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Determinants and Wage Penalty of Skills Mismatch: Cross-Country Evidence from ETF Partner Countries

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Abstract

The current literature finds that many employees in low and middle-income countries are over-qualified for their jobs or are employed in an occupation that is unrelated to their principal field of study. Vertical and horizontal mismatches signal that workers cannot fully utilise their skills, implying a potential loss of human capital. However, the current literature scarcely explores the determinants and wage penalties of horizontal and vertical skills mismatches comparably across countries, as well as their co-occurrence. We analyse the determinants of vertical and horizontal skills mismatch between 2016 and 2019 using the Labour Force Survey (LFS) of Serbia, Albania, Türkiye, Georgia, Armenia, Egypt, and Palestine. Consistent with the existing literature, the findings show that socio-demographic, job-related, and geographic characteristics determine vertical and horizontal mismatches, as well as their combined occurrence. The results also show that overeducation imposes a wage penalty, that horizontal mismatch is associated with a wage premium of approximately 7.5%, and that the combination of overeducation and horizontal mismatch yields a small positive net effect of approximately 1%.

JEL classification

J24, J31, J21, I26, O15

Keywords

skills mismatch, over-education, under-education, horizontal mismatch, cross-country analysis

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* The views reflected in this document do not necessarily reflect the corporate position of the ETF.

1. Introduction

This study provides policy-relevant insights on the determinants of skills mismatch in transition and developing countries. The literature suggests that skills mismatch is associated with wage penalties, which are typically smaller for individuals who are horizontally mismatched than for those who are vertically mismatched. Moreover, a horizontal mismatch is more likely to result in a wage penalty when accompanied by a vertical mismatch than when it occurs alone (Bergin et al., 2019; McGuinness et al., 2025, for a recent literature review). Understanding the determinants of skills mismatch, as well as understanding to which extent overeducation, horizontal mismatch and their combination cause a wage penalty, would allow implementing policies targeted to the groups at the highest risk of mismatch, improving labour market efficiency and productivity, which is usually negatively correlated with skills mismatch (Adalet McGowan & Andrews, 2015).

This article contributes to the current literature on the determinants of vertical and horizontal skills mismatch and their wage penalty, providing recent insights on some transition and developing countries currently partners of the European Training Foundation (ETF). The contribution of this study to the current literature is threefold: (i) it explores both the determinants and the wage penalty of singular and combined measures of vertical and horizontal skills mismatch, which are rarely explored together, and at the same time, (ii) it uses objective measures of skills mismatch comparing them across countries. To the best of our knowledge, the only study providing a cross-country comparison of the determinants of both vertical and horizontal mismatch defined using comparable objective indicators is Nieto et al. (2015), which focuses on differences between immigrants and natives. Finally, (iii) it contributes to the limited literature on skills mismatch in developing and transition countries. The analysis focuses on selected countries from the Southern and Eastern Mediterranean (SEMED) region, the Eastern Partnership (EaP), and Enlargement countries, including Serbia, Albania, Türkiye, Georgia, Armenia, Egypt, and Palestine.

The available literature accounting for the correlates of combined horizontal mismatch and qualification mismatch and the relationship between field-of-study mismatch and pay is scarce (see, for example, Montt, 2015; Kim et al., 2012; Béduwé and Giret, 2011; Kelly et al., 2010 and more recently Tran et al., 2025 and Cassidy and Gaulke, 2024). Studies that do not account for qualification mismatch while estimating the horizontal mismatch wage penalty risk producing biased estimates (Kim et al., 2012).

Moreover, studies examining the determinants of field-of-study mismatch allow for comparable estimates across countries but mostly rely on subjective measures of skills mismatch, which limit the comparability of the indicators (Montt, 2015; OECD, 2014; Quintini, 2011b; Wolbers, 2003). A few recent exceptions focus on both developed countries (OECD, 2024) and developing countries (ILO, 2024), although the latter still relies on a subjective measure of horizontal mismatch.

Finally, overall, the available studies on skills mismatch focus mostly on developed countries such as the US, Australia, and the European Union. The few studies focusing on developing and transition countries mainly analyse Skills Towards Employability and Productivity (STEP) survey data up to 2013 (Handel et al., 2016; Kupets, 2015a) and Labour Force Survey (LFS) data up to 2016 (Bergin et al., 2019; Morrar & Zwick, 2021; Farooq, 2011). Research in transition and developing economies, though limited, suggests that wage penalties for both vertical and horizontal mismatch can also occur but vary by country (ILO, 2024, covering several developing countries), sector (Arayssi et al., 2023, focusing on MENA region, especially Lebanon), and occupation (Elamin, 2023, covering countries in the MENA region), often reflecting broader structural labour market rigidities. Finally, recent work by Tran et al. (2025) examines vertical and horizontal mismatches using 2018-21 LFS data from Vietnam. Mismatch declines with experience, and wage penalties are associated with vertical and combined mismatches; horizontal mismatch alone has a weak impact. Prica, El Ouizgani & Bartlett (2025) examine the combined effects of qualification and skills mismatchamong graduates in Morocco and Serbia. Nevertheless, comparative cross-country analyses using objective indicators of skills mismatch in developing and transition contexts remain scarce.

The study's first objective is to explore the determinants of both vertical and horizontal skills mismatch, which happen together across countries and by country. The second objective of this study is to analyse both the likelihood and the extent of the wage penalty associated with vertical and horizontal mismatches and their combination.

The analysis is based on the Labour Force Survey (LFS) data (2016-2019) of the selected countries, which is nationally representative and allows for comparability across countries. Our methodology relies on cross-country pooled data analysis. We also use country-to-country probit regressions to explore the heterogeneity of the determinants of skills mismatch across different countries, which can be due to structural differences in the labour markets. The variables selected as potential determinants of skills mismatch are individual, job, and geographical characteristics (e.g. rural/urban) and vary across countries depending on data availability.

The results highlight the importance of socio-demographic, job, and geographical characteristics in predicting skills mismatch. Cross-country differences should be interpreted considering the institutional and economic contexts specific to each country. The study also finds that overeducation imposes a wage penalty, whereas horizontal mismatch does not, and that a combination of overeducation and horizontal mismatch can have a positive effect on wages. Finally, the analysis examines the main determinants of occupational mismatch in ETF partner countries, explores heterogeneity in outcomes across countries, and investigates the wage effects of skills mismatchto identify directions for future research. Overall, the findings are intended to inform policies to address skills mismatch.

The study is structured as follows. Section 2 introduces the literature on the determinants of skills mismatch and its impact on wages. Section 3 describes the empirical method, specifying the data used and the identification and estimation strategy. Section 4 presents the results on the determinants of skills mismatch, Section 5 shows the wage effects of skills mismatch, and Section 6 presents robustness checks. Section 7 concludes.

2. Literature review

2.1 The determinants of skills mismatch

Several studies in the literature examine the determinants of vertical and horizontal skills mismatch. Socio-demographic characteristics are consistently identified as determinants of overeducation in both developed countries (e.g., Belfield, 2010; Ramos & Sanroma, 2011; Addison et al., 2020; Brun-Schammé & Rey, 2021) and transition and developing countries (e.g., Kupets, 2015; Handel et al., 2016; ILO, 2024; Krzywda Starzyk, 2024). Overeducation tends to affect men more than women (Addison et al., 2020), as well as older workers, particularly in transition economies (Kupets, 2015a), whereas younger workers generally face higher mismatch risks due to limited labour market experience (ILO, 2024). Empirical evidence also shows that young married women (Crompton, 2002; Dorn & Sousa-Poza, 2005; Groot, 1993; Sicherman, 1991; Morrar & Zwick, 2021) and immigrants (Aleksynska & Tritah, 2013; Chiswick & Miller, 2009; Kler, 2006; Birgier & Cantalini, 2025) are more likely to be overeducated.

Job characteristics are additionally correlated with overeducation, including the field of education and part-time employment (Kupets, 2015; Handel et al., 2016; Ortiz & Kucel, 2008; OECD, 2024; Arayssi et al., 2023). Geographical variables have also been found to influence vertical mismatch (Berlingieri, 2019; Duranton & Puga, 2003; Morrar & Arman, 2024; Morrar & Zwick, 2021), as have personality traits (Esposito & Scicchitano, 2023). Similar patterns are observed when examining the determinants of overskilling (Mavromaras & McGuinness, 2012; Mavromaras et al., 2013).

The literature also shows that horizontal mismatch is related to individuals' education-related characteristics, such as field of education (e.g., Verhaest et al., 2015; Robst, 2007a; Robert, 2014; Wolbers, 2003) and level of education (Wolbers, 2003; Robst, 2007a; Hensen et al., 2009; Boudarbat & Chernoff, 2012; Bender & Roche, 2013, among others). Recent studies confirm these patterns and provide more cross-country and objective evidence, primarily focusing on developed countries (OECD, 2024).

Labour market factors also influence horizontal mismatch (e.g., Wolbers, 2003; Witte & Kalleberg, 1995; Robert, 2014). Recent evidence indicates that regional labour demand shocks, sectoral skill requirements, and economic restructuring continue to shape mismatch outcomes in both developed and transition economies (ILO, 2024; Birgier & Cantalini, 2025). Job-related characteristics, including occupational requirements and contract type, remain important (Witte & Kalleberg, 1995; Wolbers, 2003; Boudarbat & Chernoff, 2012; Robert, 2014), while individual determinants, such as gender, age, immigrant status, and family responsibilities, also correlate with horizontal mismatch (Bender & Heywood, 2011; Hensen et al., 2009; Farooq, 2011; Krzywda Starzyk, 2024; Arayssi, 2023, among others).

Most studies in the literature focus on a single country and use various skill-mismatch indicators, often based on the specific characteristics of the survey or on self-reported measures, which limits comparability. Studies that examine the determinants of skills mismatch, provide cross-country comparisons, and rely on comparable indicators remain relatively scarce compared to single-country studies (see Kupets, 2015; Handel et al., 2016; Ortiz & Kucel, 2008; Allen et al., 2013; Nieto et al., 2015; Robert, 2014; Bergin et al., 2019; Montt, 2015; OECD, 2024; ILO, 2024; Birgier & Cantalini, 2025, among others).

Recent work has begun to address this gap by leveraging updated international surveys and regional studies. For example, OECD (2024) uses PIAAC 2023 data, which provides standardized measures of literacy, numeracy, and problem-solving skills, to offer cross-country evidence of both vertical and horizontal skills mismatch using more objective indicators. Krzywda Starzyk (2024) conducts a systematic review of European studies, synthesizing evidence from national labour force surveys, PIAAC, and other administrative sources to highlight cross-national patterns in overeducation. ILO (2024) draws on the Global Employment Trends for Youth 2024 dataset, combining labour force survey data from multiple countries to document cross-country variations in skills mismatch, including in transition and developing economies. Finally, Birgier & Cantalini (2025) use country-specific administrative and survey data on immigrants' educational attainment and occupation from 17 European countries to provide comparative evidence on vertical mismatch among migrant workers.

Examining the determinants of vertical and horizontal skills mismatch separately may produce biased results, as mismatches can occur simultaneously across both dimensions. The literature on combined vertical and horizontal skills mismatch remains limited. Existing studies focus mostly on single countries, predominantly in developed contexts: Hensen et al. (2009) analysed Belgium; Verhaest et al. (2015) examined Belgium and the Netherlands; Berlingieri (2019) focused on Italy; Béduwé & Giret (2011) studied France; Schweri et al. (2020) considered Switzerland; Kim et al. (2012) investigated the United States; Kelly et al. (2010) focused on the United Kingdom; and more recently, Ege & Erdil (2023) focused on Turkey.

Collectively, these studies indicate that analyzing vertical and horizontal mismatch jointly provides a more accurate understanding of the determinants of skills mismatch. Despite these contributions, a significant gap persists: few cross-country studies examine combined vertical and horizontal skills mismatch in developing and transition economies, leaving the joint determinants of mismatch largely unexplored in these contexts.

2.2 The wage effects of skills mismatch

The evidence about wage penalties due to vertical and horizontal skills mismatch is mixed. If the studies find any pay penalty, these are typically smaller for those horizontally mismatched than for those vertically mismatched.

The impact of vertical mismatch on wages

Most of the existing theoretical and empirical literature focuses on developed countries and consistently finds a negative wage effect of overeducation (for reviews, see Hartog, 2000; Leuven & Oosterbeek, 2011; McGuinness et al., 2025). Recent cross-country research on European countries using more comparable and objective measures confirms these findings. For example, analyses based on PIAAC microdata show that overskilling - when skills exceed job requirements - is associated with earnings losses in many developed countries, although the magnitude varies substantially across contexts and is often smaller than the penalty for overeducation (OECD, 2024, focusing on Austria, Belgium, Germany, Ireland, Spain, Sweden, and the United States).

Other recent studies focusing on European countries, such as Spain (Lasso Dela Vega et al., 2023) and Portugal (Araujo & Carneiro, 2023), indicate that the vertical mismatch wage penalty is not uniform. It depends on labour market institutions, occupational structures, skill transferability (Krzywda-Starzyk, 2024; Lasso Dela Vega et al., 2023), and career stage (Araujo & Carneiro, 2023). Research in transition and developing economies, though limited, suggests that wage penalties for both vertical and horizontal mismatch can also occur but vary by country (ILO, 2024, covering several developing countries), sector (Arayssi et al., 2023, focusing on Lebanon), and occupation (Elamin, 2023, covering countries in the MENA region), often reflecting broader structural labour market rigidities.

The impact of horizontal mismatch on wages

Overall, while there is robust evidence that vertical mismatch tends to reduce wages, despite the literature suggesting that wage penalties usually depend on whether the horizontal mismatch is accompanied by a vertical mismatch (Bergin et al., 2019) both the theory and the findings on the wage penalty associated with horizontal mismatch and its combination with vertical mismatch are mixed, and the findings are also scarcely available.

There are three main theories behind the effect of field-of-study mismatch on wages: (i) the human capital theory, (ii) the job competition theory, (iii) the assignment theory (Montt, 2015). The first theory suggests that field-of-study mismatch is temporary (even if it can be prolonged and costly for individuals), and firms will adjust their demand and productive process to the available stock of human capital. The second instead predicts that there is no wage penalty associated with field-of-study mismatch, as it is driven by a shortage of workers in a certain field of education. Finally, the assignment theory suggests that productivity and wages depend on the match quality between supply (in a specific field of education) and demand (in a particular occupational group). Studies on the impacts of horizontal mismatch on wages show that field-of-study mismatched workers are expected to suffer a wage penalty compared to their well-matched peers (Robst, 2007a; Wolbers, 2003; McGuinness and Sloane, 2011), even after accounting for skill heterogeneity (Nordin et al., 2010) or qualification mismatch (Robst, 2008). However, the studies also find that the wage penalty can vary across fields of study and can be a reward instead of a penalty.

The literature continues to face challenges in disentangling the independent effects of qualification and field-of-study mismatches, and internationally comparable estimates of the wage penalties specifically associated with horizontal mismatch remain scarce. Few studies examining the individual-level correlates of field-of-study mismatch provide estimates that are comparable across countries (OECD, 2014; Quintini, 2011b; Wolbers, 2003). Most studies focus on a single country and adopt methodological choices tailored to the survey's specific characteristics, often relying on self-reported measures of field-of-study mismatch. As a result, comparable estimates of the wage penalty associated with field-of-study mismatch are limited, since many country-specific studies rely on subjective measures (e.g., Robst, 2007a, 2007b, 2008; Nordin et al., 2010; Kelly et al., 2010; Verhaest et al., 2015).

An important exception is Kim et al. (2012), who use a more objective measure of horizontal mismatch in the Korean Education and Employment Panel (KEEP) by comparing a worker's field of study with the field typically associated with their occupation. This approach allows the authors to identify whether graduates are employed in occupations unrelated to their field of study, reducing potential bias from subjective perceptions of mismatch and providing a more precise estimate of the wage penalty associated with horizontal mismatch. The few studies that allow for cross-country comparisons are based on relatively old data or do not isolate the relative effects of qualification and field-of-study mismatch (Wolbers, 2003; Quintini, 2011b).

Overall, the empirical evidence indicates that mismatched workers are more likely to earn lower wages (Kelly et al., 2010; Robst, 2007a; Wolbers, 2003; Nordin et al., 2010; Quintini, 2011b; OECD, 2014), experience lower levels of job satisfaction, and are more likely to be actively seeking alternative employment while employed (Wolbers, 2003; Béduwé & Giret, 2011). When studying the risk of a skills-mismatch wage penalty, studies that fail to account for both horizontal and vertical mismatches produce biased estimates (Kim et al., 2012). This failure to jointly account for qualification and field-of-study mismatch explains part of the variation in estimates across studies that do and do not account for other forms of mismatch. The other part of the variation may be due to restrictions applied to the sample for the analysis (e.g., specific country, field of education, age).

The impact of both vertical and horizontal mismatch on wages

The number of studies examining the joint impact of vertical (qualification) and horizontal (field-of-study) mismatch on wages remains relatively limited (Kim et al., 2012; Montt, 2015; OECD, 2014; Quintini, 2011a, 2011b; Tran et al., 2025; Cassidy & Gaulke, 2024). Their findings indicate that part of the field-of-study mismatch is related to overqualification, that qualification mismatch carries a substantial wage penalty, and that a portion of the overall field-of-study mismatch penalty arises when workers must downgrade and accept jobs outside their field of study - effectively becoming overqualified (Kim et al., 2012; OECD, 2014; Quintini, 2011a, 2011b; Cassidy & Gaulke, 2024).

Kim et al. (2012) analyse the wage effects of both vertical and horizontal mismatch using the Korean Education and Employment Panel (KEEP), focusing on young workers in South Korea. In this study, horizontal mismatch is measured by comparing a worker's field of study with the field typically associated with their occupation. Similarly, Quintini (2011a, 2011b) examines education-job mismatch using OECD cross-country datasets and PIAAC, covering a broad set of OECD countries, and emphasizes the importance of distinguishing between qualification mismatch and field-of-study mismatch when assessing labour-market outcomes.

Building on this cross-country perspective, OECD (2014) uses the PIAAC Adult Skills Survey to analyse field-of-study mismatch across age groups in multiple OECD countries. Horizontal mismatch is defined as the deviation between a worker's field of study and the occupation's typical field. The study finds that wage penalties associated with horizontal mismatch emerge mainly among prime-age and older workers, whereas younger workers may experience a small wage premium. Montt (2015) extends this analysis by simultaneously examining the wage penalties associated with field-of-study and qualification mismatches using the same PIAAC data. The results show that in most countries, field-of-study mismatch alone is not associated with significant wage penalties when workers are adequately matched in terms of qualification, suggesting that overqualification accounts for a substantial share of the total mismatch penalty, although horizontal mismatch can still influence labour-market outcomes to some extent.

More recent research continues to examine wage penalties associated with the interaction between vertical and horizontal mismatches using updated graduate and labour force datasets. For example, Tran et al. (2025) use a survey of Vietnamese graduates to measure vertical mismatch (education level versus occupation requirements) and horizontal mismatch (field of study versus occupation). Their findings indicate that workers experiencing both vertical and horizontal mismatch face the largest wage penalties, whereas a purely horizontal mismatch is associated with smaller wage effects. Similarly, Cassidy & Gaulke (2024) use U.S. Census data from 1990 to 2019 to show that the returns to overeducation - defined as years of schooling exceeding what is required for a job - have declined over time for women, though not for men. Women tend to work in occupations with lower educational requirements and, therefore, experience higher levels of "excess" schooling. Consequently, decreases in the returns to this excess schooling over time for women help explain most of the increase in their wage penalty.

Overall, the recent literature confirms that failing to account jointly for vertical and horizontal mismatch can bias estimates of wage penalties, and that the interaction between the two plays a crucial role in explaining wage differences across workers and countries.

3. Empirical method

3.1. Data and descriptive statistics

The data we used for this study are the Labour Force Surveys (LFS) (2016-2019) of Albania, Armenia, Georgia, Palestine and Serbia; the Household Labour Force Survey of Türkiye (2016-2019) and the Harmonized Labour Force Survey of Egypt (2016 and 2017)[6]. The LFS

[6] Data: Microdata provision from Albania (Ref No 216), Palestine (SLN 2020-10-22), Serbia, Türkiye (YH0102-ZAI004925), and the Economic Research Forum (ERF) is gratefully acknowledged.

provides detailed information on the individual's education level (according to the ISCED classification), occupation (according to the ISCO categories), field of education (according to the ISCED-F classification), and individual, job, education, and geographical area characteristics.

This study concentrates on two dimensions of skills mismatch: vertical and horizontal. A vertical mismatch is a matter of skill/education level, and it is usually referred to as over- and under-education or over- and under-skilling. While qualifications are usually the only measure available in labour force surveys, using them as proxies for skills could be misleading. Not always is a mismatch in education reflected in a mismatch in skills, or a mismatch in skills reflected in a mismatch in qualifications (JRC, 2014). Horizontal mismatch occurs when the qualification level is sufficient, but the type or field of qualification does not adequately match. Below, we describe the definitions used to calculate the skills mismatch indicators.

Vertical mismatch (Over/under-education)

Different studies measure education–job mismatches differently depending on the data available. The different approaches have advantages and limitations; none yields more reliable or conceptually more correct estimates than the others (Leuven & Oosterbeek, 2011).

Normative method

Over/under-education is identified using the International Standard Classification of Occupations (ISCO), which categorises major occupational groups by four levels of education per the International Standard Classification of Education (ISCED). ISCO categorises managers, professionals and technicians as requiring skill levels 3 and 4, usually obtained as the result of tertiary level studies; clerical, service and sales workers, skilled agricultural and trade workers, plant and machine operators, and assemblers, as requiring skill level 2 (intermediary level education); and elementary occupations as skill level 1 (primary or the first stage of basic education) (ILO, 2012). Some studies using this methodology when exploring the determinants of skills mismatch are (among others) Chevalier and Lindley (2009) and Green et al. (2007).

Empirical method (the statistical or the realised matches method)

This method estimates the educational requirement of an occupation by assessing the mean or modal level of education within a given occupation (the realised matches) and classifying workers with acquired education above/below the average of the employee's occupation group as over- or underqualified. We used the mode, following other studies (e.g., Kiker et al., 1997; De Oliveira et al., 2000; ILO, 2012).

Horizontal mismatch

Horizontal mismatch measures the extent to which workers, typically graduates, are employed in an occupation unrelated to their principal field of study. The issue in identifying horizontal mismatches is that informal skills acquired through labour market experience and training are not observable and might relate more to the occupation than the person's main field of study (Bergin et al., 2019). It can be defined using both subjective and objective approaches.

This study used the objective approach following Levels et al., 2014; Wolbers, 2003; Béduwé and Giret, 2011; Domadenik et al., 2013. Instead, the normative correspondence method allows occupations and educational qualifications to be aggregated into categories, and using a normative correspondence table can provide a less biased indicator of horizontal mismatch (Somers et al., 2019). However, having too many categories increases the probability that the combination of jobs and field degrees are defined as mismatched despite a large congruence of skills and knowledge (Malamud, 2011). The Tables we used to match occupations and fields of education are available in Appendix 2.

Tables A1-A7 and Figures A1-A7 in Appendix 1 show the summary statistics of the variables used for the analysis by country. The variables available and their classification differ across countries. Overall, we explored the determinants of vertical and horizontal skills mismatches (age group, gender, education level), job characteristics (e.g., permanent/temporary, full-time/part-time), occupation, field of education, and geographical location.

3.2. Estimation strategy

To explore cross-country differences in the determinants of mismatch, we performed a country-by-country estimation using a probit regression, similarly to Adalet McGowan & Andrews (2015) and calculated the marginal effects of each covariate:

Equation 1a: Probit (pooled sample):

$$Y_{itc} = ß_1 + ß_2X_{itc} + ß_3Z_{itc} + \gamma_t + \theta_c + u_{itc};$$

$$P(Y=1|\ X, Z) = \Phi(ß_1 + ß_2X_{itc} + ß_3Z_{itc} + \gamma_t + \theta_c)$$

Equation 1b: Probit (country-by-country):

$$Y_{it} = ß_1 + ß_2X_{it} + ß_3Z_{it} + \gamma_t + u_{it};$$

$$P(Y=1|\ X, Z) = \Phi(ß_1 + ß_2X_{it} + ß_3Z_{it} + \gamma_t)$$

Where Y_{it} is a binary variable equal to one if the individual (i) in the year of interest (t) in country (c) is either vertically mismatched (calculated using either the normative or the empirical method); horizontally mismatched, or both vertically (using the empirical method) and horizontally mismatched. X are covariates at the individual level, such as gender, age group and education level, and Z are covariates describing job characteristics (e.g. permanent/temporary, full-time or part-time, and firm size). Tables A1-A7 in Appendix 1 provide a complete list of the covariates analysed by country. γ_t represents year fixed effects that capture the effect of time trends on the probability of being skills mismatched. θ_c

represents country-fixed effects that capture structural differences in labour markets. $ß_2$ is the vector of coefficients of interest, and their marginal effects capture the average increase in the probability of skills mismatch when there is an increase in a covariate by one unit, while u_{ijt} is the error term.

Following Montt (2017), we also run wage regressions to determine whether, and to what extent, horizontal mismatch, vertical mismatch, and their combination cause a wage penalty (Equations 2a and 2b below).

Equation 2a: Wage regression (pooled sample):

$$\ln(wage)_{itc} = ß_1 + ß_2 F_{itc} + ß_3 Q_{itc} + ß_4 FQ_{itc} + ß_5 X_{itc} + S_i + u_{itc}$$

Equation 2b: Wage regression (country-by-country):

$$\ln(wage)_{it} = ß_1 + ß_2 F_{itc} + ß_3 Q_{it} + ß_4 FQ_{it} + ß_5 X_{it} + S_i + u_{it}$$

Where $wage_i$ is the respondents' hourly wages in PPP-corrected[7]. All wage regressions exclude observations with wages above the 99th and below the 1st percentile in each country. Missing wage values have been imputed to the country-specific mean using the dummy-variable imputation method to avoid further loss of observations (Allison, 2002). F_{it}, Q_{it} and FQ_{it} are dummy variables indicating whether the respondent is mismatched by field-of-study only, is overqualified only or is mismatched by both field-of-study and overqualified, respectively; X is a vector of individual and firm-level controls including gender, age, age-squared, education level achieved, education level achieved -squared, tenure, firm size and dummy variables indicating whether the worker is under a temporary work arrangement, working full time, working in a public organisation or NGO, as well as fixed effects for each field of study (S).

3.3. Identification strategy

We identify the coefficients of interest in the pooled regressions controlling for country-fixed effects in order to account for structural differences in labour markets (e.g. laws, minimum wage policies, gender quotas) and controlling for year-fixed effects, as time trends can capture time-varying differences in skills mismatch that cannot be directly observed, such as economic shocks or changes in labour legislation over time. We do not include occupation fixed effects in our baseline specifications because our key variables (horizontal mismatch and overeducation) are constructed using occupational information. Including occupation fixed effects would absorb much of the relevant variation and may induce multicollinearity or weak identification. Moreover, occupation is partly an outcome of the matching process, so conditioning on it would remove an important channel through which mismatch affects wages.

Threats to identification might arise from the endogeneity of some controls due to unobserved heterogeneity or the endogeneity of education. Also, as we excluded self-employed workers

[7] We used the PPP conversion factor from the World Bank: https://data.worldbank.org/indicator/PA.NUS.PRVT.PP

from the sample, our results might not be generalisable to all workers. We address these concerns by running robustness checks with different model specifications (results available in Appendix B) and discussing them in the robustness checks section.

Given the repeated cross-sectional nature of the data, wage-relevant skill differences between workers with the same qualifications and the same field of education which remain unaccounted for may still bias our results due to skills heterogeneity (Quintini 2011a; Chevalier 2003), as unobservable differences in skills (e.g. soft or social skills) of workers with the same qualifications and the same field could remain unaccounted (Duncan and Dunifon, 2012).

Finally, a limitation of the empirical approach is that the pooled probit specification imposes homogeneous marginal effects across countries. However, the country-specific estimates reveal substantial heterogeneity, including sign reversals for key coefficients, indicating that the pooled model may mask important cross-country differences. The pooled results should therefore be interpreted as average associations rather than structurally stable effects, and caution is warranted when drawing general conclusions

4. Results

4.1 Skills mismatch determinants across countries

Table 1 below presents the marginal effects of the determinants of skills mismatch, estimated using a cross-country probit model with pooled cross-sectional data for the countries of interest. The estimated model explores several determinants of skills mismatch (proxied by qualification mismatch), vertical mismatch (medium and high skills mismatch), over- and under-education, and horizontal mismatch. The marginal effects show the magnitude of changes in the probability of a skills mismatch (measured by binary dependent variables) in response to a one-unit change in the control variables. The control variables are the determinants of skills mismatch suggested by the current literature (socio-demographic characteristics, job characteristics, and, where available, geographical characteristics).

Occupational mismatch

The results in Table 1 (Column 1) show that across the countries in our sample, the probability of being occupationally mismatched (including those with upper-secondary or secondary education working in elementary occupations and those with tertiary education working in medium-skilled occupations) of those with medium education is 1.4 percentage points lower than for those with other qualification levels. The results also show that, compared to the youngest group (15-24 years old), the probability of being occupationally mismatched after 35 decreases at an increasing rate. The employees between 35 and 44 years old are 3 percentage points less likely to be occupationally mismatched than those between 15 and 24 years old, while those between 45 and 65 years old are twice as likely as those between 15 and 24 years old to be occupationally mismatched and those above 65 years old are about three times as likely. Employees aged 25 to 34 are more likely than younger employees to be occupationally mismatched (3.1 percentage points), suggesting difficulties in the job market transition after university. These results are consistent with the current literature, as country-level and cross-country studies find that young people are significantly more likely to be over-skilled than older workers (Allen et al., 2013; OECD, 2013). It could be due to search and information costs, leading to longer times spent finding a position in the labour market (Adalet McGowan & Andrews, 2015). The empirical evidence shows that as workers gain more experience and relevant information about job market opportunities, their mismatch is reduced (Alba-Ramirez, 1993), and they have more time to signal their skills to employers (OECD, 2014).

The results also show that being a full-time employee increases the probability of being occupationally mismatched by 4.2 percentage points. Working in a firm with more than ten employees increases the probability of being occupationally mismatched by about two percentage points. Being male and having a permanent job do not significantly affect the probability of being occupationally mismatched. These results are consistent with Adalet McGowan & Andrews (2015), who find that part-time workers are more likely to be mismatched. Other studies (Sparreboom, 2014; Connolly and Gregory, 2009) suggest that part-time work may be less common, increasing the likelihood of over-skilling. Also, they suggest that a switch from full-time to part-time employment could be obtained at the price of occupational downgrading.

Overeducation and undereducation

The results in Table 1 (Column 2) show that the probability of being over-educated increases by about 15.3 percentage points for employees with medium education compared with employees with other qualification levels.

Age is significantly and negatively correlated with the probability of being over-educated, with the correlation increasing at higher ages. The current literature is consistent with this finding, suggesting that the result can be explained by workers moving into jobs that better fit their skill levels as they gain experience (Adalet McGowan & Andrews, 2015). Also, it could be that workers whose over-skilling is beneficial to firm productivity are more likely to be promoted to jobs that match their skills as they get older (Ibid.). The current literature also suggests that older workers are less likely to be over-skilled and more likely to be under-skilled, as skills learned at school tend to depreciate and become obsolete over time. On the other hand, young people are more likely to be over-skilled as they may be in entry-level jobs where skills demanded do not match their actual skills (Ibid.).

The probability of being over-educated is higher for men, who are 7.7 percentage points more likely than women to be over-educated. These results are in line with Quintini (2011a) and (Adalet McGowan and Andrews, 2015), who uses a different dataset and finds that women are less likely to be over-qualified (OECD, 2013). Both results contradict the assumption that women are more likely to be over-skilled or overqualified due to family constraints or a desire to improve their work-life balance.

Working in a firm with at least 10 workers increases the probability of being overqualified by 1.9 percentage points, whereas having a permanent job has a minor impact (almost null) on overeducation. The current literature suggests that the impact of firm size on skills mismatchvaries depending on the definition and type of mismatch (Adalet McGowan and Andrews, 2015). Also, some studies (including Adalet McGowan and Andrews, 2015) suggest that larger firms can identify and anticipate future skill needs and may choose to hire more over-skilled workers. The finding that there is no significant relationship between mismatch and whether a worker is on a permanent or temporary contract is also consistent with the literature. However, there are some cross-country differences.

Undereducation (Table 1, Column 3) is also higher for those with a medium qualification level by about 3.9 percentage points, while older employees aged 35 and above are more likely than those aged 15 to 24 to be undereducated, with the gap increasing. Men and full-time employees are slightly less likely to be under-educated (by 1.6 and 0.4 percentage points, respectively) as well as those with a permanent job (7.6 percentage points), while employees working in firms with more than ten employees are 6.6 percentage points less likely to be under-educated than those working in smaller firms to be under-educated.

Horizontal mismatch

The results in Table 1 (Column 4) show that employees with medium education are almost as likely to be horizontally mismatched as those with other education levels, while those older than 35 are less likely to be horizontally mismatched than those between 15 and 24. This last result is in line with the finding from (Schweri et al. 2020) (but they use a subjective measure of skills mismatch), while the previous one is not in line with the result found by the same author, as he suggests that the highest education attained has an influence on qualification assessment: VET graduates report more horizontal mismatch, whereas graduates from universities report more overqualification.

Men are less likely than women to be horizontally mismatched (3.5 percentage points), while the opposite is for full-time workers (4.0 percentage points). Those working in firms with more than 10 employees are more likely to work in a mismatched field (by 5.1 percentage points).

Either vertical mismatch (Over/Under-education) or horizontal mismatch

Column 5 in Table 1 describes the determinants of general qualification mismatch (vertical or horizontal mismatch) by socio-demographic and job characteristics. Education is the factor with the strongest effect on mismatches; holding a medium education degree increases the likelihood of being mismatched by 10.8 percentage points. In addition, being a male worker reduces the probability of a mismatch by 1.2 percentage points. On the other hand, having a full-time job, working for a company with at least 10 workers, and having a permanent work contract worsen qualification mismatch (by +3.0, +1.9, and +6.6, respectively).

Table 1: Probit marginal effects of skills-mismatch determinants (pooled sample, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.014***	0.153***	0.039***	-0.006***	0.108***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Age (25-34)	0.031***	-0.076***	-0.016***	0.007**	-0.051***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Age (35-44)	-0.030***	-0.173***	0.020***	-0.026***	-0.164***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Age (45-54)	-0.053***	-0.219***	0.053***	-0.039***	-0.198***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Age (55-65)	-0.067***	-0.235***	0.098***	-0.064***	-0.173***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Older than 65 years old	-0.079***	-0.243***	0.195***	-0.021**	-0.081***
	(0.003)	(0.005)	(0.005)	(0.009)	(0.005)
Gender (dummy)	-0.004***	0.077***	-0.016***	-0.035***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Fulltime (dummy)	0.042***	-0.010***	-0.004**	0.040***	0.030***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Firm size >=10	0.022***	0.019***	-0.066***	0.051***	0.019***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Firm size missing	-0.010	0.101	-0.137***	0.125	-0.002
	(0.047)	(0.072)	(0.049)	(0.093)	(0.072)
Permanent job (dummy)	-0.004***	0.013***	-0.017***	0.067***	0.066***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Country F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	863,656	870,562	870,562	408,803	803,230

Source: LFS surveys (2016-2019). The data for Egypt is only available for 2016 and 2017.
Notes: The coefficients are the probit marginal effects. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

4.2 Heterogeneity of skills mismatch determinants across countries

Tables 2-8 below show the marginal effects of the determinants of skills mismatch obtained, estimating country-to-country probit models and using repeated cross-sectional data for the countries of interest. The coefficients displayed in the tables are the marginal effects of the probit model.

Occupational mismatch

The results show that occupational mismatch negatively correlates with medium education in all the countries of interest, except for Palestine and Egypt (Tables 2 and 6, Column 1). While the impact of medium education in Egypt is negligible, in Palestine, employees with medium education have a ten percentage points higher probability than employees with higher education levels of being occupationally mismatched (either at the medium or the high education level). Holding medium qualifications decreases the probability of being occupationally mismatched, especially in Albania (by 10.3 percentage points; Table 4) and Georgia (by 14.2 percentage points; Table 7). This result suggests that occupational mismatch in most countries is driven by the share of those with medium education working in elementary occupations.

The results show mixed evidence about the correlation between occupational mismatch and age. In some countries such as Egypt, Serbia, Albania and Türkiye, older cohorts of employees (older than 46 years old) have a significantly lower probability of being occupationally mismatched compared to younger ones (between 15 and 24 years old) (see Tables 2, 4, 5 and 8, Column 1). These results are consistent with the stream of literature suggesting that the older the employees get, the more experience they have and the better they can signal their skills in the labour market (Crompton, 2002; Dorn and Sousa-Poza, 2005; Bergin et., 2019). The opposite is true in Armenia, where older cohorts have significantly higher probabilities of being occupationally mismatched (Table 3, this publication). They also align with the literature on the incidence of qualification mismatch (primarily under-qualification) in Palestine (Awrad and Care, 2015).

The results also show mixed evidence about the impact of gender on occupational mismatch. In Egypt, Serbia, Palestine, and Georgia, male employees have a significantly higher probability of being occupationally mismatched (by 1.8, 0.6, 0.8 and 3.2 percentage points, respectively) (see Tables 2, 5, 6 and 7, Column 1). In all the other countries, being a male employee is negatively correlated with the probability of being occupationally mismatched. The effects are stronger in Armenia (1.8 percentage points) and Albania (2.6 percentage points) (see Tables 3 and 4, Column 1). These results confirm the findings in the current literature, which find that female workers are more likely to be overqualified or underqualified than male workers (Morrar and Zwick, 2021).

Being married is negatively correlated with the probability of being occupationally mismatched across all countries with available data (Egypt, Albania, Palestine, and Türkiye), except in Serbia, where the coefficient is not statistically significant (see Table 5, Column 1). Being born abroad[8] is positively correlated with occupational mismatch in both Serbia (an increase of 2.3 percentage points in the probability of being occupationally mismatched) and Türkiye (an increase of 3.1 percentage points in the probability of being occupationally mismatched) (see Tables 5 and 8). This result is in line with the findings of Adalet McGowan and Andrews (2015), who also suggest that immigrants are less likely to be over-skilled (Column 2) and more likely to be under-skilled in several OECD countries. At the same time, it is not significantly correlated with occupational mismatch in Albania.

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[8] The variable is not available for all the countries of interest.

Regarding job characteristics, working full-time is positively correlated with the probability of being occupationally mismatched in Egypt (Table 2, Column 1), Serbia (Table 5, Column 1), and Türkiye (Table 8, Column 1) while having a full-time job significantly decreases the probability of being occupationally mismatched compared to having a part-time job in Armenia, Albania, and Georgia. Both results are consistent with the current literature. Some studies find that part-time workers are more likely to be mismatched as occupational choices in this type of work could be more limited, raising the probability of over-skilling and a switch from full-time to part-time employment, which could entail occupational downgrading (Adalet McGowan and Andrews, 2015; Sparreboom, 2014; Connolly and Gregory, 2009). Other studies find that workers with full-time contracts, compared to others, are more likely to face qualification mismatches (especially underqualification) (Morrar and Zwick, 2021).

Having a permanent job decreases the probability of being occupationally mismatched compared with a temporary one, except in Türkiye, where a permanent job significantly increases the probability of being occupationally mismatched by 4.4 percentage points. The current literature shows that the results differ across countries (Adalet McGowan and Andrews, 2015 Bergin et al., 2019) and that young workers, who are often forced to take a temporary job to avoid unemployment or poverty, are more prone to educational mismatch than those holding longer-term jobs. Employers offering permanent jobs are usually interested in long-term employment relationships and try to match workers' skills and aspirations to jobs to avoid high labour turnover and low productivity (Bergin et al., 2019).

Consistently with the findings in the current literature, the effects of firm size on occupational mismatch are mixed. Being employed in a larger firm is positively associated with the probability of being occupationally mismatched in Egypt, Albania, Serbia, and Türkiye (Tables 2, 4, 5, and 8, Column 1). In contrast, it is negatively correlated with the probability of being occupationally mismatched in Georgia (Tables 7, Column 1). The current literature finds an ambiguous relationship between firm size and skills mismatch(Adalet McGowan and Andrews, 2015). Quintini (2011a) finds no significant relationship between skills mismatchand firm size, but other cross-country studies find that over-skilling increases with firm size (Allen et al., 2013). It could be because large firms are more complex and matching workers to the right jobs is more difficult. Another explanation could be that larger firms, which are likely to be less financially constrained, can afford to use a recruitment strategy to ensure hiring highly skilled workers and hoarding them. At the same time, they could invest in training high-skilled workers (Cedefop, 2012). Such management practices might result in over-skilling in larger firms. On the other hand, better human resource policies at large firms can enable the transfer of workers to better matches within the firm, reducing mismatches.

We also explored the influence of the geographical variable rural/urban area (where available) on the probability of being occupationally mismatched. Living in a rural area significantly increases the probability of being occupationally mismatched both in Armenia (2.3 percentage points) (see Table 3, Column 1) and in Palestine (1.7 percentage points) (see Table 6, Column 1). Such findings align with theory and empirical findings (see Berlingeri, 2019 Morrar and Zwick, 2021, for instance). Spatial isolation reduces the size of labour markets and, consequently, the number and types of employment opportunities and the probability of finding a job that matches workers' qualifications. In comparison, it decreases the probability of being occupationally mismatched in Egypt (1.8 percentage points) (see Table 2, Column 1).

Overeducation

The results show heterogeneous effects across countries regarding the influence of socio-demographic characteristics on the probability of an employee being either over- or under-educated. In some countries, having medium qualifications increases the likelihood of being occupationally mismatched, including Albania, Egypt, Palestine, and Türkiye. The positive impact of holding medium qualifications on the probability of mismatch is higher in Egypt (6 percentage points), Albania (50.9 percentage points), Palestine (49.2 percentage points) and Türkiye (29.8 percentage points). Instead, the effect is negative in Armenia, Serbia, and Georgia.

Age is negatively correlated with the probability of being over-educated in all the countries of interest, except for Georgia, Armenia, and Palestine. This likely reflects skills obsolescence: in ex-Soviet countries older cohorts were educated under the Soviet-era or early post-transition system, which lagged behind modern labour market demands (Cedefop, 2015; McGuinness, 2006). Such historical and structural factors can thus explain deviations from standard age-overeducation patterns.

Being a male employee increases the probability of being over-educated in all the countries analysed, except in Egypt, Albania, and Serbia, where it significantly increases the probability by 2.3, 5.7, and 0.4 percentage points, respectively. Being married, instead, significantly decreases the probability of being over-educated in all the countries of interest, except Serbia (where the decrease is very small) and Albania, where the probability of being overeducated increases by 2.6 percentage points for married individuals.

Regarding job-related characteristics, having a full-time job significantly decreases the probability of being over-educated in some countries of interest (Egypt, Türkiye, Georgia, and Palestine), while it increases in Albania and is not significant in others. The results show mixed evidence about the impact of having a permanent job on the probability of being over-educated. The impact is positive in Armenia and Albania but negative in Serbia and Türkiye. The effects of firm size are also mixed, though predominantly negative, in the countries in our sample, except for Egypt, Serbia, and Palestine, where they are positive (Table 2, Table 5, and Table 6, Column 2).

Finally, being an employee in a rural area increases the probability of being overqualified in Egypt and Palestine (by 3.1 and 1.8 percentage points) while decreasing it in Armenia (6 percentage points).

Undereducation

Undereducation is positively correlated with medium education in almost all the countries of interest, except for Egypt, Serbia, Palestine, and Georgia, where the probability of being undereducated decreases by about 16.4, 3.5, 14.5, and 4.3 percentage points if the employee has medium qualifications. Being a male employee is also positively correlated with being under-educated in almost all the countries of interest, except for Georgia and Türkiye, where it is negatively correlated. Married employees have a higher probability of being undereducated than unmarried ones in all the countries analysed, except in Albania, where being married decreases the probability of being undereducated by 3.5 percentage points.

Job characteristics also affect the probability of being undereducated. Working full-time significantly decreases the probability of being undereducated in all countries of interest, except in Egypt, Serbia, and Georgia (see Table 2, Table 5, and Table 7, Column 2), where it is positively correlated. A permanent job decreases the probability of being undereducated, except for Georgia, where having a permanent job increases the probability of being undereducated by about 2.1 percentage points. Firm size is negatively correlated with the probability of being under-educated in almost all the countries in the sample, except Palestine and Albania, where it is positively correlated (see Tables 4 and 6, Column 3). Working in the private sector is positively correlated with being undereducated in Albania and Palestine but negatively correlated in Georgia and Türkiye. Finally, living in a rural area increases the likelihood of being undereducated in both Egypt and Armenia, whereas it plays no significant role in Palestine.

Horizontal mismatch

Employees who hold medium qualifications are more likely to be horizontally mismatched than those with other qualifications in all the countries of interest, except for Serbia, Türkiye, and Armenia, where they are less likely to be field-mismatched (see Tables 2-5, 7-8, Column 4).

The effects of age on horizontal mismatch are mixed. Older employees are more likely to be horizontally mismatched than younger employees in Egypt (Table 2, Column 5), Albania (Table 4, Column 4) and Georgia (Table 7, Column 4). They are instead less likely to be horizontally mismatched than younger employees in Armenia (Table 3, Column 4), Serbia (Table 5, Column 4) and Türkiye (Table 8, Column 4). These last findings are consistent with Schweri et al. 2020, who find that the proportion of those suitably qualified increases slightly with age.

The impact of marriage on horizontal mismatch is mixed across the countries of interest. It is positive in Türkiye and negative in Egypt, Albania, and Serbia. The results for these last three countries are consistent with the literature, which finds that individuals who are not married or have never been married are more likely to be mismatched than married employees (Robst, 2007a; Bender and Roche, 2013).

Male employees are less likely than female employees to be horizontally mismatched in Armenia, Georgia, and Türkiye, whereas they are more likely to be horizontally mismatched in the other countries in the sample. In Egypt, however, gender plays almost no role. These results are consistent with the current literature, which shows mixed results. Some studies suggest that females are more likely to be mismatched than their male counterparts (Hensen et al., 2009; Farooq, 2011). Other studies find that males are more likely to be mismatched than females (Bender and Heywood, 2011).

Employees with permanent jobs are more likely to be horizontally mismatched than employees with temporary jobs. These results are consistent with those of Robert (2014). An explanation could be that employees might also accept a horizontal mismatch in return for job safety provided by a permanent contract. Other studies suggest the opposite (Wolbers, 2003; Boudarbat and Chernoff, 2012) and can be justified by the fact that employees with a temporary contract are expected to leave the company earlier, and employers are generally reluctant to offer company-funded training due to the shorter payback period of such investments (Becker, 1962; Booth and Bryan, 2002).

The effects of firm size on the probability of being horizontally mismatched are mixed, positive in some countries (Egypt, Serbia, Georgia, Türkiye) and negative in the other countries analysed (e.g. Armenia, Albania). Similarly, the current literature finds mixed results. Some studies suggest that employees in larger firms are more likely to be well matched (see Hamilton, 1987 and Wolbers, 2003) as they offer diverse opportunities, while other studies find the opposite (Witte and Kalleberg, 1995), which could be explained by the fact that in larger firms individuals might be more incentivized to accept horizontal mismatch due to higher wages, job security and other job advantages (Kalleberg and Van Buren, 1992).

Having a full-time job increases the probability of being horizontally mismatched in almost all the countries in the sample (Egypt, Albania, and Georgia), but it decreases in Armenia and Türkiye. In Serbia, the effect is not statistically significant. Finally, we also investigate the effects of living in rural/urban areas on horizontal mismatch where the variable is available. Results show no significant impact of residence on the field-education mismatch.

Either vertical mismatch (Over/Under-education) or horizontal mismatch

Column 5 describes the marginal effects of the determinants of general skill mismatch. An employee is defined as mismatched when they are over- or under-educated, or horizontally mismatched. Results show a negative impact of having a medium education qualification on a general mismatch in most countries, including Egypt (Table 2), Armenia (Table 3), Serbia (Table 5), and Georgia (Table 7). Whilst analysis in Albania (Table 4) and the pooled sample (Table 1) show an increase in the probability of mismatch by about 10 percentage points when having a medium education qualification.

The impacts of age on general mismatch show an interesting pattern across and within countries. In general, increasing age reduces the probability of being mismatched. The magnitude of impacts increases with age between 25 and 54 years and decreases from 55 years onwards (Table 1, 7, and 8). In some countries, the negative effects increase gradually with age, even for senior workers, as in Serbia and Albania, while in Egypt, the effect turns positive. In Armenia, being a senior worker aged 55 years or older is not impacted by mismatches.

On average, being a male worker reduces the probability of being mismatched by 1.2 percentage points (Table 1), whereas the country analysis shows a mixed pattern. For instance, in Armenia (Table 3), Albania (Table 4), Serbia (Table 5), and Georgia (Table 7), being male worsens the likelihood of being mismatched, while in Türkiye (Table 8), it reduces the probability of mismatch (by 0.4 percentage points) slightly. In addition, being married (where available) also reduces the probability of being mismatched (e.g. Egypt – Table 2, Albania – Table 5, and Türkiye – Table 8).

Regarding job characteristics, having a permanent job is associated with a higher likelihood of being a mismatched worker, on average, by 6.6 percentage points (Table 1). The result also holds for country analysis, except for Serbia (Table 5). The positive association between permanent employment and skills mismatch may reflect the persistence of suboptimal matches in segmented labour markets. Workers in permanent positions often face higher mobility costs and may remain in mismatched jobs due to job security, firm-specific human capital, or limited outside options, consistent with evidence that mismatch can persist over time rather than being purely transitory (e.g., Allen and van der Velden, 2001; Green and McIntosh, 2007). In addition, permanent contracts are more prevalent in labour market segments characterised by institutional rigidities and mobility costs, which hinder the efficient reallocation of workers to better-matched jobs (Dolado et al., 2009).

On the other hand, having a full-time job has an unclear impact on mismatch. It creates, on average, a three-percentage-point increase in the probability of mismatch across countries (Table 1), as well as in Egypt (by 3% points – Table 2) and Albania (by 12.1% points - Table 4). However, in Armenia (Table 3) and Türkiye (Table 8), having a full-time job increases the chance of a mismatch for employees. Like having a full-time job, the firm size characteristic does not show a clear trend in mismatch.

Table 2: Probit marginal effects of skills-mismatch determinants (Egypt, 2016-2017)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	0.006***	0.060***	-0.164***	0.028***	-0.033***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)
Age (25-34)	0.026***	0.011**	-0.056***	0.013*	-0.014***
	(0.003)	(0.004)	(0.004)	(0.007)	(0.004)
Age (35-44)	0.008**	-0.033***	0.010*	0.042***	-0.022***
	(0.003)	(0.005)	(0.005)	(0.008)	(0.005)
Age (45-54)	-0.029***	-0.107***	0.090***	0.077***	-0.054***
	(0.003)	(0.005)	(0.006)	(0.008)	(0.005)
Age (55-65)	-0.050***	-0.154***	0.139***	0.080***	-0.096***
	(0.003)	(0.005)	(0.007)	(0.010)	(0.006)
Older than 65 years old	-0.056***	-0.170***	0.304***	-0.022	0.028**
	(0.004)	(0.010)	(0.016)	(0.051)	(0.013)
Gender (dummy)	0.018***	-0.023***	0.072***	-0.009**	0.003
	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Married (dummy)	-0.021***	-0.034***	0.022***	-0.045***	-0.036***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)
Fulltime (dummy)	0.013***	-0.040***	0.023***	0.069***	0.030***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.004)
Permanent job (dummy)	-0.007***	0.001	-0.032***	0.161***	0.102***
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Hours worked	0.001***	-0.000	0.001***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (dummy)	-0.019***	0.031***	0.008***	-0.072***	-0.052***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.003)
Firm size (10-24)	0.034***	0.067***	-0.117***	0.110***	0.023**
	(0.006)	(0.009)	(0.010)	(0.014)	(0.010)
Firm size (25-49)	0.039***	0.071***	-0.135***	0.145***	0.035***
	(0.007)	(0.011)	(0.012)	(0.016)	(0.011)
Firm size (>=50)	0.046***	0.074***	-0.151***	0.167***	0.052***
	(0.004)	(0.006)	(0.007)	(0.009)	(0.006)
Firm size missing (dummy)	-0.009***	0.056***	-0.090***	0.138***	0.031***
	(0.002)	(0.004)	(0.005)	(0.007)	(0.004)
Sample weights	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	120,010	120,010	120,010	71,364	120,020

Source: Egyptian LFS survey (2016-2017).

Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 3: Probit marginal effects of skills-mismatch determinants (Armenia, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.025***	-0.079***	0.013***	-0.176***	-0.092***
	(0.006)	(0.006)	(0.004)	(0.016)	(0.005)
Age (25-34)	0.025**	0.014	-0.049***	-0.019**	-0.025**
	(0.010)	(0.011)	(0.008)	(0.008)	(0.010)
Age (35-44)	0.010	-0.005	-0.031***	-0.022***	-0.025**
	(0.010)	(0.011)	(0.008)	(0.008)	(0.010)
Age (45-54)	0.032***	0.014	-0.042***	-0.027***	-0.033***
	(0.011)	(0.012)	(0.008)	(0.008)	(0.010)
Age (55-65)	0.066***	0.018	-0.028***	-0.009	-0.012
	(0.011)	(0.011)	(0.009)	(0.008)	(0.010)
Older than 65 years old	0.077***	-0.003	-0.009	0.002	-0.007
	(0.018)	(0.017)	(0.013)	(0.013)	(0.015)
Gender (dummy)	-0.018***	0.060***	0.004	-0.026***	0.024***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Fulltime (dummy)	-0.044***	-0.008	-0.021***	-0.021**	-0.039***
	(0.011)	(0.012)	(0.008)	(0.010)	(0.010)
Permanent job (dummy)	-0.074***	0.044***	-0.022***	0.028***	0.036***
	(0.009)	(0.011)	(0.007)	(0.009)	(0.009)
Hours worked	0.004***	0.004***	0.000	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (dummy)	0.023***	-0.060***	0.016***	-0.007	-0.029***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Firm size (10-19)	0.014	-0.027*	-0.004	-0.012	-0.020
	(0.013)	(0.014)	(0.009)	(0.011)	(0.013)
Firm size (20-49)	0.006	-0.046***	0.002	-0.002	-0.014
	(0.014)	(0.014)	(0.009)	(0.011)	(0.013)
Firm size (>=50)	0.013	-0.028**	-0.002	-0.026***	-0.021**
	(0.010)	(0.011)	(0.007)	(0.009)	(0.010)
Firm size missing (dummy)	-0.045***	-0.098***	-0.008	0.038***	-0.019**
	(0.008)	(0.009)	(0.005)	(0.006)	(0.007)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sample weights	Yes	Yes	Yes	Yes	Yes
Observations	21,966	22,251	22,251	10,865	22,251

Source: Armenian LFS survey (2016-2019).
Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 4: Probit marginal effects of skills-mismatch determinants (Albania, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.103***	0.509***	0.055***	0.050***	0.137***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Age (25-34)	-0.030***	-0.035***	-0.069***	0.019**	-0.153***
	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
Age (35-44)	-0.040***	-0.015*	-0.079***	-0.044***	-0.214***
	(0.006)	(0.009)	(0.009)	(0.008)	(0.009)
Age (45-54)	-0.014**	-0.077***	-0.034***	-0.010	-0.130***
	(0.006)	(0.009)	(0.009)	(0.008)	(0.009)
Age (55-65)	-0.017**	-0.129***	-0.023**	0.042***	-0.110***
	(0.007)	(0.009)	(0.010)	(0.009)	(0.009)
Older than 65 years old	-0.070***	-0.137***	-0.048	0.000	-0.167***
	(0.017)	(0.031)	(0.029)	(0.028)	(0.031)
Gender (dummy)	-0.026***	-0.057***	0.061***	-0.005	0.022***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Married (dummy)	-0.040***	0.026***	-0.035***	-0.028***	-0.078***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
Born abroad (dummy)	-0.004	-0.054	0.066	0.067*	0.178***
	(0.028)	(0.045)	(0.042)	(0.039)	(0.046)
Citizenship (dummy)	0.026	-0.081*	0.038	-0.036	0.074*
	(0.031)	(0.044)	(0.044)	(0.036)	(0.042)
Fulltime (dummy)	-0.054***	0.078***	-0.034***	0.045***	0.121***
	(0.009)	(0.015)	(0.013)	(0.012)	(0.014)
Permanent job (dummy)	-0.018***	0.016*	-0.016**	0.017***	0.055***
	(0.005)	(0.008)	(0.007)	(0.006)	(0.007)
Private sector (dummy)	0.045***	-0.080***	0.113***	-0.089***	-0.084***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)

Hours worked	0.001***	-0.001***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm-size (11-19)	-0.003	-0.014**	0.029***	-0.036***	-0.053***
	(0.004)	(0.007)	(0.006)	(0.006)	(0.006)
Firm-size (20-49)	-0.003	-0.066***	0.054***	-0.074***	-0.105***
	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)
Firm-size (>=50)	0.022***	-0.083***	0.122***	-0.090***	-0.091***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
Firm-size missing (dummy)	0.004	-0.047***	0.078***	-0.080***	-0.062***
	(0.004)	(0.007)	(0.006)	(0.006)	(0.007)
Sample weights	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	52,737	37,634	53,438	53,438	53,438

Source: Albanian LFS survey (2016-2019).
Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 5: Probit marginal effects of skills-mismatch determinants (Serbia, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.046***	-0.091***	-0.035***	-0.107***	-0.181***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Age (25-34)	-0.015***	0.054***	0.007	-0.097***	0.053***
	(0.005)	(0.006)	(0.005)	(0.008)	(0.006)
Age (35-44)	-0.061***	-0.006	0.041***	-0.368***	-0.062***
	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)
Age (45-54)	-0.067***	-0.005	0.021***	-0.456***	-0.114***
	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)
Age (55-65)	-0.106***	-0.019***	0.046***	-0.492***	-0.119***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)
Older than 65 years old	-0.118***	0.008	0.001	-0.500***	-0.132***
	(0.010)	(0.015)	(0.013)	(0.009)	(0.017)
Gender (dummy)	0.006***	-0.004*	0.052***	0.023***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Married (dummy)	-0.001	-0.006**	0.009***	-0.006**	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Born abroad (dummy)	0.023***	0.033***	-0.022***	-0.009**	0.010**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Fulltime (dummy)	0.013**	-0.024***	0.037***	0.000	0.008
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)
Permanent job (dummy)	-0.029***	-0.030***	-0.024***	0.024***	-0.044***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Formal job (dummy)	0.007	-0.022***	-0.046***	0.031***	-0.026***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Firm size (11-19)	0.006	0.021***	-0.030***	0.024***	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
Firm size (20-49)	-0.004	-0.004	-0.063***	0.044***	-0.046***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Firm size (>=50)	0.020***	0.017***	-0.072***	0.048***	-0.038***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Sample weights	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	126,732	130,288	130,288	85,053	130,288

Source: Serbian LFS survey (2016-2019).
Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 6: Probit marginal effects of skills-mismatch determinants (Palestine, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education
Medium education (dummy)	0.100***	0.492***	-0.145***
	(0.003)	(0.003)	(0.006)
Gender (dummy)	0.008**	0.082***	-0.005
	(0.004)	(0.005)	(0.005)
Age (25-34)	0.059***	0.098***	-0.045***
	(0.004)	(0.005)	(0.006)
Age (35-44)	0.009**	0.061***	0.053***
	(0.004)	(0.006)	(0.007)
Age (45-54)	0.002	0.035***	0.149***
	(0.005)	(0.006)	(0.008)
Age (55-65)	0.011*	0.044***	0.213***
	(0.006)	(0.008)	(0.011)
Older than 65 years old	-0.040***	0.008	0.265***
	(0.012)	(0.024)	(0.034)
Married (dummy)	-0.022***	-0.040***	0.035***
	(0.004)	(0.005)	(0.006)
Rural (dummy)	0.017***	0.018***	-0.004
	(0.003)	(0.003)	(0.004)
Private sector (dummy)	0.025***	-0.009	0.024***
	(0.005)	(0.005)	(0.006)
Firm size (>=10)	0.002	0.015***	-0.031***
	(0.003)	(0.004)	(0.005)
Firm size missing (dummy)		-0.029	0.174
		(0.085)	(0.113)
Hours worked	0.000**	0.002***	-0.001***
	(0.000)	(0.000)	(0.000)
Fulltime (dummy)	0.010	-0.049***	-0.024**
	(0.008)	(0.010)	(0.012)
Permanent job	-0.016***	0.058***	-0.067***
	(0.005)	(0.005)	(0.006)
Sample weights	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	48,665	50,078	50,078

Source: Palestinian LFS survey (2016-2019).

Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 7: Probit marginal effects of skills-mismatch determinants (Georgia, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.142***	-0.621***	-0.043***	0.427***	-0.445***
	(0.004)	(0.040)	(0.004)	(0.025)	(0.003)
Age (25-34)	0.038***	0.050***	-0.056***	-0.006	-0.004
	(0.008)	(0.006)	(0.009)	(0.014)	(0.008)
Age (35-44)	0.019**	0.060***	-0.187***	-0.010	-0.096***
	(0.008)	(0.006)	(0.008)	(0.014)	(0.008)
Age (45-54)	-0.002	0.053***	-0.239***	0.000	-0.137***
	(0.008)	(0.006)	(0.008)	(0.015)	(0.008)
Age (55-65)	0.000	0.035***	-0.240***	0.045***	-0.133***
	(0.008)	(0.006)	(0.008)	(0.015)	(0.008)
Older than 65 years old	-0.038***	0.009	-0.227***	0.073***	-0.128***
	(0.010)	(0.008)	(0.010)	(0.018)	(0.011)
Gender (dummy)	0.032***	0.055***	-0.036***	-0.048***	0.008**
	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)
Fulltime (dummy)	-0.023**	-0.033***	-0.005	0.043***	-0.016
	(0.010)	(0.007)	(0.008)	(0.014)	(0.010)
Permanent job (dummy)	-0.060***	0.003	0.021***	0.099***	0.060***
	(0.006)	(0.007)	(0.006)	(0.019)	(0.006)
Private sector (dummy)	0.079***	0.077***	-0.039***	-0.000	0.044***
	(0.004)	(0.003)	(0.004)	(0.006)	(0.004)
Hours worked	0.003***	0.003***	-0.001***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (11-19)	-0.017***	-0.025***	0.012**	0.027***	0.001
	(0.006)	(0.005)	(0.006)	(0.010)	(0.007)
Firm size (20-49)	-0.021***	-0.047***	-0.009*	0.010	-0.056***
	(0.006)	(0.004)	(0.005)	(0.009)	(0.006)
Firm size (>=50)	-0.014***	-0.023***	-0.028***	0.046***	-0.031***
	(0.005)	(0.004)	(0.005)	(0.009)	(0.006)
Firm size missing (dummy)	0.051***	0.010	-0.041***	0.015	-0.043***
	(0.007)	(0.007)	(0.006)	(0.013)	(0.007)
Sample weights	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	46,849	47,702	47,702	23,103	47,702

Source: Georgian LFS survey (2016-2019).

Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 8: Probit marginal effects of skills-mismatch determinants (Türkiye, 2016-2019)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch	(5) Mismatch (Horizontal and vertical)
Medium education (dummy)	-0.008***	0.298***	0.187***	-0.062***	
	(0.001)	(0.001)	(0.001)	(0.003)	
Gender (dummy)	-0.008***	0.137***	-0.070***	-0.058***	-0.004**
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Married (dummy)	-0.050***	-0.034***	0.027***	0.023***	-0.044***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Age (25-34)	0.051***	-0.115***	-0.022***	-0.023***	-0.098***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
Age (35-44)	-0.010***	-0.235***	0.019***	-0.042***	-0.275***
	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)
Age (45-54)	-0.044***	-0.295***	0.079***	-0.040***	-0.307***
	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)
Age (55-65)	-0.066***	-0.351***	0.158***	-0.049***	-0.279***
	(0.002)	(0.003)	(0.003)	(0.007)	(0.004)
Older than 65 years old	-0.093***	-0.382***	0.401***	-0.022	-0.067***
	(0.004)	(0.007)	(0.009)	(0.023)	(0.009)
Born abroad (dummy)	0.031***	0.098***	-0.002	-0.010	0.106***
	(0.003)	(0.005)	(0.004)	(0.008)	(0.006)
Private sector (dummy)	-0.036***	0.060***	-0.048***	-0.058***	-0.214***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Fulltime (dummy)	0.076***	-0.013***	-0.083***	-0.014**	-0.022***
	(0.003)	(0.004)	(0.003)	(0.007)	(0.004)
Permanent job (dummy)	0.044***	-0.008***	-0.025***	0.117***	0.070***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)
Firm size (11-19)	0.017***	-0.015***	-0.041***	0.019***	-0.015***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)
Firm size (20-49)	0.013***	0.003	-0.064***	0.029***	-0.004
	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)
Firm size (>=50)	0.041***	0.052***	-0.076***	0.010***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Firm size missing (dummy)	-0.016	0.010	-0.024	-0.022	0.009
	(0.012)	(0.018)	(0.017)	(0.041)	(0.023)
Hours worked	-0.000***	0.002***	0.003***	-0.005***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sample weights	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	417,748	417,748	417,748	176,402	320,963

Source: Turkish LFS survey (2016-2019).
Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

5. The wage effects of over-education and horizontal mismatch

We analyse the impact of vertical mismatch (overeducation), horizontal mismatch, and both measures on wages. Table 9 shows the impact of overeducation, horizontal mismatch and their combination on monthly wages on the pooled sample, while the results by country are shown in Tables 10-14. For Palestine was not possible to calculate the effect of horizontal mismatch on wages due to data limitations.

In general, overeducation and horizontal mismatch significantly impact wages across countries (Table 9). Specifically, being over-educated reduces the monthly wage by 7.8%, while being horizontally mismatched increases the monthly wage by 7.5% (Table 9, columns 1 and 2). The effect of skills mismatch on wages is positive for those employees who are both over-educated and horizontally mismatched, as these two types of skills mismatches increase the monthly wage by 1% (-0.102 + 0.044 + 0.069 ≈ +0.011) (Table 9, column 3). These results are in line with the current literature (Montt, 2017; Béduwé and Giret, 2011; Kim et al., 2012; Kelly, O'Connell et al., 2010), suggesting that overqualified workers pay a wage penalty, while this is not always true for those who are mismatched to their field of education (Montt, 2017). The fact that horizontal mismatch has no effect can be explained by the fact that the human capital acquired in one field is transferable to another without negatively affecting the salary (Béduwé and Giret, 2011). However, the other studies (Montt, 2017; Kim, et al., 2012 and Kelly, O'Connell et al., 2010) also find that those who are both overqualified and horizontally mismatched pay a wage penalty in all the countries object of the study. The effects of both types of mismatches can accumulate: the salary disadvantage can be due to an insufficient job level and an underutilization of the worker's skills (Béduwé and Giret, 2011).

The impact of skills mismatch on wages in some countries (Türkiye, Albania, and Palestine) is in line with the results obtained for the pooled sample (Tables 10 and 11). The strongest impact of mismatch on wages is found in Türkiye, where horizontally mismatched employees have a monthly wage 10.1% higher than those who are not, while over-education reduces the wage by 24.2%. The combination of the two types of mismatches (over-education and horizontal) increases monthly wages by 5.9%. The negative impact of skills mismatch in Albania is less than half of the one in Türkiye. For instance, in Albania, being over-educated reduces the employee's wage by 11.6% and being horizontally mismatched increases it by 2.6%, while their combination increases it by 13.9%.

In Egypt and Armenia, the results do not match those of the pooled analysis. In Egypt, the combined effects of skills mismatch on wages are negative, while in Armenia, they are not statistically significant (Table 12 and 13). In Egypt, being over-educated results in a 3.1% reduction in monthly income while being horizontally mismatched, and both types of mismatches are +3.8% and -6.7%. Montt (2017) explains that the positive impact of horizontal mismatch on wages is due to the high salary effects of some fields of education, which attract the most productive workers from other fields of study. Another explanation is that employers may equally value graduates from different fields. Therefore, in the end, horizontally mismatched workers are not subject to a wage penalty even though they lack job-specific skills.

Table 9: The impact of over education, horizontal mismatch, and their combination on wages (pooled sample)

VARIABLES	(1) log(Wage) corrected by PPP	(2) log(Wage) corrected by PPP	(3) log(Wage) corrected by PPP
Overeducation	-0.078***		-0.102***
	(0.002)		(0.003)
Horizontal mismatch		0.075***	0.044***
		(0.002)	(0.002)
Overeducation*Horizontal mismatch			0.069***
			(0.004)
Country F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Field of education F.E.	Yes	Yes	Yes
Observations	244,592	241,347	241,338
R-squared	0.646	0.640	0.642

Source: Pooled data LFS survey (2016-2019). Data for Egypt are just available for 2016-2017.
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 10: The impact of over-education, horizontal mismatch, and their combination on wages (Türkiye)

VARIABLES	(1) log(Wage) corrected by PPP	(2) log(Wage) corrected by PPP	(3) log(Wage) corrected by PPP
Overeducation	-0.242***		-0.250***
	(0.008)		(0.010)
Horizontal mismatch		0.101***	0.059***
		(0.006)	(0.007)
Overeducation*Horizontal mismatch			0.059***
			(0.013)
Field of education F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	176,402	176,402	176,402
R-squared	0.253	0.249	0.253

Source: Turkish LFS survey (2016-2019).
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 11: The impact of over education, horizontal mismatch, and their combination on wages (Albania)

VARIABLES	(1) log(Wage) corrected by PPP	(2) log(Wage) corrected by PPP	(3) log(Wage) corrected by PPP
Overeducation	-0.115***		-0.200***
	(0.006)		(0.010)
Horizontal mismatch		0.026***	-0.003
		(0.008)	(0.008)
Overeducation*Horizontal mismatch			0.139***
			(0.012)
Field of education F.E.	Yes	Yes	Yes
Observations	10,754	10,120	10,120
R-squared	0.390	0.365	0.396

Source: Albanian LFS survey (2016-2019).
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 12: The impact of over education, horizontal mismatch, and their combination on wages (Armenia)

VARIABLES	(1) log(Wage) corrected by PPP	(2) log(Wage) corrected by PPP	(3) log(Wage) corrected by PPP
Overeducation	-0.025		0.028
	(0.019)		(0.132)
Horizontal mismatch		-0.031	-0.031
		(0.034)	(0.034)
Overeducation* Horizontal mismatch			-0.005
			(0.132)
Field of education F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	11,157	10,865	10,865
R-squared	0.126	0.122	0.122

Source: Armenian LFS survey (2016-2019). Data for Egypt are just available for 2016-2017.
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 13: The impact of over education, horizontal mismatch, and their combination on wages (Egypt)

VARIABLES	(1) log(Wage) corrected by PPP	(2) log(Wage) corrected by PPP	(3) log(Wage) corrected by PPP
Overeducation	-0.031***		0.049***
	(0.003)		(0.005)
Horizontal mismatch		0.038***	0.056***
		(0.003)	(0.003)
Overeducation* Horizontal mismatch			-0.067***
			(0.007)
Field of education F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	74,648	71,655	71,645
R-squared	0.229	0.238	0.240

Source: Egyptian LFS survey (2016-2017).
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table 14: The impact of over-education on wages (Palestine)

VARIABLES	(1) log(Wage) corrected by PPP
Overeducation	-0.147***
	(0.015)
Year F.E.	Yes
Observations	67,342
R-squared	0.110

Source: Palestinian LFS survey (2016-2017).
Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix. Field of education fixed effects not available.

6. Robustness checks

We run robustness checks to address issues with our identification strategy. The results are shown in Tables B1-B3 in the Appendix. Overall, the results are stable to other specifications of the model.

Education is an important determinant of skills mismatch. Thus, we included it in the main analysis to be consistent with other studies on the determinants of skills mismatch. However, a concern with our identification strategy is the endogeneity of the education variable, since the skills-mismatch indicators are constructed using the highest education level attained. Table B2 in the Appendix shows that our results are robust to this specification.

As most studies on skills mismatch in the current literature include only employees, our analysis excludes self-employed workers from the sample. However, that could bias our coefficients as the determinants of skills mismatch could differ for self-employed (e.g. the level of education might be less relevant to be able to work as self-employed in the agricultural sector or having a seasonal job rather than a permanent one might improve skills match for self-employed workers rather than worsening it). Table B3 in the Appendix shows that the coefficients are robust to different model specifications, including those who are self-employed in the sample.

Finally, we used a probit model for our specification, which assumes a normal distribution of our dependent variables. We also run an alternative model to the probit one, which is valid under a different assumption (a logistic distribution), a logit. The logit marginal effects in Table B4 in the Appendix are very similar to the probit marginal effects in Table 1.

7. Conclusions

This study analyses the determinants of vertical and horizontal mismatch and the impact of overeducation and horizontal mismatch on wages in Serbia, Albania, Türkiye, Georgia, Armenia, Egypt, and Palestine, using repeated cross-sections of Labour Force Survey (LFS) data between 2016 and 2019. The analysis employs a probit model to estimate the marginal effects of socio-demographic, job, and geographical characteristics, both on the pooled sample and separately for each country.

The results are consistent with findings in the existing literature. Socio-demographic factors - such as level of education, field of education, age, gender, marital status, and immigrant status - affect the probability of being both vertically and horizontally mismatched. Job characteristics, including occupational level, contract type (permanent or temporary), full-time employment, and firm size, also influence mismatch probabilities. Geographical factors, such as living in rural or urban areas and the availability and variety of jobs, further shape the likelihood of skills mismatch. The direction and magnitude of these relationships vary across countries, reflecting differences in labour market characteristics (e.g., legislation, wage structures) and broader country-specific factors, including economic and education systems.

Overall, the results indicate that, in the pooled sample, overeducation is associated with a wage penalty of approximately 7.8%, while horizontal mismatch alone is associated with a positive wage effect of approximately 7.5%. For workers experiencing both types of mismatch simultaneously, the combined net effect is a small positive wage premium of approximately 1%, as the positive contributions of horizontal mismatch and the interaction term more than offset the overeducation penalty. The magnitude of this combined effect varies across countries, being positive in some (e.g., Türkiye, Albania) and negative in others (e.g., Egypt), which, consistent with recent literature (e.g., ILO, 2024), reflects differences in labour market structures. These findings are robust to alternative model specifications.

References

Adalet McGowan, M. and D. Andrews (2015), "Skills mismatchand Public Policy in OECD Countries", *OECD Economics Department Working Papers*, No. 1210, OECD Publishing, Paris, https://doi.org/10.1787/5js1pzw9lnwk-en.

Araujo, Isabel, and Anabela Carneiro (2023). "Educational mismatches of newly hired workers: Short-and medium-term effects on wages." *International Labour Review* 162.3: 355-383. https://doi.org/10.1111/ilr.12374

Arayssi M. & Fakih A., & Haimoun N. (2023). "Skill Mismatch, Nepotism, Job Satisfaction, and Young Females in the MENA Region" Econometrics, MDPI, vol. 11(2), pages 1-20, June. https://doi.org/10.3390/econometrics11020016

Addison, J. T., Chen, L., & Ozturk, O. D. (2020) "Occupational skill mismatch: differences by gender and cohort.", *Industrial and labour relations review*, 73 (3). pp. 730-767. https://doi.org/10.1177/0019793919873864

Aleksynska, M. & Tritah, A. (2013). "Occupation-Education Mismatch of Immigrant Workers in Europe: Context and Policies", *Economics of Education Review*, Vol. 36, pp. 229-244. https://doi.org/10.1016/j.econedurev.2013.06.001

Allen, J. P., Levels, M., & Van der Velden, R. K. W. (2013). "Skills mismatchand skill use in developed countries: Evidence from the PIAAC study". ROA. ROA Research Memoranda No. 017, https://doi.org/10.26481/umaror.2013017

Allen, J., & Van der Velden, R. (2001). "Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction, and On-the-Job Search". *Oxford Economic Papers*, 53(3), 434–452. http://www.jstor.org/stable/3488627

Allison, P. D. (2002). "Missing Data". Thousand Oaks, CA: Sage. https://doi.org/10.4135/9781412985079

Alba-Ramirez, A. (1993), "Mismatch in the Spanish Labour Market", *Journal of Human Resources*, Vol. 28, No. 2, pp. 259-278. https://doi.org/10.2307/146203

Awrad and Care. "Skills Gaps and Development in the Occupied Palestinian Territory". A report funded by Department for International Development DFID, (2015).

Becker, G. S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, *70*(5), 9–49. http://www.jstor.org/stable/1829103

Béduwé, C., & Giret, J. F. (2011). "Mismatch of vocational graduates: What penalty on French labour market?". *Journal of vocational behavior*, 78(1), 68-79. https://doi.org/10.1016/j.jvb.2010.09.003

Belfield, C. (2010). "Over-education: What Influence does the Workplace Have?" *Economics of Education Review*, 29 (2): 236-245. https://doi.org/10.1016/j.econedurev.2009.08.001

Bender, K. A., & Heywood, J. S. (2011). “Educational mismatch and the careers of scientists”. *Education Economics*, *19*(3), 253–274. https://doi.org/10.1080/09645292.2011.577555

Bender, K.A. & Roche, K. (2013) “Educational mismatch and self-employment”. *Economics of Education Review*, 34: 85–95. https://doi.org/10.1016/j.econedurev.2013.01.010

Bergin, A., Delaney, J., Handel, M., McGuinness, S., Kupets, O., Pouliakas, K., & Paul R. (2019). “Skills and jobs mismatches in low- and middle-income countries”. ILO Publications.

Berlingieri, F. (2019). “Local labor Market Size and Qualification Mismatch”. *Journal of Economic Geography,* 19 (6): 1261–1286. https://doi.org/10.1093/jeg/lby045

Birgier, P. D., & Cantalini, S. (2025). “Navigating employment and overeducation: comparative study of immigrant experiences in 17 Western European nations”. *Journal of Ethnic and Migration Studies*, *51*(3), 583–608. https://doi.org/10.1080/1369183X.2024.2399638

Booth, A. L. & Bryan, M. L. (2002). “Who Pays for General Training? New Evidence for British Men and Women”. IZA Discussion Paper, 486. https://docs.iza.org/dp486.pdf

Boudarbat, B., & Chernoff, V. (2012). “Education-job match among recent Canadian university graduates”. *Applied Economics Letters*, *19*(18), 1923-1926. https://doi.org/10.1080/13504851.2012.676730

Brun-Schammé, A. and M. Rey (2021), “A new approach to skills mismatch”, *OECD Productivity Working Papers*, No. 24, OECD Publishing, Paris, https://doi.org/10.1787/e9563c2a-en.

Cassidy, H., & Gaulke, A. (2024). “The increasing penalty to occupation-education mismatch”. *Economic Inquiry*, 62(2), 607–632. https://doi.org/10.1111/ecin.13192

Cedefop (2012). “Skill Mismatch. The Role of the Enterprise”. Cedefop Research Papers, No. 21. https://www.cedefop.europa.eu/files/5521_en.pdf

Cedefop (2015). “Skills, qualifications and jobs in the EU: the making of a perfect match? Evidence from Cedefop’s European skills and jobs survey”. Luxembourg: Publications Office. Cedefop reference series; No 103. http://dx.doi.org/10.2801/606129

Chevalier, A. (2003). “Measuring Over-Education”. *Economica*, *70*(279), 509–531. http://www.jstor.org/stable/3549038

Chevalier, A., & Lindley, J. (2009). “Overeducation and the Skills of UK Graduates.” *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *172*(2), 307–337. http://www.jstor.org/stable/20622501

Chiswick, B. & Miller, P. (2009), “The International Transferability of Immigrants' Human CapitalSkills”, *Economics of Education Review*, Vol. 28 (2), pp. 162-169. https://doi.org/10.1016/j.econedurev.2008.07.002

Connolly, S., & Gregory, M. (2009). “The Part-Time Pay Penalty: Earnings Trajectories of British Women”. *Oxford Economic Papers*, *61*, i76–i97. http://www.jstor.org/stable/20529431

Crompton, S. (2002). “I Still Feel Overqualified for My Job”, Canadian Social Trends, No. 67, Winter, Statistics Canada, Catalogue No. 11-008-XIE.

De Oliveira, M. M., Santos, M. C., & Kiker, B. F. (2000). “The Role of Human Capital and Technological Change in Overeducation”. *Economics of Education Review*, *19*(2), 199-206. https://doi.org/10.1016/S0272-7757(99)00020-5

Dolado J. J., Jansen M., Jimeno J.F., “On-the-Job Search in a Matching Model with Heterogeneous Jobs and Worker”s, *The Economic Journal,* Volume 119, Issue 534, 1 January 2009, Pages 200–228, https://doi.org/10.1111/j.1468-0297.2008.02210.x

Domadenik, P., Farcnik, D. & Pastore, F. (2013). “Horizontal Mismatch in the Labour Market of Graduates: The Role of Signalling”, IZA Discussion Paper 7527. https://docs.iza.org/dp7527.pdf

Dorn, D, & Sousa-Poza, A. (2005). Over-qualification: Permanent or Transitory. Switzerland: Mimeo, University of St Gallen. https://conference.iza.org/conference_files/SUMS2006/dorn_d2647.pdf

Duncan, G. & Dunifon, R. (2012). "“Soft-Skills” and Long-Run Labor Market Success", 35th Anniversary Retrospective, Solomon W. Polachek, Konstantinos Tatsiramos. https://doi.org/10.1108/S0147-9121(2012)0000035036

Duranton, G., & Puga, D. (2003). “Micro-foundation of Urban Agglomeration Economies.” In Handbook of Regional and Urban Economics, edited by J.V. Henderson and J.F. Thisse, 2063–2117. Vol. 44, London: Elsevier.

Ege, A. A., and Erdil E. (2023). “Determinants of overlapping mismatch in the Turkish labour market.” *Journal for Labour Market Research* 57.1 (2023): 29. https://doi.org/10.1186/s12651-023-00355-6

Elamin, Obbey A. (2023). “Overeducation wage penalty for university graduates: evidence from the MENA region using machine learning techniques”. *Middle East Development Journal* 15.1 (2023): 151-188. https://doi.org/10.1080/17938120.2023.2167482

Esposito, P., & Scicchitano, S. (2023). “Drivers of skills mismatchamong Italian graduates: the role of personality traits”. *Applied Economics*, *55*(40), 4642–4663. https://doi.org/10.1080/00036846.2022.2130151

Farooq, S. (2011). “The utilisation of education and skills: incidence and determinants among Pakistani graduates”. *The Pakistan Development Review*, 50: 219–244. https://www.jstor.org/stable/23617456

Green C., Kler P. and Leeves, G. (2007). “Immigrant overeducation: Evidence from recent arrivals to Australia”. *Economics of Education Review,* vol. 26, issue 4, 420-432. https://doi.org/10.1016/j.econedurev.2006.02.005

Green, F., & McIntosh, S. (2007). “Is there a genuine under-utilization of skills amongst the over-qualified?” *Applied Economics*, *39*(4), 427–439. https://doi.org/10.1080/00036840500427700

Groot, W. (1993). “Overeducation and the Returns to Enterprise-related Schooling.” *Economics of Education Review* 12 (4): 299–309. https://doi.org/10.1016/0272-7757(93)90064-N

Hamilton, S.F. (1987). “Apprenticeship as a transition to adulthood in West Germany”. *American Journal of Education*, 95: 314–345. https://www.jstor.org/stable/1209215

Handel, M. J., Valerio, A., and Puerta, M. L. S. (2016). “Accounting for mismatch in low- and middle-income countries: measurement, magnitudes, and explanations”. World Bank Publications.

Hartog, J. (2000), “Over-Education and Earnings: “Where Are We, Where Should We Go?”, *Economics of Education Review*, 19(2), pp. 131-147. https://doi.org/10.1016/S0272-7757(99)00050-3

Hensen, M.M., De Vries, M.R. & Corvers, F. (2009) “The role of geographic mobility in reducing education-job mismatches in the Netherlands”. Papers in Regional Science 88: 667–682. https://doi.org/10.1111/j.1435-5957.2008.00189.x

ILO (International Labour Office) (2012). International Standard Classification of Occupations 2008 (ISCO-08): structure, group definitions and correspondence tables, International Labour Office.

International Labour Organization. (2024). *Global employment trends for youth 2024: Decent work, brighter futures* (1st ed.). ILO. https://doi.org/10.54394/ZUUI5430

JRC (European Commission Joint Research Centre) (2014). *Occupational mismatch in Europe: Understanding overeducation and overskilling for policy making*, Publications Office of the European Union, Luxembourg. https://dx.doi.org/10.2788/61733

Kalleberg, A.L. and Van Buren, M.E. (1992) “Organizations and economic stratification: a cross-national analysis of the size-earnings relation”. *Research in Social Stratification and Mobility*, 11: 61–93.

Kelly, E., P.J. O’Connell and E. Smyth (2010), “The Economic Returns to Field-of-study and Competencies among Higher Education Graduates in Ireland”, *Economics of Education Review*, 29(4), pp. 650-657. https://doi.org/10.1016/j.econedurev.2009.11.001

Kim, H., S.C. Ahn and J. Kim (2012), “Vertical and Horizontal Education-Job Mismatches in the Korean Youth Labor Market: A Quantile Regression Approach”, Working Papers 1201, Research Institute for Market Economy, Sogang.

Kiker, B.F. Santos, M.C. & De Oliveira, M.M. (1997). “Overeducation and undereducation: evidence for Portugal”. *Economics of Education Review*, 16(2): 111–125. https://doi.org/10.1016/S0272-7757(96)00040-4

Kler, P. (2006), “Overeducation among Tertiary Educated Immigrants to Australia: A Longitudinal Study”, Labour Economics Research Group, University of Queensland Discussion Papers, No. 9. https://doi.org/10.1108/01443580710772759

Krzywda-Starzyk, P. (2024). “There’s more to overeducation than a wage penalty: A systematic review of 2011–2021 literature on a vertical job-education mismatch in Europe.” Kultura-Społeczeństwo-Edukacja, 26(2), 14, 253-275. https://doi.org/10.14746/kse.2024.26.2.14

Kucel, A., & Vilalta-Bufí, M. (2013). “Why do tertiary education graduates regret their study program? A comparison between Spain and the Netherlands”. *Higher Education*, *65*(5), 565–579. http://www.jstor.org/stable/23473512

Kupets, O. (2015). “Education in Transition and Job Mismatch: Evidence from the Skills Survey in Non-EU Transition Economies”. Kyoto Institute of Economic Research Discussion Paper No. 915. http://www.kier.kyoto-u.ac.jp/DP/DP915.pdf

Kupets, O. (2015a). “Skills mismatchand overeducation in transition economies”. *IZA World of Labor* 2015: 224. https://doi.org/10.15185/izawol.224

Lasso-Dela-Vega E, Sánchez-Ollero JL, García-Pozo A (2023), “Effects of educational mismatch on wages across industry and occupations: sectoral comparison”. *International Journal of Manpower*, Vol. 44 No. 9 pp. 237–255, doi: https://doi.org/10.1108/IJM-02-2022-0081

Leuven, E., & Oosterbeek, H. (2011). “Overeducation and mismatch in the labor market.” *Handbook of the Economics of Education*, *4*, 283-326.

Levels, M., van der Velden, R. & Allen, J. (2014). “Educational Mismatches and Skills: New Empirical Tests of Old Hypotheses”, Oxford Economic Papers, 66 (4): 959-982. https://www.jstor.org/stable/43773042

Malamud O. (2011). “Discovering One's Talent: Learning from Academic Specialization”. *Industrial and Labor Relations Review*, *64*(2), 375–405. http://www.jstor.org/stable/41149498

Mavromaras, K. and S. McGuinness (2012). “Overskilling Dynamics and Education Pathways”, *Economics of Education Review*, 31 (5): 619-628. https://doi.org/10.1016/j.econedurev.2012.02.006

Mavromaras, K., S. Mahuteau, P. Sloane and Z. Wei (2013). “The Effect of Overskilling Dynamics on Wages”, *Education Economics*, 21 (3): 281-303. https://doi.org/10.1080/09645292.2013.797382

McGuinness, S. (2006), “Overeducation in the Labour Market”. *Journal of Economic Surveys*, 20: 387-418. https://doi.org/10.1111/j.0950-0804.2006.00284.x .

McGuinness, S, & Sloane, P.J. (2011). “Labour Market Mismatch among U.K. Graduates: An Analysis Using REFLEX Data.” *Economics of Education Review*, 30 (1): 130–145. https://doi.org/10.1016/j.econedurev.2010.07.006

McGuinness, S., Redmond, P., Staffa, E., Devlin, A., & Whelan, A. (2025). "Skills mismatch: what do we already know and what do we need to know?". In *Handbook of Education and Work* (pp. 318-339). Edward Elgar Publishing. https://doi.org/10.4337/9781035309917.00024

Montt, G. (2015), "The causes and consequences of field-of-study mismatch: An analysis using PIAAC", *OECD Social, Employment and Migration Working Papers*, No. 167, OECD Publishing, Paris, https://doi.org/10.1787/5jrxm4dhv9r2-en.

Montt, G. (2017). "Field-of-study mismatch and overqualification: labour market correlates and their wage penalty". *IZA Journal of Labor Economics*, 6(1), 1-20. https://doi.org/10.1186/s40172-016-0052-x

Morrar, R., & Arman, H. (2024). "The transformational role of a third actor within the Triple Helix Model – the case of Palestine". *Innovation: The European Journal of Social Science Research*, *37*(2), 340–360. https://doi.org/10.1080/13511610.2020.1828045

Morrar, R. & Zwick, H. S. (2021). "Determinants and wage penalty of qualification mismatches: the case of Palestine", *Journal of Education and Work*, https://doi.org/10.1080/13639080.2021.1943331

Nieto, S., Matano, A., & Ramos, R. (2015). "Educational mismatches in the EU: immigrants vs natives". *International Journal of Manpower*, Vol. 36 No. 4 pp. 540–561, doi: https://doi.org/10.1108/IJM-11-2013-0260

Nordin, M., Persson, I., & Rooth, D. (2010), "Education-Occupation Mismatch: Is there an Income Penalty?", *Economics of Education Review*, 29(6), pp. 1047-1059. https://doi.org/10.1016/j.econedurev.2010.05.005

OECD (2013). OECD skills outlook 2013: First results from the Survey of adult skills, OECD Publishing. https://doi.org/10.1787/9789264204256-en

OECD (2014), *OECD Employment Outlook 2014*, OECD Publishing, Paris, https://doi.org/10.1787/empl_outlook-2014-en.

OECD (2024), "Do Adults Have the Skills They Need to Thrive in a Changing World?: Survey of Adult Skills 2023", OECD Skills Studies, OECD Publishing, Paris, https://doi.org/10.1787/b263dc5d-en.

Ortiz, L., & A. Kucel (2008). "Do Fields of Study Matter for Over-education? The Cases of Spain and Germany", International Journal of Comparative Sociology, 49 (4-5): 305-327. https://doi.org/10.1177/002071520809307

Prica, I., El Ouizgani, I., & Bartlett, W. (2025). Overeducated yet underskilled: graduate labour market mismatch in Morocco and Serbia. *Public Sector Economics*, *49*(3), 469-492. https://doi.org/10.3326/pse.49.3.6

Quintini, G. (2011a), "Over-Qualified or Under-Skilled: A Review of Existing Literature", *OECD Social, Employment and Migration Working Papers*, No. 121, OECD Publishing, Paris, https://doi.org/10.1787/5kg58j9d7b6d-en.

Quintini, G. (2011b), "Right for the Job: Over-Qualified or Under-Skilled?", OECD Social, Employment and Migration Working Papers, 120. http://dx.doi.org/10.1787/5kg59fcz3tkd-en.

Ramos, R. & Sanroma, E. (2011). "Overeducation and Local Labour Markets in Spain", IZA Discussion Paper No. 6028.

Robert, P. (2014). "Job Mismatch in Early Career of Graduates under Post-Communism", *International Journal of Manpower,* 35 (4): 500-513. https://doi.org/10.1108/IJM-05-2013-0113

Robst, J. (2007a). "Education and Job Match: The Relatedness of College Major and Work", *Economics of Education Review*, 26 (4): 397-407. https://doi.org/10.1016/j.econedurev.2006.08.003

Robst, J. (2007b). "Education, College Major, and Job Match: Gender Differences in Reasons for Mismatch", *Education Economics*, 15:2, 159-175, https://doi.org/10.1080/09645290701263070

Robst, J. (2008). "Overeducation and College Major: Expanding the Definition of Mismatch between Schooling and Jobs", *The Manchester School*, 76 (4): 349-368. https://doi.org/10.1111/j.1467-9957.2008.01064.x

Schweri, J., Eymann, A., & Aepli, M. (2020). Horizontal mismatch and vocational education. *Applied Economics*, *52*(32), 3464–3478. https://doi.org/10.1080/00036846.2020.1713292

Sicherman, N. (1991). "Overeducation in the Labour Market." *Journal of Labour Economics* 9: 101–122. https://www.jstor.org/stable/2535236

Somers, M.A., Cabus, S.J., Groot, W. and van den Brink, H.M. (2019), "Horizontal Mismatch Between Employment and Field of Education: Evidence from a Systematic Literature Review". *Journal of Economic Surveys,* 33: 567-603. https://doi.org/10.1111/joes.12271

Sparreboom, T. (2014), "Gender Equality, Part-time Work and Segregation", International Labour Review, Vol. 153, No. 2.

Tran, T. Q., Vu, N. B. T., Van Le, D., & Vu, L. H. (2025). "Vertical and horizontal job-education mismatches and wages: A quantitative analysis of university graduates in Vietnam". *International Journal of Educational Development*, *117*, 103323. https://doi.org/10.1016/j.ijedudev.2025.103323

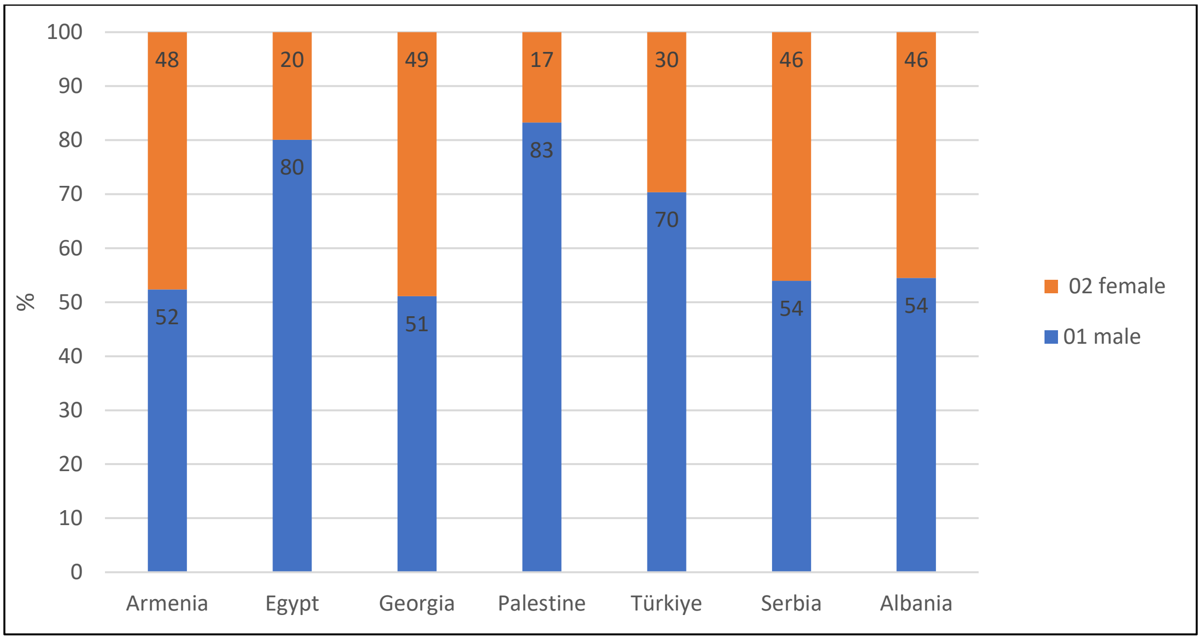
Verhaest, D., Sellami, S. & Van der Velden, R. (2015). "Differences in Horizontal and Vertical Mismatches across Countries and Fields of Study", *International Labour Review,* 153: 245-268. https://doi.org/10.1111/j.1564-913X.2014.00203.x

Witte, J. C., & Kalleberg, A. L. (1995). "Matching Training and Jobs: The Fit between Vocational Education and Employment in the German Labour Market". *European Sociological Review*, *11*(3), 293–317. http://www.jstor.org/stable/522757

Wolbers, M. H. J. (2003). “Job Mismatches and their Labour-Market Effects among School-Leavers in Europe”, *European Sociological Review*, Volume 19, Issue 3, 1 July 2003, Pages 249–266, https://doi.org/10.1093/esr/19.3.249

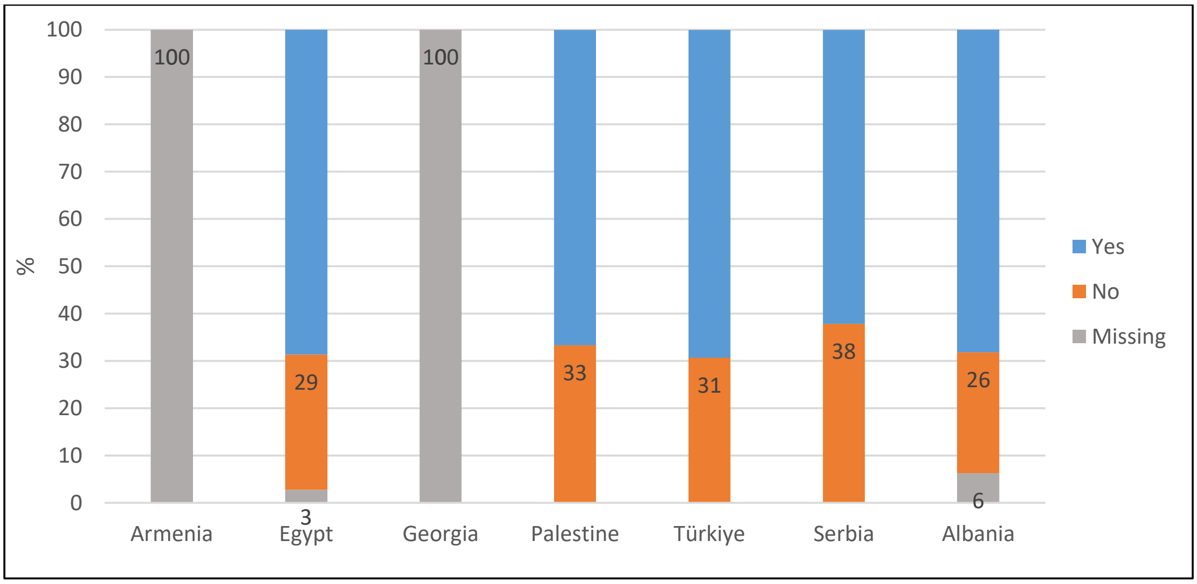
Appendix A: Data description

Figure A1. Gender distribution across countries (whole sample unweighted)



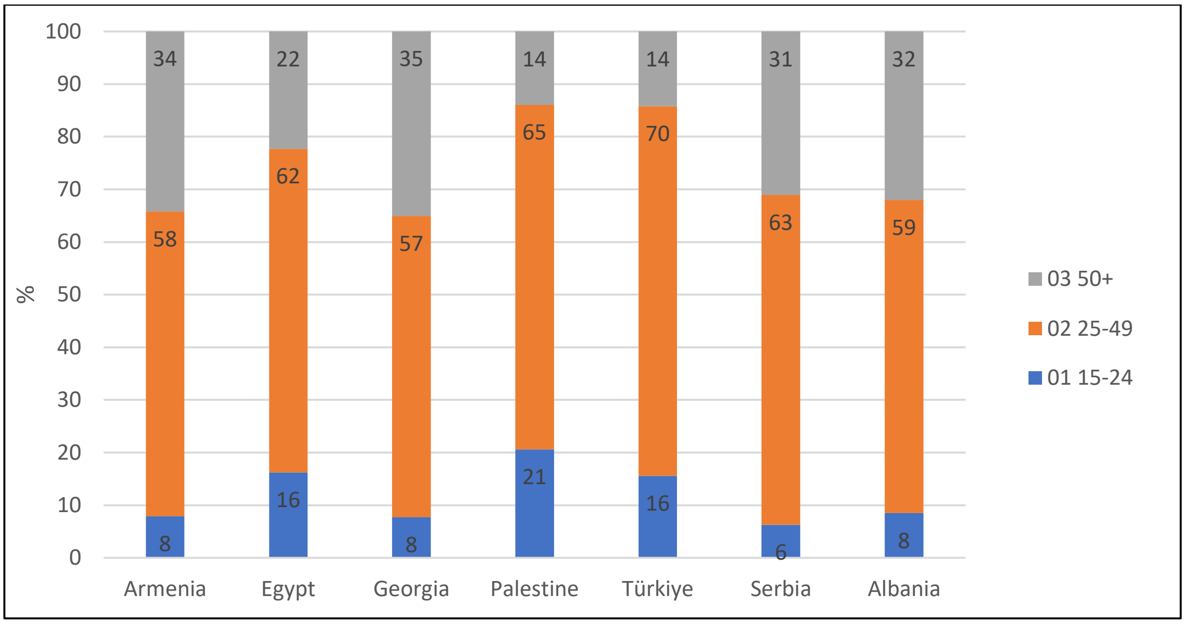
Source: Country LFS surveys (2016-2019).

Figure A2. Share of individuals being married (whole sample unweighted)



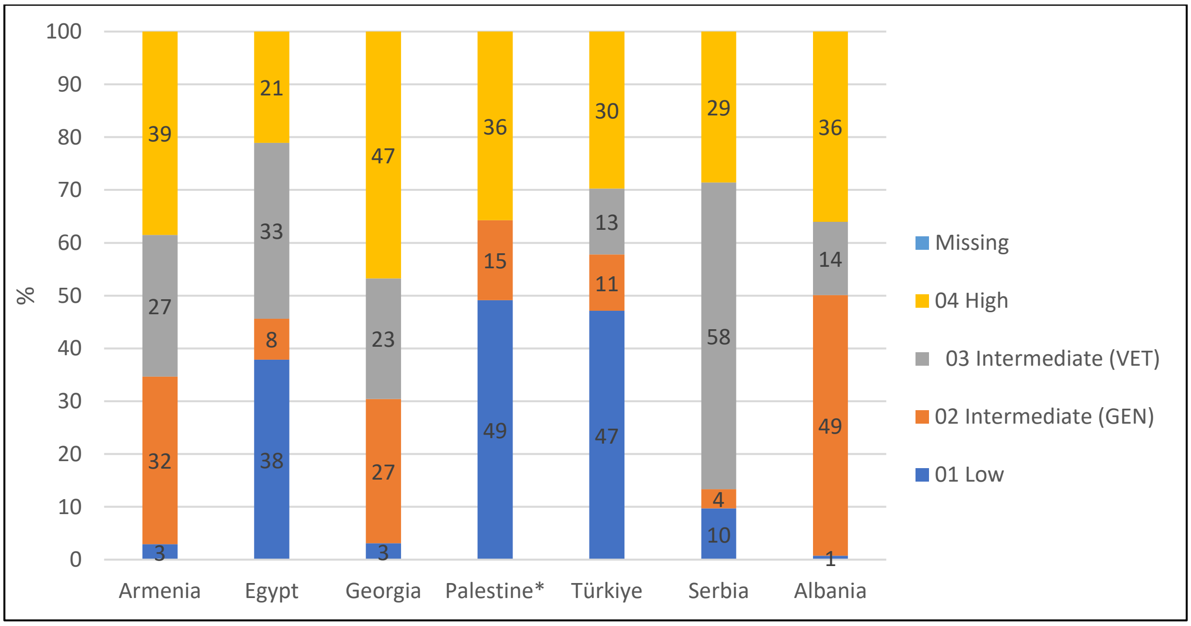
Source: Country LFS surveys (2016-2019).

Figure A3. Distribution of age groups (whole sample unweighted)



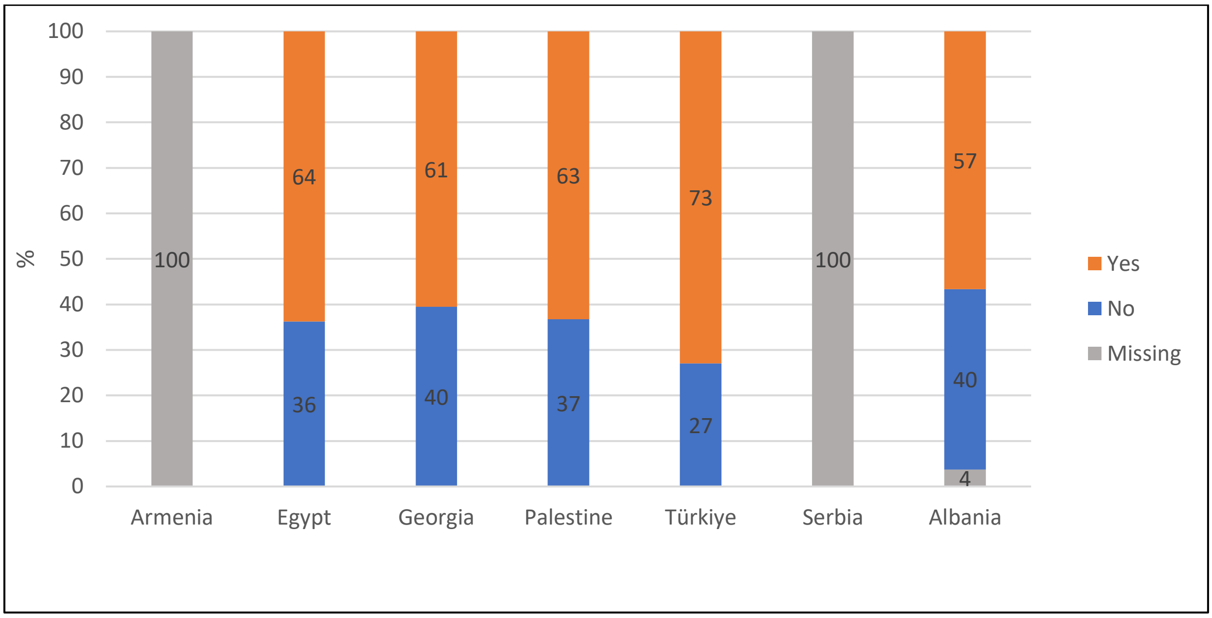
Source: Country LFS surveys (2016-2019).

Figure A4. Distribution of education level (whole sample unweighted)



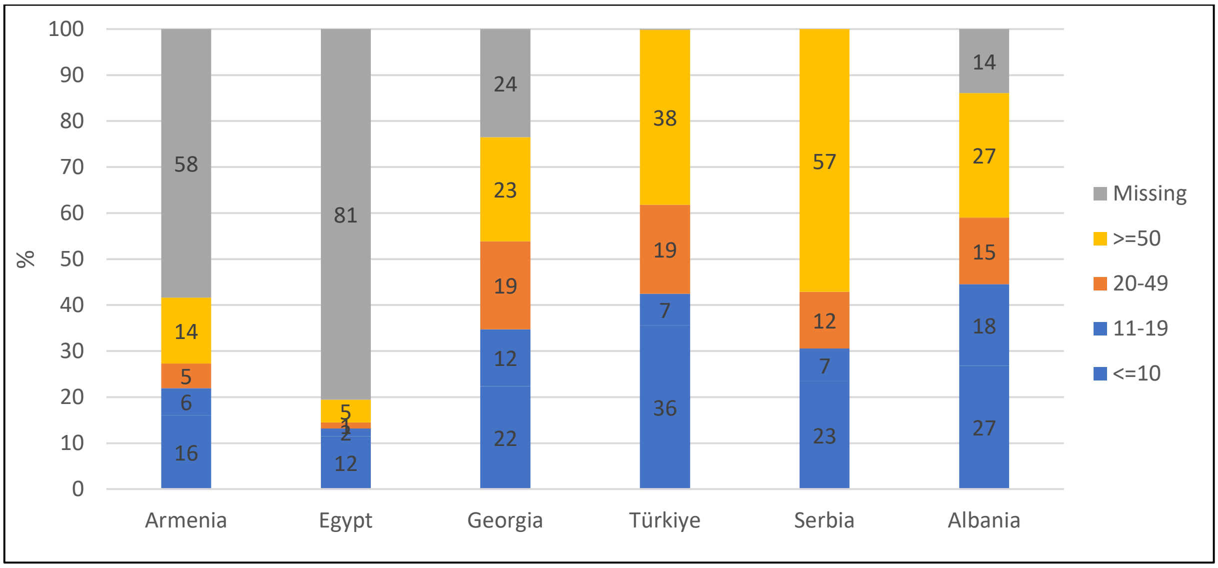
Source: Country LFS surveys (2016-2019).

Figure A5. Share of individuals working for a private company (Whole sample unweighted)



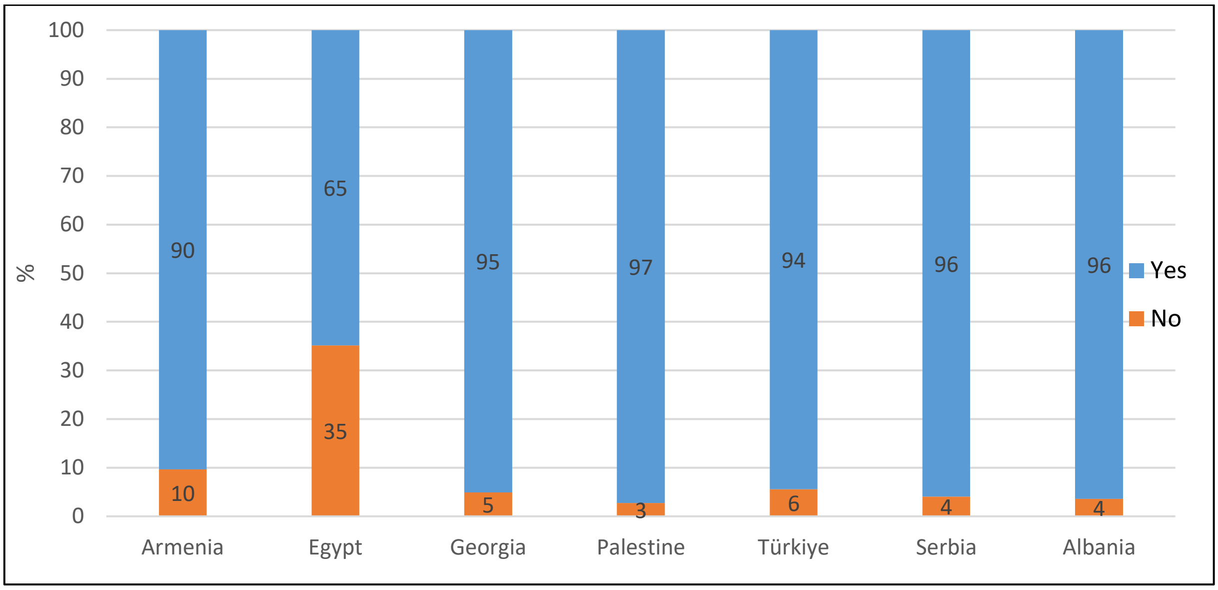
Source: Country LFS surveys (2016-2019).

Figure A6. Distribution of company size where individual is working (Whole sample unweighted)



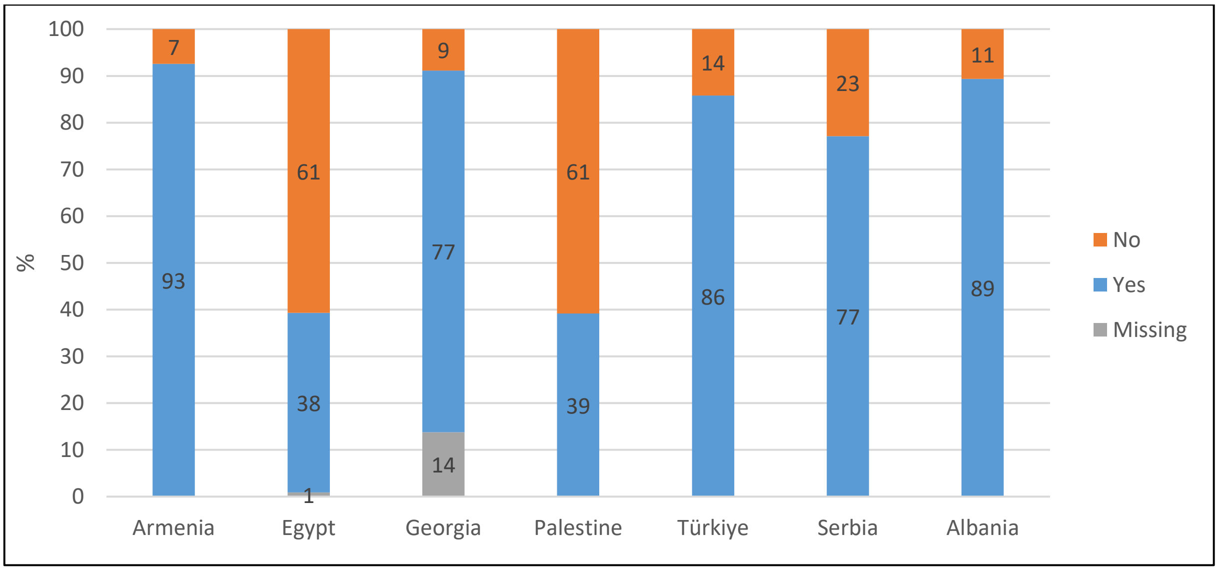
Source: Country LFS surveys (2016-2019).

Figure A7. Share of individuals having a fulltime contract (Whole sample unweighted)



Source: Country LFS surveys (2016-2019).

Figure A8. Share of individuals having a permanent contract (Whole sample unweighted)



Source: Country LFS surveys (2016-2019).

Table A0. Summary statistics (pooled sample)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Country	870,65	4.6	1.5	1.0	7
Year	870,65	2,017.4	1.1	2,016	2,019
Gender	870,65	0.7	0.5	0	1
Fulltime	870,65	0.9	0.3	0	1
Having a permanent job	852,123	0.8	0.4	0	1
Age group	867,488	2.9	1.2	1	6
Firm size2	870,65	1.2	1.1	0	3
Medium education (dummy)	870,65	0.4	0.5	0	1
Dependent variables					
Horizontal mismatch	408,845	0.5	0.5	0	1
Over-education	870,562	0.3	0.5	0	1
Under-education	870,562	0.2	0.4	0	1
Overeducation normative method	863,657	0.1	0.3	0	1

Table A1. Summary statistics (Albania)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	57,156.0	2,017.5	1.1	2,016.0	2,019.0
Sample weight	57,156.0	37.0	31.9	0.3	632.0
ISCED_F_1997	43,756.0	2.5	2.6	0.0	8.0
Gender	57,156.0	0.5	0.5	0.0	1.0
Employee	57,156.0	1.0	0.0	1.0	1.0
Being married	53,565.0	0.7	0.4	0.0	1.0
Being citizen of the country	53,565.0	1.0	0.1	0.0	1.0
Being born abroad	53,565.0	0.0	0.0	0.0	1.0
Working for a private company	57,156.0	0.6	0.5	0.0	1.0
Firm size	57,156.0	2.8	1.4	1.0	5.0
Number of hours worked	57,033.0	43.0	7.9	0.0	98.0
Income	14,218.0	365,217.1	148,683.4	0.0	2,500,000.0
Having a fulltime job	57,156.0	1.0	0.2	0.0	1.0
Having a permanent job	57,156.0	0.9	0.3	0.0	1.0
Occupation ISCO 08-1 digits	57,150.0	5.1	2.6	0.0	9.0
Age group	57,156.0	3.2	1.3	1.0	6.0
Medium education	57,156.0	0.6	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	56,386.0	0.0	0.2	0.0	1.0
Occupational mismatch (High education)	56,386.0	0.1	0.2	0.0	1.0
Horizontal mismatch	40,227.0	0.5	0.5	0.0	1.0
Over-education	57,150.0	0.3	0.4	0.0	1.0

Table A2. Summary statistics (Armenia)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	22,251	2,017.5	1.1	2,016	2,019
Sample weight	22,251.0	105.7	68.4	13.7	427.7
Gender	22,251.0	0.5	0.5	0.0	1.0
Employee	22,251	1	0	1	1
Profession ISCO88	11,157	4.7	3.0	2	9
Occupation ISCO88	11,157	4.7	2.6	1	9
Firm size	22,251.0	3.9	1.5	1.0	5.0
Number of hours worked	22,251	42.5	11.1	2	112
Having a fulltime job	22,251	0.9	0.3	0	1
Having a permanent job	22,251	0.9	0.3	0	1
Age group	22,251	3.3	1.4	1	6
Medium education	22,251	0.3	0.5	0	1
Outcome variables					
Occupational mismatch (Medium education)	21,966	0.1	0.3	0	1
Occupational mismatch (High education)	21,966.0	0.1	0.3	0	1
Horizontal mismatch	10,865.0	0.9	0.2	0	1
Over-education	22,251.0	0.2	0.4	0	1
Under-education	22,251.0	0.1	0.3	0	1

Table A3. Summary statistics (Egypt)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	125,059	2,016.5	0.5	2,016	2,017
Sample weight	125,059	283.1	143.9	0	7,955
Employee	125,059	1	0	1	1
Gender	125,059	0.8	0.4	0	1
Occupation ISCO 88-3 digits	124,986	5.3	2.4	1	9
Occupation ISCO 88-1 digits	124,986	552.8	240.1	112	933
ISCED F 1997	75,304	3.4	2	0	8
Married	121,612	0.7	0.5	0	1
Region	125,059	818,016.3	8.7	818,001	818,035
Private firm (dummy)	125,059	0.6	0.5	0	1
Firm size	24,325	2	1.3	1	4
Number of hours worked	124,502	44.0	11.9	1	96
Having a fulltime job	125,059	0.6	0.5	0	1
Having a permanent job	123,958	0.4	0.5	0	1
Age group	125,059	2.9	1.3	1	6
Medium education (dummy)	125,059	0.1	0.3	0	1
Outcome variables					
Occupational mismatch (Medium education)	124,986	0	0.2	0	1
Occupational mismatch (High education)	124,986	0	0.2	0	1
Horizontal mismatch	72,274	0.6	0.5	0	1
Over-education	124,985	0.2	0.4	0	1
Under-education	124,985	0.3	0.5	0	1

Table A4. Summary statistics (Georgia)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	50,806	2,017.8	1	2,016	2,019
Sample weight	50,806	262.6	212.0	9.4	3,340.3
Employee	50,806	1.0	0.0	1	1
Profession ISCO88	35,646	291.3	125.7	11	999
Occupation ISCO88	50,798	491.8	267.2	11	999
Gender	50,806.0	0.5	0.5	0.0	1.0
Private firm (dummy)	50,806	0.6	0.5	0	1
Firm size (Categorical)	50,806.0	3.1	1.5	1.0	5.0
Number of hours worked	47,709	38.1	20.4	1	144
Having a full-time job	50,806	1	0.2	0	1
Having a permanent job	50,806.0	1.0	0.5	0.0	2.0
Age group	50,806	3.4	1.4	1	6
Medium education (dummy)	50,806.0	0.5	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	49,894.0	0.1	0.3	0.0	1.0
Occupational mismatch (High education)	49,894.0	0.1	0.3	0.0	1.0
Horizontal mismatch	23,982.0	0.2	0.4	0.0	1.0
Over-education	50,798.0	0.2	0.4	0.0	1.0
Under-education	50,798.0	0.2	0.4	0.0	1.0

Table A5. Summary statistics (Palestine)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	67,342	2,017.5	1.1	2,016	2,019
Sample weight	67,342	0.9	0.6	0	17.2
Occupation ISCO 08-1 digit	67,342	5.2	3.1	0.0	9.0
Employee	67,342	1	0	1	1
Gender	67,342	0.8	0.4	0.0	1.0
Married	67,342	0.7	0.5	0	1
Private firm (dummy)	67,342	0.6	0.5	0	1
Firm size (Categorical)	60,836	2.0	0.9	1.0	3.0
Number of hours worked	50,078	42.8	13.0	1	168
Having a fulltime job	67,342	1.0	0.2	0.0	1.0
Having a permanent job	67,342	0.4	0.5	0.0	1.0
Age group	67,342	2.6	1.2	1.0	6.0
Medium education (dummy)	67,342	0.2	0.4	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	65,945	0	0.2	0	1
Occupational mismatch (High education)	65,945	0.1	0.2	0	1
Over-education	67,342	0.3	0.4	0	1
Under-education	67,342	0.2	0.4	0	1

Table A6. Summary statistics (Serbia)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	130,288.0	2,017.5	1.1	2,016	2,019
ISCED F 2013	44,715.0	7.4	125.1	0	9,999
Married	130,288.0	0.6	0.5	0	1
Being born abroad	130,288.0	0.1	0.3	0	1
Firm size	130,288.0	3	1.3	1	4
Formal	130,288.0	0.9	0.3	0	1
Having a full-time job	130,288.0	1	0.2	0	1
Having a permanent job	130,288.0	0.8	0.4	0	1
Occupation ISCO 08-1 digit	130,288.0	5.2	2.5	0	9
Employee	130,288.0	1	0	1	1
Sample weight	130,288.0	60.9	40.7	1.5	744.4
Age group	130,288.0	3.3	1.2	1	6
Medium education	130,288.0	0.6	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	126,732.0	0.1	0.3	0.0	1.0
Occupational mismatch (High education)	126,732.0	0.1	0.2	0.0	1.0
Horizontal mismatch	85,053.0	0.2	0.4	0.0	1.0
Over-education	130,288.0	0.3	0.4	0.0	1.0
Under-education	130,288.0	0.2	0.4	0.0	1.0

Table A7. Summary statistics (Türkiye)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	417,748.0	2,017.5	1.1	2,016	2,019
Sample weight	417,748.0	0.2	0.1	0	0.5
Gender	417,748.0	0.7	0.5	0.0	1.0
Occupation ISCO 08-1 digit	417,748.0	5.4	2.5	1	9
ISCED F 2013	176,402.0	5.0	2.6	1	10
Married	417,748.0	0.7	0.5	0	1
Being born abroad	417,748.0	0.0	0.2	0	1
Private firm (dummy)	417,748.0	0.7	0.4	0	1
Firm size	417,748.0	2.6	1.3	1.0	5.0
Number of hours worked	417,748.0	47.2	12.5	1	99
Having a full-time job	417,748.0	0.9	0.2	0	1
Having a permanent job	417,748.0	0.9	0.3	0	1
Age group	417,748.0	2.7	1.2	1.0	6.0
Medium education (dummy)	417,748.0	0.2	0.4	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	417,748.0	0.0	0.2	0.0	1.0
Occupational mismatch (High education)	417,748.0	0.1	0.3	0.0	1.0
Horizontal mismatch	176,402.0	0.5	0.5	0.0	1.0
Over-education	417,748.0	0.4	0.5	0.0	1.0
Under-education	417,748.0	0.2	0.4	0.0	1.0

Table A8. Variable description

Variable	Description
Dependent variables	
Occupational mismatch	Occupational mismatch (dummy)
Overeducation	Being over-educated (dummy)
Undereducation	Being under-educated (dummy)
Horizontal mismatch	Being horizontally mismatched (dummy)
Mismatch	Being either over-/under-educated or horizontally mismatched (dummy)
VM_HM	Being over-educated and horizontally mismatched (dummy)
Log Wage PPP	log monthly wage (adjusted for inflation rate) in PPP $
Log Wage PPP bis	log monthly wage (adjusted for inflation rate) in PPP $ (excluding the 1st and last percentile of wage)
Control variables	
Age group	Age group (categorical)
Gender	Gender (Being male=1) (dummy)
Married	Being married (dummy)
Fulltime	Having a full-time job (dummy)
Permanent job	Having a permanent job (dummy)
Hours worked	Weekly working hours (continuous)
Rural	Living in a rural area (dummy)
Firm size	Firm size (categorical)
pweight	weight (continuous)
Private	Working for a private company (dummy)
ISCED_F	Field of education (ISCED-F 99 or ISCED-F 2013) (categorical)
Age	Age (continuous)
country	Country
year	Year

Appendix B: Robustness checks

Table B1: Probit marginal effects of skills-mismatch determinants (Pooled sample), not controlling for medium education

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch
Age (25-34)	0.040***	-0.089***	-0.019***	0.011***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (35-44)	-0.022***	-0.183***	0.017***	-0.022***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (45-54)	-0.040***	-0.232***	0.049***	-0.036***
	(0.001)	(0.002)	(0.002)	(0.003)
Age (55-65)	-0.051***	-0.251***	0.092***	-0.061***
	(0.001)	(0.002)	(0.002)	(0.003)
Older than 65 years old	-0.052***	-0.218***	0.070***	-0.028***
	(0.003)	(0.006)	(0.006)	(0.010)
Gender (dummy)	-0.003***	0.089***	-0.011***	-0.036***
	(0.001)	(0.001)	(0.001)	(0.002)
Full-time (dummy)	0.036***	0.001	-0.004**	0.052***
	(0.002)	(0.002)	(0.002)	(0.003)
Firm size (<=10)	0.022***	0.015***	-0.064***	0.043***
	(0.001)	(0.001)	(0.001)	(0.002)
Firm size (missing)	-0.017***	0.027***	-0.065***	0.127***
	(0.002)	(0.003)	(0.002)	(0.004)
Permanent job (dummy)	0.002*	0.015***	-0.014***	0.047***
	(0.001)	(0.001)	(0.001)	(0.002)
Year F.E.	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes
Observations	860,495	867,400	867,400	408,367

Source: Pooled LFS survey (2016-2019).
Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table B2: Probit marginal effects of skills-mismatch determinants (Pooled sample), including self-employed workers

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch
Age (25-34)	0.025***	-0.108***	-0.030***	0.008***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (35-44)	-0.034***	-0.222***	-0.019***	-0.023***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (45-54)	-0.054***	-0.268***	-0.007***	-0.038***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (55-65)	-0.066***	-0.289***	0.021***	-0.068***
	(0.001)	(0.002)	(0.002)	(0.003)
Older than 65 years old	-0.065***	-0.210***	-0.021***	-0.033***
	(0.003)	(0.006)	(0.005)	(0.010)
Gender (dummy)	0.001	0.068***	0.000	-0.036***
	(0.001)	(0.001)	(0.001)	(0.001)
Fulltime (dummy)	0.036***	0.016***	-0.025***	0.043***
	(0.001)	(0.002)	(0.001)	(0.003)
Firm size (<=10)	0.030***	-0.008***	-0.008***	0.031***
	(0.001)	(0.001)	(0.001)	(0.002)
Firm size (missing)	-0.007***	0.034***	-0.057***	0.109***
	(0.001)	(0.003)	(0.002)	(0.004)
Permanent job (dummy)	0.017***	0.045***	-0.035***	0.055***
	(0.001)	(0.001)	(0.001)	(0.002)
Medium education (Dummy)	-0.063***	0.167***	0.060***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.002)
Year F.E.	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes
Observations	1,014,871	1,021,794	1,021,794	437,955

Source: Pooled LFS survey (2016-2019).

Notes: The coefficients are the marginal effects from a probit model. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Table B3: Logit marginal effects of skills-mismatch determinants (Pooled sample)

VARIABLES	(1) Occupational mismatch	(2) Over-education	(3) Under-education	(4) Horizontal mismatch
Age (25-34)	0.032***	-0.074***	-0.017***	0.010***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (35-44)	-0.027***	-0.170***	0.021***	-0.019***
	(0.001)	(0.002)	(0.001)	(0.003)
Age (45-54)	-0.044***	-0.215***	0.055***	-0.030***
	(0.001)	(0.002)	(0.002)	(0.003)
Age (55-65)	-0.055***	-0.230***	0.101***	-0.053***
	(0.001)	(0.002)	(0.002)	(0.003)
Older than 65 years old	-0.061***	-0.174***	0.090***	-0.025**
	(0.003)	(0.007)	(0.006)	(0.011)
Gender (dummy)	0.003***	0.077***	-0.014***	-0.036***
	(0.001)	(0.001)	(0.001)	(0.002)
Fulltime (dummy)	0.043***	-0.009***	-0.006***	0.050***
	(0.002)	(0.002)	(0.002)	(0.003)
Firm size (<=10)	0.019***	0.017***	-0.064***	0.041***
	(0.001)	(0.001)	(0.001)	(0.002)
Firm size (missing)	-0.018***	0.034***	-0.064***	0.122***
	(0.002)	(0.003)	(0.002)	(0.004)
Permanent job (dummy)	0.002**	0.009***	-0.015***	0.051***
	(0.001)	(0.001)	(0.001)	(0.002)
Medium education (Dummy)	-0.069***	0.159***	0.036***	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Year F.E.	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes
Observations	860,495	867,400	867,400	408,367

Source: Pooled LFS survey (2016-2019).

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The variables used for the analysis are described in Table A8 in the Appendix.

Appendix C: Matching occupations (ISCO) with fields of education (ISCED-f)

Table C1: Field of Education ISCED-F 2013

ISCED-F 1997	ISCED-F 2013
0-General programs	00 – Generic programmes and qualificatio
1-Education, 2- Humanities and arts	01 – Education
3-Social sciences/business/law	02 – Arts and humanities
4-Sciences	03 – Social sciences, journalism and information
5-Engineering/manufacturing/construction	04 – Business, administration and law
6-Agriculture	05 – Natural sciences, mathematics and statistics
7-Health/welfare	06 – Information and Communication Technologies
8- Services	07 – Engineering, manufacturing and construction
	08 – Agriculture, forestry, fisheries and veterinary
	09 – Health and welfare
	10 - Services

Source: Eurostat Statistics Explained (N.A.). International Standard Classification of Education (ISCED).

Table C2: Summary of horizontal mismatch matching method

Country	Matching method
Albania	ISCO 08 3-ISCED F 97*
Armenia	ISCO 88 3- ISCED F 97 ISCO 88 3-ISCED F learned
Belarus	ISCO 08 3-ISCED F 97*
BiH	ISCO 08 3-ISCED F 97*
Egypt	ISCO 88 3- ISCED-F 97*
Georgia	ISCO – ISCO
Jordan	ISCO 08 3- ISCED F 13
Kirgizstan	ISCO-88 (2016-2018); ISCO-08 in 2019 – same for field of education
Kosovo	ISCO 08 3-ISCED F 97 (2016-2017) ISCO 08 3- ISCED F 13 (2018-2019)
Moldova	ISCO 08 3-ISCO 08 3
Montenegro	ISCO 08 1-ISCED F 13*
North Macedonia	ISCO 08 3-ISCED F 13
Palestine	ISCO 08 3-ISCED F 97*
Serbia	ISCO 08 3-ISCED F 13*
Tunisia	ISCO 08 3-ISCED F 13*
Türkiye	ISCO 08 2-ISCED F 13*

Source: Authors' own elaboration; (*) ISCED-F was converted from national education classification

Table C3: Matching ISCO-08 3-digit/ ISCED-F 2013

ISCED-F 2013	ISCO-08
01_Education	531; 235; 234; 233; 342; 231; 232; 314;
02_Arts and humanities	265; 341; 522; 263; 342; 232;
03_Social sciences, journalism and information	261; 341; 262; 335; 233; 263; 232; 264;
04_Business, administration and law	242; 334; 333; 121; 422; 241; 111; 411; 141; 112; 132; 143; 131; 134; 335; 142; 332; 122; 412; 352;
05_Natural sciences, mathematics and statistics	816; 213; 331; 212; 754; 211; 311; 133; 232;
06_Information and Communication Technologies (ICTs)	252; 351; 133; 352; 251;
07_Engineering, manufacturing and construction	216; 821; 722; 712; 711; 813; 741; 742; 215; 214; 753; 731; 812; 811; 312; 834; 818; 713; 732; 313; 814; 721; 315; 835; 815; 817; 752;
08_Agriculture, forestry, fisheries and veterinary	921; 612; 622; 621; 611; 613; 225; 324;
09_Health and welfare	321; 221; 322; 222; 325; 226; 224; 532; 323; 223;
10_Services	515; 832; 523; 512; 911; 941; 751; 514; 833; 413; 831; 723; 432; 516; 143; 541; 335; 835; 511; 912; 513; 343; 524; 243; 522; 421; 431; 441; 264; 265;
No correspondence	11; 932; 21; 962; 961; 521; 951; 952; 631; 634; 632; 633; 933; 912; 31; 931;

Source: Authors' own elaboration

Table C4: Matching ISCO-08 3 digits/ ISCED-F 1997

ISCED-F 1997	ISCO-08
1 – Education	231; 232; 234; 234; 234; 235; 235; 235; 235; 315; 342; 343; 516;
2 – Humanities and arts	216; 232; 233; 243; 262; 263; 264; 265; 341; 342; 343; 522; 524;
3 – Social sciences, business and law	111; 112; 121; 121; 121; 122; 122; 131; 132; 132; 132; 133; 133; 133; 134; 134; 141; 141; 142; 142; 143; 143; 226; 232; 233; 241; 241; 242; 243; 243; 261; 262; 263; 264; 265; 265; 312; 325; 331; 331; 332; 332; 333; 333; 333; 333; 334; 334; 334; 334; 334; 334; 335; 335; 341; 341; 343; 343; 421; 422; 522; 611; 612; 613; 621; 622;
4 – Science	211; 212; 213; 213; 226; 232; 233; 251; 311; 313; 321;
5 – Engineering, manufacturing and construction	214; 215; 216; 226; 252; 311; 312; 312; 312; 312; 312; 312; 312; 312; 312; 312; 312; 312; 312; 313; 313; 313; 313; 313; 315; 321; 325; 335; 343; 351; 352; 352; 711; 711; 712; 712; 713; 721; 722; 722; 723; 731; 731; 731; 731; 731; 732; 732; 741; 741; 742; 751; 752; 752; 753; 753; 754; 754; 754; 754; 754; 811; 811; 811; 812; 812; 813; 813; 813; 814; 814; 815; 815; 816; 817; 818; 818; 818; 821; 821; 831; 832; 834; 835;
6 – Agriculture	221; 221; 223; 314; 516; 611; 612; 613; 621; 622; 754; 834; 921; 921;
7 – Health and welfare	134; 222; 224; 225; 225; 226; 226; 234; 264; 321; 321; 322; 322; 324; 325; 325; 341; 911;
8 – Services	334; 335; 341; 343; 411; 412; 413; 422; 422; 431; 432; 441; 441; 511; 512; 513; 514; 515; 516; 516; 523; 524; 531; 532; 541; 831; 833; 834; 835; 912; 941; 941;
no correspondence	111; 111; 111; 631; 632; 633; 634; 223; 323; 341; 515; 516; 521; 521; 524; 524; 541; 912; 931; 932; 933; 951; 952; 961; 961; 962; 962; 011; 021; 031;

Source: Authors' own elaboration

Table C5: Matching ISCO-08 2-digit / ISCED-F 2013

ISCED-F 2013	ISCO-08
01_Education	23; 34, 53
02_Arts and humanities	23; 26; 34; 52;
03_Social sciences, journalism and information	23; 26; 33; 34;
04_Business, administration and law	11; 12; 13; 14; 24; 33; 35; 41; 42;
05_Natural sciences, mathematics and statistics	13; 21; 23; 31; 33; 75; 81;
06_Information and Communication Technologies (ICTs)	13; 25; 35;
07_Engineering, manufacturing and construction	21; 31; 72; 71; 74; 75; 73; 81; 82; 83
08_Agriculture, forestry, fisheries and veterinary	22; 32; 61; 62; 92;
09_Health and welfare	22; 32; 53;
10_Services	14; 24; 26; 33; 34; 41; 42; 43; 44; 51; 52; 54; 75; 72; 83; 91; 94;
No correspondence	93; 96; 95; 63;

Source: Authors' own elaboration

Table C6: Matching ISCO-08 2-digit / ISCED-F 1997

ISCED-F 1997	ISCO-08
1 – Education	23; 31; 34; 51
2 – Humanities and arts	21; 23; 24; 26; 34; 52
3 – Social sciences, business and law	11; 12; 13; 14; 22; 23; 24; 26; 31; 32; 33; 34; 42; 52; 61; 62
4 – Science	21; 22; 23; 25; 31; 32
5 – Engineering, manufacturing and construction	21; 22; 25; 31; 32; 33; 34; 35; 71; 72; 73; 74; 75; 81; 82; 83
6 – Agriculture	22; 31; 51; 61; 62; 75; 83; 92
7 – Health and welfare	13; 22; 23; 26; 32; 34; 91
8 – Services	33; 34; 41; 42; 43; 44; 51; 52; 53; 54; 83; 91; 94
no correspondence	01; 02; 03; 63; 93; 95; 96

Source: Authors' own elaboration

Table C7: Matching ISCO-08 1-digit / ISCED-F 2013

ISCED-F 1997	ISCO-08
1 – Education	2; 3; 5
2 – Humanities and arts	2; 3; 5
3 – Social sciences, business and law	1; 2; 3; 4; 5; 6
4 – Science	2; 3
5 – Engineering, manufacturing and construction	2; 3; 7; 8
6 – Agriculture	2; 3; 5; 6; 7; 8; 9
7 – Health and welfare	1; 2; 3; 9
8 – Services	3; 4; 5; 8; 9

Source: Authors' own elaboration

Table C8: correspondence between isco-88 3 digits and isco-08 3 digits

ISCO 88 3-Digit (used by Wolbers 2003)	ISCO 08 3-Digit
10; 100; 110; 120; 130; 200; 210; 220; 230; 300; 310; 320; 330; 400; 410; 420; 500; 510; 520; 600; 610; 700; 710; 720; 730; 740; 800; 810; 820; 830; 900; 910; 920; 930 (*)	9999
11	11; 21; 31
111; 112; 113; 114	111
121	112
122	121; 131; 132; 133; 134; 141; 142; 143; 265; 312; 343;
123	121; 122; 132; 133;
131	121; 122; 132; 133; 134; 141; 142; 143; 522; 611; 612; 613; 621; 622
211	211; 226;
212	212
213	251; 252
214	214; 215; 216
221	213; 221; 225;
222	221; 225; 226
223	134; 222; 322
231	231; 232; 232; 232
232	232; 233; 233;
233	234
234; 235	235
241	226; 241; 242; 243; 333
242	261
243	262
244	263; 264
245	243; 264; 265
246; 247	263
311	311; 352;
312	313; 351
313	321; 343; 352;
314	315
315	226; 311; 325; 335; 754
321	213; 314; 321;
322	223; 224; 226; 321; 324; 325
323	322
324	223; 323; 341
331; 332;	234
333; 334	235
334	315; 342; 343; 516;
341	241; 243; 331; 332; 333; 422

342	332; 333
343	331; 333; 334; 335; 341; 343
344; 345	335
345; 346;	341
347	216; 264; 265; 342; 343
348	341
411	334; 412; 413
412	334; 431
413	334; 432
414	325; 334; 441
419	334; 411; 422; 441
421	421; 523;
422	334; 422
511	511
512	343; 512; 513; 515; 941
513	325; 516; 531; 532
514	514; 516
515	516
516	541
521	524
522	522; 524
523	521; 524
611	611; 921;
612	516; 612
613	613
614	621
615	622; 754
621	631; 632; 633; 634
711	312; 711; 754; 811
712	312; 711
713	712; 741
714	713; 754
721	721; 754
722	722
723	712; 723
724	741; 742
731	321; 731
732	731; 754
733	731
734	732; 813
741	751
742	731; 752
743	731; 753; 815
744	753
811	312; 811

812	313; 812
813	818
814	313; 817
815	313; 813
816	313; 818
817	312; 313
821	312; 722; 811
822	312; 812; 813
823	312; 814
824	312; 752
825	312; 732; 814
826	312; 815
827	312; 816
828	312; 821
829	312; 818; 821
831	831; 831
832	832; 833
833	834
834	835
911	521; 524; 952
912	951
913	911; 912; 941
914	515; 912
915	541; 962
916	961; 962
921	921
931	931
932	932; 961
933	933

Sources: Authors' elaboration based on ILO (2012)

(*): Only available in Wolbers (2003), not available for ILO ISCO-88 3 digits, to represent for general occupations