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Enabling Data Analytics for Actions Tackling Skills Shortages & Mismatch

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ACRONYMS

Acronym	Explanation
Cedefop	European Centre for the Development of Vocational Training
EQF	European Qualifications Framework
ESCO	European Skills, Competences, Qualifications and Occupations
ESJS	European Skills and Jobs Survey
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
NACE	Statistical Classification of Economic Activities in the European Community
NUTS	Nomenclature of Territorial Units for Statistics

EXECUTIVE SUMMARY

D3.3 brings together two complementary chapters analysing skills and educational mismatch, training and inclusiveness. Both chapters provide important insights into how mismatch is measured, and the associated outcomes for mismatched employees. The two main approaches that have been used in the international literature for measuring educational mismatch are the subjective and statistical approaches. The subjective approach is based on self-reported answers to survey questions that ask employees whether their educational attainment is above or below the level required to do their job. The statistical approach is based on comparing an employee's actual educational attainment to the average (modal) level of education within their occupation.

Mismatch is shown to be multidimensional and sensitive to how it is measured. Using Cedefop's second European Skills and Job Survey, Chapter 1 shows that the subjective and statistical approaches produce a different mismatch status for more than half (52%) of employees. A combined measure of mismatch is then constructed, which focuses on employees whose mismatch status is consistent across the subjective and statistical measures.

Approximately 60 percent of employees are considered matched using the subjective measure, compared to just 38 using the statistical approach. Using the combined measure, 55 percent of employees are matched. When comparing overeducated employees to employees with the same level of education in matched employment, the combined measure of mismatch reveals a wage penalty that is 1.5 to 2 times higher than the subjective and statistical approaches. Certain sectors are shown to be more susceptible to adverse impacts associated with mismatch. For example, overeducated employees in sectors such as transport and storage, wholesale and retail, real estate activities, and arts and entertainment, incur large wage penalties and are also most likely to fear future job loss, relative to employees with the same level of education in matched employment.

Focusing on the combined measurement approach, the incidence of undereducation is relatively high in sectors such as ICT (29%), Finance and Insurance

(26%) and Real Estate Activities (25%), while the incidence of overeducation is high in sectors such as Accommodation and Food (43%) and Wholesale and Retail (40%). The undereducation incidence is relatively high in countries such as Malta (35%), Luxembourg (33%) and France (31%), while overeducation is high in Spain (59%), Latvia (47%) and Greece (43%).

Chapter 1 goes beyond the binary measure of overeducation by calculating the proportion of overeducated workers (using the combined measure) that are severely overeducated, which is defined as a situation where the employee's actual level of education is two or more levels above that which is required to do their job. For example, a person with a master's degree (ISCED level 7) would be severely overeducated if the required education for their job, according to the subjective or statistical approach, was ISCED 5 (short-cycle tertiary) or below. The results show that severe overeducation is a serious issue across the EU. The majority of overeducated employees across countries (using the combined measure) are severely overeducated. In countries such as Czechia, Bulgaria, Slovakia and Romania, approximately 80 to 90 percent of overeducated workers are severely overeducated. The wage penalty associated with overeducation also tends to be higher in countries where severe overeducation is more prevalent.

Finally, Chapter 1 shows that training has a positive association with wages, regardless of mismatch status. That is, the wage benefit to training is approximately the same for undereducated, matched and overeducated workers, boosting wages by approximately 10 percent. Approximately 65 percent of respondents report recent job training (in the last 12 months). This varies by country and sector. It is concerning that the rate of training in France is the lowest in the EU, as France also records one of the highest rates of undereducation in the EU. Further regional analysis of training will be explored in detail in Deliverable 3.4.

Chapter 2 uses TRAILS-I data from 31 European countries to examine whether subjective and statistical mismatch classifications identify workers with different patterns of skill utilisation, skill gaps, learning participation, labour-market resilience and financial resilience. Consistent with the findings from Chapter 1, the two measures identify substantially different shares of matched workers; many

respondents classified as undereducated relative to the occupational mode do not consider themselves underqualified for their jobs. The extent and nature of this divergence also vary across sectors and subnational regions.

Chapter 2 shows a clear distinction between the subjective and statistical approaches when it comes to skill utilisation. Subjective mismatch is strongly associated with reporting partial or no use of skills, whereas statistical mismatch is much less informative for this outcome. This suggests that an education level above or below an occupational benchmark (such as the mode) should not be interpreted mechanically as evidence of unused or insufficient skills.

Regarding skill gaps, workers overqualified under both measures report fewer gaps, while those underqualified under both measures report more, particularly in digital, technical and customer-handling skills. Workers who consider themselves underqualified despite statistical matching report especially pronounced technical and job-specific needs, while some workers who consider themselves overqualified report fewer gaps even when statistically undereducated. These findings reinforce the need to distinguish qualification mismatch, skill underutilisation and skill deficits: unused capabilities and unmet job requirements can coexist within the same worker-job relationship.

The regional and sectoral evidence from Chapter 2 suggests that training policy should distinguish between workers who lack skills and workers whose existing skills are not fully used. Regional and local authorities can use the geographic evidence to identify areas with concentrated mismatch; training providers can target reported skill deficits; and employers can combine training with job redesign, task reallocation and internal mobility where underutilisation rather than a skill deficit is the main problem.

Relation with other deliverables and tasks

This deliverable contributes to Task 3.3 by examining mismatch, training and inclusiveness from two complementary data sources. It draws from previous

analyses, particularly Deliverables 3.1, 3.2 and 5.1. Chapter 1 provides harmonised evidence on mismatch and wellbeing across sectors and countries using ESJS2. Chapter 2 extends the analysis with TRAILS-I by adding subnational patterns, a nine-category joint mismatch classification, direct measures of skill utilisation and skill gaps, learning activities, and labour-market and financial resilience. Together, the chapters connect the measurement of mismatch to its consequences and to the policy question of whether further training, better use of existing skills, or both are required.

Structure of the document

The deliverable is organised as two substantive chapters. Chapter 1 analyses the impact of educational mismatch on wages, job satisfaction, job security and related outcomes using ESJS2, with separate country and sector results. Chapter 2 uses TRAILS-I to examine disagreement between subjective and statistical mismatch measures, their functional relevance for skill utilisation and skill gaps, learning participation, resilience, and regional and sectoral patterns. Each chapter retains its own table and figure numbering, followed by chapter-specific references.

1. CHAPTER 1. Does Measurement Matter? Educational Mismatch and Labour Market Outcomes across European Countries and Sectors

Paul Redmond and Luke Brosnan, ESRI

1.1 Introduction

Skills mismatch is a situation in which an employee's skills and/or education do not match the level that is required to do their job. It may be that an employee possesses surplus skills or education relative to their job requirements, in which case they are deemed to be "overeducated" or "overskilled". Conversely, an employee's education or skills may fall short of the level required to competently do their job, in which case they are deemed to be "undereducated" or "underskilled".

Measuring and understanding skills mismatch is important, as it may lead to adverse consequences for both employees and employers. For example, undereducated employees can have a negative impact on a firm's productivity and profitability (Kampelmann et al., 2020; Kampelmann and Rycx, 2012; Mahy et al., 2015). Overeducated employees have been shown to experience a wage penalty when compared to employees with similar levels of education in matched employment (see, e.g., Cultrera et al., 2025; Bender and Roche, 2018; Sánchez-Sánchez and McGuinness, 2015; McGuinness and Sloane, 2011). In addition, there is some evidence that overeducation is associated with reduced job satisfaction, a higher likelihood of changing jobs, and negative consequences for an employee's long term career prospects (Fleming and Kler, 2008; Sánchez- Sánchez and McGuinness, 2015; Mateos-Romero and Salinas-Jiminéz, 2018; Bender and Heywood, 2009; Scherer, 2004).

There are several different approaches that can be used to measure skills and educational mismatch.[1] The type of approach that is used is often dictated by the data available to the researcher. Developing a detailed understanding of the different approaches and establishing a robust and reliable method for measuring mismatch is, therefore, of critical importance. Different measurement approaches may lead to differences when it comes to identifying a worker as either matched or mismatched, leading to inconsistencies when it comes to measuring the incidence and outcomes associated with mismatch. McGuinness et al. (2018) provide a detailed overview of the different measurement approaches. The most commonly used approach in the literature is a subjective approach based on direct survey questions. For example, an employee may be asked what level of education is required to do their job. This is then compared to the employee's actual educational attainment to assess whether they are matched, overeducated or undereducated. The second most common approach is a statistical approach. The mode level of education is calculated for an employee's occupation. The employee's own educational attainment is then compared to the mode level of education for that occupation; an employee is overeducated if their education level exceeds the mode for their occupation, undereducated if it is below the mode, and matched if it equals the mode.[2]

There are strengths and limitations associated with both the subjective and statistical measurement approaches. The subjective approach is easy to incorporate into survey data, and as it is worker specific, it captures potential heterogeneity in the skill requirements of jobs, even within the same narrow occupational code (e.g., 2 or 3-digit ISCO groups). A limitation is that it is inherently subjective, and as such may suffer from reporting bias. For example, there may be a reluctance to admit overeducation, leading to workers overstating the qualifications required to do their job (McGuinness et al., 2018; McGuinness, 2006). The main advantage of the statistical approach is that it can be applied to a wide range of datasets, requiring only information on an employee's educational attainment and their occupation code. A limitation is that, as it is based on the mode level of education across relatively broad occupation groups, it may not fully capture heterogeneity in

[1] See McGuinness et al. (2018) for a detailed review of the literature on skills mismatch and the different measurement approaches.
[2] Another, less commonly used approach, is referred to as the 'job evaluation' method (McGuinness et al., 2018). This relies on the assessment of expert job analysts, who are tasked with establishing the required level of education for an occupation, against which an employee's actual educational attainment is compared.

qualification needs across individuals in the same occupation (Verhaest and Omey, 2010).

In this Deliverable, we exploit a unique feature of the second wave (2021) of the European Skills and Jobs Survey, that allows us to calculate both the subjective and statistical measures of educational mismatch for employees across all EU-27 countries. In doing so, we make a number of important contributions. First, we assess the consistency across both measurement approaches. The two approaches are utilised in the literature to measure the same thing. Therefore, identifying whether there exists consistency (or a lack of) across both approaches is important. Second, we create a stricter and more rigorous approach to mismatch by combining both measures. That is, we focus only on employees whose mismatch status is consistent across both measures. Third, using our combined mismatch measure, we estimate the impact of mismatch on wages, job satisfaction and the probability of job loss, and compare these estimates to the estimated outcomes using the subjective and statistical approach. Fourth, in addition to presenting pooled estimates for the EU, we provide separate estimates by sector and by country.

Our findings show a considerable degree of inconsistency between the statistical and subjective approaches. The subjective and statistical approaches produce a different mismatch status for more than half (52%) of employees. The incidence and outcomes also differ based on the approach used. Approximately 60 percent of employees are considered matched using the subjective measure, compared to just 38 using the statistical approach. Using the combined measure, 55 percent of employees are matched. When comparing overeducated employees to employees with the same level of education in matched employment, the combined measure of mismatch reveals a wage penalty that is 1.5 to 2 times higher than the subjective and statistical approaches. This indicates that overeducated employees earn 28 percent less than their matched counterparts. The combined measure focuses only on employees whose mismatch status is consistent across the subjective and statistical approaches and therefore does not include the 52 percent of employees for which there is inconsistency across measures. Nonetheless, to the extent that the combined measure captures a sample of employees for which we can be more certain about their mismatch status, the size of the wage penalty is of

concern. The wage penalty, and fear of job loss associated with overeducation, is particularly high in sectors such as transport and storage, wholesale and retail, real estate activities, and arts and entertainment.

Our results also show that the vast majority of overeducated individuals in the EU are severely overqualified, which we define as a situation where the employee's actual level of education is two or more levels above that which is required to do their job. For example, a person with a master's degree (ISCED level 7) would be severely overeducated if the required education for their job, was ISCED 5 (short-cycle tertiary) or below. The majority of overeducated employees in the EU (using the combined measure) are severely overeducated. In countries such as Czechia, Bulgaria, Slovakia and Romania, approximately 80 to 90 percent of overeducated workers are severely overeducated. Only two of the 27 EU countries record less than 50 percent of overeducated workers that are classified as severely overeducated. The overeducation wage penalty also tends to be higher in countries for which severe overeducation is more prevalent.

To capture within-occupation educational deficits, we also compare undereducated employees to matched employees that are working in the same ISCO 3-digit occupation and have a higher level of education (that is equal to the level required to do the job). We find a significant pay penalty – using the combined measure of mismatch, employees that have a level of education below that which is required to do their job earn 11 percent less than similar employees in the same job with a higher (matched) level of education. Our results highlight the role of job-related training in mitigating this pay deficit associated with a lack of formal education; we estimate that the wage premium associated with training is of a similar magnitude to the wage deficit incurred by undereducation.

Our findings contribute to a related strand of literature that combines overeducation and overskilling to attempt to identify 'genuine' mismatch. As noted by Green and McIntosh (2007), a person may be classified as 'overeducated' in terms of the qualifications required to get their job but may not be mismatched in terms of their skills and abilities. Using subjective employee responses to capture overeducation and overskilling, Green and McIntosh (2007) find only a weak

correlation (of 0.2) between being two measures. Note, however, that in our paper we use a question that asks individuals the level of education required "to do" their job, as opposed to "to get" the job. To the extent that individuals respond correctly, measuring educational mismatch as that which is required "to do" the job should align more closely with actual skills mismatch compared to the education required "to get" the job which could, for example, be more likely to reflect credentialism or grade inflation.

Similarly, Green and Zhu (2010) distinguish between 'real' and 'formal' overeducation, with the distinction being that the former is accompanied by an underutilisation of skills. Overeducation is measured using subjective employee responses and is based on the level of education required 'to get' the job. Skill underutilisation is also based on employee responses to a survey question.[3] Those associated with 'real' overeducation suffered larger wage penalties than the 'formal' education group, while adverse impacts relating to job satisfaction were only present among the 'real' overeducation group.

Using data from 2014 for 28 European countries, Giuliano et al. (2024) examine how overeducation and overskilling, both separately and in combination, impact job satisfaction. They find that overskilling and overeducation, separately, are associated with lower job satisfaction, but the reduction in job satisfaction is almost double for genuinely overeducated employees (those who are both overskilled and overeducated).

Another related research area combines educational mismatch with field-of-study mismatch, defined as a situation where an individual works in a field that differs from their main education field. Across 23 countries, Montt (2017) finds that 13 percent of workers are both overeducated and mismatched by field of study. Furthermore, Montt (2017) finds that field-of-study mismatch is only associated with a wage penalty if accompanied by overeducation. Mahuteau et al. (2015) find the same result using Australian data. Using survey data from 2005 covering 15 countries, Verhaest et al. (2017) find that approximately eight percent of recent

[3] The specific question is "How much of your past experience, skill and abilities can you make use of in your present job?". Those responding 'very little' or 'a little' were classified as having underutilized skills.

graduates are both overeducated and mismatched by field of study. Cross-country variation in this type of mismatch is found to be related to factors such as collective bargaining coverage, employment protection regulations, the level of unemployment benefits and cyclical and structural labour market imbalances.

1.2 Data and descriptive statistics

The analysis uses Cedefop's second European Skills and Jobs Survey (ESJS2), a cross-national survey of adult workers carried out across the EU-27 Member States, Norway and Iceland. Fieldwork ran from May to August 2021 and covered adults aged 25-64 in wage or salary employment, yielding 46,213 completed interviews. The survey collects harmonised information on job-skill requirements, digitalisation, skills mismatch and workplace training using a common methodology, which allows comparisons across countries, sectors and occupations.

We measure educational mismatch in three ways. First, the subjective measure compares an employee's actual attained level of education with the level of education that they indicate is required to do their current job. Specifically, we utilise the question, *'What is the level of education usually needed nowadays to do a job like your main job?'* If the respondent's actual level of educational attainment is below (above) the level required to do their job, they are classified as undereducated (overeducated). If their level of education matches that which is required to do their job, they are considered matched. Second, the statistical measure calculates the modal level of education within each three-digit ISCO occupational group.[4] If an employee's attained education is below (above) the occupational mode, they are classified as undereducated (overeducated). If their educational attainment is the same as the mode, they are considered matched.

The third is a combined measure that identifies workers for whom the subjective and statistical classifications agree. Workers are classified as combined matched, combined undereducated or combined overeducated only where both

[4] The mode is calculated across countries at the 3-digit ISCO level. At this level of disaggregation, the sample sizes of some ISCO 3-digit occupations within some countries is very small. As such, we do not calculate country specific modes at the 3-digit ISCO level. As a robustness test, we run our analysis using country specific modes at the 2-digit ISCO level. The results are consistent with the pooled 3-digit ISCO mode analysis.

measures assign them to the same category. Both the subjective and statistical approach have limitations, but combining them in this way results in a stricter, and to some degree, more robust measure which may alleviate some of the concerns associated with each measure in isolation. For example, a limitation of the subjective approach is that employees may be reluctant to admit that they are overqualified for their job, leading them to overstate the educational requirements required for their occupation. To the extent that the mode level of education captures the actual requirement for that job, combining the subjective measure with the statistical approach should, to some extent, overcome this issue. Similarly, there are limitations with the statistical approach in isolation, as it may fail to capture heterogeneity in educational requirements within 3-digit ISCO occupation levels. Such variation will, however, be more likely to be picked up by the subjective approach.

Table 1.1 shows the extent to which there is consistency across both approaches. The two measurement approaches produce inconsistent mismatch results from more than half (52%) of the sample. This means that, for just 48% of employees, the statistical and subjective measures produce the same mismatch status. For example, 21% are classified as matched using the subjective approach, but undereducated using the statistical approach. A further 14% are classified as overeducated using the statistical approach but matched using the subjective approach, while 10% are matched using the statistical approach and overeducated using the subjective approach.

Table 1.1: Consistency across mismatch measures

		Statistical Approach	
Subjective Approach	**Matched**	**Undereducated**	**Overeducated**
Matched	11,375 (26%)	9,245 (21%)	6,417 (14%)
Undereducated	1,088 (2%)	3,344 (8%)	683 (2%)
Overeducated	4,337 (10%)	1,995 (4%)	6,041 (14%)

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

Figures 1.1 to 1.3 show the incidence of educational mismatch by sector using the subjective, statistical and combined approaches, respectively. There are notable differences. Compared to the statistical measure, the subjective measure indicates a far greater share of matched employment, and therefore a lower share of

over and undereducation. On average, approximately 60 percent of employees are considered matched using the subjective measure, with 12 percent being undereducated and 28 percent being overeducated. The statistical measure, on the other hand, indicates that just 38 percent of employees are matched, with 33 percent undereducated and 29 percent overeducated. The incidence of mismatch using the combined measure falls somewhere between the subjective and statistical measures, but among the two it more closely resembles the subjective estimates. According to the combined measure, 55 percent of employees are matched, 16 percent are undereducated and 29 percent are overeducated.

Figure 1.1: Subjective mismatch by sector

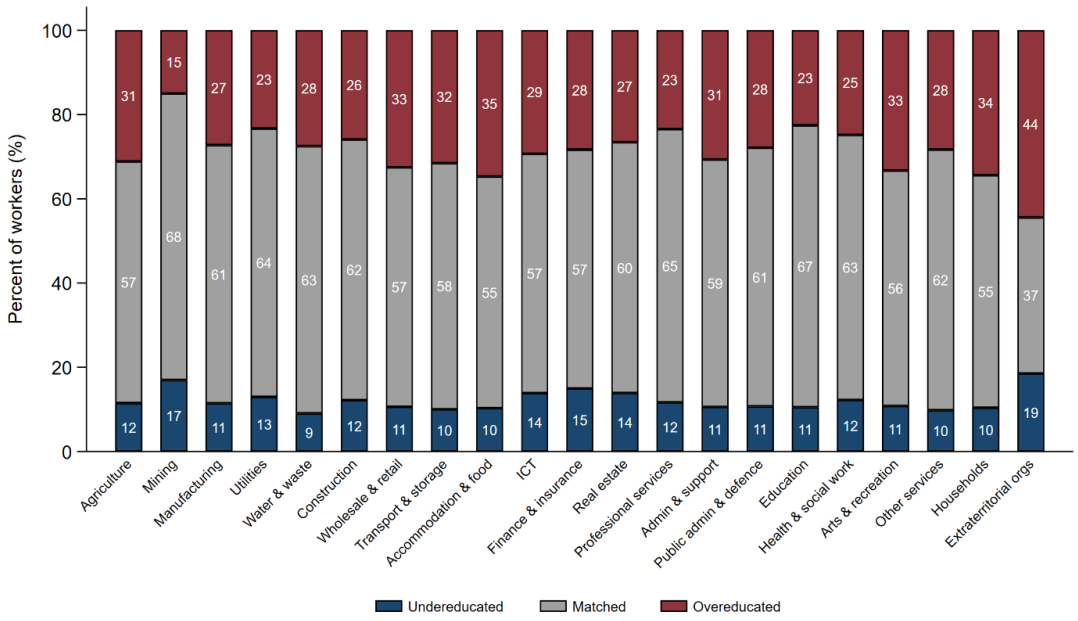


Figure 1.2: Statistical mismatch by sector

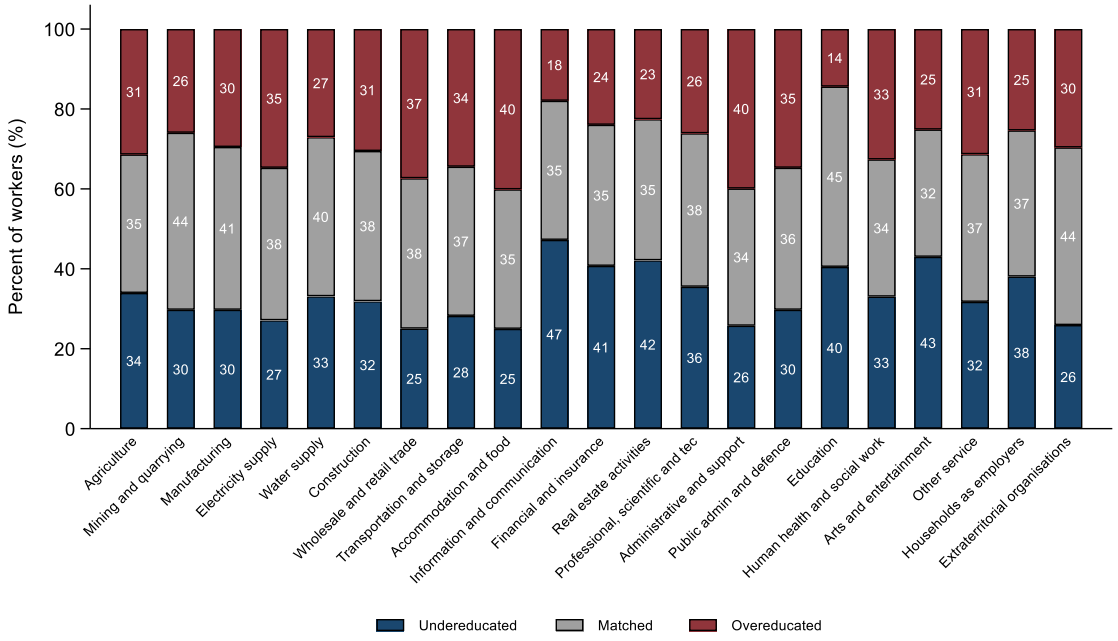
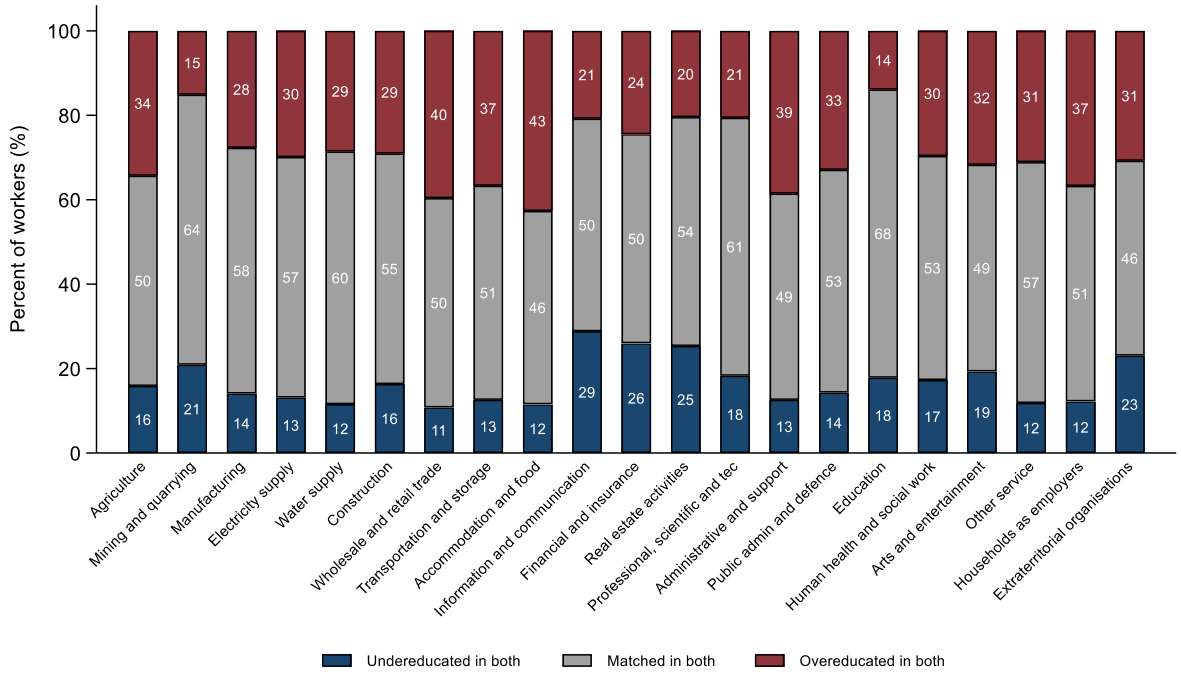


Figure 1.3: Combined mismatch by sector



While the sectoral patterns vary depending on the measurement approach, there are some consistent findings. The incidence of undereducation (overeducation)

tends to be relatively high (low) among employees working in sectors that are associated with higher pay and higher skill requirements, such as ICT, finance and insurance, real estate and professional services. Conversely, the incidence of undereducation (overeducation) is relatively low (high) in lower skilled / lower paid sectors such as accommodation and food, transport and storage, wholesale and retail trade. The education sector consistently records one of the highest rates of matched employment across all measures.

Figures 1.4 to 1.6 show the incidence of mismatch by country using the subjective, statistical and combined approaches, respectively. Again, while there are differences depending on the approach used, certain countries tend to have relatively high levels of mismatch. Focusing on the combined mismatch measurement approach (Figure 6), the five countries with the highest overeducation rates are: Spain (59%), Lithuania (47%), Greece (43%), Ireland (40%), Norway (40%). The five countries with the highest undereducation rates are: Malta (35%), Luxembourg (33%), France (31%), Portugal (23%), Sweden (23%).

Figure 1.4: Subjective mismatch by country

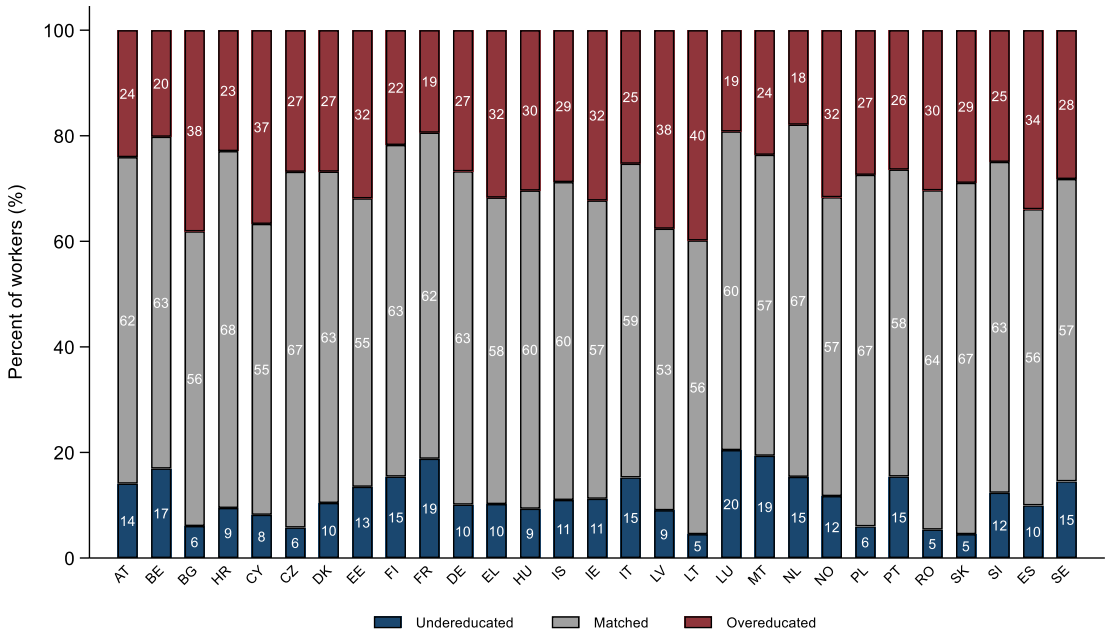


Figure 1.5: Statistical mismatch by country

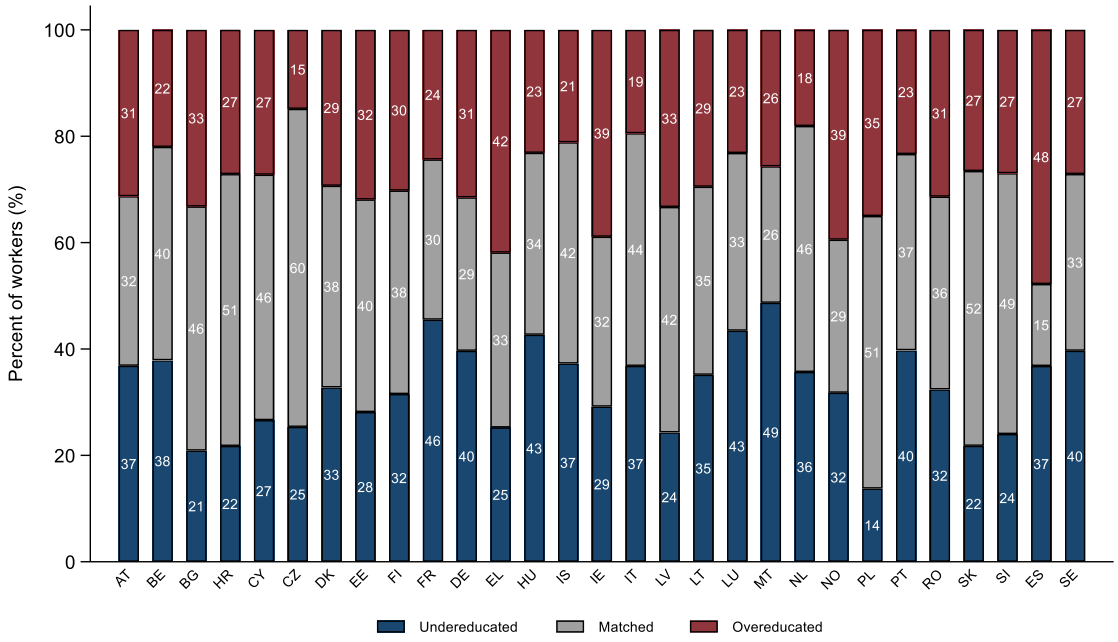
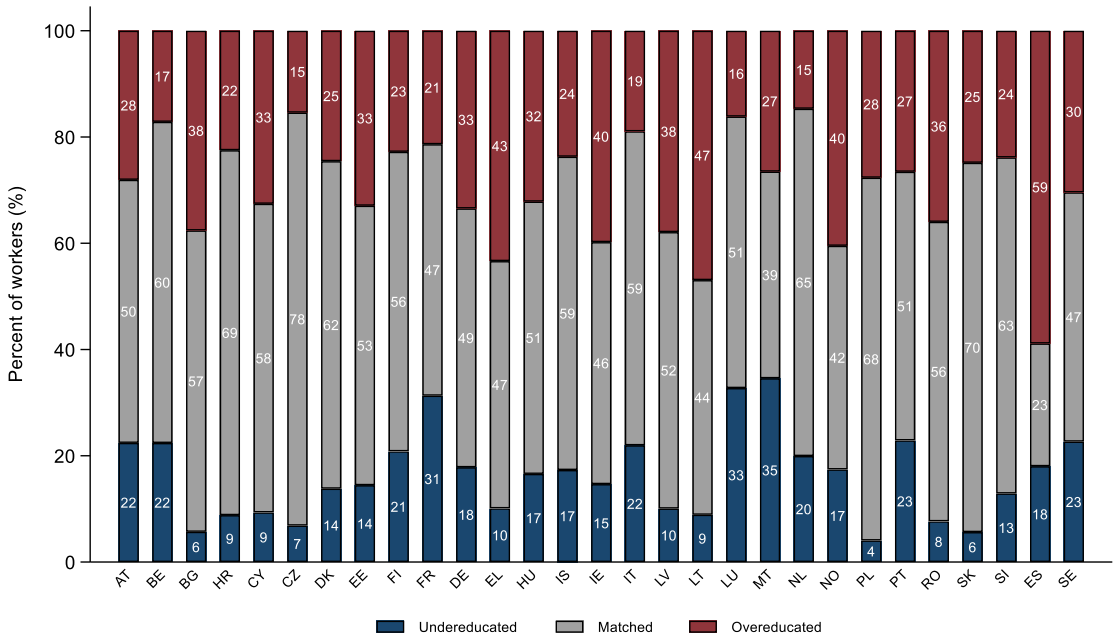


Figure 1.6: Combined mismatch by country



The analysis considers three labour-market outcomes. The monetary outcome is log hourly pay, derived from monthly earnings and usual weekly hours

worked.[5] The non-monetary outcomes include job satisfaction and employee's fear of job loss. A binary measure of job satisfaction is constructed from an underlying 0-10 scale. The following question is asked in relation to overall job satisfaction, "*On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you, overall, with your job?*". From this, we create a binary satisfaction variable, with a score of 6 or above classified as satisfied. For fear of job loss, we utilise the following survey question, *"Do you think there is any chance at all of you losing your main job in the next twelve months?"* A binary variable is constructed from three categories; respondents answering "Yes, a very high chance" or "yes, some chance" are coded one and respondents answering "No chance at all" are coded zero.

Table 1.2 shows the average values for the outcome variables. Average hourly pay across all countries is €12.08 per hour. Almost 80 percent of respondents are satisfied (overall) with their job. Approximately 40 percent of employees fear losing their job in the next twelve months.

Table 1.2: Outcome variable descriptives

VARIABLES	(1) N	(2) mean
Hourly pay (€)	33,132	12.08
Log hourly pay	33,132	2.198
Satisfied with the job overall	46,153	0.772
Fears job loss	45,738	0.397

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

Table 1.3 shows the actual and required educational attainment distributions among survey respondents.[6] Some notable patterns emerge when comparing the two distributions. Approximately 41 percent of employees report that the level of education required to do their job is Upper Secondary (ISCED 3) or below. However, 65 percent of employees have educational attainment above this level. This is

[5] Hourly pay is calculated by dividing monthly net pay (in euros) by the number of hours worked in the month (calculated as weekly hours multiplied by 4.3).
[6] We condition on respondents that report both their actual and required level of educational attainment. Approximately 800 of the 46,000 respondents report their actual education level but do not report the level required to do their job.

consistent with the findings of relatively high overeducation using the subjective approach (see Figures 1.1 and 1.4). At the higher end of the education distribution, it is notable that while 25 percent of respondents have a master's degree (ISCED 7), just 18 percent of respondents indicate that a master's degree is required to do their job.

Table 1.3: Actual and required educational attainment

Education Level	**Actual Educational Attainment (%)**	**Required to do the Job (%)**
Below primary (ISCED 0)	0.20	2.33
Primary (ISCED 1)	0.98	1.79
Lower secondary (ISCED 2)	7.90	9.48
Upper secondary (ISCED 3)	25.75	27.58
Post-secondary, non-tertiary (ISCED 4)	10.19	9.18
Short-cycle tertiary (ISCED 5)	6.78	7.05
Bachelor's (ISCED 6)	21.23	23.15
Master's (ISCED 7)	24.53	17.81
Doctoral (ISCED 8)	2.42	1.62
Observations (N)	45,284	45,284

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

Table 1.4 shows the average characteristics for survey respondents in terms of age, gender, contract type, working time (part-time / full-time) and sector of work. The average age of respondents is 43. Approximately one in five work part-time and half of respondents are women. The vast majority of employees (85 percent) have a permanent contract, with the remaining 15 percent having a temporary (or no) contract. The top five sectors, in terms of the highest percentage of overall employees, are Manufacturing (13%), Education (12%), Human Health & Social Work (11%), Wholesale & Retail Trade (10%), Professional, Scientific & Technical (7.7%).

Table 1.4: Average characteristics of respondents

VARIABLES	(1) N	(2) mean
Age	46,213	43.32
Part-time	44,452	0.210
Female	46,183	0.497
Contract		
Permanent	36,482	0.85
Temporary	5,465	0.13
No Contract	982	0.02
Sector (NACE)		
Agriculture	526	1.2
Mining and quarrying	139	0.3
Manufacturing	5559	13
Electricity supply	525	1.2
Water supply	312	0.7
Construction	1640	3.8
Wholesale and retail trade	4406	10
Transportation and storage	2424	5.6
Accommodation and food	1711	4
Information and communication	3063	7.1
Financial and insurance	1981	4.6
Real estate activities	323	0.8
Professional, scientific and technical	3305	7.7
Administrative and support	2949	6.9
Public admin and defence	2874	6.7
Education	4942	12
Human health and social work	4669	11
Arts and entertainment	764	1.8
Other service	665	1.5
Households as employers	114	0.3
Extraterritorial organisations	26	0.1

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

1.3 Empirical strategy

We estimate the relationship between educational mismatch and three labour-market outcomes (hourly pay; job satisfaction; fear of job loss). For hourly pay, we estimate the following ordinary least squares regression,

$$ln(Wage_{i,c}) = \alpha + \beta_U Undereducated_{i,c} + \beta_O Overeducated_{i,c} + X'_{i,c}\delta + \gamma_c + \sigma_S + \varepsilon_{i,c}$$

(1)

where $ln(Wage_{i,c})$ is the log hourly pay of person *i* in country *c*. $Undereducated_{ic}$ and $Overeducated_{ic}$ are dummy variables indicating whether person i in country c is undereducated or overeducated, respectively. The omitted category is being educationally matched. Therefore, the coefficients β_U and β_O capture the relationship between undereducation and overeducation on wages, relative to those in matched employment. $X'_{i,c}$ is a vector of control variables. An employee's actual educational attainment is included as a control variable in X'. This is important when it comes to interpreting the estimates for educational mismatch (β_U and β_O), as we are comparing individuals in mismatched employment to individuals *with the same level of education* in matched employment. That is, β_O estimates the wage penalty associated with being in an occupation for which the employee is overeducated, relative to a person with the same level of education in an occupation for which they are matched. Other control variables in X' include age, gender, contract type (permanent / temporary), work status (part-time / full-time). Country fixed effects are denoted by γ_c and sector fixed effects by σ_S. Equation (1) is estimated separately using each of the three measures of educational mismatch (subjective, statistical and combined). Furthermore, in addition to estimating the pooled model shown in equation (1), we also estimate separate wage effects for each country and each sector.

For the binary labour-market outcomes (job satisfaction and fear of job loss), the following probit model is estimated,

$$Pr(Y_{i,c} = 1) = \Phi(\alpha + \beta_U Undereducated_{i,c} + \beta_O Overeducated_{i,c} + X'_{i,c}\delta + \gamma_c + \sigma_S)$$

(2)

where Y_i denotes the relevant binary outcome and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. The right-hand side variables are the same as those defined earlier (for equation (1)). Results from the probit models are reported as average marginal effects. Again, we also show separate estimates using each of the three measures of educational mismatch (subjective, statistical and combined), and for each country and each sector.

1.4 Results

1.4.1 Wage Effects

Table 1.5 shows the estimated wage effects associated with educational mismatch using each of the three measurement approaches. While the sign and statistical significance of the estimates is consistent across measurement approaches, the magnitude of the effects is far higher for the combined measure. Relative to employees with the same level of education in matched jobs, overeducation is associated with a wage penalty of approximately 13 to 16 percent when we use the subjective and statistical measures. However, when we use the combined measure of educational mismatch, overeducated employees experience a wage penalty of almost 30 percent, relative to employees with the same level of education in matched jobs. Conversely, when compared to individuals with the same level of education in matched jobs, undereducated employees experience a wage premium of approximately 10 percent when we use the subjective and statistical measurement approaches, but this increases to 16 percent for the combined measurement approach. These results have important implications. For example, our estimated impacts of overeducation using the statistical and subjective approaches are broadly consistent with the estimated impacts from the previous literature in this area over the last two decades.[7] However, to the extent that the combined measure represents a more 'genuine' or reliable type of mismatch, this suggests that the actual relationship between wages and overeducation may be double the magnitude of what was previously reported based on past empirical research.

[7] In a survey of the literature, McGuinness et al. (2018) collect 74 published estimates of the overeducation pay penalty and report an average estimated impact of 13.6 percent.

Table 1.5: Wage effects of educational mismatch

VARIABLES	(1)	(2)	(3)
Subjective mismatch (ref: Matched)			
Undereducated	0.098***		
	(0.009)		
Overeducated	-0.154***		
	(0.007)		
Statistical mismatch (ref: Matched)			
Undereducated		0.089***	
		(0.009)	
Overeducated		-0.121***	
		(0.009)	
Combined mismatch (ref: Matched)			
Undereducated			0.153***
			(0.015)
Overeducated			-0.252***
			(0.013)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	32,229	32,749	15,207
R-squared	0.583	0.581	0.620

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Focusing on the combined measure of educational mismatch, Figures 1.7 and 1.8 show separate wage effects by country for overeducation and undereducation, respectively. The top five countries in the EU, in terms of the highest overeducation wage penalty, are Latvia, Germany, Spain, Cyprus and Portugal, with pay penalties in the order of 30 to 60 percent lower pay. In these countries, an employee that finds themselves in a job for which the required education is below their actual educational attainment, face a severe wage penalty relative to similar individuals with the same level of education in matched employment.

Figure 1.7: Overeducation wage effects by country

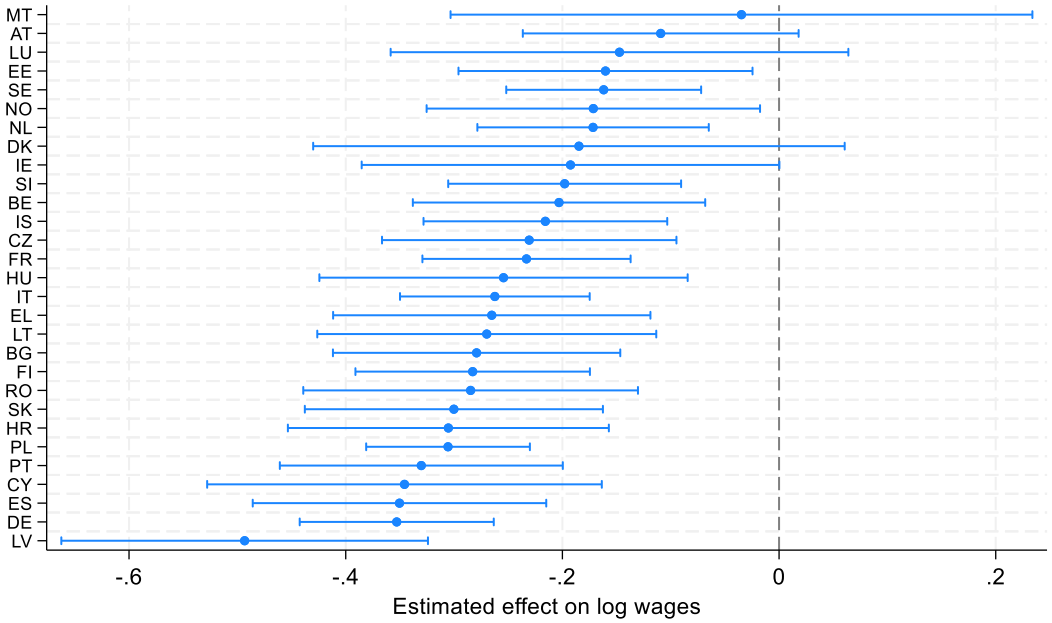
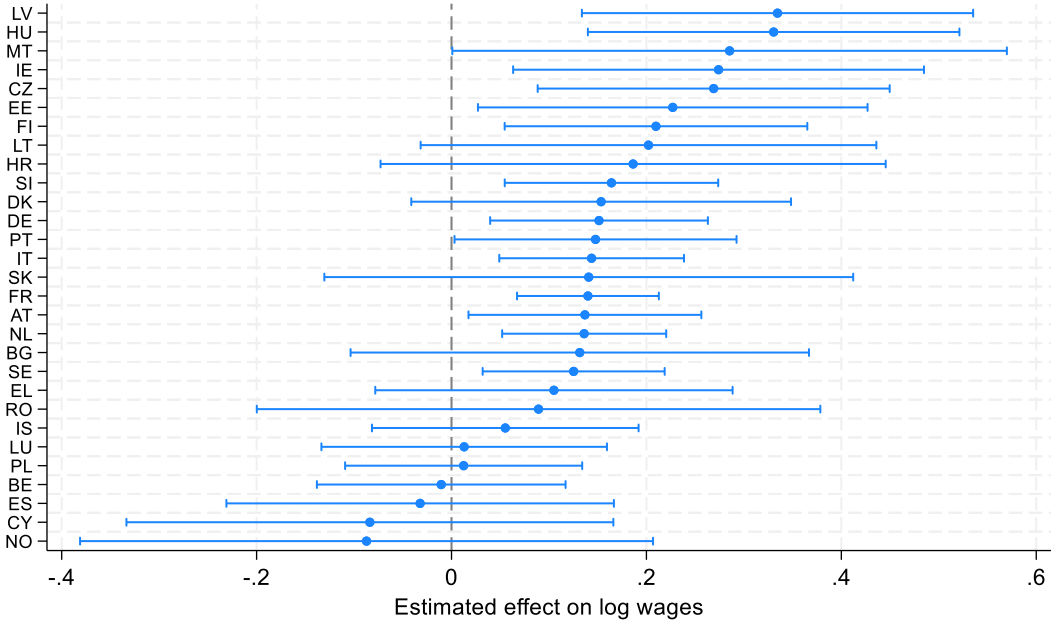


Figure 1.8: Undereducation wage effects by country



Disentangling the exact reasons why some countries face a far larger overeducation wage premium than others is beyond the scope of the current study but is an important area for future research. It is likely related to institutional and country-specific factors around the composition of employment. For example, conditional on education, the group of 'matched' occupations will be higher skilled compared to the

group of 'overeducated' occupations. To see this, take the example of two individuals with similar characteristics and the same level of education – let us assume a master's degree. The first finds a matched job that requires the master's degree to do the job and is therefore high skilled. The second ends up in a job that requires only an undergraduate degree to do the job and is therefore lower skilled. The magnitude of the estimates in countries such as Latvia, Germany and Spain, suggest that the gap between the wages in these high and low skilled jobs is very high. This gap will likely be related to regional, sectoral and firm-level wage inequality within countries. For example, high-skilled jobs may be located in a small number of urban centres within a country. Some highly educated individuals may face geographical constraints which do not enable them to move to these jobs, instead taking up jobs outside of these urban centres. If this regional wage differential is large, then this could exacerbate the overeducation pay penalty.

Other policy factors, such as statutory minimum wages, could impact the overeducation pay penalty. If overeducated workers are in lower-skilled jobs than their matched counterparts, a statutory minimum wage could reduce the wage inequality between these two types of jobs. Focusing on Latvia, Eurofound (2026) show that Latvia has the second lowest nominal hourly minimum wage in the EU. It is also notable that Latvia is among a small group of EU countries for which the ratio of the minimum wage to average wage declined between 2016 and 2024 (Eurofound, 2026). While this is not definitive evidence of the role of minimum wages in determining the overeducation pay penalty, it provides information about potential within country wage differences. It is notable that Latvia is also the country with the highest undereducation pay premium. An employee in Latvia in a job for which their actual educational attainment is below that which is required to do the job earns approximately 40 percent more than an individual with the same level of education in a matched job. Other countries with a relatively high undereducation wage premium include Hungary, Malta, Ireland and Czechia.

In Figures 1.9 and 1.10 we show the wage effects of over and undereducation, respectively, by sector. Again, we present estimates using the combined measurement approach. There is considerable variation in the estimated wage effects by sector. The five sectors with the largest statistically significant overeducation wage penalty are transportation and storage, wholesale and retail trade, real estate activities, arts and entertainment, and electricity supply. The overeducation wage penalties for these sectors are large, in the order of 35 to 50 percent. The five sectors with the largest

statistically significant undereducation pay premium are real estate activities, ICT, finance and insurance, arts and entertainment, and transport and storage.

The size of the wage effects may be related to the severity of the mismatch. Take overeducation as an example. Using our combined measurement approach, a person is considered overeducated if their actual level of education is above the subjectively required level of education and the statistically required (mode) level of education. However, the severity of mismatch can vary depending on the distance between the required and actual levels of education. For example, take a person with a master's degree (ISCED level 7). This person would be overeducated if they were in a job requiring a bachelor's degree (ISCED level 6). However, they would be more severely overeducated if they were in a job that only required an upper secondary education (ISCED level 3), and it is reasonable to expect that the magnitude of the wage effects will vary depending on how far the actual and required levels of education are. We calculate the proportion of overeducated workers (using the combined measure) that are severely overeducated, which we define as a situation where the employee's actual level of education is two or more levels above that which is required to do their job using either the subjective or statistical approach. For example, a person with a master's degree (ISCED level 7) would be severely educated if the required education for their job, according to the subjective or statistical approach, was ISCED 5 (short-cycle tertiary) or below. In Figure 1.11, we plot the percentage of overeducated workers that are severely overeducated, at the country level, against the overeducation wage penalty. The overeducation wage penalty is larger for countries with a high proportion of overeducated employees that are categorised as severely overeducated.

Figure 1.9: Overeducation wage effects by sector

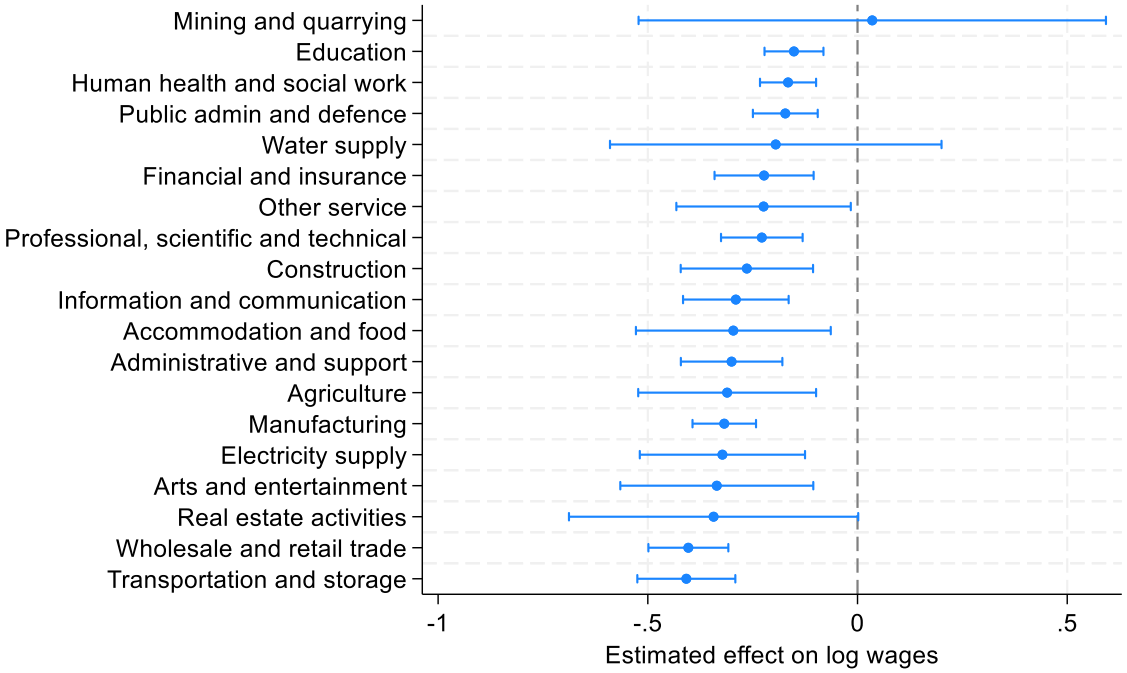


Figure 1.10: Undereducation wage effects by sector

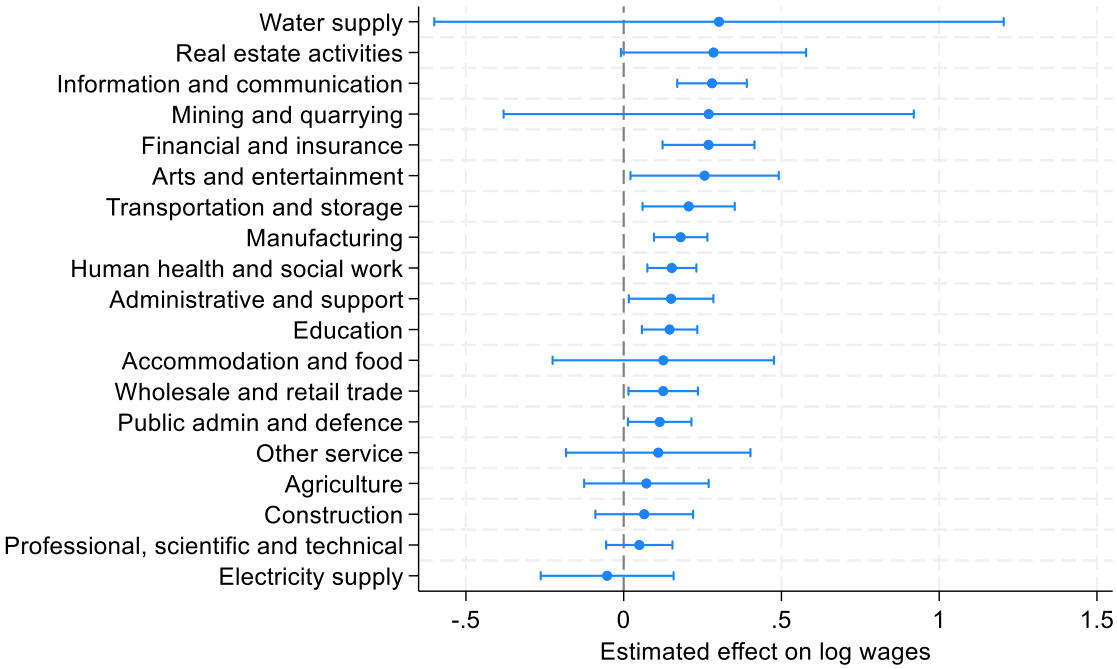
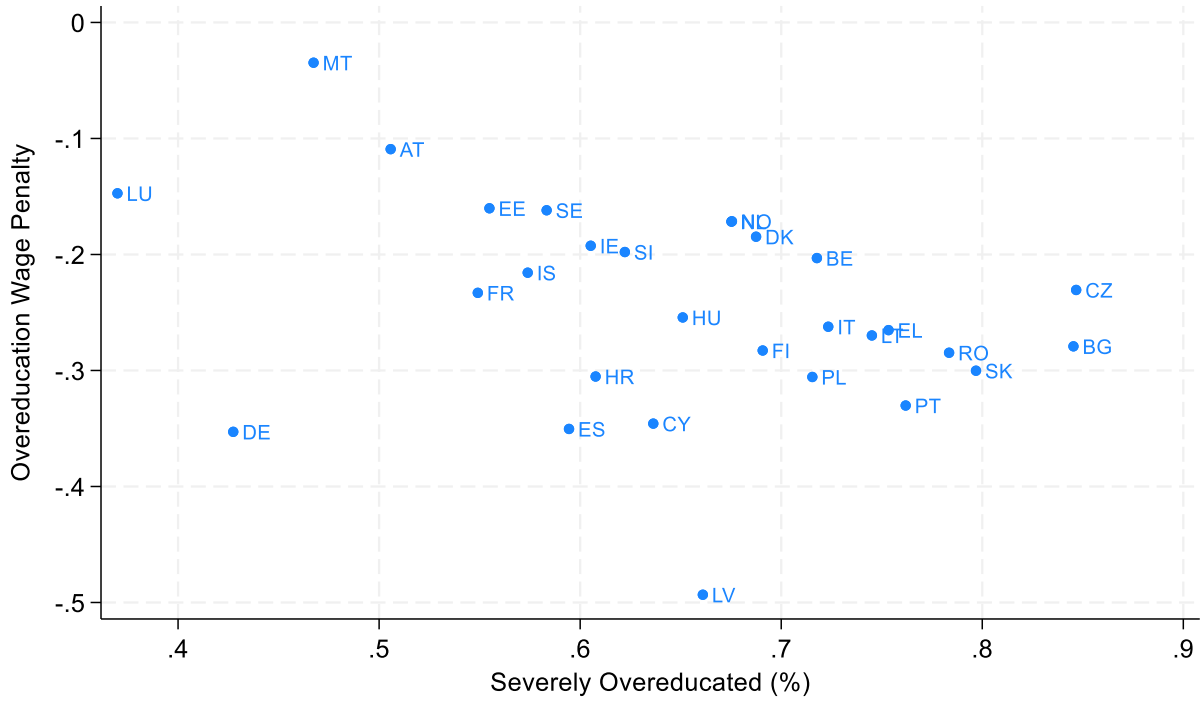


Figure 1.11: The overeducation wage penalty versus the percentage of overeducated workers that are severely overeducated, by country

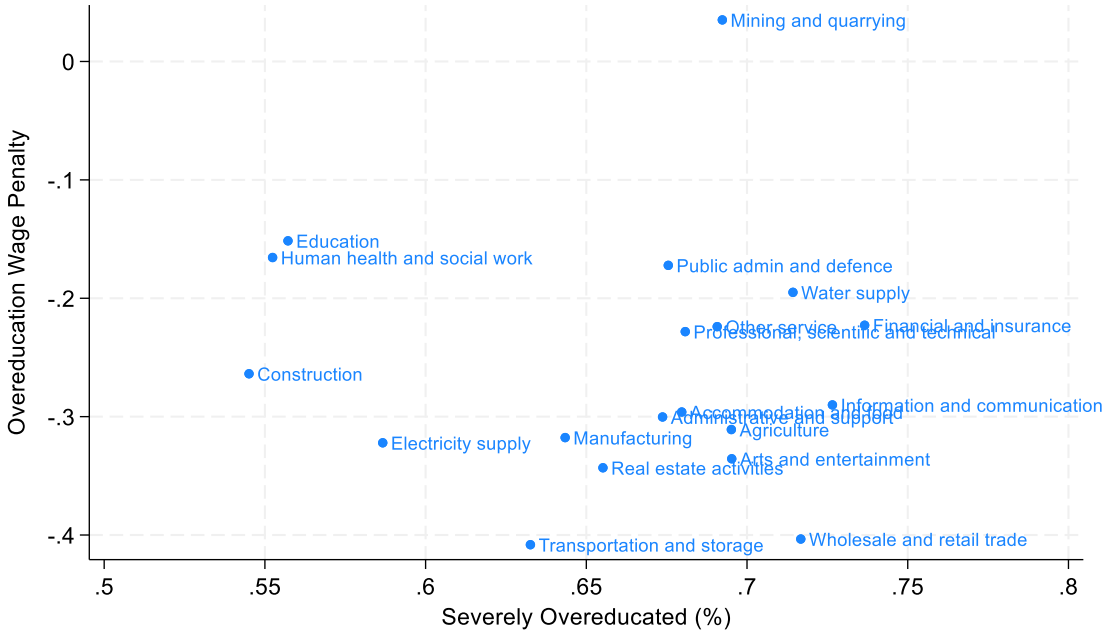


In addition to highlighting the relationship between the overeducation wage penalty and the severity of overeducation, a striking feature of Figure 1.11 is the prevalence of severe overeducation in the EU. The majority of overeducated employees across countries (using the combined measure) are severely overeducated. In countries such as Czechia, Bulgaria, Slovakia and Romania, approximately 80 to 90 percent of overeducated workers are severely overeducated. Only two of the 27 EU countries record less than 50 percent of overeducated workers that are classified as severely overeducated. This shows that it is important to go beyond binary classifiers of overeducation and demonstrates that for most overeducated employees in the EU, there is a severe misalignment between their actual and required education level. To further illustrate this point, consider the following. Of the employees for which we have a combined measure of mismatch, 8 percent are master's graduates working in jobs which require only a post-secondary (non-tertiary) qualification or below.

In Figure 1.12, we plot the percentage of overeducated workers that are severely overeducated, at the sectoral level, against the overeducation wage penalty. A similar pattern emerges; sectors in which a higher proportion of overeducated workers are severely overeducated tend to have higher wage penalties. For example, almost three

quarters of overeducated workers in the wholesale and retail sector are severely overeducated, and this sector records one of the highest wage penalties (at almost 50 percent). Other sectors such as education and human health and social work have a lower concentration of severely overeducated workers and exhibit a lower wage penalty.

Figure 1.12: The overeducation wage penalty versus the percentage of overeducated workers that are severely overeducated, by sector



1.4.2 Fear of Job Loss

Table 1.6 shows the relationship between educational mismatch and the fear of job loss. There are some inconsistencies between the subjective and statistical measures. The subjective approach indicates that undereducated employees exhibit a 1.6 percentage point higher likelihood of perceived job loss relative to matched employees with similar characteristics and the same level of education. When looking at the statistical measure, the opposite is true – it is overeducated employees that exhibit a 2.7 percentage point higher likelihood of perceived job loss, relative to similar employees with the same level of education in matched employment. There are reasons why both undereducated and overeducated employees could fear job loss. An undereducated employee may be underqualified to do their job, thereby putting their job at risk. Overeducated employees, relative to their matched counterparts, are likely to be in lower paid and "lower quality"

jobs, thereby increasing the risk of job loss. When we focus on the combined measurement approach, however, the heightened fear of job loss is only present for overeducated employees.

In Figure 1.13, we show the estimated marginal effects for each country, using the combined measurement approach, showing the relationship between overeducation and the fear of job loss. The majority (21 of 29) of the estimated effects have a positive sign, indicating a positive association between overeducation and the fear of job loss. However, most of the individual country effects are not statistically significant at conventional levels. Denmark, Cyprus and Czechia are the countries with the largest (and statistically significant) impacts. In these countries, being overeducated is associated with a 15 percentage-point increase in the likelihood of perceived job loss, compared to similar employees in matched employment with the same level of education. Malta is the only country with a negative association that is approaching statistical significance at conventional levels (p value = .105). It is also notable that, among all 29 countries, Malta is the country with the smallest (in magnitude) overeducation wage penalty (which is not statistically significant – see Figure 1.7).

Table 1.6: Relationship between fear of job loss and educational mismatch

VARIABLES	**(1)**	**(2)**	**(3)**
Subjective mismatch (ref: Matched)			
Undereducated	0.016**		
	(0.008)		
Overeducated	0.006		
	(0.005)		
Statistical mismatch (ref: Matched)			
Undereducated		-0.011	
		(0.007)	
Overeducated		0.027***	
		(0.007)	
Combined mismatch (ref: Matched)			
Undereducated			0.004
			(0.013)
Overeducated			0.027**
			(0.011)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	42,525	43,203	19,838

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Figure 1.14 shows the estimated effects for the relationship between undereducation and fear of job loss for each country. Regarding the sign of the estimates, roughly half are positive and half are negative. While most country-specific estimates are not statistically significant, Poland and Estonia show a positive relationship between undereducation and the perceived probability of job loss.

Figure 1.13: Relationship between overeducation and fear of job loss, by country (marginal effects)

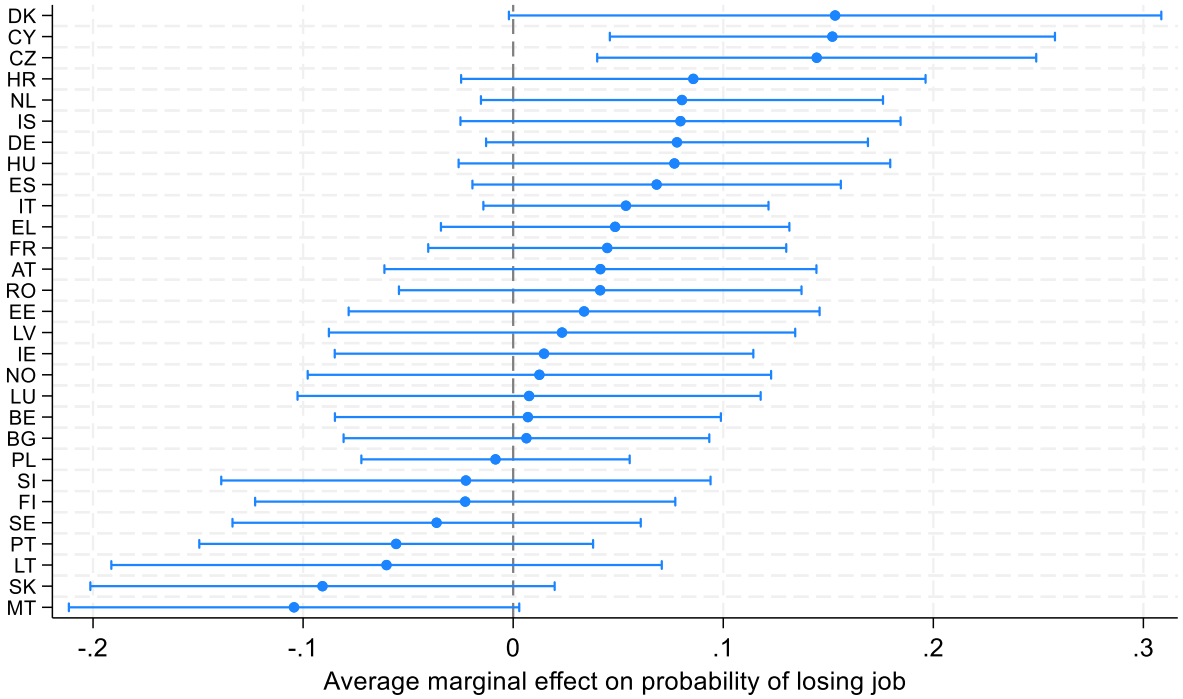
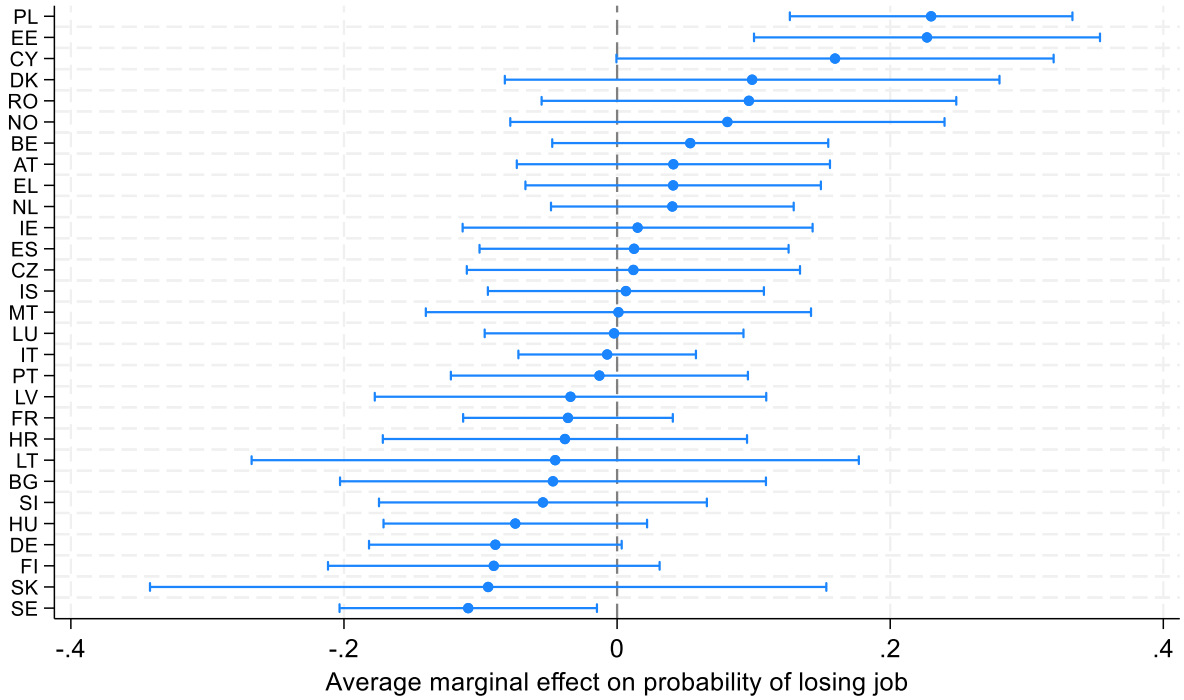


Figure 1.14: Relationship between undereducation and fear of job loss, by country (marginal effects)



We also provide sector-specific estimates of the impact of educational mismatch on the perceived probability of job loss (Figure 1.15). In the water supply and mining and quarrying sectors, being overeducated is associated with a 45 percentage-point higher probability of job loss relative to similar employees in the same sector with the same level of education in matched employment. It is notable that several of the other sectors with the strongest relationship between overeducation and fear of job loss are also the sectors with the largest overeducation wage penalty – e.g., transport and storage, wholesale and retail, real estate activities, and arts and entertainment. Therefore, holding an educational qualification that is above the level required in these sectors appears to lead to particularly large adverse outcomes in terms of wages and job security. With regard to the relationship between undereducation and fear of job loss (Figure 1.16), there is little in terms of statistical significance.

Figure 1.15: Relationship between overeducation and fear of job loss, by sector (marginal effects)

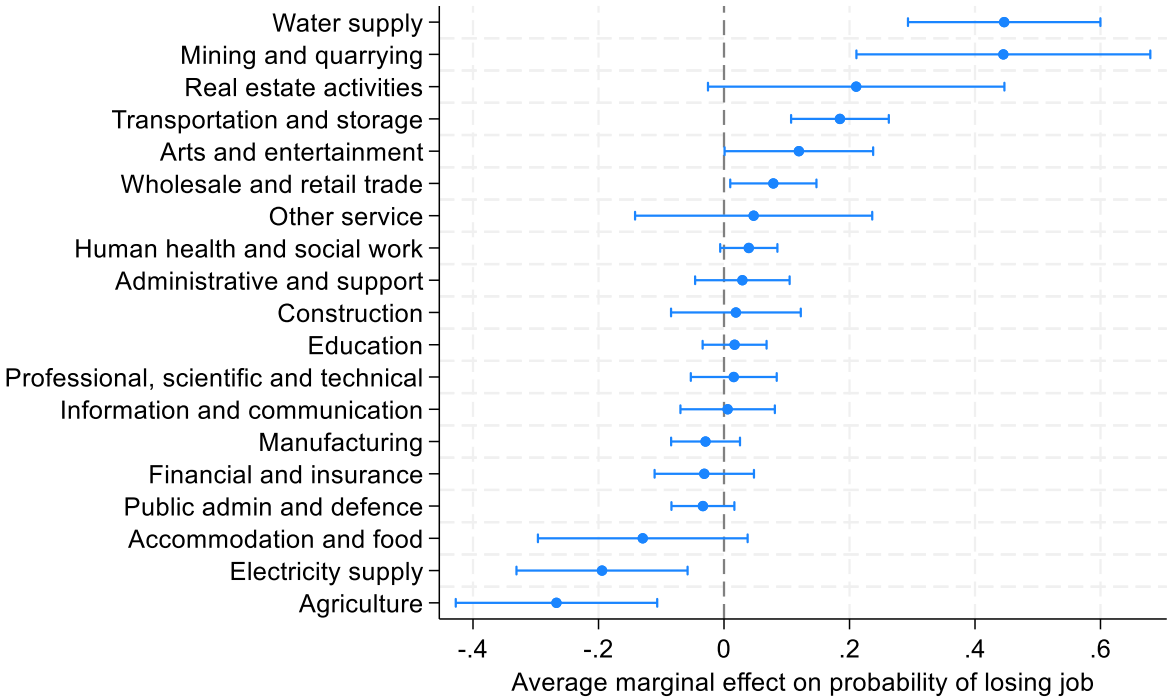
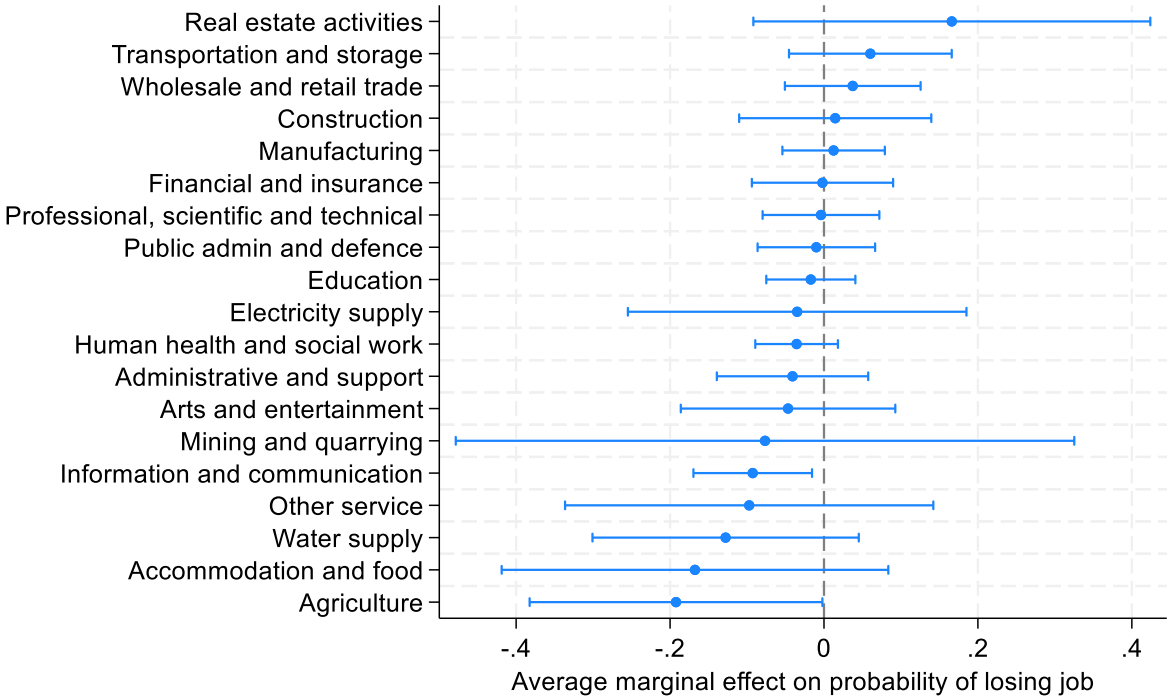


Figure 1.16: Relationship between undereducation and fear of job loss, by sector (marginal effects)



In Figure 1.17, we plot the percentage of overeducated workers that are severely overeducated, at the country level, against the estimated impact of overeducation on the perceived probability of job loss. When looking at all countries, there is no clear relationship. However, the country with the highest percentage of overeducated employees that are severely overeducated, Czechia, does have one of the highest estimated impacts of overeducation on the probability of job loss. There appears to be some relationship between the estimated job loss effects and severity of overeducation by sector (Figure 1.18); employees in sectors with a high rate of severe overeducation tend to be more likely to report that they fear job loss in the near future.

Figure 1.17: Impact of overeducation on the probability of job loss versus the percentage of overeducated workers that are severely overeducated, by country

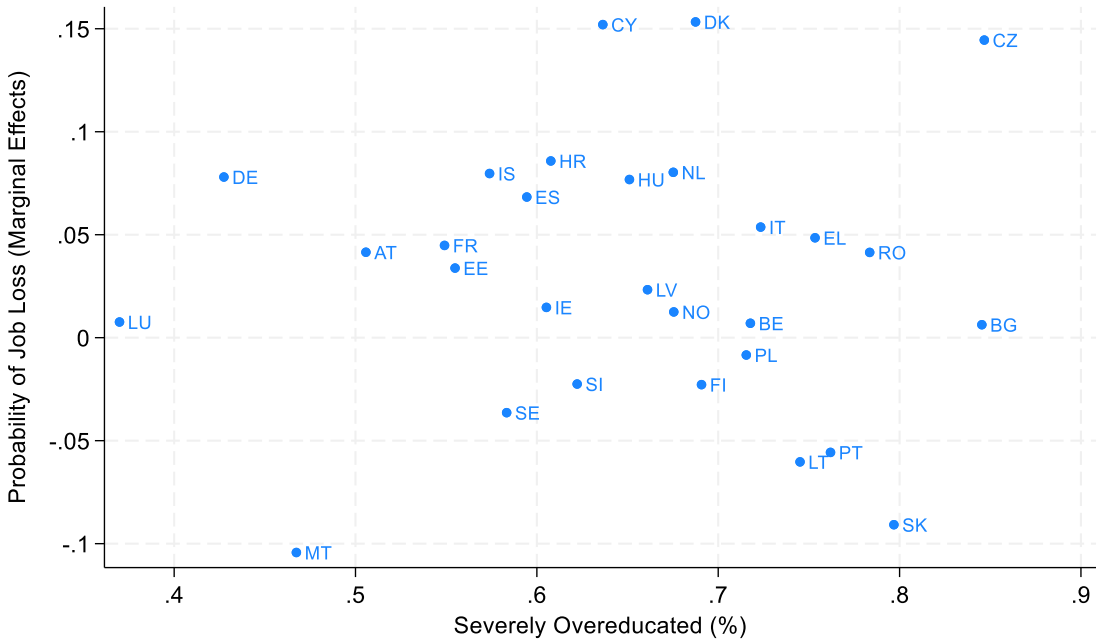
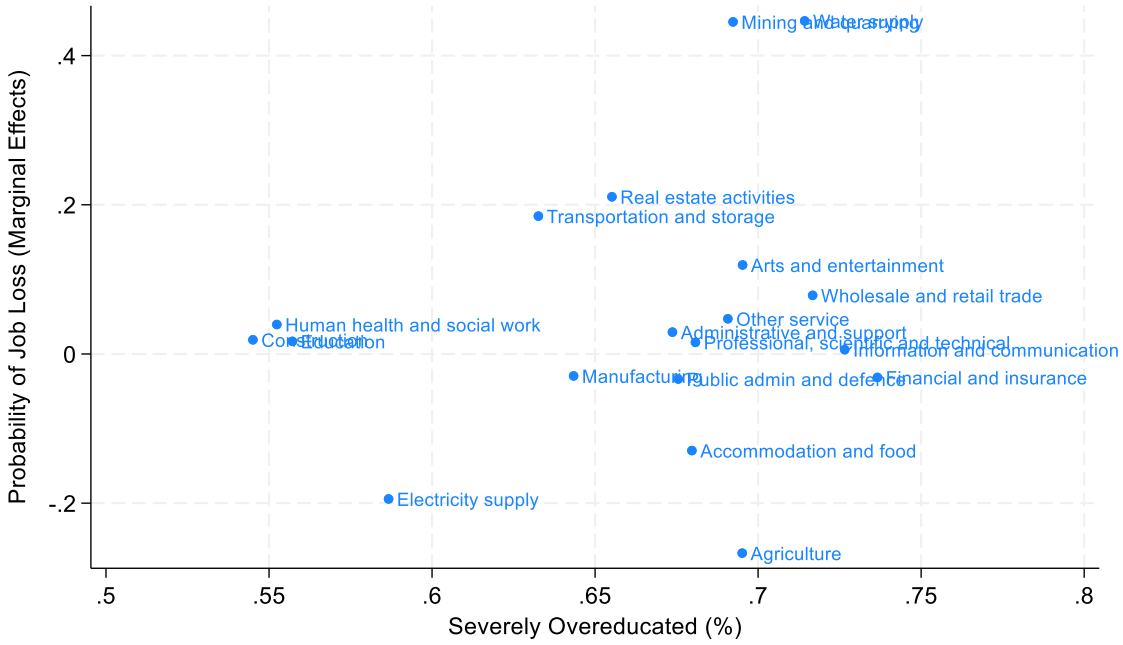


Figure 1.18: Impact of overeducation on the probability of job loss versus the percentage of overeducated workers that are severely overeducated, by sector



1.4.3 Job Satisfaction

Table 1.7 shows the relationship between educational mismatch and job satisfaction. Across all measurement approaches (subjective, statistical and combined), being undereducated is associated with a higher probability of being satisfied with your job. The magnitude varies from approximately 3-4 percentage points using the subjective and statistical measures, respectively, to almost six percentage points using the combined measures. Undereducated individuals are in jobs that typically require a higher level of education than they possess. Therefore, these jobs are likely to be of higher quality than their counterparts with the same level of education in a matched job. Furthermore, as we have seen earlier, these better-quality jobs can also result in a wage premium for some. This is also reflected in higher job satisfaction.

Table 1.7: Relationship between job satisfaction and educational mismatch

VARIABLES	(1)	(2)	(3)
Subjective mismatch (ref: Matched)			
Undereducated	0.029***		
	(0.006)		
Overeducated	-0.062***		
	(0.005)		
Statistical mismatch (ref: Matched)			
Undereducated		0.035***	
		(0.006)	
Overeducated		-0.040***	
		(0.007)	
Combined mismatch (ref: Matched)			
Undereducated			0.056***
			(0.010)
Overeducated			-0.097***
			(0.010)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	42,839	43,565	19,980

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Overeducated individuals, on the other hand, are less likely to be satisfied in their jobs, relative to their matched counterparts with the same level of education. Overeducated employees are likely in lower quality jobs in which their education and skills are underutilised, and as we saw earlier, also face a wage penalty. The magnitude of the job satisfaction effect varies by measurement approach. Using the subjective and statistical measures, overeducated employees are 6 and 4 percentage points, respectively, less likely to be satisfied in their job relative to matched employees with the same education level. Using the combined measure, the estimate increases to almost 10 percentage points.

Focusing on the combined measure, Figure 1.19 shows the country specific estimated impacts of overeducation on the probability an employee is satisfied in their job. While all of the estimates are negative, the magnitude varies substantially. In countries such as Croatia, Luxembourg, Estonia, Spain, Malta and Iceland, overeducation is associated with a large reduction in the probability of being satisfied in the job. In other countries, such as Sweden, Romania and Germany, the effect is small

and not statistically significant. Figure 1.20 shows the relationship between undereducation and job satisfaction. Being undereducated is associated with a relatively large increase in job satisfaction in countries such as Sweden, Germany, Bulgaria, Denmark and Portugal.

Figure 1.21 shows the sector specific estimates of the relationship between overeducation and job satisfaction. It is notable that sectors such as Transportation and storage, Wholesale and retail trade, and electricity supply have both a large overeducation job satisfaction penalty and a large overeducation pay penalty. The lower job satisfaction, therefore, is likely to reflect the fact that overeducated workers in these sectors earn much less pay compared to their peers with the same level of education in matched jobs. On the other hand, undereducated employees across several sectors are more likely to be satisfied relative to matched employees, with the largest effect in the Arts and Entertainment sector (Figure 1.22).

In Figures 1.23 and 1.24, we examine whether the overeducation job satisfaction penalty by country and sector, respectively, is related to the extent to which overeducated employees are severely overeducated. There is no clear relationship, either by country or sector.

Figure 1.19: Relationship between overeducation and probability of being satisfied in the job, by country (marginal effects)

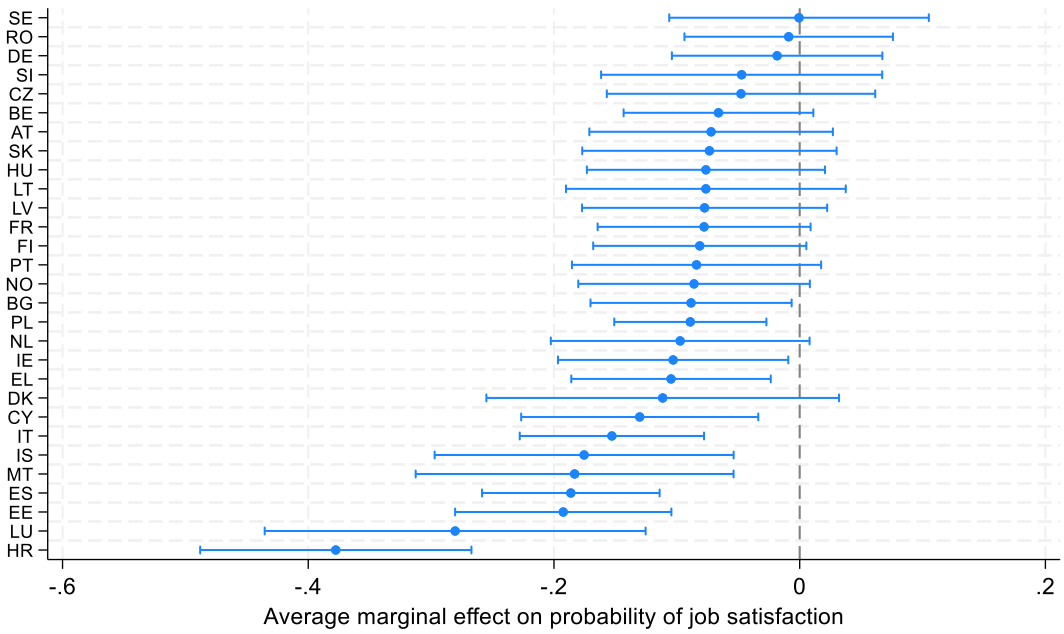


Figure 1.20: Relationship between undereducation and probability of being satisfied in the job, by country (marginal effects)

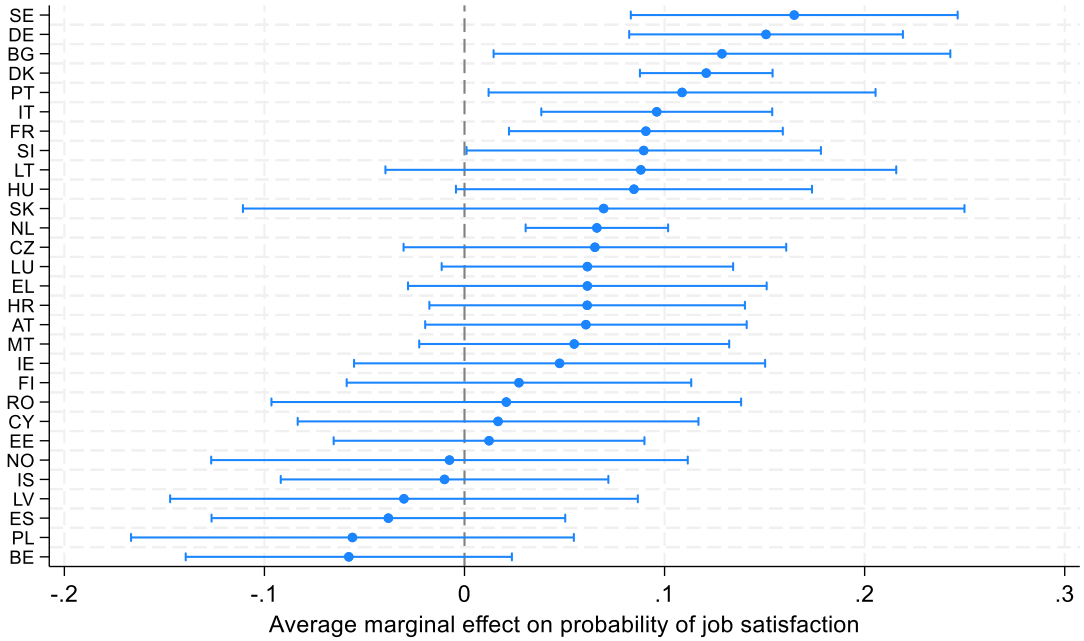


Figure 1.21: Relationship between overeducation and probability of being satisfied in the job, by sector (marginal effects)

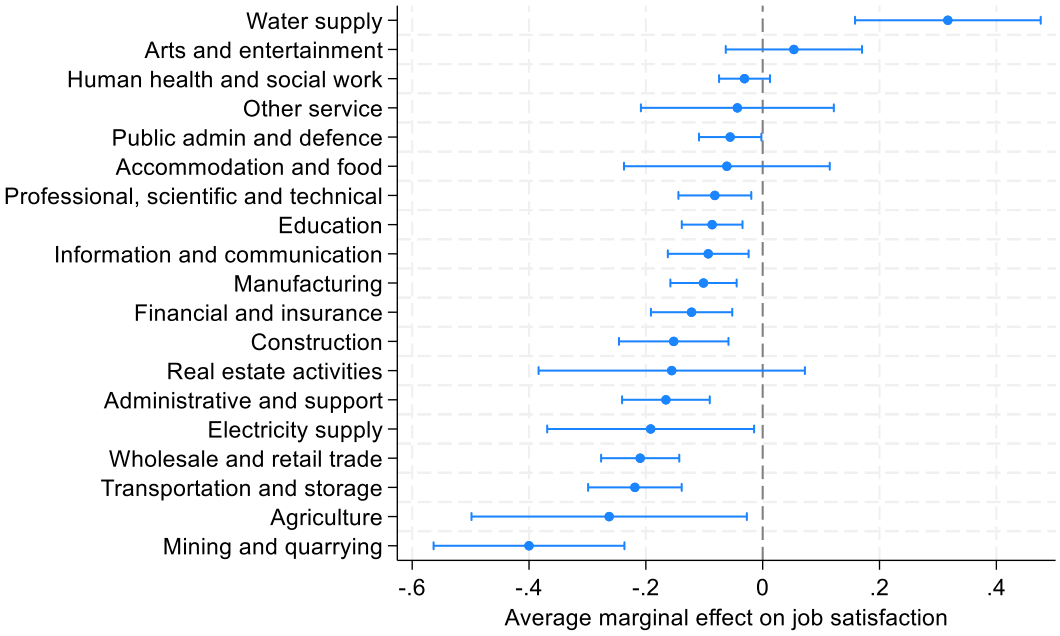


Figure 1.22: Relationship between undereducation and probability of being satisfied in the job, by sector (marginal effects)

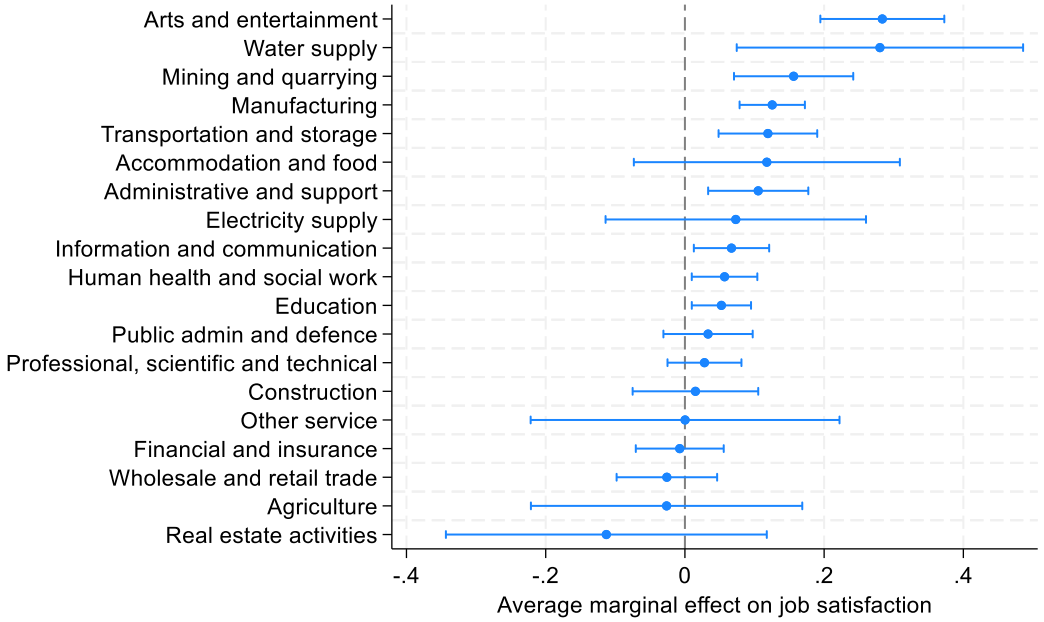


Figure 1.23: Impact of overeducation on job satisfaction versus the percentage of overeducated workers that are severely overeducated, by country

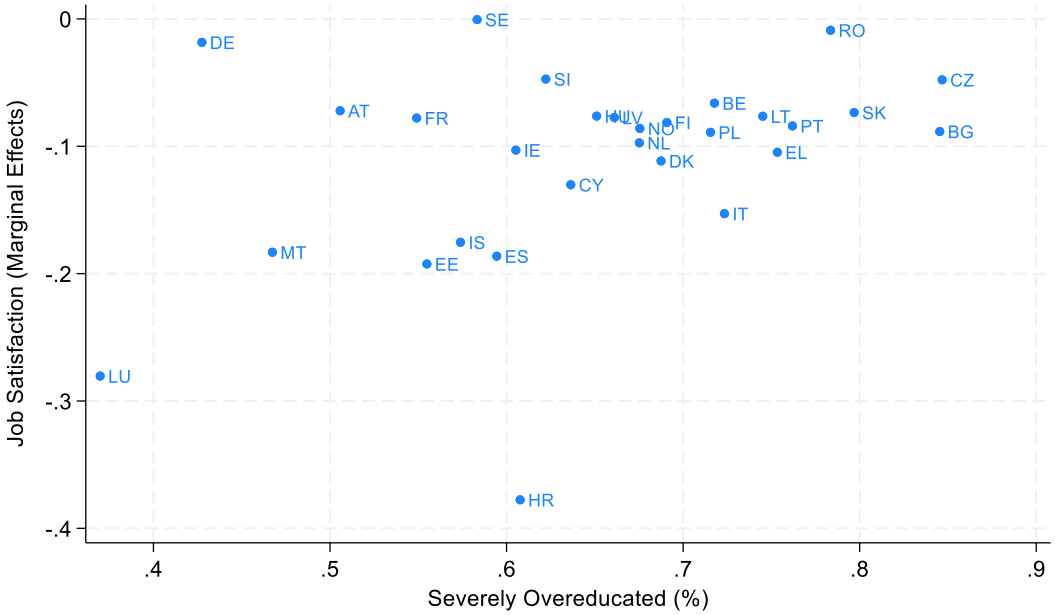
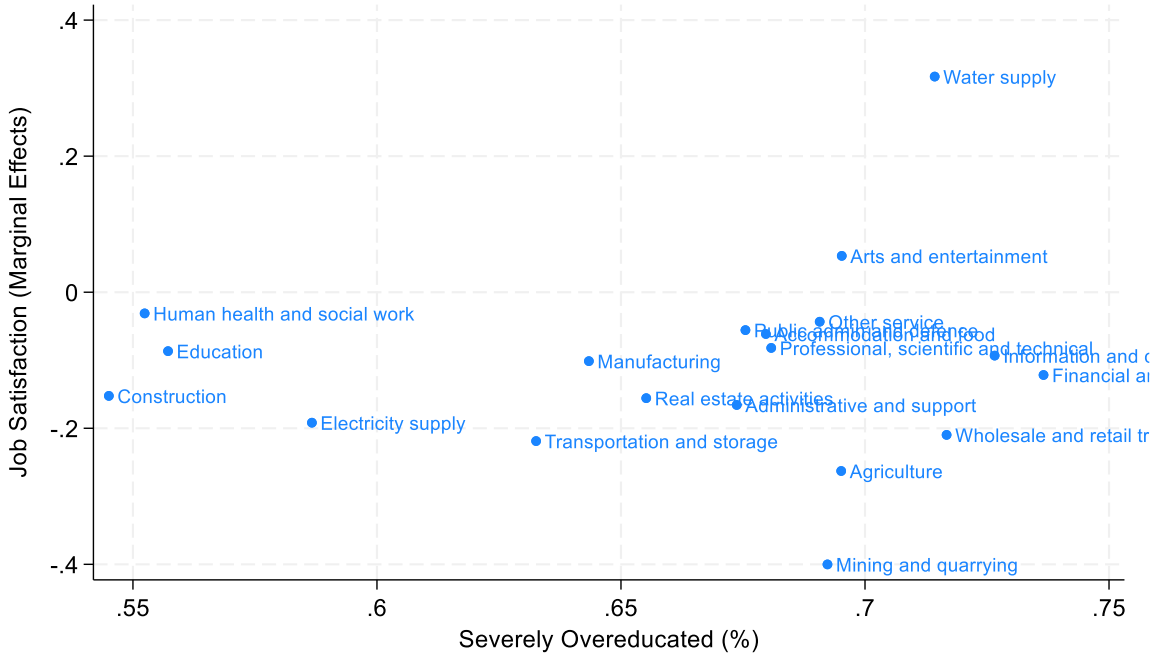


Figure 1.24: Impact of overeducation on job satisfaction versus the percentage of overeducated workers that are severely overeducated, by sector



1.4.4 Within-Occupation Education Deficits and the Role of Training

We have shown that an undereducation wage premium can exist when undereducated workers are compared to workers with the *same level of education* in matched employment. There is an alternative way of framing undereducation. One can look at an undereducated employee and compare them to a matched employee *with higher education* in the same occupation. This can lead to an undereducation wage penalty, as we are now capturing the effect of having an occupation-specific education deficit relative to workers in the same occupation with a *higher (matched) level of education*. We can estimate this in a similar way to regression equation (1), with the difference being that we include occupation controls instead of education controls. Specifically, we estimate,

$$ln(Wage_{i,c}) = \alpha + \beta_U Undereducated_{i,c} + \beta_O Overeducated_{i,c} + X'_{i,c}\delta + \gamma_c + \sigma_S + \rho_O + \varepsilon_{i,c} \quad (3)$$

Where everything is defined as earlier, but *X'* no longer includes education controls. In addition, 3-digit ISCO occupation dummies are included (ρ_O).

Equation (3) is estimated using the three measurement approaches (subjective, statistical, and combined) and the results are shown in Table 1.8. Being undereducated, relative to employees with higher levels of education in the same occupation, is associated with a wage penalty across all measurement approaches. However, the magnitude varies from 2 percent using the subjective measure, to 11 percent for both the statistical and combined measures. Note that the combined measure is based on the subsample of employees for which the subjective and statistical measures agree, hence the smaller sample size.

There is an important methodological consideration here. By construction, with the statistical and combined measures, an undereducated person is compared to a matched person with a higher level of education in that same occupation.[8] When looking at the subjective approach only, an undereducated person could be compared to a person in the same occupation that says they are matched but has the same level of education as the undereducated person. For example, within a given 3-digit occupation, one person with a master's degree could report that they are undereducated. Another person in that same occupation, also with a master's degree, could report that they are matched. The difference between the two could, to some extent, relate to the perceived quality and hence difficulty of the job. Nonetheless, they are both educated to the same high level. This may be why the undereducation wage deficit for the subjective approach is of a lower magnitude than the statistical and combined measures, which by construction ensure that the undereducated person must have a lower level of education than their matched counterpart.

[8] The reason is that undereducation is constructed as having an education level below the mode, meaning the matched comparison has an education level equal to the mode, which is higher by construction than the undereducated person.

Table 1.8: Within occupation educational mismatch and wages

VARIABLES	(1)	(2)	(3)
Subjective mismatch (ref: Matched)			
Undereducated	-0.021**		
	(0.009)		
Overeducated	-0.052***		
	(0.006)		
Statistical mismatch (ref: Matched)			
Undereducated		-0.114***	
		(0.007)	
Overeducated		0.102***	
		(0.008)	
Combined mismatch (ref: Matched)			
Undereducated			-0.107***
			(0.012)
Overeducated			0.038***
			(0.010)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes
Observations	32,229	32,749	15,207

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

With regard to overeducation, we observe a wage premium when looking at the statistical and combined measures. However, there is an overeducation wage deficit when looking at the statistical approach. Again, this likely relates to the methodological differences discussed above. With the statistical and combined measures, an overeducated person by definition is compared to a matched person of a lower level of education in the same occupation. Hence, we observe a wage premium. With the subjective approach, an overeducated person and a matched person within the same occupation could have the same level of education. The difference with regard to their subjective mismatch status could, to some extent, reflect differences in job quality. The overeducated individual could be in a lower quality job that does not utilise their full level of education, relative to the matched counterpart with the same education level in the same three-digit occupation. Therefore, we could observe an overeducation wage deficit for the subjective approach, while observing an overeducation wage premium for the statistical and combined approaches.

We also estimate the relationship between within-occupation mismatch and the fear of job loss. This involves the analogous probit model for equation (3), with fear of job loss as the outcome variable. The results are shown in Table 1.9. There is no clear relationship. While the subjective measure indicates a slight increase in the fear of job loss for undereducated employees, the statistical measure indicates a slight increase in the fear of job loss for overeducated employees. However, the combined measure shows no statistically significant increase in the fear of job loss for either overeducated (undereducated) workers, relative to matched workers in the same occupation with lower (higher) education. Table 1.10 shows similar results when job satisfaction is the outcome. Again, there is no consistent result. For the subjective measure, overeducation is associated with a slight reduction in the probability of being satisfied in the job, while there is a slight increase in satisfaction for the statistical approach. When using the combined measure, there is no statistically significant effect for overeducation or undereducation.

Table 1.9: Within occupation educational mismatch and fear of job loss

VARIABLES	**(1)**	**(2)**	**(3)**
Subjective mismatch (ref: Matched)			
Undereducated	0.016**		
	(0.007)		
Overeducated	0.003		
	(0.005)		
Statistical mismatch (ref: Matched)			
Undereducated		0.003	
		(0.006)	
Overeducated		0.018***	
		(0.006)	
Combined mismatch (ref: Matched)			
Undereducated			0.016
			(0.010)
Overeducated			0.009
			(0.008)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes
Observations	42,518	43,196	19,832

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table 1.10: Within occupation educational mismatch and job satisfaction

VARIABLES	(1)	(2)	(3)
Subjective mismatch (ref: Matched)			
Undereducated	0.006		
	(0.006)		
Overeducated	-0.034***		
	(0.005)		
Statistical mismatch (ref: Matched)			
Undereducated		-0.013**	
		(0.005)	
Overeducated		0.015***	
		(0.005)	
Combined mismatch (ref: Matched)			
Undereducated			-0.010
			(0.009)
Overeducated			-0.008
			(0.007)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes
Observations	42,830	43,556	19,966

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

We investigate the role of training in mitigating the within-occupation wage penalties associated with undereducation, where the combined measurement approach shows that undereducated workers earn 11 percent less than matched workers with higher education in the same occupation (refer to Table 1.8 above). We utilise a question in the ESJS that asks respondents, "In the last 12 months, have you participated in any education or training activities to learn new job-related skills?" Respondents can answer "Yes" or "No", and we create a binary indicator equal to one for those that received training.

In Column (1) of Table 1.11, we estimate equation (3) with the addition of this training dummy variable. The combined measurement approach is used for educational mismatch. The wage benefit of receiving training is of a similar magnitude to the wage deficit associated with within-occupation undereducation. Employees that have received training in the last 12 months earn 9 percent more than similar employees that did not receive training. We then estimate the impact of training separately for each match / mismatch category of employee (using the combined measure). In column (2) of

Table 1.11 we focus on employees that are in matched employment. Matched employees that received training in the last 12 months earn 7 percent more than matched employees that did not receive training. In columns (3) and (4), we focus on undereducated and overeducated employees, respectively. The magnitude of the training effect is similar for both groups, with those receiving training earning between 11 and 12 percent more than similar employees, with the same mismatch status, that did not receive training.

The magnitude of the wage premium associated with job-related training is approximately the same as the magnitude of the wage deficit associated with having an education level below that which is required for the job. This highlights the importance of job-specific training in helping to offset the lower wages associated with within-occupation education deficits. However, note that training benefits all employees to a similar degree, whether they are matched, overeducated or undereducated. Therefore, while training in general is associated with higher wages, it does not mitigate the within-occupation undereducation wage penalty. For this to happen, the positive wage association from training would have to be larger for undereducated employees relative to other employees, which is not the case.[9]

Table 1.11: Effect of Training on Wages

VARIABLES	**(1) All Employees**	**(2) Matched Employees**	**(3) Undereducated Employees**	**(4) Overeducated Employees**
Training	0.092***	0.073***	0.111***	0.118***
	(0.008)	(0.011)	(0.022)	(0.016)
Combined mismatch (ref: Matched)				
Undereducated	-0.105***	-	-	-
	(0.012)	-	-	-
Overeducated	0.035***	-	-	-
	(0.010)	-	-	-
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes	Yes
Observations	15,207	8,305	2,438	4,464

Note: Robust standard errors. *** p<0.01, ** p<0.05, * p<0.1

[9] An alternative strategy is to interact the training dummy variable with the mismatch variables. This indicates whether the effect of training is stronger for undereducated employees. When this is done, the interaction variable is not statistically significant. This is because the positive wage association with training is similar across all employees, regardless of match status.

Approximately 65 percent of ESJS respondents report receiving training. However, this incidence varies substantially across sectors and countries (Figures 1.25 and 1.26). Sectors that experience high rates of undereducation, such as finance and insurance, ICT, and mining and quarrying, are shown to have relatively high rates of training. The incidence of training is also high in the education sector. Low-paid and low-skilled sectors such as accommodation and food and households as employers have the lowest training incidence. With regard to countries, Ireland has the highest incidence of employee training, with almost 80 percent of ESJS respondents reporting receiving training in the last 12 months. It is concerning that France has the lowest incidence of training, given that it records one of the highest rates of undereducation in the EU.

Figure 1.25: Incidence of training by sector

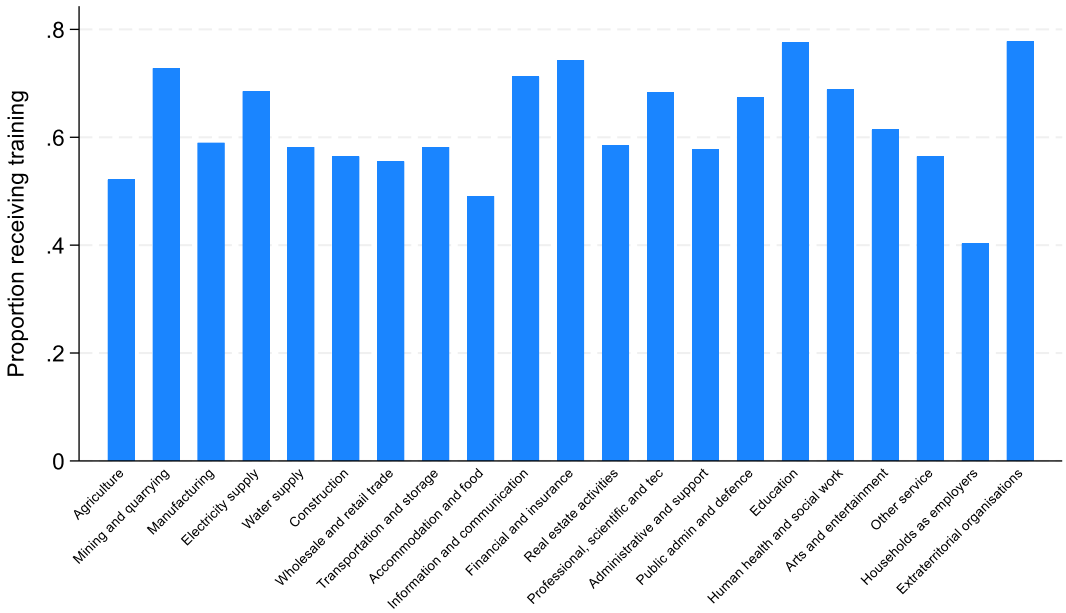
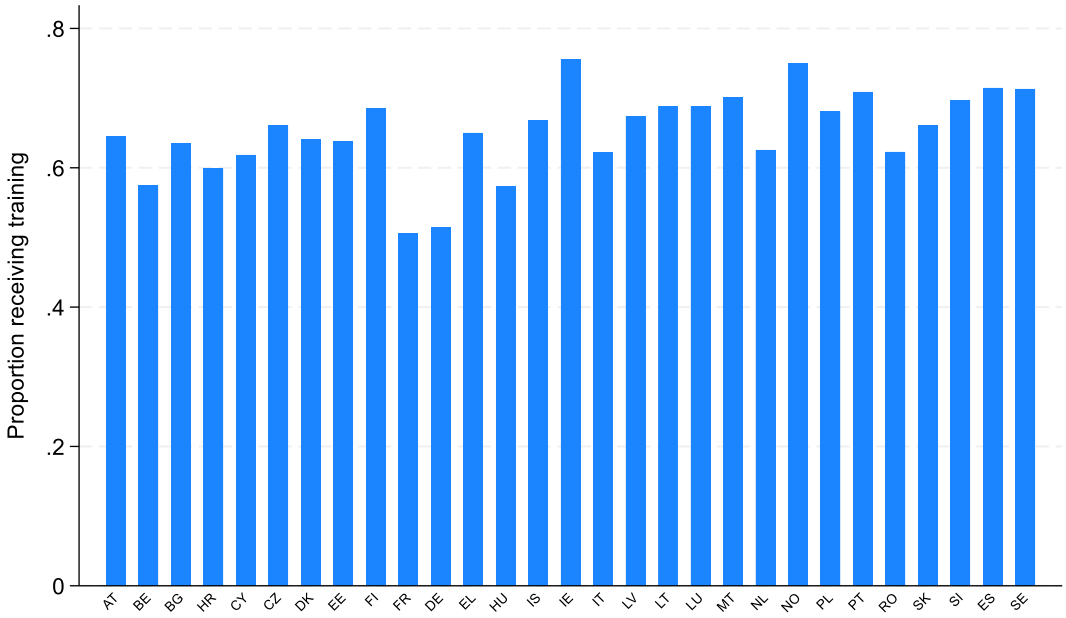


Figure 1.26: Incidence of training by country



1.5 Conclusion

Situations in which an employee's educational attainment does not match the level required for their job receives a great deal of attention from both academics and policymakers. The reason is that educational mismatch can lead to sub-optimal outcomes for employees, employers, and the economy at large, in terms of lower wages and lower productivity.

Measuring educational mismatch can be challenging. There are different ways to measure it, and the measurement approach is often governed by the data that researchers have available to them. The two most common approaches are the subjective (self-reported) approach and the statistical approach, whereby a person's actual educational attainment is compared to the mode level of education among employees within the same occupation. While results from studies using both approaches are often discussed and weighted equally, there has been little critical analysis of how they may differ and whether or not the different measurement approaches produce conflicting results. We attempt to address this issue by utilising a pan-European dataset that allows us to construct both the subjective and statistical measures of educational mismatch. Our analysis reveals substantial inconsistencies across measurement approaches. The statistical and subjective measures produce a

different mismatch status for more than half (52%) of employees. In light of this, we construct a more rigorous, and potentially more robust measure of mismatch, in which we focus on employees for which there is a consistent classification of educational mismatch across both statistical and subjective measures. We call this the 'combined' measure of educational mismatch.

There are also differences in the incidence of mismatch depending on the measurement approach. On average, approximately 60 percent of employees are considered matched using the subjective measure, with 12 percent being undereducated and 28 percent being overeducated. The statistical measure, on the other hand, indicates that just 38 percent of employees are matched, with 33 percent undereducated and 29 percent overeducated. The incidence of mismatch using the combined measure falls somewhere between the subjective and statistical measures, but among the two it more closely resembles the subjective estimates. According to the combined measure, 55 percent of employees are matched, 16 percent are undereducated and 29 percent are overeducated.

We show that the incidence of mismatch varies substantially across sectors and across countries. Focusing on the combined measurement approach, the incidence of undereducation is relatively high in sectors such as ICT (29%), Finance and Insurance (26%) and Real Estate Activities (25%), while the incidence of overeducation is high in sectors such as Accommodation and Food (43%) and Wholesale and Retail (40%). The undereducation incidence is relatively high in countries such as Malta (35%), Luxembourg (33%) and France (31%), while overeducation is high in Spain (59%), Latvia (47%) and Greece (43%).

One of the most consistent findings from the existing overeducation literature relates to the overeducation pay penalty. That is, a worker whose educational attainment exceeds the level required to do their job, are typically paid less than workers with the same educational attainment in a job that requires their education. Our analysis shows that there an overeducation pay penalty exists regardless of the measurement approach used. However, the magnitude of the effect varies substantially. For example, the overeducation pay penalty using the combined measure of mismatch is approximately twice as large as the estimates using the subjective and statistical approaches, and our analysis reveals that overeducated employees earn 28 percent less than similar employees with the same level of education in a matched job. Certain sectors are shown to be more susceptible to adverse impacts associated with overeducation. For example,

overeducated employees in sectors such as transport and storage, wholesale and retail, real estate activities, and arts and entertainment, incur large wage penalties and are also most likely to fear future job loss. Therefore, holding an educational qualification that is above the level required in these sectors appears to lead to particularly large adverse outcomes in terms of wages and job security.

Most existing studies simply consider overeducation as a binary variable. However, this simple binary classification can overlook differences in the severity of overeducation. For example, a person with a master's degree in a job that requires an upper secondary level of education is more severely overqualified than a master's graduate in a job requiring an undergraduate degree. We calculate the proportion of overeducated workers (using the combined measure) that are severely overeducated, which is defined as a situation where the employee's actual level of education is two or more levels above that which is required to do their job using either the subjective or statistical approach. For example, a person with a master's degree (ISCED level 7) would be severely overeducated if the required education for their job, according to the subjective *or* statistical approach, was ISCED 5 (short-cycle tertiary) or below. Our results suggest that severe overeducation a serious issue across the EU. The majority of overeducated employees across countries (using the combined measure) are severely overeducated. In countries such as Czechia, Bulgaria, Slovakia and Romania, approximately 80 to 90 percent of overeducated workers are severely overeducated. Only two of the 27 EU countries record less than 50 percent of overeducated workers that are classified as severely overeducated. Of the employees for which we have a combined measure of mismatch, 8 percent are master's graduates working jobs which may require only a post-secondary (non-tertiary) qualification or below. The wage penalty associated with overeducation also tends to be higher in countries where severe overeducation is more prevalent.

The existing research in this area typically compares overeducated (undereducated) employees with employees with the *same level of education* in a matched job. As in our study, this approach reveals an overeducation wage penalty. This approach also reveals an undereducation pay premium, as undereducated employees earn more than similar employees with the same level of education in matched jobs. This reflects the fact that undereducated employees are likely in higher quality and more demanding jobs than their counterparts in matched jobs with the same educational attainment. However, there is an alternative framework which uses a different basis of

comparison. This involves comparing undereducated employees to matched employees that work in the same job but have higher education. In this instance, there is an undereducation pay penalty, as we are comparing an employee whose educational attainment is below that which is typically required to do the job to an employee with higher (matched) education in the same job. Using our combined measure, we estimate this 'within-occupation' undereducation wage penalty at 11 percent. This wage penalty resulting from a deficit in formal educational attainment may be overcome by training. We estimate that the wage premium associated with training is of a similar magnitude to the wage deficit incurred by undereducation.

Our results have several important policy implications. First, from a methodological perspective, we have shown that more caution needs to be given to the measurement approach used for educational mismatch. The conventional and often-used statistical and subjective approach can produce inconsistent estimates and results. We suggest that, where possible, a more robust 'combined approach' be used as the basis for evidence-based policymaking. Our findings suggest that the pay penalty associated with educational mismatch may be even more severe than found in previous studies that rely on the subjective approach. Policymakers should also be aware that the effects of mismatch, in terms of wages and fear of job loss, appear to be particularly acute in certain sectors, such as transport and storage, wholesale and retail, real estate activities, arts and entertainment. Also of policy concern is the fact that severe overqualification appears to be prevalent across the EU. We estimate that 8 percent of master's graduates work in jobs that require only a post-secondary (non-tertiary) qualification or below. This points to a severe underutilisation of skills and education. Future work should be aimed at understanding the precise reasons for mismatch and implementing policies that allow highly qualified individuals to find high-quality jobs. Previous research has suggested that barriers to residential mobility and geographic barriers such as commuting / lack of transport can exacerbate mismatch.

Finally, our analysis points to training as a potential solution for employees that are on lower wages due to an educational deficit at work. The boost to earnings associated with training is of a similar magnitude to the earnings loss associated with having insufficient education for a job. Currently, the EU has a target of having at least 60% of all adults participating in training every year by 2030. Our analysis underpins the importance of achieving this target.

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2. CHAPTER 2. When Mismatch Measures Disagree: Skills Utilisation, Training and Labour-Market Resilience Across Europe

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2.1 Introduction

The economic value of human capital depends on where and how it is utilized. Workers with similar qualifications may perform different tasks, while workers with different qualifications may meet the requirements of the same job. This makes the measurement of worker-job mismatch particularly important: a mismatch indicator based on the typical educational attainment within an occupation does not necessarily imply the existence of underutilized skills or an inability to perform the required tasks. This distinction is significant for policymaking. Additional training may address a specific skills shortage but may not substantially improve matching in cases where existing capabilities are not being utilized. Consequently, a useful diagnosis requires distinguishing educational mismatch from skills underutilisation and skills gaps (Allen and van der Velden, 2001; McGuinness et al., 2018).

Two widely used approaches to skills mismatch can lead to different diagnoses. The self-assessment method asks employees to judge whether their qualifications and skills meet the requirements of their job. The statistical approach compares their educational level with that of other workers in the same occupation. The former method can capture variations in tasks within occupations, but it also reflects expectations and reporting tendencies. The latter provides a replicable benchmark based on the prevailing educational profile within an occupation, complementing employees' assessments of their specific job requirements. Previous research has demonstrated substantial differences among mismatch indicators both in the prevalence of mismatch and in its estimated effects on labour market outcomes (Verhaest and Omey, 2006; Capsada-

Munsech, 2019). These differences raise an important question: how do alternative classifications relate to workers' reports of skill underutilisation, specific skill deficits and labour market outcomes?

There is no reason to assume that convergence between the two approaches is either sufficient or necessary for identifying these issues. A worker whose educational level falls below an occupational benchmark may have acquired the relevant skills through experience and workplace learning. Conversely, a worker whose education matches that benchmark might perform tasks that use little of their knowledge. Even agreement on overeducation does not imply a surplus in every relevant skill. Multidimensional human capital models show why workers can be mismatched along certain dimensions and well matched along others (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). The research question, therefore, is not simply how often indicators agree, but what their agreement and divergence reveal about the work people do.

This paper addresses this question using TRAILS-I survey data from 31 European countries. We measure mismatch using a subjective approach based on respondents' assessments of whether their education and training match their job requirements, and a statistical approach comparing their educational attainment with the modal educational level within country-occupation groups. Each approach distinguishes workers whose qualifications or education fall below, match or exceed the respective benchmark. Combining the subjective and statistical classifications yields nine categories capturing both agreement and the direction of disagreement between the measures. We then examine whether workers across these categories differ in reported skill utilisation, skill gaps and training participation.

The descriptive evidence motivates this approach. The two measures identify substantially different shares of matched workers. In particular, many respondents classified as undereducated relative to the occupational benchmark do not consider themselves underqualified for their jobs. The extent and nature of this divergence also vary across sectors and subnational regions. These patterns suggest that the choice of indicator has implications beyond aggregate mismatch rates, shaping which workers are identified as mismatched. Our analysis investigates whether retaining this information reveals systematic differences in reported skills used and gaps, after accounting for observed worker and job characteristics.

The paper contributes to three related strands of literature. First, it builds on the distinction between educational and skill mismatch (Chevalier, 2003; Green and McIntosh, 2007; Green and Zhu, 2010). Second, it extends research combining alternative mismatch indicators. Recent studies examine different measures of job requirements and the overlap between overeducation and overskilling (Pérez Rodríguez et al., 2024; Longobardi and Pagliuca, 2026). We investigate the additional information obtained by combining subjective and statistical mismatch measures, employing all nine categories rather than focusing solely on cases of agreement.

Third, we connect mismatch measurements to training participation and workers' perceived adaptability and employability. The recent study of Kelly et al. (2026) examines how skill mismatch is linked to changing occupational requirements and the potential role of training in addressing them. We complement this work by examining whether training participation and workers' perceived capacity to adapt differ according to whether subjective and statistical mismatch classifications agree or disagree. Building on evidence of geographical and local labour market differences in overeducation in Europe (Iammarino and Marinelli, 2015; Baran, 2024), we also explore regional and sectoral variation in these differences.

The analysis provides evidence after accounting for observed worker and job characteristics. Training participation, job allocation and reported mismatch may be jointly determined, while self-assessments of mismatch and skill utilisation may reflect common reporting tendencies. Perceived adaptability and employability may also differ from subsequent employment outcomes. We therefore assess whether alternative approaches to measuring mismatch provide complementary information about workers' skill needs. The findings can inform more targeted approaches to training and inclusiveness by examining whether these classifications distinguish workers who report skill gaps from those whose capabilities are underutilised, while recognising that both situations may coexist.

2.2 Related literature

2.2.1 Qualifications, skills and worker-job allocation

The distinction between qualifications and skills is central to interpreting worker-job mismatch. Educational attainment reflects formal investment in human capital, whereas the ability to meet job requirements also depends on experience, workplace learning and the tasks performed. As pointed out in the literature, an educational surplus or deficit can reflect different combinations of skills, experience, and job requirements (McGuinness, 2006; Leuven and Oosterbeek, 2011; McGuinness et al., 2018). Consequently, workers assigned to the same qualification category need not face the same skill needs. This raises the question of whether alternative qualification classifications, considered jointly, provide additional information about how fully workers use their skills and which capabilities they need to improve.

Empirical evidence shows that educational mismatch and skills mismatch capture different aspects of the worker-job relationship. For example, Allen and van der Velden (2001) find that skill mismatch does not explain the association between educational mismatch and wages, although it is more informative for job satisfaction and job search while employed. Subsequent studies distinguish formal overqualification from the underutilisation of skills, showing why workers classified as overeducated may differ in their opportunities to use their capabilities (Chevalier, 2003; Green and McIntosh, 2007; Green and Zhu, 2010). These findings indicate that educational mismatch cannot be interpreted as a direct measure of unused or insufficient skills. They also motivate examining variation within qualification categories, rather than assuming that a common classification implies a common experience of mismatch.

Understanding these differences requires considering both the skills that workers possess and those they use at work. Van der Velden and Bijlsma (2019) integrate proficiency and utilisation through the concept of effective skill, while Kawaguchi and Toriyabe (2022) demonstrate the importance of measuring skills and their use separately when examining wage differences across groups. Evidence on changing returns to noncognitive skills further indicates that educational attainment captures only part of workers' productive capabilities (Edin et al., 2022). Together, these studies suggest that skills, proficiency and education represent related but distinct dimensions of the worker-

job match and provide a basis for examining reported skill utilisation and gaps alongside qualification-based classifications.

In addition, multidimensional models explain why unused capabilities and unmet requirements can coexist. Guvenen et al. (2020) link mismatch to wage growth and occupational mobility in a framework incorporating learning about abilities to acquire different skills. Lise and Postel-Vinay (2020) similarly emphasise the dynamic relationship between workers' capabilities and job requirements, modelling skill accumulation through use and depreciation through non-use. These frameworks imply that match quality depends on the alignment of specific skills with job requirements, rather than on a single ranking of workers' qualifications. A qualification-based indicator may therefore conceal differences both between workers and across the skills required within a job.

The alignment of workers' capabilities with job requirements also depends on the availability and composition of employment opportunities. Iammarino and Marinelli (2015) examine education-job matching in relation to interregional migration, while McGuinness et al. (2018) analyse overeducation trends and their drivers across European countries. Baran (2024) and Sevinc et al. (2020) provide further evidence on regional differences in overeducation and the alignment of qualification supply and demand. This literature provides context for examining regional variation in mismatch measures, while sectoral differences in tasks, qualification requirements and learning opportunities may also shape how workers use and develop their skills. Iakovlev and Tealdi (2026) show how accounting for parenthood reveals differences in educational and skill mismatch within aggregate gender comparisons. Together, these studies suggest that a given qualification classification need not represent a uniform experience, as workers classified alike may face different constraints on using their capabilities and accessing further learning.

Our study brings these perspectives together by examining whether subjective and statistical qualification classifications provide additional information about workers' reported skill needs. Considering both agreement and disagreement allows us to assess whether workers classified alike by one measure differ in skill utilisation and gaps when the other measure is taken into account. Our contribution lies in identifying the additional information provided by the joint classification, without assuming that qualification mismatch necessarily implies a skill surplus or deficit. Examining utilisation and gaps separately also recognises that unused capabilities and unmet requirements may coexist. We further account for sectoral and occupational differences, linking the

distinction between qualifications and skills to the labour-market contexts in which workers use and develop their capabilities.

2.2.2 Measuring mismatch and interpreting disagreement

Alternative mismatch measures differ in how they define job requirements. Self-assessments draw on workers' evaluations of their own jobs, statistical measures use the educational distribution within occupations, and external assessments rely on expert evaluation or job analysis. Verhaest and Omey (2006) and Capsada-Munsech (2019) show that these choices affect the prevalence of mismatch and the overlap between the groups identified. Measurement differences, therefore, concern more than the aggregate incidence of mismatch, and they also determine which workers are classified as underqualified, matched or overqualified. Interpreting these classifications requires considering the information captured by each approach and the reasons they may yield different assessments of the same worker-job relationship.

Subjective and statistical classifications offer complementary information for addressing this question. Workers' assessment can reflect differences in tasks within occupations and capabilities acquired through experience or training but may also be influenced by expectations and reporting tendencies. Statistical measures provide a reproducible measurement approach based on the modal educational level within an occupation, which may not reflect the requirements of every job. Disagreement can therefore arise when workers assess their qualifications against the requirements of their own jobs rather than the occupational benchmark. Differences in the scope of the underlying questions can further contribute to divergence. In TRAILS-I, for example, the subjective measure refers to education and training, whereas the statistical measure is based on formal educational attainment. Agreement between the measures is therefore not sufficient to establish their accuracy, nor does disagreement necessarily indicate that either measure is uninformative.

Studies incorporating assessed proficiency further demonstrate the importance of distinguishing workers' capabilities from the requirements against which they are evaluated. Pellizzari and Fichen (2017) combine skill assessments with information from workers who consider themselves well matched to construct occupational skill ranges. Pérez Rodríguez et al. (2024) use expert assessments of literacy and numeracy requirements, while Bischof (2024) compares alternative test-based measures. These approaches highlight that measurement of skills mismatch depend on how both skills

and job requirements are operationalised. They also clarify the distinction between qualification-based indicators, assessed proficiency and reported experiences of skill use. Reports of underutilisation or skill gaps can help interpret qualification classifications, but they remain conceptually distinct from independent assessments of proficiency or observed productivity.

A related strand of research considers multiple forms of mismatch jointly. Longobardi and Pagliuca (2026) examine overeducation, overskilling and their overlap alongside subjective and statistical measures in European labour markets. This perspective brings together two questions that should nevertheless be distinguished: whether alternative qualification indicators classify workers similarly, and whether educational mismatch coincides with skill mismatch. The former concerns agreement between measurement approaches, while the latter concerns the relationship between formal qualifications and the use or adequacy of workers' skills. Considering these questions together provides a basis for investigating whether disagreement between qualification measures corresponds to meaningful differences in workers' reported skill experiences.

Retaining all nine combinations allows us to test whether agreement and the direction of disagreement contain information that either classification alone may conceal, without assuming in advance that agreement is more accurate. Building on the existing evidence and approaches, we employ nine combinations of subjective and statistical qualification mismatch and relate them to separate reports of skill utilisation and gaps. This allows us to assess whether the second classification distinguishes workers with different skill needs within a category defined by the first. For example, statistically undereducated workers who consider their qualifications adequate may report different skill gaps from those classified as underqualified by both approaches. We treat such differences as empirical questions, without assuming that agreement identifies the more accurate assessment or that disagreement necessarily indicates greater difficulty. We therefore assess whether agreement and the direction of disagreement between the measures provide information beyond either measure alone, establishing a basis for the subsequent analysis of training participation, adaptability and perceived employability.

2.2.3 Training participation and perceived adaptability and employability

The distinction between skill gaps and underutilisation has implications for both the purpose of training and the opportunities it can provide. Learning directed towards current tasks may address specific gaps, whereas broader skill acquisition may support movement into a more suitable job. Where existing capabilities are underutilised, however, improving the match may also require changes in task allocation or access to alternative employment. The incentives to provide and undertake training therefore depend partly on the circumstances underlying mismatch. For example, Acemoglu and Pischke (1999) explain how labour-market frictions and wage compression can encourage employer investment in general training, while McGuinness and Ortiz (2016) relate workplace skill gaps to firms' training decisions. These contributions connect training provision to employment and the skill needs arising within it, suggesting that workers with similar qualifications may face different learning needs and opportunities.

Changes in occupational requirements add a dynamic dimension to this relationship. Even when workers initially meet the requirements of their jobs, technological and organisational change may alter the skills needed to perform them. McGuinness et al. (2023) examine skills-displacing technological change and its implications for job content, while Kelly et al. (2026) link occupational skill change to workers' skill gaps and examine the role of employer-funded training. These studies place training within a continuing process of adjustment between workers' capabilities and job requirements. They also highlight the importance of distinguishing different training arrangements, since employer-provided and self-arranged learning may respond to different needs. Hence, these distinctions require careful interpretation on how training is organised does not necessarily identify how it is financed.

The implications of mismatch, however, extend beyond current learning needs to workers' capacity to respond to future changes. The dynamic models of Guvenen et al. (2020) and Lise and Postel-Vinay (2020) connect match quality with skill accumulation, wage trajectories and occupational mobility, while Neffke et al. (2024) provide related evidence from job displacement, examining how skill shortages are associated with occupational transitions. Together, these studies suggest that the skills workers use, retain and acquire may shape their ability to respond to changing job requirements and employment opportunities. This motivates examining perceived adaptability and

employability, while distinguishing workers' confidence in adapting or finding another job from their subsequent employment outcomes.

These perceptions need not follow directly from current qualification or skill mismatch. Workers who report gaps in the skills required for present tasks may nevertheless feel capable of acquiring new capabilities. Conversely, workers whose existing skills are underutilised may perceive either opportunities to move into more suitable employment or constraints that make such a transition difficult. Continuous learning provides a further dimension, capturing the frequency with which workers engage in activities to maintain or develop their skills. Thus, examining adaptability, learning frequency and employment confidence separately distinguishes current skill needs, learning behaviour and perceived future opportunities.

Training participation is relevant to each of these dimensions, but its interpretation depends on both need and access. It may reflect an attempt to address an existing gap, employer support for skill development or preparation for a different job. On the other hand, non-participation may indicate limited need, restricted opportunities or both. Greater training participation need not indicate a better worker-job match, nor does its association with reported skill gaps necessarily imply that training is ineffective. Workers facing greater difficulties may be more likely to seek training, while employers may selectively provide learning opportunities. Therefore, differences in outcomes between mismatch groups may reflect both training participation and the needs and opportunities that shape access to it, rather than the causal effects of training alone.

These relationships may also vary across sectors and occupations because access to suitable employment and learning opportunities is uneven. Workers with similar qualifications may face different prospects for improving their match, while sectoral differences in tasks and training provision may shape their opportunities to develop and use skills. This links mismatch to inclusiveness by highlighting differences in workers' capacity to respond to skill needs and pursue more suitable employment. More broadly, recent research connects mismatch mechanisms and measurement to policy design (Coraggio et al., 2026), while model-based estimates of output costs demonstrate the economic relevance of educational and skill mismatch (Garibaldi et al., 2025). Understanding what mismatch indicators capture can help identify whether policy should support further learning, expand opportunities to use existing skills, or address both needs.

2.3 Data and measurements

We use TRAILS-I survey data to examine whether subjective and statistical measures of mismatch provide complementary information about workers' reported skill needs and capacity to adjust to changing employment requirements. The survey combines information on education and occupation with assessments of qualification matching, skill utilisation, learning, labour market and financial resilience. This allows us to distinguish between workers' educational attainment relative to others in the same occupation and their own assessment of whether their education and training meet their job requirements. We first describe the sample and construction of the measures, then compare weighted means across qualification groups and examine the distributions of the alternative classifications.

The TRAILS-I survey was conducted in 2025 across 31 countries: the 27 European Union member states, the United Kingdom, Switzerland, Türkiye and Serbia, covering almost 30,000 respondents aged 18-80. Its coverage allows us to examine qualification mismatch across different national labour markets using information collected within a common survey framework. Table 2.1 presents the number of respondents by country and overall, distinguishing the full survey sample from the employed sample.

For the descriptive statistics and regression analysis, we restrict the sample to currently employed respondents aged 18–67. This restriction aligns the measurement of qualification mismatch, skill utilisation and skill gaps with respondents' current jobs. Respondents without current employment are excluded, even where the questionnaire permits answers concerning their most recent job. All summary statistics and regressions use population weights. The number of observations available for individual comparisons and regressions may vary with the availability of information on the mismatch measures, outcomes and control variables.

Table 2.1: Number of respondents by country: total and employed samples

Country	Employed sample	Total sample
Austria	1,044	597
Belgium	1,031	540
Bulgaria	1,019	644
Croatia	1,021	561
Cyprus	404	290
Czechia	1,003	572
Denmark	1,045	555
Estonia	1,010	696
Finland	1,029	474
France	1,082	640
Germany	1,000	582
Greece	1,032	551
Hungary	1,039	615
Ireland	1,030	646
Italy	1,024	511
Latvia	1,000	663
Lithuania	1,002	659
Luxembourg	404	242
Malta	403	280
Netherlands	1,001	597
Poland	1,005	615
Portugal	1,072	671
Romania	1,038	608
Serbia	1,030	581
Slovakia	1,006	573
Slovenia	1,002	557
Spain	1,001	608
Sweden	1,000	578
Switzerland	1,008	618
Türkiye	1,030	526
United Kingdom	1,057	661
Total	**17,511**	**29,872**

2.3.1 Measuring mismatch

Subjective mismatch is measured using the following question: “Do you feel that your education and training match what’s needed for your main job?” Respondents select one of three answers: “Yes, they match well”, “I am overqualified” or “I am underqualified”. These responses define subjective matching, overqualification and underqualification, respectively. The measure captures workers’ assessment of both education and training in relation to their specific job, extending beyond formal educational attainment. It may

also reflect differences in expectations and in how respondents interpret job requirements.

The statistical measure compares each worker's educational attainment with the modal educational level within the same country and 4-digit ISCO occupation. Educational attainment is recorded in eight ordered ISCED categories, from primary to doctoral education. Workers are classified as matched if their attainment equals the mode, overeducated if it exceeds the mode and undereducated if it falls below it. This country-occupation benchmark is used consistently throughout the tables, figures and combined classification. It measures workers' educational level relative to others in the same occupational cell, rather than the qualifications required by each individual job. Differences in tasks, experience and learning outside formal education can therefore contribute to disagreement with subjective assessments.

The statistical benchmark uses the International Standard Classification of Occupations (ISCO) because the TRAILS-I occupation variable is coded to harmonised ISCO groups and the modal-education approach requires sufficiently populated, comparable country-occupation cells. The European Skills, Competences, Qualifications and Occupations (ESCO) classification offers a richer occupation-skills taxonomy, but using it here would require an additional mapping from the survey occupation codes and would create much finer cells, increasing the risk of small-cell instability and classification error. ISCO is therefore the more transparent benchmark for this analysis. Educational attainment is coded using the International Standard Classification of Education (ISCED) and the mismatch measure is constructed from the harmonised ISCED attainment data recorded in the survey.

This distinction is also consistent with Cedefop's work on matching skills and jobs. Cedefop's European Skills and Jobs Survey treats qualification mismatch, specific skill gaps and deficits, job-skill requirements and continuing learning as related but distinct dimensions. The present analysis follows the same diagnostic logic by examining qualification-based classifications alongside reported skill utilisation and improvement needs, rather than treating education-job mismatch as a direct measure of missing or unused skills.

To assess whether subjective and statistical classifications jointly provide additional information about workers' reported skill utilisation and gaps, we construct a combined measure by cross-classifying subjective and statistical matching status

among respondents with valid information on both. Table 2.2 reports the resulting nine categories that are mutually exclusive and exhaustive within this sample. Three categories indicate agreement, i.e., matched under both measures, overqualified under both, or underqualified under both. Four categories capture mismatch identified by only one measure, i.e., subjective overqualification or underqualification among statistically matched workers, and statistical overeducation or undereducation among subjectively matched workers. The final two categories distinguish disagreement in opposite directions: subjective overqualification vs statistical undereducation, and subjective underqualification vs statistical overeducation. We retain these categories separately to examine whether different forms of disagreement correspond to different skill needs.

Table 2.2: Combined mismatch classification using subjective and statistical measures

	Statistical measure: Matched	**Statistical measure: Overeducated**	**Statistical measure: Undereducated**
Subjective measure: Matched	Matched in both	Statistical overeducated only	Statistical undereducation only
Subjective measure: Overqualified	Subjective overqualification only	Overqualified in both	Subjective overqualification vs statistical undereducation
Subjective measure: Underqualified	Subjective overqualification only	Subjective underqualification vs statistical overeducation	Underqualified in both

The label “only” indicates that the other measure classifies the worker as matched. Overqualification and underqualification under both measures refer to agreement between subjective assessments and statistical overeducation or undereducation, respectively. Workers matched under both measures form the reference category in the combined-measure regressions. This classification allows us to examine whether each measure distinguishes workers with different reported outcomes within categories defined by the other, without assuming that agreement establishes accuracy. For the learning-interaction specifications, we pool categories 4-9 into a single disagreement group, yielding four categories: matched under both measures, overqualified under both, underqualified under both, and mismatch disagreement. This grouping simplifies the interpretation of interactions while retaining

the distinction between agreement and disagreement, although it no longer separates the different forms of disagreement.

2.3.2 Skill utilisation, skill gaps, learning and resilience

Skill underutilisation is measured by asking respondents how well their main job utilises their skills and knowledge. The response categories distinguish full utilisation ("My job makes excellent use of my skills and knowledge"), partial utilisation ("My job uses some of my skills and knowledge") and no utilisation ("My job does not utilize my skills and knowledge"). We construct a binary outcome equal to one for partial or no utilisation and zero for full utilisation. It thus identifies workers reporting that their existing capabilities are not fully used in their current job.

Reported skill gaps are based on the question: "In your opinion, which of the following skills do you need to improve to perform your current main job, or most recent main job, better?" Respondents may select all applicable categories: digital/ICT skills; communication or teamwork; technical/job-specific skills; foreign languages; customer handling; basic literacy or numeracy; and none. Within the employed sample, the responses refer to the current main job. We construct six binary indicators for the individual categories and a skill gap (multiple) indicator equal to one for reported improvement needs in at least two categories and zero for fewer than two. This distinction allows us to examine both the breadth and the specific content of reported skill needs.

We analyse utilisation and gaps separately because workers may possess capabilities that are insufficiently used while needing to improve others. Equally, qualification matching need not imply either full skill utilisation or an absence of gaps. The outcomes provide evidence on the functional relevance of the qualification classifications but remain self-reported assessments rather than independent tests of proficiency or productivity. Associations involving the subjective mismatch measure may consequently reflect shared reporting influences as well as differences in the worker-job match.

Learning participation is measured through the question: "What types of upskilling or learning activities do you take part in?" We distinguish four non-exclusive categories in the analysis: on-the-job training, formal courses or workshops, volunteering or peer learning, and self-directed learning. Each is represented by a binary participation

indicator. A separate indicator of diversified learning activities equals one for participation in at least two recorded learning types and zero for fewer than two. This measure distinguishes workers who participate in two or more types of learning activities from those who participate in only one type or none.

The term "upskilling" is used deliberately because the survey records activities undertaken to update or improve existing skills. "Reskilling" usually refers more specifically to acquiring a substantially different skill set, often for movement into a different role or occupation, which is not directly observed by these questions. We therefore reserve "reskilling" for broader policy discussion rather than using it as a label for the measured learning activities.

The learning interactions follow these definitions. Interactions with diversified learning activities compare mismatch-related outcome differences between workers undertaking at least two learning types and those undertaking fewer than two. Activity-specific interactions instead compare these differences between participants and non-participants in the relevant activity. The indicators describe the form of learning and do not necessarily identify who provides or finances it. As participation may reflect both existing skill needs and access to learning opportunities, these relationships are interpreted as conditional associations.

Labour-market resilience is measured by an index ranging from zero to seven, with higher values indicating greater resilience. Its components concern perceived adaptability to changes in technologies, processes or work environments, engagement in upskilling, and confidence in finding employment within one’s field. We also analyse three binary indicators corresponding to these dimensions: selecting the highest adaptability response, reporting regular or occasional participation in upskilling, and being very confident of finding work. The composite and the separate indicators capture reported upskilling behaviour and perceived adjustment capacity, rather than observed employment transitions.

The financial-resilience index ranges from zero to four, with higher values indicating greater resilience. It combines an income-adequacy score for the previous 12 months, ranging from zero to three, with a binary indicator for the absence of selected last-resort coping strategies in response to a prolonged financial shock. The income-adequacy component is calculated as three minus the financial-strain score, so that lower strain contributes to higher resilience. The coping component equals one if

respondents select none of the following strategies: liquidating substantial assets, relocating to reduce costs or relying on long-term welfare or support; it equals zero if they select at least one. Higher index values therefore reflect lower recent financial strain and the absence of these anticipated coping responses.

2.3.3 Weighted means and differences across classifications

Tables 2.3 and 2.4 present weighted means for the employed sample. Table 2.3 describes demographic characteristics, educational attainment and learning participation, while Table 2.4 reports skill utilisation, skill gaps and resilience outcomes. These comparisons provide an unconditional description of differences across matching classifications. Each table reports weighted means for nine groups: matched in both, overqualified in both, and underqualified in both measures; the three statistical categories; and the three subjective categories. These groups overlap and should be distinguished from the nine mutually exclusive categories of the combined measure. For example, workers matched under both measures are also included in the statistically matched and subjectively matched groups. The final two columns report the weighted mean for workers matched under both measures minus the weighted mean for statistically matched workers and subjectively matched workers, respectively. These comparisons assess whether requiring agreement changes the characteristics and outcomes associated with matching under either measure alone.

The weighted means are estimated jointly, allowing tests of their differences to account for the covariance arising from overlapping group membership. Statistical significance is indicated by asterisks attached to the estimated mean differences. In the discussion below, differences in binary outcomes are expressed in percentage points, while differences in age, indices and scores retain their original units. Significance statements refer to the two matched-group comparisons reported in the tables; other comparisons are descriptive.

Both tables contain 17,511 employed respondents for the statistical classification and 16,883 respondents with valid information for the joint subjective-statistical classification; outcome-specific regression samples are slightly smaller because of item non-response. Age and age squared enter as continuous controls to

allow for a non-linear age profile. Marital status was obtained from IPSOS's existing records of respondents who had previously participated in its surveys rather than collected through the questionnaire; respondents without this information are retained in a separate category (labelled "unknown"). Sector categories follow the Statistical Classification of Economic Activities in the European Community (NACE).

Table 2.3 shows more pronounced differences in education than in age or gender across the matched groups. Workers matched under both measures have a mean age of 43.55 years, compared with 43.17 among statistically matched workers and 43.39 among subjectively matched workers. The difference from statistically matched workers is 0.375 years and significant at the 1% level, whereas the difference from subjectively matched workers is insignificant. The male share also varies only modestly across these groups. By contrast, 47% of workers matched under both measures have upper-secondary education, compared with 35% of subjectively matched workers. The estimated difference of 12.0 percentage points is significant at the 1% level. This compositional difference partly reflects the construction of the statistical measure, which explicitly classifies workers according to their educational attainment relative to the occupational benchmark.

Learning participation also varies across definitions of matching. Participation in at least two types of learning activities is reported by 52% of workers matched under both measures, compared with 50% of statistically matched workers and 54% of subjectively matched workers. The corresponding differences are 1.8 and -1.7 percentage points, both significant at the 1% level. Workers matched under both measures also report greater participation in on-the-job training and formal courses or workshops than statistically matched workers, with differences of 1.7 and 2.3 percentage points, respectively, both significant at the 1% level. Relative to subjectively matched workers, however, their formal-course participation is 1.5 percentage points lower, also significant at the 1% level, while the difference in on-the-job training is insignificant. Agreement on matching therefore identifies a different learning profile, but not one characterised by uniformly greater participation.

Table 2.4 reveals substantial differences in skill underutilisation. Partial or no use of skills is reported by approximately 35% of workers matched under both measures, 81% of those overqualified under both and 63% of those underqualified under both. The high prevalence among the latter group illustrates that perceived qualification deficits can coexist with unused skills. Underutilisation is also more prevalent among workers

overqualified under both measures than among the broader groups defined by subjective overqualification or statistical overeducation, whose respective rates are 76% and 50%. Agreement on overqualification thus identifies a group with particularly high reported underutilisation.

The matched-group comparisons provide a complementary perspective. Workers matched under both measures report underutilisation 9.5 percentage points less frequently than statistically matched workers, a difference significant at the 1% level. Their difference from subjectively matched workers is only -0.1 percentage points and statistically insignificant. Supplementing statistical matching with subjective agreement therefore identifies workers with substantially lower underutilisation. Within the subjectively matched category, requiring statistical agreement makes little difference to this outcome. This finding concerns the matched category and does not rule out additional information from the statistical measure within subjective overqualification or underqualification.

Multiple skill gaps exhibit a different pattern. Their prevalence is 38% among workers matched under both measures, 30% among those overqualified under both and 49% among those underqualified under both. By comparison, rates across the three statistical categories are closely grouped at approximately 36-37%. The combined agreement categories therefore display greater descriptive variation in reported gaps than the statistical categories alone. The differences also depend on the skill category. Workers underqualified under both measures report digital, technical and customer-handling gaps at rates of 35%, 40% and 25%, respectively, compared with 31%, 32% and 17% among workers matched under both measures. Foreign language gaps, however, are less prevalent among those underqualified under both measures, at 28% compared with 32%. Agreement on underqualification is therefore associated with a particular profile of reported needs rather than uniformly greater gaps across all categories.

Despite their lower underutilisation, workers matched under both measures are 1.4 percentage points more likely to report multiple skill gaps than statistically matched workers, with the difference significant at the 1% level. Their multiple-gap difference from subjectively matched workers is insignificant. For individual skill gap categories, workers matched under both measures have a 1.1 percentage-point lower prevalence of digital gaps than subjectively matched workers, significant at the 1% level, while the remaining category differences are insignificant. These comparisons highlight the need to examine qualification matching, skill utilisation and skill gaps separately, as agreement between

subjective and statistical measures of qualification matching does not necessarily identify workers who report fewer improvement needs.

The resilience outcomes reveal further differences across qualification groups. Workers underqualified under both measures have lower mean labour-market and financial-resilience scores, at 3.72 and 2.15, than workers matched under both measures, whose corresponding scores are 4.25 and 2.51. A smaller share also reports regular or occasional upskilling, at 60% compared with 66%, and being very confident of finding work within their field, at 27% compared with 39%. Workers overqualified under both measures report lower employment confidence, at 31%, although high adaptability is slightly more prevalent than among workers matched under both measures. The different dimensions of perceived adjustment capacity therefore do not vary uniformly with matching status.

The matched-group comparisons again depend on which separate measure is used. Workers matched under both measures have a labour-market resilience score 0.111 units higher than statistically matched workers but 0.059 units lower than subjectively matched workers. The corresponding financial-resilience differences are 0.072 and -0.035 units. All four differences are significant at the 1% level. Income adequacy follows the same pattern, whereas neither comparison is significant for the absence of long-term last-resort coping strategies.

Overall, the descriptive comparisons indicate that subjective and statistical matching are not interchangeable and that agreement can distinguish workers with different reported skill needs and adjustment capacities. The particularly high underutilisation among workers overqualified in both measures and the greater prevalence of multiple skill gaps among those underqualified in both motivate examining the full combined classification. The empirical analysis in the next section assesses whether these distinctions remain informative after accounting for observed worker and job characteristics.

Table 2.3: Control variables by qualification-match status: Weighted means and mean differences

	Matched in both	Overqualified in both	Underqual. in both	Statistical matched	Statistical overeducated	Statistical undereducated	Subjective matched	Subjective overqual.	Subjective underqual.	T-test: matched in both vs stat. match	T-test: matched in both vs subj. match
#Observations	*16,883*	*16,883*	*16,883*	*17,511*	*17,511*	*17,511*	*16,883*	*16,883*	*16,883*		
Gender: Male	51.0%	45.0%	52.0%	51.0%	48.0%	51.0%	51.0%	49.0%	51.0%	0.006*	0.004
"-" : Nonbinary	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.001	0.001
"-" : Female	49.0%	54.0%	48.0%	49.0%	52.0%	49.0%	49.0%	51.0%	49.0%	-0.005*	-0.004
Age of respondent	43.55	42.29	41.43	43.17	42.18	43.10	43.39	42.51	40.38	0.375***	0.155
Age of respondent (squared)	2.04	1.93	1.87	2.01	1.91	2.01	2.03	1.95	1.77	0.031***	0.014*
Age category: 18-24	7.0%	7.0%	11.0%	7.0%	5.0%	8.0%	6.0%	7.0%	11.0%	-0.006***	0.002
"-": 25-34	21.0%	24.0%	23.0%	21.0%	25.0%	21.0%	21.0%	24.0%	25.0%	-0.005*	-0.004
"-": 35-44	24.0%	27.0%	22.0%	24.0%	29.0%	25.0%	25.0%	25.0%	26.0%	-0.003	-0.009**
"-": 45-54	26.0%	24.0%	28.0%	26.0%	23.0%	25.0%	26.0%	24.0%	24.0%	0.008***	0.008**
"-": 55-67	22.0%	19.0%	17.0%	21.0%	18.0%	22.0%	22.0%	20.0%	1.0%	0.006***	0.003
Marital status: Single	18.0%	27.0%	17.0%	19.0%	22.0%	18.0%	18.0%	22.0%	24.0%	-0.009***	-0.001
"-": Married/ cohabiting	46.0%	38.0%	39.0%	44.0%	44.0%	41.0%	45.0%	40.0%	41.0%	0.012***	0.007*
"-": Widowed/divorced	6.0%	6.0%	6.0%	6.0%	5.0%	6.0%	6.0%	6.0%	5.0%	0.000	0.003*
"-": Unknown	30.0%	29.0%	38.0%	31.0%	29.0%	36.0%	31.0%	33.0%	30.0%	-0.003	-0.009**
Education: Primary education	0.0%	0.0%	5.0%	0.0%	0.0%	3.0%	1.0%	0.0%	2.0%	0.000	-0.006***
"-": Lower secondary	1.0%	0.0%	16.0%	1.0%	0.0%	9.0%	3.0%	2.0%	6.0%	0.000	-0.018***
"-": Upper secondary	47.0%	1.0%	41.0%	48.0%	1.0%	32.0%	35.0%	29.0%	48.0%	-0.012***	0.120***
"-": Post-secondary non-tertiary	1.0%	3.0%	5.0%	1.0%	3.0%	5.0%	2.0%	2.0%	3.0%	0.000	-0.017***
"-": Short-cycle tertiary	5.0%	11.0%	15.0%	5.0%	14.0%	14.0%	9.0%	9.0%	10.0%	0.000	-0.039***
"-": Bachelor level	24.0%	42.0%	14.0%	24.0%	37.0%	23.0%	25.0%	32.0%	21.0%	-0.002	-0.016***
"-": Master's level	21.0%	38.0%	4.0%	20.0%	39.0%	13.0%	22.0%	24.0%	9.0%	0.012***	-0.009***
"-": Doctoral level	1.0%	5.0%	1.0%	1.0%	7.0%	2.0%	2.0%	2.0%	1.0%	0.002***	-0.014***
Learning activities: any type	52.0%	56.0%	48.0%	50.0%	58.0%	52.0%	54.0%	52.0%	43.0%	0.018***	-0.017***
"-": on-job training	39.0%	39.0%	37.0%	37.0%	40.0%	39.0%	40.0%	36.0%	33.0%	0.017***	-0.007
"-": formal course	48.0%	46.0%	44.0%	46.0%	53.0%	48.0%	50.0%	45.0%	39.0%	0.023***	-0.015***
"-": peer learning/community	27.0%	25.0%	22.0%	26.0%	28.0%	26.0%	27.0%	27.0%	21.0%	0.005*	-0.005
"-": self-directed	46.0%	51.0%	48.0%	45.0%	49.0%	45.0%	46.0%	48.0%	45.0%	0.002	-0.006

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

Table 2.4: Dependent variables by qualification-match status: Weighted means and mean differences

	Matched in both	Overqualified in both	Underqual. in both	Statistical matched	Statistical overeducated	Statistical undereducated	Subjective matched	Subjective overqual.	Subjective underqual.	T-test: matched in both vs stat. match	T-test: matched in both vs subj. match
#Observations	*16,883*	*16,883*	*16,883*	*17,511*	*17,511*	*17,511*	*16,883*	*16,883*	*16,883*		
Skills underutilisation	35.0%	81.0%	63.0%	44.0%	50.0%	43.0%	35.0%	76.0%	68.0%	-0.095***	-0.001
Skill gaps (multiple)	38.0%	30.0%	49.0%	36.0%	36.0%	37.0%	38.0%	32.0%	45.0%	0.014***	-0.001
Skill gap category: Digital/ ICT	31.0%	25.0%	35.0%	29.0%	31.0%	31.0%	32.0%	24.0%	32.0%	0.015***	-0.011***
"-": Teamwork/ communication	28.0%	24.0%	32.0%	27.0%	28.0%	28.0%	28.0%	24.0%	29.0%	0.009***	-0.004
"-": Technical/ job-specific	32.0%	28.0%	40.0%	32.0%	32.0%	32.0%	32.0%	28.0%	44.0%	0.004	0.001
"-": Foreign languages	32.0%	27.0%	28.0%	31.0%	32.0%	29.0%	32.0%	26.0%	29.0%	0.012***	0.003
"-": Customer handling	17.0%	20.0%	25.0%	17.0%	19.0%	19.0%	17.0%	18.0%	20.0%	-0.001	-0.005
"-": Basic literacy, numeracy	10.0%	7.0%	13.0%	9.0%	9.0%	10.0%	10.0%	8.0%	10.0%	0.003*	-0.001
Labour market resilience index	4.25	4.12	3.72	4.14	4.35	4.20	4.31	4.09	3.54	0.111***	-0.059***
High labour-market adaptability	36.0%	38.0%	27.0%	35.0%	38.0%	36.0%	37.0%	37.0%	26.0%	0.008***	-0.007*
Upskilling: regular/occasional	66.0%	64.0%	60.0%	64.0%	71.0%	66.0%	68.0%	63.0%	54.0%	0.019***	-0.018***
Very confident of finding work	39.0%	31.0%	27.0%	37.0%	38.0%	37.0%	40.0%	33.0%	23.0%	0.022***	-0.005
Financial resilience index	2.51	2.38	2.15	2.43	2.57	2.45	2.54	2.28	2.11	0.072***	-0.035***
No financial strain past 12m	2.08	1.99	1.76	2.01	2.15	2.02	2.11	1.88	1.72	0.069***	-0.032***
No long-term last-resort coping	44.0%	39.0%	40.0%	44.0%	43.0%	44.0%	44.0%	41.0%	40.0%	0.001	-0.003

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

2.3.4 Geographical, sectoral and inclusiveness patterns

Figures 2.1-2.6 compare the country distributions under the two separate measures. Subjective matching is especially common in Denmark, Poland and Romania, each in the displayed band of 81% or above. Statistical matching instead reaches its highest displayed band, at 69% or above, in Czechia and Latvia. The United Kingdom and Ireland illustrate the distinction particularly clearly, as both have relatively high subjective matching, but statistical matching is below 44% and statistical undereducation is at least 39%. A favourable assessment of the adequacy of one's qualifications can therefore coexist with education below the country-occupation benchmark. The statistical measure identifies a different configuration of matching across countries, rather than simply reproducing the subjective distribution at a different overall level.

The differences also concern the direction of mismatch. Greece and Türkiye are in the highest displayed band for subjective overqualification, at 25% or above, but neither is in the highest band for statistical overeducation. Conversely, statistical overeducation is at least 22% in Portugal, Spain, Italy, Germany, Sweden and Finland, although these countries are not in the highest subjective-overqualification band. Subjective underqualification is comparatively prevalent in Finland, Latvia, Lithuania, Czechia, Slovenia and Türkiye, at 8% or above. This differs from the geographical concentration of statistical undereducation in the United Kingdom, Ireland, the Netherlands and Cyprus. The maps thus indicate that the two measures do not identify the same countries as having the greatest prevalence of qualification surpluses or deficits.

(Note for figures 2.1-2.6: Author's calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)).

Figure 2.1: Matched employees by country (subjective measure)

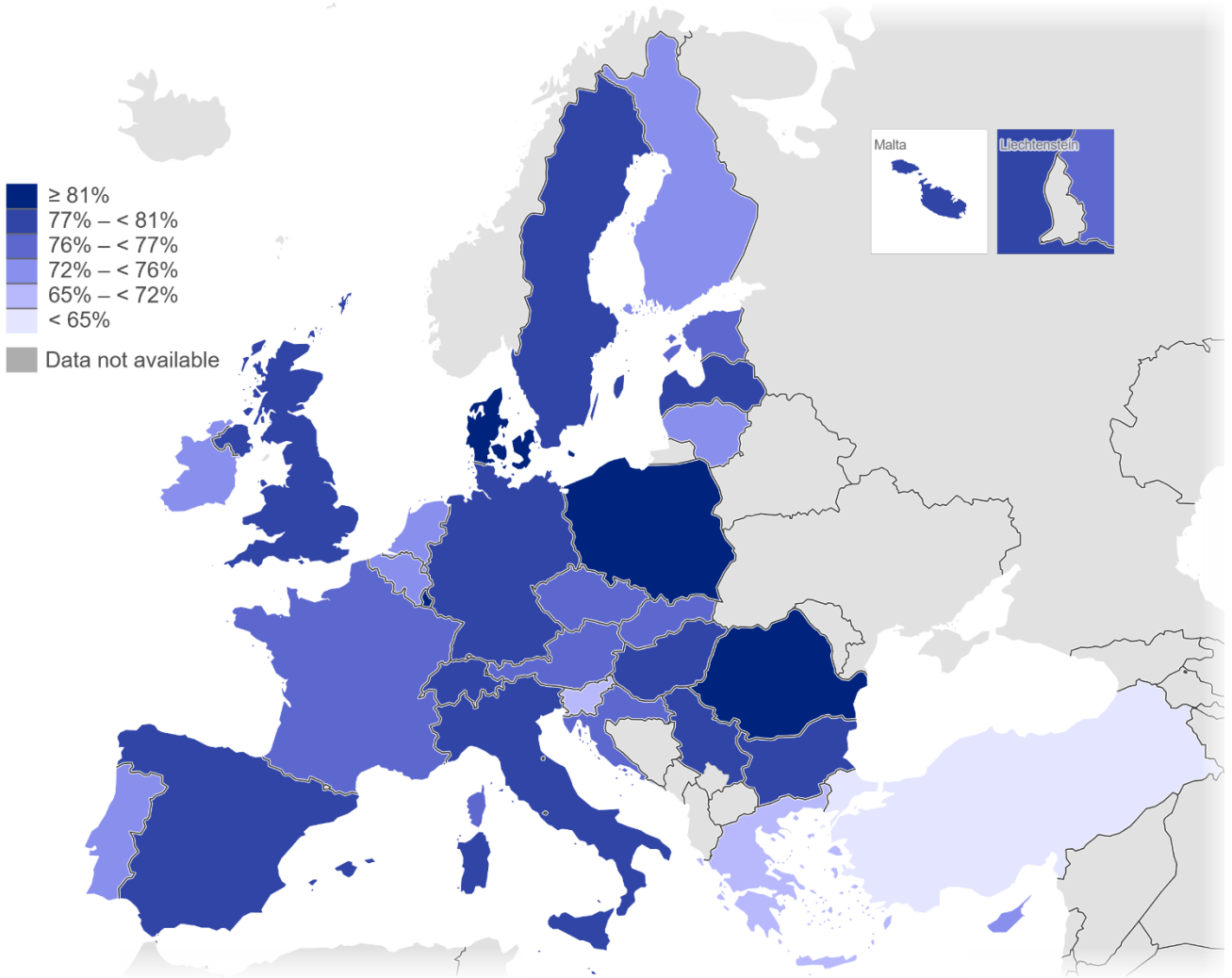


Figure 2.2: Overqualified employees by country (subjective measure)

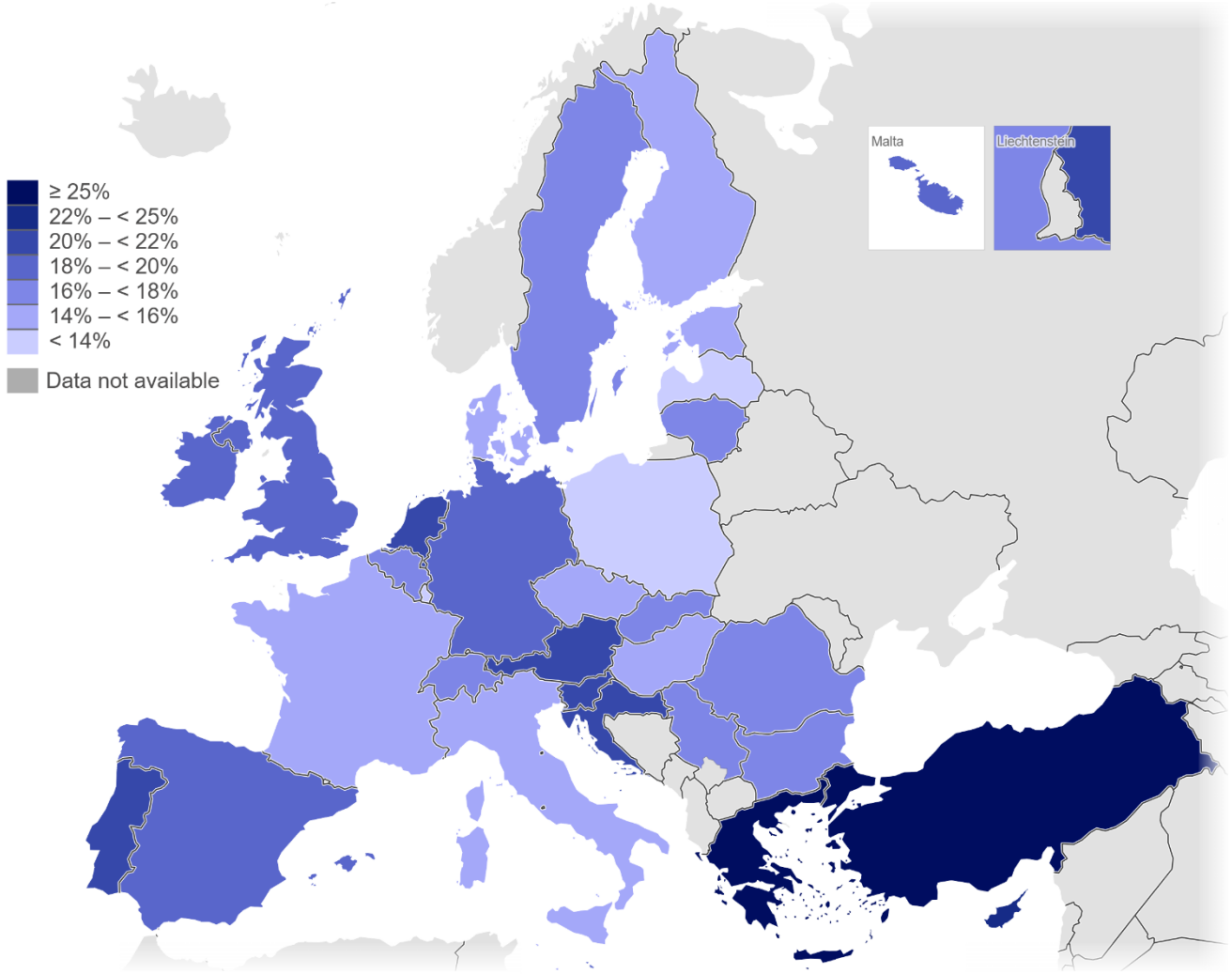


Figure 2.3: Underqualified employees by country (subjective measure)

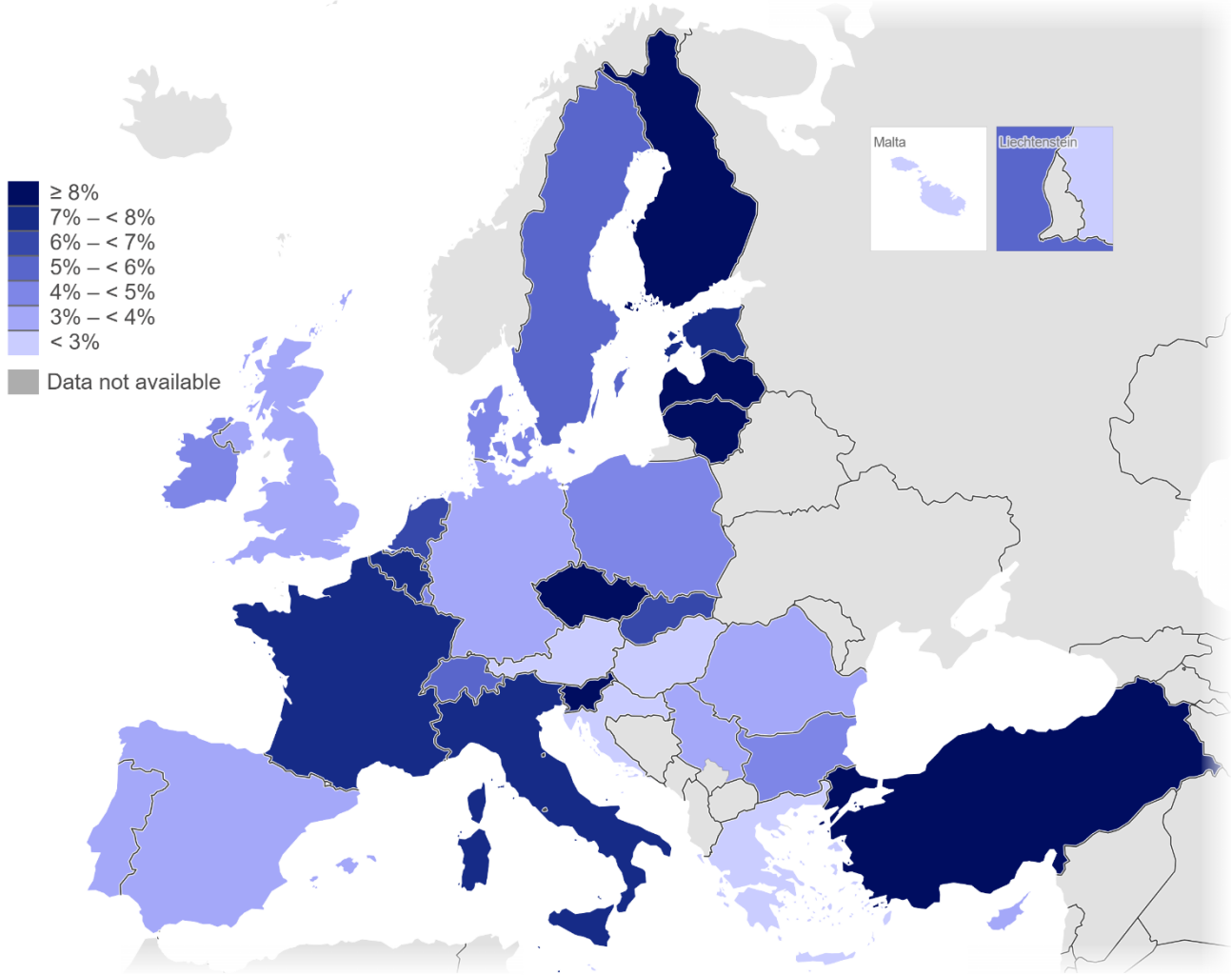


Figure 2.4: Matched employees by country (statistical measure)

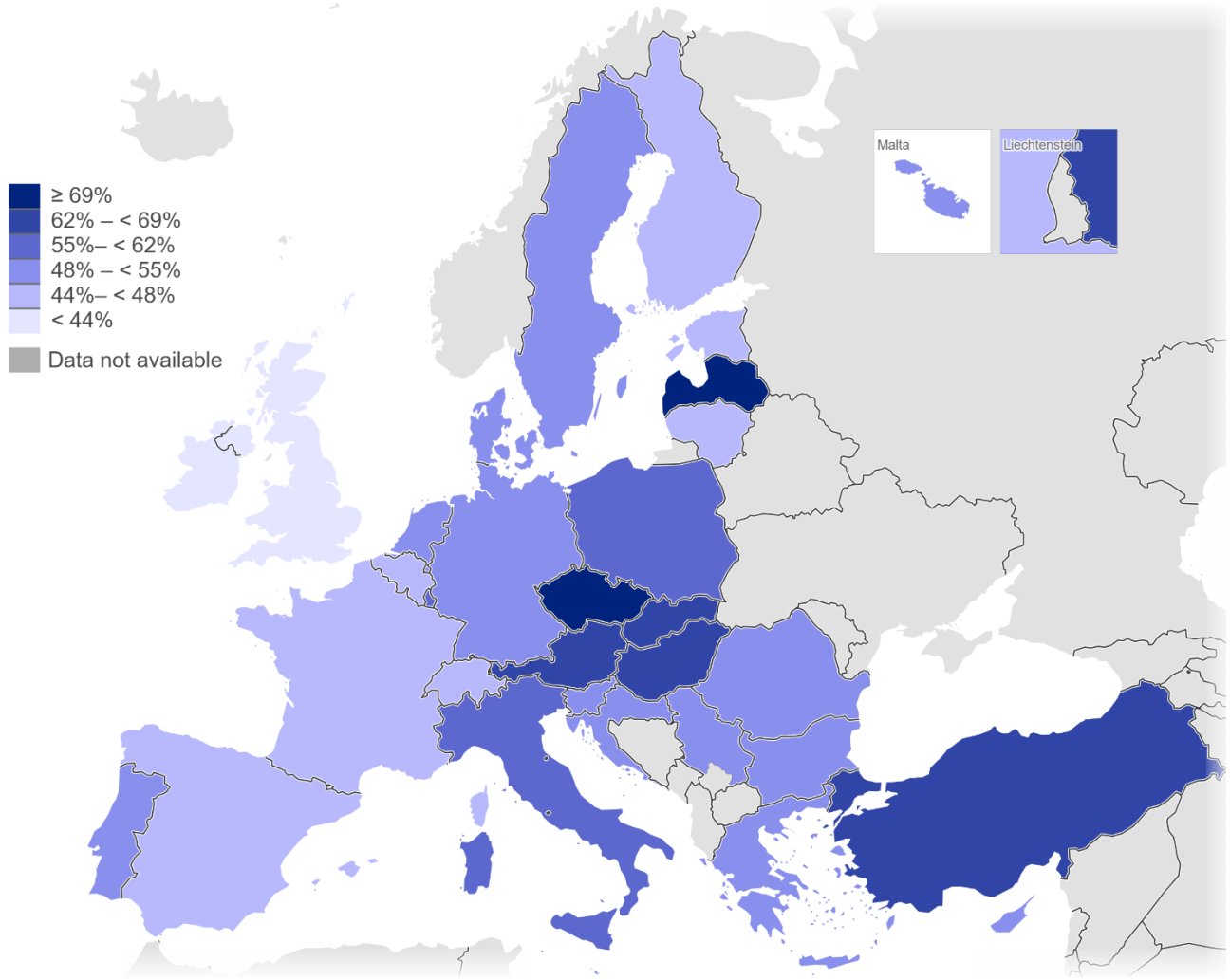


Figure 2.5: Overeducated employees by country (statistical measure)

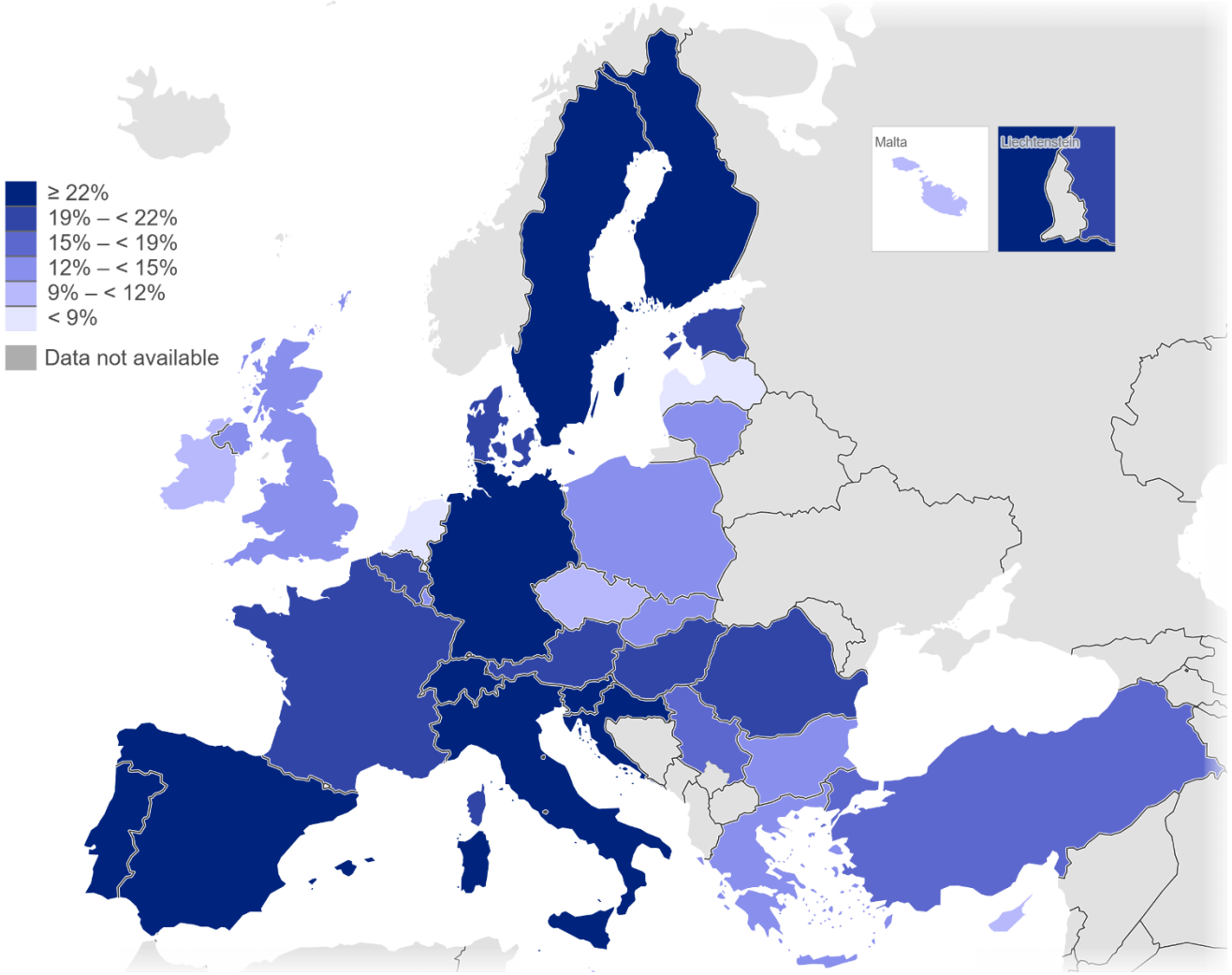
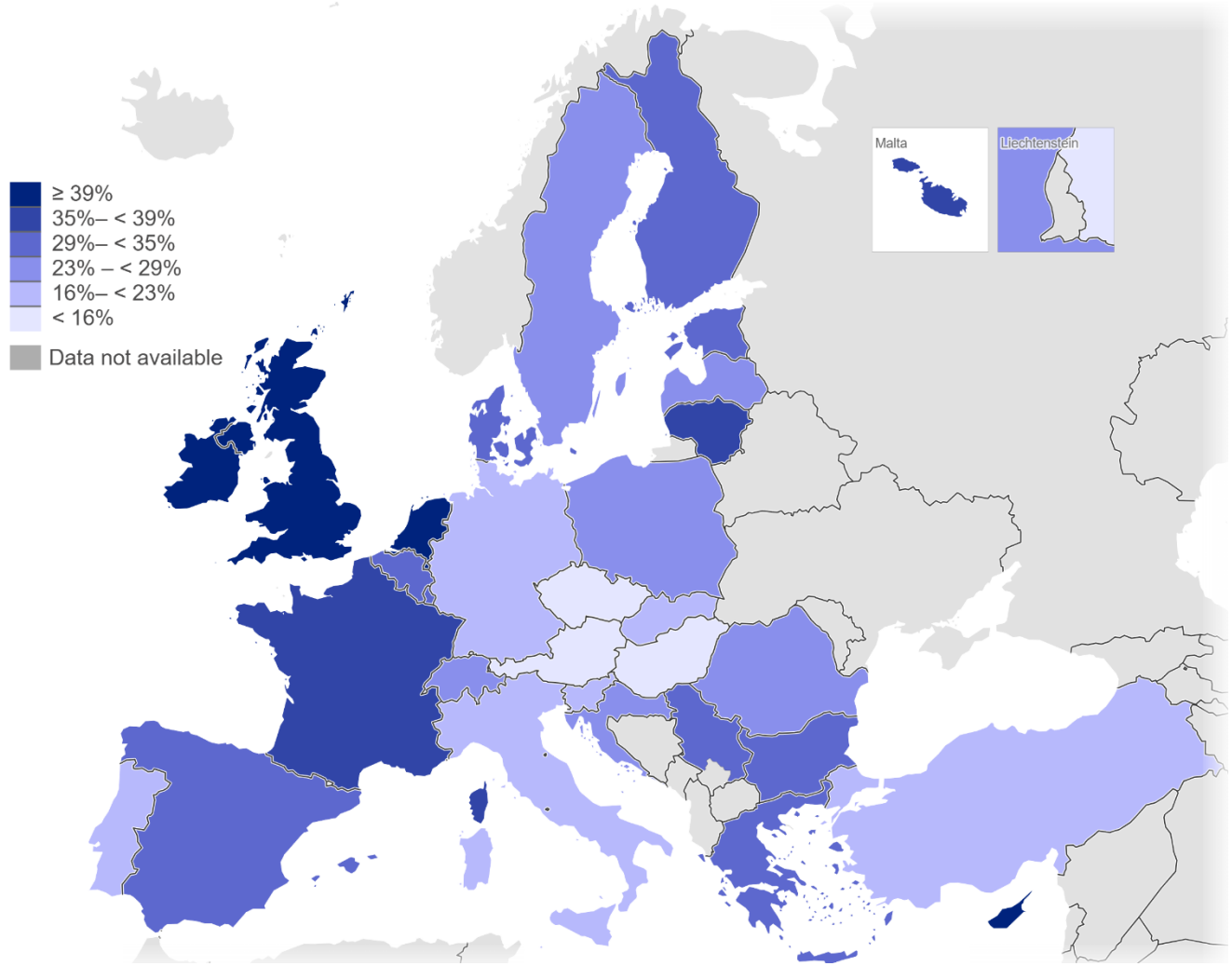


Figure 2.6: Undereducated employees by country (statistical measure)



Figures 2.7, 2.9 and 2.11 show how the distributions change when there is agreement between the measures. The share of matched workers in both measures is at least 55% in Czechia and Hungary but below 31% in the United Kingdom and Ireland. The latter comparison shows that high subjective matching need not translate into a similarly high prevalence of matching under both measures. Agreement on overqualification is at least 7% in Portugal and Croatia; by contrast, Türkiye combines high subjective overqualification with a combined-overqualification share between 2% and 3%. Agreement on underqualification also produces a narrower distribution: Czechia has subjective underqualification of at least 8% but agreement on underqualification below 1%. These contrasts demonstrate that the combined categories identify subsets with different geographical profiles. Their smaller shares are partly mechanical, because agreement requires satisfying both classifications, and should not themselves be interpreted as evidence of greater accuracy.

Figures 2.8, 2.10 and 2.12 disaggregate the three agreement categories regionally, using the Nomenclature of Territorial Units for Statistics (NUTS) level 2 for most countries and NUTS level 1 for Germany, the United Kingdom and Türkiye. The statistical component remains the country-occupation (4-digit ISCO code) benchmark, while the maps describe regional variation in the resulting classifications rather than constructing new regional benchmarks. Variation within France, Spain, Italy and Türkiye indicates that national agreement shares do not describe every region equally. However, these figures cover only the combined categories and therefore cannot establish how regional rankings would change under the subjective or statistical measure alone. Across all maps, class boundaries are specific to each indicator and should therefore be interpreted directly, namely similar colours do not necessarily represent similar percentages. The figures show point estimates only and do not include confidence intervals, so geographical differences should be interpreted descriptively rather than as evidence of statistically significant regional differences.

(Note for figures 2.7-2.12: Author's calculations and visualisation using Eurostat/GISCO Interactive Map Generator (IMAGE)).

Figure 2.7: Matched employees in both measures by country (combined measure)

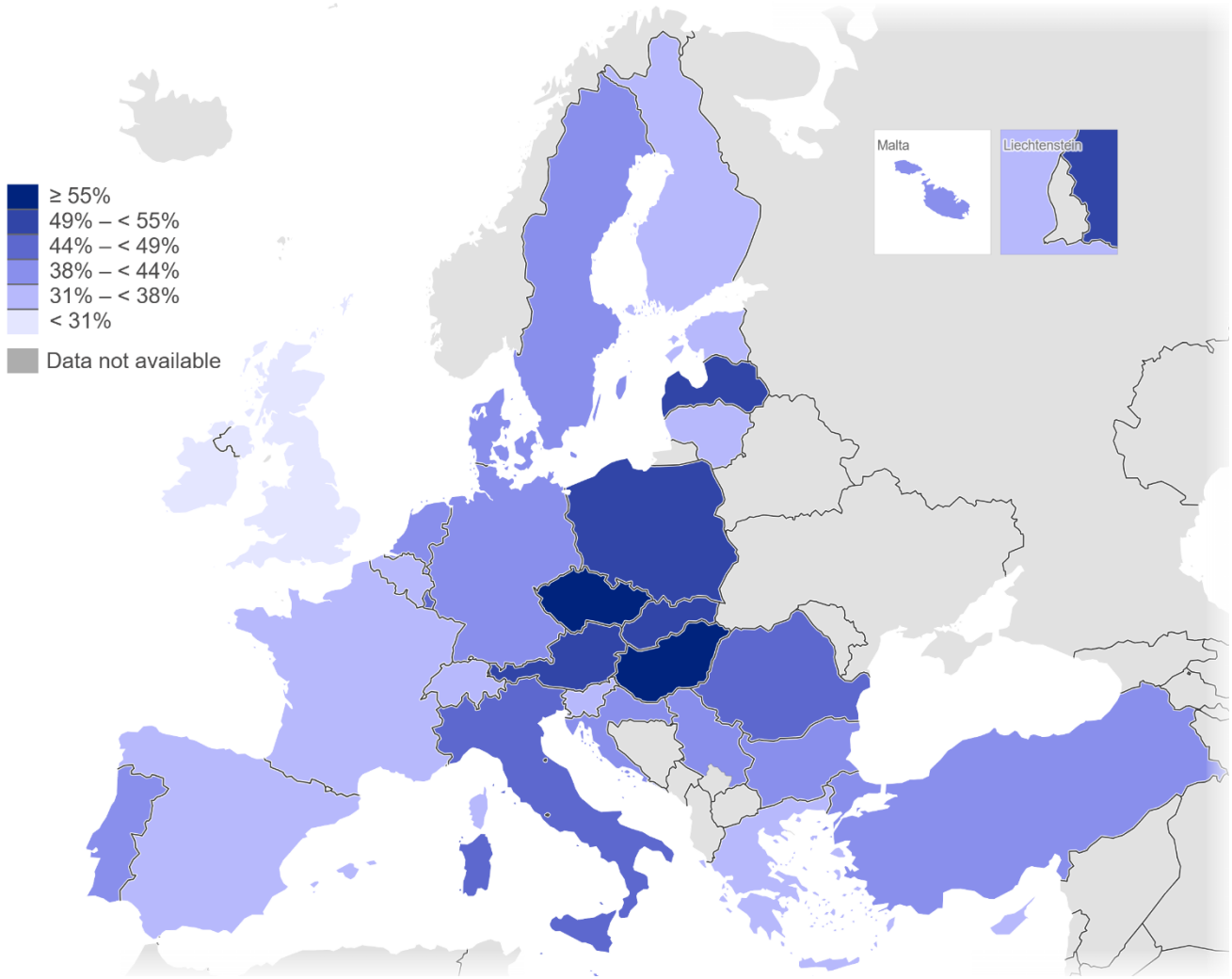


Figure 2.8: Matched employees in both measures by region (combined measure)

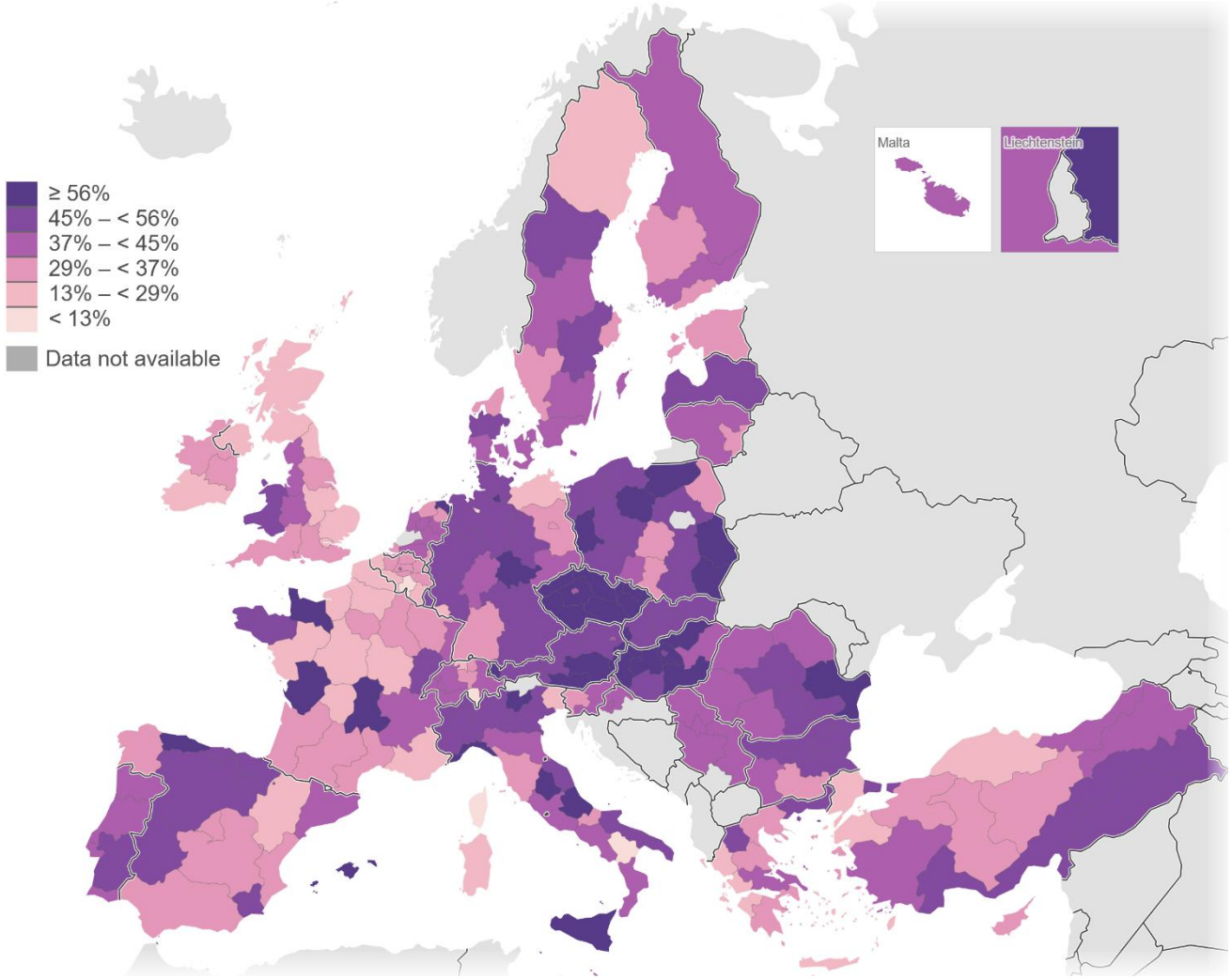


Figure 2.9: Overqualified employees in both measures by country (combined measure)

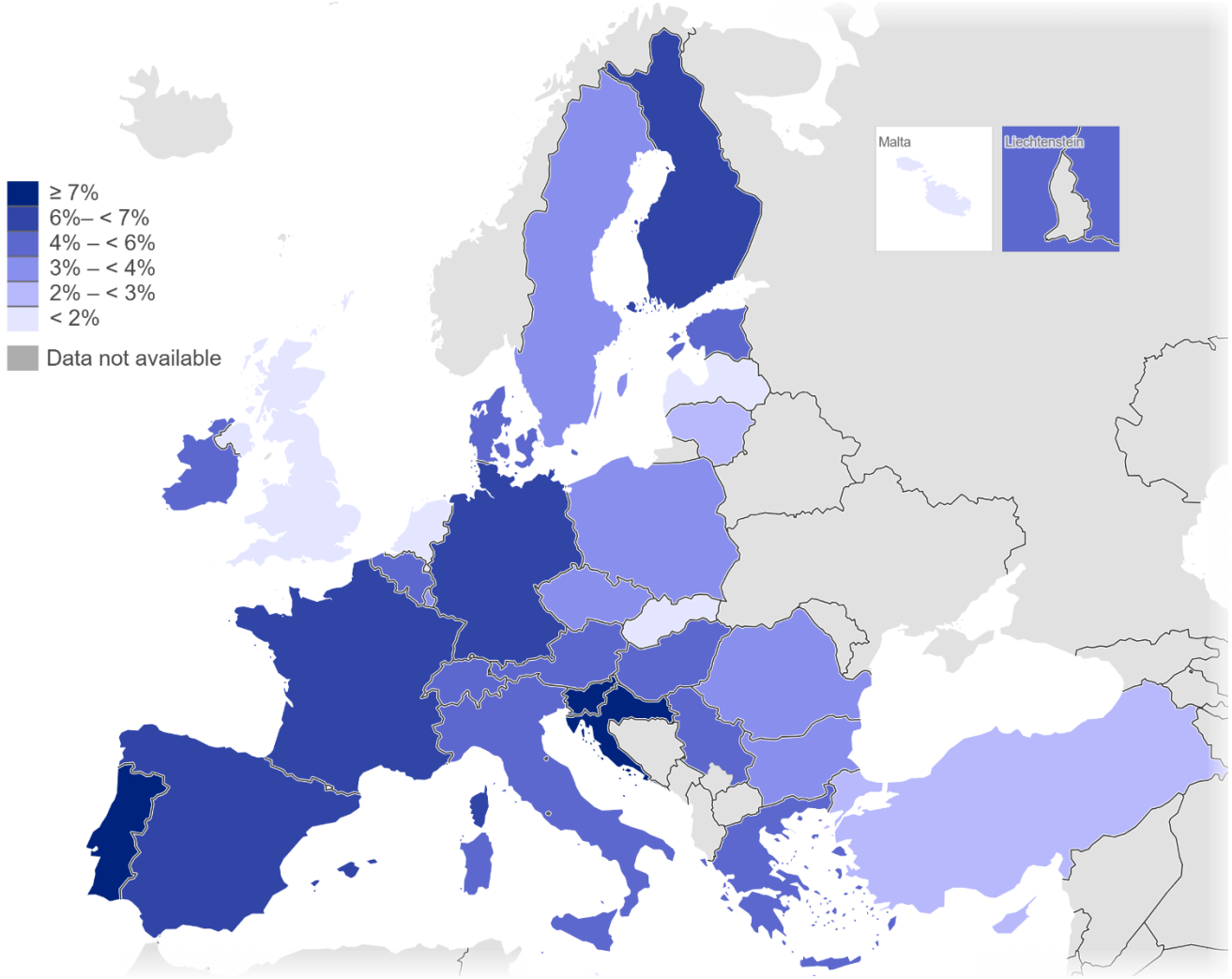


Figure 2.10: Overqualified employees in both measures by region (combined measure)

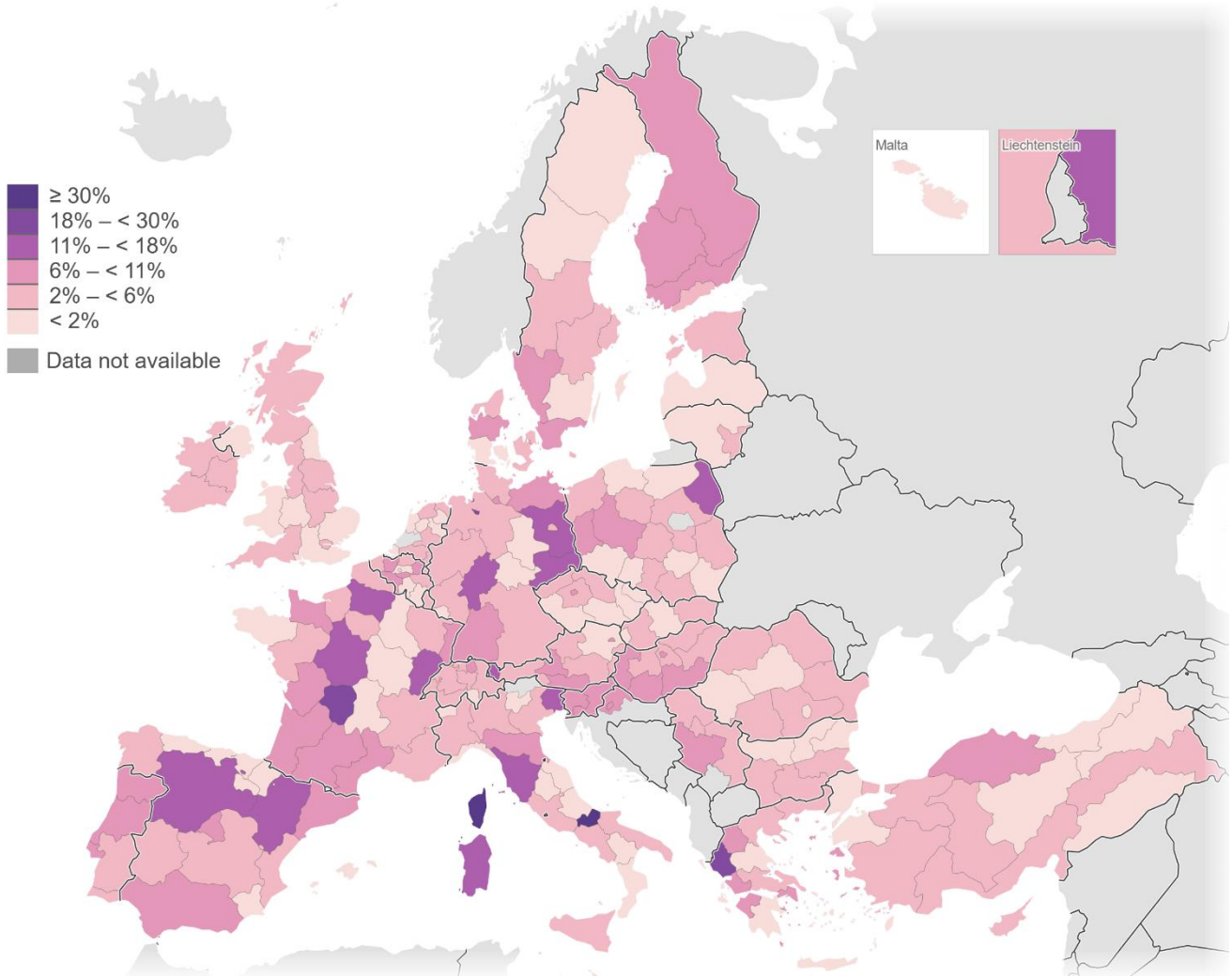


Figure 2.11: Underqualified employees in both measures by country (combined measure)

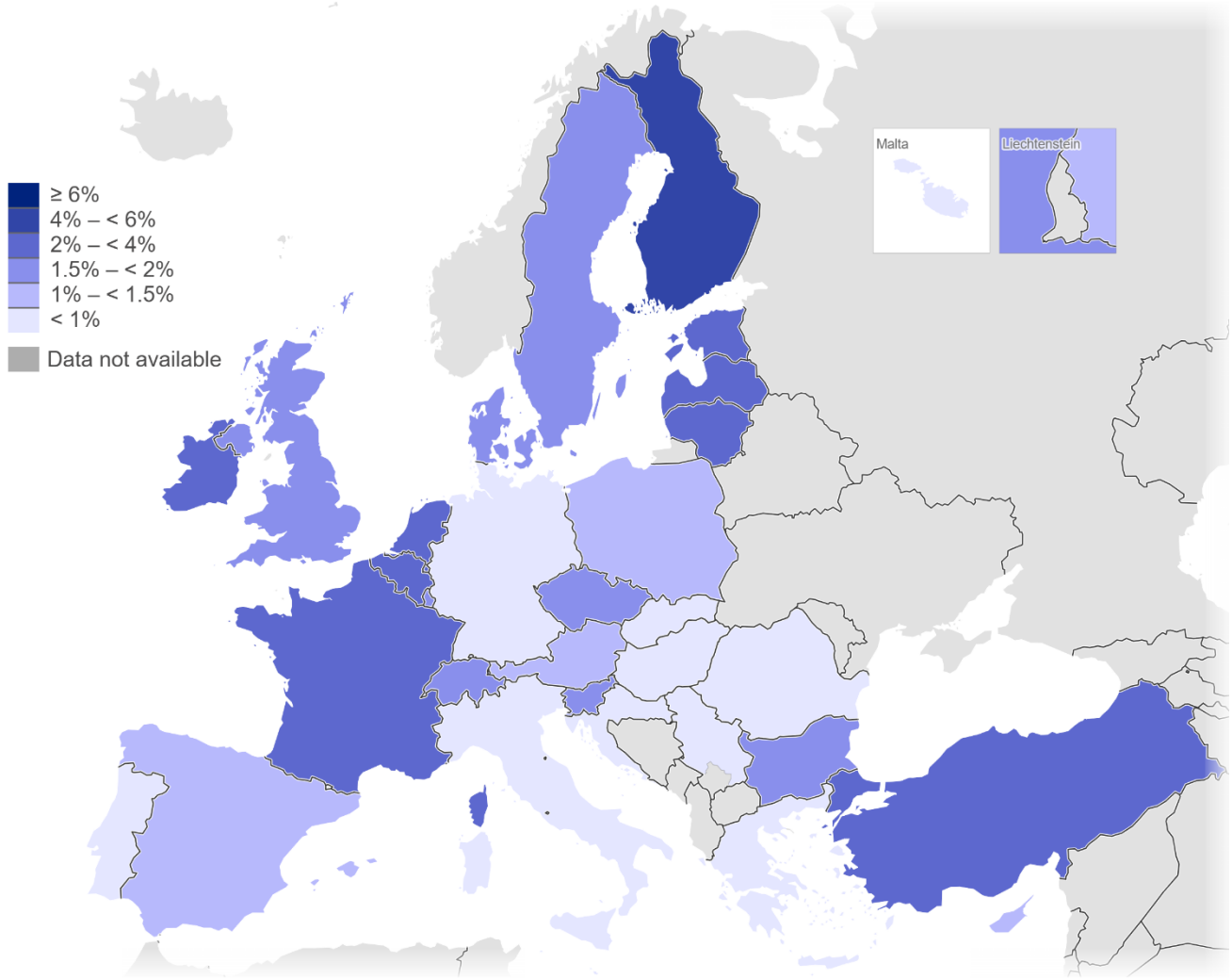
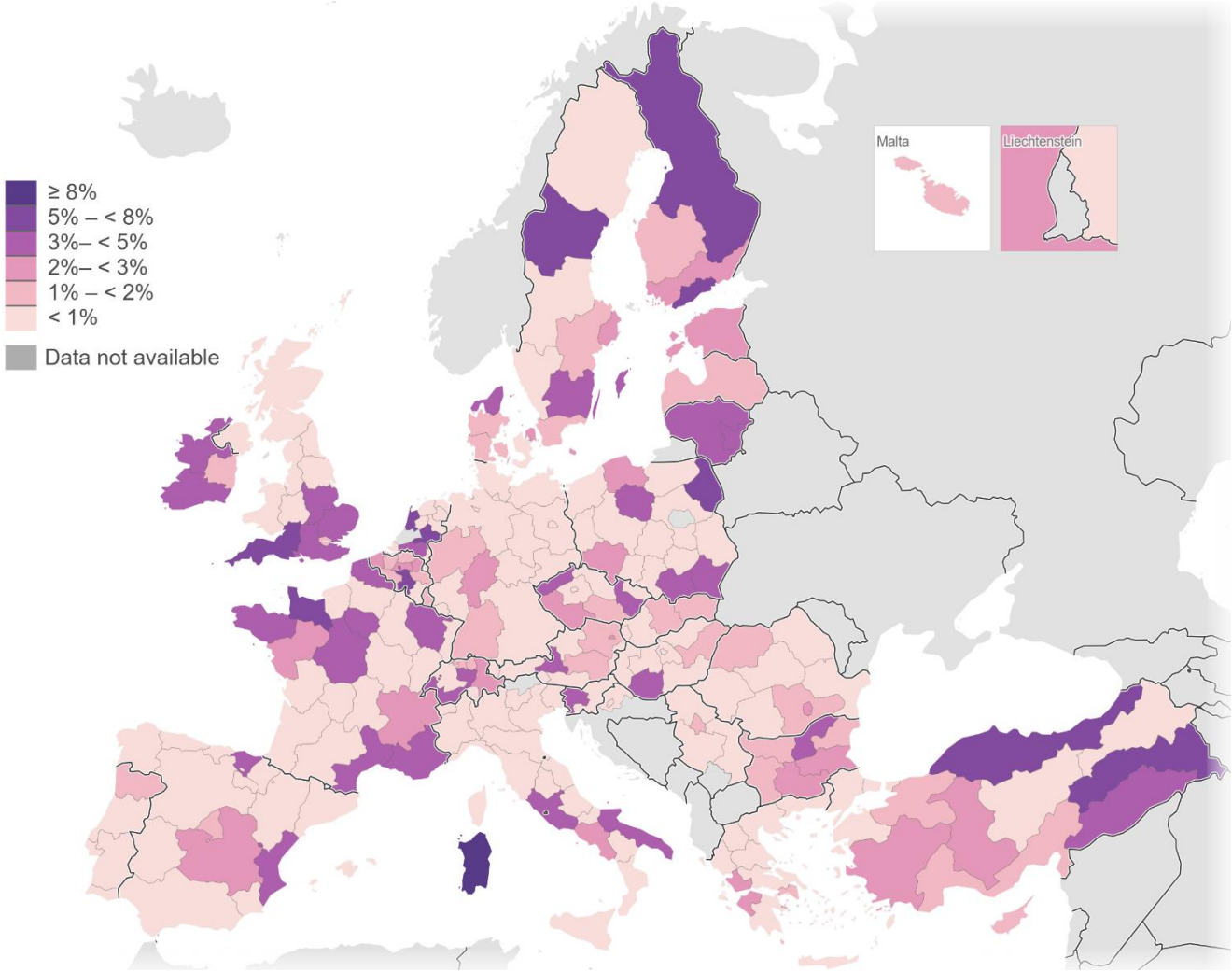


Figure 2.12: Underqualified employees in both measures by region (combined measure)



Figures 2.13 and 2.14 compare male-female differences under the separate measures. At the pooled level (All countries), the male advantage in matching is approximately 1.1 percentage points under each measure. Subjective overqualification is about 1.1 percentage points less prevalent among men, compared with a 1.5 percentage-point lower prevalence of statistical overeducation among men. The underqualification difference is close to zero under the subjective measure, while statistical undereducation is approximately 0.4 percentage points more prevalent among men. The similar pooled matching gaps therefore do not imply identical gender patterns across all categories or countries. In Luxembourg, for example, subjective overqualification is more prevalent among men, whereas statistical overeducation is more prevalent among women. These are unconditional differences; the figures do not report significance tests.

Figure 2.15 shows that the combined classification preserves the direction of the pooled (*All countries*) gender differences while altering their magnitude. Men are approximately 1.24 percentage points more likely than women to be matched under both measures, compared with around 1.1 percentage points under either measure alone. Overqualification under both measures is 0.92 percentage points less prevalent among men, while underqualification under both is 0.11 percentage points more prevalent. The country comparisons also distinguish agreement from the broader separate classifications. In Luxembourg, overqualification under both measures is approximately 3.2 percentage points more prevalent among men, consistent in direction with subjective overqualification despite the opposite gender difference in statistical overeducation. The combined measure therefore isolates a gender pattern that statistical overeducation alone does not convey. These three agreement groups exclude workers classified differently, so their gender differences need not sum to zero.

Figure 2.13: Gender differences in matching status by country (subjective measure)

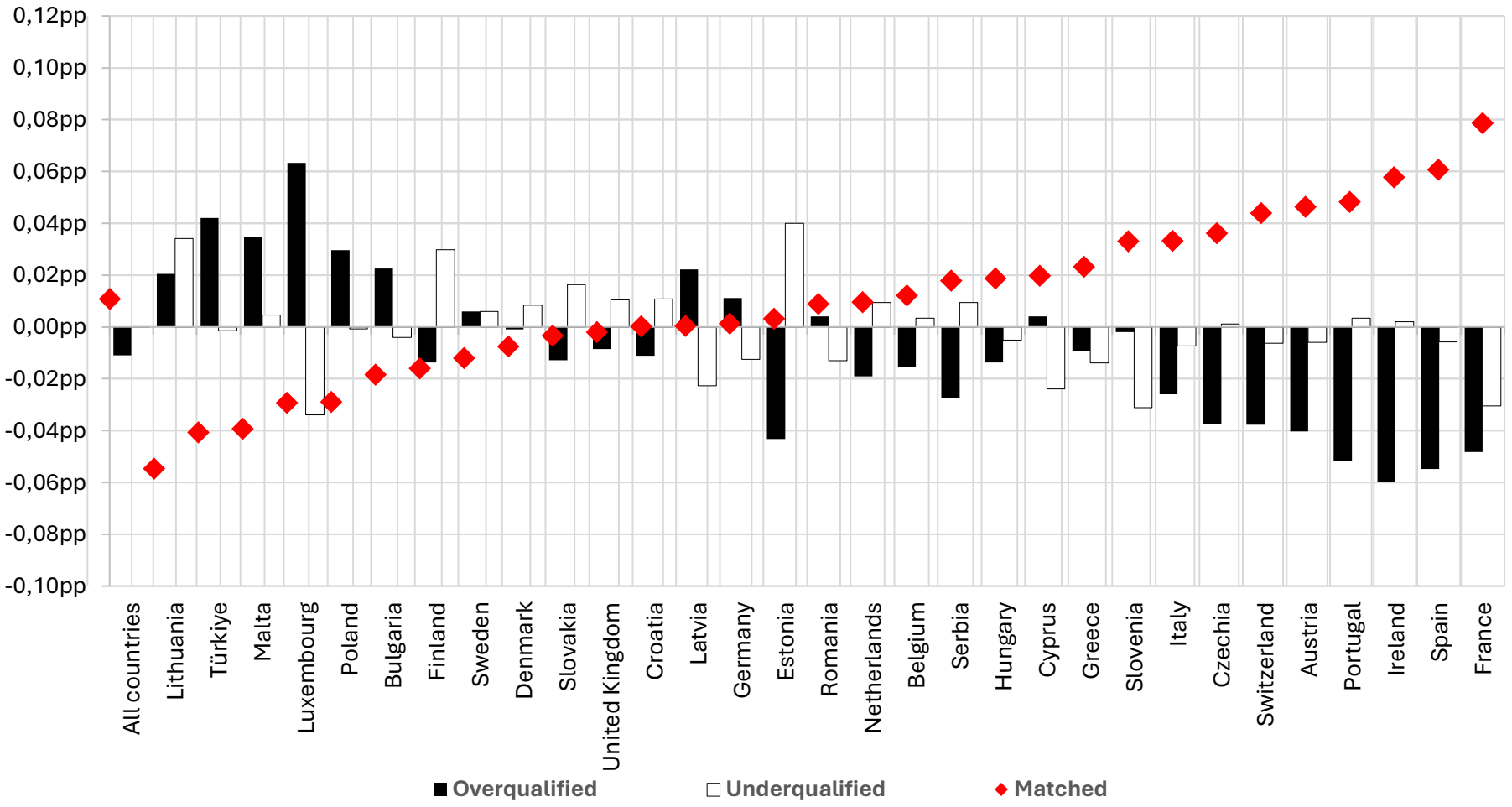


Figure 2.14: Gender differences in matching status by country (statistical measure)

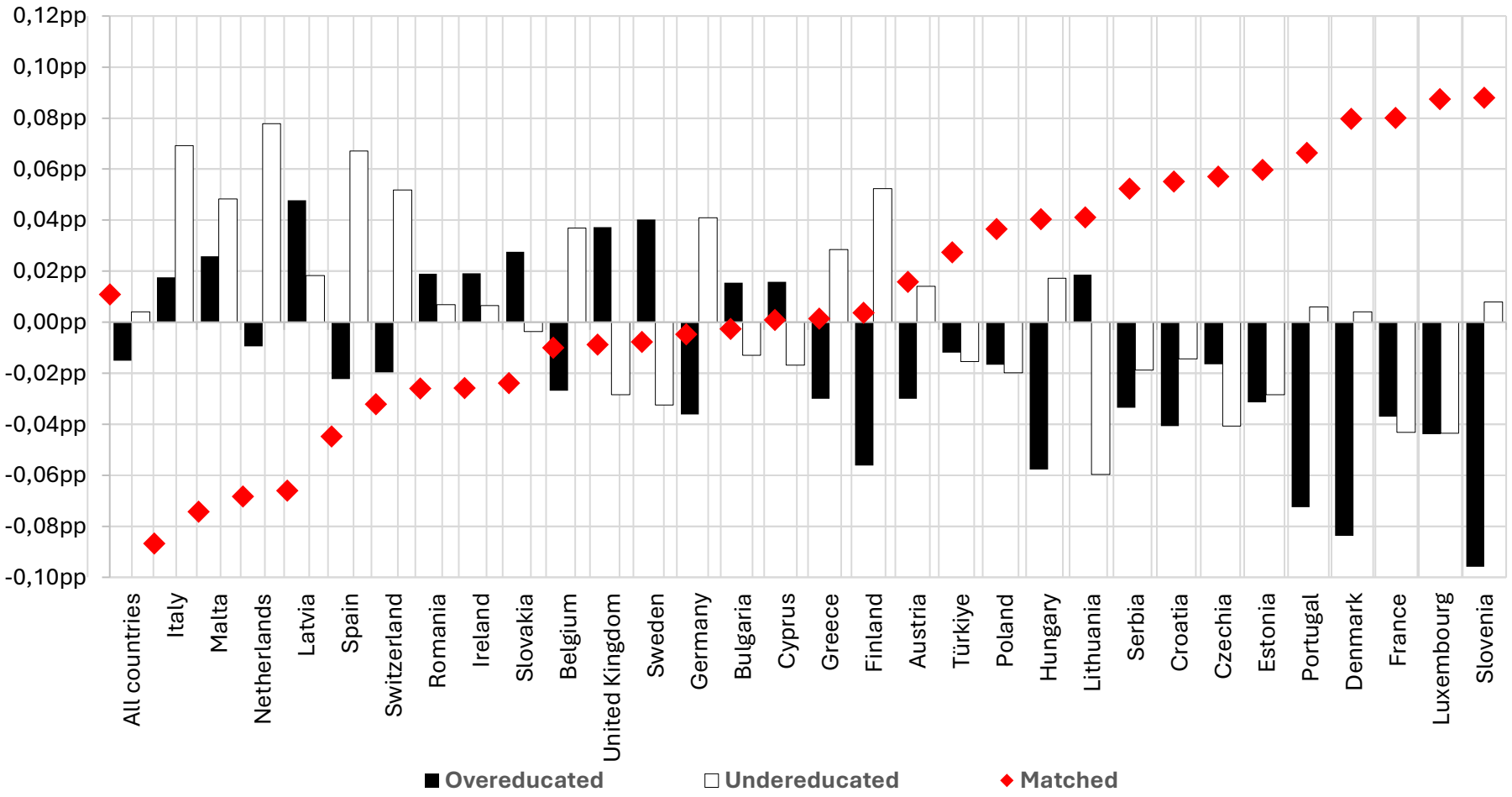
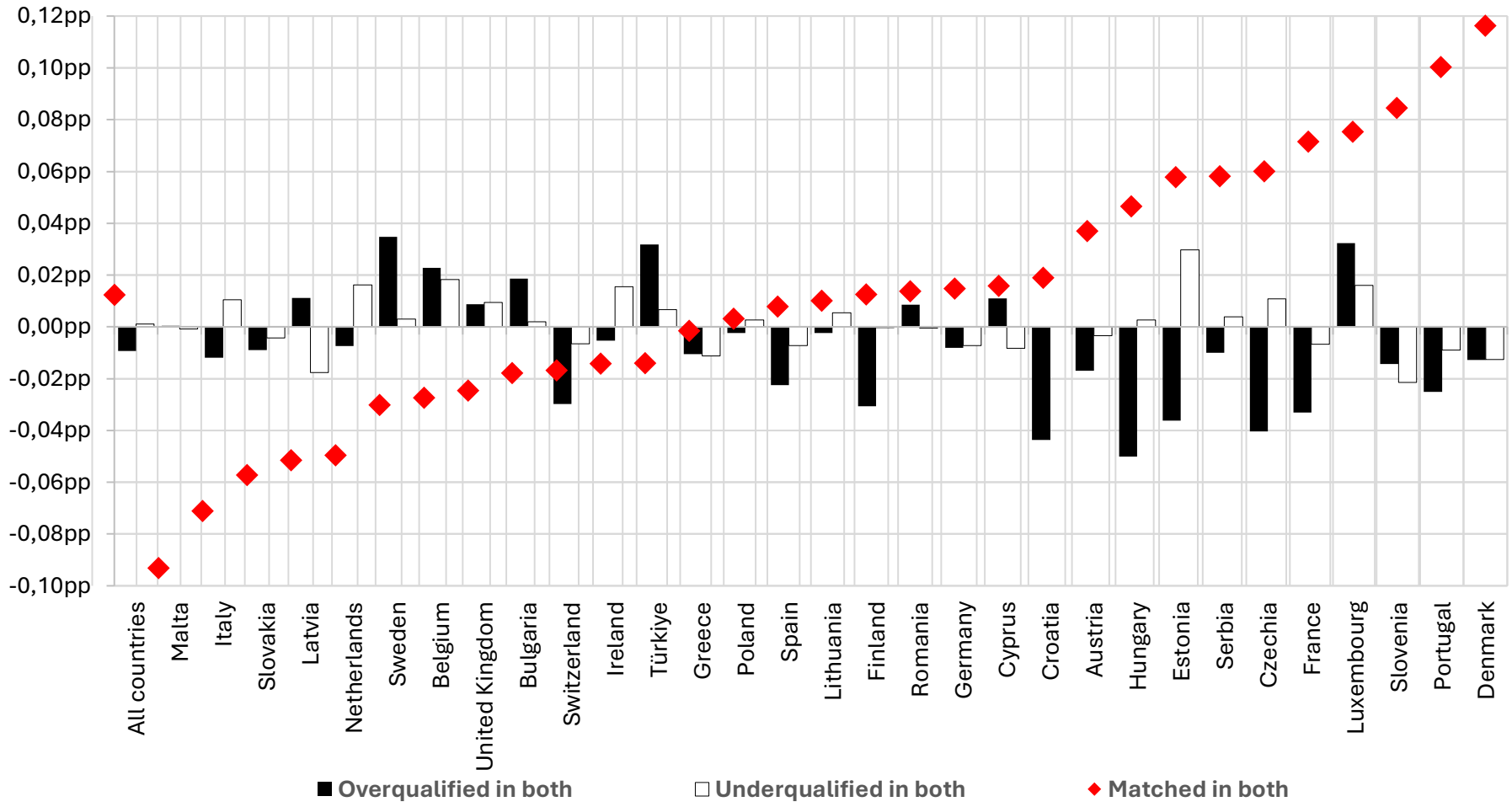


Figure 2.15: Gender differences in matching status by country (combined measure)



Figures 2.16-2.18 compare sectoral distributions under the subjective, statistical and combined classifications. Overall, 77% report subjective matching, 18% overqualification and 5% underqualification, compared with 53.7%, 15.5% and 30.9%, respectively, under the statistical measure. The largest discrepancy concerns underqualification, indicating that education below the occupational mode is much more common than a perceived shortfall in qualifications. The combined distribution identifies approximately 41.9% as matched under both measures, 4.0% as overqualified under both and 2.0% as underqualified under both.

The combined sectoral figure shows which forms of disagreement drive this difference. Around 23.4% of the sample are subjectively matched but statistically undereducated, while 11.1% are subjectively matched but statistically overeducated. A further 8.9% are subjectively overqualified but statistically matched, and 2.9% are subjectively underqualified but statistically matched. Opposite-direction mismatches account for another 5.8%, bringing total disagreement to approximately 52.2%. Figure 2.18 combines the two opposite-direction categories into eight groups, whereas the regression analysis retains them separately, yielding nine categories. The large share of workers who are subjectively matched but statistically undereducated highlights why statistical undereducation should not be interpreted as equivalent to a perceived qualification deficit.

Sectoral comparisons further illustrate the distinctions retained by the combined classification. Agreement on overqualification accounts for approximately 6.5% of workers in accommodation and food services and 7.2% in wholesale and retail trade. In the latter sector, statistical overeducation is approximately 19%, indicating that a substantial proportion of statistically overeducated workers do not also report subjective overqualification. In professional, scientific and technical activities, approximately 19.1% are statistically overeducated, while 15.7% of the sector are statistically overeducated but subjectively matched. Financial and insurance activities similarly contain a large group, approximately 28.1%, who consider their qualifications appropriate despite statistical undereducation. The combined classification thus separates agreement on mismatch from educational positions that workers regard as adequate for their jobs.

Taken together, the descriptive evidence shows that the choice of measure changes both the composition of matching groups and their observed characteristics. The combined classification separates cases of agreement from several forms of

disagreement that are obscured when either measure is considered alone. The regression analysis that follows examines whether these distinctions remain associated with skill needs, learning and resilience after accounting for worker and job characteristics, country-level differences and occupational composition.

The regional and sectoral component of this chapter is descriptive rather than causal. The country and NUTS maps show that national averages conceal substantial subnational variation, and that subjective and statistical mismatch do not identify the same geographic concentrations of overqualification and underqualification. Sectoral charts likewise show that the composition of mismatch differs across activities. Inclusiveness is considered beyond gender through age and education profiles, differences in learning participation, labour-market resilience and financial resilience, alongside geographic and sectoral heterogeneity. These comparisons identify groups with different exposure to mismatch and adjustment capacity, while the cross-sectional design does not establish that mismatch causes those differences.

Figure 2.16: Subjective mismatch measure by sector

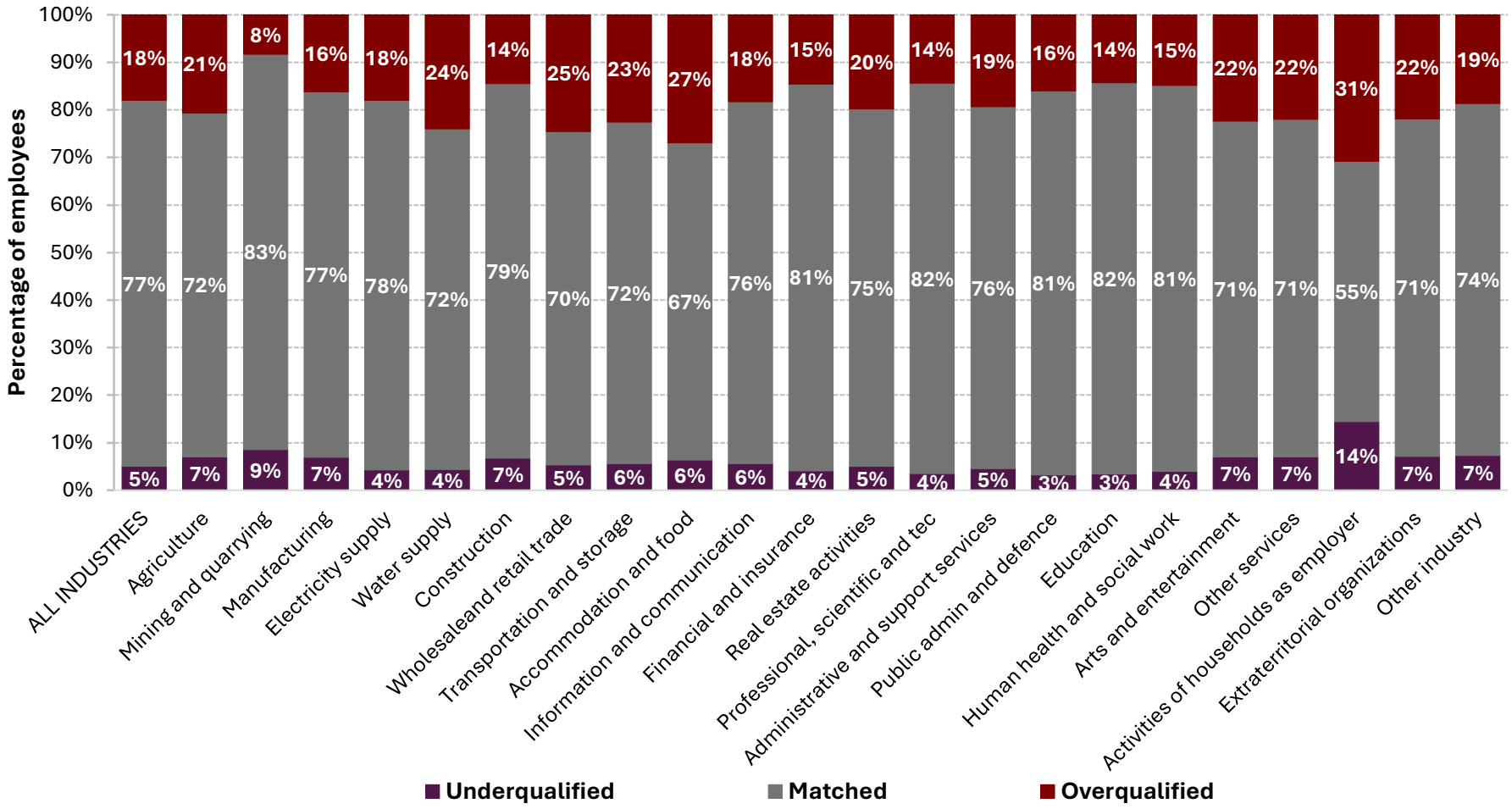


Figure 2.17: Statistical mismatch measure by sector

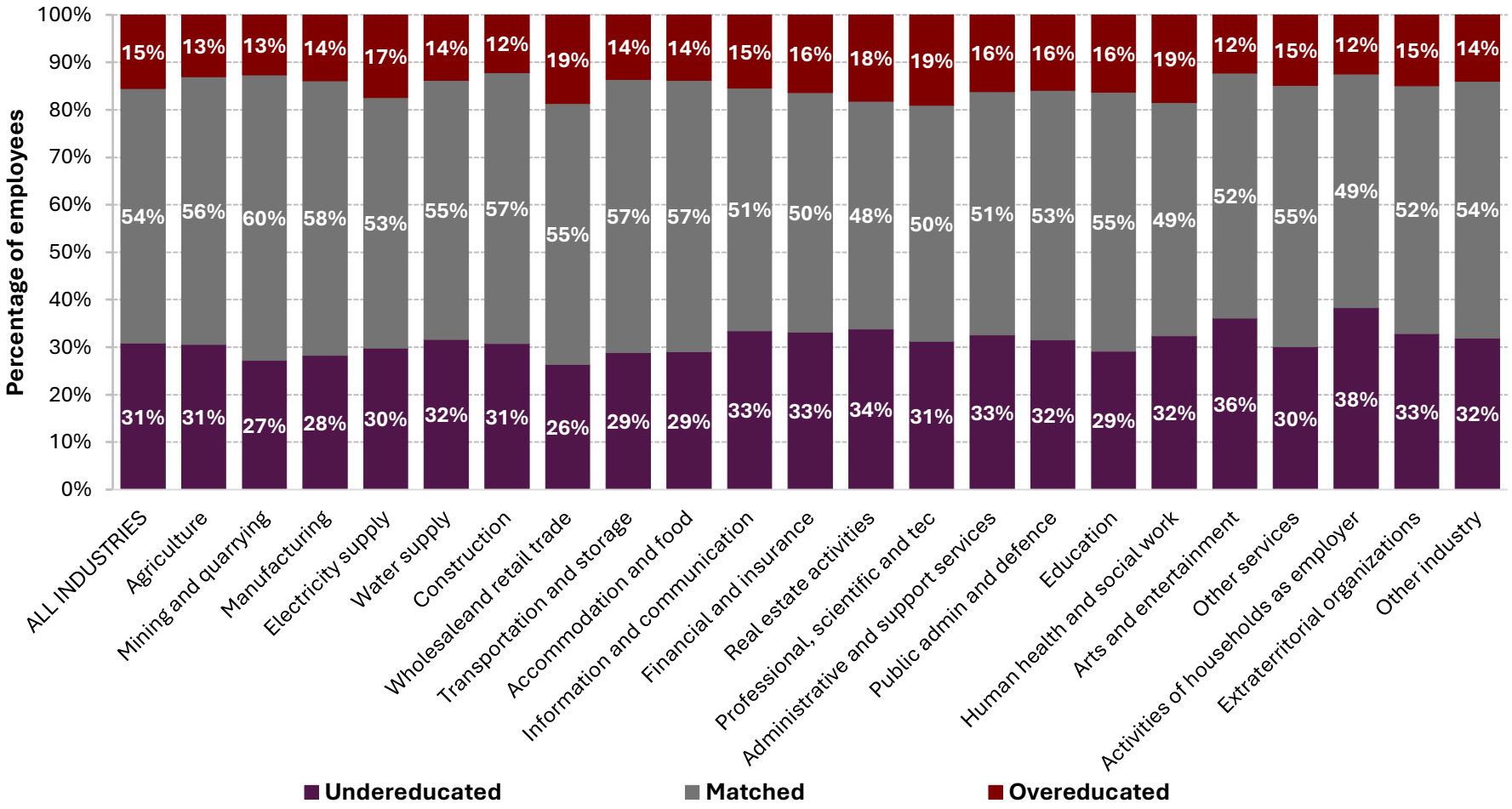
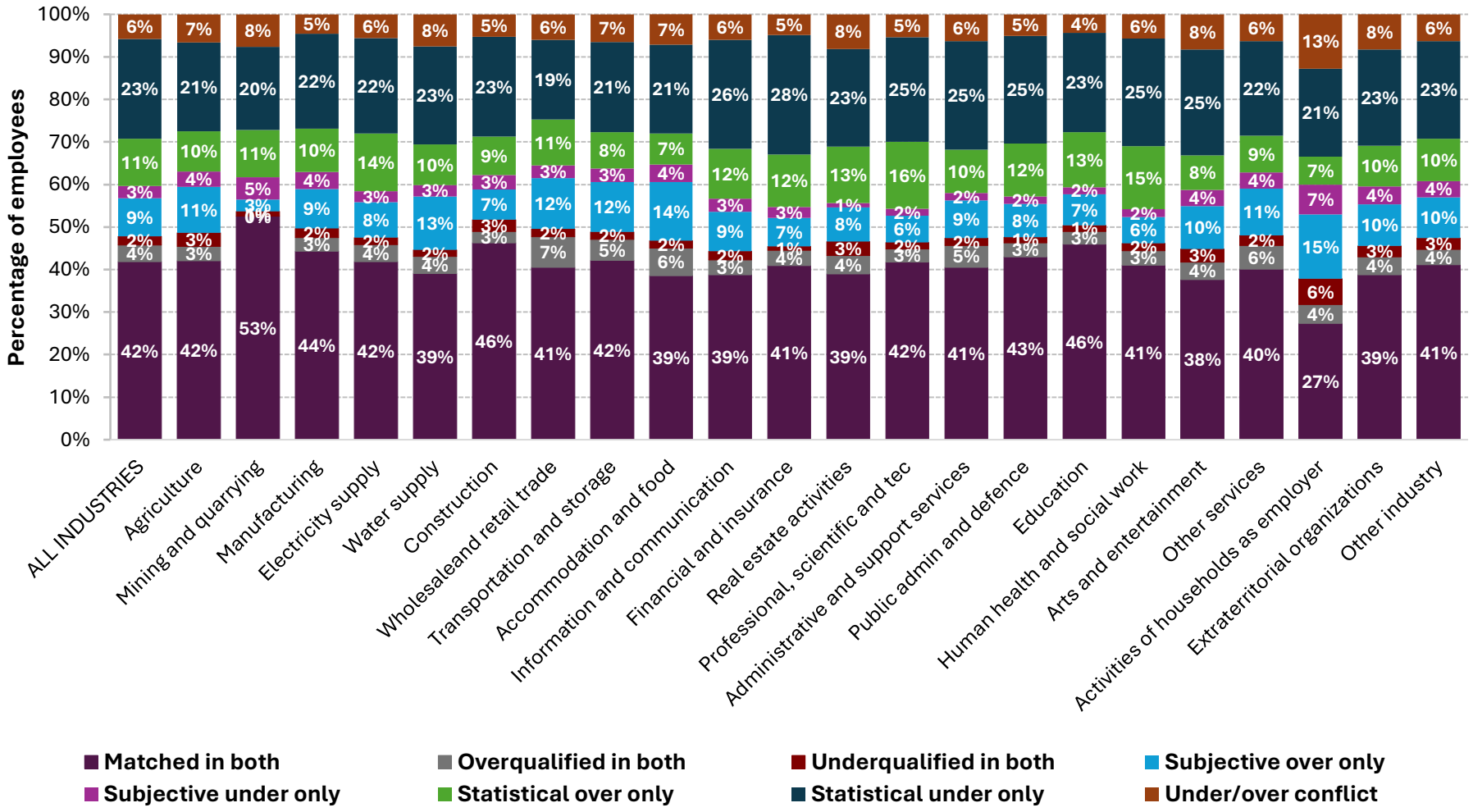


Figure 2.18: Combined subjective and statistical mismatch measures by sector



2.4 Empirical results

This section empirically examines whether combining subjective and statistical measures of qualification mismatch provides additional information about workers' reported skill needs and perceived capacity to adapt to changing employment requirements. We first compare the measures in relation to skill underutilisation and multiple skill gaps, before examining differences across skill gap categories. We then investigate how these relationships vary with learning participation and extend the analysis to labour-market and financial resilience. All regressions are estimated by ordinary least squares (OLS) using sampling weights and include country and 2-digit ISCO occupational fixed effects, alongside controls for gender, age and its square, marital status, education, sector, income and wealth categories. Hence, binary outcomes are estimated as linear probability models, with coefficients expressed below as percentage-point differences, while coefficients for indices and scores are interpreted in their respective units.

2.4.1 Measuring mismatch and reported skill needs

Table 2.5 shows how different approaches to measuring mismatch are linked to skills utilisation and skill gaps. Estimates in columns (1) and (2) reveal a clear distinction between the subjective and statistical measures. Subjective overqualification is associated with a 38.8 percentage-point higher probability of partial or no skill utilisation relative to subjective matching. The corresponding difference for subjective underqualification is 31.2 percentage points, with both coefficients significant at the 1% level. Statistical overeducation, by contrast, is associated with a difference of only 4.0 percentage points, while statistical undereducation has a small, insignificant coefficient. Subjective measures therefore appear more closely related to reported underutilisation than deviations from the modal education level within the occupation. The positive coefficient for subjective underqualification also indicates that workers who consider themselves underqualified are also more likely to report underutilised skills, suggesting that a perceived qualification deficit can coexist with unused capabilities.

The combined classification in column (3) clarifies which workers account for these effects. Relative to workers who are matched under both measures, those overqualified under both have a 42.4 percentage-point higher probability of underutilisation, while those underqualified under both have a 28.2 percentage-point

higher probability. Substantial differences also arise when the measures disagree. Subjective overqualification is associated with underutilisation differences of 38.9 percentage points when the statistical measure indicates matching and 36.4 percentage points when it indicates undereducation. Subjective underqualification is associated with differences of 31.6 percentage points when statistically matched and 37.3 percentage points when statistically overeducated. All four disagreement coefficients are significant at the 1% level. By contrast, statistical overeducation and undereducation accompanied by subjective matching have statistically insignificant coefficients.

These results highlight heterogeneity between overqualification and underqualification that the statistical measure alone does not capture. Workers whose education matches the occupational benchmark may still report substantial skill underutilisation, whereas statistically mismatched workers who consider their qualifications appropriate show no significant difference from workers matched under both measures. The combined classification distinguishes these groups, with the largest estimated underutilisation difference observed among workers classified as overqualified by both measures. This pattern suggests that the statistical measure provides additional information within subjective overqualification.

Results regarding the multiple-skill-gap in columns (4)-(6) provide a different comparison. Subjective overqualification is associated with a 6.1 percentage-point lower probability of having multiple skill gaps, whereas subjective underqualification is associated with a 6.3 percentage-point higher probability of reporting skill gaps. The estimate in column (6), using the combined classification shows that agreement on overqualification and underqualification is associated with differences of -9.9 and 10.7 percentage points, respectively. Thus, the two forms of agreement correspond to different patterns of reported skill needs, despite both being associated with underutilisation. These findings reinforce the distinction between the extent to which workers use their capabilities and whether those capabilities meet all the requirements of their jobs.

Disagreement between the measures identifies distinct patterns in reported skill gaps. Relative to workers who are matched under both measures, those who consider themselves overqualified but are classified as matched by the statistical measure have a 5.2 percentage-point lower probability of reporting multiple skill gaps. Those who consider themselves overqualified but are classified as undereducated have a 6.6 percentage-point lower probability. Both estimates are significant at the 1% level.

Instead, workers who consider themselves underqualified but are statistically matched or those who consider their qualifications appropriate but are statistically undereducated report insignificant coefficients. Those who consider themselves underqualified but are classified as overeducated have a positive coefficient of 6.8 percentage points, significant at the 10% level. While workers who consider their qualifications appropriate but are classified as overeducated have a small negative coefficient of -2.0 percentage points, significant at the 10% level.

The combined measure distinguishes these groups within each separate classification. Among workers who consider themselves underqualified, those also classified as statistically undereducated have the largest estimated skill-gap difference relative to workers matched under both measures, namely 10.7 percentage points, compared with 2.7 for those classified as statistically matched and 6.8 for those classified as statistically overeducated. Conversely, among statistically undereducated workers, the coefficients range from -6.6 percentage points for those who consider themselves overqualified to near zero for those who consider their qualifications appropriate and 10.7 for those who consider themselves underqualified. The combined classification thus provides a more differentiated link to reported skill needs than either measure alone.

Table 2.5: The effect of alternative mismatch measures on skills utilisation and skill gaps

	Skills underutilisation			**Skill gaps (multiple)**		
	(1)	(2)	(3)	(4)	(5)	(6)
Subjective overqualified	0.388***			-0.061***		
	[0.012]			[0.011]		
Subjective underqualified	0.312***			0.063***		
	[0.019]			[0.015]		
Subjective matched	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Statistical overeducated		0.040***			-0.026***	
		[0.013]			[0.009]	
Statistical undereducated		-0.008			-0.002	
		[0.009]			[0.009]	
Statistical matched	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Overqualified in both			0.424***			-0.099***
			[0.018]			[0.017]
Underqualified in both			0.282***			0.107***
			[0.029]			[0.026]
Subjective overqualified only			0.389***			-0.052***
			[0.014]			[0.015]
Subjective underqualified only			0.316***			0.027
			[0.030]			[0.024]
Statistical overqualified only			0.018			-0.020*
			[0.014]			[0.011]
Statistical underqualified only			-0.007			-0.006
			[0.010]			[0.011]
Subj. overqualified (vs stat. undereducated)			0.364***			-0.066***
			[0.020]			[0.018]
Stat.overeducated (vs subj. underqual.)			0.373***			0.068*
			[0.044]			[0.038]
Matched in both	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Gender: Male	-0.013	-0.014	-0.013	0.064***	0.061***	0.064***
	[0.010]	[0.010]	[0.010]	[0.009]	[0.009]	[0.009]
"-" : Nonbinary	-0.024	0.005	-0.026	0.11	0.074	0.116
	[0.082]	[0.103]	[0.082]	[0.087]	[0.078]	[0.088]
"-" : Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.003	0.004	0.003	-0.005**	-0.004**	-0.005**
	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
Age of respondent (squared)	-0.066**	-0.079**	-0.066**	0.023	0.016	0.023
	[0.032]	[0.033]	[0.031]	[0.024]	[0.024]	[0.024]
Marital status: Married/ cohabiting	-0.039**	-0.051***	-0.039**	-0.016	-0.013	-0.016
	[0.015]	[0.016]	[0.015]	[0.011]	[0.011]	[0.011]
"-": Widowed/divorced	-0.006	-0.008	-0.006	-0.002	0.005	-0.003
	[0.019]	[0.019]	[0.019]	[0.024]	[0.025]	[0.024]
"-": Other	-0.061***	-0.070***	-0.061***	0.018	0.021	0.018
	[0.016]	[0.018]	[0.016]	[0.014]	[0.014]	[0.014]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Education: Primary education	-0.163**	-0.168**	-0.149**	-0.087	-0.069	-0.098
	[0.063]	[0.074]	[0.063]	[0.060]	[0.061]	[0.061]
"-": Lower secondary	-0.076**	-0.081**	-0.065*	0.003	-0.006	-0.005
	[0.033]	[0.036]	[0.034]	[0.029]	[0.028]	[0.029]
"-": Upper secondary	-0.052*	-0.042	-0.047*	0.017	0.012	0.008
	[0.027]	[0.032]	[0.028]	[0.018]	[0.018]	[0.019]
"-": Post-secondary non-tertiary	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
"-": Short-cycle tertiary	-0.039	-0.021	-0.04	0.028	0.027	0.026
	[0.027]	[0.032]	[0.027]	[0.022]	[0.020]	[0.022]
"-": Bachelor level	-0.005	0.023	-0.01	0.036**	0.032*	0.035*
	[0.027]	[0.032]	[0.028]	[0.017]	[0.017]	[0.018]
"-": Master's level	-0.024	-0.004	-0.032	0.035*	0.032	0.037*
	[0.027]	[0.032]	[0.028]	[0.019]	[0.019]	[0.020]

"-": Doctoral level	-0.062**	-0.051*	-0.074**	0.036	0.037	0.043
	[0.026]	[0.029]	[0.029]	[0.036]	[0.034]	[0.036]
NACE (a): Agriculture, forestry & fishing	0.074*	0.067	0.074*	-0.016	-0.008	-0.016
	[0.039]	[0.043]	[0.039]	[0.035]	[0.035]	[0.035]
"-" (b): Mining & quarrying	0.003	-0.04	0.004	0.11	0.119	0.112
	[0.078]	[0.079]	[0.079]	[0.090]	[0.079]	[0.089]
"-" (c): Manufacturing	0.047***	0.037**	0.046**	0.012	0.027*	0.014
	[0.017]	[0.018]	[0.017]	[0.016]	[0.015]	[0.016]
"-" (d): Electricity, gas & air conditioning	-0.032	-0.031	-0.032	-0.021	-0.011	-0.02
	[0.039]	[0.037]	[0.038]	[0.026]	[0.026]	[0.026]
"-" (e): Water, sewerage & waste	-0.002	0.02	-0.003	0.001	0.015	0.004
	[0.036]	[0.048]	[0.036]	[0.047]	[0.047]	[0.048]
"-" (f): Construction	-0.059**	-0.075***	-0.060**	0.023	0.035	0.023
	[0.023]	[0.023]	[0.023]	[0.024]	[0.024]	[0.024]
"-" (g): Wholesale, retail & vehicle repair	0.042***	0.049***	0.042***	-0.01	-0.004	-0.01
	[0.015]	[0.015]	[0.015]	[0.025]	[0.023]	[0.024]
"-" (h): Transportation & storage	0.024	0.031	0.023	0.037*	0.048**	0.038*
	[0.023]	[0.023]	[0.023]	[0.021]	[0.022]	[0.021]
"-" (i): Accommodation & food	-0.014	-0.004	-0.013	0.031	0.041	0.03
	[0.022]	[0.022]	[0.023]	[0.030]	[0.030]	[0.030]
"-" (j): Information & communication	0.01	0	0.01	0.047**	0.062***	0.048**
	[0.020]	[0.023]	[0.020]	[0.021]	[0.021]	[0.021]
"-" (k): Financial & insurance	0	-0.027	0	0.059**	0.074***	0.060***
	[0.019]	[0.021]	[0.019]	[0.022]	[0.022]	[0.022]
"-" (l): Real estate	-0.023	-0.025	-0.022	0.038	0.046	0.039
	[0.050]	[0.053]	[0.050]	[0.041]	[0.044]	[0.041]
"-" (m): Professional & technical service	-0.025	-0.054**	-0.024	0.042	0.061**	0.042
	[0.022]	[0.021]	[0.022]	[0.026]	[0.026]	[0.026]
"-" (n): Administrative services	0.018	0.006	0.017	0.056**	0.070***	0.057**
	[0.022]	[0.024]	[0.022]	[0.021]	[0.020]	[0.021]
"-" (o): Public administration & defence	0.053**	0.042*	0.052**	-0.028	-0.011	-0.027
	[0.021]	[0.022]	[0.021]	[0.019]	[0.018]	[0.019]
"-" (p): Education	-0.006	-0.014	-0.005	0.009	0.024	0.009
	[0.022]	[0.024]	[0.022]	[0.023]	[0.023]	[0.023]
"-" (q): Health & social work	-0.030*	-0.051***	-0.032*	-0.016	0.012	-0.015
	[0.017]	[0.018]	[0.017]	[0.018]	[0.017]	[0.018]
"-" (r): Arts, entertainment & recreation	0.037	0.044	0.039	-0.016	0.011	-0.018
	[0.026]	[0.030]	[0.027]	[0.027]	[0.026]	[0.027]
"-" (s): Other services	0.026	0.02	0.025	0.002	0.014	0.004
	[0.016]	[0.017]	[0.016]	[0.021]	[0.021]	[0.021]
"-" (t): Households as employers	0.023	0.043	0.02	0.032	0.067	0.032
	[0.047]	[0.049]	[0.046]	[0.047]	[0.049]	[0.046]
"-" (u): Extraterritorial organisations	-0.053	-0.032	-0.055	0.179***	0.180***	0.180***
	[0.045]	[0.048]	[0.045]	[0.059]	[0.059]	[0.059]
"-" : Other	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: 10th Decile	-0.072***	-0.097***	-0.072***	0.033*	0.038*	0.034*
	[0.021]	[0.021]	[0.021]	[0.019]	[0.020]	[0.019]
"-":9th	-0.046*	-0.062**	-0.045*	0.030*	0.035**	0.030*
	[0.025]	[0.025]	[0.025]	[0.015]	[0.015]	[0.015]
"-":8th	-0.017	-0.017	-0.017	0.02	0.022	0.02
	[0.023]	[0.023]	[0.023]	[0.017]	[0.018]	[0.017]
"-":7th	0.01	0.008	0.01	0.017	0.018	0.016
	[0.020]	[0.020]	[0.020]	[0.017]	[0.018]	[0.017]
"-":6th	0.005	0.009	0.006	0.012	0.012	0.012
	[0.021]	[0.020]	[0.020]	[0.021]	[0.020]	[0.021]
"-":5th	0.013	0.023	0.013	-0.017	-0.014	-0.017
	[0.020]	[0.022]	[0.021]	[0.016]	[0.016]	[0.015]
"-":4th	-0.001	0.005	-0.001	0	0.003	0
	[0.023]	[0.024]	[0.023]	[0.022]	[0.022]	[0.021]
"-":3rd	0.019	0.039	0.019	-0.023	-0.023	-0.023
	[0.024]	[0.024]	[0.025]	[0.019]	[0.020]	[0.019]
"-":2nd	0.015	0.034	0.015	0.012	0.01	0.013
	[0.020]	[0.021]	[0.020]	[0.026]	[0.025]	[0.026]

"-":1st	0.026	0.060***	0.026	0.004	-0.002	0.003
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: 10th Decile	0.006	-0.003	0.006	0.027	0.023	0.026
	[0.019]	[0.017]	[0.019]	[0.017]	[0.017]	[0.017]
"-":9th	-0.027	-0.043	-0.028	0.038	0.033	0.038
	[0.024]	[0.027]	[0.024]	[0.024]	[0.023]	[0.024]
"-":8th	-0.025	-0.040*	-0.026	0.049**	0.045**	0.049**
	[0.023]	[0.023]	[0.023]	[0.019]	[0.019]	[0.019]
"-":7th	-0.033	-0.039**	-0.034*	0.049**	0.047**	0.049**
	[0.020]	[0.019]	[0.020]	[0.018]	[0.018]	[0.018]
"-":6th	-0.007	-0.013	-0.007	0.057***	0.056***	0.057***
	[0.022]	[0.023]	[0.022]	[0.018]	[0.018]	[0.018]
"-":5th	-0.009	-0.014	-0.009	0.048***	0.044***	0.048***
	[0.017]	[0.018]	[0.017]	[0.016]	[0.015]	[0.016]
"-":4th	-0.024	-0.031*	-0.024	0.063***	0.056***	0.064***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.015]	[0.016]
"-":3rd	-0.013	-0.023	-0.014	0.066***	0.062***	0.067***
	[0.014]	[0.016]	[0.014]	[0.022]	[0.021]	[0.022]
"-":2nd	-0.006	-0.021	-0.006	0.088***	0.083***	0.088***
	[0.018]	[0.020]	[0.018]	[0.017]	[0.017]	[0.017]
"-":1st	-0.008	-0.019	-0.01	0.021	0.018	0.022
	[0.021]	[0.020]	[0.020]	[0.020]	[0.019]	[0.020]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Occupational fixed effects	+	+	+	+	+	+
Country fixed effects	+	+	+	+	+	+
No. of Observations	16,515	16,864	16,515	15,986	16,538	15,986
R-squared	0.158	0.063	0.159	0.074	0.074	0.075

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

2.4.2 The composition of reported skill gaps

Table 2.6 shows how combined mismatch measures are associated with different skill gap categories. Workers who are overqualified under both measures are less likely than those matched under both to report digital and ICT gaps, communication and teamwork gaps, foreign-language gaps, and basic literacy and numeracy gaps, with the corresponding coefficients to be negative and statistically significant at 1% level. The technical and job-specific coefficient is also negative but significant only at the 10% level, while the customer-handling coefficient is insignificant. Agreement between the measures on overqualification is thus associated with fewer reported skill gaps across several categories, rather than the absence of every type of skill need.

Workers classified as underqualified by both measures report skill gaps concentrated in specific domains. Relative to workers matched under both measures, they are 5.8 percentage points more likely to report digital and ICT gaps, 8.3 percentage points more likely to report technical and job-specific gaps, and 6.3 percentage points

more likely to report customer-handling gaps. Coefficients in the remaining skill gap categories are statistically insignificant. This pattern suggests that underqualification is associated with particular skill needs rather than uniformly greater deficits across tasks.

The disagreement categories between measures provide further information about the composition of skill gaps. Relative to workers who are matched under both measures, those who consider themselves overqualified but are classified as statistically matched are less likely to report digital, communication, technical, language and basic-skill gaps, with statistically significant coefficients ranging from -6.3 to -1.6 percentage points. Workers who consider themselves overqualified but are classified as statistically undereducated also have negative, significant and slightly higher in absolute terms coefficients for digital, communication, language and basic skills. Neither group differs significantly from the reference group in customer-handling gaps. These results indicate that education below the occupational benchmark can coexist with fewer reported gaps across several domains among workers who regard their qualifications as exceeding their job requirements.

Workers who consider themselves underqualified but are classified as statistically matched have an 11.2 percentage-point higher probability of reporting technical and job-specific gaps, despite their insignificant multiple skill gap coefficient in column (6) of Table 5. Those who consider themselves underqualified but are classified as statistically overeducated have a corresponding coefficient of 10.7 percentage points. The latter group is also 7.4 percentage points less likely to report foreign-language gaps, although this estimate is significant only at the 10% level. Thus, perceived underqualification can be associated with greater needs in one skill category and fewer gaps in another. Conversely, workers who consider their qualifications matched but are classified as statistically overeducated or undereducated show no significant differences from workers matched under both measures across any of the six skill gap categories. The combined classification therefore distinguishes different profiles of reported skill needs within broader qualification categories.

In sum, workers who are underqualified under both measures report greater digital, technical and customer-handling gaps, whereas those who consider themselves underqualified but are classified as statistically matched primarily report greater technical gaps.

Table 2.6: The effect of combined mismatch measure across skill gap categories

	Digital, ICT	**Teamwork, comm.**	**Technical, job-specific**	**Foreign languages**	**Customer handling**	**Basic literacy, numeracy**
	(1)	(2)	(3)	(4)	(5)	(6)
Overqualified in both	-0.088***	-0.060***	-0.033*	-0.067***	-0.002	-0.033***
	[0.017]	[0.018]	[0.017]	[0.017]	[0.014]	[0.008]
Underqualified in both	0.058**	0.023	0.083***	-0.022	0.063***	0.018
	[0.022]	[0.027]	[0.026]	[0.025]	[0.022]	[0.028]
Subjective overqualified only	-0.063***	-0.036***	-0.050**	-0.050***	-0.008	-0.016**
	[0.012]	[0.012]	[0.019]	[0.013]	[0.012]	[0.007]
Subjective underqualified only	0.011	-0.011	0.112***	-0.027	-0.017	-0.022
	[0.024]	[0.021]	[0.029]	[0.024]	[0.018]	[0.014]
Statistical overqualified only	-0.013	-0.018	-0.008	0.010	-0.006	-0.008
	[0.016]	[0.013]	[0.015]	[0.016]	[0.009]	[0.008]
Statistical underqualified only	0.004	-0.005	-0.001	0.002	0.007	-0.006
	[0.010]	[0.011]	[0.009]	[0.010]	[0.009]	[0.006]
Subj. overqualified (vs stat. undereducated)	-0.083***	-0.051**	-0.015	-0.063***	-0.012	-0.024*
	[0.014]	[0.021]	[0.018]	[0.016]	[0.018]	[0.012]
Stat.overeducated (vs subj. underqual.)	0.057	0.021	0.107**	-0.074*	0.013	-0.016
	[0.045]	[0.042]	[0.052]	[0.042]	[0.032]	[0.027]
Matched in both	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Gender: Male	0.013	0.044***	0.072***	0.007	0.028***	0.013**
	[0.009]	[0.010]	[0.009]	[0.007]	[0.007]	[0.006]
"-" : Nonbinary	0.144*	0.006	0.021	0.089	-0.006	-0.013
	[0.079]	[0.099]	[0.101]	[0.085]	[0.071]	[0.041]
"-" : Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.002	-0.005**	0.000	0.000	-0.010***	-0.002
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.001]
Age of respondent (squared)	0.003	0.013	-0.036	-0.010	0.094***	0.005
	[0.023]	[0.022]	[0.023]	[0.026]	[0.021]	[0.014]
Marital status: Married/ cohabiting	-0.010	-0.005	0.008	0.000	-0.001	0.014**
	[0.011]	[0.014]	[0.014]	[0.008]	[0.008]	[0.006]
"-": Widowed/divorced	-0.008	0.002	0.008	-0.021	0.015	0.009
	[0.019]	[0.026]	[0.022]	[0.013]	[0.017]	[0.012]
"-": Other	0.017	0.019	-0.007	0.012	0.024*	0.027***
	[0.014]	[0.012]	[0.016]	[0.010]	[0.012]	[0.009]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Education: Primary education	0.029	-0.111***	-0.118*	-0.027	-0.033	0.020
	[0.042]	[0.035]	[0.064]	[0.044]	[0.045]	[0.038]
"-": Lower secondary	-0.024	0.016	-0.131***	0.003	0.010	0.035
	[0.027]	[0.029]	[0.021]	[0.033]	[0.027]	[0.024]
"-": Upper secondary	0.028	-0.027	-0.061***	0.020	-0.001	0.004
	[0.025]	[0.025]	[0.018]	[0.023]	[0.017]	[0.021]
"-": Post-secondary non-tertiary	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
"-": Short-cycle tertiary	0.056*	-0.006	-0.053**	0.008	-0.008	0.011
	[0.028]	[0.024]	[0.022]	[0.026]	[0.018]	[0.023]
"-": Bachelor level	0.073***	-0.010	-0.026	0.028	0.000	0.008
	[0.019]	[0.026]	[0.017]	[0.024]	[0.015]	[0.022]
"-": Master's level	0.089***	0.003	-0.034**	0.023	-0.006	0.000
	[0.020]	[0.024]	[0.015]	[0.027]	[0.018]	[0.024]
"-": Doctoral level	0.100***	-0.023	-0.033	0.072**	-0.025	0.027
	[0.033]	[0.037]	[0.026]	[0.031]	[0.025]	[0.030]
NACE (a): Agriculture, forestry & fishing	0.014	0.028	-0.005	-0.012	0.043	0.015
	[0.031]	[0.036]	[0.030]	[0.029]	[0.029]	[0.021]
"-" (b): Mining & quarrying	0.118	-0.093	0.047	0.093	0.052	0.038
	[0.073]	[0.070]	[0.085]	[0.067]	[0.065]	[0.043]
"-" (c): Manufacturing	0.030**	0.023	0.064***	0.001	-0.025	0.010
	[0.015]	[0.016]	[0.018]	[0.015]	[0.016]	[0.012]
"-" (d): Electricity, gas & air conditioning	-0.011	0.021	0.027	-0.018	-0.010	0.011

	[0.029]	[0.032]	[0.028]	[0.030]	[0.021]	[0.022]
"-" (e): Water, sewerage & waste	0.038	-0.012	-0.018	-0.015	-0.003	-0.014
	[0.039]	[0.034]	[0.040]	[0.050]	[0.028]	[0.023]
"-" (f): Construction	0.059***	0.015	0.089***	-0.018	0.028	0.024
	[0.016]	[0.024]	[0.026]	[0.021]	[0.018]	[0.018]
"-" (g): Wholesale, retail & vehicle repair	0.033*	0.010	-0.015	-0.027	0.030	0.022
	[0.017]	[0.025]	[0.018]	[0.020]	[0.020]	[0.016]
"-" (h): Transportation & storage	0.060***	0.007	0.002	0.003	0.015	0.008
	[0.021]	[0.019]	[0.017]	[0.016]	[0.019]	[0.012]
"-" (i): Accommodation & food	0.030	0.015	-0.018	0.055*	0.064***	0.017
	[0.030]	[0.026]	[0.024]	[0.032]	[0.022]	[0.015]
"-" (j): Information & communication	0.110***	0.053**	0.042	-0.009	0.053***	0.009
	[0.023]	[0.021]	[0.025]	[0.023]	[0.017]	[0.016]
"-" (k): Financial & insurance	0.081***	0.015	0.046*	-0.026	0.061***	0.021
	[0.020]	[0.019]	[0.025]	[0.019]	[0.014]	[0.015]
"-" (l): Real estate	0.050	0.005	0.046	0.013	0.043	-0.006
	[0.042]	[0.036]	[0.045]	[0.039]	[0.029]	[0.022]
"-" (m): Professional & technical service	0.059***	0.041*	0.072***	-0.014	0.026	0.003
	[0.021]	[0.021]	[0.024]	[0.021]	[0.019]	[0.015]
"-" (n): Administrative services	0.086***	0.073***	0.014	0.001	0.060***	0.026
	[0.022]	[0.022]	[0.027]	[0.021]	[0.018]	[0.018]
"-" (o): Public administration & defence	0.046**	0.006	-0.012	-0.051**	-0.045**	-0.008
	[0.021]	[0.021]	[0.022]	[0.025]	[0.017]	[0.012]
"-" (p): Education	0.067***	0.040**	-0.014	-0.015	0.000	0.033*
	[0.019]	[0.019]	[0.020]	[0.021]	[0.016]	[0.016]
"-" (q): Health & social work	0.032*	0.053***	-0.023	-0.038**	0.009	0.004
	[0.017]	[0.019]	[0.022]	[0.016]	[0.014]	[0.011]
"-" (r): Arts, entertainment & recreation	0.051	0.016	-0.016	0.002	-0.018	0.023
	[0.037]	[0.025]	[0.029]	[0.029]	[0.017]	[0.018]
"-" (s): Other services	0.024	-0.008	-0.001	-0.019	0.046***	0.020
	[0.019]	[0.015]	[0.019]	[0.020]	[0.016]	[0.012]
"-" (t): Households as employers	0.031	0.108	-0.047	-0.070	0.030	0.086*
	[0.044]	[0.066]	[0.074]	[0.057]	[0.044]	[0.048]
"-" (u): Extraterritorial organisations	0.067	0.131***	0.046	0.124*	0.052	0.088**
	[0.043]	[0.038]	[0.041]	[0.065]	[0.038]	[0.034]
"-" : Other	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: 10th Decile	0.026	0.020	0.031	0.034*	-0.007	0.000
	[0.022]	[0.013]	[0.020]	[0.019]	[0.013]	[0.009]
"-":9th	0.032*	0.022	0.025	-0.006	-0.001	0.016*
	[0.016]	[0.017]	[0.016]	[0.017]	[0.014]	[0.009]
"-":8th	0.014	-0.002	0.017	-0.001	0.002	0.026**
	[0.021]	[0.014]	[0.019]	[0.021]	[0.014]	[0.010]
"-":7th	0.020	0.003	0.011	0.008	0.002	0.006
	[0.016]	[0.017]	[0.018]	[0.023]	[0.014]	[0.012]
"-":6th	0.008	0.003	0.019	-0.014	-0.014	0.006
	[0.020]	[0.015]	[0.020]	[0.020]	[0.012]	[0.012]
"-":5th	-0.010	-0.025	0.029	-0.004	-0.022	0.012
	[0.015]	[0.015]	[0.024]	[0.023]	[0.013]	[0.011]
"-":4th	0.009	-0.010	-0.002	-0.004	0.011	0.008
	[0.018]	[0.020]	[0.016]	[0.022]	[0.018]	[0.011]
"-":3rd	-0.013	-0.025	-0.007	-0.037	0.005	0.004
	[0.019]	[0.020]	[0.021]	[0.023]	[0.023]	[0.012]
"-":2nd	0.004	-0.002	0.009	-0.005	-0.003	0.018
	[0.019]	[0.020]	[0.024]	[0.024]	[0.014]	[0.013]
"-":1st	-0.002	0.001	0.000	-0.011	0.024*	0.029**
	[0.016]	[0.017]	[0.021]	[0.019]	[0.014]	[0.012]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: 10th Decile	0.017	0.009	0.007	0.032	-0.002	0.021*
	[0.018]	[0.013]	[0.016]	[0.020]	[0.013]	[0.011]
"-":9th	0.006	0.019	0.032	0.025	0.032*	0.009
	[0.017]	[0.018]	[0.021]	[0.018]	[0.017]	[0.010]
"-":8th	0.013	0.022	0.038*	0.025	0.021	-0.009
	[0.019]	[0.020]	[0.022]	[0.021]	[0.015]	[0.012]

"-":7th	-0.010	0.027	0.015	0.031**	0.049***	0.019
	[0.018]	[0.017]	[0.021]	[0.014]	[0.012]	[0.013]
"-":6th	0.025	0.041**	0.023	0.032*	0.033**	0.038**
	[0.019]	[0.018]	[0.016]	[0.018]	[0.012]	[0.014]
"-":5th	0.029	0.009	-0.002	0.037**	0.041**	0.027**
	[0.020]	[0.014]	[0.013]	[0.015]	[0.016]	[0.011]
"-":4th	-0.002	0.035**	0.008	0.048***	0.029**	0.010
	[0.017]	[0.014]	[0.016]	[0.017]	[0.014]	[0.014]
"-":3rd	0.018	0.045***	0.028*	0.027	0.039**	0.022
	[0.021]	[0.014]	[0.017]	[0.017]	[0.014]	[0.013]
"-":2nd	0.008	0.055***	0.028	0.033**	0.057***	0.028**
	[0.021]	[0.012]	[0.017]	[0.015]	[0.014]	[0.012]
"-":1st	-0.029*	0.024*	-0.003	0.023*	0.019	0.001
	[0.017]	[0.012]	[0.016]	[0.012]	[0.015]	[0.011]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Occupational fixed effects	+	+	+	+	+	+
Country fixed effects	+	+	+	+	+	+
No. of Observations	15,986	15,986	15,986	15,986	15,986	15,986
R-squared	0.065	0.053	0.087	0.070	0.070	0.044

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

2.4.3 Learning participation and skill outcomes

Tables 2.7 and 2.8 examine whether the relationship between different measures of mismatch and reported skill outcomes differs with participation in learning activities. In both tables, the specifications distinguish overall participation (column 1), work-based learning (column 2), formal courses (column 3), peer or community learning (column 4), and self-directed learning (column 5). Workers are grouped into four categories: matched under both measures, overqualified under both measures, underqualified under both measures, and classified differently by the two measures. The last category pools all six forms of mismatch disagreement, so its estimates do not distinguish between their individual patterns.

The coefficient of learning activities/training compares participants with non-participants among workers matched under both measures. For each mismatch group, the same comparison is obtained by adding the learning coefficient to that group's interaction coefficient. To compare mismatched workers with matched workers among learning participants, we instead add the mismatch coefficient to its interaction coefficient. The interaction thus shows how the mismatch-related difference varies between participants and non-participants.

Table 2.7 indicates that the effects on skills underutilisation associated with some mismatch categories are smaller among learning participants. In the overall-participation specification in column (1), workers who are underqualified under both

measures have an interaction coefficient of -11.3 percentage points, significant at the 10% level. Their estimated difference relative to workers who are matched under both measures is 35.7 percentage points among non-participants and 24.4 percentage points among participants. For workers classified differently by the two measures, the corresponding differences are 15.7 and 12.1 percentage points, with an interaction of -3.6 percentage points significant at the 5% level. By contrast, workers who are overqualified under both measures have an interaction close to zero, leaving their estimated underutilisation effect at approximately 43 percentage points across both participation groups. Each comparison is with matched workers sharing the same participation status. These patterns suggest that learning participation is associated with smaller skills underutilisation for workers who are underqualified under both measures and those classified differently, but not for workers who are overqualified under both measures.

Comparing participants with non-participants within each mismatch group provides a complementary interpretation. Among workers matched under both measures, the learning coefficient is 2.0 percentage points and statistically insignificant. Adding the relevant interactions gives estimated participation differences of 2.2 percentage points among workers overqualified under both measures, -9.3 among workers who are underqualified under both measures, and -1.6 among workers classified differently. Thus, learning participants who are underqualified under both measures have a lower estimated probability of reporting skills underutilisation than non-participants in the same group, but remain more likely to report skills underutilisation than matched participants.

The activity-specific results in columns (2)-(5) suggest that these associations also depend on the type of learning activity. Formal-course participation is associated with a 2.6 percentage-point lower probability of skills underutilisation among workers who are matched under both measures. After adding the interactions, the estimated participation differences are -2.3 percentage points among workers overqualified under both measures, -8.9 among workers who are underqualified under both measures, and -4.9 among workers classified differently. However, only the interaction for the mismatch disagreement group is statistically significant, at the 10% level. Peer or community learning also has a negative interaction for workers underqualified under both measures, significant at the 10% level, yielding an estimated participation effect of -13.8 percentage points within this group. These results suggest that formal-course participation among

workers classified differently by the two measures, and peer or community learning among workers underqualified under both measures, are associated with smaller underutilisation differences relative to workers matched under both measures.

Self-directed learning shows contrasting associations across mismatch groups. After adding the learning and interaction coefficients, participants classified as overqualified by both measures have an estimated 11.9 percentage-point higher probability of reporting skills underutilisation than non-participants in the same group. Among workers who are underqualified under both measures, participants have an estimated 7.7 percentage-point lower probability. The interactions are significant at the 5% and 10% levels, respectively. These results suggest that the association between learning and underutilisation varies across both learning activities and mismatch groups.

Table 2.7: The effect of combined mismatch measure on skills utilisation by learning participation

	Any type	**On-job training**	**Formal courses**	**Peer learning, community**	**Self-directed**
	(1)	(2)	(3)	(4)	(5)
Overqualified in both	0.432***	0.421***	0.429***	0.440***	0.394***
	[0.024]	[0.023]	[0.023]	[0.021]	[0.026]
Learning activities/ training	0.020	-0.013	-0.026**	-0.008	0.043***
	[0.014]	[0.013]	[0.012]	[0.017]	[0.010]
Overqualified in both # Learning/training	0.002	0.031	0.003	-0.026	0.076**
	[0.028]	[0.031]	[0.025]	[0.040]	[0.029]
Underqualified in both	0.357***	0.306***	0.330***	0.330***	0.356***
	[0.042]	[0.039]	[0.039]	[0.037]	[0.045]
Underqualified in both # Learning/training	-0.113*	-0.014	-0.063	-0.130*	-0.120*
	[0.058]	[0.070]	[0.052]	[0.075]	[0.069]
Mismatch disagreement	0.157***	0.143***	0.148***	0.140***	0.138***
	[0.012]	[0.010]	[0.013]	[0.010]	[0.011]
Mismatch disagreement # Learning/training	-0.036**	-0.017	-0.023*	-0.012	-0.003
	[0.015]	[0.018]	[0.013]	[0.020]	[0.013]
Matched in both	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Gender: Male	-0.015	-0.014	-0.015	-0.014	-0.014
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
"-" : Nonbinary	-0.022	-0.024	-0.029	-0.020	-0.033
	[0.090]	[0.091]	[0.091]	[0.092]	[0.088]
"-" : Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	0.004	0.004	0.004	0.004	0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Age of respondent (squared)	-0.082**	-0.082**	-0.084**	-0.081**	-0.079**
	[0.031]	[0.031]	[0.031]	[0.031]	[0.030]
Marital status: Married/ cohabiting	-0.042**	-0.042**	-0.042**	-0.042**	-0.042**
	[0.017]	[0.017]	[0.017]	[0.017]	[0.016]
"-": Widowed/divorced	-0.011	-0.011	-0.011	-0.011	-0.012
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
"-": Other	-0.063***	-0.062***	-0.062***	-0.062***	-0.062***
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Education: Primary education	-0.188***	-0.189***	-0.192***	-0.187***	-0.185***
	[0.067]	[0.067]	[0.067]	[0.066]	[0.066]
"-": Lower secondary	-0.084**	-0.083**	-0.086**	-0.080**	-0.078**
	[0.032]	[0.032]	[0.033]	[0.032]	[0.032]
"-": Upper secondary	0.026	0.023	0.024	0.026	0.023
	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]
"-": Post-secondary non-tertiary	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
"-": Short-cycle tertiary	-0.007	-0.010	-0.004	-0.007	-0.010
	[0.028]	[0.027]	[0.028]	[0.028]	[0.027]
"-": Bachelor level	0.051*	0.049*	0.056**	0.052*	0.047*
	[0.028]	[0.027]	[0.027]	[0.028]	[0.027]
"-": Master's level	0.028	0.027	0.034	0.029	0.022
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
"-": Doctoral level	-0.054*	-0.057**	-0.050*	-0.053*	-0.064**
	[0.028]	[0.028]	[0.028]	[0.028]	[0.027]
NACE (a): Agriculture, forestry & fishing	0.066	0.067	0.070	0.067	0.065
	[0.042]	[0.042]	[0.042]	[0.042]	[0.041]
"-" (b): Mining & quarrying	-0.007	-0.004	-0.004	-0.004	-0.002
	[0.080]	[0.081]	[0.079]	[0.080]	[0.081]
"-" (c): Manufacturing	0.033*	0.034*	0.033*	0.034*	0.031*

	[0.018]	[0.018]	[0.019]	[0.019]	[0.018]
"-" (d): Electricity, gas & air conditioning	-0.056	-0.055	-0.055	-0.055	-0.058
	[0.037]	[0.037]	[0.037]	[0.037]	[0.038]
"-" (e): Water, sewerage & waste	0.000	0.002	-0.001	0.000	0.001
	[0.039]	[0.039]	[0.040]	[0.039]	[0.040]
"-" (f): Construction	-0.067***	-0.068***	-0.068***	-0.067***	-0.067***
	[0.022]	[0.022]	[0.023]	[0.022]	[0.022]
"-" (g): Wholesale, retail & vehicle repair	0.044**	0.044**	0.043**	0.044***	0.042**
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
"-" (h): Transportation & storage	0.029	0.031	0.030	0.031	0.031
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]
"-" (i): Accommodation & food	0.000	0.000	0.001	0.002	-0.002
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-" (j): Information & communication	0.001	0.001	0.003	0.002	-0.002
	[0.021]	[0.022]	[0.021]	[0.022]	[0.021]
"-" (k): Financial & insurance	-0.021	-0.019	-0.020	-0.019	-0.019
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-" (l): Real estate	-0.025	-0.025	-0.024	-0.023	-0.028
	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]
"-" (m): Professional & technical service	-0.044*	-0.044**	-0.042*	-0.043*	-0.046**
	[0.022]	[0.021]	[0.022]	[0.022]	[0.021]
"-" (n): Administrative services	-0.001	-0.001	0.000	-0.001	-0.002
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]
"-" (o): Public administration & defence	0.046**	0.048**	0.047**	0.045**	0.046**
	[0.022]	[0.021]	[0.022]	[0.022]	[0.021]
"-" (p): Education	-0.021	-0.018	-0.016	-0.018	-0.021
	[0.024]	[0.024]	[0.023]	[0.024]	[0.023]
"-" (q): Health & social work	-0.049**	-0.048**	-0.046**	-0.048**	-0.050***
	[0.018]	[0.018]	[0.018]	[0.018]	[0.017]
"-" (r): Arts, entertainment & recreation	0.042	0.042	0.043	0.044	0.039
	[0.030]	[0.031]	[0.031]	[0.030]	[0.030]
"-" (s): Other services	0.016	0.017	0.017	0.017	0.015
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
"-" (t): Households as employers	0.059	0.058	0.057	0.062	0.061
	[0.052]	[0.052]	[0.052]	[0.052]	[0.050]
"-" (u): Extraterritorial organisations	-0.031	-0.027	-0.028	-0.029	-0.030
	[0.047]	[0.047]	[0.047]	[0.046]	[0.046]
"-" : Other	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: 10th Decile	-0.091***	-0.091***	-0.086***	-0.091***	-0.094***
	[0.022]	[0.023]	[0.023]	[0.023]	[0.022]
"-":9th	-0.058**	-0.057**	-0.055**	-0.059**	-0.061**
	[0.027]	[0.027]	[0.027]	[0.027]	[0.026]
"-":8th	-0.018	-0.017	-0.015	-0.018	-0.021
	[0.024]	[0.024]	[0.024]	[0.024]	[0.023]
"-":7th	0.008	0.009	0.009	0.008	0.006
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-":6th	0.007	0.007	0.008	0.007	0.005
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-":5th	0.018	0.018	0.019	0.017	0.017
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-":4th	0.006	0.005	0.006	0.005	0.003
	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]
"-":3rd	0.032	0.032	0.030	0.032	0.030
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
"-":2nd	0.023	0.022	0.022	0.023	0.019
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
"-":1st	0.046*	0.046*	0.045*	0.046*	0.045*
	[0.022]	[0.023]	[0.023]	[0.023]	[0.022]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: 10th Decile	0.006	0.007	0.009	0.008	0.005
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
"-":9th	-0.031	-0.030	-0.029	-0.030	-0.031
	[0.026]	[0.026]	[0.027]	[0.027]	[0.026]

"-":8th	-0.036	-0.036	-0.034	-0.035	-0.037
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
"-":7th	-0.035*	-0.036*	-0.034*	-0.034*	-0.036*
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
"-":6th	-0.010	-0.010	-0.009	-0.009	-0.009
	[0.024]	[0.023]	[0.024]	[0.024]	[0.023]
"-":5th	-0.005	-0.005	-0.005	-0.004	-0.004
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
"-":4th	-0.024	-0.024	-0.023	-0.023	-0.023
	[0.015]	[0.015]	[0.016]	[0.015]	[0.015]
"-":3rd	-0.019	-0.018	-0.018	-0.018	-0.017
	[0.015]	[0.015]	[0.016]	[0.015]	[0.015]
"-":2nd	-0.013	-0.012	-0.013	-0.012	-0.012
	[0.020]	[0.020]	[0.020]	[0.020]	[0.019]
"-":1st	-0.016	-0.015	-0.016	-0.015	-0.014
	[0.020]	[0.021]	[0.021]	[0.021]	[0.021]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Occupational fixed effects	+	+	+	+	+
Country fixed effects	+	+	+	+	+
No. of Observations	16,515	16,515	16,515	16,515	16,515
R-squared	0.099	0.099	0.100	0.099	0.101

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.8 presents the corresponding results for reporting multiple skill gaps. Among workers who are matched under both measures, learning participation is positively associated with reporting skill gaps in every specification. The estimated associations range from 5.0 percentage points for self-directed learning to 14.1 percentage points for overall participation. These positive associations can reflect learning undertaken in response to existing gaps or greater awareness of skill needs among participants. However, they should not be interpreted as evidence that learning creates gaps or fails to address them.

The interaction terms show how the participation effects differ from those observed among matched workers. For workers overqualified under both measures, the interaction with overall participation is -8.0 percentage points and statistically significant at the 5% level. Combining this interaction with the participation coefficient yields an estimated within-group association of 6.1 percentage points, compared with 12.8 percentage points for workers underqualified under both measures and 11.5 percentage points for those whose classifications differ across measures. The negative overqualification interaction therefore indicates a weaker positive correlation than that observed among matched employees, rather than a negative correlation between participation and the reporting of multiple skill gaps.

Work-based learning shows a similar pattern. The estimated participation association is 7.8 percentage points among matched workers, compared with 0.6

percentage points among workers who are overqualified under both measures, 1.2 percentage points among those underqualified under both measures, and 3.0 percentage points among those classified differently. The interaction for the mismatch disagreement group is statistically significant at the 1% level, while the interaction for workers who are overqualified under both measures is significant at the 10% level. Formal-course participation, by contrast, has positive estimated associations across all four groups, but none of the interaction terms is statistically significant.

A particularly pronounced contrast across learning activities emerges among workers who are underqualified under both measures. The interaction is -18.3 percentage points for peer or community learning and 10.9 percentage points for self-directed learning, with both coefficients to be statistically significant. The implied within-group participation associations are -10.4 and 15.9 percentage points, respectively. These contrasting estimates suggest that different learning activities are associated with different patterns of reported skill needs.

Table 2.8: The effect of combined mismatch measure on skill gaps by learning participation

	Any type	**On-job training**	**Formal courses**	**Peer learning, community**	**Self-directed**
	(1)	(2)	(3)	(4)	(5)
Overqualified in both	-0.049*	-0.068**	-0.090***	-0.080***	-0.091***
	[0.025]	[0.026]	[0.026]	[0.018]	[0.023]
Learning activities/ training	0.141***	0.078***	0.077***	0.079***	0.050***
	[0.012]	[0.013]	[0.013]	[0.012]	[0.011]
Overqualified in both # Learning/training	-0.080**	-0.072*	-0.003	-0.056	-0.016
	[0.034]	[0.039]	[0.038]	[0.041]	[0.034]
Underqualified in both	0.110***	0.130***	0.100***	0.148***	0.047
	[0.032]	[0.027]	[0.034]	[0.028]	[0.037]
Underqualified in both # Learning/training	-0.013	-0.066	0.009	-0.183***	0.109**
	[0.056]	[0.055]	[0.051]	[0.058]	[0.047]
Mismatch disagreement	-0.006	-0.001	-0.016	-0.022**	-0.014
	[0.011]	[0.008]	[0.014]	[0.009]	[0.011]
Mismatch disagreement # Learning/training	-0.026*	-0.048***	-0.006	0.005	-0.015
	[0.013]	[0.017]	[0.017]	[0.015]	[0.018]
Matched in both	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Gender: Male	0.063***	0.064***	0.066***	0.063***	0.064***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
"-": Nonbinary	0.093	0.110	0.122	0.104	0.102
	[0.083]	[0.088]	[0.086]	[0.088]	[0.086]
"-": Female	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Age of respondent	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Age of respondent (squared)	0.029	0.026	0.029	0.025	0.027
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]
Marital status: Married/ cohabiting	-0.018*	-0.018	-0.017	-0.017	-0.015
	[0.011]	[0.011]	[0.011]	[0.010]	[0.011]
"-": Widowed/divorced	-0.007	-0.004	-0.003	-0.005	-0.004

	[0.024]	[0.025]	[0.024]	[0.025]	[0.024]
"-": Other	0.013	0.017	0.016	0.015	0.018
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Education: Primary education	-0.076	-0.092	-0.085	-0.093	-0.094
	[0.058]	[0.059]	[0.060]	[0.060]	[0.060]
"-": Lower secondary	0.020	0.002	0.006	0.001	0.003
	[0.029]	[0.029]	[0.030]	[0.030]	[0.030]
"-": Upper secondary	0.018	0.009	0.010	0.008	0.005
	[0.018]	[0.017]	[0.019]	[0.018]	[0.018]
"-": Post-secondary non-tertiary	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
"-": Short-cycle tertiary	0.025	0.027	0.019	0.026	0.023
	[0.023]	[0.022]	[0.023]	[0.021]	[0.022]
"-": Bachelor level	0.024	0.031*	0.023	0.030*	0.028
	[0.017]	[0.016]	[0.017]	[0.017]	[0.017]
"-": Master's level	0.017	0.031*	0.020	0.028	0.026
	[0.019]	[0.018]	[0.019]	[0.018]	[0.019]
"-": Doctoral level	0.029	0.041	0.031	0.036	0.035
	[0.035]	[0.034]	[0.035]	[0.034]	[0.034]
NACE (a): Agriculture, forestry & fishing	-0.019	-0.018	-0.022	-0.015	-0.018
	[0.036]	[0.036]	[0.036]	[0.036]	[0.036]
"-" (b): Mining & quarrying	0.104	0.112	0.108	0.107	0.117
	[0.088]	[0.090]	[0.086]	[0.087]	[0.089]
"-" (c): Manufacturing	0.012	0.012	0.016	0.013	0.013
	[0.016]	[0.016]	[0.017]	[0.016]	[0.016]
"-" (d): Electricity, gas & air conditioning	-0.030	-0.021	-0.021	-0.023	-0.022
	[0.026]	[0.027]	[0.027]	[0.026]	[0.026]
"-" (e): Water, sewerage & waste	-0.004	-0.004	0.002	0.000	0.000
	[0.047]	[0.048]	[0.046]	[0.050]	[0.047]
"-" (f): Construction	0.024	0.024	0.025	0.023	0.025
	[0.024]	[0.024]	[0.025]	[0.024]	[0.024]
"-" (g): Wholesale, retail & vehicle repair	-0.012	-0.010	-0.008	-0.011	-0.012
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]
"-" (h): Transportation & storage	0.034	0.033	0.036*	0.034	0.038*
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-" (i): Accommodation & food	0.020	0.028	0.027	0.025	0.024
	[0.029]	[0.030]	[0.030]	[0.030]	[0.030]
"-" (j): Information & communication	0.037*	0.049**	0.044**	0.045**	0.046**
	[0.020]	[0.020]	[0.021]	[0.020]	[0.021]
"-" (k): Financial & insurance	0.056**	0.058**	0.061**	0.061***	0.063***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
"-" (l): Real estate	0.032	0.038	0.037	0.031	0.038
	[0.042]	[0.042]	[0.042]	[0.043]	[0.041]
"-" (m): Professional & technical service	0.039	0.043	0.039	0.040	0.042
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
"-" (n): Administrative services	0.051**	0.056**	0.055**	0.054**	0.058**
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-" (o): Public administration & defence	-0.036*	-0.033*	-0.031	-0.028	-0.028
	[0.018]	[0.019]	[0.018]	[0.019]	[0.018]
"-" (p): Education	-0.001	0.006	0.003	0.005	0.008
	[0.022]	[0.023]	[0.023]	[0.023]	[0.023]
"-" (q): Health & social work	-0.025	-0.017	-0.020	-0.018	-0.014
	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]
"-" (r): Arts, entertainment & recreation	-0.033	-0.019	-0.023	-0.021	-0.024
	[0.027]	[0.027]	[0.028]	[0.027]	[0.027]
"-" (s): Other services	0.001	0.003	0.005	0.003	0.003
	[0.021]	[0.021]	[0.021]	[0.021]	[0.021]
"-" (t): Households as employers	0.029	0.027	0.034	0.018	0.035
	[0.047]	[0.047]	[0.048]	[0.048]	[0.047]
"-" (u): Extraterritorial organisations	0.162**	0.174***	0.174***	0.174***	0.180***
	[0.060]	[0.059]	[0.058]	[0.059]	[0.059]
"-" : Other	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Income: 10th Decile	0.023	0.036*	0.027	0.034*	0.032

	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]
"-":9th	0.021	0.029*	0.026*	0.030*	0.027*
	[0.014]	[0.015]	[0.015]	[0.015]	[0.015]
"-":8th	0.011	0.018	0.015	0.019	0.017
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
"-":7th	0.011	0.017	0.015	0.014	0.014
	[0.017]	[0.017]	[0.017]	[0.018]	[0.017]
"-":6th	0.007	0.011	0.010	0.013	0.009
	[0.020]	[0.021]	[0.020]	[0.021]	[0.021]
"-":5th	-0.022	-0.018	-0.019	-0.017	-0.020
	[0.014]	[0.016]	[0.015]	[0.016]	[0.016]
"-":4th	-0.004	0.000	-0.003	-0.002	-0.004
	[0.021]	[0.022]	[0.021]	[0.022]	[0.022]
"-":3rd	-0.025	-0.024	-0.022	-0.025	-0.027
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
"-":2nd	0.013	0.016	0.015	0.012	0.011
	[0.025]	[0.025]	[0.025]	[0.026]	[0.026]
"-":1st	0.003	0.002	0.003	-0.001	0.000
	[0.021]	[0.021]	[0.021]	[0.022]	[0.022]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Wealth: 10th Decile	0.017	0.024	0.021	0.022	0.026
	[0.016]	[0.017]	[0.016]	[0.016]	[0.017]
"-":9th	0.030	0.035	0.034	0.034	0.039
	[0.023]	[0.024]	[0.024]	[0.024]	[0.024]
"-":8th	0.041**	0.050**	0.046**	0.046**	0.050**
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
"-":7th	0.042**	0.048**	0.045**	0.044**	0.050**
	[0.018]	[0.018]	[0.018]	[0.018]	[0.018]
"-":6th	0.054***	0.057***	0.056***	0.054***	0.059***
	[0.019]	[0.019]	[0.018]	[0.018]	[0.019]
"-":5th	0.047***	0.047***	0.047***	0.045***	0.050***
	[0.015]	[0.016]	[0.016]	[0.016]	[0.016]
"-":4th	0.063***	0.064***	0.063***	0.062***	0.066***
	[0.016]	[0.017]	[0.016]	[0.016]	[0.017]
"-":3rd	0.065***	0.065***	0.066***	0.064***	0.069***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
"-":2nd	0.090***	0.089***	0.091***	0.087***	0.093***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
"-":1st	0.027	0.023	0.024	0.024	0.024
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]
"-": Don't know	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Occupational fixed effects	+	+	+	+	+
Country fixed effects	+	+	+	+	+
No. of Observations	15,986	15,986	15,986	15,986	15,986
R-squared	0.088	0.076	0.078	0.078	0.075

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

2.4.4 Perceived adaptability and employability

Table 2.9 examines the labour-market resilience index, ranging from 0-7 (columns 1-2), and its components, namely high adaptability (columns 3-4), regular or occasional upskilling (columns 5-6), and confidence in finding work (columns 7-8). Relative to workers who are matched under both measures, those overqualified under both measures have a 0.246-unit lower resilience index, while those underqualified under both measures have a 0.371-unit lower index. Workers who consider themselves

underqualified but are classified as statistically matched have a larger negative estimate of -0.619. Similarly, those who consider themselves underqualified but are classified as statistically overeducated have an estimate of -0.864. In contrast, workers who consider their qualifications matched but are classified as statistically overeducated or undereducated have smaller and statistically insignificant index coefficients.

The component outcomes reveal distinct patterns across mismatch groups. Relative to workers who are matched under both measures, those overqualified under both measures have lower probabilities of regular or occasional upskilling and of being very confident of finding work, by 5.8 and 7.4 percentage points, respectively, but show no statistically significant difference in adaptability. Workers who are underqualified under both measures have lower probabilities of high adaptability and high employment confidence, by 8.6 and 11.8 percentage points, respectively, but show no statistically significant difference in upskilling.

Distinguishing the direction of mismatch disagreement reveals further variation. Workers who consider themselves underqualified but are statistically matched have lower probabilities of high adaptability, regular or occasional upskilling, and high employment confidence, by 8.3, 9.6, and 16.9 percentage points, respectively. Those who consider themselves underqualified but are statistically overeducated have particularly large negative point estimates for adaptability and employment confidence, at -16.9 and -17.9 percentage points, respectively. Thus, workers who are statistically matched or overeducated may nevertheless consider themselves underqualified and be less likely to report high adaptability or strong confidence in finding work

Workers who consider themselves overqualified but are statistically matched have a resilience index that is 0.139 units lower and a probability of high employment confidence that is 4.9 percentage points lower than those of workers matched under both measures. Their estimated upskilling effect is -2.3 percentage points and statistically significant at the 10% level. For workers who consider themselves overqualified but are statistically undereducated, the corresponding effects are -0.168 units for the resilience index and -7.6 percentage points for employment confidence, with no statistically significant coefficients for adaptability or upskilling. By contrast, workers who consider their qualifications matched but are statistically mismatched show no statistically significant differences from the reference group across any of the four outcomes.

The combined classification thus reveals differences in labour market resilience, adaptability, upskilling, and employment confidence that either measure alone may not fully capture. Statistically matched workers who consider themselves underqualified or overqualified report weaker effects on some measures than workers matched under both measures. Conversely, statistically mismatched workers who consider their qualifications appropriate show no significant differences from this reference group, although this does not establish that their effects are the same. Workers classified as overqualified or underqualified by both measures do not always have the largest estimated disadvantages. Overall, these patterns support distinguishing the different combinations of statistical and subjective measures.

The interaction specifications show positive estimated associations between learning participation and both the labour market resilience index and upskilling across all four groups. Combining the learning participation coefficient with the relevant interaction terms yields estimated within-group associations with the resilience index of 0.986 units among matched workers, 1.146 among workers overqualified under both measures, 0.808 among workers underqualified under both measures, and 1.052 among those classified differently. The corresponding upskilling associations range from 28.3 to 33.4 percentage points. Most interaction terms are not statistically significant, providing limited evidence that these participation associations differ from those among matched workers.

The associations with adaptability and employment confidence are less uniform. Among matched workers, the estimated participation associations are 11.6 percentage points for high adaptability and 6.8 percentage points for high employment confidence. For workers who are underqualified under both measures, the corresponding interactions are -14.0 and -12.3 percentage points, statistically significant at the 5% and 10% levels, respectively. Adding these interactions to the learning participation coefficients yields within-group point estimates of -2.4 percentage points for adaptability and -5.5 percentage points for employment confidence. The corresponding estimates remain positive among workers overqualified under both measures, at 17.3 and 4.6 percentage points, and among workers classified differently, at 12.1 and 5.9 percentage points. The significant negative interactions for underqualified workers therefore indicate that their participation associations are lower than those of matched workers.

Table 2.9: The effect of combined mismatch measure on labour market resilience

	Labour market resilience index		**High labour-market adaptability**		**Upskilling: regular/occasional**		**Very confident of finding work**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overqualified in both	-0.246***	-0.311***	-0.001	-0.029	-0.058***	-0.082***	-0.074***	-0.066**
	[0.064]	[0.100]	[0.021]	[0.026]	[0.020]	[0.028]	[0.021]	[0.032]
Underqualified in both	-0.371***	-0.309*	-0.086***	-0.019	-0.018	-0.021	-0.118***	-0.059
	[0.103]	[0.178]	[0.025]	[0.031]	[0.027]	[0.043]	[0.034]	[0.056]
Subjective overqualified only	-0.139***		-0.005		-0.023*		-0.049***	
	[0.046]		[0.017]		[0.012]		[0.015]	
Subjective underqualified only	-0.619***		-0.083***		-0.096***		-0.169***	
	[0.068]		[0.022]		[0.022]		[0.021]	
Statistical overqualified only	0.022		-0.005		0.018		0.015	
	[0.035]		[0.016]		[0.012]		[0.014]	
Statistical underqualified only	0.031		-0.001		0.005		-0.003	
	[0.032]		[0.009]		[0.009]		[0.012]	
Subj. overqualified (vs stat. undereducated)	-0.168***		-0.014		-0.003		-0.076***	
	[0.060]		[0.022]		[0.018]		[0.019]	
Stat. overeducated (vs subj. underqual.)	-0.864***		-0.169***		-0.083		-0.179***	
	[0.171]		[0.043]		[0.059]		[0.043]	
Learning activities/ training		0.986***		0.116***		0.286***		0.068***
		[0.038]		[0.012]		[0.013]		[0.012]

Overqualified in both # Learning/training		0.160		0.057*		0.048		-0.022
		[0.115]		[0.032]		[0.032]		[0.035]
Underqualified in both # Learning/training		-0.178		-0.140**		-0.003		-0.123*
		[0.231]		[0.063]		[0.060]		[0.070]
Mismatch disagreement		-0.102***		-0.012		-0.019*		-0.022**
		[0.031]		[0.013]		[0.011]		[0.009]
Mismatch disagreement # Learning/training		0.066*		0.005		0.026		-0.009
		[0.038]		[0.016]		[0.016]		[0.011]
Matched in both	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Gender: Male	0.051	0.051*	0.042***	0.042***	-0.005	-0.005	0.008	0.008
	[0.031]	[0.028]	[0.010]	[0.009]	[0.011]	[0.011]	[0.011]	[0.011]
"-": Nonbinary	0.093	-0.072	0.027	0.009	-0.009	-0.065	0.128	0.118
	[0.308]	[0.281]	[0.080]	[0.077]	[0.094]	[0.090]	[0.107]	[0.111]
"-": Female	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Age of respondent	-0.007	-0.007	-0.011***	-0.011***	-0.008***	-0.007**	0.001	0.001
	[0.008]	[0.007]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
Age of respondent (squared)	-0.153*	-0.105	0.064***	0.069***	0.054*	0.062*	-0.061*	-0.057*
	[0.090]	[0.085]	[0.023]	[0.023]	[0.030]	[0.031]	[0.031]	[0.031]
Marital status: Married/ cohabiting	0.153***	0.142***	0.023**	0.022*	0.034**	0.030**	0.025**	0.026**
	[0.038]	[0.034]	[0.011]	[0.011]	[0.013]	[0.011]	[0.011]	[0.011]
"-": Widowed/divorced	0.191***	0.162**	0.039*	0.036	0.043	0.033	0.037**	0.036**
	[0.068]	[0.068]	[0.021]	[0.022]	[0.025]	[0.024]	[0.017]	[0.017]
"-": Other	0.282***	0.248***	0.050***	0.046**	0.085***	0.074***	0.044**	0.043**

	[0.059]	[0.055]	[0.017]	[0.018]	[0.018]	[0.016]	[0.018]	[0.018]
"-": Single	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Education: Primary education	-0.587***	-0.400**	-0.010	0.009	-0.150**	-0.104*	-0.111**	-0.101**
	[0.203]	[0.190]	[0.048]	[0.047]	[0.060]	[0.052]	[0.045]	[0.044]
"-": Lower secondary	-0.470***	-0.260**	-0.015	0.005	-0.077*	-0.020	-0.067**	-0.061*
	[0.110]	[0.097]	[0.027]	[0.026]	[0.041]	[0.035]	[0.031]	[0.031]
"-": Upper secondary	-0.189***	-0.155***	-0.024	-0.018	-0.039	-0.024	-0.051***	-0.063***
	[0.060]	[0.053]	[0.025]	[0.025]	[0.030]	[0.024]	[0.018]	[0.018]
"-": Post-secondary non-tertiary	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
"-": Short-cycle tertiary	-0.052	-0.070	-0.013	-0.015	0.018	0.016	-0.074***	-0.078***
	[0.077]	[0.060]	[0.025]	[0.026]	[0.035]	[0.028]	[0.022]	[0.021]
"-": Bachelor level	0.025	-0.076	-0.009	-0.021	0.058*	0.036	-0.069***	-0.082***
	[0.062]	[0.051]	[0.023]	[0.024]	[0.029]	[0.022]	[0.018]	[0.017]
"-": Master's level	0.188***	0.033	0.020	0.001	0.110***	0.072***	-0.050**	-0.063***
	[0.057]	[0.045]	[0.023]	[0.025]	[0.031]	[0.023]	[0.021]	[0.018]
"-": Doctoral level	0.168	0.033	0.051	0.032	0.095**	0.061*	-0.065	-0.067*
	[0.113]	[0.088]	[0.032]	[0.032]	[0.042]	[0.033]	[0.039]	[0.036]
NACE (a): Agriculture, forestry & fishing	0.146	0.139	-0.036	-0.036	0.087***	0.081***	0.024	0.025
	[0.093]	[0.098]	[0.039]	[0.040]	[0.029]	[0.028]	[0.032]	[0.032]
"-" (b): Mining & quarrying	0.369	0.300	0.012	0.006	0.077	0.062	0.159**	0.152**
	[0.286]	[0.261]	[0.073]	[0.071]	[0.079]	[0.071]	[0.073]	[0.073]
"-" (c): Manufacturing	0.082	0.065	-0.011	-0.014	0.014	0.010	-0.014	-0.013
	[0.069]	[0.062]	[0.016]	[0.015]	[0.020]	[0.017]	[0.017]	[0.017]
"-" (d): Electricity, gas & air conditioning	0.148	0.092	-0.023	-0.030	0.083***	0.064***	-0.011	-0.010

	[0.103]	[0.107]	[0.027]	[0.027]	[0.023]	[0.023]	[0.031]	[0.032]
"-" (e): Water, sewerage & waste	0.127	0.109	-0.054	-0.054	0.062	0.058	-0.009	-0.008
	[0.143]	[0.127]	[0.040]	[0.039]	[0.043]	[0.039]	[0.041]	[0.041]
"-" (f): Construction	0.082	0.083	-0.037	-0.037	0.029	0.029	0.012	0.014
	[0.072]	[0.074]	[0.023]	[0.024]	[0.018]	[0.017]	[0.024]	[0.024]
"-" (g): Wholesale, retail & vehicle repair	0.055	0.061	-0.023	-0.021	-0.029	-0.026	0.022	0.022
	[0.064]	[0.066]	[0.023]	[0.023]	[0.025]	[0.025]	[0.022]	[0.023]
"-" (h): Transportation & storage	0.069	0.039	-0.033	-0.037	0.025	0.019	-0.023	-0.025
	[0.076]	[0.070]	[0.024]	[0.024]	[0.022]	[0.018]	[0.031]	[0.030]
"-" (i): Accommodation & food	0.192*	0.118	-0.021	-0.029	0.051	0.029	0.070**	0.064**
	[0.100]	[0.086]	[0.021]	[0.021]	[0.033]	[0.029]	[0.027]	[0.026]
"-" (j): Information & communication	0.250***	0.165**	0.045*	0.036	0.106***	0.079***	-0.045*	-0.049**
	[0.073]	[0.069]	[0.025]	[0.024]	[0.018]	[0.016]	[0.023]	[0.023]
"-" (k): Financial & insurance	0.250***	0.214***	-0.009	-0.014	0.113***	0.102***	-0.034*	-0.034*
	[0.071]	[0.067]	[0.021]	[0.021]	[0.015]	[0.015]	[0.017]	[0.017]
"-" (l): Real estate	0.479***	0.419***	0.030	0.023	0.055	0.039	0.096**	0.092**
	[0.115]	[0.105]	[0.037]	[0.036]	[0.048]	[0.046]	[0.037]	[0.037]
"-" (m): Professional & technical service	0.258***	0.226***	0.006	0.003	0.062***	0.051***	0.023	0.025
	[0.080]	[0.077]	[0.023]	[0.023]	[0.019]	[0.018]	[0.022]	[0.022]
"-" (n): Administrative services	0.129	0.090	0.005	0.001	0.051**	0.040**	-0.034	-0.032
	[0.079]	[0.074]	[0.021]	[0.021]	[0.020]	[0.018]	[0.029]	[0.028]
"-" (o): Public administration & defence	0.057	-0.008	-0.032	-0.039*	0.072***	0.051***	-0.064***	-0.066***
	[0.056]	[0.053]	[0.019]	[0.020]	[0.020]	[0.018]	[0.016]	[0.017]
"-" (p): Education	0.239***	0.158*	-0.014	-0.024	0.098***	0.073***	0.020	0.016

	[0.084]	[0.079]	[0.025]	[0.025]	[0.024]	[0.022]	[0.026]	[0.026]
"-" (q): Health & social work	0.288***	0.210***	-0.023	-0.032*	0.081***	0.057***	0.071***	0.070***
	[0.073]	[0.071]	[0.018]	[0.018]	[0.019]	[0.018]	[0.020]	[0.020]
"-" (r): Arts, entertainment & recreation	-0.085	-0.181*	-0.041	-0.052*	0.028	-0.003	-0.037	-0.043*
	[0.108]	[0.102]	[0.027]	[0.027]	[0.028]	[0.025]	[0.024]	[0.024]
"-" (s): Other services	0.021	0.001	-0.013	-0.015	0.024	0.018	-0.019	-0.019
	[0.064]	[0.057]	[0.020]	[0.020]	[0.022]	[0.020]	[0.017]	[0.017]
"-" (t): Households as employers	0.227	0.147	0.034	0.022	0.131**	0.111**	-0.019	-0.032
	[0.190]	[0.204]	[0.053]	[0.056]	[0.053]	[0.054]	[0.059]	[0.062]
"-" (u): Extraterritorial organisations	0.394***	0.224*	-0.031	-0.050	0.198***	0.155***	0.029	0.012
	[0.105]	[0.125]	[0.034]	[0.036]	[0.036]	[0.033]	[0.046]	[0.049]
"-": Other	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Income: 10th Decile	0.466***	0.373***	0.077***	0.066***	0.060**	0.034*	0.110***	0.108***
	[0.078]	[0.076]	[0.018]	[0.018]	[0.022]	[0.020]	[0.026]	[0.027]
"-":9th	0.242***	0.170**	0.021	0.014	0.035	0.016	0.013	0.011
	[0.075]	[0.067]	[0.013]	[0.013]	[0.023]	[0.021]	[0.026]	[0.026]
"-":8th	0.184**	0.116*	-0.001	-0.008	0.013	-0.004	0.017	0.014
	[0.069]	[0.063]	[0.015]	[0.016]	[0.025]	[0.023]	[0.023]	[0.024]
"-":7th	0.150**	0.100	-0.010	-0.015	-0.002	-0.013	0.027	0.024
	[0.069]	[0.069]	[0.016]	[0.016]	[0.022]	[0.021]	[0.020]	[0.021]
"-":6th	0.030	-0.011	-0.038**	-0.042**	-0.029	-0.037**	0.004	0.001
	[0.068]	[0.065]	[0.015]	[0.016]	[0.018]	[0.015]	[0.025]	[0.025]
"-":5th	0.032	0.000	-0.008	-0.010	-0.025	-0.032	-0.006	-0.009
	[0.064]	[0.061]	[0.014]	[0.014]	[0.023]	[0.021]	[0.025]	[0.025]

"-":4th	-0.065	-0.085	-0.042**	-0.042**	-0.050**	-0.053***	-0.033	-0.035
	[0.070]	[0.065]	[0.015]	[0.016]	[0.021]	[0.017]	[0.024]	[0.024]
"-":3rd	-0.195**	-0.190**	-0.051**	-0.048**	-0.087***	-0.080***	-0.062**	-0.063**
	[0.087]	[0.086]	[0.019]	[0.019]	[0.026]	[0.025]	[0.023]	[0.023]
"-":2nd	-0.214**	-0.238**	-0.057***	-0.058***	-0.070***	-0.072***	-0.063**	-0.067**
	[0.093]	[0.087]	[0.020]	[0.019]	[0.023]	[0.021]	[0.029]	[0.029]
"-":1st	-0.125*	-0.127*	-0.010	-0.010	-0.052**	-0.046**	-0.044**	-0.048**
	[0.071]	[0.068]	[0.017]	[0.018]	[0.021]	[0.018]	[0.021]	[0.021]
"-": Don't know	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Wealth: 10th Decile	0.446***	0.369***	0.069***	0.060***	0.058**	0.039*	0.082***	0.078***
	[0.076]	[0.069]	[0.015]	[0.015]	[0.025]	[0.021]	[0.021]	[0.021]
"-":9th	0.419***	0.353***	0.064***	0.057***	0.048**	0.033	0.059***	0.056***
	[0.061]	[0.061]	[0.017]	[0.018]	[0.023]	[0.021]	[0.019]	[0.020]
"-":8th	0.360***	0.282***	0.038*	0.029	0.054**	0.034	0.019	0.017
	[0.076]	[0.071]	[0.019]	[0.019]	[0.022]	[0.022]	[0.023]	[0.022]
"-":7th	0.340***	0.282***	0.030	0.024	0.057***	0.043**	0.021	0.020
	[0.056]	[0.054]	[0.023]	[0.023]	[0.021]	[0.018]	[0.017]	[0.018]
"-":6th	0.329***	0.297***	0.036*	0.034	0.044*	0.038*	0.002	0.001
	[0.068]	[0.062]	[0.020]	[0.020]	[0.023]	[0.021]	[0.019]	[0.019]
"-":5th	0.329***	0.310***	0.024	0.022	0.085***	0.084***	0.019	0.017
	[0.075]	[0.070]	[0.021]	[0.021]	[0.022]	[0.021]	[0.022]	[0.022]
"-":4th	0.356***	0.336***	0.051**	0.050**	0.061***	0.060***	0.018	0.017
	[0.073]	[0.073]	[0.021]	[0.021]	[0.022]	[0.020]	[0.020]	[0.021]
"-":3rd	0.340***	0.314***	0.050***	0.047***	0.070***	0.066***	0.014	0.013

	[0.061]	[0.056]	[0.016]	[0.017]	[0.019]	[0.017]	[0.017]	[0.017]
"-":2nd	0.327***	0.319***	0.037**	0.037**	0.072***	0.075***	-0.003	-0.003
	[0.057]	[0.055]	[0.015]	[0.015]	[0.020]	[0.018]	[0.017]	[0.018]
"-":1st	0.167***	0.194***	0.047***	0.049***	0.017	0.031**	-0.027	-0.024
	[0.056]	[0.050]	[0.015]	[0.016]	[0.018]	[0.015]	[0.019]	[0.020]
"-": Don't know	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Occupational fixed effects	+	+	+	+	+	+	+	+
Country fixed effects	+	+	+	+	+	+	+	+
No. of Observations	16,571	16,571	16,300	16,300	16,235	16,235	15,992	15,992
R-squared	0.156	0.240	0.067	0.080	0.108	0.196	0.077	0.076

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

2.4.5 Financial resilience

Table 2.10 examines whether combining the two mismatch measures reveals differences in workers' financial resilience. Compared with workers matched under both measures, financial resilience is 0.156 units lower among those overqualified under both and 0.263 units lower among those underqualified under both. Among statistically matched workers, the estimates are -0.159 for subjective overqualification and -0.321 for subjective underqualification. Opposite classifications yield estimates of -0.195 for subjective overqualification with statistical undereducation and -0.247 for subjective underqualification with statistical overeducation, the latter significant at 10%. Statistical mismatch accompanied by subjective matching shows no significant index differences. Statistical matching can, therefore, coexist with subjective mismatch and lower financial resilience. Conversely, statistically mismatched subjectively matched workers do not differ significantly from workers who are matched under both measures.

The component results point mainly to differences in income adequacy. The income adequacy score ranges from 0 to 3 with higher values indicating greater income adequacy and hence lower financial strain. Compared with workers who are matched under both measures, workers overqualified and underqualified under both measures have lower scores by 0.126 and 0.239 units, respectively. The estimated effect is -0.287 units among statistically matched workers who consider themselves underqualified. By contrast, most mismatch coefficients for reporting none of the selected long-term, last-resort coping strategies are not statistically significant. Because the financial resilience index combines strain and coping responses, the index and component estimates should not be treated as independent evidence. By contrast, most mismatch groups do not differ significantly from workers matched under both measures in reporting none of the selected last-resort coping strategies.

Finally, none of the learning interaction terms are statistically significant at conventional levels. Among workers who are matched under both measures, learning participation is associated with a 0.054-unit higher score of income adequacy, but a 9.2-percentage-point lower probability of reporting none of the selected last-resort coping strategies. The estimated association with the financial resilience index is -0.036 units and is not statistically significant. Adding the relevant interactions yields within-group index associations of -0.156 units among workers overqualified under both measures, -0.026 among those underqualified under both measures, and -0.006 among those classified differently.

Table 2.10: The effect of combined mismatch measure on financial resilience

	Financial resilience index		**Income adequacy past 12m**		**No long-term last-resort coping**	
	(1)	(2)	(3)	(4)	(5)	(6)
Overqualified in both	-0.156***	-0.101	-0.126***	-0.075	-0.025	-0.021
	[0.043]	[0.069]	[0.032]	[0.049]	[0.019]	[0.030]
Underqualified in both	-0.263***	-0.277***	-0.239***	-0.270***	-0.011	0.013
	[0.069]	[0.089]	[0.064]	[0.077]	[0.028]	[0.043]
Subjective overqualified only	-0.159***		-0.145***		-0.016	
	[0.031]		[0.023]		[0.016]	
Subjective underqualified only	-0.321***		-0.287***		-0.037	
	[0.053]		[0.052]		[0.025]	
Statistical overqualified only	0.043		0.022		0.023*	
	[0.031]		[0.025]		[0.012]	
Statistical underqualified only	0.034		0.018		0.015	
	[0.023]		[0.020]		[0.010]	
Subj. overqualified (vs stat. undereducated)	-0.195***		-0.177***		-0.018	
	[0.037]		[0.035]		[0.020]	
Stat. overeducated (vs subj. underqual.)	-0.247*		-0.241**		0.002	
	[0.137]		[0.105]		[0.055]	
Learning activities/ training		-0.036		0.054**		-0.092***
		[0.025]		[0.022]		[0.012]
Overqualified in both # Learning/training		-0.120		-0.104		-0.016

		[0.083]		[0.066]		[0.033]
Underqualified in both # Learning/training		0.010		0.046		-0.052
		[0.097]		[0.089]		[0.047]
Mismatch disagreement		-0.065**		-0.056**		-0.007
		[0.025]		[0.024]		[0.013]
Mismatch disagreement # Learning/training		0.030		0.006		0.021
		[0.031]		[0.033]		[0.016]
Matched in both	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Gender: Male	0.025	0.027	0.078***	0.079***	-0.051***	-0.051***
	[0.018]	[0.019]	[0.015]	[0.015]	[0.009]	[0.009]
"-": Nonbinary	-0.416	-0.422	-0.387	-0.403	-0.077	-0.064
	[0.324]	[0.326]	[0.299]	[0.301]	[0.088]	[0.082]
"-": Female	{Ref.}	{Ref.}	{Ref.}	{Ref.}		
Age of respondent	-0.025***	-0.025***	-0.029***	-0.029***	0.004	0.004
	[0.006]	[0.006]	[0.005]	[0.005]	[0.003]	[0.003]
Age of respondent (squared)	0.336***	0.345***	0.365***	0.374***	-0.027	-0.029
	[0.064]	[0.064]	[0.055]	[0.054]	[0.030]	[0.029]
Marital status: Married/ cohabiting	-0.027	-0.022	-0.032	-0.030	0.005	0.007
	[0.023]	[0.023]	[0.022]	[0.022]	[0.012]	[0.012]
"-": Widowed/divorced	-0.103**	-0.097**	-0.097**	-0.096**	-0.008	-0.004
	[0.041]	[0.042]	[0.036]	[0.036]	[0.020]	[0.019]
"-": Other	-0.089*	-0.084	-0.082**	-0.082**	-0.007	-0.003
	[0.050]	[0.050]	[0.037]	[0.037]	[0.024]	[0.023]

"-": Single	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Education: Primary education	0.026	0.046	-0.035	-0.008	0.065*	0.056
	[0.143]	[0.136]	[0.133]	[0.125]	[0.037]	[0.035]
"-": Lower secondary	-0.083	-0.081	-0.079	-0.062	0.004	-0.014
	[0.079]	[0.080]	[0.064]	[0.065]	[0.033]	[0.032]
"-": Upper secondary	-0.034	-0.084	-0.051	-0.084	0.022	0.005
	[0.073]	[0.071]	[0.058]	[0.057]	[0.028]	[0.027]
"-": Post-secondary non-tertiary	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
"-": Short-cycle tertiary	0.066	0.049	0.069	0.055	0.001	-0.002
	[0.073]	[0.072]	[0.062]	[0.061]	[0.026]	[0.026]
"-": Bachelor level	0.095	0.064	0.094	0.064	0.006	0.005
	[0.070]	[0.069]	[0.059]	[0.059]	[0.026]	[0.025]
"-": Master's level	0.151*	0.126	0.159**	0.130**	-0.005	-0.001
	[0.075]	[0.075]	[0.063]	[0.063]	[0.027]	[0.025]
"-": Doctoral level	0.118	0.121	0.140**	0.135**	-0.018	-0.008
	[0.074]	[0.072]	[0.062]	[0.060]	[0.033]	[0.030]
NACE (a): Agriculture, forestry & fishing	-0.015	-0.007	-0.026	-0.021	0.013	0.015
	[0.073]	[0.073]	[0.065]	[0.065]	[0.037]	[0.038]
"-" (b): Mining & quarrying	-0.179	-0.180	-0.115	-0.121	-0.068	-0.062
	[0.198]	[0.202]	[0.181]	[0.185]	[0.067]	[0.066]
"-" (c): Manufacturing	0.040	0.049	0.062*	0.068*	-0.026*	-0.022
	[0.037]	[0.037]	[0.033]	[0.034]	[0.015]	[0.016]
"-" (d): Electricity, gas & air conditioning	-0.128*	-0.108	0.001	0.012	-0.132***	-0.123***
	[0.074]	[0.075]	[0.070]	[0.069]	[0.031]	[0.033]

"-" (e): Water, sewerage & waste	-0.166*	-0.163*	-0.011	-0.011	-0.159***	-0.155***
	[0.087]	[0.087]	[0.079]	[0.080]	[0.039]	[0.039]
"-" (f): Construction	-0.118**	-0.111**	-0.022	-0.016	-0.086***	-0.085***
	[0.050]	[0.050]	[0.046]	[0.046]	[0.028]	[0.027]
"-" (g): Wholesale, retail & vehicle repair	-0.028	-0.028	0.027	0.027	-0.054**	-0.054**
	[0.047]	[0.047]	[0.044]	[0.044]	[0.021]	[0.021]
"-" (h): Transportation & storage	-0.095**	-0.095**	-0.043	-0.045	-0.053**	-0.051**
	[0.041]	[0.043]	[0.033]	[0.034]	[0.021]	[0.022]
"-" (i): Accommodation & food	-0.082	-0.084	-0.062	-0.070	-0.016	-0.011
	[0.061]	[0.061]	[0.051]	[0.049]	[0.028]	[0.028]
"-" (j): Information & communication	-0.083*	-0.078*	0.008	0.006	-0.094***	-0.086***
	[0.041]	[0.041]	[0.033]	[0.033]	[0.021]	[0.021]
"-" (k): Financial & insurance	-0.078*	-0.064	-0.020	-0.012	-0.060***	-0.054**
	[0.039]	[0.039]	[0.032]	[0.032]	[0.020]	[0.020]
"-" (l): Real estate	-0.116	-0.111	0.004	0.005	-0.122***	-0.118***
	[0.090]	[0.090]	[0.082]	[0.081]	[0.035]	[0.035]
"-" (m): Professional & technical service	-0.020	-0.007	0.063	0.071	-0.086***	-0.080***
	[0.054]	[0.054]	[0.053]	[0.052]	[0.021]	[0.021]
"-" (n): Administrative services	-0.068	-0.054	-0.016	-0.010	-0.051***	-0.044**
	[0.050]	[0.051]	[0.047]	[0.047]	[0.018]	[0.018]
"-" (o): Public administration & defence	-0.054*	-0.047	0.010	0.011	-0.062***	-0.056***
	[0.030]	[0.029]	[0.029]	[0.028]	[0.014]	[0.014]
"-" (p): Education	-0.076	-0.064	-0.026	-0.023	-0.046**	-0.037*
	[0.051]	[0.050]	[0.043]	[0.042]	[0.021]	[0.021]

"-" (q): Health & social work	-0.028	-0.014	0.009	0.014	-0.031	-0.022
	[0.046]	[0.046]	[0.040]	[0.040]	[0.019]	[0.019]
"-" (r): Arts, entertainment & recreation	-0.091	-0.086	-0.076	-0.079	-0.014	-0.006
	[0.063]	[0.062]	[0.060]	[0.058]	[0.021]	[0.021]
"-" (s): Other services	-0.119***	-0.114**	-0.084*	-0.082*	-0.029*	-0.027*
	[0.042]	[0.042]	[0.042]	[0.041]	[0.015]	[0.015]
"-" (t): Households as employers	0.026	0.008	0.093	0.074	-0.065	-0.066
	[0.113]	[0.113]	[0.110]	[0.111]	[0.061]	[0.058]
"-" (u): Extraterritorial organisations	-0.350***	-0.369***	-0.174*	-0.199*	-0.180***	-0.172***
	[0.120]	[0.122]	[0.101]	[0.102]	[0.046]	[0.046]
"-": Other	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Income: 10th Decile	0.175***	0.186***	0.214***	0.217***	-0.061***	-0.051***
	[0.049]	[0.049]	[0.043]	[0.043]	[0.014]	[0.013]
"-":9th	0.063	0.071	0.124***	0.125***	-0.081***	-0.074***
	[0.048]	[0.048]	[0.041]	[0.041]	[0.019]	[0.019]
"-":8th	0.044	0.045	0.067*	0.063*	-0.046**	-0.040**
	[0.045]	[0.044]	[0.034]	[0.034]	[0.018]	[0.017]
"-":7th	-0.026	-0.025	0.012	0.010	-0.059***	-0.055***
	[0.045]	[0.046]	[0.039]	[0.039]	[0.019]	[0.019]
"-":6th	-0.097*	-0.100*	-0.041	-0.046	-0.077***	-0.074***
	[0.056]	[0.057]	[0.047]	[0.048]	[0.020]	[0.020]
"-":5th	-0.196***	-0.199***	-0.149***	-0.154***	-0.069***	-0.067***
	[0.059]	[0.060]	[0.044]	[0.045]	[0.023]	[0.022]
"-":4th	-0.218***	-0.223***	-0.158***	-0.162***	-0.084***	-0.083***

	[0.057]	[0.058]	[0.047]	[0.048]	[0.025]	[0.024]
"-":3rd	-0.290***	-0.298***	-0.241***	-0.247***	-0.073***	-0.074***
	[0.057]	[0.057]	[0.053]	[0.053]	[0.023]	[0.023]
"-":2nd	-0.314***	-0.321***	-0.235***	-0.242***	-0.099***	-0.100***
	[0.075]	[0.075]	[0.064]	[0.063]	[0.025]	[0.024]
"-":1st	-0.341***	-0.354***	-0.296***	-0.305***	-0.070***	-0.073***
	[0.061]	[0.061]	[0.059]	[0.058]	[0.019]	[0.019]
"-": Don't know	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Wealth: 10th Decile	0.203***	0.207***	0.259***	0.256***	-0.063***	-0.056**
	[0.037]	[0.037]	[0.038]	[0.038]	[0.022]	[0.021]
"-":9th	0.175***	0.179***	0.219***	0.218***	-0.050**	-0.044*
	[0.047]	[0.048]	[0.052]	[0.053]	[0.022]	[0.022]
"-":8th	0.047	0.057	0.123***	0.125***	-0.083***	-0.075***
	[0.053]	[0.052]	[0.044]	[0.042]	[0.020]	[0.020]
"-":7th	-0.017	-0.014	0.077	0.075	-0.101***	-0.095***
	[0.050]	[0.049]	[0.050]	[0.050]	[0.019]	[0.018]
"-":6th	-0.063	-0.061	0.021	0.020	-0.090***	-0.087***
	[0.044]	[0.044]	[0.040]	[0.040]	[0.017]	[0.017]
"-":5th	-0.080*	-0.083*	0.006	0.003	-0.091***	-0.090***
	[0.046]	[0.047]	[0.045]	[0.045]	[0.017]	[0.016]
"-":4th	-0.110**	-0.109**	-0.019	-0.020	-0.099***	-0.097***
	[0.051]	[0.052]	[0.049]	[0.049]	[0.017]	[0.017]
"-":3rd	-0.156***	-0.152***	-0.070	-0.070	-0.092***	-0.089***
	[0.053]	[0.053]	[0.052]	[0.052]	[0.014]	[0.014]

"-":2nd	-0.271***	-0.268***	-0.182***	-0.180***	-0.097***	-0.096***
	[0.055]	[0.055]	[0.052]	[0.051]	[0.015]	[0.015]
"-":1st	-0.631***	-0.628***	-0.514***	-0.511***	-0.118***	-0.119***
	[0.049]	[0.049]	[0.048]	[0.047]	[0.014]	[0.014]
"-": Don't know	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}	{Ref.}
Occupational fixed effects	+	+	+	+	+	+
Country fixed effects	+	+	+	+	+	+
No. of Observations	16,231	16,231	16,231	16,231	16,571	16,571
R-squared	0.151	0.147	0.178	0.174	0.064	0.070

Notes: OLS estimates for employed respondents, using sampling weights, country and two-digit ISCO fixed effects. Standard errors in brackets.* p<0.10, ** p<0.05, *** p<0.01.

2.5 Conclusions

This paper examines whether subjective and statistical measures of mismatch provide interchangeable assessments of worker-job alignment or capture distinct dimensions of that relationship. Using TRAILS-I data for employed respondents across 31 European countries, we compare workers' assessments of whether their education and training match job requirements with a statistical benchmark based on modal educational attainment within country-occupation cells. The evidence shows that the measures are not interchangeable. They identify substantially different shares of matched, overqualified and underqualified workers, and their disagreement varies across countries, regions and sectors. Combining them therefore provides information that is lost when either measure is used alone.

The clearest distinction concerns skill utilisation. Subjective mismatch is strongly associated with reporting partial or no use of skills, whereas statistical mismatch is much less informative for this outcome. In the combined classification, workers who report overqualification or underqualification display substantial underutilisation even when the statistical measure classifies them as matched or places them in the opposite direction. By contrast, workers who regard their qualifications as appropriate but are statistically overeducated or undereducated generally do not differ significantly from workers matched under both measures. Education above or below an occupational benchmark should therefore not be interpreted mechanically as evidence of unused or insufficient skills.

Skill gaps show a different pattern. Workers overqualified under both measures report fewer multiple gaps, while those underqualified under both measures report more, particularly in digital, technical and customer-handling skills. Disagreement categories reveal further heterogeneity. Workers who consider themselves underqualified despite statistical matching report especially pronounced technical and job-specific needs, while some workers who consider themselves overqualified report fewer gaps even when statistically undereducated. These findings reinforce the need to distinguish qualification mismatch, skill underutilisation and skill deficits: unused capabilities and unmet job requirements can coexist within the same worker-job relationship.

Learning and resilience outcomes provide a similar message. Associations between learning participation, underutilisation and reported gaps differ across activities

and mismatch groups, indicating that training may reflect both existing needs and opportunities to develop skills. Labour-market and financial resilience are generally weaker among workers reporting subjective mismatch, including some workers who are statistically matched or overeducated. Conversely, statistical mismatch without perceived mismatch is not systematically associated with poorer resilience. Agreement between measures therefore does not consistently identify the most favourable circumstances, nor does disagreement necessarily imply weaker outcomes.

The policy implication is that mismatch indicators should be used diagnostically rather than as direct proxies for individual skill needs. Statistical measures are useful for identifying structural differences in educational allocation across occupations, but they cannot reveal whether a worker's existing capabilities are used effectively or which skills require improvement. Subjective assessments add information about the requirements of the specific job but may also reflect expectations and reporting tendencies. Combining both measures with information on actual skill use and domain-specific gaps can better distinguish cases requiring additional learning from those requiring changes in task allocation, job mobility or access to more suitable employment.

Taken together, the findings reinforce the view that skills mismatch is inherently multidimensional and cannot be fully captured by a single indicator. Subjective and statistical measures identify different aspects of the worker-job relationship, while their combination reveals important variation in skill utilisation, reported skill gaps, learning patterns and resilience that would otherwise remain obscured. The central implication is therefore not that one measure should replace the other, but that their agreement and disagreement provide complementary information about workers' circumstances. Distinguishing these dimensions offers a more informative basis for understanding skill needs, the use of existing capabilities and workers' capacity to adjust to changing labour-market conditions.

2.6 Policy implications for regional and local authorities, training providers and employers

The two chapters point to a diagnostic rather than one-size-fits-all approach to skills policy. Regional and local authorities can use the country and NUTS evidence to identify areas where mismatch is concentrated, but should distinguish between qualification mismatch, reported skill gaps and underutilisation before choosing an intervention. Training providers should prioritise the specific gaps reported by workers, particularly where underqualification is accompanied by technical, digital or other job-related needs. Employers should not assume that additional training will solve overqualification: where workers already possess capabilities that are not being used, job redesign, task reallocation, internal mobility and access to more suitable vacancies may be more appropriate. The sectoral results also suggest that these responses should be adapted to the organisation of work and training opportunities in different industries.

2.7 Limitations

Several limitations should be kept in mind. First, both chapters rely substantially on self-reported information, so reported mismatch, skill utilisation, skill gaps, adaptability and employability may share common reporting influences. Second, the data are cross-sectional and describe associations at one point in time; training participation, job allocation and mismatch may be jointly determined, so the estimates should not be interpreted as causal effects. Third, pooled cross-country models necessarily abstract from institutional differences that may shape both mismatch and training, although country fixed effects and separate country or regional descriptions mitigate this concern. Fourth, the statistical mismatch measure uses modal education within occupational cells as a benchmark rather than an independent assessment of job requirements. Finally, the regional analysis is primarily descriptive, and the present survey coding supports a harmonised ISCO-based occupational benchmark rather than a direct ESCO skills-based measure.

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3. CHAPTER 3 Concluding Remarks and Policy Implications

D3.3 examines skills and educational mismatch from two related perspectives. Chapter 1 uses the European Skills and Jobs Survey to study the consequences of educational mismatch for wages, job satisfaction and job security across European countries and sectors. It also considers the relationship between training and the outcomes of mismatched workers. Chapter 2 uses TRAILS-I to ask a different question: whether qualification-based measures of mismatch identify workers who actually report unused skills, specific skill deficits, weaker labour-market resilience or lower financial resilience.

The two analyses point to the same methodological problem. Educational mismatch is sensitive to how it is measured. A worker's formal education can be compared with the education usually required for the job, with the education most commonly held by workers in the same occupation, or with the worker's own assessment of whether their education and training are adequate. These measures do not classify the same people in the same way.

This is not a minor measurement issue. In Chapter 1, the subjective and statistical approaches assign a different mismatch status to more than half of employees. Around 60% of employees are classified as matched by the subjective measure, compared with 38% under the statistical measure. The combined measure, which retains cases in which the two measures agree, produces a matched share of approximately 55%. Chapter 2 reaches a related result with TRAILS-I. The two measures again produce substantially different classifications, and disagreement is visible across countries, sectors and regions.

The practical implication is that a measured qualification mismatch should not automatically be read as evidence of a skills problem. Someone whose education is below the occupational mode may have acquired the skills needed for the job through experience, workplace learning or previous training. Conversely, a worker whose education is typical for the occupation can still be in a job that uses only a limited share of their capabilities.

The TRAILS-I evidence is useful here because it allows qualification mismatch to be compared with direct reports of skill use and skill needs. Subjective mismatch has a much closer relationship with reported skill underutilisation than statistical mismatch. Workers who describe themselves as overqualified or underqualified are considerably more likely to report that their job uses only some, or none, of their skills. Statistical overeducation or undereducation without perceived mismatch is much less consistently associated with this outcome.

This does not mean that the subjective measure is inherently superior. It reflects workers' assessments of their own jobs and can be affected by expectations or reporting behaviour. Statistical measures remain useful for identifying broader patterns in educational allocation across occupations. The point is narrower: the two measures contain different information. Policy analysis is therefore more informative when qualification mismatch is considered together with measures of skill use, reported gaps and training needs.

The nine-category classification used in Chapter 2 illustrates the value of retaining disagreement between measures rather than treating it as error. Workers who fall into the same statistical category can report very different experiences of their jobs depending on whether they themselves regard their qualifications as adequate. Some statistically undereducated workers report no corresponding difficulty, while workers who consider themselves underqualified despite statistical matching report substantial technical and job-specific skill needs.

For D3.3, this distinction matters because the objective is not simply to count mismatched workers. The task is concerned with the consequences of mismatch for inclusive labour markets and worker wellbeing. A useful policy indicator must therefore say something about the problem that workers actually face.

3.1 Overqualification & underqualification are different policy problems

The results also show why overqualification and underqualification should not be treated as opposite ends of a single scale. Chapter 1 finds a substantial wage penalty for

overeducation. Under the combined mismatch measure, overeducated employees earn around 28% less than workers with the same level of education who are in matched jobs. The penalty is larger than the corresponding estimates based on either the subjective or statistical measure alone. The severity of overeducation is also relevant. In most countries, a large share of workers classified as overeducated under the combined measure are at least two educational levels above the level associated with their job. In several countries, roughly four out of five overeducated workers fall into this severe category. The analysis also identifies master's graduates working in jobs associated with post-secondary non-tertiary qualifications or below.

Chapter 2 gives a clearer indication of what this may mean at the level of the worker-job relationship. Workers who are overqualified under both measures report particularly high levels of skill underutilisation. At the same time, they do not report a general excess of skill gaps. In several skill domains they report fewer gaps than matched workers. This combination is consistent with an allocation problem. These workers appear to possess capabilities that their jobs do not fully use. Further training may still be valuable for career development, but it is unlikely to address the main source of mismatch if the worker already has skills that are not being deployed.

The policy response in such cases should therefore extend beyond training provision. Employers can examine whether tasks can be reorganised so that existing capabilities are used more fully. Internal progression and movement between roles may reduce persistent underutilisation. Public employment services can improve information about vacancies and transferable skills. Regional economic-development policy also matters where the local economy does not generate enough jobs that make use of the qualifications available in the workforce.

Underqualification presents a different picture. Workers classified as underqualified by both measures are more likely to report several kinds of skill deficit. Technical and job-specific gaps are especially visible, alongside digital and customer-handling needs. The TRAILS-I results therefore provide stronger grounds for interpreting at least some forms of underqualification as a skill-development problem.

Chapter 1 reaches a complementary result from the wage analysis. When undereducated workers are compared with appropriately educated workers performing similar occupations, the estimated wage disadvantage is around 11%. Job-related training is positively associated with wages, and the estimated training premium is

similar in magnitude to this within-occupation penalty. The evidence does not establish a causal effect of training. Participation in training is not randomly assigned, and workers with larger needs may be more likely to seek training or be selected for it. Even so, the result suggests that training is more closely aligned with the type of problem observed among underqualified workers than with the underutilisation experienced by many overqualified workers.

This distinction has a straightforward policy consequence. Where workers lack capabilities required for their current jobs, targeted upskilling is a plausible response. Where workers already possess capabilities that are not being used, policy should pay more attention to matching, mobility and the content of jobs. Some workers may face both problems at once, since a job can underuse certain skills while requiring improvement in others. That is another reason to avoid assigning a single intervention on the basis of qualification mismatch alone.

3.2 Sectoral differences matter for both diagnosis and intervention

The sectoral analysis shows that mismatch is not distributed evenly across the European economy. The incidence of undereducation is relatively high in ICT, finance and insurance, and real estate activities. Overeducation is particularly common in accommodation and food services and in wholesale and retail. The consequences also differ by sector. Chapter 1 identifies particularly large wage penalties and greater fear of job loss among overeducated workers in transport and storage, wholesale and retail, real estate, and arts and entertainment. A sector with a high mismatch rate is therefore not necessarily equivalent to another sector with a similar rate. The type of mismatch and its consequences for workers both matter.

Sector-specific policy should start from that distinction. In activities where underqualification accompanies changing technical requirements, training can be closely linked to current occupational needs. Employer-supported learning, recognised certification and opportunities to update technical skills are likely to be more relevant there.

Where overqualification and underutilisation are more prominent, the issue may lie partly in the structure of jobs. Firms can consider whether existing roles provide enough scope to use the capabilities of their workforce. A sector with persistent overqualification may also face weak progression pathways, limited task discretion or a concentration of jobs below the qualification level of available workers. The evidence therefore argues for closer links between training policy and the organisation of work. Training is most useful when workers can apply what they learn. If a job provides little opportunity to use existing skills, adding further training without changes in job content can leave the original problem untouched.

Sectoral partnerships can help make this distinction operational. Employers, training providers, social partners and public authorities have access to different information about emerging requirements and current gaps. Bringing these sources together can improve the targeting of provision and reduce the risk of designing programmes around broad educational categories that do not correspond to the needs reported by workers.

The findings also support greater use of information that connects qualifications with occupations and skills. Qualification frameworks such as the EQF provide a common language for formal educational levels. ISCO provides a harmonised occupational structure. ESCO adds a detailed skills dimension. Used together, these classifications can support a richer account of mismatch than formal qualifications alone.

3.3 The regional dimension and labour-market inclusiveness

D3.3 also finds substantial geographic variation. Chapter 1 identifies large differences between countries in both the incidence and consequences of mismatch. Chapter 2 shows that variation remains visible below the national level. This matters because the opportunities available to mismatched workers depend on local labour-market conditions. A highly educated worker can be overqualified because suitable jobs are scarce within reasonable commuting distance. A worker who needs technical training may live in a region with limited access to appropriate provision. The same worker characteristics can therefore lead to different outcomes in different places.

The regional results in D3.3 should be read mainly as evidence on where mismatch is concentrated and on how the pattern changes depending on the measure used. They show that national averages are not enough for identifying local pressure points. They do not yet provide a complete account of why training participation differs between regions.

For regional and local authorities, the first practical step is therefore diagnostic. Areas with high overqualification should be examined alongside the local occupational structure and the availability of jobs able to use highly qualified labour. Areas with stronger underqualification and reported skill deficits may require closer examination of adult-learning provision and employer demand for particular skills. This also changes how inclusiveness should be understood. Access to employment is only one part of an inclusive labour market. Workers may be employed but remain in positions that use relatively little of their accumulated human capital. Others may have jobs but lack the skills needed to adapt to changes in their occupations.

The TRAILS-I resilience measures provide some evidence on this wider dimension. Workers reporting subjective mismatch tend to have weaker labour-market resilience in several specifications. Some mismatch categories are also associated with weaker financial resilience. These are associations rather than causal estimates, but they indicate that mismatch can coexist with vulnerabilities extending beyond current job fit.

A policy designed around employment rates alone may therefore miss part of the problem. The quality of matching affects whether workers can use what they know, continue learning and move when their current job no longer fits. These considerations are particularly relevant in regions undergoing structural change, where the composition of jobs can shift faster than workers can adjust.

3.4 Training policy should focus on needs, access and use

Training is prominent in both chapters, but the evidence does not support a simple equation in which more training automatically means better matching. Chapter 1 reports that around 65% of employees participated in recent job-related training. Participation differs substantially across countries and sectors. The wage association with training is

positive across mismatch groups, which supports continued attention to adult learning. The variation in participation is also informative. France, for example, combines a relatively high incidence of undereducation with a comparatively low training rate in the ESJS evidence. This is the type of combination that warrants closer examination because the workers who might benefit from additional skill development may not be those with the greatest access to training.

Chapter 2 shows why participation rates require careful interpretation. Workers with identified skill gaps may be more likely to undertake learning precisely because they recognise a need. Employers may direct training towards workers whose jobs are changing. Participation can therefore be associated with greater measured need without implying that training is ineffective.

The policy question should be framed around the purpose of the training. Some learning is intended to close a current deficit. Other provision prepares workers for changes in technology or job content. A different form of learning may help workers move out of jobs that underuse their existing capabilities.

Evaluation should follow the same logic. A participation target can show whether adults are entering training, but it cannot show whether the relevant gap was reduced or whether the new skill is subsequently used at work. More informative evaluation would connect participation to changes in identified skill needs, progression within the organisation, movement to more suitable employment and measures of resilience.

Employers have an important role because the usefulness of learning depends partly on the work environment to which the employee returns. Training that is followed by greater responsibility or access to different tasks may improve matching. Training that produces additional skills without any possibility of using them may instead increase the stock of underutilised human capital.

For public authorities and training providers, accessibility remains equally important. Cost, working hours, caring responsibilities, information about available programmes and the geographic distribution of providers can all affect participation. These factors cannot be inferred from an aggregate training rate and need to be examined directly.

3.5 How D3.3 leads into D3.4

D3.3 establishes where several of the main problems lie. It shows that mismatch varies across countries and sectors, that subnational differences are visible in TRAILS-I, and that workers classified as mismatched can face very different problems. It also documents substantial differences in training participation. The next stage is to explain these differences in greater depth. The regional analysis of training will be completed in detail in D3.4. D3.3 provides the empirical starting point for that work, but it does not attempt to provide a full regional model of training participation or a complete account of the barriers that prevent workers from taking part.

This division is consistent with the design of WP3. D3.4 examines the behavioural, social and cultural factors that can affect participation in adult learning, VET and other forms of upskilling. It also gives greater attention to groups for whom such barriers may be particularly relevant, including younger people, women, unemployed workers, migrants and public-sector employees. The distinction between the two deliverables is substantive. D3.3 identifies regional concentrations of mismatch, variation in training and differences in worker outcomes. D3.4 will examine the mechanisms that can produce unequal participation in training across locations and population groups.

Low training participation in a region can have several explanations. Provision may be limited. Workers may face costs or time constraints. Employers may provide few opportunities. People may have incomplete information about available programmes or uncertain expectations about the return to participation. Social and cultural factors can also affect willingness to engage with adult learning. These mechanisms require different policy responses, so they should not be inferred from the regional patterns alone. D3.4 will provide the more detailed analysis needed to distinguish between them.

The sequencing across WP3 is therefore deliberate. Earlier work examined the incidence and changing nature of mismatch and the relationship between technological change and upskilling. D3.3 connects mismatch with worker outcomes and shows where different forms of mismatch are concentrated. D3.4 will use this evidence as a basis for examining participation in training more closely, with particular attention to regional context and barriers faced by groups at risk of exclusion.

3.6 Policy implications and closing remarks

The results of D3.3 support a more differentiated approach to skills policy in Europe. The starting point is better diagnosis. Statistical indicators based on education and occupation remain useful for monitoring structural mismatch, but the results show that they should not be interpreted as direct measures of individual skill mismatches. Where the necessary information is available, they should be complemented by workers' assessments of match, measures of skill utilisation and evidence on specific skill gaps.

This distinction is especially important when choosing an intervention. Overqualification accompanied by substantial underutilisation points towards a problem in the use and allocation of human capital. In such cases, further training may be useful for career development but is unlikely to resolve the underlying mismatch by itself. Better matching, job redesign, internal progression and occupational mobility are more directly relevant. Underqualification accompanied by technical, digital or other job-related gaps presents a stronger case for targeted upskilling.

Sectoral policy should similarly reflect differences in both the incidence and the consequences of mismatch. D3.3 identifies sectors in which overeducation is associated with particularly large wage or job-security penalties. These cases merit attention even when aggregate mismatch rates alone would not place the sector at the top of the policy agenda. Employers, training providers, social partners and public authorities can use sector-specific evidence to distinguish between shortages that call for additional skills and cases in which existing capabilities are poorly used.

The same principle applies geographically. National averages conceal important differences between local labour markets. Regional authorities need sufficiently detailed indicators to identify concentrations of overqualification, underqualification and reported skill needs and to relate these to local labour demand and training provision. The subnational evidence in Chapter 2 provides an initial basis for this work. The regional training analysis developed in D3.4 will allow these patterns to be examined more closely.

Adult-learning policy should also look beyond participation itself. Raising the proportion of adults entering training remains an important objective, but participation does not establish that the training addresses the relevant deficit or that the skills acquired are

subsequently used. Evaluation should therefore consider whether identified gaps narrow, whether workers gain access to different tasks or roles, whether mobility improves and whether workers become better able to adapt to future labour-market changes.

The findings also give a broader meaning to inclusiveness. An inclusive labour market is not defined only by whether people are employed. It also concerns the extent to which workers can make use of their capabilities, acquire new ones when requirements change and move towards more suitable employment when necessary. The associations between mismatch and labour-market and financial resilience found in TRAILS-I suggest that poor matching can coexist with wider vulnerabilities. Although these results are not causal, they strengthen the case for considering skills policy together with employment quality and resilience.

D3.3 therefore shows that the policy meaning of mismatch depends on what lies behind the classification. A qualification surplus may indicate unused human capital, while a qualification deficit may indicate a genuine training need. Neither conclusion should be drawn from formal qualifications alone. Chapter 1 establishes that educational mismatch can have substantial consequences for wages and job security. Severe overeducation is widespread in several countries, and the penalties associated with mismatch vary considerably across sectors. Training is positively associated with wages and appears particularly relevant where workers face a deficit in formal education relative to occupational requirements. Chapter 2 adds information on what workers experience within these categories. Subjective mismatch is closely associated with skill underutilisation, while underqualification is more clearly connected to reported deficits in several skill domains. Statistical mismatch in the absence of perceived mismatch is often much less strongly associated with these outcomes. The evidence on labour-market and financial resilience extends the analysis beyond current job fit.

The resulting policy message is therefore quite specific. Training is an appropriate response when workers lack capabilities needed for their jobs. It is less likely to resolve a mismatch caused by jobs that fail to use capabilities workers already possess. In those cases, matching, mobility and the organisation of work become part of the policy response.

D3.3 also establishes that these conditions differ across sectors and places. It provides evidence on where mismatch is concentrated and on the outcomes associated with

different forms of mismatch. The detailed regional analysis of training will be completed in D3.4, which will examine participation in adult learning more closely and investigate the behavioural, social and cultural factors that may help explain differences across regions and population groups.

The progression from D3.3 to D3.4 is therefore important. D3.3 identifies the form and consequences of mismatch and provides the empirical basis for deciding what type of response may be needed. D3.4 will examine why workers facing these needs do or do not engage with available learning opportunities. Together, the two deliverables can support a move away from uniform approaches to skills policy towards interventions that distinguish genuine skill deficits from underutilisation, respond to sectoral and regional conditions, and take account of the barriers faced by groups with unequal access to training and suitable employment.