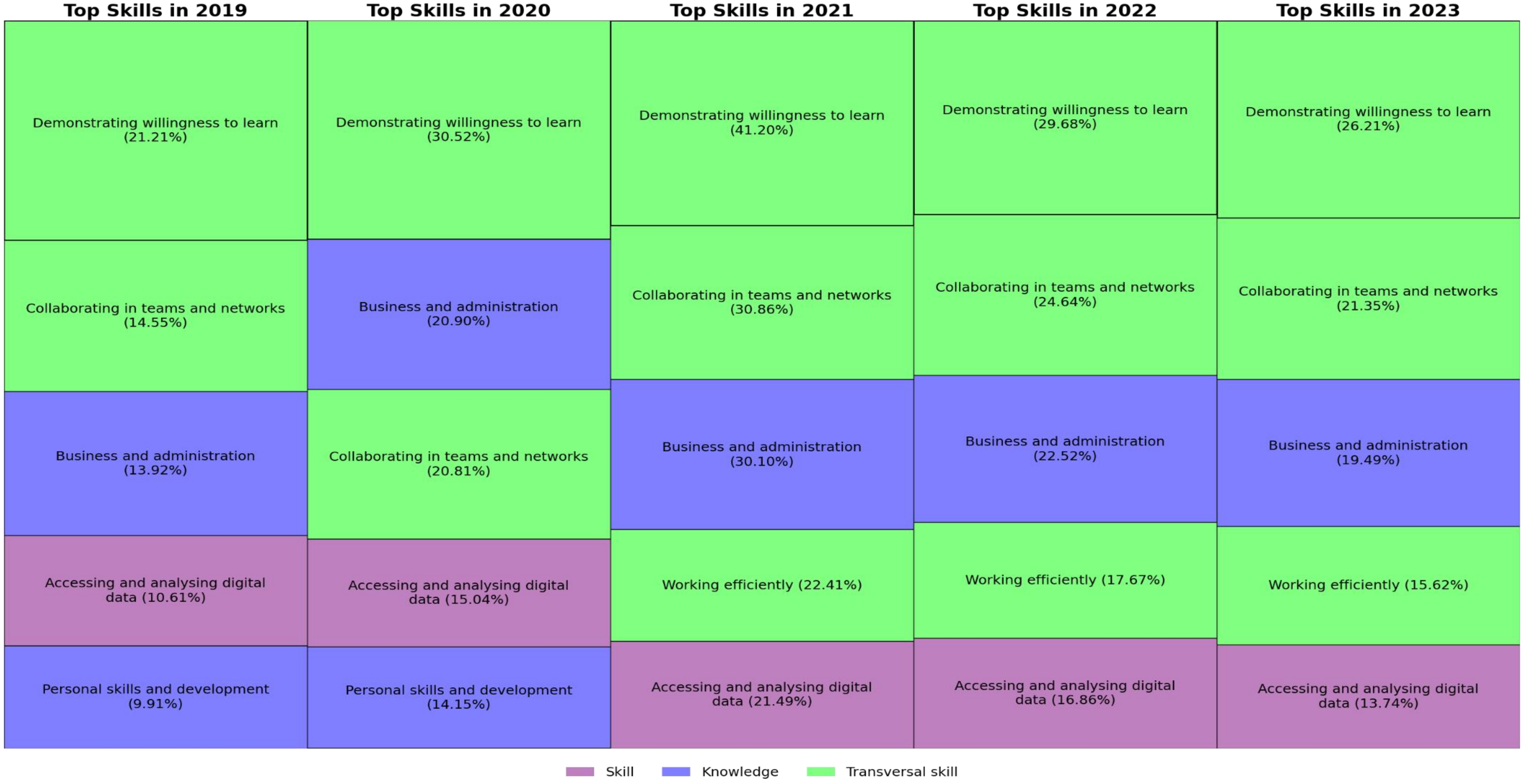
Table 6-1: SKILLSOVATE – Number of job advertisements by country in 2023

	ONLINE JOB ADS 2023	% TOTAL JOB ADS 2023
All Countries	*17,181,068*	100.00%
France	4,639,264	27.00%
Germany	4,169,289	24.27%
Italy	1,780,971	10.37%
Belgium	1,332,199	7.75%
Netherlands	1,226,431	7.14%
Sweden	834,394	4.86%
Spain	595,624	3.47%
Poland	530,760	3.09%
Czechia	299,688	1.74%
Ireland	294,153	1.71%
Slovakia	270,456	1.57%
Portugal	256,862	1.50%
Austria	251,088	1.46%
Denmark	169,675	0.99%
Hungary	111,681	0.65%
Bulgaria	87,291	0.51%
Croatia	83,780	0.49%
Lithuania	69,783	0.41%
Greece	64,512	0.38%
Latvia	45,035	0.26%
Slovenia	34,195	0.20%
Estonia	11,001	0.06%
Malta	8,990	0.05%
Cyprus	6,135	0.04%
Romania	5,986	0.03%
Finland	1,074	0.01%
Luxembourg	751	0.004%

Table 6-2: SKILLSOVATE –Proportion of job ads coming from each country over time

	2019	2020	2021	2022	2023
France	18.43%	18.77%	21.16%	25.34%	32.31%
United Kingdom	23.62%	30.28%	24.35%	23.26%	18.16%
Germany	27.90%	22.01%	20.73%	17.12%	16.59%
Italy	5.26%	6.84%	4.91%	5.39%	5.23%
Netherlands	4.68%	5.00%	5.49%	5.32%	4.89%
Poland	2.55%	3.33%	3.62%	5.02%	4.78%
Belgium	2.98%	2.53%	3.93%	3.92%	3.71%
Sweden	1.62%	1.79%	3.37%	4.03%	3.09%
Spain	3.62%	1.69%	2.20%	1.85%	1.87%
Czechia	1.18%	0.63%	0.89%	1.35%	1.22%
Portugal	0.56%	0.61%	1.39%	0.98%	1.11%
Ireland	1.01%	1.12%	1.32%	1.14%	0.92%
Romania	0.83%	0.53%	0.69%	0.75%	0.89%
Denmark	0.25%	0.21%	0.49%	0.48%	0.80%
Austria	2.55%	2.21%	1.63%	0.95%	0.73%
Slovakia	0.43%	0.29%	0.51%	0.44%	0.71%
Hungary	0.38%	0.29%	0.81%	0.51%	0.57%
Croatia	0.15%	0.20%	0.38%	0.38%	0.41%
Lithuania	0.22%	0.27%	0.39%	0.35%	0.33%
Bulgaria	0.62%	0.55%	0.61%	0.32%	0.32%
Finland	0.42%	0.21%	0.22%	0.19%	0.30%
Latvia	0.15%	0.15%	0.24%	0.28%	0.27%
Greece	0.12%	0.16%	0.20%	0.18%	0.25%
Slovenia	0.12%	0.13%	0.14%	0.15%	0.20%
Cyprus	0.06%	0.04%	0.06%	0.07%	0.12%
Estonia	0.13%	0.10%	0.19%	0.13%	0.08%
Luxembourg	0.13%	0.05%	0.05%	0.07%	0.08%
Malta	0.02%	0.02%	0.04%	0.04%	0.04%

Table 6-3: SKILLSOVATE –Top skills and competences demanded 2019 to 2023
(as a proportion of total advertisements in that year that the skill appeared in)



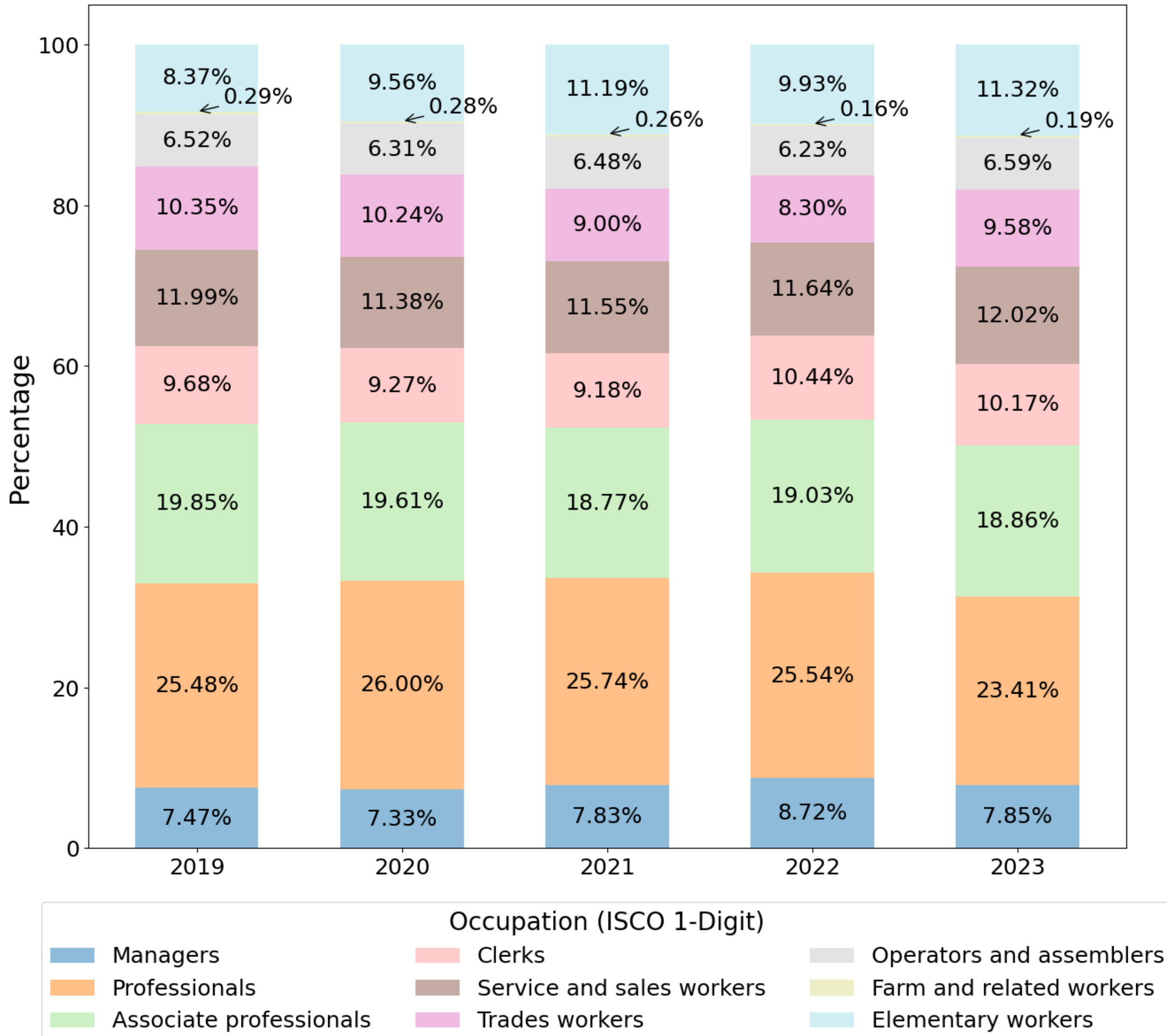


Figure 6-1: SKILLSOVATE – %Breakdown of online vacancies by 1-digit ISCO occupation (2019-2023)

Figure 6-1 presents the percentage breakdown of total online job vacancies by ISCO 1-Digit occupation 2019-2023 in skills-OVATE data. In each year, job ads are dominated by high-skilled professions such as professionals, associate professionals and managers, which account for over half of all job ads in each year. There doesn't seem to be any notable trend in job ads over time, as the proportion for each occupation doesn't change too much over time. Very few farming jobs are advertised in each year (< 0.3% of total ads in each year).

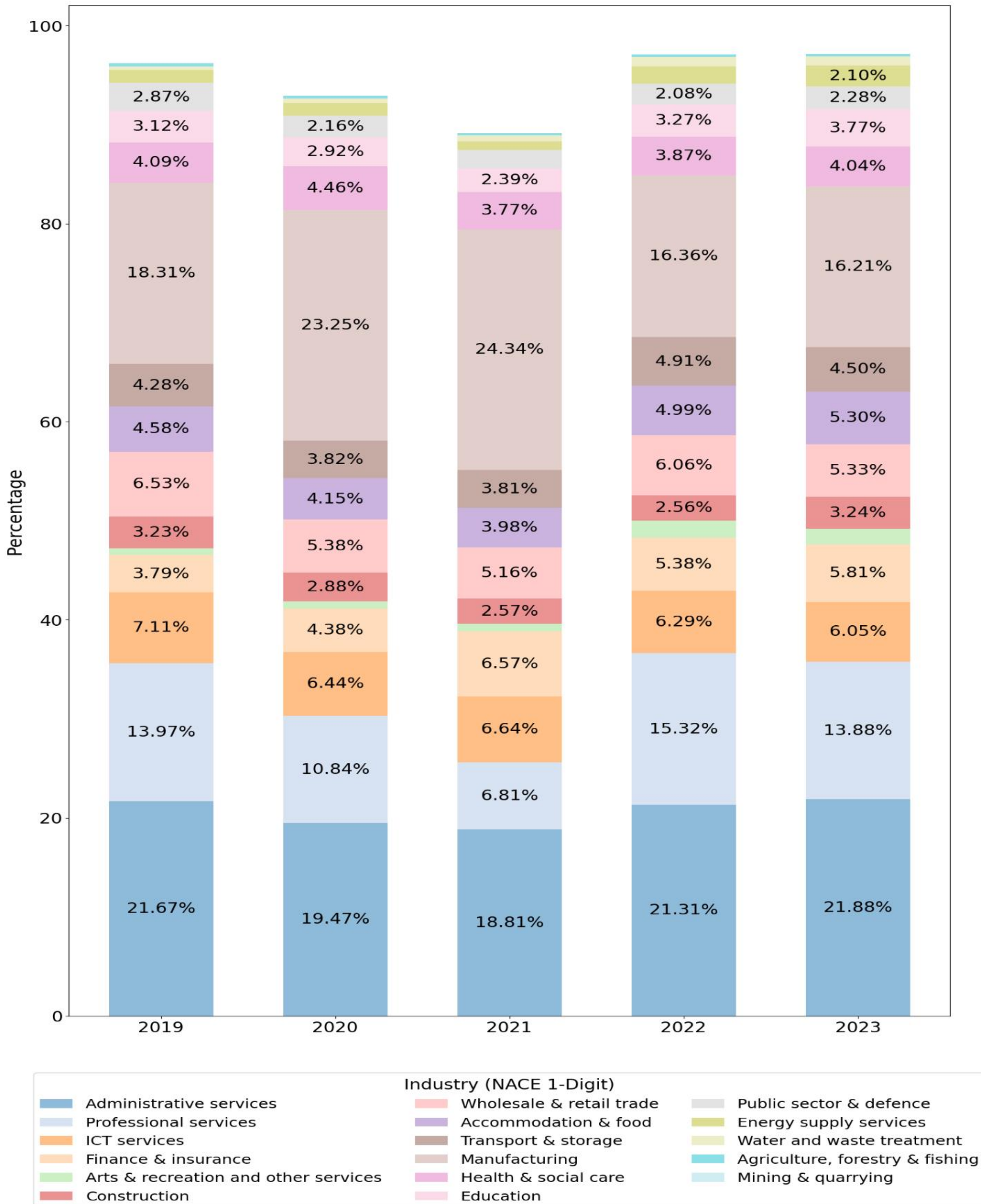


Figure 6-2: SKILLSOVATE –%Breakdown of online vacancies by 1-digit NACE industry (2019-2023)

Figure 6-2 presents the percentage breakdown of total online job vacancies by NACE 1-Digit industry 2019-2023 in skills-OVATE data. There is more temporal variation for industry than there is for occupation. Notable industries where the proportion of jobs ads changed over time are manufacturing and professional services, where job ads for manufacturing followed an inverse u-shaped distribution, accounting for a notably larger proportion of job ads in 2021, and job ads for professional services following an analogous trend. The proportion of job bads for professional services more than halved from 2019 to 2021, and more than doubled from 2021 to 2022.

Figure 6-3 shows the percentage breakdown of total online job vacancies by ISCO 1-Digit occupation 2023 (by Country) from skills-OVATE data. Professional generally make up the largest proportion of job advertisements, along with associate professionals and service and sales workers, while farming has the lowest proportion. Large variation between countries. For example, Estonia has a large proportion of jobs ads for elementary workers and small proportion for associate professionals, when compared to other countries.

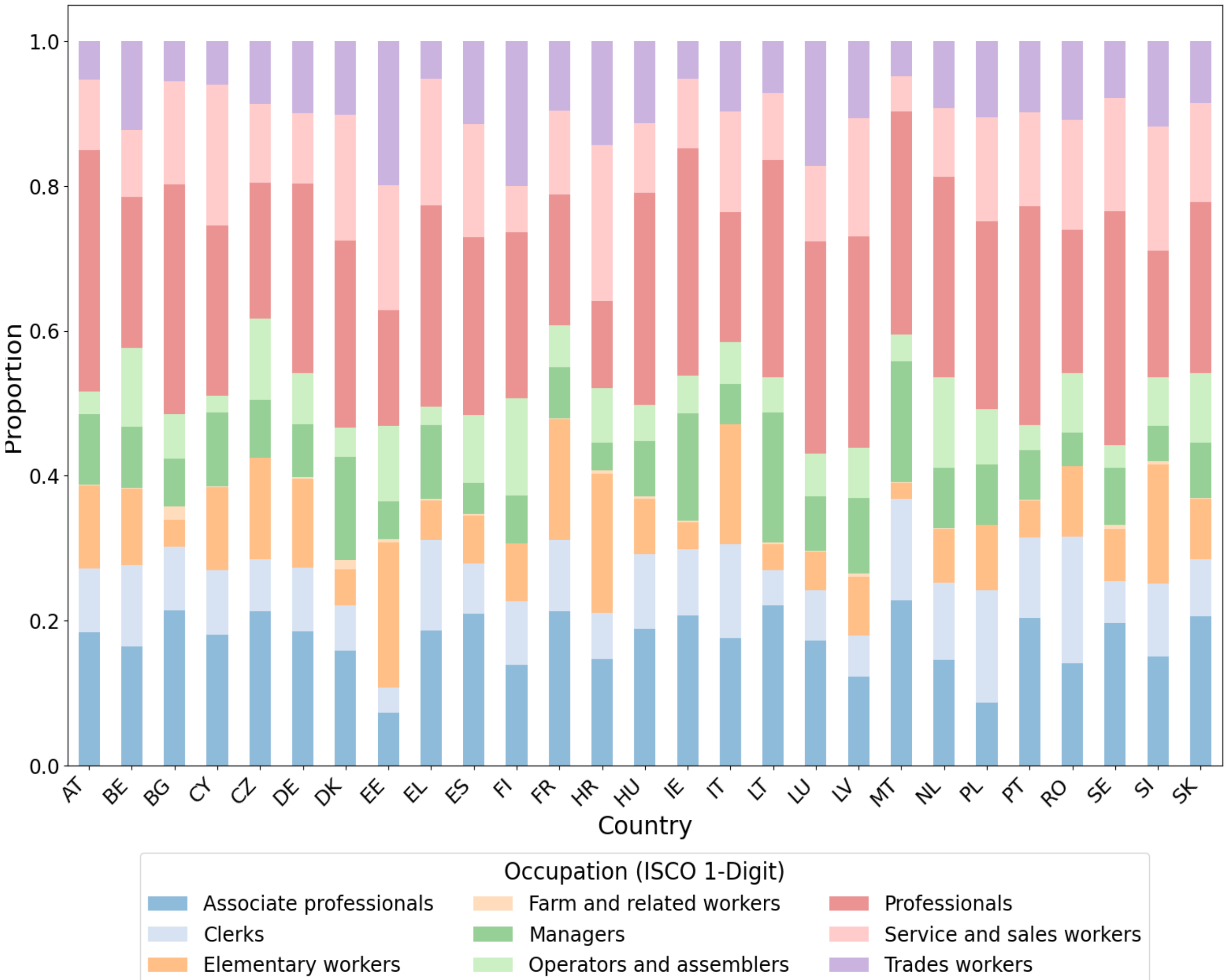


Figure 6-3: SKILLSOVATE –%Breakdown of online vacancies by 1-digit ISCO occupation (2023)

Figure 6-4 presents the percentage breakdown of total online job vacancies by Contract type 2019-2023 (pooled for EU countries) from skills-OVATE data. A large proportion of job ads do not report the contract type, and this phenomenon has actually increased since 2019. In relation to the proportion of job ads that do report contract type, the proportion of advertisements for permanent positions has increased, while those for internships has decreased marginally.

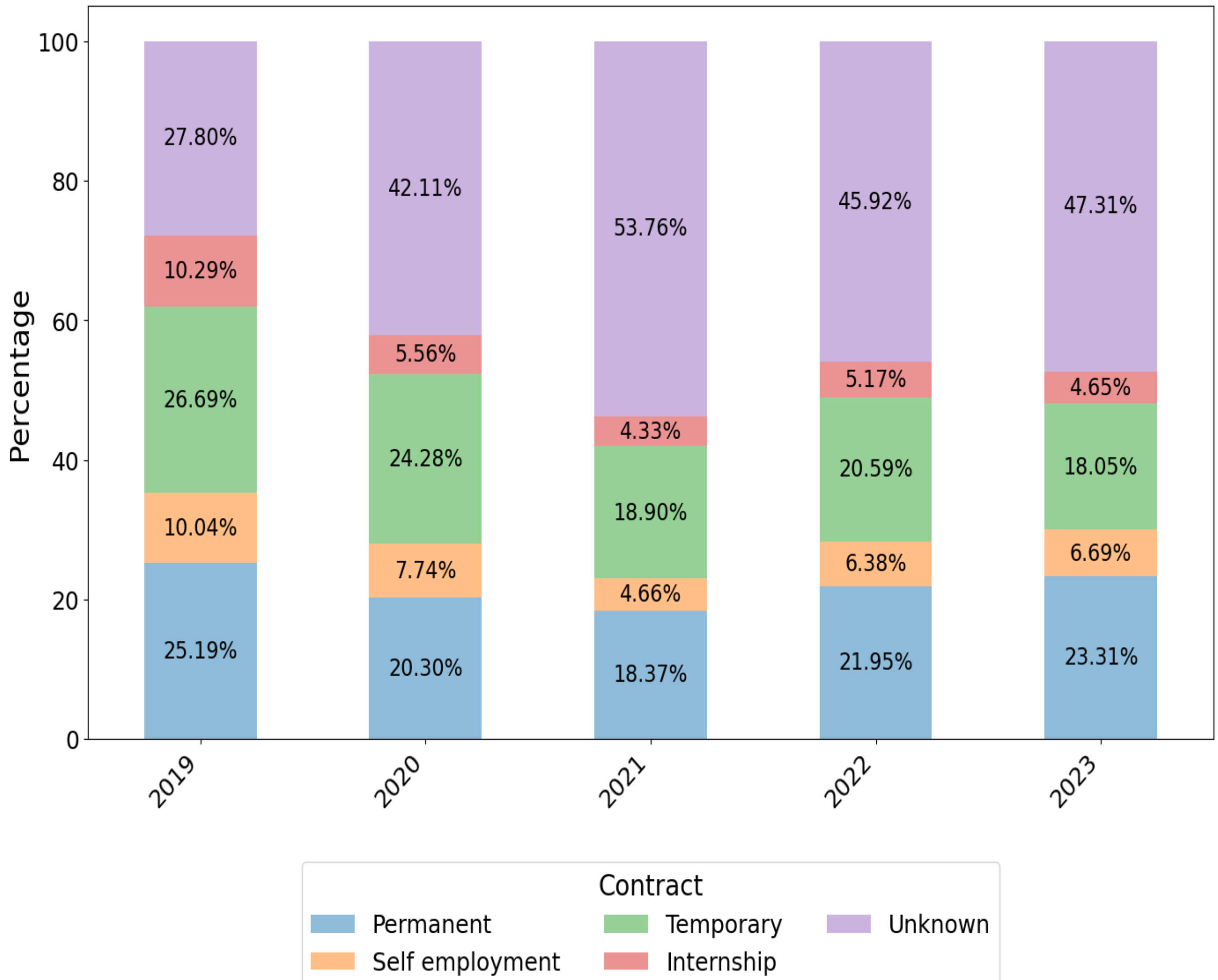


Figure 6-4: SKILLSOVATE -%Breakdown of online vacancies by contract type (2019-2023)

Figure 6-5 presents the percentage breakdown of total online job vacancies by Hours 2019-2023 (pooled for EU countries) from skills-OVATE data. Contrary to what was the case for contract type, hours have become more frequently stated in job ads in recent years. There are between 3.7 (2020) and 5.5 (2021) more full-time jobs advertised than part-time jobs.

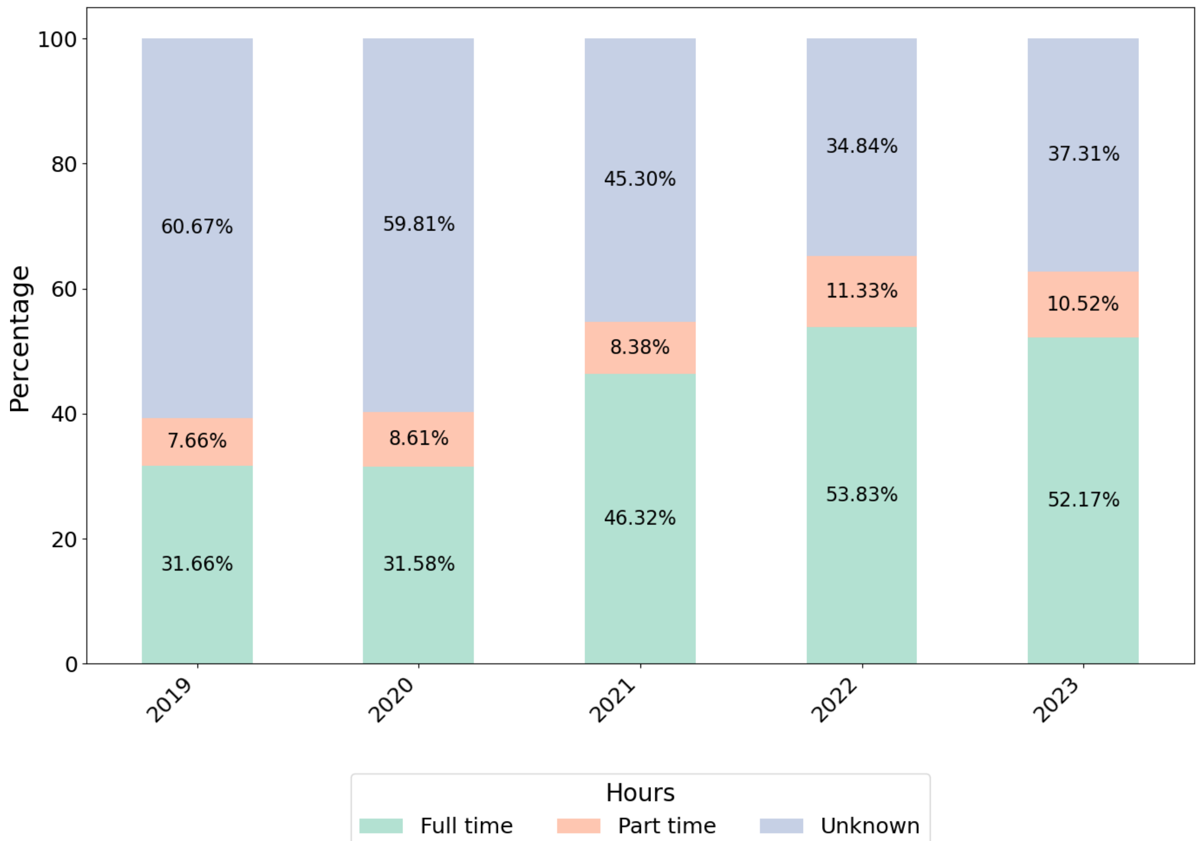


Figure 6-5: SKILLSOVATE –%Breakdown of online vacancies by hours if work (2019-2023)

6.1.2 RELEVANT LITERATURE

An inquiry using the Scopus database suggests some 8 articles using the SKILLSOVATE database. In Figure 6-6 we present a wordcloud of the most frequently appearing words in the index and author keywords of these 8 articles. Then, in Table 6-4, we identify 7 thematic categories, in terms of their content.

The most frequent words in the 8 articles are learning, education, skills, health, secondary, office, 21st century, teaching, delphi, remote, students, inter alia. Table 6-4 shows 7 diverse thematic areas of research using the SAFE. These are: (1) Artificial Intelligence & 21st Century Competencies; (2) Learner-Centered Education & 21st Century Skills; (3) Skills Demand in Emerging Technologies (Blockchain); (4) Employability & Transnational Online Collaboration; (5) Sector-Specific Future Skills (Fitness Industry); (6) Data & Computational Methods in Tourism; (7) Employer Priorities in Hiring Processes (Latvia).

Table 6-4: SKILLSOVATE –Classification of the relevant 8 articles

Thematic Area	Citations
Artificial Intelligence & 21st Century Competencies	Tuomi (2022)
Learner-Centered Education & 21st Century Skills	Dolezal et al. (2021); Posekany et al. (2021)
Skills Demand in Emerging Technologies (Blockchain)	Matei & Năstasă (2023)
Employability & Transnational Online Collaboration	Koris et al. (2024)
Sector-Specific Future Skills (Fitness Industry)	Moustakas et al. (2020)
Data & Computational Methods in Tourism	Romanillos & Moya-Gómez (2023)
Employer Priorities in Hiring Processes (Latvia)	Lice & Sloka (2022)

Figure 6-6: SKILLSOVATE -Word cloud of the keywords of 8 relevant articles

6.2 LIGHTCAST

Lightcast is a data platform that provides insights into labour market trends, workforce dynamics, and skills demand. Formerly known as Emsi Burning Glass, Lightcast leverages a wide range of data sources to offer comprehensive labour market analytics. Its goal is to help organizations, educational institutions, policymakers, and individuals make informed decisions about workforce development, education, and career planning.

Lightcast aims to offer actionable insights into the labour market by analyzing job postings, workforce skills, industry trends, and employment patterns. The platform helps users understand demand for various skills, predict future labour market trends, and make data-driven decisions.

The data provides the following information and functions:

- Labour Market Data: Aggregates and analyses data from job postings, company websites, and other sources to provide a detailed view of job market trends, including in-demand skills and emerging job roles.
- Skills and Occupations: Offers detailed information about the skills required for various occupations, including skill gaps, salary expectations, and career progression.
- Education and Training: Provides insights into educational and training programs that align with current and future job market needs, helping institutions and individuals choose relevant programs.
- Economic and Industry Insights: Analyses economic trends and industry-specific data to provide context for workforce planning and economic development.

Lightcast aspires to help organizations understand the skills in demand, optimize job descriptions, and refine recruitment strategies. It can assist in identifying future skills needs, managing talent pipelines, and aligning workforce capabilities with business goals. It aims to provide competitive intelligence on industry trends, salary benchmarks, and labour market conditions. For education purposes, Lightcast can supports the development of educational programs and curricula that align with labour market needs and skill demands. It can enhance career services by providing data on job market trends and skills requirements, helping students and alumni make informed career decisions.

Moreover, it provides insights that can assist in designing policies and initiatives to address skills gaps, support workforce development, and promote economic growth. It provides data for evidence-based policymaking related to employment, education, and training. Lightcast offers up-to-date information on job postings, skills demand, and labour market trends, allowing users to stay informed about the latest developments. It utilizes machine learning and data analytics to identify trends, predict future labour market changes, and provide actionable insights. It provides customizable reports and dashboards to visualize data according to specific needs and preferences. It delivers localized data to understand labour market conditions at regional, state, or city levels.

Lightcast integrates data from various sources, including job boards, company websites, and economic reports, to provide a comprehensive view of the labour market. It employs advanced algorithms to analyse large datasets, uncover patterns, and make predictions about future trends. Among its benefits, Lightcast can enable organizations, educational institutions, and individuals to make informed decisions based on current and projected labour market trends. It can support strategic workforce and educational planning by providing insights into skills demand, job market conditions, and industry trends. It can help career counselors and advisors provide relevant advice and guidance based on up-to-date labour market data.

Lightcast plays a crucial role in the modern labour market by providing comprehensive and actionable insights into employment trends, skills demand, and workforce dynamics. Its data-driven approach supports effective decision-making for workforce development, educational program design, and economic policy. By offering a detailed understanding of labour market conditions, Lightcast helps organizations, institutions, and individuals navigate the complexities of the job market and align their strategies with current and future needs.

Access to the Lightcast data has just been acquired at the time of completion of this deliverable. Hence, the processing and presentation of its data is left for future deliverable tasks.

7. TAXONOMIES

This section describes the two taxonomies that will be utilised in forthcoming deliverable tasks of the TRAILS project, namely (a) ESCO and (b) the EU Taxonomy of Sustainable Activities.

7.1 EUROPEAN SKILLS, COMPETENCES, QUALIFICATIONS AND OCCUPATIONS (ESCO)

The European Skills, Competences, Qualifications and Occupations (ESCO) is a European Commission initiative aimed at creating a comprehensive multilingual classification system that describes and categorizes skills, competences, qualifications, and occupations across Europe. It is designed to support transparency and understanding in the labour market, enhance job matching, and facilitate workforce development and mobility.

The main goal of ESCO is to provide a standardized and detailed framework that enables better alignment between job seekers, employers, and educational institutions. It aims to enhance labour market efficiency by creating a common language for skills, qualifications, and occupations across European countries.

Its core components are the following:

- Skills: Detailed descriptions of various skills required for different job roles, including both soft skills (e.g., communication, teamwork) and hard skills (e.g., technical skills, specialized knowledge).
- Competences: Broader than skills, competences encompass a combination of knowledge, skills, and personal attributes that are necessary for performing tasks and achieving results in specific contexts.
- Qualifications: Descriptions of educational and training credentials, certifications, and professional qualifications that are recognized across Europe.
- Occupations: Detailed classifications of job roles and professions, including job titles, descriptions, and the typical tasks and responsibilities associated with each occupation.

ESCO is structured hierarchically with three main levels:

- Level 1: High-level categories for skills, competences, qualifications, and occupations.
- Level 2: More detailed subcategories and specific terms within each high-level category.
- Level 3: The most granular level, providing detailed definitions and descriptions for individual skills, competences, qualifications, and occupations.

Its applications involve:

- Job Matching: Enhances the ability to match job seekers with job vacancies by providing a standardized way to describe job requirements and candidate qualifications.
- Career Guidance: Supports career counselors and advisors by offering a clear understanding of the skills and qualifications needed for various career paths.

- Education and Training: Assists educational institutions in designing and aligning curricula and training programs with the needs of the labour market.
- Policy Making: Aids policymakers in developing strategies and policies related to employment, education, and training by providing a standardized framework for skills and qualifications.

ESCO is available in multiple European languages, making it accessible and useful across different countries and linguistic contexts. It is built upon extensive data from labour market research, job descriptions, and industry standards, ensuring that the classifications are relevant and up-to-date.

Dynamic Updates: Regularly updated to reflect changes in the labour market, emerging skills, and evolving job roles. ESCO is available through an online platform where users can access and search for information on skills, competences, qualifications, and occupations. It is designed to be compatible with other classification systems and databases, facilitating integration and use in various applications.

ESCO provides a clear and standardized framework for understanding and communicating skills, qualifications, and job roles across different countries and sectors. It facilitates better job matching and career development by providing a common language and framework for skills and occupations. It can help organizations, educational institutions, and policymakers align their efforts with labour market needs and emerging trends.

ESCO is a vital tool for improving labour market efficiency and enhancing the alignment between skills supply and demand across Europe. By providing a standardized classification system, ESCO supports better job matching, career guidance, and educational planning. It facilitates mobility within the European labour market and helps ensure that skills and qualifications are recognized and valued consistently across different countries and sectors. This comprehensive framework contributes to a more transparent, efficient, and adaptable labour market in Europe.

The **ESCO (European Skills, Competences, Qualifications, and Occupations)** taxonomy is a classification system developed by the European Commission to standardize the terminology related to the labour market, education, and training in the EU. It serves to bridge the gap between the world of work and education by creating a common language for skills, competences, qualifications, and occupations.

In summary, the ESCO taxonomy plays a critical role in aligning education, training, and employment across the EU, fostering better job matching, skill development, and labour market mobility. Table 7-1 provides a breakdown of the key pillars of the ESCO taxonomy, and Table 7-2 summarizes its features.

Table 7-1: ESCO – Key pillars of the taxonomy

ESCO PILLAR	DETAILS
Occupations	- Over **3,000 occupations**. - Linked to skills and qualifications. - Based on ISCO-08 for international alignment.
Skills and Competences	- Over **13,000 skills**. - Includes both **hard (technical)** and **soft skills**. - Defined with varying proficiency levels.

Qualifications	- Formal qualifications linked to occupations and skills. - Covers academic degrees, vocational qualifications, and certifications.

Table 7-2: ESCO – Main features

FEATURE	DESCRIPTION
Purpose	ESCO is designed to identify and categorize skills, competences, qualifications, and occupations across the EU labour market. It facilitates job matching, career guidance, and curriculum development.
Structure	ESCO is structured into three interrelated pillars: Occupations, Skills/Competences, and Qualifications. Each pillar is linked, allowing for a comprehensive view of job roles and their required skills.
Occupations Pillar	- Description: Defines and categorizes occupations based on their specific activities and roles in the labour market. - Classification: Based on the International Standard Classification of Occupations (ISCO), it includes over 3,000 occupations. - Examples: Software developer, mechanical engineer, nurse, teacher.
Skills/Competences Pillar	- Description: Lists specific skills, knowledge, and competences required for each occupation. - Classification: Contains more than 13,000 skills and competences, categorized into technical and soft skills. - Examples: Programming skills (technical), communication skills (soft).
Qualifications Pillar	- Description: Provides information about recognized qualifications (e.g., diplomas, degrees) linked to occupations and skills. - Classification: Includes formal qualifications from different educational systems and countries. - Examples: Bachelor's degree in engineering, vocational certificates, professional licenses.
Cross-Language Compatibility	ESCO is available in all EU official languages to support mobility across the EU, making it easier for job seekers and employers to understand job requirements across borders.
Link to ISCO	The occupations pillar is aligned with ISCO-08 (International Standard Classification of Occupations) to ensure global compatibility and consistency with international labour standards.
Skills Proficiency Levels	ESCO describes proficiency levels for various skills to provide a clearer understanding of the expected expertise (e.g., beginner, intermediate, advanced).
Use in Digital Platforms	ESCO is integrated into EUROPASS, EURES, and other digital platforms to assist with CV building, job matching, and career exploration. It can also be used in AI-driven recruitment tools.
Contextual Information	For each occupation, ESCO provides contextual information, including skill descriptions, job-specific tasks, required qualifications, and links to related occupations and skills.
Dynamic Updates	The taxonomy is continuously updated in response to changing labour market demands, new technologies, and evolving job roles, ensuring its relevance to employers and educators.

Interoperability	ESCO is designed to be interoperable with other classification systems, databases, and tools used by public employment services, educational institutions, and private sector platforms.
Support for Policy and Research	ESCO supports labour market analysis, policy-making, and research by providing detailed data on occupational trends, skills gaps, and qualification needs. It helps identify skills mismatches and inform training and education programs.
Main Users	Job seekers; Employers; Educators and trainers; Policy makers.
Application	Career guidance; Job matching; Curriculum design

7.2 EU TAXONOMY OF SUSTAINABLE ACTIVITIES

The EU Taxonomy of Sustainable Activities is a classification system that provides a clear and standardized framework for determining which economic activities can be considered environmentally sustainable. It is a central element of the European Union's Green Deal and its broader efforts to achieve the EU's climate and environmental objectives by 2050, particularly through its climate neutrality goals. Here's a comprehensive breakdown of the taxonomy:

The framework was formally established by the EU Taxonomy Regulation, adopted in June 2020, and is designed to be dynamic, adapting to evolving environmental goals, scientific progress, and sectoral innovations. The EU Taxonomy was introduced as part of the EU's broader action plan on financing sustainable growth, aiming to:

- Redirect capital flows towards more sustainable investments.
- Establish a common language for businesses and investors about what qualifies as "sustainable."
- Help prevent "greenwashing," where companies or investments are misleadingly marketed as environmentally friendly.

The Taxonomy defines environmentally sustainable activities based on six environmental objectives:

1. Climate Change Mitigation: Activities that contribute substantially to reducing or preventing greenhouse gas emissions.
2. Climate Change Adaptation: Activities that improve resilience to the impacts of climate change.
3. Sustainable Use and Protection of Water and Marine Resources: Activities that reduce pollution and enhance the conservation of water ecosystems.
4. Transition to a Circular Economy: Promoting resource efficiency, waste reduction, recycling, and reuse.
5. Pollution Prevention and Control: Reducing the generation of waste and pollution.
6. Protection and Restoration of Biodiversity and Ecosystems: Activities focused on conserving habitats and species.

There are 4 key criteria for an activity to be classified as sustainable under the EU Taxonomy, it must:

1. Substantially Contribute to at least one of the six environmental objectives mentioned above.
2. Do No Significant Harm (DNSH) to any of the other five objectives. This ensures that an activity promoting one objective (e.g., renewable energy) doesn't negatively impact another (e.g., biodiversity).

3. Comply with Minimum Safeguards, such as labour rights and international human rights standards, ensuring alignment with global social and governance standards.
4. Meet Technical Screening Criteria, which are sector-specific and science-based thresholds established to determine what constitutes a "substantial contribution" or "significant harm."

The Technical Screening Criteria (TSC) are the operational guidelines and performance thresholds developed for different economic sectors to assess whether their activities meet the standards of the EU Taxonomy. These criteria are tailored to individual sectors, making them specific and measurable. They are set through delegated acts, with input from various stakeholders, including scientists, industry experts, and environmental groups. For example, for climate change mitigation: An activity like electricity production from renewable energy must meet specific carbon intensity thresholds to qualify. Moreover, for climate change adaptation: An infrastructure project might need to ensure that it incorporates climate resilience measures.

The EU Taxonomy applies to a wide range of sectors, including but not limited to:

- Energy: Renewable energy production (e.g., wind, solar), nuclear energy (which has been controversial), and energy efficiency improvements.
- Transportation: Electric vehicles, rail transport, and sustainable urban planning.
- Agriculture: Practices promoting biodiversity, reducing emissions, and improving soil health.
- Manufacturing: Activities promoting circular economy principles like recycling and remanufacturing.
- Construction and Real Estate: Buildings that meet high energy efficiency standards.
- Information and Communication Technology (ICT): Data centers that meet energy efficiency and water usage standards.

The EU Taxonomy has a direct impact on companies, investors, and financial institutions, particularly in terms of transparency. Under the Sustainable Finance Disclosure Regulation (SFDR) and the Corporate Sustainability Reporting Directive (CSRD), companies must disclose the extent to which their activities align with the Taxonomy. Financial market participants are required to: (a) Disclose how their investments align with the EU Taxonomy, whether their portfolios are sustainable, and how they are addressing environmental risks; (b) Large companies are required to report on how much of their revenue, capital expenditure, and operational expenditure is linked to sustainable activities under the Taxonomy.

The Taxonomy is being implemented gradually. Initially, it focused on climate change mitigation and adaptation, with criteria for these objectives starting to apply from January 2022. The other four environmental objectives (water and marine resources, circular economy, pollution, and biodiversity) will have criteria phased in by 2023.

While the EU Taxonomy has been lauded as a groundbreaking effort to standardize sustainable finance, it has also faced criticism and challenges. Businesses argue that compliance with the Taxonomy can be difficult, particularly in terms of gathering and verifying the required data. Controversial sectors like nuclear energy and natural gas have sparked debates over their inclusion in the Taxonomy, as some argue they are necessary for the transition, while others believe they are not truly sustainable. The Technical Screening Criteria are updated regularly, which can create uncertainty for businesses trying to plan long-term investments.

The EU Taxonomy is a key tool in shaping the sustainable finance landscape. It is expected to:

- Encourage financial institutions to invest more in green technologies and sustainable projects.
- Help bridge the financing gap needed to achieve the EU's climate goals, which is estimated to be hundreds of billions of euros annually.
- Set a global standard that other regions and countries may follow or adapt.

The EU Taxonomy of Sustainable Activities represents a significant step in the EU's efforts to promote sustainability across its economy and financial system. By providing a clear framework for what qualifies as environmentally sustainable, the Taxonomy aims to guide investments, ensure transparency, and prevent greenwashing, ultimately driving the EU closer to its climate neutrality goals by 2050. However, it remains a dynamic and evolving system, continually adapting to new scientific findings, technologies, and political realities. Table 7-3 provides an overview of the key sustainable economic activities covered under the EU Taxonomy framework.

Table 7-3: The EU Taxonomy of Sustainable Activities

ENVIRONMENTAL OBJECTIVE	KEY SUSTAINABLE ECONOMIC ACTIVITIES	EXAMPLE CRITERIA/TECHNICAL THRESHOLDS
Climate Change Mitigation	- Renewable energy production (e.g., wind, solar, hydro)	Carbon intensity below specific thresholds (e.g., gCO_2/kWh for energy production)
	- Manufacture of low-carbon technologies (e.g., wind turbines, solar panels)	Efficiency in energy use and material recycling
	- Construction of energy-efficient buildings	Primary energy demand is 20% lower than national thresholds
	- Transport: Electric vehicles (EVs), rail transport, public transport	EVs must meet zero-emission standards; public transport must use renewable energy
	- Afforestation, reforestation, and forest management	Carbon sequestration targets
Climate Change Adaptation	- Climate-resilient infrastructure and buildings	Adaptation to climate risks (e.g., flood-proofing, heat-resilient designs)
	- Adaptation in agriculture and forestry (e.g., drought-resistant crops)	Reduced vulnerability to climate risks, with monitoring of impacts
	- Water management and flood protection infrastructure	Infrastructure to manage increased water flows due to climate change
Sustainable Use & Protection of Water and Marine Resources	- Water supply and wastewater management	Reduction of water leakage below set thresholds
	- Marine ecosystem conservation (e.g., sustainable fisheries)	Sustainable quotas, practices that protect ecosystems
	- Desalination plants using renewable energy	Use of renewable energy for desalination
Transition to a Circular Economy	- Waste management, recycling, and composting	Recycling rates meet EU Circular Economy targets
	- Manufacturing using recycled or sustainably sourced materials	Percentage of recycled content in final products
	- Repair, remanufacturing, and product-life extension (e.g., appliances)	Durable design, repairability, and recyclability requirements
	- Circular construction practices (e.g., material reuse in buildings)	Use of secondary raw materials in construction
Pollution Prevention and Control	- Air pollution control technology (e.g., emission filters, scrubbers)	Compliance with EU air quality standards
	- Waste prevention and treatment	Reduction of hazardous waste generation
	- Production of low-toxicity chemicals and sustainable agriculture inputs	Reduced use of harmful pesticides or chemicals
	- Renewable energy (biogas) from waste	Waste-to-energy technologies compliant with environmental standards
Protection and Restoration of Biodiversity and Ecosystems	- Conservation projects (e.g., wetland, forest, and coastal habitat restoration)	Maintenance and restoration of natural habitats
	- Sustainable agriculture (e.g., organic farming, agroforestry)	Agricultural practices promoting biodiversity and soil health
	- Eco-tourism activities that protect biodiversity	Activities that do not harm local ecosystems, meet conservation standards

Notes: Each activity must meet Technical Screening Criteria established for each objective, which are specific and measurable. Activities must also adhere to the "Do No Significant Harm (DNSH)" principle for other environmental objectives. The table is not exhaustive, and the EU Taxonomy is continually evolving with new sectors and activities being added.

8. CONCLUDING REMARKS

The objectives of deliverable task D2.1 are a threefold:

- To initiate work with the big European secondary datasets, and familiarize all the partners and members of the TRAILS project regarding the available menu, features and likely options.
- To provide the preliminary analysis of the core secondary datasets, in a manner that enables the visual inspection of country-level differences, alongside differences across key population groups of primary interest, i.e., gender, generational, and vulnerable groups, in domains that are pivotal to skills matching, and the choice of and the organization of training.
- To provide input to forthcoming deliverable tasks in the majority of workpackages of the TRAILS project, including inputs useful for visualization at the TRAILS platform.

The analysis presented some 21 datasets, covering all (a) individual, (b) household, (c) firm, (d) matched employer-employee, and (e) vacancy datasets. 11 if these datasets were presented in some great detail. Then, a basic description of two relevant taxonomies was provided, which will be processed in some great detail as part of workpackage 5. Moreover, there are also 6 datasets, which are still pending approval by the data collector for use at the TRAILS project. There are 2 additional datasets, for which approval was granted only a few days before the submission of task D2.1. These will be presented as part of the tasks of workpackage 3, 4, and 5.

Via over 120 pages of text, 20 pages of referenes, and more than 80 tables and 160 figures, task D2.1 has achieved the three main objectives set at the proposal and consortium agreement. Furthermore, the analysis of the data has provided some interesting insights which could merit further investigation in following deliverable tasks, but they could also serve as dissemination material for newsletters and policy briefs.

More specifically, the analysis of the individual-level data has provided with the following key points:

- The overview of the EU-LFS illustrated that 2014 was a detrimental year for skills mismatching in Europe. Most of the countries witnesses large drops in skills matching by employees, and Europe appears to still be in recovery up to the year 2022. This pattern is not shown by datasets provided snapshots in the post-2014 period, and it is also not shown by datasets that do not approximate occupation matching at least at the 3-digit ISCO level, like the EU-LFS does. Training participation during the recent past appears to be low at the EU-LFS, although the analysis suggests that informal job-related training has been rising.
- The inspection of the ESJS showed that underutilization of skills or overskilling seems to be more prevalent than both horizontal and vertical mismatch in nearly all countries, sometimes even being twice as high as either of them. Social skills are most frequently reported as an area where employees need to improve, followed by job-specific skills, then numeracy skills, with digital skills being generally reported the least as an aspect that needs improvement. Moreover, VET completion rates seem to have fallen in most of the countries between 2014 and 2021.
- The presentation of the AES highlighted that it is evident that most countries show increasing participation in both formal and non-formal education activities, although there are instances

of declining trends in some countries. Moreover, there are more individuals and better off in terms of the income distribution among those who participate in training, particularly in formal education and training.

Moreover, the presentation of the household-level data has indicated the following:

- The overview of the EU-SILC suggested that the new member states of Eastern Europe showcase better skills matching statistics among their workforce, a finding in agreement with the EU-LFS analysis. Mismatched individuals are less financially resilient at the EU-SILC, as they are less likely to make ends meet and be able to face unexpected expenses. They are also more likely to face a heavy financial burden. The young tend to be more overeducated and the old more undereducated, with Western Europe witnessing increases in skills mismatching by the old, primarily due to undereducation.
- The inspection of the HFCS indicated that the wealth and income gap between the matched and mismatched individuals is large and rising over the large decade, with diverse patterns in favour of the over- or the undereducated in different countries.

Furthermore, the review of firm-level data provided with the following insights:

- The overview of the WBES highlighted that despite the rise in skilled workers among production workers around the world, the fraction of firms that identify the limited availability of skilled workers as among the biggest obstacles is also rising. At the same time the fractions of firms and workers offering and being offered formal training has not increased consistently around the world and in Europe.
- The inspection of the SAFE indicated that there is a likely role for access to finance for facilitate skills development and recruitment of skilled staff, but financial constraints and obstacles in access to finance might induce additional constraints in facilitating skills matching and the provision of formal training.
- The inspection of the Eurobarometer indicated that while SMEs acknowledge the importance of investment in skills and training, particularly in new types of skills, the also express mixed feelings regarding financing transferrable training that is not specific to the job. Apart from finance, they acknowledge workplace organizational strategies and collaboration with relevant pubic bodies as among the most important means of tackling skills shortages and mismatch.

In addition, the matched employer-employee data have provided the following key points:

- The overview of the EU-SES suggested improvements in matching over time, and differences between public and private firms, along with the importance of operationalising and enabling EU-level trademark datasets that have not been adequately used in the literature and public dialogue.
- The inspection of the LISA/FEK signaled the importance of using administrative data and novel definitions of mismatching for the enhanced understanding of its precedents and antecedents.

The introduction to the online vacancy data has indicated that:

- The overview of SKILLSOVATE highlighted the importance of using real-time big data, in understanding requirements and trends and in nowcasting skills needs.

Finally, the overview of the two taxonomies signalled the intension of the TRAILS project to operationalise them in its follow-up deliverable tasks of this workpackage and workpackage 5, in better understanding the causes and consequences of skills mismatching, along with the intension to participate in vocational training and adult learning.

TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

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