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DETERMINANTS AND WAGE PENALTY OF SKILLS MISMATCH

A cross-country analysis

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PREFACE

Skills mismatches are a complex phenomenon expressed in different types and aspects of labour market imbalances. Tackling the various types of skills mismatches is an important topic for the ETF partner countries as well as for the Member States of the European Union (EU). This is linked to EU priorities to enhance the relevance of education and training and provide further opportunities for learning, as reflected by the European Skills Agenda and European Pillar of Social Rights. Research in this area allows countries to better target their efforts to match supply and demand and to assess the effectiveness of their skills and employment policies.

Many employees in the ETF partner countries are over-qualified for their jobs or are employed in an occupation that is unrelated to their principal field of study. Recent ETF data for a majority of partner countries shows that at least one in four tertiary graduates held a job that required lower levels of formal qualifications in a vast majority of countries.[1] This may suggest that graduation does not necessarily always lead to a matched integration in the labour market and could signal a loss of human capital.[2] There could be many reasons for this, and further evidence is surely required in order to identify the determinants and most effective solutions to prevent or counteract such imbalances.

The available literature shows that across geographical regions and countries the level and profile of education, qualifications or skills of many workers do not match their jobs. This is likely to cause labour shortages and to affect negatively both businesses and the career prospects of the young and adult workforce. These two forms of skills mismatch (i.e. vertical/horizontal) could signal that workers cannot fully utilise their skills and potential loss of human capital. However, their determinants and the wage penalty associated as well as of their occurrence together, have been rarely explored and analysed, particularly in a cross-country perspective.

In this paper, we analyse the determinants of vertical and horizontal skills mismatch between 2016 and 2019 using the Labour Force Survey (LFS) in selected ETF partner countries[3]. Consistently with the available literature, the findings show that socio-demographic, job-related and geographic characteristics are among the determinants of the vertical and horizontal mismatch, and they can affect them jointly. The results also show that overeducation imposes a wage penalty, while horizontal mismatch and a combination of overeducation and horizontal mismatch can positively affect wages.

The paper contributes to the current literature on the determinants of vertical and horizontal skills mismatch and their wage penalty. The contribution is threefold: (i) by exploring both singular and combined measures of vertical/horizontal skills mismatch; (ii) by using objective measures of skills mismatch comparing them across countries, (iii) by discussing the determinants of skills mismatch in transition countries.

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[1] ETF (2022), Skills mismatch measurement in ETF partner countries
[2] Ibid.
[3] Albania, Armenia, Egypt, Georgia, Palestine, Serbia and Türkiye.

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SUMMARY

Skill mismatch is a term that is frequently referred to in policy debates. However, the concept itself is very broad and can include several variations. It is usually defined as a discrepancy between the demand for and supply of skills in the labour market but can be expressed in many different forms and with respect to a number of dimensions. Specifically, skills mismatch can be used to describe vertical mismatch (usually measured in terms of over-education, under-education, over-skilling and under-skilling), horizontal mismatch (typically comparing fields of study and work), skills gaps (the extent to which workers lack the skills necessary to perform their current job), skills shortages (usually measured in terms of unfilled and hard to-fill vacancies) and skills obsolescence (certain skills can become obsolete due to ageing, through technological or economic change which renders them unnecessary or through the underutilisation of particular expertise).

This study provides policy-relevant insights on the determinants of skills mismatch in transition and developing countries. 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. The objective of this paper is twofold: to explore the determinants of both vertical and horizontal skills mismatch, which happen together across countries and by country and to analyse the likelihood and the extent of the wage penalty associated with vertical and horizontal mismatch and their combination.

The analysis is based on the Labour Force Survey (LFS) data (2016-2019) in selected ETF partner countries[4], 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[5] 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 show the relevance of socio-demographic, job, and geographical characteristics in predicting skills mismatch. The cross-country differences should be interpreted considering the institutional and economic country-specific circumstances. Also, the study finds that overeducation imposes a wage penalty while horizontal mismatch does not and that a combination of overeducation and horizontal mismatch can positively affect wages. Finally, this study discusses the main determinants of occupational mismatch in ETF partner countries and the heterogeneity of outcomes across countries, as well as attempts to explain the wage effects of skills mismatch to recommend avenues for future analysis. The results aim to inform policies to tackle skills mismatch.

The study is structured as follows. Section 1 introduces the current evidence on determinants of skills mismatch. Section 2 describes the empirical method, specifying the data used and the identification and estimation strategy. Section 3 presents the results on the skills mismatch determinants. Section 4 shows the results on the wage effects of skills mismatch; Section 5 shows the robustness checks. Section 6 concludes.

Overall, we explored the determinants of vertical and horizontal skills mismatch (age-group, gender, educational level), job characteristics (e.g. permanent/temporary, full-time/part-time), occupation, field of education, and regional level. The information used to match occupations and fields of education are also available for each country[6].

[4] Albania, Armenia, Egypt, Georgia, Palestine, Serbia and Türkiye.
[5] Probit models are statistical models that are used to model binary or dichotomous dependent variables. This means that the outcome of interest can only take on two possible values. In most cases, these models are used to predict whether or not something will happen.
[6] ETF (2022), Skills mismatch measurement in ETF partner countries

What is skills mismatch?

Skills mismatch can be defined as a description of gaps and imbalances of the skills in the labour market due to either qualification or skills levels. Surplus of human capital is typically measured in terms of over-education or over-skilling. However, surplus of education may also be related to horizontal (or field of study) mismatch, whereby workers are employed in jobs that are not relevant to the skills and knowledge they acquired in formal education. Skills mismatch is important to consider because its incidence reflects changes in the labour market, some at a rapid pace, and it is interconnected with human capital. Specifically, skills mismatch can be used to describe:

• vertical mismatch - usually measured in terms of over-education, under-education, over-skilling and under-skilling,

• horizontal mismatch - a comparison of fields of study and work (occupations),

• skills gaps - the extent to which workers lack the skills necessary to perform their current job,

• skills shortages - usually measured in terms of unfilled and hard-to-fill vacancies,

• skill obsolescence - skills can become obsolete due to ageing, through technological or economic change which renders certain skills unnecessary, or through the underutilisation of skills.

Source: ETF (2022), Skills mismatch measurement in ETF partner countries

1. Skills mismatch determinants: literature review and empirical evidence

1.1 The determinants of skills mismatch

Several studies in the current literature explore the determinants of vertical and horizontal skills mismatch. Socio-demographic characteristics are found to be overeducation determinants both in developed (e.g. Belfield, 2010; Ramos & Sanroma, 2011; Addison et al., 2020; Brun-Schammé and Rey, 2021) and transition and developing countries (e.g. Kupets, 2015 and Handel et al., 2016). Overeducation affects more men than women (Addison et al., 2020) as well as older workers, especially in transition economies (see Kupets, 2016). Also, the empirical evidence shows that young married women (Crompton, 2002; Dorn and Sousa-Poza, 2005; Groot, 1993; Sicherman, 1991, Morrar and Zwick, 2021) and immigrants (Aleksynska & Tritah, 2013; Chiswick and Miller, 2009; Kler, 2006) are likely to be more educated. Job characteristics are also correlated with overeducation, such as the field of education and part-time work (Kupets, 2015; Handel et al., 2016, Ortiz and Kucel, 2008, among others). Finally, geographical variables are also found to be determinants of vertical mismatch (see Berlingieri, 2019; Duranton and Puga, 2003; Morrar and Arman, 2020; Morrar and Zwick, 2021) as well as personality traits (Esposito and Scicchitano, 2022). Similar results can be found when looking into the determinants of overskilling (see Mavromaras & McGuinness, 2012; Mavromaras et al., 2013, among others).

The literature also shows that horizontal mismatch relates to the individual's education-related characteristics, such as the field of education (see, for example, Verhaest et al., 2015; Robst, 2007a and Robert, 2014; Wolbers, 2003), the level of education (see Wolbers, 2003; Robst, 2007a; Hensen et al., 2009; Boudarbat and Chernoff, 2012; Bender and Roche, 2013, among others), labour market determinants (see for example Wolbers, 2003; Witte and Kalleberg, 1995 and Robert, 2014), job-related (Witte and Kalleberg, 1995; Wolbers, 2003; Boudarbat and Chernoff, 2012; Robert, 2014) and individual determinants (see Bender and Heywood, 2011 and Hensen et al., 2009; Farooq, 2011, among others). A recent and comprehensive review of the studies analysing the determinants of vertical and horizontal mismatch can be found in Kofol et al. (2022, forthcoming).

Most studies in the current literature focus on one country and use different skills mismatch indicators depending on the specific characteristics of the survey or using self-reported skills mismatch measures which limits their comparability. The number of studies looking at the determinants of skills mismatch, offering cross-country comparisons and relying on comparable indicators is relatively scarce compared to the number of studies focusing only on one country (see Kupets, 2015; Handel et al., 2016; Ortiz and Kucel, 2008; Alle et al., 2013; Nieto et al., 2015; Robert, 2014; Bergin et al., 2019 and Montt, 2015, among others).

Studying the determinants of vertical and horizontal skills mismatch separately might bias the results, as skills mismatch could occur simultaneously according to both dimensions. Very few studies in the current literature look at the determinants of both vertical and horizontal measures of skills mismatch (combined) (Hensen et al., 2009; Verhaest et al., 2015; Berlingeri, 2019; Béduwé and Giret, 2011; Schweri et al., 2020; Kucel and Vilalta-Bufi, 2013; Kim et al., 2012 and Kelly et al., 2010).

1.2 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. Also, wage penalties usually depend on whether the horizontal mismatch is accompanied by a vertical mismatch (Bergin et al., 2019). While most of the current theoretical and empirical literature agree on the negative wage effect of overeducation (for a review, see Hartog, 2000 and Leuven and Oosterbeek, 2011), 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 are no wage penalties 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.

Few studies exploring the individual-level correlates of the field of study mismatch allow for comparable estimates across countries (for three approaches to a comparative analysis of field-of-study mismatch, see OECD, 2014; Quintini, 2011b; and Wolbers, 2003). Most studies focus on one country, and each adopts methodological choices given the specific characteristics of the survey or uses a self-reported measure field-of-study mismatch. At the same time comparable figures for the wage penalty associated with field-of-study are hindered by the fact that many country-specific studies use self-reported measures of field-of-study mismatch (e.g. Robst, 2007a, 2007b, 2008; Nordin, et al., 2010; and Kelly et al., 2010, Verhaest et al., 2015) (Kim et al., (2012) represents an exception). The few studies which 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 (e.g. Wolbers, 2003; Quintini, 2011b).

Overall, the empirical evidence shows that mismatched workers are more likely to receive lower wages (Kelly et al., 2010; Robst, 2007a; Wolbers, 2003; Nordin et al., 2010; Quintini, 2011b; OECD, 2014), and experience lower levels of job satisfaction and are more likely to be actively looking for a job while in the job (Wolbers, 2003; Béduwé and Giret, 2011). However, some studies showed how a part of field-of-study mismatch is related to overqualification, that a large penalty is associated with qualifications mismatch and that part of the overall field-of-study mismatch penalty is due to workers having to downgrade when they find work in other fields (become overqualified) (Kim et al., 2012; OECD, 2014; Quintini, 2011a, 2011b). When studying the skills mismatch wage penalty risk, studies that fail to account for both horizontal and vertical mismatch produce biased estimates (Kim et al., 2012). This failure to jointly take qualification and field-of-study mismatch into account explains a 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 can be due to the restrictions applied to the sample for the analysis (e.g. specific country, field of education, age).

The few studies which look at the impact of both vertical and horizontal mismatch on wages are (Kim et al., 2012; OECD, 2014; Quintini, 2011a, 2011b) on specific countries and OECD (2014) and Montt (2015), which are the only ones providing cross-country comparisons. OECD (2014) uses data from the PIAAC Adult Skills survey and focuses on the change in the penalty across age groups and finds a relationship between field-of-study mismatch and wages at all age groups, although a penalty is observed only among prime-age and older workers (among young workers there is a wage premium associated with field-of-study mismatch). Montt (2015) extends the findings from OECD (2014) by simultaneously identifying the relationship between the wage penalty to field-of-study mismatch and qualification mismatch. The author finds that in most countries, there is no significant wage penalty associated with field-of-study mismatch, when workers are not overqualified and that overqualification accounts for only a part of the total mismatch. The reason explaining these results could be that training is already producing sufficient skills to allow at least some, but not all, workers to move across fields at the same qualification level (OECD, 2014).

2. The empirical method

2.1. Data and descriptive statistics

The data we used for this study are the Labour Force Surveys (LFS) (2016-2019) of Albania, Armenia, Georgia, and Palestine; the Household Labour Force Survey of Türkiye (2016-2019) and the Harmonized Labour Force Survey of Egypt (2016 and 2017). The LFS provides detailed information on the education level of the individual (according to the ISCED classification), his occupation (following the ISCO categories), his field of education (according to the ISCED-F classification) and an 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 described 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), classifying workers with acquired education above/below the average of the employee's occupation group as over/under-qualified. We used the mode following other studies (Kiker et al., 1997; Mendes de Oliveira et al., 2000; ILO, 2012).

Horizontal mismatch

Horizontal mismatch measures the extent 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 a subjective and an objective approach.

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).

2.2. 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):

$$Yitc = ß1 + ß2Xitc + ß3Z\ itc + ɣt + θc + uitc;$$

$$P(Y=1|\ X, Z) = Φ(ß1 + ß2Xitc + ß3Z\ itc + ɣt + θc)$$

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

$$Yit = ß1 + ß2Xit + ß3Z\ it + ɣt + uit;$$

$$P(Y=1|\ X, Z) = Φ(ß1 + ß2Xit + ß3Z\ it + ɣt)$$

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 1-7 in Appendix 1 provide a complete list of the covariates analysed by country. $ɣ_t$ 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_{itc} is the error term.

Like Montt (2017), we also run wage regressions to find if and to which extent horizontal mismatch, vertical mismatch and their combination cause a wage penalty (Equation 2a and Equation 2b below).

Equation 2a: Wage regression (pooled sample):

$$\ln(wage)itc = ß1 + ß2Fitc + ß3Qitc + ß4FQitc + ß5Xitc + Si + uitc$$

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

$$\ln(wage)it = ß1 + ß2Fitc + ß3Qit + ß4FQit + ß5Xit + Si + uit$$

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 values on wages have been imputed to the country-specific mean using the dummy-variable imputation method to avoid losing further 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).

2.3. 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.

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

Threats to identification might be the endogeneity of some controls due to either unobserved heterogeneity or the endogeneity of education. Also, as we excluded self-employed workers from the sample; our results might not be generalisable to all workers. We tackle these concerns by running some robustness checks using different model specifications (results available in Appendix B) and discussing them in the robustness checks section.

Finally, 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).

3. The results

3.1 Skills mismatch determinants across countries

Tables 1-7 in the annex contains the results (the marginal effects of the skills mismatch determinants). In the annex we also show the summary statistics of the variables used for each country (see Tables A1-A7); they differ across countries. Table 1 in the annex shows the marginal effects of the determinants of skills mismatch obtained, estimating a cross-country probit model using 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 skills mismatch (defined by binary dependent variables) as a response to a one-unit change in the control variables. The control variables are the skills mismatch determinants suggested by the current literature (socio-demographic characteristics, job characteristics, geographical characteristics, where available).

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 the probability of being occupationally mismatched after 35 is compared to the youngest group (15-24 years old) 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 about as double as likely as them to be occupationally mismatched and those above 65 years about as three times as likely. The employees between 25 and 34 years old are more likely than the younger ones 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 and thus longer times in finding a position in the labour market (Adalet Mc Gowan & Andrews, 2015). The empirical evidence shows that, as workers get more experience and relevant information on job market opportunities, their mismatch is reduced (Alba-Ramirez, 1993), and they have the time to signal their skills to employers (OECD, 2014a).

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 does not play a significant role in the probability of being occupationally mismatched. These results are consistent with Adalet Mc Gowan & Andrews (2015), who find that part-time workers are more likely to be mismatched. Other studies (Sparreboom, 2014; Connolly and Gregory, 2008) suggest that occupational choices in part-time work could be rarer, increasing the probability 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 negatively correlated with the probability of being over-educated at increasing rates. The current literature is consistent with this finding, suggesting that the result can be explained by the fact that, as workers gain more experience, they move into jobs that better fit their skill levels

(Adalet Mc Gowan & Andrews, 2015). Also, it could be that workers whose over-skilling is beneficial for firm productivity are more likely to be promoted to a job matching 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 are contrary to the assumption that women are more likely to be over-skilled/qualified because of family constraints or the wish to improve their work-life balance.

Working in a firm with at least 10 workers increases the probability of being over-qualified by 1.9 percentage points while having a permanent job has a minor impact (almost null) on over-education. The current literature suggests that the impact of firm size on skills mismatch tends to vary 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 a temporary contract is also in line 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 above 35 years old are more likely than employees between 15 and 24 years old to be under-educated at an increasing level. 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 years old are less likely to be horizontally mismatched than younger employees between 15 and 24 years old. 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 above ten employees are more likely to work in a mismatched field (by 5.1 percentage points).

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

Column 5 in Table 1 describes the determinants of general qualification mismatched (vertical or horizontal mismatch) by socio-demographic and job characteristics. Education is one factor that has the strongest effects on mismatches, i.e. holding a medium education degree increases the possibility of being mismatched by 10.8 percentage points. In addition, being a male worker negatively impacts mismatch by reducing the probability of 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	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)	Horizontal & Vertical (5)
Medium education (dummy)	-0.014*** (0.001)	0.153*** (0.001)	0.039*** (0.001)	-0.006*** (0.002)	0.108*** (0.001)
Age (25-34)	-0.014*** (0.001)	0.153*** (0.002)	0.039*** (0.001)	-0.006*** (0.003)	0.108*** (0.002)
Age (35-44)	0.031*** (0.001)	-0.076*** (0.002)	-0.016*** (0.001)	0.007** (0.003)	-0.051*** (0.002)
Age (45-54)	-0.053*** (0.001)	-0.219*** (0.002)	0.053*** (0.002)	-0.039*** (0.003)	-0.198*** (0.002)
Age (55-65)	-0.067*** (0.001)	-0.235*** (0.002)	0.098*** (0.002)	-0.064*** (0.003)	-0.173*** (0.002)
Older than 65 years old	-0.079*** (0.003)	-0.243*** (0.005)	0.195*** (0.005)	-0.021** (0.009)	-0.081*** (0.005)
Gender (dummy)	-0.004*** (0.001)	0.077*** (0.001)	-0.016*** (0.001)	-0.035*** (0.002)	-0.012*** (0.001)
Fulltime (dummy)	0.042*** (0.002)	-0.010*** (0.002)	-0.004** (0.002)	0.040*** (0.003)	0.030*** (0.002)
Firm size >=10	0.022*** (0.001)	0.019*** (0.001)	-0.066*** (0.001)	0.051*** (0.002)	0.019*** (0.001)
Firm size missing	-0.010 (0.047)	0.101 (0.072)	-0.137*** (0.049)	0.125 (0.093)	-0.002 (0.072)
Permanent job (dummy)	-0.004*** (0.001)	0.013*** (0.001)	-0.017*** (0.001)	0.067*** (0.002)	0.066*** (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

3.2 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 (Table 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). These last results coincide with the literature about the incidence of qualification mismatch (basically 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 (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 finds 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 in all the countries where the information is available (Egypt, Albania, Palestine, and Türkiye), with an exception for Serbia, where the coefficient is not statistically significant (see Table 5, Column 1). Being born abroad[8] instead is positively correlated with occupational mismatch both in Serbia (with an increase in the probability of being occupationally mismatched by 2.3 percentage points) and in Türkiye (with an increase in the probability of being occupationally mismatched by 3.1 percentage points) (see Tables 5 and 8). This result is in line with the findings from Adalet Mc Gowan and Andrews (2015), who also suggests that immigrants are less likely to be over-skilled (Column 2), while they are more likely to be under-skilled in several OECD countries. At the same time, it is not significantly correlated with occupationally mismatched in Albania.

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,

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

raising the probability of over-skilling and a switch from full-time to part-time employment, which could entail occupational downgrading (Adalet Mc Gowan and Andrews, 2015; Sparreboom, 2014; Connolly and Gregory, 2008). 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 with respect to having a temporary one, except for Türkiye, where having 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 Mc Gowan 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 providing permanent jobs are usually interested in a long-term employment relationship 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 bigger firm positively correlates 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 skill mismatch (Adalet Mc Gowan and Andrews, 2015). Quintini (2011a) finds no significant relationship between skill mismatch and 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 make it possible to transfer their workers to better matches inside the firm, lowering mismatch.

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 Belingieri, 2019 Morrar and Zwick, 2021, for instance). Spatial isolation negatively affects the size of labour markets and automatically decreases the number and types of employment opportunities and, therefore, 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 probability of being occupationally mismatched, such as in Albania, Egypt, Palestine, and Türkiye. The positive impact of holding medium qualifications on the probability of mismatched 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. Being a male employee increases the probability of being over-educated in all the countries analysed, except Egypt, Albania, and Serbia, where being a male employee significantly increases the probability of being over-educated respectively 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 increased 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, even if prevalently 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 under-educated 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 under-educated. Working full-time significantly decreases the probability of being under-educated in all the countries of interest, except 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 under-educated, 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 positively correlates with being under-educated in Albania and Palestine, while negatively correlated in Georgia and Türkiye. Finally, living in a rural area increases the probability of being under-educated both in Egypt and Armenia, while it does not play any 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 Table 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 relative to these last three countries are consistent with the literature, which finds that individuals who are not 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 females to be horizontally mismatched in Armenia, Georgia, and Türkiye, while 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 a permanent job 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 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 et al., 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 of education mismatch.

Either vertical mismatched (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 he/she is over/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 pooled sample (Table 1) show an increase in the probability of mismatched 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, getting old reduces the probability of being mismatched. The magnitude of impacts increases by age between 25-54 years old and reduces from 55 years old onwards (Table 1, 7, and 8). In some countries, the negative effects increase gradually with age, even for senior workers, including Serbia or Albania, while in Egypt, the effect turns into a positive sign. In Armenia, being a senior worker aged 55 years old or more is not impacted by mismatches.

On average, being a male worker reduces the probability of being mismatched by 1.2 percentage points (Table 1), while it shows a mixed pattern for the country analysis. 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 results in a higher likelihood of being a mismatched worker on average by 6.6 percentage points (Table 1). The result is also valid for country analysis except for Serbia (Table 5). On the other hand, having a full-time job has an uncleared 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. Similarly to having a full-time job, firm size characteristic does not show any clear effect trend on mismatch.

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

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

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

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

Source: Armenian LFS survey (2016-2019).

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

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

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)	Horizontal & Vertical (5)
Medium education (dummy)	-0.103*** (0.003)	0.509*** (0.003)	0.055*** (0.005)	0.050*** (0.004)	0.137*** (0.005)
Age (25-34)	-0.030*** (0.006)	-0.035*** (0.007)	-0.069*** (0.008)	0.019** (0.007)	-0.153*** (0.008)
Age (35-44)	-0.040*** (0.006)	-0.015* (0.009)	-0.079*** (0.009)	-0.044*** (0.008)	-0.214*** (0.009)
Age (45-54)	-0.014** (0.006)	-0.077*** (0.009)	-0.034*** (0.009)	-0.010 (0.008)	-0.130*** (0.009)
Age (55-65)	-0.017** (0.007)	-0.129*** (0.009)	-0.023** (0.010)	0.042*** (0.009)	-0.110*** (0.009)
Older than 65 years old	-0.070*** (0.017)	-0.137*** (0.031)	-0.048 (0.029)	0.000 (0.028)	-0.167*** (0.031)
Gender (dummy)	-0.026*** (0.003)	-0.057*** (0.004)	0.061*** (0.004)	-0.005 (0.004)	0.022*** (0.004)
Married (dummy)	-0.040*** (0.004)	0.026*** (0.006)	-0.035*** (0.005)	-0.028*** (0.005)	-0.078*** (0.006)
Born abroad (dummy)	-0.004 (0.028)	-0.054 (0.045)	0.066 (0.042)	0.067* (0.039)	0.178*** (0.046)
Citizenship (dummy)	0.026 (0.031)	-0.081* (0.044)	0.038 (0.044)	-0.036 (0.036)	0.074* (0.042)
Fulltime (dummy)	-0.054*** (0.009)	0.078*** (0.015)	-0.034*** (0.013)	0.045*** (0.012)	0.121*** (0.014)
Permanent job (dummy)	-0.018*** (0.005)	0.016* (0.008)	-0.016** (0.007)	0.017*** (0.006)	0.055*** (0.007)
Private sector (dummy)	0.045*** (0.004)	-0.080*** (0.005)	0.113*** (0.005)	-0.089*** (0.004)	-0.084*** (0.005)
Hours worked	0.001*** (0.000)	-0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
Firm-size (11-19)	-0.003 (0.004)	-0.014** (0.007)	0.029*** (0.006)	-0.036*** (0.006)	-0.053*** (0.006)
Firm-size (20-49)	-0.003 (0.005)	-0.066*** (0.007)	0.054*** (0.006)	-0.074*** (0.006)	-0.105*** (0.007)
Firm-size (>=50)	0.022*** (0.004)	-0.083*** (0.006)	0.122*** (0.005)	-0.090*** (0.005)	-0.091*** (0.006)
Firm-size missing (dummy)	0.004 (0.004)	-0.047*** (0.007)	0.078*** (0.006)	-0.080*** (0.006)	-0.062*** (0.007)

Sample weights	0.000*** (0.000)	-0.000 (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)
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 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

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

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)	Horizontal & Vertical (5)
Medium education (dummy)	-0.046*** (0.002)	-0.091*** (0.003)	-0.035*** (0.002)	-0.107*** (0.002)	-0.181*** (0.003)
Age (25-34)	-0.015*** (0.005)	0.054*** (0.006)	0.007 (0.005)	-0.097*** (0.008)	0.053*** (0.006)
Age (35-44)	-0.061*** (0.006)	-0.006 (0.006)	0.041*** (0.005)	-0.368*** (0.008)	-0.062*** (0.006)
Age (45-54)	-0.067*** (0.006)	-0.005 (0.006)	0.021*** (0.005)	-0.456*** (0.008)	-0.114*** (0.006)
Age (55-65)	-0.106*** (0.006)	-0.019*** (0.006)	0.046*** (0.006)	-0.492*** (0.008)	-0.119*** (0.007)
Older than 65 years old	-0.118*** (0.010)	0.008 (0.015)	0.001 (0.013)	-0.500*** (0.009)	-0.132*** (0.017)
Gender (dummy)	0.006*** (0.002)	-0.004* (0.002)	0.052*** (0.002)	0.023*** (0.002)	0.031*** (0.003)
Married (dummy)	-0.001 (0.002)	-0.006** (0.003)	0.009*** (0.003)	-0.006** (0.003)	-0.001 (0.003)
Born abroad (dummy)	0.023*** (0.003)	0.033*** (0.004)	-0.022*** (0.004)	-0.009** (0.004)	0.010** (0.005)
Fulltime (dummy)	0.013** (0.006)	-0.024*** (0.007)	0.037*** (0.006)	0.000 (0.007)	0.008 (0.008)
Permanent job (dummy)	-0.029*** (0.002)	-0.030*** (0.003)	-0.024*** (0.003)	0.024*** (0.003)	-0.044*** (0.003)
Formal job (dummy)	0.007 (0.004)	-0.022*** (0.005)	-0.046*** (0.005)	0.031*** (0.006)	-0.026*** (0.006)
Firm size (11-19)	0.006 (0.004)	0.021*** (0.005)	-0.030*** (0.005)	0.024*** (0.005)	-0.001 (0.006)
Firm size (20-49)	-0.004 (0.003)	-0.004 (0.004)	-0.063*** (0.004)	0.044*** (0.004)	-0.046*** (0.005)

Firm size (>=50)	0.020*** (0.002)	0.017*** (0.003)	-0.072*** (0.003)	0.048*** (0.003)	-0.038*** (0.003)
pweight	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	126,732	130,288	130,288	85,053	130,288

Source: LFS surveys (2016-2019).

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

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

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)
Medium education (dummy)	0.100*** (0.003)	0.492*** (0.003)	-0.145*** (0.006)
Gender (dummy)	0.008** (0.004)	0.082*** (0.005)	-0.005 (0.005)
Age (25-34)	0.059*** (0.004)	0.098*** (0.005)	-0.045*** (0.006)
Age (35-44)	0.009** (0.004)	0.061*** (0.006)	0.053*** (0.007)
Age (45-54)	0.002 (0.005)	0.035*** (0.006)	0.149*** (0.008)
Age (55-65)	0.011* (0.006)	0.044*** (0.008)	0.213*** (0.011)
Older than 65 years old	-0.040*** (0.012)	0.008 (0.024)	0.265*** (0.034)
Married (dummy)	-0.022*** (0.004)	-0.040*** (0.005)	0.035*** (0.006)
Rural (dummy)	0.017*** (0.003)	0.018*** (0.003)	-0.004 (0.004)
Private sector (dummy)	0.025*** (0.005)	-0.009 (0.005)	0.024*** (0.006)
Firm size (>=10)	0.002 (0.003)	0.015*** (0.004)	-0.031*** (0.005)
Firm size missing (dummy)		-0.029 (0.085)	0.174 (0.113)
Hours worked	0.000** (0.000)	0.002*** (0.000)	-0.001*** (0.000)

Fulltime (dummy)	0.010 (0.008)	-0.049*** (0.010)	-0.024** (0.012)
Permanent job	-0.016*** (0.005)	0.058*** (0.005)	-0.067*** (0.006)
pweight	-0.008*** (0.003)	-0.007** (0.003)	0.006 (0.004)
Year F.E.	Yes	Year	Year
Observations	48,665	50,078	50,078

Source: Palestinian LFS survey (2016-2019).

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

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

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)	Horizontal & Vertical (5)
Medium education (dummy)	-0.142*** (0.004)	-0.621*** (0.040)	-0.043*** (0.004)	0.427*** (0.025)	-0.445*** (0.003)
Age (25-34)	0.038*** (0.008)	0.050*** (0.006)	-0.056*** (0.009)	-0.006 (0.014)	-0.004 (0.008)
Age (35-44)	0.019** (0.008)	0.060*** (0.006)	-0.187*** (0.008)	-0.010 (0.014)	-0.096*** (0.008)
Age (45-54)	-0.002 (0.008)	0.053*** (0.006)	-0.239*** (0.008)	0.000 (0.015)	-0.137*** (0.008)
Age (55-65)	0.000 (0.008)	0.035*** (0.006)	-0.240*** (0.008)	0.045*** (0.015)	-0.133*** (0.008)
Older than 65 years old	-0.038*** (0.010)	0.009 (0.008)	-0.227*** (0.010)	0.073*** (0.018)	-0.128*** (0.011)
Gender (dummy)	0.032*** (0.004)	0.055*** (0.003)	-0.036*** (0.003)	-0.048*** (0.006)	0.008** (0.004)
Fulltime (dummy)	-0.023** (0.010)	-0.033*** (0.007)	-0.005 (0.008)	0.043*** (0.014)	-0.016 (0.010)
Permanent job (dummy)	-0.060*** (0.006)	0.003 (0.007)	0.021*** (0.006)	0.099*** (0.019)	0.060*** (0.006)
Private sector (dummy)	0.079*** (0.004)	0.077*** (0.003)	-0.039*** (0.004)	-0.000 (0.006)	0.044*** (0.004)
Hours worked	0.003*** (0.000)	0.003*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
Firm size (11-19)	-0.017*** (0.006)	-0.025*** (0.005)	0.012** (0.006)	0.027*** (0.010)	0.001 (0.007)

Firm size (20-49)	-0.021*** (0.006)	-0.047*** (0.004)	-0.009* (0.005)	0.010 (0.009)	-0.056*** (0.006)
Firm size (>=50)	-0.014*** (0.005)	-0.023*** (0.004)	-0.028*** (0.005)	0.046*** (0.009)	-0.031*** (0.006)
Firm size missing (dummy)	0.051*** (0.007)	0.010 (0.007)	-0.041*** (0.006)	0.015 (0.013)	-0.043*** (0.007)
pweight	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)
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 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

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

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)	Horizontal & Vertical (5)
Medium education (dummy)	-0.008*** (0.001)	0.298*** (0.001)	0.187*** (0.001)	-0.062*** (0.003)	
Gender (dummy)	-0.008*** (0.001)	0.137*** (0.002)	-0.070*** (0.001)	-0.058*** (0.003)	-0.004** (0.002)
Married (dummy)	-0.050*** (0.001)	-0.034*** (0.002)	0.027*** (0.002)	0.023*** (0.003)	-0.044*** (0.002)
Age (25-34)	0.051*** (0.002)	-0.115*** (0.003)	-0.022*** (0.002)	-0.023*** (0.004)	-0.098*** (0.003)
Age (35-44)	-0.010*** (0.002)	-0.235*** (0.003)	0.019*** (0.002)	-0.042*** (0.005)	-0.275*** (0.003)
Age (45-54)	-0.044*** (0.002)	-0.295*** (0.003)	0.079*** (0.002)	-0.040*** (0.005)	-0.307*** (0.003)
Age (55-65)	-0.066*** (0.002)	-0.351*** (0.003)	0.158*** (0.003)	-0.049*** (0.007)	-0.279*** (0.004)
Older than 65 years old	-0.093*** (0.004)	-0.382*** (0.007)	0.401*** (0.009)	-0.022 (0.023)	-0.067*** (0.009)
Born abroad (dummy)	0.031*** (0.003)	0.098*** (0.005)	-0.002 (0.004)	-0.010 (0.008)	0.106*** (0.006)
Private sector (dummy)	-0.036*** (0.001)	0.060*** (0.002)	-0.048*** (0.001)	-0.058*** (0.003)	-0.214*** (0.002)
Fulltime (dummy)	0.076*** (0.003)	-0.013*** (0.004)	-0.083*** (0.003)	-0.014** (0.007)	-0.022*** (0.004)

Permanent job (dummy)	0.044*** (0.002)	-0.008*** (0.002)	-0.025*** (0.002)	0.117*** (0.006)	0.070*** (0.002)
Firm size (11-19)	0.017*** (0.002)	-0.015*** (0.003)	-0.041*** (0.003)	0.019*** (0.005)	-0.015*** (0.003)
Firm size (20-49)	0.013*** (0.001)	0.003 (0.002)	-0.064*** (0.002)	0.029*** (0.004)	-0.004 (0.002)
Firm size (>=50)	0.041*** (0.001)	0.052*** (0.002)	-0.076*** (0.001)	0.010*** (0.003)	-0.007*** (0.002)
Firm size missing (dummy)	-0.016 (0.012)	0.010 (0.018)	-0.024 (0.017)	-0.022 (0.041)	0.009 (0.023)
Hours worked	-0.000*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	-0.005*** (0.000)	-0.000 (0.000)
pweight	-0.059*** (0.005)	-0.121*** (0.007)	0.149*** (0.006)	-0.020 (0.012)	0.037*** (0.008)
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 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

4. 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.

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 6.9% (Table 9, column 3). These results are like those found in the current literature (Montt, 2017; Béduwé and Giret, 2011; Kim, Ahn 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, Ahn 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 respect to 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*** (0.002)		-0.102*** (0.003)
Horizontal mismatch		0.075*** (0.002)	0.044*** (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: 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

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*** (0.008)		-0.250*** (0.010)
Horizontal mismatch		0.101*** (0.006)	0.059*** (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: 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

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*** (0.006)		-0.200*** (0.010)
Horizontal mismatch		0.026*** (0.008)	-0.003 (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: 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

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 (0.019)		0.028 (0.132)
Horizontal mismatch		-0.031 (0.034)	-0.031 (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: 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

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*** (0.003)		0.049*** (0.005)
Horizontal mismatch		0.038*** (0.003)	0.056*** (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: 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

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: 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. Field of education fixed effects not available.

5. The robustness checks

We run some robustness checks to tackle the issues of 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, as the skills mismatch indicators are constructed using the highest education level achieved. 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.

6. Conclusions

This study analyses the vertical and horizontal mismatch determinants and the impact of over-education and horizontal mismatch on wages in Serbia, Albania, Türkiye, Georgia, Armenia, Egypt, and Palestine using repeated cross-sections of the LFS surveys between 2016 and 2019. The analysis relies on a probit model, calculating the marginal effects of both socio-demographic, job and geographical characteristics running the analysis both on the pooled sample and separately for each country.

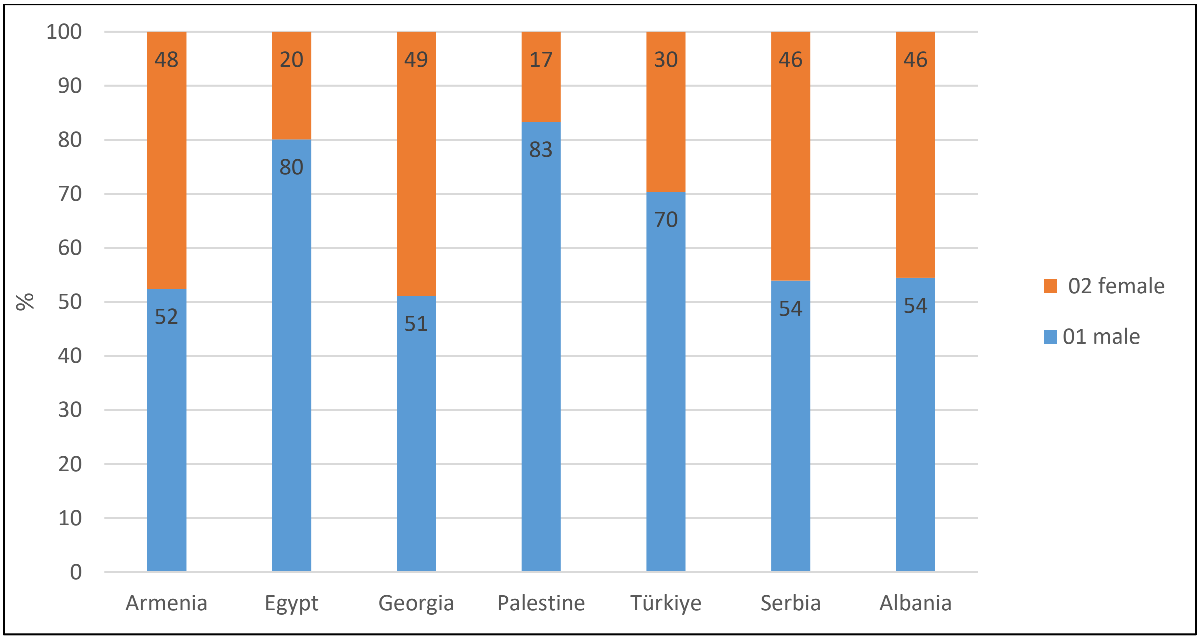
The results are consistent with those found in the current literature, showing that socio-demographic determinants such as the level of education, the field of education, age, gender, marital status, and being born abroad or not influence both the probability of being vertically and horizontally mismatched. Also, job characteristics such as the occupation level, having a permanent or temporary job, being a full-time employee, and the firm's size play a role in predicting the probability of being mismatched in the labour market. Finally, geographical factors such as living in a rural/urban area might reduce/increase the number, and the variety of jobs available influences the probability of skills mismatch. The findings show that the direction and the magnitude of the correlation between our skills mismatch measures and the determinants of skills mismatch are heterogeneous across the countries analysed. The cross-country differences can be explained by differences in labour market characteristics (such as legislation and wage structure) and country characteristics (e.g., the economic and the education structure).

The results also show that overall, in the pooled sample, being overeducated is associated with a wage penalty, as well as being over-educated and horizontally mismatched, while being horizontally mismatched has a positive effect on wages. The effect of the two measures of skills mismatch combined differs across countries, being positive in some and negative in others. The results are robust to different model specifications.

ANNEX

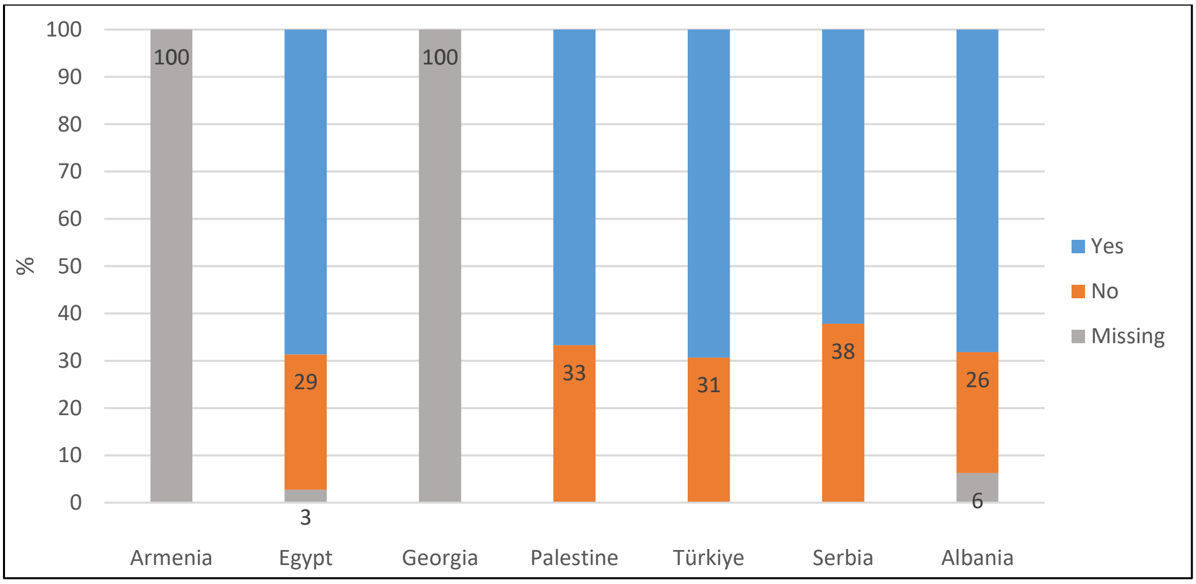
Annex A: Data description

Figure A 1: Gender distribution across countries (whole sample unweighted)



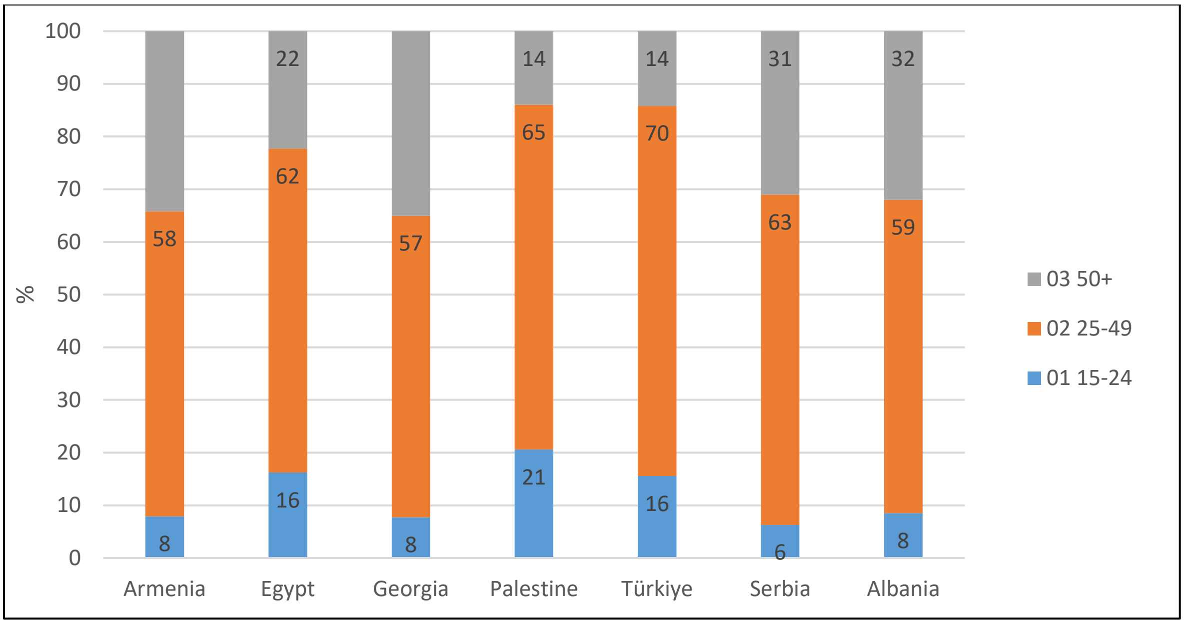
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 2: Share of individuals being married (whole sample unweighted)



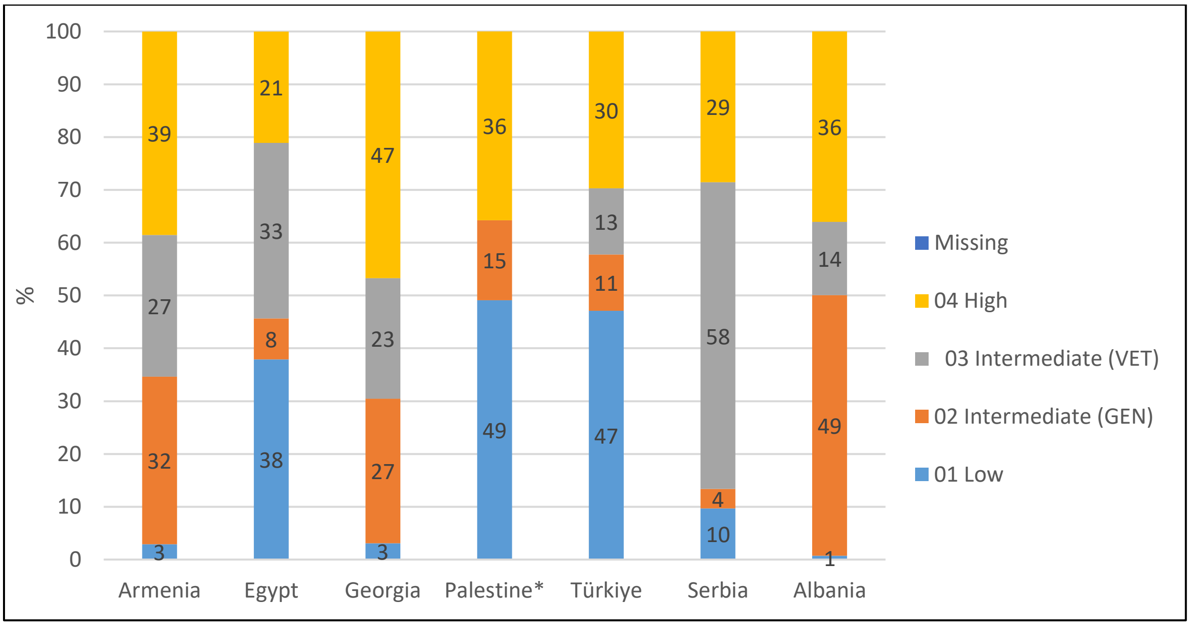
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 3: Distribution of age groups (whole sample unweighted)



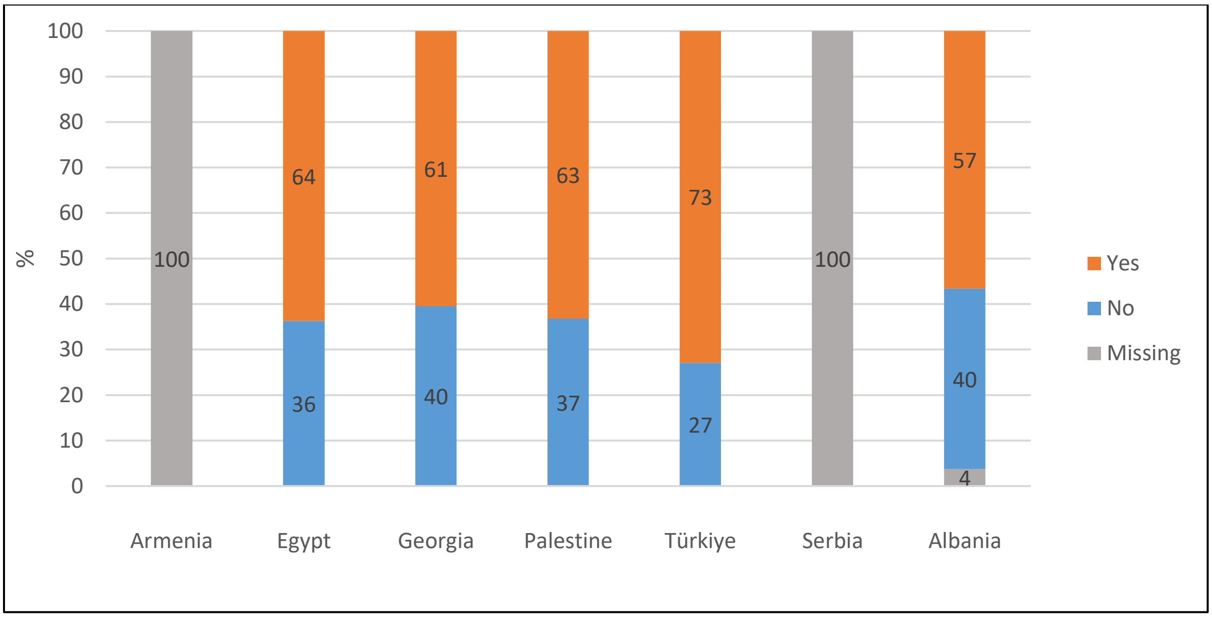
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 4: Distribution of education level (whole sample unweighted)



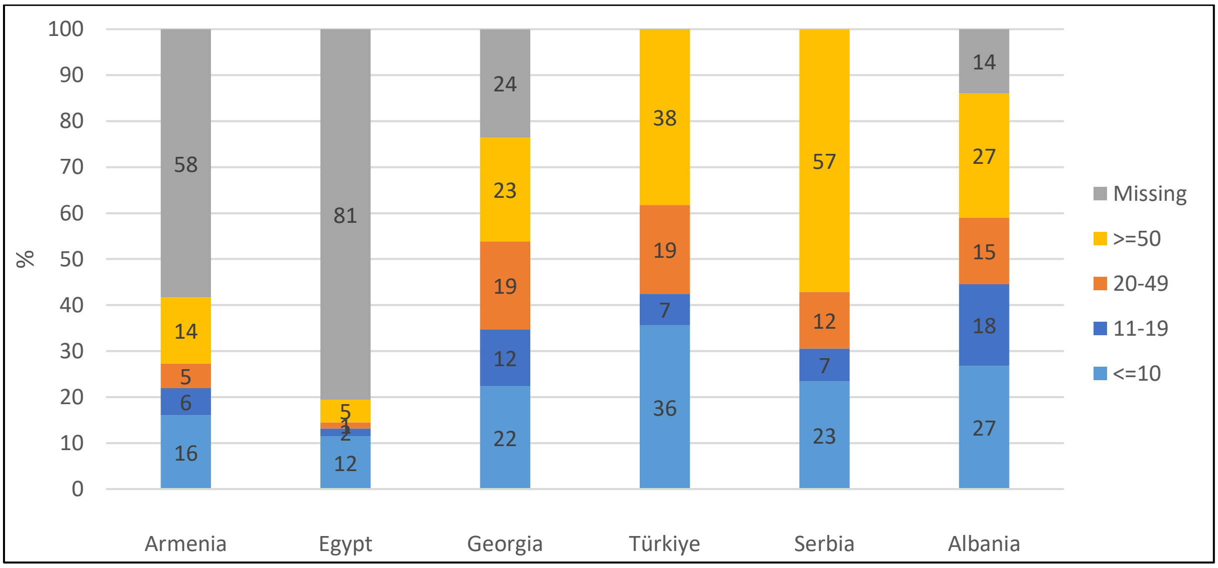
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 5: Share of individuals working for a private company (Whole sample unweighted)



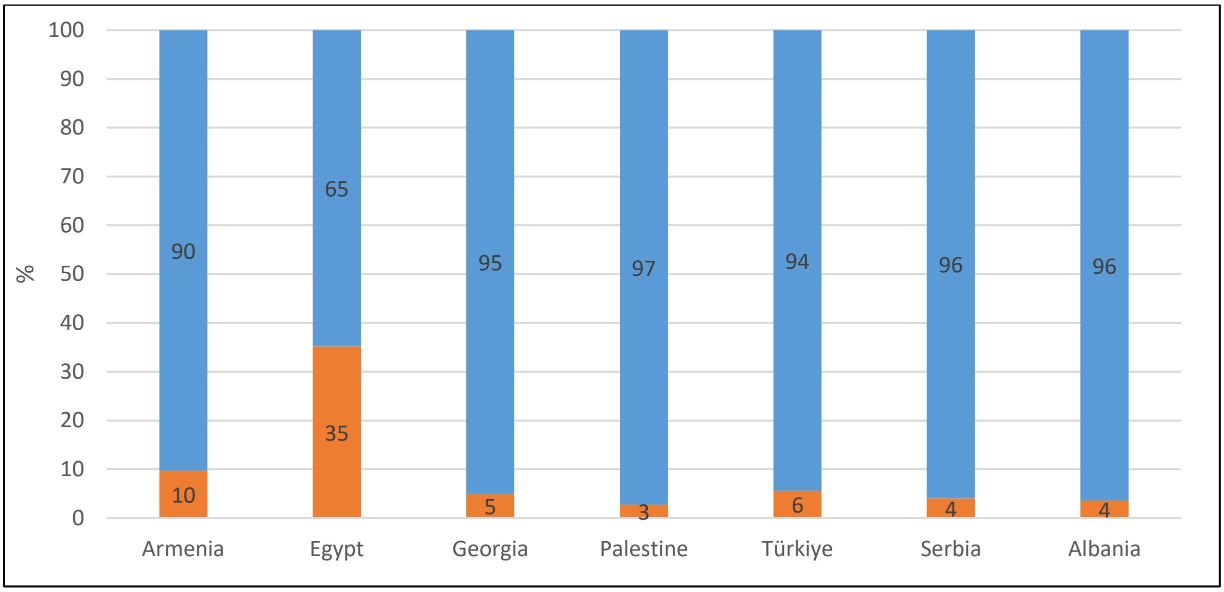
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 6: Distribution of company size where individual is working (Whole sample unweighted)



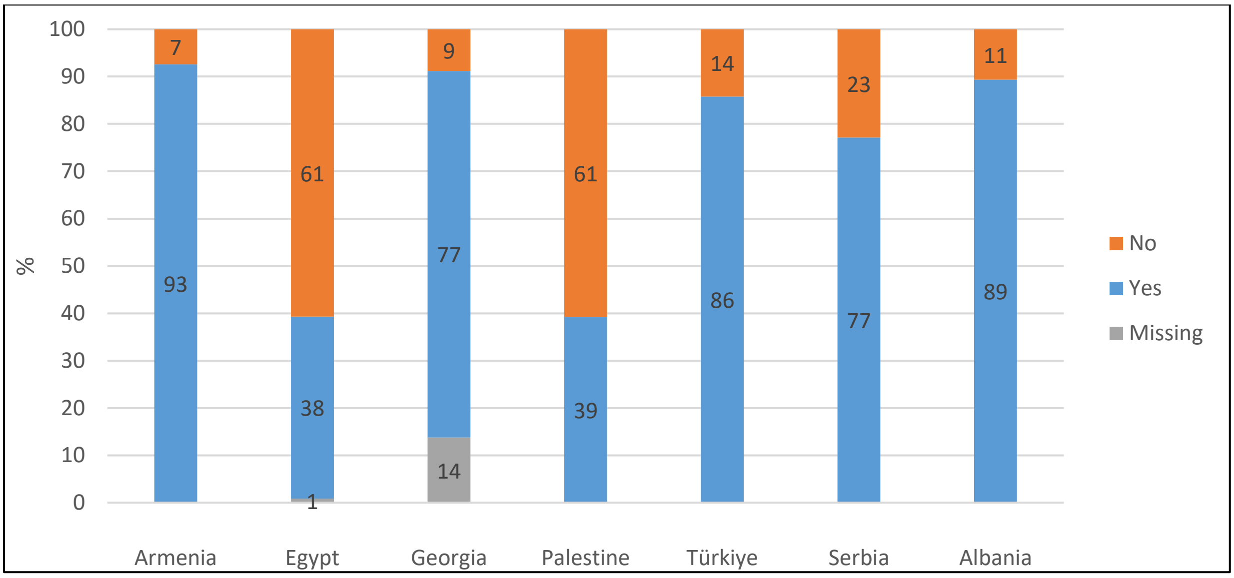
Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 7: Share of individuals having a fulltime contract (Whole sample unweighted)



Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

Figure A 8: Share of individuals having a permanent contract (Whole sample unweighted)



Source: Country LFS surveys (2016-2019).
Notes: bars do not reach 100% due to missing information on category.

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 size	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 A 1: Summary statistics (Albania)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	57,156	2,017.5	1.1	2,016.0	2,019.0
Sample weight	57,156	37.0	31.9	0.3	632.0
ISCED_F_1997	43,756	2.5	2.6	0.0	8.0
Gender	57,156	0.5	0.5	0.0	1.0
Employee	57,156	1.0	0.0	1.0	1.0
Being married	53,565	0.7	0.4	0.0	1.0
Being citizen of the country	53,565	1.0	0.1	0.0	1.0
Being born abroad	53,565	0.0	0.0	0.0	1.0
Working for a private company	57,156	0.6	0.5	0.0	1.0
Firm size	57,156	2.8	1.4	1.0	5.0
Number of hours worked	57,033	43.0	7.9	0.0	98.0
Income	14,218	365,217.1	148,683.4	0.0	2,500,000.0
Having a fulltime job	57,156	1.0	0.2	0.0	1.0
Having a permanent job	57,156	0.9	0.3	0.0	1.0
Occupation ISCO 08-1 digits	57,150	5.1	2.6	0.0	9.0
Age group	57,156	3.2	1.3	1.0	6.0
Medium education	57,156	0.6	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	56,386	0.0	0.2	0.0	1.0

Occupational mismatch (High education)	56,386	0.1	0.2	0.0	1.0
Horizontal mismatch	40,227	0.5	0.5	0.0	1.0
Over-education	57,150	0.3	0.4	0.0	1.0

Table A 2: 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	105.7	68.4	13.7	427.7
Gender	22,251	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	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	0.1	0.3	0	1
Horizontal mismatch	10,865	0.9	0.2	0	1
Over-education	22,251	0.2	0.4	0	1
Under-education	22,251	0.1	0.3	0	1

Table A 3: 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	125,059.0	0.8	0.4	0.0
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 A 4: 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	0.5	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 fulltime job	50,806	1	0.2	0	1
Having a permanent job	50,806	1.0	0.5	0.0	2.0
Age group	50,806	3.4	1.4	1	6
Medium education (dummy)	50,806	0.5	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	49,894	0.1	0.3	0.0	1.0
Occupational mismatch (High education)	49,894	0.1	0.3	0.0	1.0
Horizontal mismatch	23,982	0.2	0.4	0.0	1.0
Over-education	50,798	0.2	0.4	0.0	1.0
Under-education	50,798	0.2	0.4	0.0	1.0

Table A 5: 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 A 6: Summary statistics (Serbia)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	130,288	2,017.5	1.1	2,016	2,019
ISCED F 2013	44,715	7.4	125.1	0	9,999
Married	130,288	0.6	0.5	0	1
Being born abroad	130,288	0.1	0.3	0	1
Firm size	130,288	3	1.3	1	4
Formal	130,288	0.9	0.3	0	1
Having a fulltime job	130,288	1	0.2	0	1
Having a permanent job	130,288	0.8	0.4	0	1
Occupation ISCO 08-1 digit	130,288	5.2	2.5	0	9
Employee	130,288	1	0	1	1
Sample weight	130,288	60.9	40.7	1.5	744.4
Age group	130,288	3.3	1.2	1	6
Medium education	130,288	0.6	0.5	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	126,732	0.1	0.3	0.0	1.0
Occupational mismatch (High education)	126,732	0.1	0.2	0.0	1.0
Horizontal mismatch	85,053	0.2	0.4	0.0	1.0
Over-education	130,288	0.3	0.4	0.0	1.0
Under-education	130,288	0.2	0.4	0.0	1.0

Table A 7: Summary statistics (Türkiye)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Control variables					
Year	417,748	2,017.5	1.1	2,016	2,019
Sample weight	417,748	0.2	0.1	0	0.5
Gender	417,748	0.7	0.5	0.0	1.0
Occupation ISCO 08-1 digit	417,748	5.4	2.5	1	9
ISCED F 2013	176,402	5.0	2.6	1	10
Married	417,748	0.7	0.5	0	1
Being born abroad	417,748	0.0	0.2	0	1
Private firm (dummy)	417,748	0.7	0.4	0	1
Firm size	417,748	2.6	1.3	1.0	5.0
Number of hours worked	417,748	47.2	12.5	1	99
Having a fulltime job	417,748	0.9	0.2	0	1
Having a permanent job	417,748	0.9	0.3	0	1
Age group	417,748	2.7	1.2	1.0	6.0
Medium education (dummy)	417,748	0.2	0.4	0.0	1.0
Outcome variables					
Occupational mismatch (Medium education)	417,748	0.0	0.2	0.0	1.0
Occupational mismatch (High education)	417,748	0.1	0.3	0.0	1.0
Horizontal mismatch	176,402	0.5	0.5	0.0	1.0
Over-education	417,748	0.4	0.5	0.0	1.0
Under-education	417,748	0.2	0.4	0.0	1.0

Table A 8: 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 marriage (dummy)
Fulltime	Having a full-time job (dummy)
Permanent job	Having a permanent job (dummy)
Hours worked	Weekly working hours (continous)
Rural	Living in 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

Annex B: Robustness checks

Table B 1: Probit marginal effects of skills-mismatch determinants (Pooled sample), not controlling for medium education

VARIABLES	Occupational mismatch (1)	Overeducation (2)	Undereducation (3)	Horizontal mismatch (4)
Age (25-34)	0.040*** (0.001)	-0.089*** (0.002)	-0.019*** (0.001)	0.011*** (0.003)
Age (35-44)	-0.022*** (0.001)	-0.183*** (0.002)	0.017*** (0.001)	-0.022*** (0.003)
Age (45-54)	-0.040*** (0.001)	-0.232*** (0.002)	0.049*** (0.002)	-0.036*** (0.003)
Age (55-65)	-0.051*** (0.001)	-0.251*** (0.002)	0.092*** (0.002)	-0.061*** (0.003)
Older than 65 years old	-0.052*** (0.003)	-0.218*** (0.006)	0.070*** (0.006)	-0.028*** (0.010)
Gender (dummy)	-0.003*** (0.001)	0.089*** (0.001)	-0.011*** (0.001)	-0.036*** (0.002)
Fulltime (dummy)	0.036*** (0.002)	0.001 (0.002)	-0.004** (0.002)	0.052*** (0.003)
Firm size (<=10)	0.022*** (0.001)	0.015*** (0.001)	-0.064*** (0.001)	0.043*** (0.002)
Firm size (missing)	-0.017*** (0.002)	0.027*** (0.003)	-0.065*** (0.002)	0.127*** (0.004)
Permanent job (dummy)	0.002* (0.001)	0.015*** (0.001)	-0.014*** (0.001)	0.047*** (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 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

Table B 2: Probit marginal effects of skills-mismatch determinants (Pooled sample), including self-employed workers

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

Table B 3: Logit marginal effects of skills-mismatch determinants (Pooled sample)

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

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

Table C 1: Field of Education ISCED-F 2013

ISCED-F 1997	ISCED-F 2013
0-General programs	00 – Generic programmes and qualifications
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 C 2: 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 C 3: 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 C 4: 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 C 5: 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 C 6: 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 C 7: 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 C 8: correspondence between isco-88 3 digits and isco-08 3 digits

ISCO 88 3-Digit (used by Wolbers 2013)	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

Source: Authors' elaboration based on ILO (2012)

(*): Only available in Wolbers (2013), not available for ILO ISCO-88 3 digits, to represent for general occupations

ACRONYMS

ETF: European Training Foundation

LFS: Labour Force Survey

ISCED: International Standard Classification of Education

ISCO: International Standard Classification of Occupations

NGO: Non-Governmental Organization

PPP: Purchasing Power Parity

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