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SKILLS MISMATCH IN ETF PARTNER COUNTRIES

Cross-country report

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Preface

Skills mismatch problems in the labour market have been widely recognized by both current literature and policymakers. Skills mismatch indicators inform policies to improve the matching between labour demand and labour supply, making labour markets more efficient and reducing the wage penalties due to over-education or other types of mismatches. The skills mismatch indicators have been measured, so far, only for a limited number of the European Training Foundation (ETF) partner countries and they are not always comparable. This report provides an update and an extension of the work which has already been done to measure skills mismatch in ETF partner countries. The analysis following the choice and the construction of skills mismatch indicators provides a timely overview of this labour market issue which will be important for governments, stakeholders, and other stakeholders to shape future labour market policies.

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** This designation shall not be construed as recognition of a State of Palestine and is without prejudice to the individual position of the Member States on this issue.

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Executive summary

This report focuses on a critical concern for the ETF's partner countries and other countries worldwide. Skills mismatch is a major challenge to policy makers, practitioners, and social partners. It is often associated with dynamic social and economic contexts such as restructuring processes, changing trade patterns, technological progress, demographic change, or negative social aspects (e.g., informality, long-term unemployment, inactivity).

Skills mismatch is a complex phenomenon expressed in different types and aspects of labour market friction. A combination of indicators and analyses of results obtained using different methods is required to measure and understand the magnitude and interrelatedness of the different forms of skills mismatch. However, the data sources needed to measure and predict the different forms of skills mismatch are not always readily available in all ETF partner countries. Only a few international studies have included ETF partner countries. An expanded set of indicators needs to be calculated and analysed from multiple angles. The aim of the project on which this report is based was to assess the suitability of selected skills mismatch indicators for practical implementation in ETF partner countries.

In 2017, the ETF launched a project on skills mismatch measurement in the ETF partner countries. Its objective was twofold: to identify available data sources and to test a series of indicators capable of capturing various angles and implications of skills mismatches. That project built on previous conceptual work conducted by the ETF on skills mismatch measurement and applied research carried out in 2011 (ETF, 2012), and on another recent ETF project measuring skills mismatch in some of the ETF partner countries (Kriechel and Vetter, 2019).

Compared to the previous initiative (2017-2018), more ETF partner countries have been included in the 2020-2021 project's two phases, from South-East Europe, Eastern Europe, Central Asia, and the Southern and Eastern Mediterranean region. Country-specific analyses have been done to contextualise the skills mismatch measurement for each country and analyse the insights gained from each indicator.

This report complements the country analyses and findings. It highlights commonalities across countries while discussing the challenges encountered while collecting data from the Statistical Offices, calculating skills mismatch indicators, and comparing them across countries, and over time. The indicators as well as the definitions and methods used in this report are in line with international practices and were developed based on the activities mentioned above conducted by the ETF (ETF 2012, Kriechel and Vetter 2019), as well as other studies on skills mismatch by Flisi et al. (2014), Cedefop (2015), ILO (2014), the European Commission (2015), and Eurostat (2016).

The available data and the nature of the indicators used have strengths and weaknesses. In this ETF project, skills mismatch is mostly measured using Labour Force Survey (LFS) data on education (qualification levels and programme orientation) and occupation. The methodology used has some limitations regarding both the cross-country comparability and the interpretability of the results. For example, the proportion of unemployed people versus employed people indicates the direction of the mismatch (i.e. the deficit or surplus of specific education levels) and generalises at the macro level. Other indicators, such as the vertical (calculated with two alternative methods) and the horizontal mismatch indicators, the coefficient of variation and the variance of relative rates, show the magnitude of mismatch and generalise at the micro-level.

Deeper knowledge about skills mismatch can help countries better target their efforts to match supply and demand for different demographic groups (e.g., women, youth). It can be done through a wider set of policies and measures covering education, training, employment, and other policy interventions to better utilise skills and labour resources. Such an analytical exercise may also help institutions and partners to assess the effectiveness of their skills policies.

This report describes skills mismatch indicators, including a comparative cross-country analysis of indicators calculated for 17 ETF partner countries. We also provide information about the methodology and data sources used to measure skills mismatch, including a discussion of challenges in the skills mismatch indicator calculation, the limits of comparability between countries, and data accessibility.

Chapter 1 introduces the background to this initiative, the methodological anchors and previous work done by the ETF on the subject. Chapter 2 reviews the methodology on the definition, measurement, and interpretation of skills mismatches. Chapter 3 includes the methods chosen and the steps implemented in the ETF project to collect and prepare the datasets for selected countries This chapter highlights the challenges to the implementation of the project, the measurement of the indicators, and their cross-country comparability. Chapter 4 focuses on the actual findings of the mismatch measurement in the selected partner countries. The findings include calculation results, interpretation, possible caveats, and a discussion on data limitations. Chapter 5 discusses innovative practices in data collection and measurement of the indicators; as well as the lessons learned in implementing the methodology using national Labour Force Survey data, draws conclusions, and recommends possible avenues for the partner countries and the ETF to replicate and further analyse skills mismatches and assesses the key policy implications.

1. Introduction

Skills mismatch is broadly defined as a result of gaps and imbalances in skills (over- or under-qualification, labour market shortages or surpluses by qualification or skill, hiring difficulties, underemployment). It is currently recognised as a major challenge by policy makers as it can have adverse labour market impacts, for example, on firm and worker productivity, earnings, and job satisfaction. Skills mismatch, in particular overeducation or over skilling, may also have possible positive impacts on firm productivity (Jones et al., 2009; Büchel, 2002). However, it is not beneficial when taking workers' concerns into account. Therefore, it is important not only to inform policymakers on skills mismatch measurement methodologies, but also on the limitations of the information that skills mismatch indicators can provide.

Labour market research has analysed skills mismatches in labour markets from many different angles, e.g., by using specific groups of workers (e.g., in different age brackets), the relationship between the formal qualifications and actual occupation of workers, and the relationship between the use and non-use of skills at the workplace. A recent ILO study (ILO, 2019) offers a detailed and updated review of the literature about the causes and consequences of skills mismatches. However, skills mismatch indicators are not always readily available in all countries, and only a few international studies have included ETF partner countries.

The current literature shows the existence of skills mismatches both across geographical regions and countries. A recent study on European countries (Nikolov et al., 2018) shows that skills mismatches are likely to cause labour shortages and negatively affect EU businesses. A World Bank study focusing on both low and middle-income countries (Handel et al., 2016) shows that also in lower-income contexts, many workers are over-qualified for their jobs and unable to take full advantage of their skills. In a more recent study published by the International Labour Organization (ILO) (Bergin A., 2019), the authors review the literature on skills mismatch, highlight areas where further research is needed, and present new research findings on low and middle-income countries[1].

The literature offers several general explanations for the existence of skills mismatches (see Comyn et al., 2019 and Sloane et al., 2020, among others). More specifically, over-qualification in developing countries is influenced by informality due to a lack of formal employment opportunities (Bergin A., 2019). In Europe, matched firm-worker surveys (McGuinness et al., 2017) and either firm or worker surveys (CEDEFOP, 2015) show that differences between skills and qualifications mismatch can also result from perceived underutilisation of skills.

The contribution of this 2020/21 study is to update the skills mismatch indicators that were constructed and analysed by Kriechel and Vetter (2019) for some of the ETF partner countries and extend the exercise to other ETF Partner Countries. These latter groups of countries were selected in collaboration with the ETF team. To undertake this study, it was crucial to have the support of the national statistical offices, which in most cases provided us with remote statistical support where it was not possible to have direct access to microdata.

This report is intended for experts and researchers working in statistics offices, data management and analytical departments of ministries, as well as agencies active in the education and employment fields; it is also aimed at policy shapers and the wider European and international community supporting the stronger relevance of education outcomes and efficient matching between the supply and demand in the ETF partner countries.

[1] The authors use data from national labour force surveys, the ILO and MasterCard Foundation School-to-Work-Transition Surveys, and the World Bank's Skills Towards Employability and Productivity Survey.

Country selection

The first phase of the skills mismatch project (carried out in 2020) attempted to include some selected Southeast European countries, the Eastern Partnership region (EaP), and the Southern and Eastern Mediterranean region (SEMED). In collaboration with the ETF team, the second phase of the project (carried out in 2021) attempted to extend the analysis from other countries to these regions, and to Central Asia. ETF partner countries were contacted and asked to participate in and support this initiative. For the project to be successful, the support and direct involvement of the national statistics offices (NSO) was crucial.

The countries were selected because:

- The relevant department of the National Statistics Office ensured availability, reliability and cross-country comparability of datasets and accepted to collaborate closely on the project.
- The ETF had already completed significant projects in the respective countries.
- The countries have similar features of economic development and the population has a similar educational profile.
- The countries have done innovative research in education and have employment statistics that may inspire other countries and help the ETF identify innovative data gathering and interpretation approaches.

Overall, the NSOs showed interest in the project and were keen to collaborate. Sometimes the remote statistical assistance necessary to work with the microdata took longer because of the Covid-19 restrictions.

2. Methodological overview

Skills mismatch in the broader sense is measured, or better, examined, by using a variety of different methods of analysis. Skills mismatch can be used to describe vertical mismatches (usually measured in terms of over-education, under-education, over-skilling and under-skilling), skill gaps (they arise where the skills required are unavailable in the workforce, for example, due to technological advances (Cedefop, 2015)), skills shortages (usually measured in terms of unfilled and hard-to-fill vacancies), horizontal mismatches (field of study for the type of occupation), and skills obsolescence. This report concentrates on vertical and horizontal qualification mismatches, which can be measured either subjectively or objectively (using existing data). Many of the mismatch indicators adopted in the literature have drawbacks. However, the various approaches used to measure the same type of mismatch are not often highly correlated (McGuinness et al., 2017).

Measuring skills mismatch

The ETF methodological note (ETF, 2012b) and another ETF study (ETF, 2012a) represent the current study's essential conceptual and methodological starting point. It was concluded that no single methodology and indicator could capture the diversity of these issues and it was recommended to use a combination of methods based on data availability and analytical capacities and country-specific aspects and their relevance to skills and employment. In particular, the latter ETF study (ETF, 2012a) initiated the development of six methodological guides on skills anticipation and matching in collaboration with Cedefop and ILO. It was a further practical step in assisting national governments in implementing adequate measures to anticipate and identify skills trends and overcome skills mismatches (ETF et al., 2016a; 2016b, 2016c; 2016d).

Dimensions and types of skills mismatches

In this report, we concentrate on two dimensions of skills mismatch:

1. Vertical mismatch is a matter of skill/education level. In other words, a person may or may not have the right qualification level for a specific occupation, or the skill level maybe higher or lower than required for the specific occupation. This is usually referred to as vertical mismatch, over- and under-education, or over- and under-skilling. Vertical skills mismatch can be of two types concerning either education (qualifications) or skills. While qualifications are usually the only measure available in labour force surveys, using them as proxies for skills could be misleading. A mismatch in education is not always reflected in a mismatch of skills, or a mismatch in skills reflected as a mismatch of qualifications, as the JRC (2014) finds. Cedefop's initiative to measure education outcomes and skills mismatches through the European Skills and Jobs Survey overcomes some of these challenges. The survey was replicated in 2022 in six ETF Partner Countries, and the results will be published in 2023.
2. Horizontal mismatch occurs when the qualification level is sufficient, but the type or field of qualification does not adequately match the field required by the job held. It is more common – and less problematic - if a person is working in a related field, e.g. computer programmers, mathematicians, engineers, and more problematic if the fields of education and work differ significantly.

Researchers have made efforts to collect data and develop adequate methodologies to measure skills mismatches. There are fewer published studies of horizontal mismatch than vertical mismatch (Bergin A., 2019). In this last group, most studies are on over/under-education compared to those that are about being over/under-skilled (McGuinness et al., 2017). The evidence about wage penalties due to these types of mismatches is mixed. If the studies find any pay penalty, these are typically smaller for those horizontally mismatched than for those vertically mismatched. Moreover, wage penalties usually depend on whether the horizontal mismatch is also accompanied by a vertical mismatch

(Bergin A., 2019). Underqualified persons are usually underpaid in relation to peers who are matched within the occupation but overpaid in relation to peers with the right qualification level. Similarly, overeducated workers often tend to receive a premium over colleagues within the same occupation, while they are underpaid relative to their qualification level.

Measuring vertical mismatch

Vertical mismatch can be measured either as a qualification or skills mismatch. While educational attainment can reasonably be used to proxy individuals' skills, this does not necessarily imply that the individual has the skills required for the job (Flisi et al., 2014). Qualifications and skills mismatch, although related, are not the same concept since they lead to different types of analysis and policy implications (Desjardins and Rubenson, 2011).

Different indicators have been used to approach the issue of vertical mismatch measurement, focusing mostly on education mismatch (Groot and Maasen van den Brink, 2000; Hartog, 2000; Verhaest and Omey, 2006; CEDEFOP, 2010; Quintini, 2011 or Desjardins and Rubenson, 2011; Flisi et al., 2014). However, more and more studies have focused on skills mismatch (e.g., Mavromaras et al., 2010).

Over/under-education (Over/under qualification)

Different studies measure education–job mismatches differently depending on the data available. The different approaches have advantages and limitations, and none has proved to yield more reliable or conceptually more correct estimates than the others (Leuven and Oosterbeek, 2011). The current literature uses four different approaches to measure over-qualification and under-qualification: the subjective method, the empirical method (sometimes referred to as the statistical method), the normative method and the job evaluation method. The most used are the first three (Bergin A., 2019).

Subjective method

This approach is generally based on worker self-assessments of the level of qualifications required "to get" or "to do" the job. It is then compared to the highest level of education acquired by the worker to determine if they are matched (have a level of education equal to that required), overqualified (have a level of education above that required) or underqualified: i.e., have a level of education below the one required (Bergin A., 2019).

Among others, subjective indicators were used by Allen and Van der Velden (2001) and Bergin A. (2019). They used an employee self-rating the level of education most appropriate for the current job, with response categories and compared it with their highest attained level of education. Some of the distinctions made in the literature are either between the educational level required to *get* the job and the one required to *do* the job (Allen and van der Velden, 2001) or, among others, between formal and informal schooling and the concept of best preparation vs preparation needed to perform (Leuven and Oosterbeek, 2011).

An advantage of self-assessment is that it is based on all the relevant information. However, the disadvantage is that workers may be very poorly informed about the performance in the same job of people with different levels of completed schooling, which is also relevant for the assessment (Leuven and Oosterbeek, 2011).

A variation of workers' self-assessment of the schooling requirements of their jobs is to ask them directly whether they are over-schooled, under-schooled or rightly educated for their job (e.g., Chevalier, 2003 and Verhaest and Omey, 2006), even if this methodology can be prone to measurement error due to subjective bias.

Normative method

Over/under-education using the normative method, also called occupation mismatch, is identified using the mapping between the International Standard Classification of Occupations (ISCO) and the categorising of major occupational groups by four levels of education following the International

Standard Classification of Education (ISCED). The ISCO categorizes 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). In our method, the measurement of mismatch by level of education uses information on the highest level of education attainment of the employed person (ILO, 2018). This method is, in theory, more reliable than the *Realized Match* and *Self-declared* approaches explained below since it relies on the evaluation made by trained job analysts, which should be more reliable and experienced in grading jobs (Flisi et al., 2014). However, this measure relies on the strict assumption that all jobs with the same titles require the same level of education. This assumption is even accentuated by the fact that the ISCO categories are further aggregated to four. The variation in the ISCED levels within the ISCO groups is usually large. Thus, this skills mismatch measure will significantly underestimate its incidence. Often this indicator is obtained only by matching the national classification of education with the international ISCO classification of occupations (Quintini, 2011, Leuven and Oosterbeek, 2011 and Bergin A., 2019).

Empirical method (the statistical or the realized matches method)

This method estimates the educational requirement of occupation by assessing the mean or modal level of education within a given occupation (the realized matches), classifying workers with acquired education above/below the average level (Verdugo and Verdugo, 1989; Bauer, 2002, Bergin A., 2019) or the modal level (Kiker et al., 1997; and Mendes de Oliveira et al., 2000; ILO, 2012) of the employee´s occupation group as over/under-qualified. The current literature refers to one standard deviation difference (either with respect to the mean or the mode), although two standard deviations are also used (Flisi et al., 2014).

The key advantage of this approach lies in the ease of calculations: it can be easily applied to existing micro data sets containing information on educational attainment and occupation, such as national labour force surveys, facilitating cross-country comparisons (Bergin A., 2019). Its drawbacks are that it does not contain information on the actual skill requirements of the job. Still, it reflects the average (or major) credentials of all workers within a given occupation (Bergin A., 2019) and that the required educational level within an occupation is an outcome of supply and demand forces, and thus endogenous (Flisi et al., 2014). Also, this method assumes that all jobs with the same occupational title have identical educational requirements, which may not always be the case, and it is sensitive to cohort effects, especially in case of a rapid change in the educational level required for a given occupation (Flisi et al., 2014). To address this last concern, some authors in the literature either implemented the method by cohort (Elias and Purcell, 2004) or allowed the required education to vary with a year of birth and survey year (Quinn and Rubb, 2006). Finally, the choice of the acceptable range of education levels, e.g. one standard deviation on the years of schooling, is completely arbitrary and results depend on the level of aggregation necessary to obtain a reliable distribution of education (Flisi et al., 2014).

Job evaluation method

The job evaluation method is based on assessments by professional job analysts who are tasked with measuring the educational requirements of occupations to construct occupational dictionaries (e.g., SOC in the United Kingdom) (Bergin A., 2019).

The advantage of this approach is that it is perceived to be more accurate as it is based on field expertise (Bergin A., 2019). Its disadvantages are that it is very expensive to carry out and is not widely available. Occupational requirements can also change rapidly, making the job evaluation method outdated if the analysis is not regularly updated. Although the classifications are based on experts' opinions, the approach still involves some subjectivity (Bergin A., 2019).

Over/under-skilled

Over-skilling has been argued to be a more accurate measure of mismatch among existing workers than over-qualification. The over-qualification approach ignores the fact that job entry requirements may only be weakly related to job content (as qualifications might be needed only to get the job but not to do the job). While over-skilling describes the situation where a worker possesses more skills than their current job requires, under-skilling describes the situation where the current skills of a worker do not meet the demands of the job (Bergin A., 2019).

Direct measures of skills are rarely captured in data sets. Thus, over/under-skilling are typically measured subjectively through a question e.g. “Are your skills higher/matched/lower than those needed to do your job?” Over-skilling and under-skilling measures are prone to the disadvantage of subjective bias in the same way as over-qualification (Bergin A., 2019).

Measuring horizontal skills mismatch

Horizontal mismatch measures the extent to which workers, typically graduates, are employed in an occupation unrelated to their principal field of study. The issue in identifying horizontal mismatches is that informal skills acquired through labour market experience and training are not observable and might relate more to the occupation than the person’s main field of study (Bergin A., 2019).

Somers et al. (2019) provide a recent systematic literature review on how horizontal mismatch can be measured and they discuss the validity of different approaches. They find that this form of mismatch may be measured both subjectively and objectively. The subjective approach measures the educational requirements for a job based on employees’ self-reports. The objective method determines the educational requirements for an occupation using an expert or by assigning occupational codes for statistical purposes to educational fields. Most of the papers in the available literature use subjective measures (see Verhaest et al. (2015), Robst (2007 and 2008) and Allen and de Weert (2007)). Others use objective methods or mappings (see Levels et al. (2014), Wolbers (2003), Beduwe and Giret (2011) and Domadenik et al. (2013)). Other studies use objective and subjective methods (Schweri et al., 2020, Beduwe and Giret, 2011).

The potential advantage of the subjective approach is that it is specifically concerned with the content of the respondent’s specific job rather than referring to more general aggregations at the occupation level. Therefore, the subjective approach might provide a more valid measure of a horizontal mismatch as an employee’s field degree is directly compared with the content or the educational requirements for the job. A potential disadvantage of the subjective method is that an employee’s perception of a horizontal match is, by definition, subject to self-reporting bias. Moreover, some employers might require more general skills obtained through various fields of study (Somers et al., 2019).

Instead, the normative correspondence method allows occupations and educational qualifications to be aggregated in 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).

Table 2.1 summarizes the methods used in the literature to identify the main types and dimensions of skills mismatches.

Table 2.1 Indicators for the main types and dimensions of skills mismatches

Dimension	Type	Definition	Method
Vertical	Over-education (over-qualification)	Worker’s level of education (qualification) exceeds the required level for the job (occupation)	Subjective Normative (refers to the level of skills (education) required to work in a specific occupation category Empirical (the statistical or realized matches method) using either the mean or the mode of education within an occupation category Job evaluation method

Dimension	Type	Definition	Method
	Under-education (under-qualification)	Worker's level of education (qualification) is lower than the required level for the job (occupation)	As above
	Over-skilled	Worker's level of skills exceeds the required level for the job requirements	Subjective (but rare to find datasets including questions such as "to what extent are your skills utilized in this work?"
	Under-skilled	Worker's level of skills is below the required level for the job requirements	As above
Horizontal	Field of education to occupation mismatch	The field of study does not match the main required occupational area of the job	Subjective (e.g., is your job matching your field of education?) Objective (using ISCO and ISCED-F codes)

Source: Compiled by the authors

Measuring skills mismatch in ETF countries

Building on previous ETF work from 2012, the ETF launched a study on skills mismatch measurement in the ETF partner countries in 2017. Its objective was twofold: to identify available data sources and to test a series of indicators capable of capturing the various angles and implications of skills mismatches. It resulted in the ETF report *Skills mismatch measurement in ETF partner countries* (Kriechel and Vetter, 2019). The report reviewed the suitability of the indicators and methods for measuring the incidence of mismatch in seven ETF partner countries (Egypt, Georgia, Moldova, Montenegro, Morocco, North Macedonia, and Serbia). It provided country-specific analyses to contextualize the skills mismatch measurement for each country and analysis of the insights gained from each indicator. The present study is built on a methodological note published by the ETF on skills mismatch measurement and applied research in 2012 (ETF, 2012b).

A quantitative approach was proposed in the 2021/22 initiative to study the collection of secondary data, in particular the updated labour force surveys, to build up the labour market indicators (previously agreed on with the ETF) so as to analyse skills mismatches.

In this 2022 report, we use indirect measures of skills mismatch which generalize the direction of the mismatch at the macro-level (e.g. the proportion of unemployed people versus employed people indicates the direction of the mismatch, i.e. the deficit or surplus of specific education levels). Other commonly used indicators, such as the coefficient of variation and the variance of relative (un-)employment rates, which show the magnitude of mismatch generalising at the macro level, are added to contextualize the results. We also use direct measures of skills mismatch. We measure over/under-qualification using both the normative and the statistical indicator (using the mode) and horizontal mismatch using the normative correspondence method following the normative correspondence tables of Wolbers (2013) for those countries using the ISCO-88 and ISCED-F 1997 classifications[2]. The set of skills mismatch indicators, the definitions and the methods used in the 2020-2021 initiative considered both the ILO recommendation and the Eurostat and CEDEFOP methodologies (Kriechel & Vetter (2019); Flisi et al. (2014); Cedefop (2015); ILO (2018); the European Commission (2015); and Eurostat (2016)). The same methods were applied and developed in the previous initiative for measuring skills mismatches, even if with some innovations. In this report, the indicators are calculated according to narrower groups (e.g., intermediate VET/non-VET qualifications, age groups, etc.) as instruments for more meaningful input to policy design.

[2] For countries using different classifications, we specified the matching between ISCO and ISCED codes in the Appendix.

3. Methodological considerations and data situation

In the following sections, we present the methodological approach of the research project and its implementation in selected SEE (Bosnia and Herzegovina, Northern Macedonia, Kosovo, Montenegro, Albania, Serbia, and Turkey), EaP (Belarus, Georgia, Ukraine, Armenia, Moldova), Central Asian (Kyrgyzstan) and SEMED countries (Palestine, Tunisia, Egypt, and Jordan), including an overview of the national labour force surveys (LFS) and limitations of access to such sources. A description of the skills mismatch indicators is also provided.

In the first section there is a discussion of the availability of the LFS survey in all countries. It also covers the indicators based mainly on micro-level labour market data from the labour force surveys available in most countries. In the comparative analysis, however, we restrict our focus to unemployment, NEET, and horizontal and vertical mismatch indicators.

Each indicator covers a certain aspect of skills mismatch. One set of indicators might be more useful than others depending on a country's policy issues and other factors. Many indicators also overlap or show the same aspect of mismatch to varying degrees, helping create a better understanding of the overall mismatch in the labour market.

Mapping of data sources: data availability and reliability

This aim of the 2020/21 project was to assess the suitability of selected skills mismatch indicators for practical implementation in ETF partner countries using a combination of international and local expertise in consultation with national stakeholders. The mismatch measurement focuses on skills mismatches by level (vertical), by occupations (occupational) and field of education (horizontal) for the years 2016 to 2019, depending on data available in the countries. The project extended previous projects to include all SEE countries and EaP and SEMED countries potentially. All data sources and inputs were updated, and mismatch indicators were calculated. Common methodologies and classification were used so as to highlight commonalities across countries while ensuring, as much as possible, comparability across ETF partner countries and with European or international research on similar topics (e.g., Cedefop, OECD, ILO).

During the project's inception phase, the international experts and the ETF team analysed which countries to include, based on country background, a country's time capacity, and data availability. The importance of different indicators to capture skills mismatches and the methodology used, was also discussed within the team and with outside experts. As outlined in the next section, labour force surveys were identified as the most reliable and commonly available sources of information: they are established in all ETF partner countries, collected in regular intervals, and follow, broadly speaking, similar practices and methodologies.

Steps of implementation

The first implementation step was to identify and access the national data for each country. ETF contacted the national statistical offices (NSOs) for participation in the project. In a second step, the data access was determined. The NSOs shared the full LFS microdata to calculate the mismatch indicators with the research team, or they shared only small samples of observations that allowed for the development of a processing syntax to be run by remote execution within the premises of the national statistical office. Economix prepared these scripts to calculate the indicators using data samples received. The NSOs who executed the prepared scripts and assisted in adapting for the indicator calculation. The implementation procedure can be broken down into three steps.

In the first step, ETF contacted the partner countries by letter, describing the project and exploring the interest of the NSO in the collaboration. Meanwhile, the project team prepared generic scripts to be used to calculate the skills mismatch indicators.

In the second step, following the prior approval of ETF, Economix contacted the NSOs asking for access to the LFS survey, providing a list of the indicators to be calculated and the variables needed. There was always the proposition of three possible options for the statistical assistance:

- To share LFS microdata for the years 2016, 2017, 2018, 2019 (depending on data availability) directly so that the research team can calculate the skills mismatch indicators by itself. The NSO was also given the opportunity to check the calculations and the choice of variables made by the research team, receiving either Stata or SPSS script files. This approach gave the highest flexibility and allowed the NSO to reproduce or update our results later.
- If sharing LFS microdata was not possible, the NSO could opt to carry out the calculations of the skills mismatch indicators in their institution. The research team offered support in setting up the calculations, e.g. by providing a script file in Stata, SPSS, R, or Python. In this case, more information on the national LFS, for example, questionnaires, data dictionaries, or small samples of microdata, were requested to prepare the scripts.
- If neither 1 or 2 were feasible for all or some indicators, aggregated LFS data or alternate indicators from other sources could be used. Public or scientific use of LFS data sometimes lacked the level of detail needed to carry out our calculations.

The final step involved calculating the indicators based on the microdata or remote collaboration with the NSOs.

Choice of indicators

The methodology used in this study is based on the ETF methodological note: ETF (2012) and the pilot study on skills mismatches in ETF partner countries: Kriechel and Vetter (2019). It incorporates insights from Flisi et al. (2014), Cedefop (2015), ILO (2018), the European Commission (2015) and Eurostat (2016). The practical approach adopted to calculate the indicators in this report differs from previous studies in the direct involvement of NSOs in the construction and calculation of the indicators. The approach allowed knowledge transfer and capacity building to calculate indicators and skills mismatch analysis using the LFS survey. Moreover, the indicators in this study are broken down by narrower categories, e.g. they are calculated for both VET and non-VET intermediate education to provide policy insights on the effectiveness of vocational training qualifications. Another example of the innovations of this study, for the involved countries, is the calculation of the NEET rates both for several age groups and by distinguishing the share of inactive NEET individuals from the share of the unemployed ones. Constructing the indicators for different groups of individuals allowed us to achieve more policy relevance in our results.

All the indicators used were based on labour market data (LFS surveys), usually available in most countries. Labour force surveys are representative at the national level and provide sufficient demographic, employment status, education background to produce useful labour market statistics in terms of education by level and type, employment by sector or occupation, broken down by age and gender. We use these breakdowns to calculate the main indicators.

Meaningful indicators should rely on easily accessible data, updated regularly to prevent the indicators from becoming outdated. Moreover, the underlying data should be consistent across survey waves to avoid changes in indicators resulting from breaks in the time series of underlying variables. Finally, the data must have a sufficient base of underlying values. If necessary, an indicator with less detail would be reported.

Table 3.1 provides an overview of the indicators used in this study to calculate skills mismatch. These indicators are based on LFS data, which are widely available in all ETF partner countries. A more accurate description of the indicators is provided in Chapter 4.

Table 3.1 Mismatch indicators: brief description

Indicator	Calculation[3] / Description
Unemployment rates (context)	U/(E+U)
Ratios (context)	For example, U/E, I/POP, E/POP, (U+I)/E...
Not in Employment, Education or Training rate	NEET/POP
Occupational mismatch (Normative method)	The ratio of people with a given education level (ISCED) working at an inappropriate skill level (measured by the International Standard Classification of Occupations – ISCO) for all workers within that ISCED level.
Horizontal Mismatch	Calculation of the share of employees with horizontal mismatch: % not in occupations matched to the field of studies.
Over-education, Under-education (Empirical method)[4]	Percentage with education levels of at least one standard deviation above the standard education for the occupation (group).
Coefficient of Variation (Optional)	Ratio of standard deviation of qualification levels within a group (e.g., gender, age) with respect to the mean. This indicator compares the distribution of skills within different groups in an attempt to determine the variation between the two distributions.
Variance of relative (un)employment rates (Optional)	The calculation of the variance of the (un)employment rates of various groups shows how the (un)employment rates differ between these groups.
Duration of unemployment by educational attainment levels (Optional)	The duration of unemployment by each level of educational attainment.

Data preparation

Before calculating the indicators, the data had to be harmonized, by aggregating them into broader but more homogeneous education groups, occupation levels, and fields of education. When discussing the data, we did not report on the indicators based on insufficient (underlying) observations, and we signalled when data seemed to be inconsistent over time.

Harmonisation

The chosen dimensions reflect a compromise between detail and comparability. They are developed based on the commonly available dimension in most countries.

[3] U=Unemployed, E=Employed, I=Inactive, POP=Population, NEET=Not in Employment, Education and Training.

[4] The thresholds to determine the boundary of matching are based on the empirical alternative approach suggested by ILO (2018).

Although the variable labour market status was 'harmonised' by NSOs in most LFSs, some countries had to create a variable to capture this information.

Other variables that were harmonised similarly include educational attainment level (see tables in Appendix A1), age groups, gender, duration of unemployment, an indicator for persons who are currently in school, or in an occupation, or more specific variables used to calculate skills mismatch indicators (e.g. a variable identifying persons with upper secondary education in elementary occupations, which is needed to calculate the occupational mismatch indicator). The harmonisation process is described more in detail in the next sections.

Calculation of skills mismatch indicators

The data cleaning and the calculation of the indicators were programmed in either Stata or SPSS, depending on the preference of the NSOs. Apart from the Tunisian and the Northern Macedonian NSOs, all the other NSOs preferred to receive the scripts in SPSS.

Each indicator could be easily calculated for several age groups, by education level, several combinations of subgroups of the labour market (unemployed, inactive, employed), or by other characteristics. The results were exported for all countries into a single Excel file, and all indicators for each country were collected in a single worksheet.

Data availability, comparability, and limitations

Tables 3.2a and 3.2b below show each country's data availability and the process of contacting the NSOs. The table also describes the option chosen by the NSOs for the data sharing: (i) Option 1 is to share the LFS microdata; (ii) Option 2 is to let the NSOs send us the data samples so that we can prepare the SPSS files for the NSOs, and they can calculate the indicators; and (iii) Option 3 is to let the NSOs send us aggregated microdata. Most of the statistics offices opted for option 2 (remote statistical assistance) due to the restrictions on data access.

Data availability

Tables 3.2a and 3.2b show the countries' allocation into Phase I (July 2020 – January 2021) and Phase II (Spring 2021 – Winter 2021).

Table 3.2a Data availability by country – phase 1

Country	Project phase	Data availability	Data sharing option chosen by the NSO
Albania	1	LFS 2016-2019	Shared microdata
Armenia	1	LFS 2016-2019	Microdata available online
Belarus	1	LFS 2016-2019	Remote statistical assistance using SPSS
Bosnia and Herzegovina	1	LFS 2016-2019	Remote statistical assistance using SPSS
Egypt	1	Harmonised LFS 2016-2017	Microdata available online
Georgia	1	LFS 2016-2019	Microdata available online The scripts were shared in SPSS
Jordan	1	Harmonized LFS 2016	Microdata available online
Kosovo	1	LFS 2016-2019	Remote statistical assistance using SPSS

Country	Project phase	Data availability	Data sharing option chosen by the NSO
Montenegro	1	LFS 2016-2019	Remote statistical assistance using SPSS
North Macedonia	1	LFS 2016-2019	Remote statistical assistance using STATA
Palestine	1	LFS 2016-2019	Shared microdata
Tunisia	1	Enquête Nationale sur la Population et l'Emploi 2016-2019	Remote statistical assistance using STATA
Ukraine	1	LFS 2016-2019	Remote statistical assistance using SPSS

Table 3.2b Data availability by country – phase 2

Country	Project phase	Data availability	Data sharing option chosen by the NSO
Kyrgyzstan	2	LFS 2016-2019	Remote statistical assistance using SPSS
Moldova	2	LFS 2016-2019	Remote statistical assistance using STATA
Serbia	2	LFS 2016-2019	The microdata was made available by the NSO
Turkey	2	Household Labour Force Survey 2016-2019	The data were made available by the NSO

Challenges

Availability of support from the NSO

Overall, the statistics offices responded when approached in a timely way and chose the preferred option to make the data available for the project according to the specified options. However, in many cases the project was an additional burden on the departments responsible for labour market surveys or analysis. Many NSOs are overwhelmed – at times – with requests and work to fulfil their role so that the levels of responsiveness varied throughout the project. All NSOs tried to accommodate our requests for project collaboration and assisted in providing a proper understanding of the data.

Bureaucracy

In most cases, the process to request the NSOs collaboration was limited. The ETF or the research team usually needed to sign the data-sharing agreement based on a short project description. In some countries, data access took longer or suffered from requirements that could not easily be met. For example, the NSO in Montenegro required detailed documentation and proof that the project team was a 'certified research centre' in order to access the microdata. As the research team was not a *Montenegrin* research centre, our information proved insufficient to comply with their national data-sharing policy. Even though remote assistance in calculating the indicators was agreed upon, no data samples could be shared, so the scripts were developed using only questionnaires and codebooks. The release of the aggregated results was also pre-screened by the NSO before being included in the report. Even if it was not mentioned in many countries, this last step was common practice to avoid releasing aggregated results that would allow the identification of individuals given small cell sizes in some breakdowns. We assisted in such 'output checking' by providing the number of underlying observations for each calculated indicator.

Remote work

Working remotely with the NSOs caused some challenges due to the long waiting time between e-mail exchanges. Contact persons in the NSOs– at times – found it a challenge to react quickly and this was aggravated by changes to the work organisation due to the evolving COVID-19 pandemic. The remote statistical assistance did not allow Economix to check in-depth why a script did not work correctly. Corrections could be made, where necessary, only after the NSOs shared the results or error messages after running the scripts. As a response to this issue, we updated the standardised scripts by including code that generated information that allowed us to analyse better why implausible results occurred (e.g. by reporting the number of observations that the calculations were based on next to the indicator output and including a code that produced a document of all the errors that the statistical software displayed while running the scripts).

Pandemic

The COVID-19 pandemic represented, to a certain extent, a challenge for the calculation of the skills mismatch indicators as it delayed the responsiveness of some of the statistics offices while they were providing us remote statistical support. The NSO personnel sometimes clarified that the cause of the delay in the collaboration was because they had to work from home because of the national COVID restrictions, which sometimes meant the temporary inability to access the LFS data.

Harmonization

Most data needed to construct the skills mismatch indicators were comparable across surveys. An exception is the education level (including the field of education/education specialisation) and the occupational classification, as they are sometimes subject to national classifications. Mapping these national classifications in a common and comparable international classification (ISCED and ISCO classifications) proved challenging. In some cases, harmonizing data across survey waves proved challenging as classifications changed over time.

Education categories

The education level was specified differently in each survey according to the national classification. In the calculation of the skills mismatch indicators, education levels were harmonized across countries and across the survey waves according to a simplified mapping into an aggregation of the ISCED levels: low (ISCED level 0-2), intermediate (ISCED level 3-4), which can be split into vocational training (intermediate-VET), and upper secondary and post-secondary non-tertiary intermediate education non-VET; and high education (above ISCED level 4). The harmonization process is set out in the Appendix (Section A1) by country. It was discussed with the ETF and some country experts and was finally approved by the ETF before calculating the indicators.

In most countries, it was challenging to identify vocational education (VET). Sometimes it was reported as post-secondary education or not identified (e.g., for Belarus). In Palestine, it was challenging to assign some education programs (e.g., associate diploma, high diploma) either to the intermediate or to the high education categories. The guidance provided by the ETF, the NSOs and the country experts was key to achieving a cross-country comparable broad education classification (low, medium-GEN, and medium-VET, high).

Occupational categories

In the available surveys, the occupational category is reported differently across countries and sometimes across the survey waves. It is important to correctly define the occupation category as it is needed to calculate both the occupational mismatch indicator and the vertical and the horizontal mismatch indicators.

Table 3.3 below shows that the occupations are coded at the four-digit level in most countries according to ISCO-08 (Georgia, Kosovo, Bosnia and Herzegovina, North Macedonia, Albania, Tunisia, and Belarus). In contrast, in some other countries (Palestine, Montenegro and Turkey), the information on occupation is less detailed and available only at the one- or two-digit level. In some other countries (Georgia), occupations are coded according to ISCO-88 or follow a national classification (Ukraine). Thus, occupational mismatch and over or under education indicators are calculated among those countries, referencing either a different occupational code or a less detailed occupational level.

Changes to the classifications or naming of variables across survey waves

One of the challenges was harmonising variables that were either coded or named differently across survey waves during the data preparation phase. For example, in Georgia, the variables of the 2016 survey wave were named and coded differently in 2016 than in the other years.

Table 3.3 Occupation code availability across countries (LFS survey)

Country	Occupation code 2016-2019
Georgia	ISCO-88 (4 digit level)
Kosovo	ISCO-08 (4 digit level)
Bosnia and Herzegovina	ISCO-08 (4 digit level)
North Macedonia	ISCO-08 (4 digit level)
Tunisia	ISCO-08 (4 digit level)
Belarus	ISCO-08 (4 digit level)
Ukraine	National classification (2 digits)
Montenegro	ISCO-08 (1 digit level)
Palestine	ISCO-08 (2 digit level)
Armenia	ISCO-88 (1 digit)
Jordan	ISCO-08 (3 digits)
Egypt	ISCO-88 (4 digits)
Albania	ISCO-08 (3 digits)
Serbia	ISCO-08 (3 digits)
Turkey	ISCO-08 (2 digits)
Moldova	ISCO-08 (3 digits)
Kyrgyzstan	ISCO-88 (2 digits) for 2016-2018, ISCO-08 (2 digits) for 2019 (originally OKZ-88\08 3 digits classification, converted)

Harmonization for specific indicators

Horizontal Mismatch

To calculate the horizontal mismatch, we used the following qualification information and the occupation category (the harmonisation of this variable was explained above):

- the field of education, according to ISCED-F 2013 or ISCED-F (1997) (see table C1 Appendix C),

- the ISCO-CODE for the profession (belonging to the qualification).

The field of education was coded in the LFS survey according to the ISCED-F 1997 classification, and the occupation code followed the ISCO-88 classification. The codes were matched (using the three digits occupation code) according to the method suggested by Wolbers (2003). In some countries, the field of education was coded according to the ISCED-F 1997 classification. The occupation classification was coded according to ISCO-08, for which a similar matching method was applied. It is described in Table C3[5] in Appendix C. Below, we summarize the challenges we faced when calculating the horizontal mismatch.

Format of the field of education variable. The first challenge that had to be dealt with when calculating the horizontal mismatch indicator was the information regarding the field of education. When it was not available in the format needed, a re-coding was necessary into standard categories following the ISCED-classifications of the field of education to ensure cross-country comparability. Thus, to calculate horizontal mismatch, the field of education had to conform with either the ISCED-F 1997 or to ISCED-F 2013 categories (see Table C1 in Appendix C).

Harmonising the national classifications with the ISCED-F field of education was hindered by some data limitations. Even if some countries applied ISCED-F-classifications, they were not always aggregated in the same way. For some countries (as mentioned above), the fields of education had to be grouped to make them as similar as possible to ISCED-F 1997/ISCED-F 2013 (e.g., in Belarus, Montenegro, Serbia and Bosnia and Herzegovina). When this was not possible, the national classification was used (e.g., in Ukraine). In Bosnia and Herzegovina, the national classification of education was slightly different to the ISCED-F 1997 one, and it had to be grouped into the broad fields of 03 (Social Sciences, journalism and information) and 04 (Business, administration and law). In Belarus, the LFS survey followed a national classification for education, which could be converted in ISCED-F 1997 but not in ISCED-F 2013 as it was not detailed enough. The ISCO-08 code was transformed into ISCO-88[6] using a conversion table produced by ILO (2012) so that the horizontal mismatch could be calculated using the method described by Wolbers (2003). In Ukraine, the field of education and the occupation code were classified using a national classification at the two-digit level to calculate the horizontal mismatch indicator. In the LFS surveys of Jordan (2016) and Egypt (2016-2017), the field of education was also recoded to reflect the ISCED-F classification. In Palestine, the standard ISCED-F-1997 (6 digits) field of education is available in all education levels, except in secondary education. For this education qualification, the field of education had to be re-coded to reflect the ISCED-F-1997 (1 digit level) classification.

In other countries, the field of education was recorded according to ISCO occupational classifications. If the current occupation was also available in the same ISCO classification, we directly compared both entries (occupation learned and current occupation) to calculate the horizontal mismatch. In these cases, an alternative way would be to convert the ISCO classification on the occupation learned into a field of education classification (ISCED-F) and then applied). Subsequently, Wolbers' matching method is applied to match the field of education to the current occupation, or an alternative matching method when the occupation classification was coded according to the ISCO-08 classification (details on matching methods are available in Appendix C). However, it would mean significantly altering the information recorded in the LFS, so we chose the approach mentioned earlier in these cases.

Changes to the field of education and occupation classifications over time. In addition, education classifications changed over time in some countries and had to be harmonized across the survey waves (e.g., in Georgia, Palestine, and Bosnia and Herzegovina, the classification changed between 2016 and the other survey years). On the other hand, the changes to the occupation classification over time also made the matching methodology more complicated and less straightforward.

Matching methods. In some countries, both ISCED-F and ISCO are available. However, the ISCO code for occupation is available only at 1-digit or 2-digit levels instead of the 3-digit level in the original

5 The method was developed by Economix and revised and approved by the ETF.

6 Based on ILO (2012) correspondence table for ISCO 4-digit, we created a correspondence table between ISCO 08 (3-digit) and ISCO 88 (3-digit). See Table C8 (in Appendix C).

method used by Wolbers. In this case, the original matching table between the ISCO 3-digit and ISCED-F is used as the matching foundation adapt for similar ISCO classification at lower levels. In Turkey, for instance, given that the ISCED-F 2013 and ISCO-08 2-digit are available, the matching method between ISCED-F 2013 and ISCO-08 3-digit is used and generalized for ISCED-F 2013 and ISCO-08 2-digit[7].

We adapted several matching methods for different countries because of the differences in occupations and education classifications across countries, and over time. Table C2 (in Appendix C) summarizes the mapping method used to identify horizontal mismatches in ETF partner countries, while Tables C3-C7 (in Appendix C) describe the different types of mapping between ISCO and ISCED in detail.

Table 3.4 describes the classification followed by the LFSs across the countries involved.

Table 3.4 Occupation code and field of education availability across the participating countries (LFS survey)

Country	Field of education 2016-2019	Conversion
Georgia	ISCO-88 classification	The information on the field of education was extracted converting the profession classification (available according to the ISCO-88 code) in ISCED-F 1997.
Kosovo	ISCED-F 97 (2016/17), ISCED-F 2013 (2018/19)	
Bosnia and Herzegovina	The national classification was converted in ISCED-F 1997, but the fields 03 (Social Sciences, journalism and information) and 04 (Business, administration and law) had to be aggregated as they could not be disentangled.	
North Macedonia	ISCED-F 2013	
Tunisia	National classification	Converted into ISCED-F 2013
Belarus	National classification	Converted in ISCED-F 1997 but not in ISCED-F 2013 (not detailed enough)
Ukraine	National classification (2 digits)	
Montenegro	National classification	Converted in ISCED-F 1997
Palestine	ISCED 1997 (and ten broad fields for secondary education levels, aggregated according to ISCED)	
Armenia	ISCO-88 classification	Converted in ISCED-F 1997
Jordan	National classification	Converted in ISCED-F 1997
Egypt	National classification (3 digits)	Converted in ISCED-F 1997
Albania	National classification	Converted in ISCED-F 1997

[7] As the heterogeneity of the fields of education can differ across occupations measured according to different ISCO digit levels, we explore the potential comparability issues of the results across countries in the sensitivity analysis.

Country	Field of education 2016-2019	Conversion
Serbia	National classification	Converted in ISCED-F 2013
Turkey	National classification	Converted into ISCED-F 2013
Moldova	ISCO-08 classification (3 digits)	
Kyrgyzstan	OKZ-88/08 3 digits	Converted into ISCO-88 (2 digits) for 2016-2018, ISCO-08 (2 digits) for 2019

Over-education (normative method)

To calculate over-education according to the normative method, it was necessary to define employees with upper-secondary education working in elementary occupations (ISCO-08 category 9) and employees with tertiary education working in semi-skilled occupations (ISCO-08 categories 4-8) (ETF, 2012b). However, when calculating the indicator, it was not always possible to identify upper-secondary education. In some LFSs (e.g. North Macedonia, Palestine, and Tunisia), the national classification is more general and identifies more general secondary education.

When upper-secondary education could not be precisely identified, the indicator was calculated based on employees with secondary education in general. Therefore, the indicator might suggest a higher share of mismatched employees, as all persons with secondary education (instead of only those with upper-secondary education) will be classified as over-qualified when working in elementary occupations.

Another method to calculate this indicator would be by distinguishing between skills mismatches for those with intermediate-VET and intermediate non-VET education levels. Constructing the indicator according to its original definition would require defining employees as mismatched if they work in elementary occupations and have upper-secondary VET education (or upper-secondary non-VET education). However, in most countries, upper-secondary education is classified solely as VET (in Serbia or Bosnia and Herzegovina, for example) or solely as non-VET, making this distinction impossible. Distinguishing upper-secondary VET and non-VET upper-secondary education levels also meant decreasing the number of observations for each indicator variant further, leading to implausible results (e.g. Kosovo).

The definition of mismatched employees could be extended from upper-secondary education employees to intermediate-VET education levels (or intermediate-GEN education levels) working in elementary occupations. However, this is like the cases in which identification of upper-secondary education was not possible. Such an indicator variant suggests that all those with an intermediate level of education are overqualified for elementary occupations. This is a very different statement from saying that those with upper-secondary education are overqualified. To conclude, differentiating the occupational mismatch indicator into VET and non-VET mismatch is not feasible from a methodological point of view.

Over/under-education (empirical method)

In the LFS surveys, there is no objective measure available to determine whether an individual is vertically mismatched (over/under-educated). The empirical method is used to construct a comparable vertical mismatch indicator. It is a purely statistical measure using the distribution of education for each occupation. According to the ILO Guidelines Concerning Measurement of Qualifications and Skills Mismatches of Persons in Employment (adopted by the 20th ICLS) (2018), for the measurement of mismatch by level of education, either the modal level of education or the mean, or the median of the completed years of schooling could be used. In our analysis, the weighted distribution of education is calculated for each occupation. Over-education is defined as existing when the level of education is more than one standard deviation higher than the mode[8]; under-education is instead defined as

8 As there can be more than one mode in a variable distribution, we chose to use the minimum mode.

existing when the level of education is more than one standard deviation lower. The level of education is measured by using the national classification of education grouped into four broader categories low, intermediate-VET, intermediate non-VET, and high[9].

The assumption made when deciding to use the indicator above as a vertical mismatch indicator is that the educational mode for each occupation is a match for that occupation, but this may be a misleading assumption as in theory, everybody employed in a given occupation could be mismatched (ETF, 2012). In some countries, the LFS survey included a question about the individual's subjective feeling about being over/undereducated.

Not in Employment, Education or Training (NEET)

It was necessary to define which individuals were in education to identify the *Not in Employment, Education or Training* (NEET) rate. The questions to identify this variable varied across survey waves. For example, in Georgia, the questionnaire explicitly referred to currently being in 'formal education'. In contrast, in other countries (e.g. Tunisia), the question referred more in general to currently being 'in school'.

Data limitations

Comparability across LFS survey waves

For Moldova, the indicators calculated using the LFS survey wave of 2019 were not strictly comparable with those calculated using the previous survey waves. Specifically, in 2019 there was a break in the LFS time series caused by the revision of the survey methodology.

As of 2019:

- The 'employment' definition was aligned with the new international standard (Resolution 1 of the 19 ICLS, ILO). This category no longer includes persons producing agricultural products mainly for their use consumption. (For the period up to 2018, inclusive, the persons employed in the auxiliary household, producing agricultural products exclusively for their own consumption (of the household), were included in employment if they worked 20 hours and over per week).
- The LFS was carried out according to a new sample of households and a new rotation scheme (2-(2)-2).
- The number of the usual resident population was used to estimate the LFS results (for the period up to 2018, inclusive, for the registered population).

Sensitivity of the indicators to differences in classifications across LFS survey waves

Questions inevitably arise. For example, how does the magnitude of the indicators change when the occupation classification follows a different number of digits? Or when can we not strictly identify upper secondary education? In Appendix E, we provide some data on the sensitivity of the indicators which could affect the comparability of the results.

[9] A more granular categorization could not be used as it would have harmed the comparability of the indicators across countries (both the classification of national education systems and the distribution of workers by education level significantly differs across countries).

4. Cross country comparative analysis

This chapter provides an overview of the results obtained when calculating both the labour market background and the skills mismatch indicators for the selected countries. The findings are briefly discussed by geographical area. There are differences between the countries and across geographical regions due to diverse economic and social backgrounds.

Unemployment and inactivity rates and ratios

LABOUR MARKET BACKGROUND INDICATORS: UNEMPLOYMENT RATES AND UNEMPLOYED/EMPLOYED RATIOS

The unemployment rate calculates the rate of unemployed relative to the active population in the labour market, namely the sum of employed and unemployed. Higher rates show a potential increase in the mismatch between the supply and demand. Similarly, the unemployed to employed ratio expresses the magnitude of the unemployed. A ratio of 0.1 implies that there are ten employed persons for each unemployed person, while 1 implies a one-on-one relation (ETF, 2012).

Trends

In all the SEE countries where the indicators are currently available, the unemployment rate decreased between 2016 and 2019 (except Turkey), even if not homogeneously across groups (age, gender, education level) (Figure 4.1). In Bosnia and Herzegovina, the unemployment rate decreased significantly (Figure 4.1), especially for intermediate non-VET and highly educated workers and the gender gap in unemployment narrowed. In 2019 VET-educated individuals remained among those groups at a higher risk of unemployment. Youth unemployment is still very high in the country despite decreasing over time. In Northern Macedonia, the unemployment rate also significantly decreased, yet it remains relatively high (Figure 4.1). However, the drop in unemployment in the country was accompanied by increased inactivity rates, especially among low-educated workers. In Kosovo, the unemployment rate only slightly decreased (Figure 4.1), and it remained higher over time than in the other SEE countries while the inactivity rate remained stable. The labour force participation instead dropped significantly over time (10 pp). Albania and Serbia also experienced a moderate reduction in the unemployment rate between 2016-2019. They were the countries with the lowest unemployment rate among the SEE countries in the period of interest. In Montenegro, the unemployment rate was stable over time, while Turkey remained static between 2016 and 2018 before it increased by three percentage points, reaching 14% in 2019 (Figure 4.1).

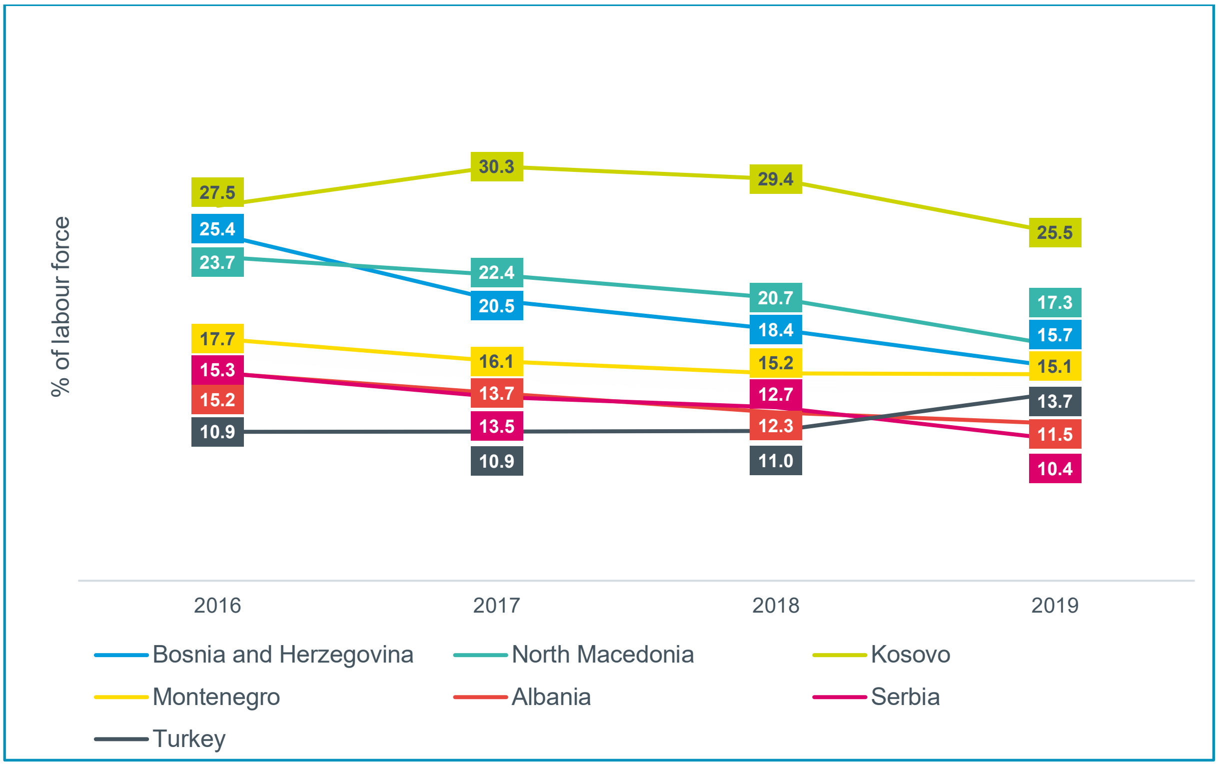
In the SEMED countries where the indicator is available over time (Tunisia, Palestine, and Egypt until 2017), the unemployment rate was relatively stable, showing only a slight increase in Palestine and Tunisia (Figure 4.2). In Palestine, the unemployment gap across gender, age and education levels was stable over time. In 2019, youth, women and those with high qualifications were more likely to be unemployed. Decreasing unemployment trends over the years do not necessarily mean better labour market outcomes or less mismatch. It might reflect higher rates of labour market disengagement (inactivity).

In most EaP countries, the unemployment rate slightly decreased over time (except for Armenia, which was stable). In Moldova, the trends decreased until 2018. The increase between 2018-2019 was caused by changes in the survey methodology described in Section 4. In Georgia, Belarus, and Ukraine, the unemployment rate slightly decreased, but the inactivity rate increased at a higher rate (Figure 4.3). Georgia in 2019 still showed high levels of youth unemployment. Both the VET training and higher levels of education seem to have provided better chances for finding employment.

In Ukraine, youth unemployment significantly decreased, and the unemployment rate was higher among those with intermediate education (both GEN and VET).

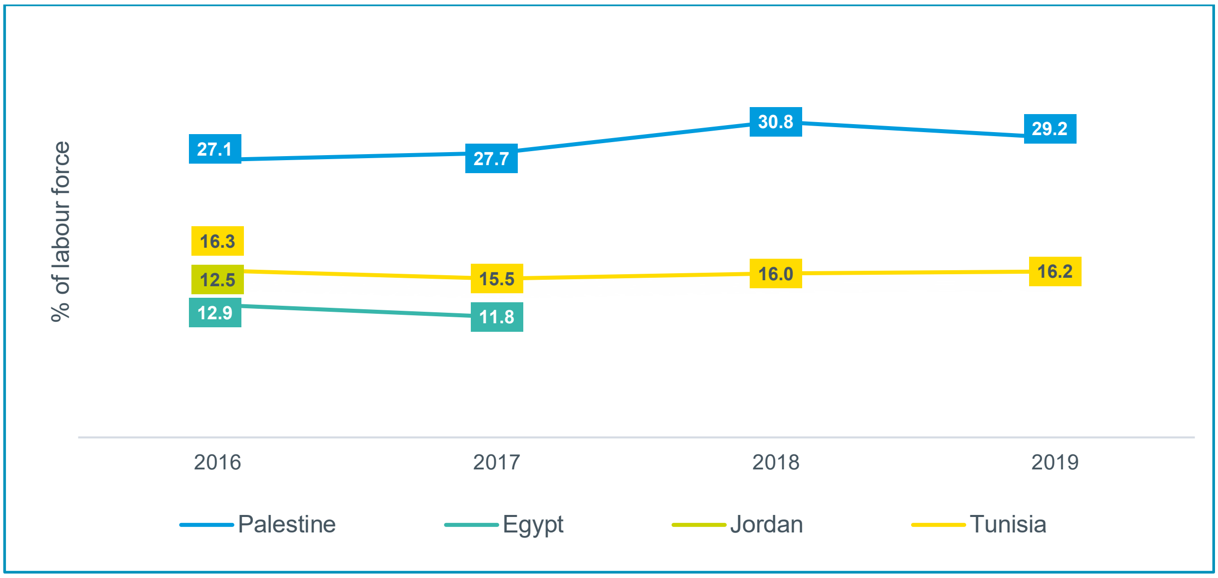
Figure 4.4 shows the unemployment rate in Central Asian countries. In Kyrgyzstan, the unemployment rate was low compared to other countries in the period of interest, and it slightly decreased over time (2 pp).

Figure 4.1 Unemployment rate, see countries, 2016-2019



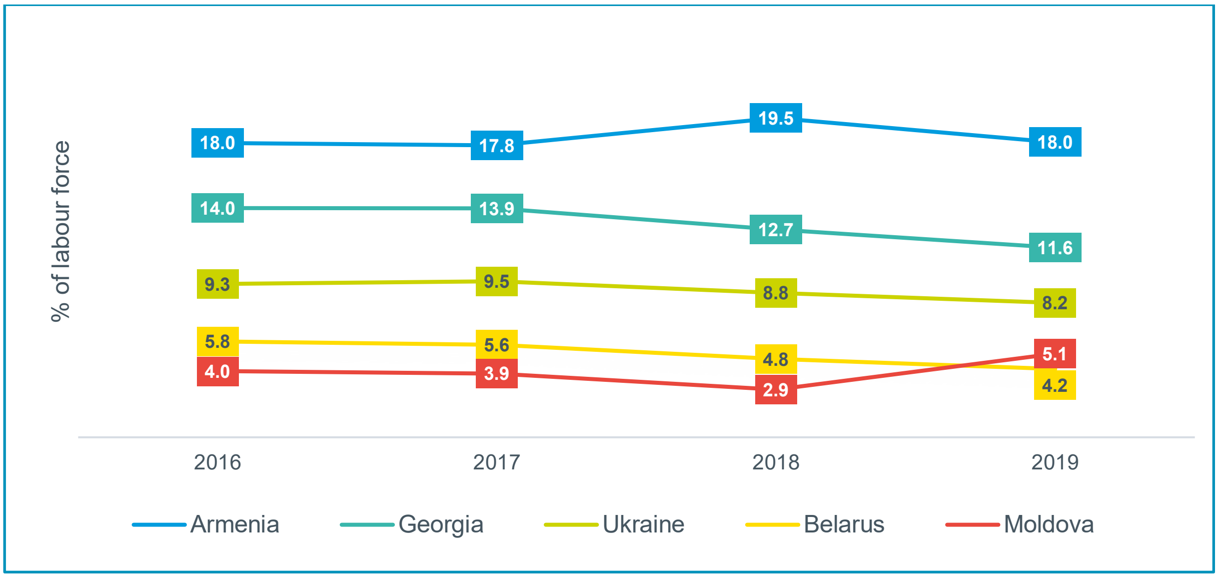
Source: Authors' calculation based on national LFSs.

Figure 4.2 Unemployment rate, SEMED countries, 2016-2019



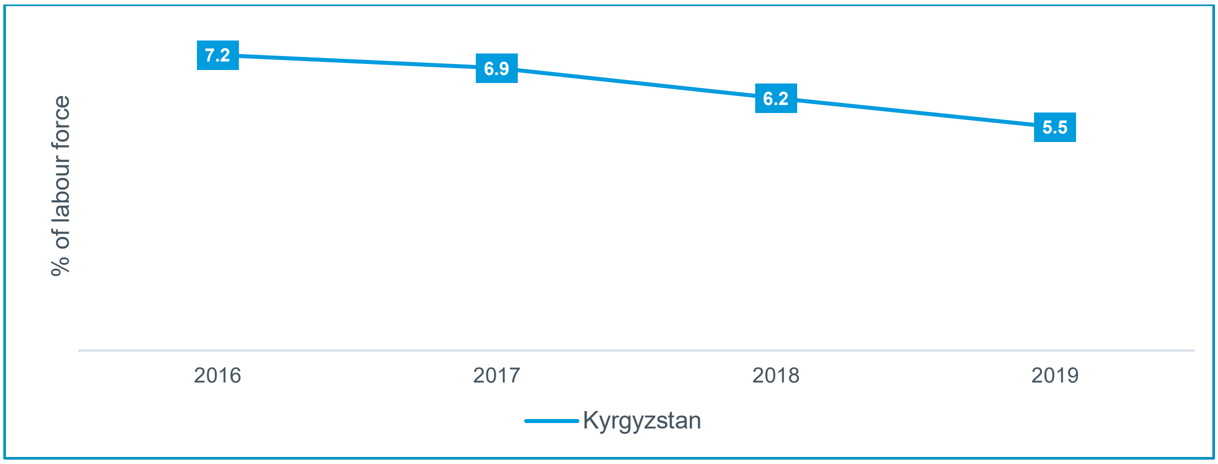
Source: LFS (national surveys)

Figure 4.3 Unemployment rate, EaP countries, 2016-2019



Notes: For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data are not comparable with the previous data series.
Source: LFS (national surveys)

Figure 4.4 Unemployment rate, central Asian countries, 2016-2019



Source: LFS (national surveys)

Unemployment and inactivity rates

Tables 4.1-4.4 below show both the unemployment and the inactivity rate in 2019 in the countries involved in the project. In all the countries, the unemployment rate was higher than the EU average in the same year (7.4%)[10]. The discrepancy between the active labour supply and labour demand was especially high in Palestine and Kosovo, where one in four individuals above 15 years was unemployed. In addition, the inactivity rate is high in all the countries, with about half of the population being inactive in Tunisia, Palestine, Egypt, Turkey, Jordan and Bosnia and Herzegovina and above 70 per cent of the population in Kosovo. Belarus and Georgia had the lowest inactivity rate in 2019 (29.3% and 37.1%, respectively).

[10] https://ec.europa.eu/eurostat/documents/2995521/10159296/3-30012020-AP-EN.pdf/b9a98100-6917-c3ea-a544-ce288ac09675

Gender differences

In all SEE countries, women were more likely than men to be unemployed and more likely to be inactive (Tables 4.1-4.4). The gender gap was significantly high in inactivity rates compared to unemployment rates. Inactivity was the biggest driver of low unemployment rates for women in this region. The country with the highest unemployment and inactivity rate and the largest gender differences both in unemployment and inactivity rates in this group was Kosovo (Table 4.1).
In Bosnia and Herzegovina, women are less likely to be employed, less likely to take up further education, and more likely to be discouraged from the labour market. Although showing relatively lower rates in unemployment and inactivity compared to the other SEE countries, Turkey was ranked among the countries with the greatest gender gap in the share of inactive workers, and this gap was persistent over time (32% in 2019) (Table 4.1).

In EaP countries (Table 4.3), while there were no big gender differences in the unemployment rates, there were large differences in the inactivity rates across gender. Armenia was the EaP country that showed the largest differences in the inactivity rate across gender (about 20 percentage points), explained by high inactivity rates for women, followed by Ukraine and Georgia. The indicators showed that women in the EaP countries were less likely to be unemployed; however, they still had a higher probability of being inactive in the labour market.

The largest differences in unemployment rates across countries could be observed in the SEMED region (Table 4.2), where women are less likely to actively search for a job and more likely to face barriers entering the labour market. In 2019 both Tunisia and Palestine women were twice as likely as men to be unemployed and eight in ten women were inactive in the labour market. In Egypt[11] and Jordan[12] , women were also less likely than men to be employed, and the inactivity rate of women almost doubled one of the men.

In 2019 in Central Asia, in Kyrgyzstan, unemployment rates were similar across gender. There were big differences in the inactivity rate across men and women, as women were doubly likely to be more inactive than men (54.%5 vs 24.3%) (Table 4.4).

Table 4.1 Unemployment, inactivity rates (see countries) by gender, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
Unemployment rate (% of labour force)							
Total	15.7	17.3	25.5	15.1	11.5	10.4	13.7
Male	13.6	16.5	22.4	14.7	11.6	9.8	12.4
Female	18.8	18.4	34.4	15.7	11.4	11.1	16.5
Inactivity rate (% of population)							
Total	57.9	42.8	64.7	42.6	39.6	45.4	47.0
Male	48.3	32.2	47.4	34.8	32.0	37.3	28.0
Female	67.1	53.4	81.8	50.1	47.0	52.9	65.6

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

[11] The latest LFS data available are for 2017.
[12] The latest LFS data available are for 2016.

Table 4.2 Unemployment, inactivity rates (SEMED countries) by gender, 2019

	Palestine	Tunisia	Egypt*	Jordan**
Unemployment rate (% of labour force)				
Total	29.2	16.2	11.8	12.5
Male	23.6	13.1	8.2	11.8
Female	49.0	23.8	23.1	16.1
Inactivity rate (% of population)				
Total	53.27	52.1	55.0	59.1
Male	28.03	30.2	33.1	36.5
Female	79.17	72.9	78.0	84.8

Notes: The population of reference is the one above 15 years old. *The last year available for Egypt is 2017. **The last year available for Jordan is 2016.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.3 Unemployment, inactivity rates (EaP countries) by gender, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
Unemployment rate (% of labour force)					
Total	4.2	11.6	8.2	18.0	5.1
Male	5.1	12.8	8.5	17.4	5.8
Female	3.2	10.1	7.9	18.8	4.4
Inactivity rate (% of population)					
Total	29.3	37.1	43.7	41.3	57.7
Male	24.5	27.4	35.2	29.3	53.0
Female	33.7	45.5	50.8	51.9	61.8

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.4 Unemployment, inactivity rates (central Asian countries) by gender, 2019

	Kyrgyzstan
Unemployment rate (% of labour force)	
Total	5.5
Male	5.0
Female	6.2

	Kyrgyzstan
Inactivity rate (% of population)	
Total	39.8
Male	24.3
Female	54.5

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names)

Differences across age groups

Despite the decrease in unemployment between 2016 and 2019, the youth unemployment rate remained high in all regions. In 2019, more than one-fourth of youth between 15 and 24 years old was unemployed except in Moldova, Ukraine, and Belarus, where the share was lower (see Table 4.5-Table 4.8). The countries with the highest youth unemployment rate were Kosovo (Table 4.5), where half of the youth was unemployed, and Palestine (Table 4.6), where four out of ten young individuals between 15 and 24 years were unemployed. Belarus, followed by Moldova and Ukraine (Table 4.7), and Kyrgyzstan (Table 4.8), had the lowest percentage of youth unemployment across all age groups.

Table 4.5 Unemployment, inactivity rates (see countries) by age group, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
Unemployment rate (% of labour force)							
15+	15.7	17.3	25.5	15.1	11.5	10.4	13.7
15-24	33.7	35.6	49.4	25.2	27.2	27.5	25.4
25-49	17.2	16.9	24.3	16.0	11.0	10.9	12.6
50+	8.7	12.2	9.6	9.4	6.9	5.9	8.0
Inactivity rate (% of population)							
15+	57.9	42.8	64.7	42.6	39.6	45.4	47.0
15-24	64.6	67.8	74.0	63.5	63.3	70.4	55.6
25-49	26.6	19.1	49.7	19.5	15.6	15.7	29.9
50+	72.2	61.3	76.6	58.9	52.0	63.2	68.2

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.6 Unemployment, inactivity rates (SEMED countries) by age group, 2019

	Palestine	Tunisia	Egypt*	Jordan**
Unemployment rate (% of labour force)				
15+	29.23	16.2	11.8	12.5
15-24	44.49	36.3	29.6	33.4
25-49	26.93	16.4	8.9	8.4
50+	13.75	2.5	0.5	3.6
Inactivity rate (% of population)				
15+	53.27	52.1	55.0	59.1
15-24	67.33	64.8	71.0	72.9
25-49	38.63	35.7	39.8	41.9
50+	67.67	69.6	60.7	82.7

Notes: The population of reference is the one above 15 years old. *The last year available for Egypt is 2017. **The last year available for Jordan is 2016.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.7 Unemployment, inactivity rates (EaP countries) by age group, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
Unemployment rate (% of labour force)					
15+	4.2	11.6	8.2	18.0	5.1
15-24	10.2	30.4	15.4	31.8	10.4
25-49	3.7	13.5	8.0	18.3	5.3
50+	3.5	5.7	6.7	13.5	3.6
Inactivity rate (% of population)					
15+	29.3	37.1	43.7	41.3	57.7
15-24	55.2	61.9	63.8	62.7	78.8
25-49	4.8	22.8	16.1	26.8	41.1
50+	50.8	42.3	66.6	49.1	68.1

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.8 Unemployment, inactivity rates (EaP countries) by age group, 2019

	Kyrgyzstan
Employment rate (% of labour force)	
15+	5.5
15-24	12.8
25-49	4.7
50+	2.6

	Kyrgyzstan
Inactivity rate (% of population)	
15+	39.8
15-24	63.1
25-49	24.0
50+	49.4

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Differences across education levels

The relationship between unemployment and educational attainment levels is mixed. In most countries in 2019, the unemployment rate was lower for people with either higher or medium levels of education (including VET graduates) than for those who had low levels of education (Table 4.9, 4.11 and 4.12). However, in some countries (such as Albania, Georgia, Egypt, Jordan, Turkey, and Palestine), those with higher attainment levels had higher unemployment rates than lower-educated persons (Table 4.10 and Table 4.11). At the same time, the ETF study on youth in SEMED (2021) showed that in Egypt and Jordan youth with higher educational levels have the highest probability of being employed.

The share of students involved in vocational programmes is diverse across the countries. Three out of four upper secondary students in Bosnia and Herzegovina are enrolled in vocational programmes, which is also the average in the European Union (Badescu, 2018). At least half of the students in North Macedonia and Kosovo are enrolled in vocational programmes. In other countries such as Palestine, Tunisia, and Georgia, fewer than 10% are enrolled in these programmes (Badescu, 2018). In all countries, with the exception of Egypt, Jordan, Moldova and Kyrgyzstan, a higher percentage of people with medium-GEN education was unemployed compared to those with medium-VET education in 2019[13], while the evidence about the propensity to be inactive across medium-GEN and medium-VET qualifications was mixed (Table 4.9-4.12).

Table 4.9 Unemployment, inactivity rates (see countries) by education level, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
Unemployment rate (% of labour force)							
Low	14.1	23.2	31.2	25.4	6.46	10.7	13.0
Medium-VET	16.8	8.6	25.1	15.4	11.2*	11.1	15.3
Medium-GEN	17.1	16.6	28.3	14.7	11.6*	13.4	16.1
High	12.0	14.7	22.5	11.3	12.28	8.3	13.7
Inactivity rate (% of population)							
Low	81.8	67.8	96.0	75.8	78.2	67.6	34.9
Medium-VET	45.4	49.4	51.4	35.7	36.8*	37.5	45.8
Medium-GEN	54.4	33.9	77.2	54.7	38.9*	60.8	20.7
High	32.6	14.8	23.1	20.3	24.3	28.2	55.9

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.10 Unemployment, inactivity rates (SEMED countries) by education level, 2019

	Palestine***	Tunisia***	Egypt*	Jordan**
Unemployment rate (% of labour force)				
Low	26.5	11.7	3.8	11.4
Medium-VET	25.6	14.5	17.0	11.6
Medium-GEN			9.0	8.0
High	34.6	27.3	20.8	21.0
Inactivity rate (% of population)				
Low	59.0	59.5	65.4	62.4
Medium-VET	66.5	48.8	39.3	19.4
Medium-GEN			71.9	62.2
High	25.8	30.7	23.9	37.7

Notes: The population of reference is the one above 15 years old. *The last year available for Egypt is 2017. **The last year available for Jordan is 2016. ***Medium education includes both intermediate-VET and GEN qualifications.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

[13] The issue with reporting this statistic is that medium-GEN education leads more often to higher levels of education. Thus, there is a selectivity bias issue (i.e. the least able medium-GEN graduates try to enter the labour market).

Table 4.11 Unemployment, inactivity rates (EaP countries) by education level, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
Unemployment rate (% of labour force)					
Low	8.7	10.9	13.2	20.5	8.4
Medium-VET	4.4	9.8	9.2	19.7	5.0
Medium-GEN	7.2	13.0	9.5	18.6	5.5
High	2.2	11.3	7.1	15.4	2.8
Inactivity rate (% of population)					
Low	82.73	65.7	87.5	68.5	74.2
Medium-VET	23.80	34.0	34.3	39.8	53.2
Medium-GEN	44.92	36.9	55.8	44.3	60.9
High	16.61	28.0	32.3	27.1	36.6

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.12 Unemployment, inactivity rates (central Asian countries) by education level, 2019

	Kyrgyzstan
Unemployment rate (% of labour force)	
Low	8.5
Medium-VET	4.9
Medium-GEN	4.9
High	6.0

	Kyrgyzstan
Inactivity rate (% of population)	
Low	68.6
Medium-VET	30.7
Medium-GEN	38.2
High	27.9

Notes: The population of reference is the one above 15 years old.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.13 Unemployment/employment rates and ratios between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Unemployment/ employment rates and ratios	*Bosnia and Herzegovina* ▪ The unemployment rate sharply decreased, especially for intermediate non-VET and highly educated workers ▪ The gender gap in unemployment slightly narrowed ▪ In 2019 VET-educated individuals remained among those groups at higher risk of unemployment ▪ Youth unemployment is still very high in the country despite sharply decreasing over time *Northern Macedonia* ▪ Unemployment rates decreased only slightly (despite still being relatively high), especially for low-educated workers ▪ The drop in unemployment was accompanied by an increase in inactivity rates and was especially high for low-educated workers *Kosovo* ▪ The unemployment rate slightly decreased while the inactivity rate was stable ▪ The employment rate significantly increased between 2016 and 2019 (10 pp.) for those with high education, while the labour force participation dropped at the same rate *Montenegro* ▪ Both the unemployment and the inactivity rate slightly decreased over time ▪ Youth unemployment sharply decreased over time	*Palestine* ▪ Stable ▪ Youth, women, and those with high qualifications were more likely to be unemployed *Tunisia* ▪ The unemployment rate was quite stable between 2017 and 2019 ▪ The unemployment rate slightly increased for those with high education *Egypt* ▪ The unemployment rate was quite stable for both men and women between 2016 and 2017 ▪ The inactivity rate slightly increased ▪ The unemployment rate slightly decreased over time both for individuals with low and intermediate non-VET education *Jordan* ▪ No info on trends as microdata were available only for 2016 at the time of report drafting ▪ In 2016 the inactivity rate in the country was higher than 50% and about one in eight people was unemployed	*Belarus* ▪ Low unemployment rates compared to other countries within and across regions ▪ Employment rate slightly increased, unemployment rates slightly decreased, while inactivity rates remained stable. *Georgia* ▪ The unemployment rate decreased but the inactivity rate increased at a higher rate. ▪ High levels of youth unemployment. ▪ Unemployment rates were highest among those with intermediate GEN and high education. ▪ Inactive rate was highest among people with low education. *Ukraine* ▪ The unemployment rate decreased but the inactivity rate increased at a higher rate ▪ Youth unemployment significantly decreased over time *Armenia* ▪ Both inactivity and unemployment rate were stable over time.	*Kyrgyzstan* ▪ Relatively low unemployment rates compared to the other countries ▪ The unemployment rate slightly decreased, while both the employment and the inactivity rates remained stable

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	▪ In 2019, no gender gap in the unemployment rate but there was a gender gap in the inactivity rate; women are more likely to be inactive *Albania* ▪ The unemployment rate decreased over time both for men and for women and across all education levels ▪ In 2019 no gender gaps in unemployment rates ▪ The inactivity rate decreased over time for both men and women (half women in 2019 are inactive) ▪ Youth unemployment rate (15-24 years old) decreased over time *Serbia* ▪ The employment rate slightly increased while unemployment rates slightly reduced. ▪ Youth age group's employment rates were relatively high (75% in 2019) and increased by around 5 percentage points between 2016-2019 *Turkey* ▪ The unemployment rate was relatively low and was stable between 2016-2018 before increasing by three percentage points until 2019 ▪ Persistent gender and age disparity in the unemployment and inactivity rates over time. Women and youth between 15-24 years old were more likely to be both unemployed and inactive ▪ Individuals with both medium-GEN and high education qualifications were more likely to be unemployed. High educated people experienced lower increasing trends in the unemployment rate in 2019 compared to other education groups.	▪ Young people between 15 and 24 years old were more likely to be either unemployed or inactive ▪ Gender differences were stronger in the inactivity rate with women being almost as double as likely as men to be inactive ▪ The unemployment rate was higher among those with high education reflecting a higher activity rate among people with tertiary education attainment as opposed to a strong propensity towards inactivity among people with lower levels of education attainment ▪ The inactivity rate was higher among those with either low or intermediate-GEN education	▪ No gender gap in unemployment ▪ The inactivity rate slightly increased for men. ▪ In 2019 the inactivity rate of women was double the inactivity rate of men. *Moldova* ▪ Low unemployment rates compared to other countries within and across regions. ▪ Unemployment rates slightly decreased (until the last comparable year (2017) ▪ High youth unemployment rate compared to other age groups (double)	

NEET rates

LABOUR MARKET BACKGROUND INDICATORS: NOT IN EDUCATION, EMPLOYMENT OR TRAINING (NEET)

This indicator presents the share of young people who are not in employment, education, or training (NEET) as a percentage of the total number of young people in the corresponding age group (by gender) in the age class, e.g. 15-24. Higher rates indicate higher shares of (young) people who are not in employment, education or training. (ETF, 2012).

Trends

NEETs are at a higher risk of being socially and economically excluded and are more likely to become vulnerable in the long term. The high incidence of NEETs in the ETF partner countries is often related to lower educational attainment, gender, lower employability due to skill gaps, and socio-economic background. The indicators show the existence of country-specific differences in NEET rates trends and levels.

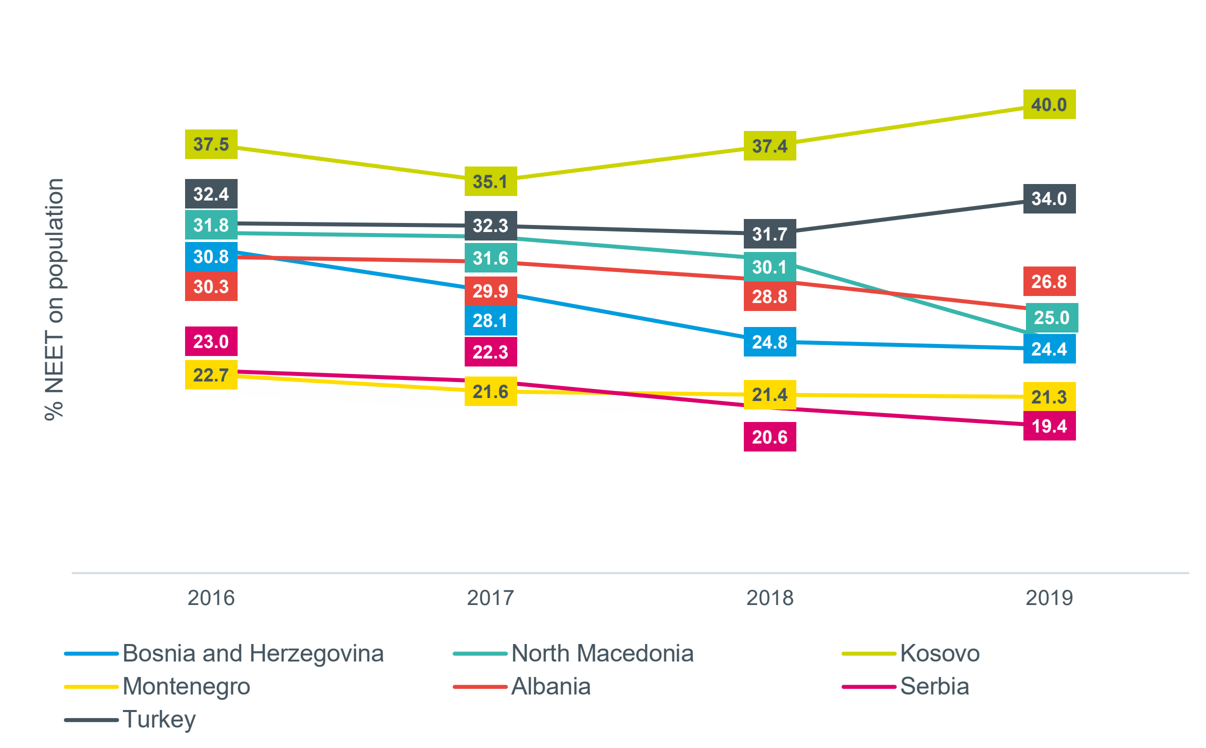
In SEE countries, the NEET rates decreased between 2016 and 2019, especially among youth between 15-29 years old, suggesting an improvement in the school-to-work transition, with an exception for Kosovo and Turkey (Figures 4.5 - 4.7). In Bosnia and Herzegovina, North Macedonia and Albania, the NEET rates substantially decreased despite being persistently high (Figure 4.5). In North Macedonia, there were gender differences in NEET trends as the NEET rate decreased more significantly for men than for women. However, in Kosovo and Turkey, the share of NEETs between 15-29 years old slightly increased, especially for men. The differences in trends in the country were also visible across education levels. The NEET share slightly increased for those with medium-VET education while it decreased for those with medium-GEN education. Also, the share of unemployed among NEET youth slightly increased. In 2019, the highest share of NEETs (about 40%) in the country was among 20-24 years old, suggesting a difficult school-to-work transition. Between 2016-2019, Serbia experienced a four percentage-point decrease in the NEET rate, becoming the country with the lowest youth NEET rates in 2019 (Figure 4.5).

Among SEMED countries, in Palestine (Figure 4.6), the NEET rates were stable over time and high, with one-third of the youth being NEET. In 2019, a larger share of NEET youth between 15 and 29 was found among inactive individuals than unemployed ones. Most NEETs with intermediate qualifications have VET qualifications. In Tunisia and Egypt (between 2016 and 2017), the NEET rate slightly decreased.

Finally, the indicators show that in all the EaP countries part of this study, the NEET rate slightly decreased over time but was persistently high (except for Belarus and Moldova, where it was stable). In Georgia, Moldova, and Armenia, about one in three individuals between 15 and 29 years old were NEETs in the period of interest (Figure 4.7).

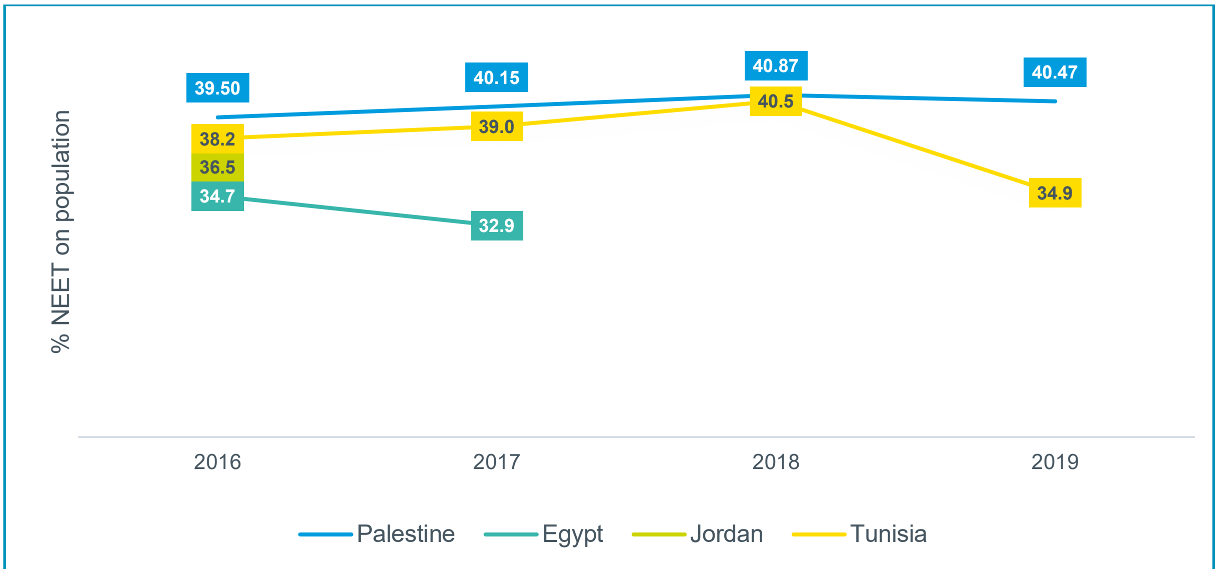
Figure 4.8 shows that between 2016 and 2019 in Kyrgyzstan, the NEET rate of those between 15 and 29 was fairly stable (it only increased by one pp), and in 2019 about one in four young people were NEET.

Figure 4.5 NEET rates trends, age 15-29 (see countries) 2016-2019



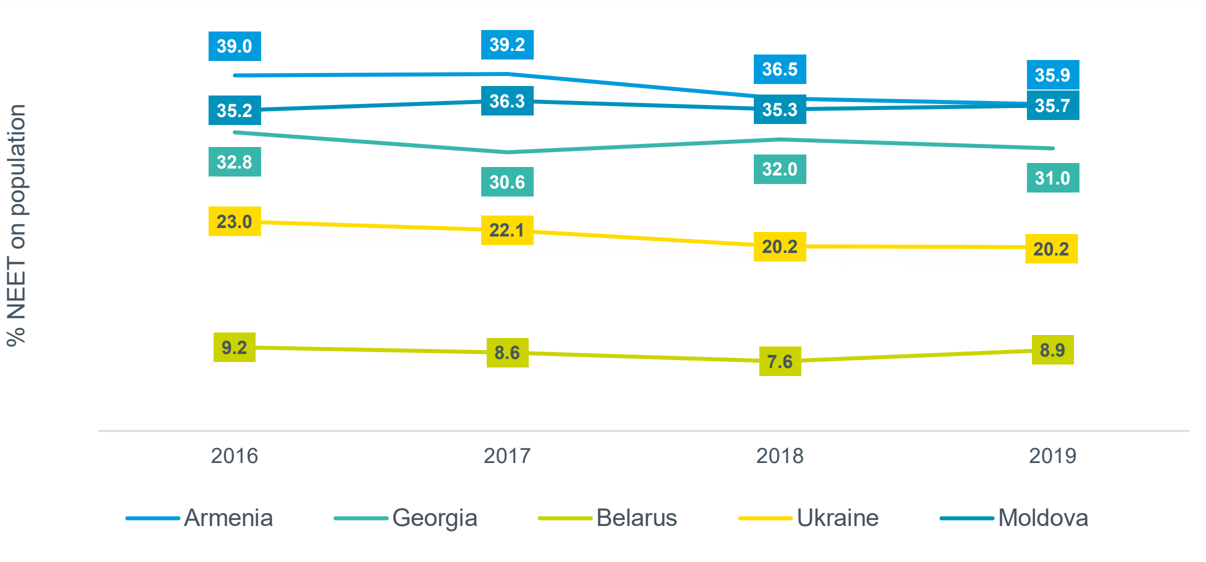
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.6 NEET rates trends, age 15-29 (SEMED countries) 2016-2019



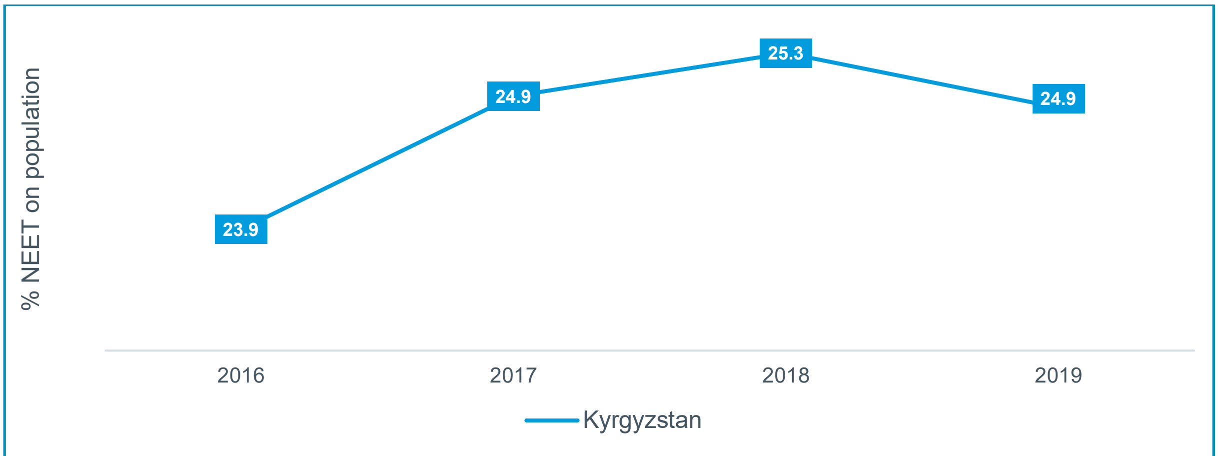
Notes: (*) The last year available for Egypt is 2017. (**) The last year available for Jordan is 2016.
Source: Author´s calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.7 NEET rates trends, age 15-29 (EaP countries) 2016-2019



Notes: For Moldova, there are some methodological changes in the survey in 2019 (sampling, employment definition, weights) so that starting with 2019, the LFS data are not comparable with the previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.8 NEET rates trends, age 15-29 (central Asian countries) 2016-2019



Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Gender and age-group differences

In all the countries in 2019, the NEET rates were highest among 20-24 years old compared to the other age groups suggesting a difficult school-to-work transition (Table 4.14-Table 4.17). The NEET rates were lower in Belarus and Ukraine across all age groups.

Gender differences are visible across all age groups. Women between 15 and 29 years old are more likely than men to be part of NEET. Palestine, Turkey, and Ukraine were nearly twice as likely to show high NEET (Table 4.15). In Moldova, Serbia and Albania, women are one-fourth more likely than men to be NEET. However, in Belarus and Kyrgyzstan, NEET rates were similar across gender. In SEMED countries, young girls are typically over-represented in the NEET group, and in these countries, the proportion of young girls who are NEETs is above 40%. Several factors explain these differences, such as socio-cultural norms, less favourable working environments and family duties (Badescu, 2018). The age group where the gender difference in the NEET rate is higher than in the other groups is the one between 20-24 years old in all the countries (with an exception for Ukraine and Moldova), suggesting the existence of gender differences in access to the labour market after the studies.

Table 4.14 NEET rates (see countries) by gender, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
% of NEET (15-29 years old)							
Total	24.4	25.0	40.0	21.3	26.8	19.4	34.0
Male	21.8	21.3	35.6	21.1	24.7	17.5	22.2
Female	27.5	28.9	45.0	21.4	29.0	21.5	45.9
% of NEET (15-24 years old)							
Total	20.2	18.7	32.9	17.2	25.8	15.7	30.6
Male	19.7	17.7	31.5	18.5	26.2	15.2	22.5
Female	20.8	19.7	34.5	15.8	25.5	16.2	38.9
% of NEET (15-19 years old)							
Total	12.5	9.7	21.7	9.4	18.9	9.6	20.5
Male	12.7	9.1	22.1	9.7	20.5	10.4	17.0
Female	12.2	10.3	21.3	9.1	17.3	8.9	24.2
% of NEET (20-24 years old)							
Total	26.8	26.7	44.3	25.0	31.9	21.0	41.6
Male	25.9	25.4	40.9	27.3	31.1	19.4	28.9
Female	27.8	28.1	48.0	22.5	32.7	22.7	54.1

Notes: The population of reference is the one above 15 years old.
Source: Authors’ calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.15 NEET rates (SEMED countries) by gender, 2019

	Palestine	Tunisia	Egypt*	Jordan**
% of NEET (15-29 years old)				
Total	40.5	34.9	32.9	36.5
Male	28.2	29.9	19.4	22.8
Female	53.3	39.9	47.3	52.1

	Palestine	Tunisia	Egypt*	Jordan**
% of NEET (15-24 years old)				
Total	32.6	26.4	26.9	33.1
Male	26.4	26.9	19.4	24.6
Female	39.2	25.9	35.1	43.2
% of NEET (15-19 years old)				
Total	18.0	16.3	12.5	20.5
Male	19.8	19.4	7.4	17.0
Female	16.1	13.0	18.0	24.2
% of NEET (20-24 years old)				
Total	48.0	35.9	42.6	41.2
Male	33.2	34.2	32.6	26.7
Female	63.5	37.7	53.5	59.4

Notes: (*)The last year available for Egypt is 2017. (**)The last year available for Jordan is 2016.
Source: Author´s calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.16 NEET rates (EaP countries) by gender, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
% of NEET (15-29 years old)					
Total	8.9	31.0	20.2	35.9	35.7
Male	9.3	25.4	13.2	30.2	32.4
Female	8.5	37.2	27.5	42.0	39.1
% of NEET (15-24 years old)					
Total	9.9	26.6	16.1	26.6	26.7
Male	11.2	24.0	12.0	32.7	26.7
Female	8.6	29.6	20.5	29.7	26.7
% of NEET (15-19 years old)					
Total	6.7	17.2	6.4	17.2	11.7
Male	6.1	18.0	6.1	29.1	12.7
Female	7.4	16.4	6.7	11.9	10.5

	Belarus	Georgia	Ukraine	Armenia	Moldova
% of NEET (20-24 years old)					
Total	12.0	36.3	24.3	36.3	40.1
Male	14.5	30.1	16.9	36.1	39.9
Female	9.4	43.6	32.1	44.1	40.4

Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.17 NEET rates (central Asian countries) by gender, 2019

	Kyrgyzstan
% of NEET (15-29 years old)	
Total	24.9
Male	11.7
Female	38.5
% of NEET (15-24 years old)	
Total	20.8
Male	12.5
Female	29.5

	Kyrgyzstan
% of NEET (15-19 years old)	
Total	12.5
Male	8.5
Female	12.2
% of NEET (20-24 years old)	
Total	20.8
Male	16.1
Female	45.3

Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.18 NEET rates between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
NEET rates	*Bosnia and Herzegovina* ▪ Suggest an improvement in skills mismatches ▪ Persistently high numbers of NEET youth. ▪ Improvement in the school-to-work transition. ▪ Decrease in NEET rates driven by youth between 20-24 years old *Northern Macedonia* ▪ The share of NEETs substantially decreased, especially among 20-24 years old and for males. *Kosovo* ▪ Between 15-29 years old, slightly increasing, especially for men. ▪ Slightly increasing for those with medium-VET education, decreasing for those with medium-GEN education ▪ Slightly increasing the share of NEET among the unemployed ▪ The highest share of NEET (about 40%) is among 20-24 years old, suggesting difficult school-to-work transition *Montenegro* ▪ NEET rates slightly decreased over time for both men and women, in 2019, no more gender gap in NEET rates (15-29 years old) ▪ Slightly decreasing for medium-VET graduates, increasing for medium-GEN graduates ▪ Slight decrease in the share of NEET among the unemployed and a slight increase in the share of NEET among the inactive	*Palestine* ▪ Stable and high (almost half of the youth) ▪ In 2019 women were about as double as likely as men to be NEET ▪ The largest share of NEET youth is among the inactive rather than the unemployed ▪ Most NEETs with intermediate-qualifications have VET qualifications *Tunisia* ▪ Between 2017 and 2019, the NEET rate decreased by about one-third ▪ In 2019 about four in ten persons between 15 and 29 years old were NEET. A higher share of those were women *Egypt* ▪ The NEET rate between 15 and 29 years old slightly decreased over time between 2016 and 2017 similarly for both men and women, after a period of a significant decrease in NEET incidence between 2010-2016 (ETF, 2021); ▪ In 2019 the NEET share of women between 15 and 29 years old was double the NEET share of men	*Belarus* ▪ Remained low and stable over the period ▪ Males in the age group 15-29 tend to have higher NEET rates *Georgia* ▪ Stable. Persistently high share of NEET *Ukraine* ▪ Stable, only slightly decreasing ▪ The NEET rate over time looks the lowest among the selected EaP countries, but the reason might be the exclusion from the analysis of those with low education levels *Armenia* ▪ The NEET rate (15-29 years old) slightly decreased, both for men and for women ▪ In 2019 about one-third of the youth between 15-29 years old was NEET *Moldova* ▪ The NEET rate (15-29 years old) was stable over time ▪ In 2019, more than one-third of the youth between 15-29 years old was NEET, with women slightly more likely to be NEET than men	*Kyrgyzstan* ▪ Overall, the NEET rate remained stable over the period. It slightly increased for women and slightly decreased for men

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	Albania ▪ The NEET rates slightly decreased over time for both men and women ▪ In 2019 about one in four young people between 15-29 and 15-24 years old were NEET *Serbia* ▪ NEET rates slightly reduced ▪ Despite the low gender gap in NEET rates, females were more likely to be NEET than males *Turkey* ▪ There is a relatively high NEET rate among youth between 15 and 29 years old (about 34% in 2019) ▪ Persistent gaps in NEET rates across both age groups and gender. Women and youth aged 20-24 years old were more likely to be NEET ▪ The NEET share of people with intermediate GEN qualifications was lower than those with VET education for all age groups. In addition, this share also increased gradually across all education levels and age groups between 2016 to 2019	*Jordan* ▪ No trends available ▪ In 2016 more than one-third of youth between 15 and 29 years old was NEET ▪ Women were more than doubly likely than men to be NEET ▪ The NEET share is higher among those between 25 and 29 years old ▪ Among 15-29 years, the share of NEETs among the inactive was higher than the share of NEETs among the unemployed		

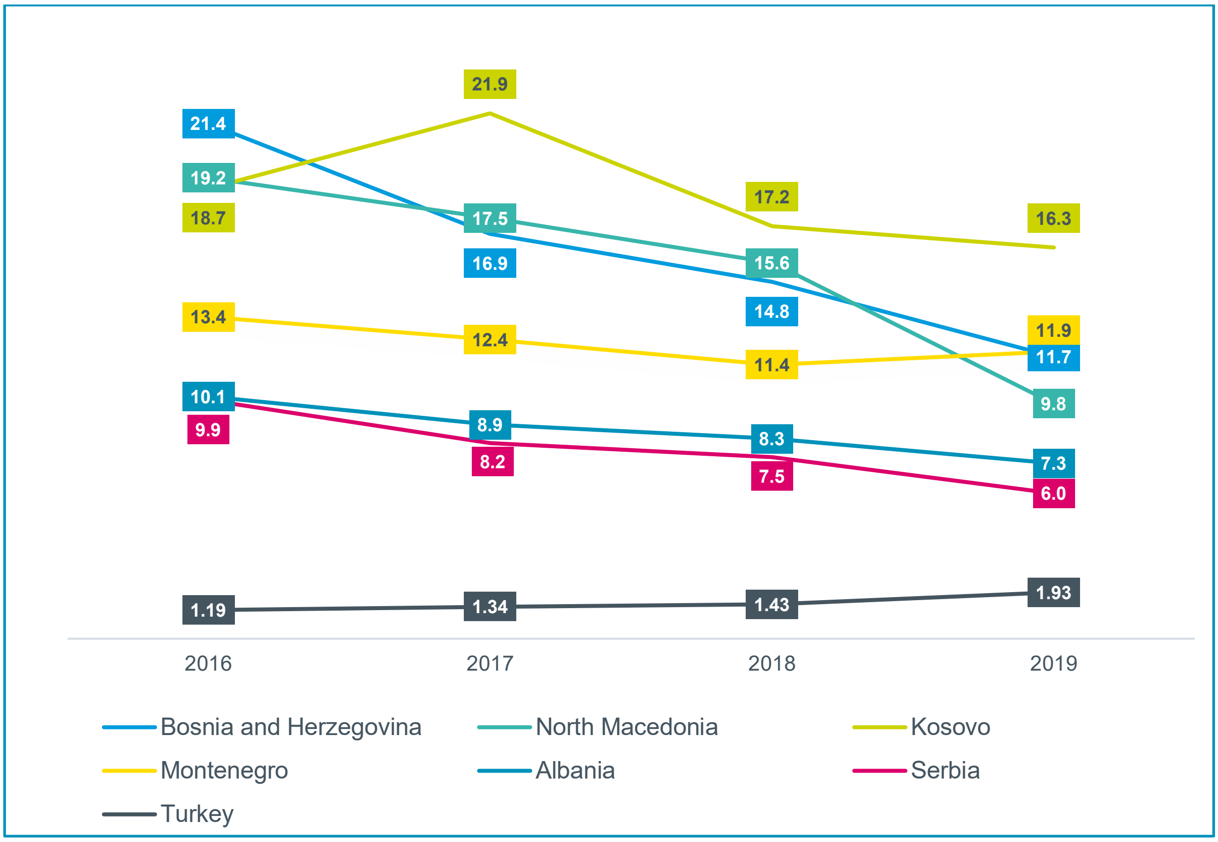
Unemployment rate by unemployment duration

The long-term unemployment rate can be considered to a certain extent, not only as a background indicator describing imbalances between labour demand and labour supply, but also a skills mismatch indicator. However, it has to be interpreted with caution as it can also depend on many other factors which differ across countries (social insurance benefits, active labour market policies (ALMPs), public employment services (PES) efficiency and quality, personal responsibilities/care, etc.).

Trends

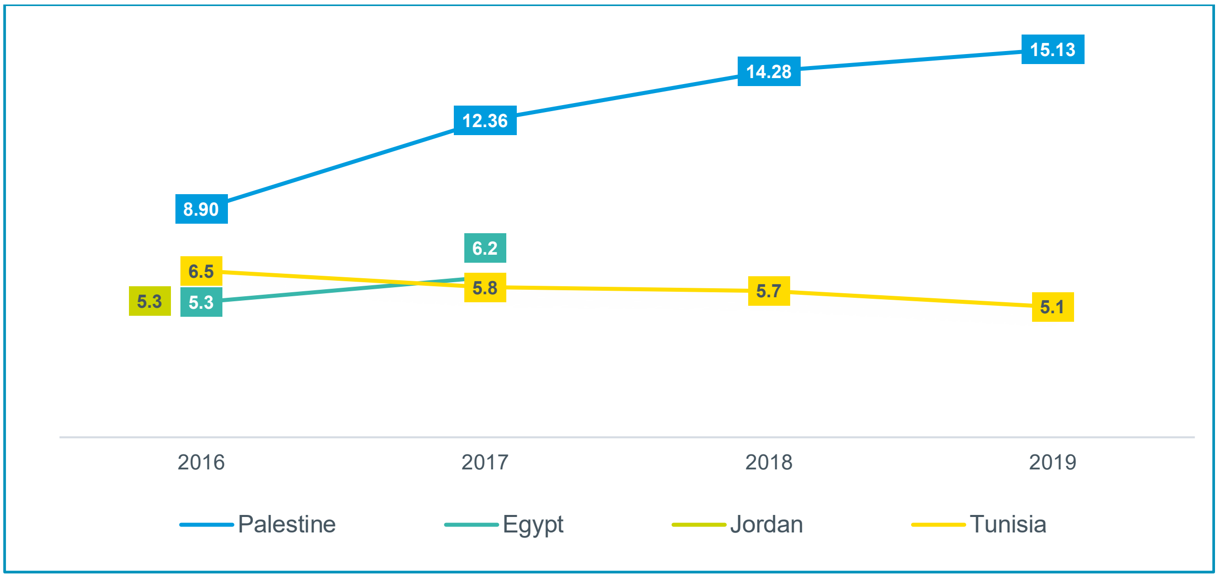
In almost all the selected partner countries, the share of long-term unemployed significantly decreased between 2016 and 2019 (Bosnia and Herzegovina, North Macedonia, Palestine, and Armenia) (Figures 4.9-4.11). Other countries decreased only for some groups of individuals. In Kosovo, long-term unemployment slightly decreased over time for men, while it slightly increased for women. In Georgia, long-term unemployment sharply decreased (halved) for those with higher education while increasing for those with low and intermediate-VET education. Belarus, Tunisia, and Turkey had more stable and lower long-term unemployment rates than all the other countries (around 2%) and Moldova.

Figure 4.9 Long-term unemployment rate in see countries, 2016-2019 (%)



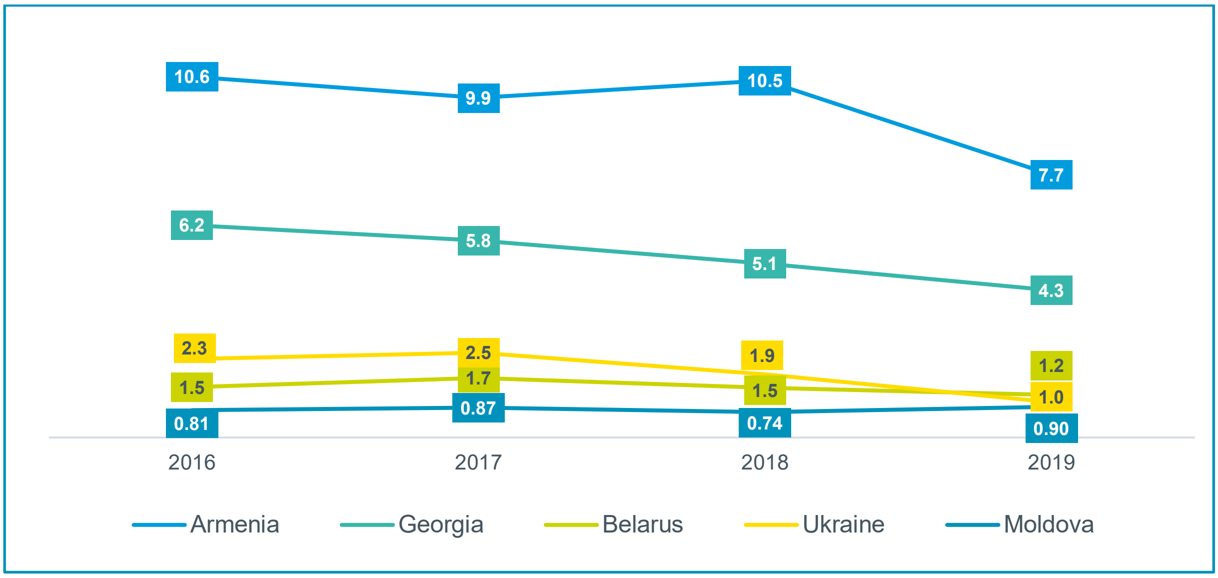
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.10 Long-term unemployment rate in SEMED countries, 2016-2019 (%)



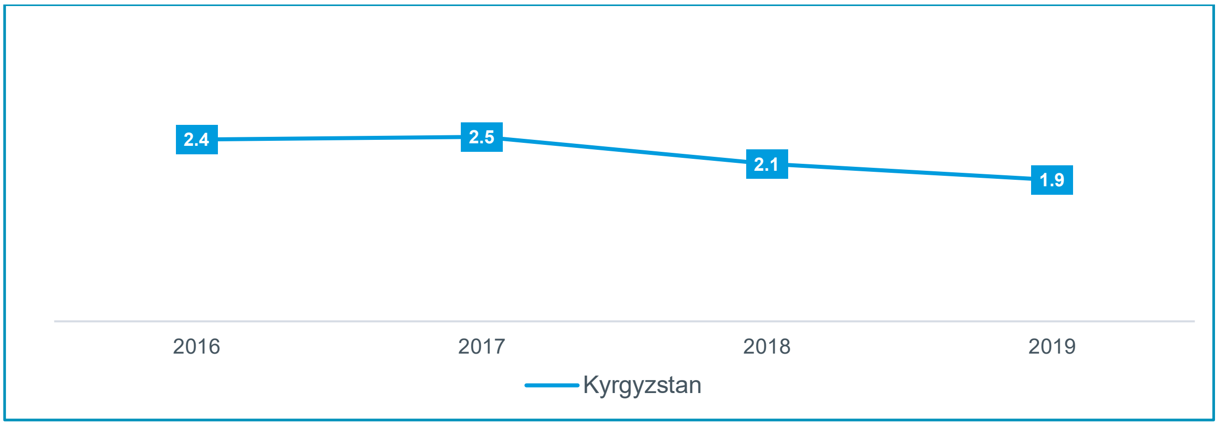
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.11 Long-term unemployment rate in EaP countries, 2016-2019 (%)



Notes: For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data are not comparable with the previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.12 Long-term unemployment rate in central Asian countries, 2016-2019 (%)

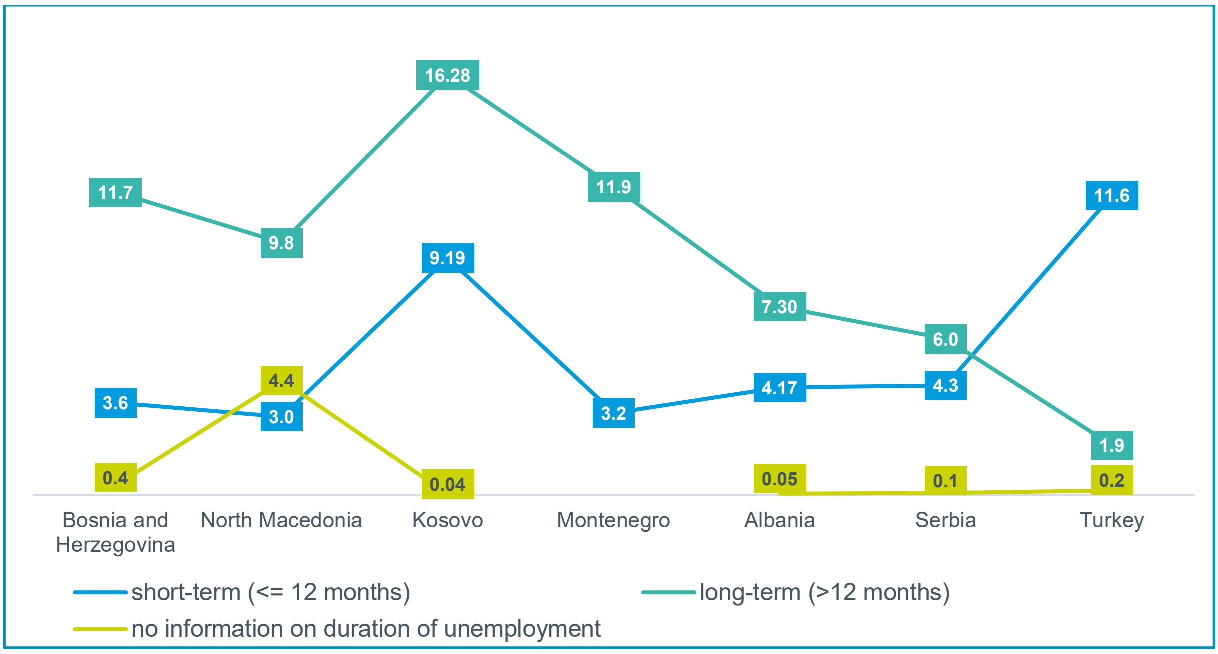


Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Levels

Figures 4.13-4.16 show the unemployment rate by unemployment duration in 2019. The country with the highest share of long-term unemployment among the selected countries is Kosovo, Bosnia and Herzegovina and Montenegro (Figure 4.13). In contrast, Turkey, Belarus, Ukraine, Moldova, and Kyrgyzstan have the lowest share of long-term unemployed. In most countries, the share of long-term unemployment was significantly higher than the short-term one, with an except for Serbia, Egypt, Jordan, Belarus, Georgia, Kyrgyzstan, and Armenia, where the proportion of long short-term unemployed was similar. Finally, on the contrary, Tunisia, Turkey, Palestine, Moldova, and Ukraine[14] had a higher share of short-term unemployed than long-term ones (Figure 4.15). The indicators also show differences in the length of unemployment across groups of individuals. For example, in 2019 in Kosovo, long-term unemployment was two-thirds higher for those with low education than those with high education levels.

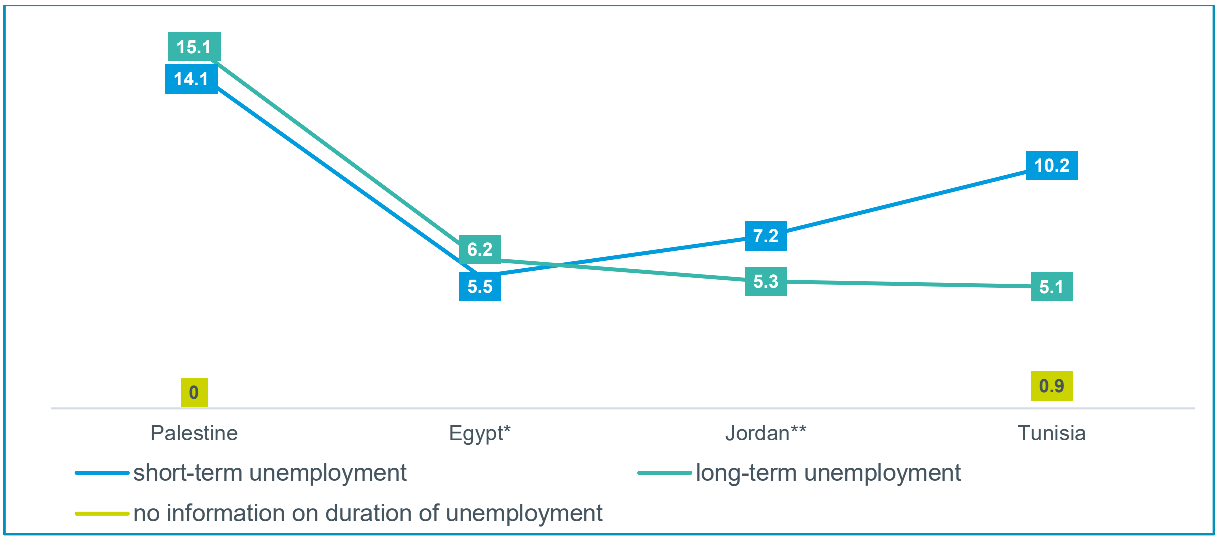
Figure 4.13 Unemployment rate by unemployment duration in see countries, 2019 (%)



Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

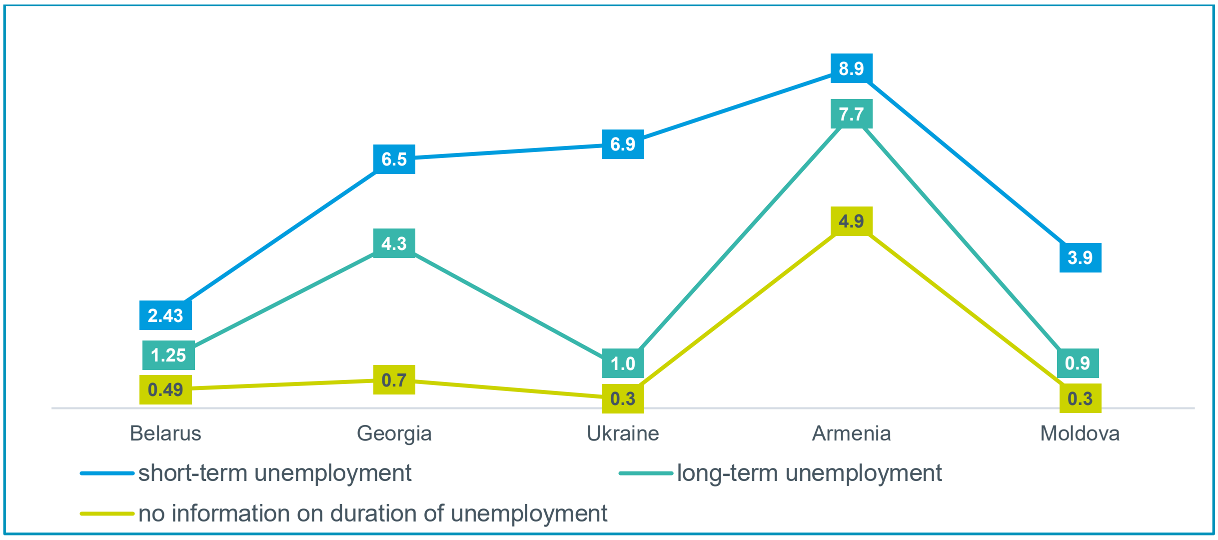
[14] In Ukraine, the low share of long-term unemployed compared to other countries can be due to the exclusion from the sample of those with low education levels

Figure 4.14 Unemployment rate by unemployment duration in SEMED countries, 2019 (%)



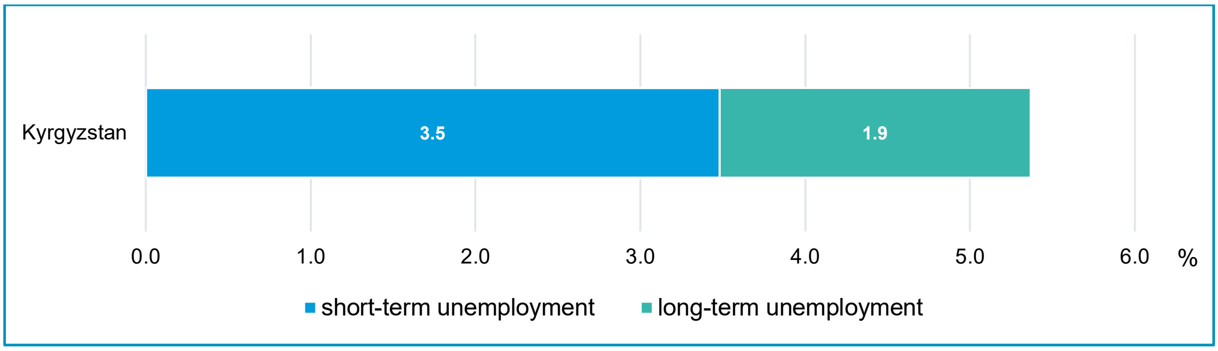
Notes: The population of reference is the one above 15 years old. *The last year available for Egypt is 2017. **The last year available for Jordan is 2016.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.15 Unemployment rate by unemployment duration in EaP countries, 2019 (%)



Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.16 Unemployment rate by unemployment duration in central Asian countries, 2019



Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.19 below summarises our findings of the level and the trends of unemployment duration across regions between 2016 and 2019.

Table 4.19 Unemployment rates by unemployment duration between 2016 AND 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Duration of unemployment by educational attainment levels (optional)	*Bosnia and Herzegovina* ▪ A sharp decrease in the share of long-term unemployed *Northern Macedonia* ▪ A sharp decrease in the share of long-term unemployed *Kosovo* ▪ Long-term unemployment slightly decreased over time for men, while it slightly increased for women. ▪ In 2019 long-term unemployment was two-thirds higher for those with low education than those with high education levels *Montenegro* ▪ The share of long-term unemployed slightly decreased over time across all levels of education and ages, but only for men *Albania* ▪ The long-term unemployment rate decreased over time, both for men and for women. ▪ In 2019 the long-term unemployment rate was 7,3%, no gender gap *Serbia* ▪ Experienced a higher reduction in the value of long-term unemployment rates compared to short-term unemployment rates in the period of interest	*Palestine* ▪ Long-term unemployment significantly increased over time, while short-term unemployment was stable *Tunisia* ▪ The share of long-term unemployed was stable over time (2017-2019) *Egypt* ▪ The long-term unemployment rate slightly increased between 2016 and 2017 for both men and women and especially for highly educated individuals *Jordan* ▪ Trends not available ▪ In 2016 the long-term unemployment rate was 5,3%, women were more likely than men to be long-term unemployed ▪ Youth between 15-24 years old was more likely to be unemployed than older people	*Belarus* ▪ Long-term unemployment rates were low and did not change over time *Georgia* ▪ Long-term unemployment sharply decreased (halved) for those with high and intermediate-VET education. *Ukraine* ▪ The long-term unemployment rate decreased over time and was lower than in other countries *Armenia* ▪ The long-term unemployment rate decreased by more than one-third over time ▪ In 2019, there were similar long-term unemployment rates for both men and women *Moldova* ▪ Long-term unemployment rates were low and did not change over time	*Kyrgyzstan* ▪ Long-term unemployment rates were low and stable over time

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	▪ Persons with medium education (VET and GEN) were more likely to be suffered from both long-term and short-term unemployed *Turkey* ▪ The long-term unemployment rate in 2019 was lower than in other countries ▪ Unemployment is dominant by short-term unemployed ▪ Compared to men, women experienced a higher probability of being unemployed both in the short-term and in the long-term ▪ People with an intermediate education qualification (GEN or VET) tended to be less unemployed (short-term and long-term) than those with low or high education qualifications.			

Indicators of skills mismatch

For the measurement of mismatch by level of education, the guidelines concerning measurement of qualifications and skills mismatches of persons in employment (adopted by the 20th ICLS in 2018) recommend that, where the normative approach cannot be applied, the empirical method using the modal level of education or the mean, median or modal values of the completed years of schooling can be used (ILO, 2018).

As mentioned in Section 2, the various studies in the current literature measure education–job mismatches (overeducation) differently depending on the data available, and each approach has advantages and limitations. In our study, we use both the normative method which is reliable under the strict assumption that all jobs with the same titles require the same level of education and the empirical method, which is easy to calculate for each country even if it relies on the assumption that all jobs with the same occupational title have identical educational requirements.

Over-education (occupational mismatch - normative method)

OCCUPATIONAL MISMATCH (NORMATIVE METHOD)

This method is based on comparisons of the ratio of employees with a given education level (ISCED) working at an inappropriate skill level (measured by the International Standard Classification of Occupations – ISCO) to all workers within that ISCED level. The indicator is also broken down by age classes (15+, 15-24, 25-49, 50+):

- The ratio of workers in the age group not in education with an upper secondary education (both VET and GEN), who are working at skill level 1 (ISCO 9) relative to all workers not in education with an upper secondary education.
- The ratio of workers in the age group not in education with a tertiary education degree, working at skill levels 1 or 2 (ISCO 4-8) to all workers, not in education with tertiary education.

(ETF, 2012) and OECD (2010)

Trends

In general, among the three country-groups analysed, SEE countries tended to experience higher shares of high-skilled mismatch while countries in the EaP area were more likely to experience vertical skills mismatch at a medium education level. The share of medium-skilled mismatched employees working in elementary education between 2016 and 2019 was stable in most SEE countries, except in Kosovo (where it slightly decreased) and in Kyrgyzstan (where it increased by nine percentage points). The same share slightly decreased in Palestine, Tunisia, and Egypt,[15] and significantly decreased in Georgia, which suggests an improvement in the vertical skills mismatch for medium-educated workers in these countries (Figures 4.17-4.22). Both Armenia and Ukraine represent an exception, as the share increased over time.

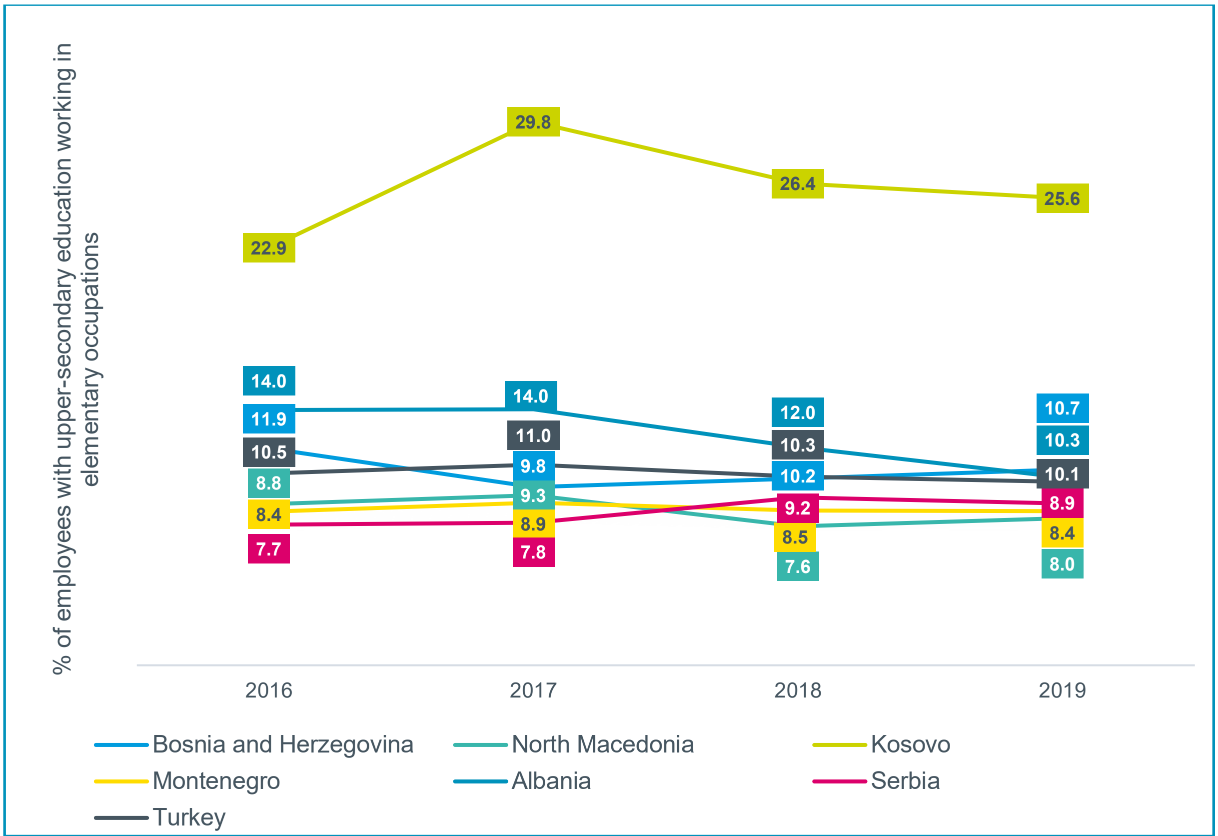
The share of highly skilled employees with tertiary qualifications working in semi-skilled occupations increased slightly over time in Tunisia, Moldova and all SEE countries except for Montenegro (Figure 4.18), Armenia and Ukraine (Figure 4.22), whereas it was stable in Palestine (Figure 4.20), in Georgia (Figure 4.22) and in Kyrgyzstan (Figure 4.23 and Figure 4.24). In 2019, Turkey, Georgia, and Ukraine experienced the highest share of a high-level skills mismatch with about 30% of total employees with tertiary education having to work in semi-skilled occupations.

[15] The last year available of the LFS survey for Egypt is 2017.

There were almost no differences between the share of medium and high-level occupationally mismatched employees in the EaP countries in the study. The only exceptions were Belarus and Moldova. The share of highly-educated occupationally mismatched individuals was three times as high as that of occupationally mismatched individuals with medium-level education (Figure 4.21 – Figure 4.22). In contrast, most of the SEE countries in the study had a higher share of mismatched highly skilled employees rather than mismatched medium-skilled ones. The greatest gap can be found in Serbia and North Macedonia, followed by Albania and Bosnia and Herzegovina (Figures 4.17-4.18) and Kyrgyzstan (Figures 4.23-4.24).

Overall, in 2019 in European countries (EU27), the over-education rate was about 22%[16]. In some countries, the vertical mismatch indicator trends increased for some groups but decreased for others. An example is Bosnia and Herzegovina, where the share of young occupationally mismatched employees decreased over time. The share of those occupationally mismatched increased for highly educated employees above 25 years old. In Northern Macedonia, the indicator shows an improvement in the skills mismatch driven by a drop in the share of employees occupationally mismatched with upper-secondary education working in elementary occupations (medium educated). In Kosovo, over-qualified employees slightly increased over time (both for high and medium educated). In Georgia, the decrease in the share of over-educated employees was driven by those with intermediate-VET education. In contrast, the share of over-educated employees with intermediate-GEN qualifications increased as well as the share of those with tertiary education.

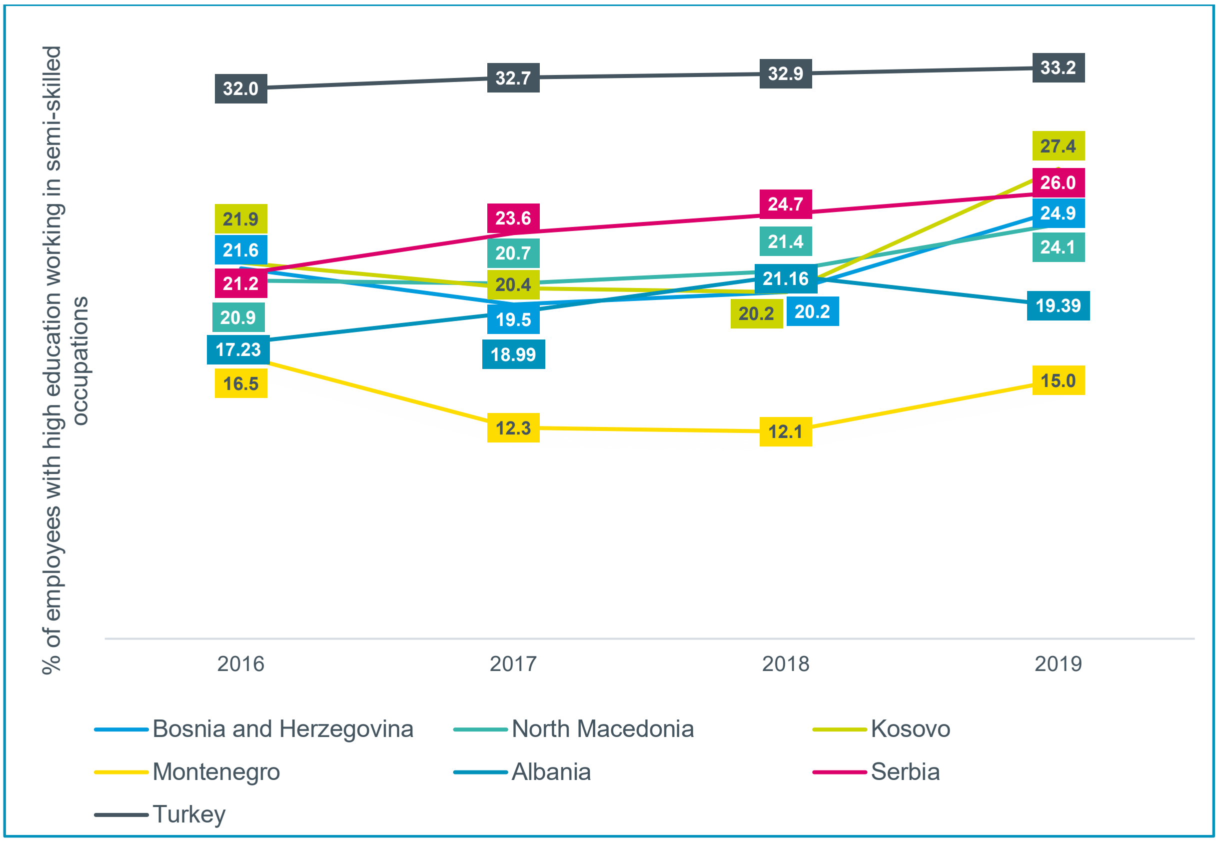
Figure 4.17 Occupational mismatch (medium-skilled), see countries, 2016-2019



Notes: Employees not in education. % of all people with upper-secondary education. It was impossible to identify upper-secondary education in North Macedonia, Bosnia and Herzegovina, and Montenegro, so we used secondary education. In Montenegro, the occupation was defined at the one-digit level, in Turkey at two digits, in the other countries at three-digit level.
Source. Authors' calculation based on national LFSs (see Table 3.2A for survey names).

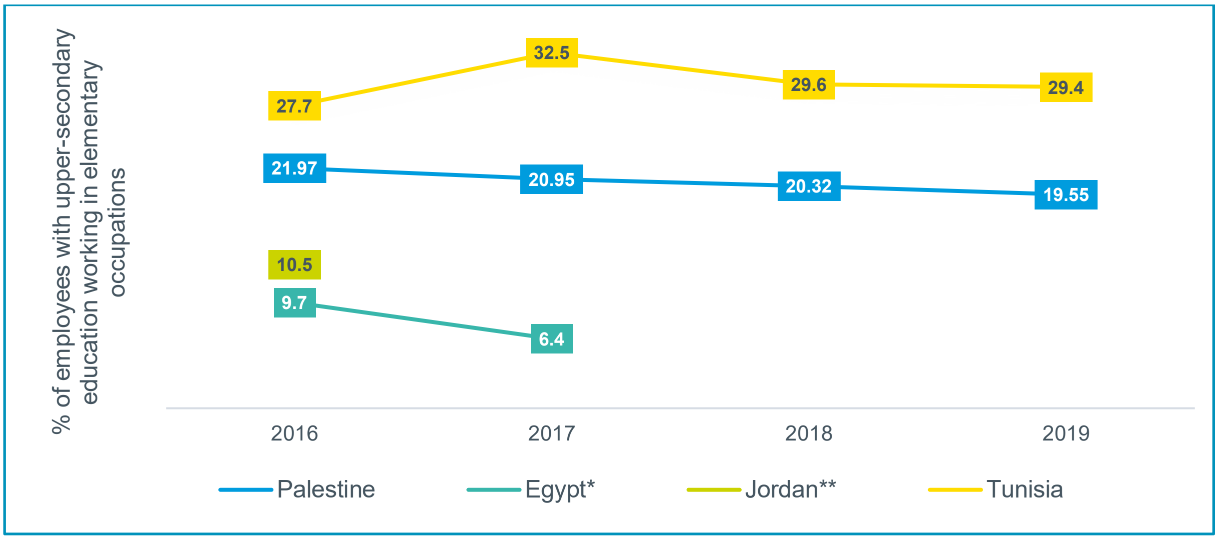
16 https://ec.europa.eu/eurostat/web/experimental-statistics/skills

Figure 4.18 Occupational mismatch (highly skilled), see countries, 2016-2019



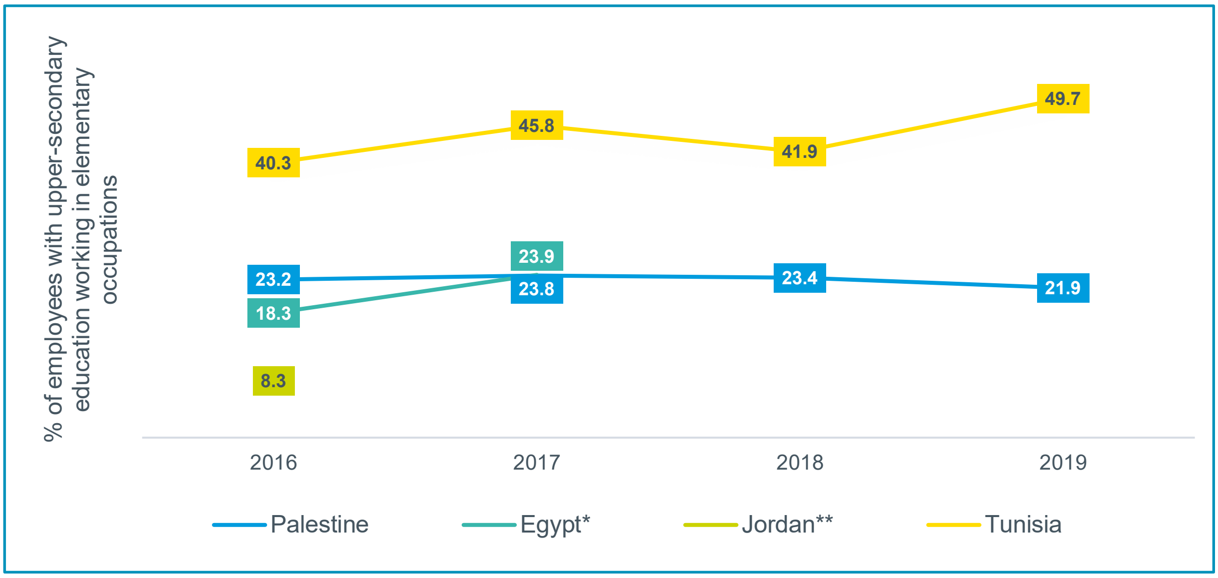
Notes: Employees not in education. % of all people with tertiary education. In Montenegro, the occupation was defined at the one-digit level, in Turkey at two digits, in the other countries at three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.19 Occupational mismatch (medium-skilled), SEMED countries, 2016-2019



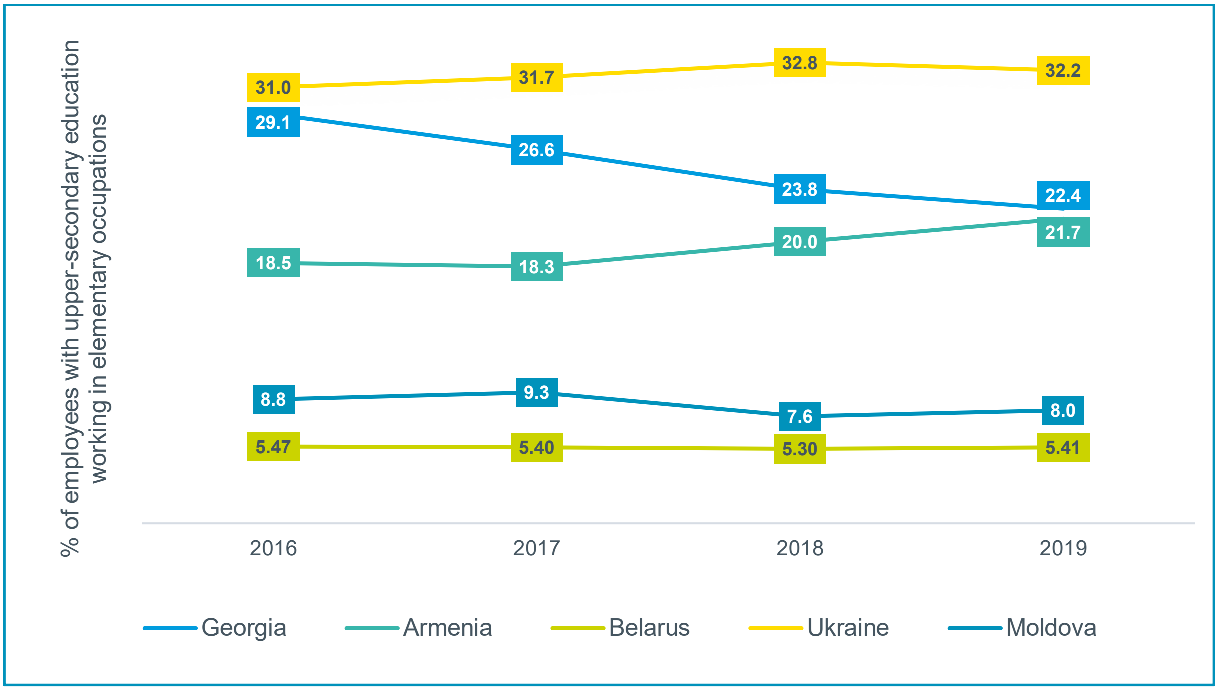
Notes: Employees not in education. % of all people with upper-secondary education. In both Palestine and Tunisia, it was not possible to identify upper-secondary education, so we used secondary education. In Palestine, the occupation was defined at the one-digit level and three digits in the other countries.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.20 Occupational mismatch (highly skilled), SEMED countries, 2016-2019



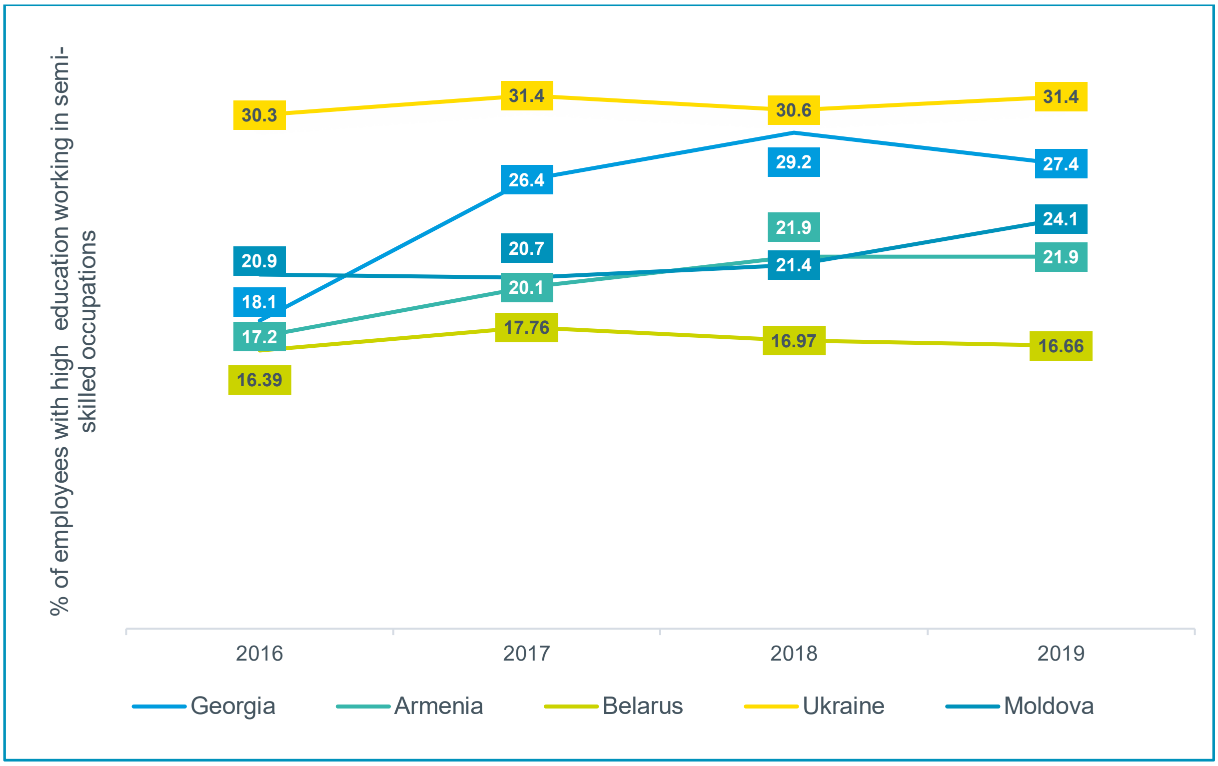
Notes: Employees not in education. % of all people with tertiary education. In Palestine, the occupation was defined at the one-digit level, in the other countries at the three-digit level. In Palestine and Tunisia, it was impossible to identify upper-secondary education, so we used secondary education.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.21 Occupational mismatch (medium-skilled), EaP, 2016-2019



Notes: Employees not in education. % of all people with upper-secondary education. In both Belarus and Moldova, it was not possible to identify upper-secondary education, so we used secondary education. In Ukraine and Armenia, the occupation was defined at the two-digit level, in the other countries at the three-digit level. For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data are not comparable with the previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

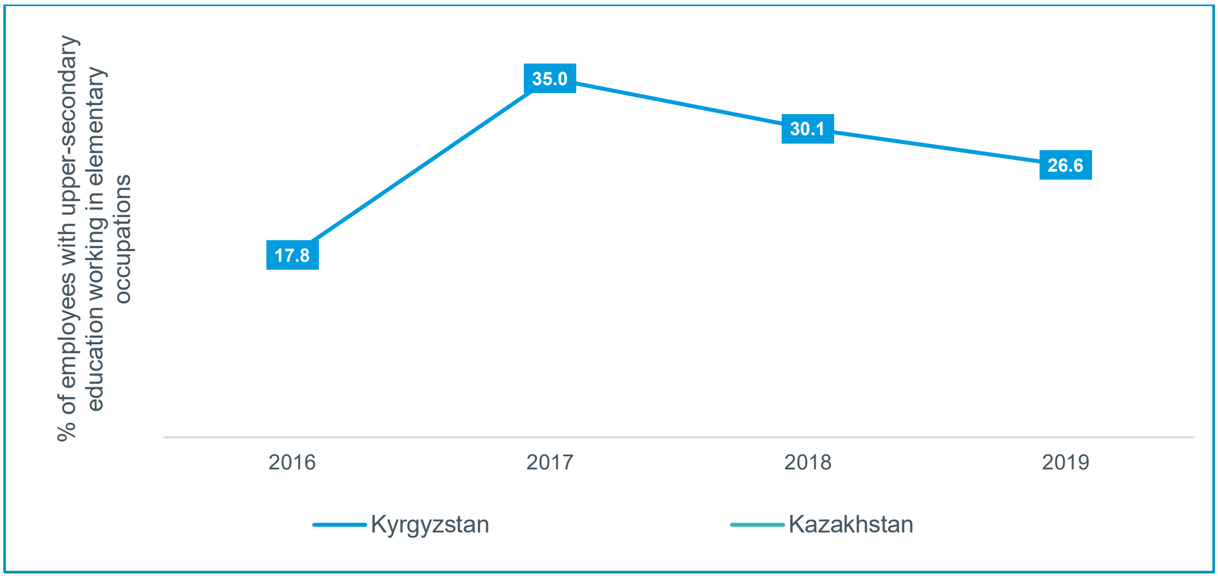
Figure 4.22 Occupational mismatch (highly skilled), EaP countries, 2016-2019



Notes: Employees not in education. % of all people with tertiary education. In Ukraine and Armenia, the occupation was defined at the 2-digit level, In the other countries at the three-digit level. For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data are not comparable with the previous data series.

Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

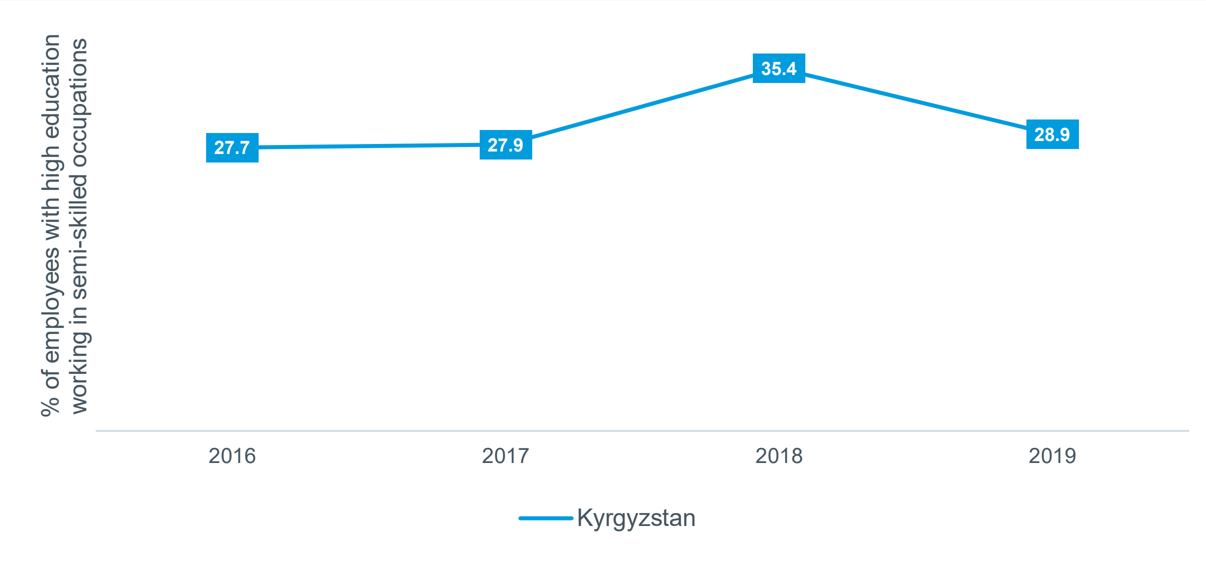
Figure 4.23 Occupational mismatch (medium-skilled), central Asian countries, 2016-2019



Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education.

Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.24 Occupational mismatch (highly skilled), central Asian countries, 2016-2019



Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Gender differences

Tables 4.20-4.23 show the overall level of vertical mismatch by gender in the selected ETF partner countries. In most countries in the SEE and the EaP region, women were more likely to experience a skills mismatch at the medium level. At the same time, men were more likely to experience high-level skills mismatch, with an exception for Moldova, where both men and women were more likely to experience a high-skills mismatch. However, in both SEMED countries and Central Asia, the share of both types of mismatches was higher for men.

Gender differences were more striking in Tunisia, Palestine, Georgia, Ukraine, Kyrgyzstan, Armenia, and Kosovo (in the latter two countries among those with medium education and in Ukraine among those with high education), with men more likely than women to be over-educated. These results are compatible with those obtained using the Cedefop´s European skills and jobs survey (Cedefop, 2018). Significant gender differences were also visible in Georgia, where in 2019, the share of over-educated employees was higher among higher-educated women compared to men. In Belarus, the differences between males and females were greater and higher for those with tertiary degrees working in semi-skilled occupations. Despite a substantial gap between the medium and highly-skilled mismatches in Serbia, there were nearly no gender differences in the country's share of occupationally mismatched employees (Table 4.20). It would be interesting for future research to explore to what extent such differences are related to gender equality policies.

Table 4.20 Occupational mismatch (see countries) by gender, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
Employees with upper-secondary education* working in elementary occupations, 2019**							
Total	10.7	8.0	25.6	8.4	10.3	8.9	10.0
Male	9.9	7.6	27.4	6.6	6.1	7.4	9.2
Female	12.4	8.7	16.3	10.9	18.2	10.5	12.1

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
% of employees with tertiary education working in semi-skilled occupations*, 2019**							
Total	24.9	24.1	27.4	15.0	19.4	26.0	33.2
Male	27.3	25.8	29.5	16.6	20.4	25.6	36.2
Female	22.7	22.8	24.3	13.9	18.7	26.3	29.0

Notes: Employees not in education. In North Macedonia it was not possible to identify upper-secondary education, so we used secondary education; (**) % of all people with upper-secondary education; (***) % of all people with tertiary education. In Montenegro, the occupation was defined at the one-digit level, in Turkey at two digits, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.21 Occupational mismatch (SEMED countries) by gender, 2019

	Palestine	Tunisia	Egypt****	Jordan****
Employees with upper-secondary education working in elementary occupations*, 2019				
Total	19.6	29.4	6.4	10.5
Male	20.3	32.9	7.2	36.9
Female	7.8	14.2	3.4	8.9
Employees with tertiary education working in semi-skilled occupations, 2019**				
Total	21.9	49.7	23.9	8.3
Male	29.7	61.4	29.6	12.3
Female	8.5	43.4	13.4	1.9

Notes: Employees not in education. In Palestine and Tunisia, it was impossible to identify upper-secondary education, so we used secondary education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education. (***) The last year available for Egypt is 2017. (****) The last year available for Jordan is 2016. In Palestine, the occupation was defined at the one-digit level, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.22 Occupational mismatch (EaP countries) by gender, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
Employees with upper-secondary education working in elementary occupations*, 2019					
Total	5.4	22.4	32.2	21.7	8.0
Male	5.7	19.6	30.6	22.0	7.6
Female	5.2	27.7	34.2	21.3	8.7
Employees with tertiary education working in semi-skilled occupations, 2019**					
Total	16.7	27.4	31.4	21.9	24.1
Male	21.9	32.9	37.6	27.3	25.8
Female	13.3	23.2	26.6	17.1	22.8

Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education. In Ukraine, the occupation was defined at the two-digit level, in Armenia at the one-digit level, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.23 Occupational mismatch (central Asian countries) by gender, 2019

	Kyrgyzstan
Employees with upper-secondary education working in elementary occupations*, 2019	
Total	26.6
Male	30.1
Female	20.7

	Kyrgyzstan
Employees with tertiary education working in semi-skilled occupations, 2019**	
Total	28.9
Male	35.8
Female	22.6

Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education. (***).
Source: Authors' calculation based on national LFSs.

Age differences

It is possible that over-education is correlated with specific age groups, which would indicate the employees that are more likely to be overqualified and pay a wage penalty. Tables 4.24-4.27 show the share of occupationally mismatched employees by age group. In 2019, the largest share of over-educated employees in all the countries (except Armenia, and among medium-educated Bosnia and Herzegovina, Tunisia, Georgia, Ukraine, Albania, North Macedonia, and Moldova) was among those aged 15-24 years old. There was an occupational mismatch for more than one-fourth of the employees, both with upper-secondary and tertiary education. The results suggest that finding an occupation that matches the level of education in most countries is harder when entering the labour market after those studies[17]. However, senior employees (aged over 50 years old) with upper-secondary education were more likely to be employed in elementary occupations than employees in other age groups (across the countries analysed in this study).

Table 4.24 Occupational mismatch (see countries) by age group, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
% of employees with upper-secondary education* working in elementary occupations*, 2019							
15+	10.7	8.0	25.6	8.4	10.3	8.9	10.1
15-24	8.4	7.3	30.4	8.3	6.4	12.5	11.4
25-49	10.9	7.7	26.6	8.3	9.3	8.1	9.6
50+	11.2	9.4	20.5	8.7	13.2	9.3	11.4
% of employees with tertiary education working in semi-skilled occupations, 2019**							
15+	24.9	24.1	27.4	15.0	19.4	26.0	33.3
15-24	28.3	35.7	41.7	26.1	42.4	48.8	51.6
25-49	28.1	25.8	29.1	17.8	20.0	28.6	32.8
50+	18.7	16.6	19.1	5.4	8.7	17.6	19.0

Notes: (*) % of all people with upper-secondary education; (**) % of those with tertiary education. Source: Authors' calculation based on national LFSs. Employees not in education. % of all people with upper-secondary education. In North Macedonia was not possible to identify upper-secondary education, so we used secondary education. In Montenegro, the occupation was defined at the one-digit level, in Turkey at two digits, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

[17] It could also be due to the fact that some of those in this age group might still be finishing their studies.

Table 4.25 Occupational mismatch (SEMED countries) by age group, 2019

	Palestine	Tunisia	Egypt***	Jordan****
% of employees with upper-secondary education* working in elementary occupations*, 2019				
15+	19.6	29.4	6.4	10.5
15-24	31.0	33.4	4.9	9.2
25-49	16.7	27.8	7.5	10.7
50+	19.9	34.0	7.3	8.9
% of employees with tertiary education working in semi-skilled occupations, 2019**				
15+	21.9	49.7	23.9	8.3
15-24	35.7	59.1	42.9	10.2
25-49	22.8	48.9	25.1	8.6
50+	9.3	27.1	5.4	5.4

Notes: Employees not in education. (*) % of all people with upper-secondary education; (**) % of all people with tertiary education. (***) In Egypt, the last data is available for 2017. (****) In Jordan, the last data available is for 2016. In Palestine, the occupation was defined at the one-digit level, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.26 Occupational mismatch (EaP countries) by age group, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
Employees with upper-secondary education working in elementary occupations*, 2019					
15+	5.4	22.4	32.2	21.7	8.0
.5-24	1.9	14.2	27.3	15.6	7.3
25-49	4.7	18.8	31.3	17.9	7.7
50+	7.8	33.8	35.8	28.3	9.4
Employees with tertiary education working in semi-skilled occupations, 2019**					
15+	16.7	27.4	31.4	21.9	24.1
15-24	13.8	40.2	38.1	18.6	35.7
25-49	17.0	30.4	30.7	24.3	25.8
50+	16.1	21.0	31.4	17.2	16.6

Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education. In Ukraine, the occupation was defined at the two-digit level, in Armenia at the one-digit level, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.27 Occupational mismatch (central Asian countries) by age group, 2019

	Kyrgyzstan
Employees with upper-secondary education working in elementary occupations*, 2019	
15+	26.6
15-24	28.2
25-49	25.5
50+	28.3

	Kyrgyzstan
Employees with tertiary education working in semi-skilled occupations, 2019**	
15+	28.9
15-24	48.4
25-49	31.4
50+	12.4

Notes: Employees not in education; (*) % of all people with upper-secondary education; (**) % of all people with tertiary education.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Type of intermediate education differences

The occupational skills mismatch indicator was calculated for those with both medium-GEN and medium-VET education to compare the skills mismatch between the two qualifications. However, the results were not always comparable across countries. The indicator was not always meaningful, either because of the low number of observations or because upper-secondary education could not be clearly defined. The limitations on calculating the indicator for these groups were discussed in this report in Section 3.

Table 4.28 below summarises our findings of the level and the trends of occupational mismatch across regions between 2016 and 2019.

Table 4.28 Occupational mismatch (normative method) between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Occupational mismatch (Vertical mismatch)	*Bosnia and Herzegovina* ▪ Mixed evidence ▪ The share of young occupationally mismatched employees decreased ▪ The share of occupationally mismatched highly educated employees increased among those above 25 years old *Northern Macedonia* ▪ Improvement ▪ Drop in the share of individuals occupationally mismatched with upper-secondary education working in elementary occupations *Kosovo* ▪ The share of over-qualified employees slightly increased over time (both for those with tertiary education and a medium-level of education) ▪ In 2019, about one-fourth of employees were occupationally mismatched *Montenegro* ▪ The share of over-qualified women with both medium and high levels of education slightly increased over time, while the share of over-qualified men with tertiary education decreased *Albania* ▪ Medium-skilled mismatches slightly decreased while highly-skilled	*Palestine* ▪ The share of occupationally mismatched employees over time slightly dropped *Tunisia* ▪ The share of occupationally mismatched employees over time slightly dropped among those with a medium-level of education, while it slightly increased among those with tertiary education *Jordan* ▪ Trends not available ▪ In 2016 the share of over-educated workers was double the share of under-educated workers ▪ The share of over-educated employees with upper-secondary education working in elementary occupations was higher than the share of employees with tertiary education ▪ The share of over-educated employees with upper-secondary education was higher for women than men, while the opposite was true for	*Belarus* ▪ The share of occupationally mismatched was lower than in all the other countries part of this study and remained stable over time ▪ Male employees with tertiary degrees were more likely to be occupationally mismatched compared to females. *Georgia* ▪ Decrease in the share of medium-skilled over-qualified workers, while the share of highly-skilled mismatched increased. ▪ Male workers were more likely to be mismatched with tertiary education while female workers with a medium-level of education tended to be mismatched. *Ukraine* ▪ The share of occupationally mismatched employees slightly increased over time (both for those with higher and medium levels of education) ▪ In 2019, about one-third of the individuals were occupationally mismatched	*Kyrgyzstan* ▪ The share of occupationally mismatched medium-educated employees slightly decreased ▪ The share of occupationally mismatched highly-educated employees slightly increased ▪ In 2019 men with both medium and higher education were more likely to be occupationally mismatched than women

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	mismatches gradually increased between 2016 and 2019. ▪ There were significant gaps in occupational mismatches among groups, i.e. women were more likely to experience medium-skilled mismatches and individuals aged 15-24 were more likely to experience highly-skilled mismatches *Serbia* ▪ The share of occupationally mismatched employees (both with medium-level and higher education) increased over time between 2016-2019 ▪ In 2019, almost half of the highly skilled employees between 15-24 years old worked in a semi-skilled occupation *Turkey* ▪ Among the countries with the highest share of mismatched highly-skilled ▪ The share of mismatched employees with medium skills was stable, while the share of mismatched highly-skilled employees gradually increased over time ▪ There was almost no difference in the share of both types of skills mismatches across genders. There was a significant disparity in the share of high skills mismatched across age groups, i.e. the highest mismatch was found among youth between 15-24 years old, followed by workers aged 25-49 years old, and senior workers who are older than 50 years old	employees with higher education *Egypt* ▪ The share of over-qualified employees with upper-secondary education working in elementary occupations decreased by one-third in the period of interest, while the share of over-qualified employees with tertiary education working in semi-skilled occupations increased over time ▪ In 2019, the share of over-qualified employees with tertiary education was four times higher than the share of over-qualified employees with upper-secondary education	*Armenia* ▪ The share of occupationally mismatched employees increased over time both for men and overall *Moldova* ▪ The share of occupationally mismatched was lower than in all the other countries and remained stable over time ▪ The share of occupationally mismatched employees with higher education was higher than the share of occupationally mismatched employees with medium-level education ▪ Male employees with tertiary degrees were slightly more likely to be occupationally mismatched compared to females. ▪ The highest share of employees with tertiary education working in semi-skilled occupations was among 15-24 years old	

Vertical mismatch (over-education and under-education) – empirical method

OVER- (UNDER-) EDUCATION (EMPIRICAL METHOD)

This method can be used in cases where data sets do not include specific questions on over-education or over-skilling; it is a mechanistic measurement and should be interpreted as a proxy. The empirical method is a purely statistical measure where the distribution of education is calculated for each occupation. Over-education is defined as existing when the level of education is more than one standard deviation above the mean (Bauer, 2002 and ILO, 2014) or the mode (Mendes de Oliveira et al., 2000) for the education level of a given occupation. Each occupation's educational mean or mode is thus assumed to match that occupation, but this may very well be a false assumption. In theory, everybody employed in each occupation could be mismatched. (ETF, 2012).

We base our estimation strategy following the empirical approach on the ILO (2018) guideline. The weighted distribution of education is calculated for each occupation[18]. Over-education is defined as existing when the level of education is higher than the minimum mode; under-education is instead defined as existing when the level of education is lower than the minimum mode. The level of education is measured by using the national classification of education.

Trends

This section shows the trends in the share of over and under-educated employees across countries over time, using an alternative vertical mismatch indicator calculated using the empirical method (using the mode).

The indicators in Figures 4.25-4.32 show mixed evidence about the trends in the share of over-and under-educated employees compared to most countries. Turkey had the highest share of over-educated employees (about 35% in 2019). The highest share of under-educated employees can be found in Moldova, Bosnia and Herzegovina and Montenegro. In Bosnia and Herzegovina, Tunisia and Ukraine, the share of over-educated employees decreased, while the share of under-educated employees increased. In North Macedonia, the vertical mismatch worsened but only for some groups as only the share of under-educated employees increased, while the share of over-educated ones was stable (Figures 4.25-4.26). The indicator shows mixed evidence also for both Palestine and Egypt, where the increase in the share of over-educated employees was offset by the decrease in the share of under-educated ones (Figures 4.27-4.28). In 2019, most employees in Palestine were under-educated, and the share of over-educated male employees was higher than the share for women. The indicator shows mixed evidence about the trends of the vertical skills mismatch in Georgia, too, as the share of over-educated employees slightly decreased over time (especially among men) while the share of under-educated employees (especially among women) increased (Figure 4.29-4.30).

In Kosovo and Moldova, the indicator was overall stable over time (Figure 4.25-4.26 and Figures 4.29-4.30)[19]. However, in Kosovo, there were gender differences in the trends for over-educated employees (a decreasing share for men, and increasing for women) and gender differences in both trends and levels for under-educated employees (an increasing share for men, and decreasing for women). In 2019, the share of under-educated male employees was almost double the share for women. The results obtained using the empirical method show that the percentage of over-educated workers in Belarus is higher than the percentage of under-educated workers. These percentages remained stable between 2016-2019 (Figures 4.29-4.30). Vertical skills mismatches in Serbia were characterized by moderate and stable rates over the four years (Figures 4.25-4.26). In addition, there

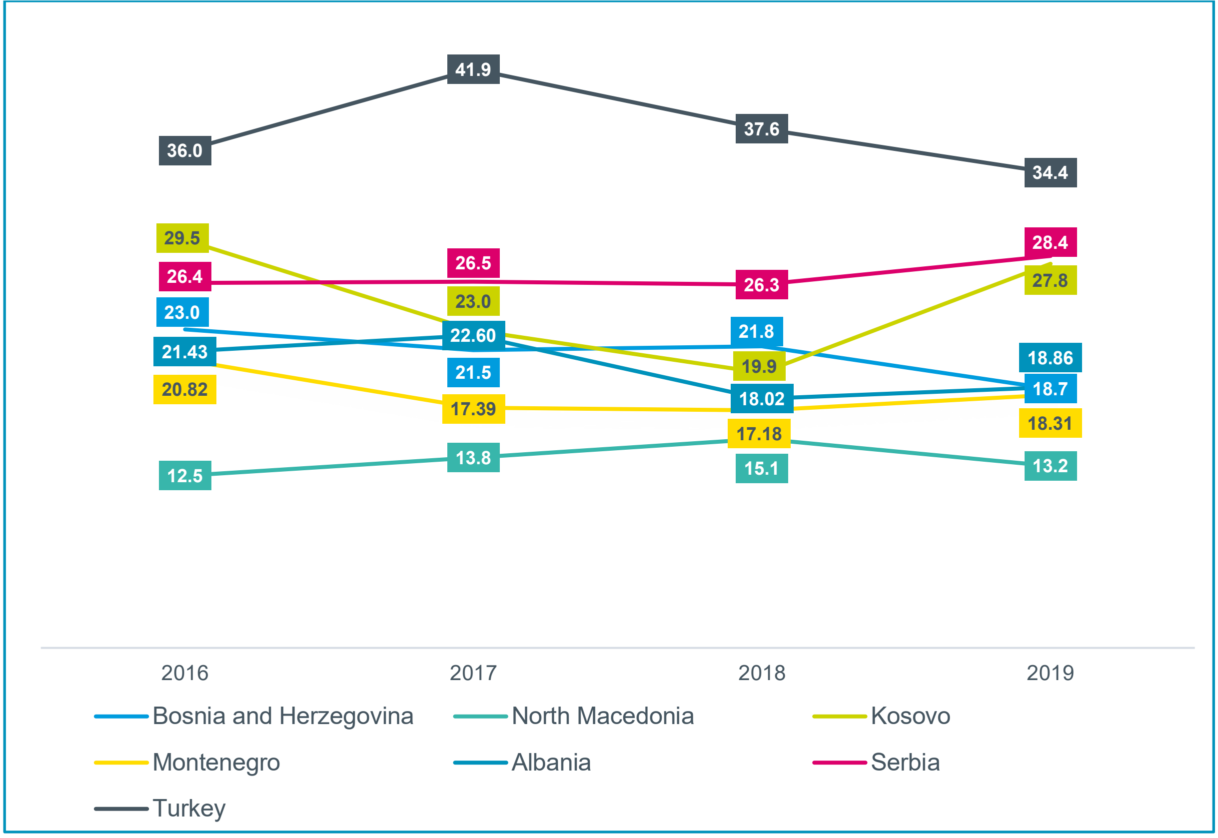
[18] We used the occupation codes following the ISCO-88 or ISCO-08 classifications at different digit-levels, e.g.one-, two-, or three-digit-levels. The differences in the results using ISCO codes at different digit levels are discussed in the sensitivity check section in the Appendix.

[19] In Kosovo, the indicator trends might be affected by the relatively low sample size compared to other countries.

were nearly no disparities in vertical mismatches across gender. However, 25-49 year olds had a higher share of mismatched employees than other age groups (i.e. in 2019, one in three young employees in Serbia was over-educated, and one in four was under-educated for the occupation).

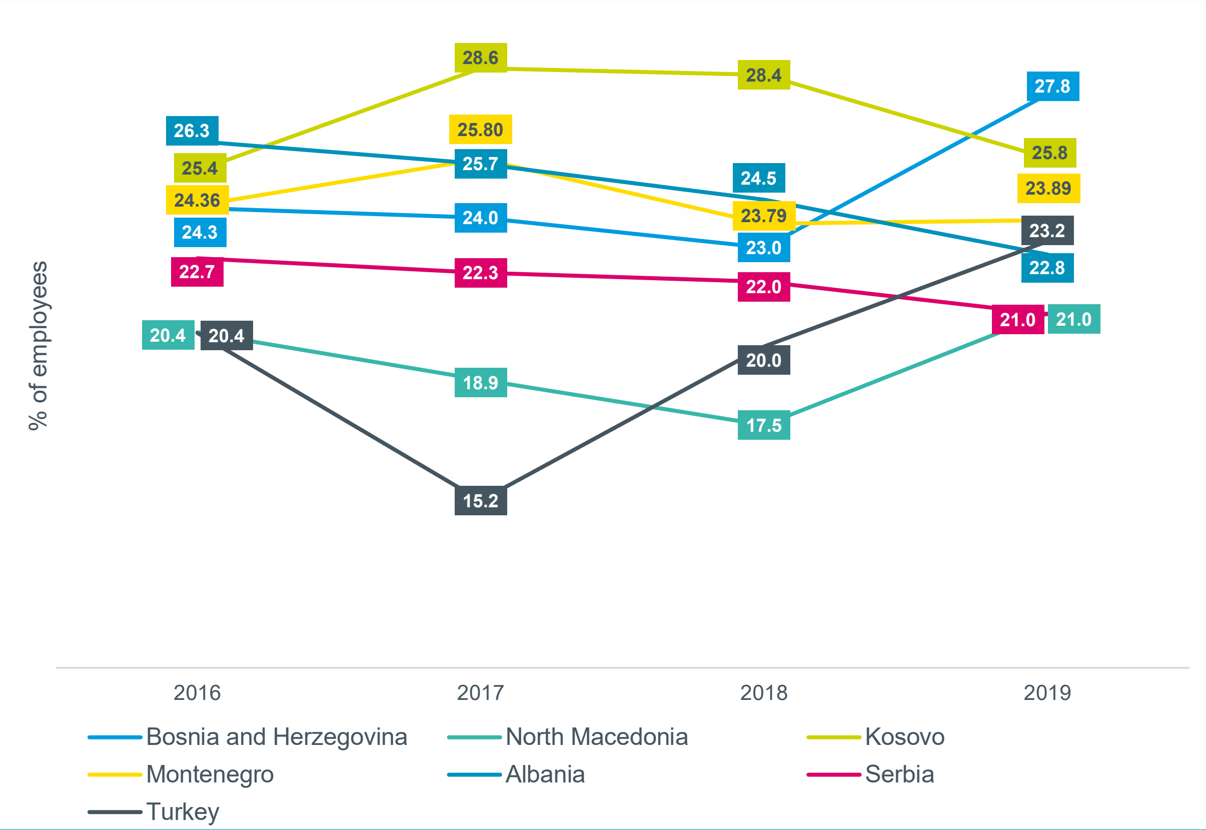
Finally, the indicators show a moderate decrease in the vertical mismatch in Albania (around 3 percentage-points), where the share of over and under-educated workers decreased over time (Figures 4.25-4.26). In Armenia, on the contrary, the share of under-educated workers slightly decreased in the period of interest while the share of over-educated workers increased (Figures 4.29-4.30).

Figure 4.25 Empirical method (over-education), see countries, 2016-2019 (%)



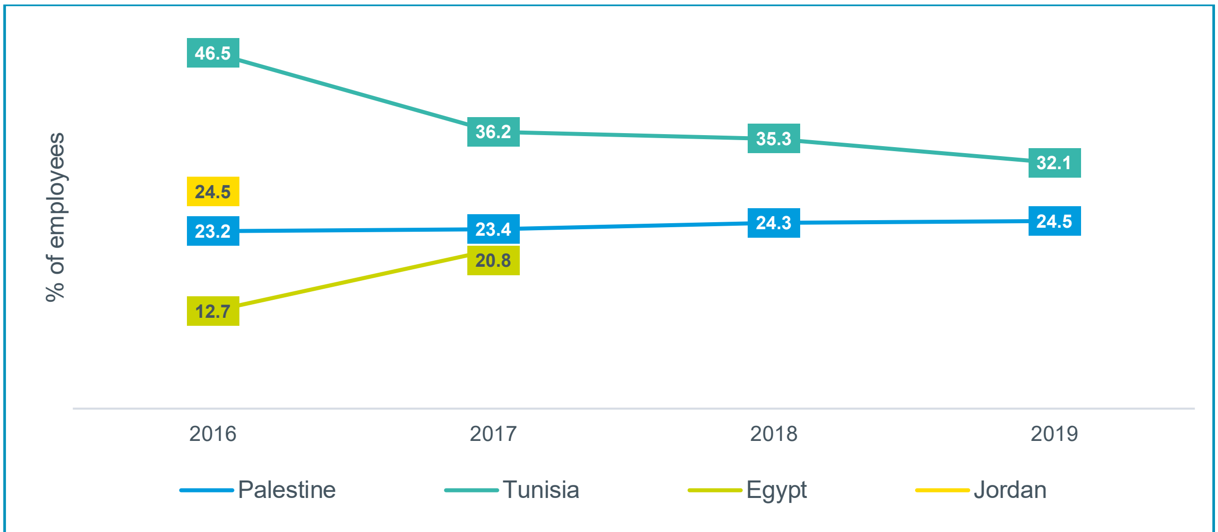
Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.26 Empirical method (under-education), see countries, 2016-2019



Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

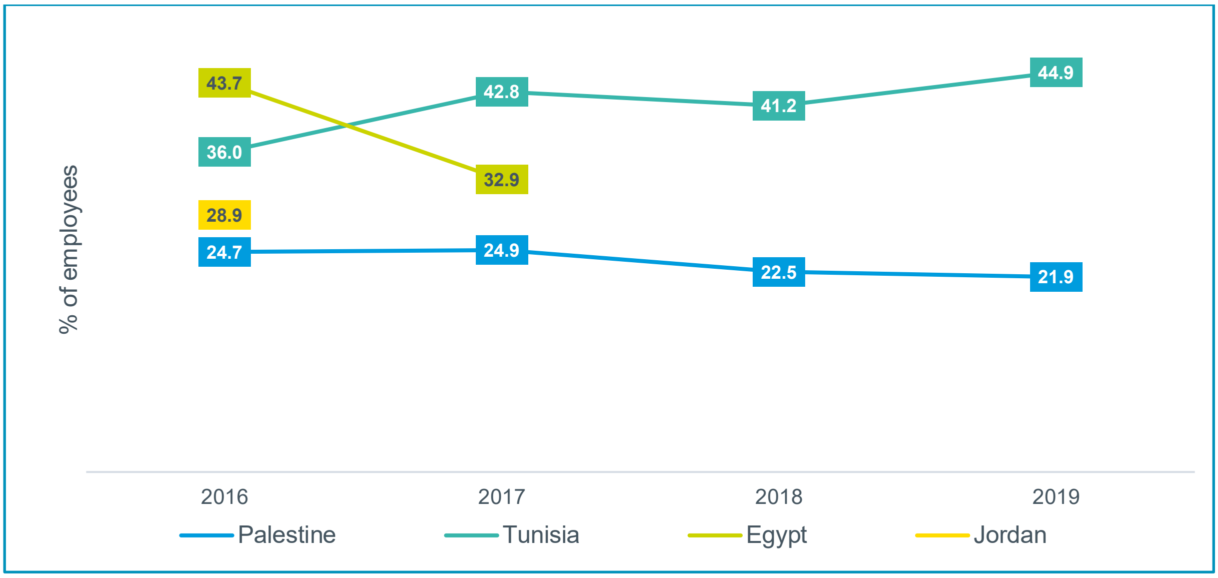
Figure 4.27 Empirical method (over-education), SEMED countries, 2016-2019[20]



Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

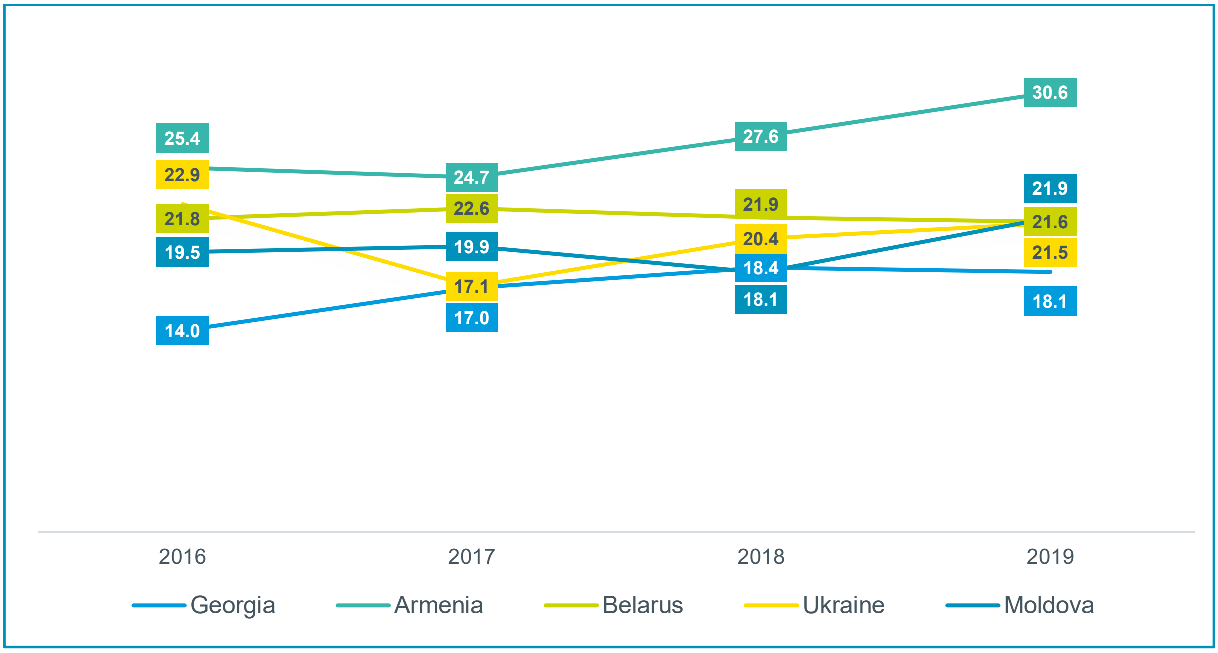
[20] The sudden drop of the indicator for Tunisia from 2016 to 2017 could be caused by a change in the survey methodology.

Figure 4.28 Empirical method (under-education), SEMED countries, 2016-2019



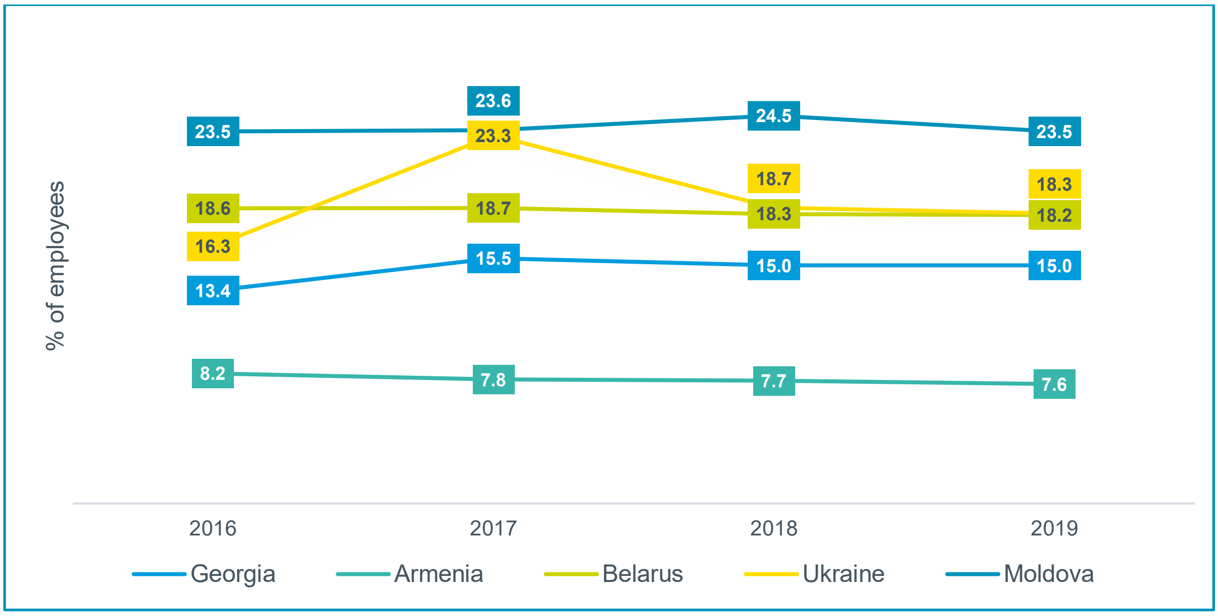
Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.29 Empirical method (over-education), EaP countries, 2016-2019 (%)



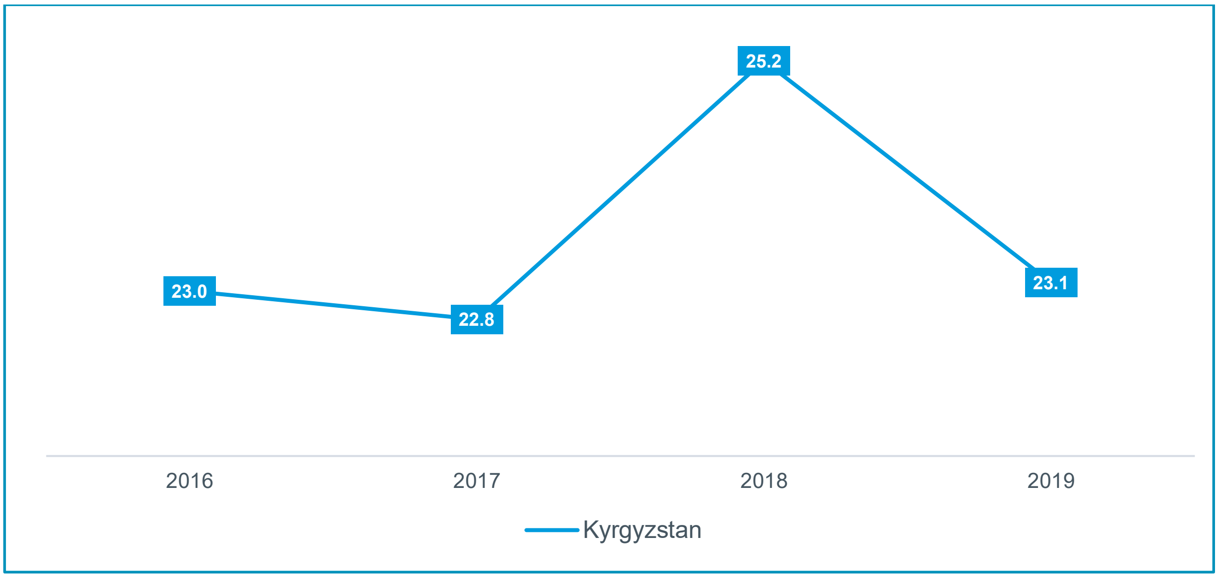
Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level. For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data were not comparable with previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.30 Empirical method (under-education), EaP countries, 2016-2019



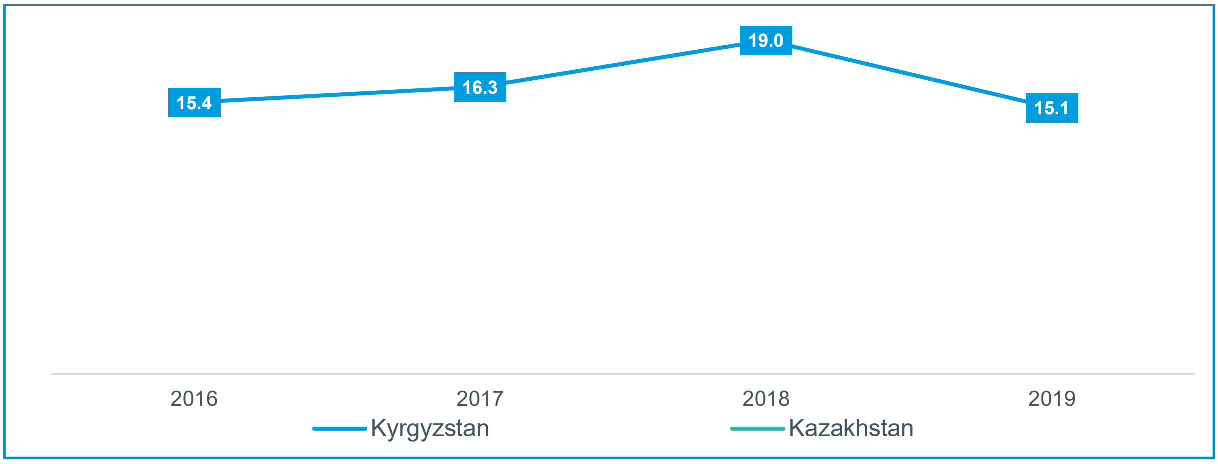
Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level. For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data were not comparable with previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.31 Empirical method (over-education), central Asian countries, 2016-2019 (%)



Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.32 Empirical method (under-education), central Asian countries, 2016-2019 (%)



Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Gender differences

In most of the selected ETF partner countries, about one in four employees was either over- or under-educated in 2019[21], with the exception of Egypt, Bosnia and Herzegovina, and North Macedonia, where the share was lower. In the same year, in some of the selected countries (Kosovo, Bosnia and Herzegovina, Ukraine and Georgia, Kyrgyzstan), men were more likely to be over-educated than women, and, in most of those countries, women were more likely to be under-educated than men (Tables 4.29-4.32). This contrasts with almost all the other countries in this study. In some countries (Kosovo, Palestine, Turkey, Albania, Turkey, and Armenia), male employees experienced higher levels of skills mismatch as they were more likely to be both more over-educated and under-educated than women. At the same time, in most countries analysed in 2019, the share of under-educated women was lower than the share of under-educated men.

Table 4.29 Empirical method (see countries) by gender, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
% of over-educated employees, 2019							
Total	18.7	13.2	27.8	18.3	18.9	28.4	34.4
Male	23.3	13.3	27.5	16.1	20.3	27.0	37.4
Female	18.2	13.3	26.0	20.7	18.5	28.1	32.6
% of under-educated employees, 2019							
Total	27.8	21.0	25.8	23.9	22.8	21.0	23.2
Male	22.2	21.6	27.2	27.2	23.4	24.4	23.1
Female	27.7	17.8	19.4	20.3	18.7	21.3	16.5

Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

[21] For Egypt the latest year available is 2017, and for Jordan it is 2016.

Table 4.30 Empirical method (SEMED countries) by gender, 2019

	Palestine	Tunisia	Egypt*	Jordan**
% of over-educated employees, 2019				
Total	24.5	32.1	20.8	24.5
Male	26.7	36.5	18.8	16.4
Female	14.3	27.8	11.2	26.1
% of under-educated employees, 2019				
Total	21.9	44.9	32.9	28.9
Male	22.5	46.2	36.8	21.4
Female	18.2	30.2	32.2	30.4

Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level. *The last year available for Egypt is 2017. **The last year available for Jordan is 2016.
Source. Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.31 Empirical method (EaP countries) by gender, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
% of over-educated employees, 2019*					
Total	21.6	18.1	21.5	30.6	21.9
Male	22.3	20.6	21.0	30.5	19.0
Female	22.4	14.3	21.6	25.7	19.9
% of under-educated employees, 2019*					
Total	18.2	15.0	18.3	7.6	23.5
Male	20.8	12.8	20.1	10.3	28.3
Female	15.9	17.6	15.6	7.4	21.6

Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.32 Empirical method (EaP countries) by gender, 2019

	Kyrgyzstan
% of over-educated employees, 2019*	
Total	23.1
Male	25.2
Female	19.6

	Kyrgyzstan
% of under-educated employees, 2019*	
Total	15.1
Male	16.0
Female	14.0

Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Age differences

There was no evident pattern in the share of over- and under-educated workers across age groups in the selected countries (Table 4.33-4.36).

Table 4.33 Empirical method* (see countries) by age group, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Montenegro	Albania	Serbia	Turkey
% of over-educated employees, 2019							
15+	18.7	13.2	27.8	18.3	18.9	28.4	34.4
15-24	13.1	6.7	32.0	18.5	13.0	17.2	37.6
25-49	20.5	16.0	29.4	23.4	18.3	29.3	25.7
50+	24.7	14.4	21.5	8.1	16.4	27.2	23.2
% of under-educated employees, 2019							
15+	27.8	21.0	25.8	23.9	22.8	21.0	23.2
15-24	18.0	11.1	22.8	21.7	25.8	21.0	12.0
25-49	26.2	15.7	22.6	22.4	17.9	22.1	28.5
50+	18.5	20.2	25.1	25.9	28.8	19.8	18.8

Notes: Employees not in education. (*) The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.34 Empirical method* (SEMED countries) by age group, 2019

	Palestine	Tunisia	Egypt*	Jordan**
% of over-educated employees, 2019				
15+	24.5	32.1	20.8	24.5
15-24	21.9	41.7	6.3	16.6
25-49	25.8	35.2	14.5	25.3
50+	24.1	16.4	32.8	21.0
% of under-educated employees, 2019				
15+	21.9	44.9	32.9	28.9
15-24	19.6	33.3	51.4	21.5
25-49	20.0	38.8	36.3	29.2
50+	30.0	42.6	13.3	21.7

Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level. *The last year available is 2017. ** The last year available is 2016.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.35 Empirical method (EaP countries) by age group, 2019

	Belarus	Georgia	Ukraine	Armenia	Moldova
% of over-educated employees, 2019					
15+	21.6	18.1	21.5	30.6	21.9
15-24	23.6	10.5	22.2	32.7	23.3
25-49	21.5	19.3	20.9	31.4	21.4
50+	24.6	12.7	22.0	31.8	17.3
% of under-educated employees, 2019					
15+	18.2	15.0	16.2	7.6	23.5
15-24	17.0	11.0	21.8	10.1	14.2
25-49	17.6	18.7	18.1	6.4	19.4
50+	18.9	8.0	16.2	4.7	21.1

Notes: Employees not in education; the threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.36 Empirical method (central Asian countries) by age group, 2019

	Kyrgyzstan
% of over-educated employees, 2019	
15+	25.9
15-24	21.7
25-49	23.2
50+	23.1

	Kyrgyzstan
% of under-educated employees, 2019	
15+	18.4
15-24	13.9
25-49	15.2
50+	15.1

Notes: Employees not in education. The threshold is the mode of education within the occupation defined according to ISCO-08 or ISCO-88 codes at the one-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.37 below summarises our findings of the level and the trends of vertical mismatch across countries between 2016 and 2019.

Table 4.37 Vertical mismatch (empirical method) between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Over/under education	*Bosnia and Herzegovina* ▪ Mixed evidence ▪ Decrease in the share of over-educated employees. ▪ Increase in the share of under-educated employees *Northern Macedonia* ▪ It worsened for some groups. ▪ The share of over-educated workers was constant over time, while the share of under-educated workers slightly increased *Kosovo* ▪ Overall stable over time ▪ Gender differences in trends for over-educated employees (decreasing share for men, increasing for women) ▪ Gender differences in both trends and levels for under-educated employees (increasing share for men, decreasing for women). In 2019, the share of under-educated male employees was almost double the share for women *Montenegro* ▪ The share of both over and under-qualified employees was stable over time. ▪ The share of under-educated employees slightly increased over time for men but decreased for women. The opposite happened for over-educated employees	*Palestine* ▪ Mixed evidence ▪ The increase in the share of over-educated employees was offset by the decrease in the share of under-educated ones ▪ In 2019, most employees in Palestine were under-educated ▪ A higher share of over-educated male employees compared to women *Tunisia* ▪ Mixed evidence ▪ The increase in the share of over-educated employees was offset by the decrease in the share of under-educated ones ▪ In 2019, most employees in Tunisia were under-educated *Egypt* ▪ The share of over-educated employees almost doubled between 2016 and 2017, while under-educated workers decreased by one-fourth.	*Belarus* ▪ Compared to other countries, Belarus had a lower share of vertically mismatched employees ▪ The share of over-educated employees was higher than the share of under-educated ones. ▪ There were almost no differences in the vertical mismatch among age groups *Georgia* ▪ Increase in the share of over-educated employees, (especially among men). ▪ Increase in the share of under-educated employees (especially among women) *Ukraine* ▪ Mixed evidence ▪ Decrease in the share of over-educated employees. ▪ Increase in the share of under-educated employees ▪ A higher share of over-educated men employees compared to women.	*Kyrgyzstan* ▪ Stable trends for both over- and under-educated employees ▪ The share of over-educated employees was higher than the share of under-educated ones ▪ In 2019, about one in four workers were over-educated

<table>
<tr><th>Indicator</th><th>SEE countries</th><th>SEMED countries</th><th>EaP</th><th>Central Asia</th></tr>
<tr><td></td><td>Albania
▪ Both over- and under-education decreased in the period of interest.
▪ Male employees tended to experience being over- and under-educated for their jobs.
▪ Senior employees (aged 50+) were more likely to be over-educated, while those aged 15-24 had the highest share of under-education
Serbia
▪ Stable and moderate rates (compared to other countries) over four years
▪ There were nearly no disparities in vertical mismatch across gender
▪ In 2019 one in three young employees in Serbia was over-educated, and one in four of them was under-educated
Turkey
▪ A high share of over-educated employees and this share marginally decreased since 2017 while the share of under-educated workers slightly increased
▪ Men were more likely to experience both over- and under-education mismatches compared to women, and this difference was stable over time
▪ Young employees between 25-49 and 15-24 years old were more likely to be employed in jobs that had lower requirements than their education qualifications</td><td>▪ The share of over-educated employees almost halved between 2016 and 2017 for women, while it was constant for men.
▪ The share of under-educated employees slightly increased over time for women but decreased for men
Jordan
▪ Trends not available
▪ In 2016, the share of under-educated employees was higher than the share of over-educated employees.
▪ The share of over-educated employees was higher among women than among men, while the opposite was true about the share of under-educated employees.</td><td>Armenia
▪ The share of over-educated employees increased both for those with medium-level education and those with tertiary education and both for men and women
▪ The gap in the share of over- and under-educated employees among the age groups and genders continued over the years
Moldova
▪ The share of both over- and under-qualified employees was quite stable over time.
▪ In 2019 the share of under-educated employees was higher than in the other EaP countries (one out of four).</td><td></td></tr>
</table>

Horizontal mismatch

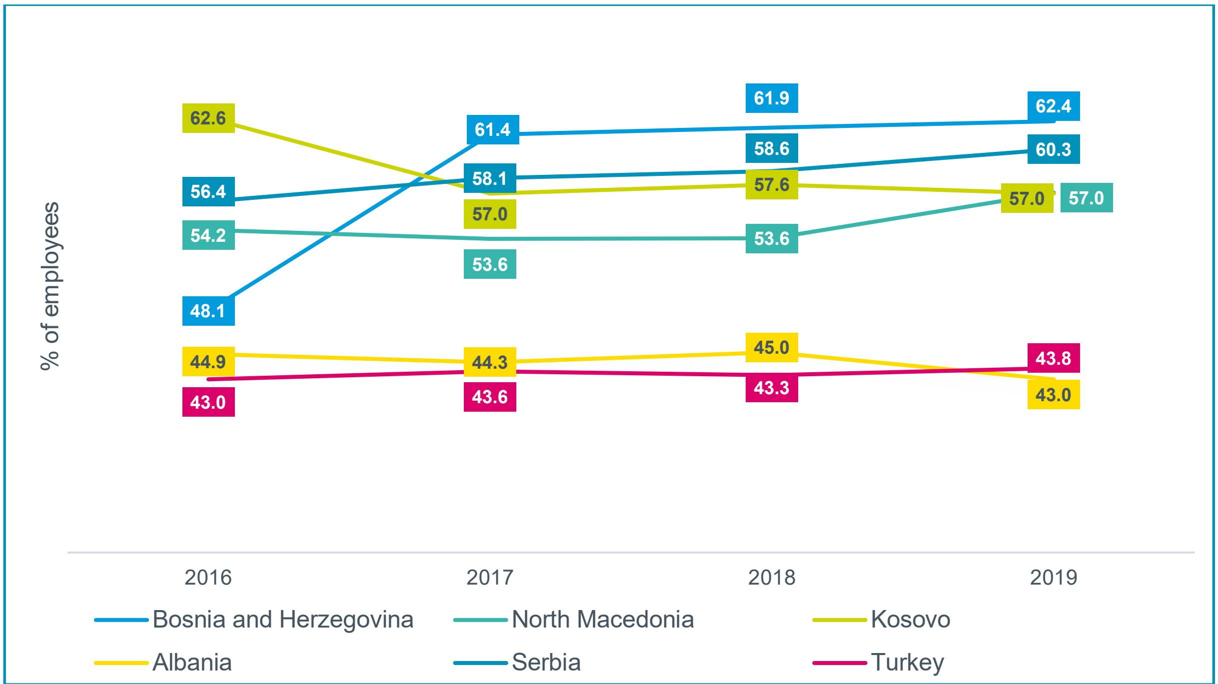
HORIZONTAL MISMATCH

The horizontal skills mismatch rate (HSMR) by field of education (FoE) is defined as the discrepancy between a person's current occupation and their field of education related to the highest level of education attainment. The basic criterion used when assigning occupational codes to a field of education is the assumed unity of skills acquired through education and those needed on the job.1 Skills mismatch by field of education is relevant for labour market analyses: 'Non-matched' persons (i) might face frustration because of the lack of a direct return to education; and (ii) may generate economic losses for businesses working at lower productivity or generate additional costs of training to acquire specific skills on the job (ETF, 2012). However, the current literature offers little evidence about the productivity costs of horizontal mismatch, unless it is accompanied by vertical mismatch.

Trends

The horizontal mismatch indicator shows that in most of the ETF partner countries where the indicator is available, the share of horizontally mismatched employees between 2016 and 2019 slightly increased (North Macedonia, Bosnia and Herzegovina, Georgia, Kyrgyzstan and Moldova). The exceptions were Egypt[22], Kosovo, Tunisia and Palestine where the share of horizontally mismatched employees slightly decreased over time, and the other countries where the share was constant over time (Figures 4.33-4.36). For Montenegro and Armenia, the indicator was not calculated as the occupation code was available only at the one-digit level (there was too much variation in the field of education by occupation to obtain reliable estimates).

Figure 4.33 Horizontal mismatch trends (15+ including only employees with higher education), see countries, 2016-2019

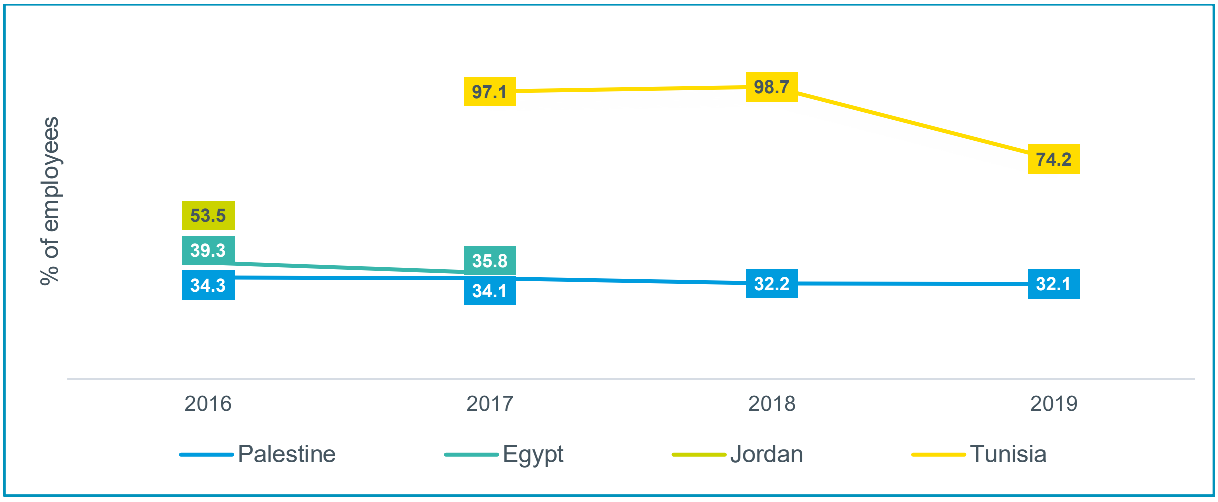


Notes: Employees not in education. The method used to match the education field to occupations is described in detail in Appendix C. In Turkey, the occupation is defined at the two-digit level, in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

[22] Trend available up to 2017.

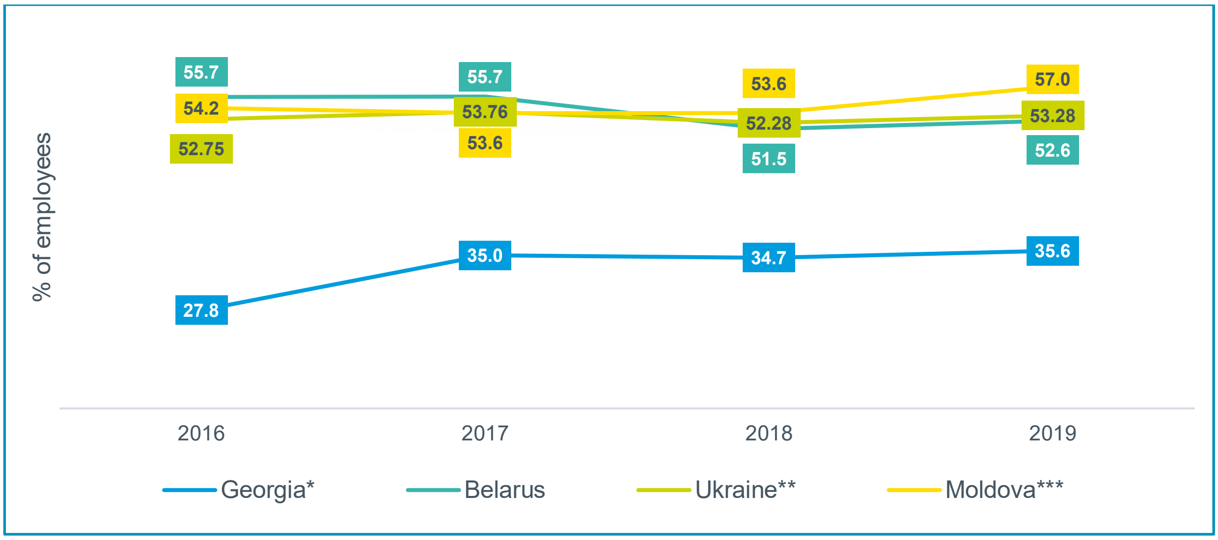
In some of the countries analysed, the trends of horizontally mismatched employees differed across groups. For example, in Bosnia and Herzegovina, horizontally mismatched employees showed an increase, especially among those with tertiary education. In North Macedonia, the share of horizontally mismatched employees slightly increased over time, except those with intermediate VET qualifications (for which it significantly decreased). In Kosovo, the share trends of horizontally mismatched employees differed across groups as the share increased for those with medium level education. At the same time, there were decreases among those with higher education.

Figure 4.34 Horizontal mismatch (15+ including only employees with higher education) trends, SEMED countries, 2016-2019



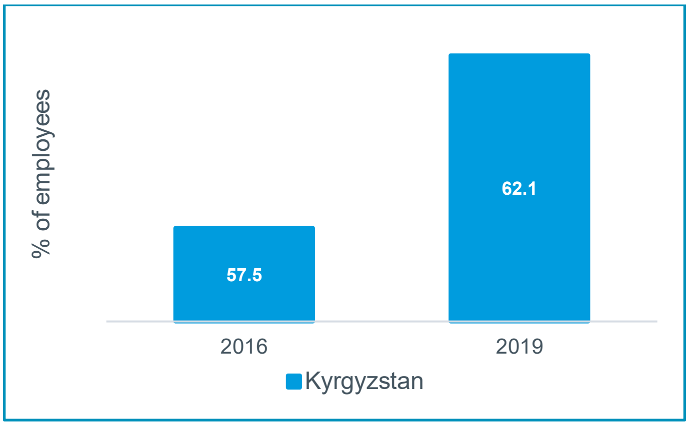
Notes: Employees not in education. The method used to match the education field to occupations is described in detail in Appendix C. The education field was not available for Tunisia in 2016. The occupation is defined at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.35 Horizontal mismatch (15+ including only employees with higher education) trends, EaP countries, 2016-2019



Notes: Employees not in education. (*) In Georgia, the indicator was calculated to match the field of education retrieved from the profession and occupation, coded according to ISCO-88 (3 digits). (**) In Ukraine, the horizontal mismatch indicator was calculated using the national classification for the field of education and occupation at the two-digit level. (***) For Moldova, there were some methodological changes in the survey in 2019 (sampling, employment definition, weights). Therefore, as of 2019, the LFS data were not comparable with previous data series.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Figure 4.36 Horizontal mismatch (15+ including only employees with higher education) trends, central Asian countries, 2019



Notes: Employees not in education: the indicator was calculated using the occupation category at the two-digit level.
Source: Authors' calculation based on national LFS.

Age differences

Table 4.37-4.40 shows no significant differences in the horizontal mismatch indicator across age groups. However, while interpreting the results, it is important to keep in mind some limitations of the analysis. According to our matching method, individuals with general education qualifications, which are not in any specific fields of education, are all mismatched. Also, the sample size of groups of employees defined by both age and education level in some countries was too low to provide meaningful data.

Table 4.38 Horizontal mismatch (see countries) by age group, 2019

	Bosnia and Herzegovina	North Macedonia	Kosovo	Albania	Serbia	Turkey
% of employees with tertiary education, 2019						
15+	62.4	57	57	43.0	60.3	43.8
20-24	62.8	62.4	58.4	41.8	61.3	45.2
25-49	62.8	59.2	57.6	42.6	60.7	44.0

Notes: Employees not in education. The method used to match the education field to occupations is described in detail in Appendix C. In Montenegro, the occupation was defined at the one-digit level (too broad, so the indicator is not reported), in Turkey it was at the two-digit level, and in the other countries it was at the three-digit level. No data available for Montenegro.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names)

Table 4.39 Horizontal mismatch (SEMED countries) by age group, 2019

	Palestine	Tunisia	Egypt*	Jordan**
% of employees with tertiary education, 2019				
15+	32.1	74.2	35.8	53.5
20-34	34.0	74.0	40.3	50.4
25-49	32.5	74.7	35.8	54.6

Notes: Employees not in education. (*) The last year available is 2017; (**) the last year available is 2016. The method used to match the education field to occupations is described in detail in Appendix C. In Palestine, the occupation was defined at the one-digit level, and in the other countries at the three-digit level.
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.40 Horizontal mismatch (EaP countries) by age group, 2019

	Belarus	Georgia	Ukraine	Moldova
% of employees with tertiary education, 2019				
15+	52.6	81.0	53.3	57.0
20-34	49.0	81.2	55.2	62.4
25-49	49.8	82.1	53.3	59.2

Notes: Employees not in education. The method used to match the education field to occupations is described in detail in Appendix C. In Armenia, the occupation category was only available at the one-digit level (too broad, so the indicator is not reported). In Ukraine, the horizontal mismatch indicator was calculated using the national classification for the field of education and the occupation at the two-digit level. In Georgia, the indicator was calculated to match profession and occupation, coded according to ISCO-88 (3 digits). No data available for Armenia. (*) Data were available for 2017
Source: Authors' calculation based on national LFSs (see Table 3.2A for survey names).

Table 4.41 Horizontal mismatch (EaP countries) by age group, 2019

	Kyrgyzstan
% of employees with tertiary education, 2019	
15+	62.1
20-34	70.1
25-49	64.1

Notes: Employees not in education.
Source: Authors' calculation based on national LFSs.

Differences across fields of education and occupations

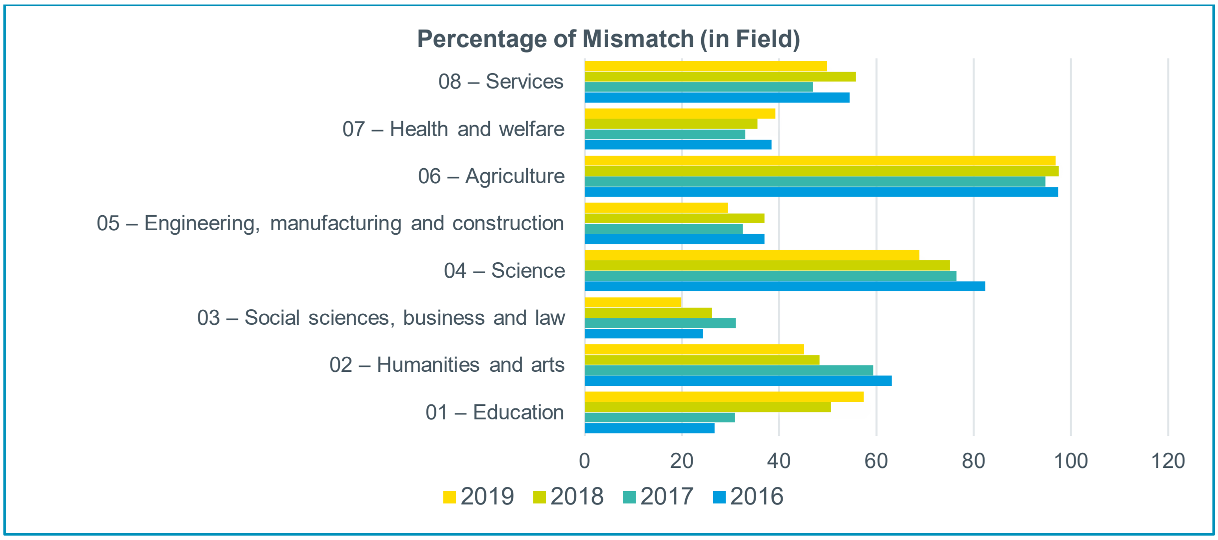
It is important to understand how the share of horizontal mismatch varies across occupations and qualifications. To understand the sources of mismatch, the share of mismatched employees is calculated across both occupations (ISCO) and fields of education (ISCED-F).

Figure 4.41-4.43 reflect the share of horizontally mismatched employees by field of education in Albania (2019), Turkey (2016-2019), and Egypt (2016), respectively. The horizontal mismatch was high in relatively narrower fields, e.g. agriculture, mathematics, and statistics. In broader education fields, such as social science and business, the share of horizontally mismatched employees was lower.

The percentage of mismatches varies significantly across education fields. For instance, in Albania 2019 (Figure 4.41), most employees who studied agriculture and science subjects worked in occupations that did not match their field of study. In addition, increasing trends in digitalization opened more job opportunities for workers who have qualifications in Information and Communication Technologies (ICT) and led to a decrease in mismatches in this field across countries. Science, mathematics, and computing, for instance, experienced a dramatic decrease in the share of horizontally mismatched employees. People who studied foreign languages in Humanities and arts (Albania) were able to find better job matchings, thus decreasing the share of horizontally mismatched employees (by approximately 20 percentage points in Albania).

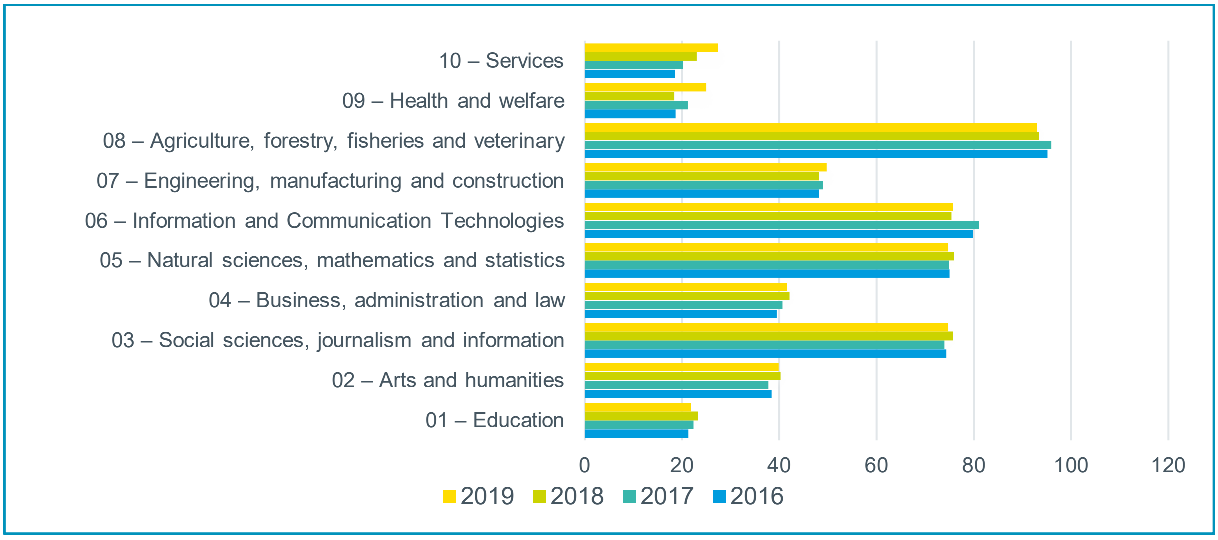
Horizontal mismatch data should be interpreted with caution as a too strict definition of occupational areas and educations fields may lead to a higher incidence of mismatch even though in practice workers may have the right skills and competences to work in an occupation that does not strictly matching a specific educational field.

Figure 4.37 Percentage of horizontal mismatch (by field of education) in Albania, 2016-2019



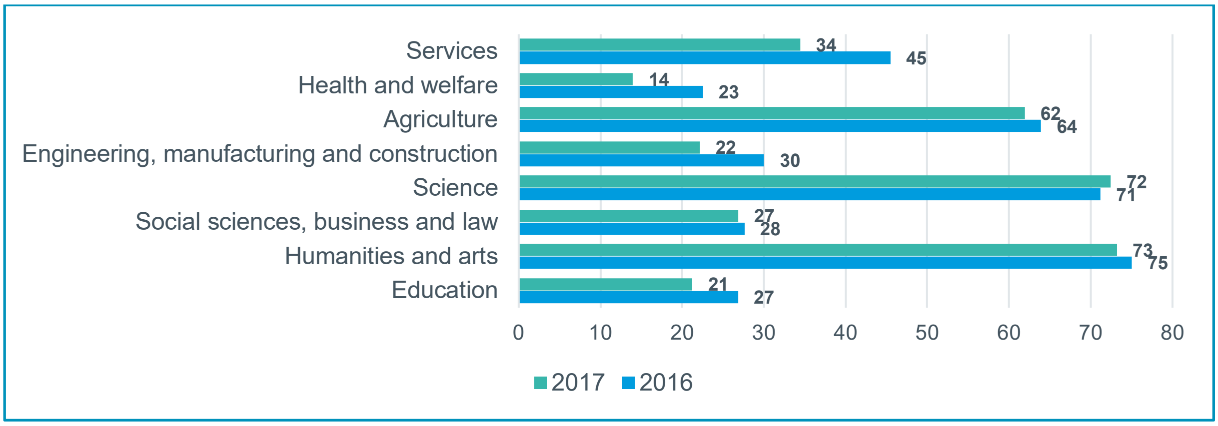
Note: The field of education field was originally coded according to the ISCED-F 2013 classification.

Figure 4.38 Percentage of horizontal mismatch (by field of education) in Turkey, 2016-2019



Note: The field of education was originally coded according to the ISCED-F 2013 classification.

Figure 4.39 Percentage of horizontal mismatch (by field of education) in Egypt, 2016



Note: The field of education was originally coded according to the ISCED-F 1997 classification.

Table 4.42: Horizontal mismatch between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Horizontal mismatch	*Bosnia and Herzegovina* ▪ It slightly increased over time. *Northern Macedonia* ▪ It slightly increased over time. *Kosovo* ▪ Overall, it slightly decreased. *Albania* ▪ Stable over time. *Serbia* ▪ The share of horizontal mismatch was stable over time. *Turkey* ▪ The share of horizontal mismatch was stable over time.	*Palestine* ▪ Stable over time. *Tunisia* ▪ High but decreasing between 2017 and 2019. *Egypt* ▪ It slightly increased over time. *Jordan* ▪ No trends available.	*Belarus* ▪ Stable over time. *Georgia* ▪ Increased. In 2019, the share of horizontally mismatched individuals was higher than in the other EaP countries. *Ukraine* ▪ The share of horizontally mismatched employees was constant over time. *Moldova* ▪ Stable over time.	*Kyrgyzstan* ▪ It slightly increased over time.

5. Conclusions and recommendations

In this study, we updated and extended to other ETF partner countries the data collection and calculation of skills mismatch indicators done by Kriechel and Vetter (2019). In the project, several different labour market and skills mismatch indicators in fifteen countries were updated. The countries included all the SEE countries (Bosnia and Herzegovina, North Macedonia, Kosovo, Montenegro, Albania) and some selected SEMED and EaP countries (such as Palestine, Egypt, Tunisia, Belarus, Armenia, Georgia, and Ukraine) in the first round, with other selected partner countries added in the second round (Serbia, Turkey, Moldova, and Kyrgyzstan). The process used to calculate the indicators was chosen to make them easy to update, whether using microdata (Georgia, Palestine, Albania, Serbia, Egypt, Armenia, and Turkey) or the remote statistical support offered by the NSOs (all the other countries).

Using the experience from the pilot countries, in Chapter 2 there is a literature review highlighting the advantages and the disadvantages of using each skills mismatch indicator and the most common indicators used. In Chapter 3 are described the challenges that were faced in the project when constructing the indicators and the limitations in comparability across countries and survey years. The set of indicators, presented in Chapter 4, was calculated when the available data were generally sufficient. Important background indicators included the unemployment rates (or ratios), the NEET rates and to a lesser degree, the coefficient of variation by skills level. We also included in the analysis two indicators measuring over-education according to both the normative and the empirical method suggested in the literature. The scientific literature suggests that over-educated workers experience a wage penalty. It also points to the general inefficiencies of such misallocations. Measuring the indicator using two different methods with different advantages and limitations allowed us to improve our interpretation of the results and their comparability. In addition, we calculated the horizontal mismatch indicator, which provides information on another dimension of skills mismatch, by looking at how the occupation matches the field of study. In this project, we used objective indicators of skills mismatch as subjective indicators which are not always available in the LFS surveys. Moreover, subjective indicators of vertical and horizontal skills mismatch are likely to be biased and not comparable across countries as they are usually collected by asking different questions in different surveys.

Key findings

The study finds strong evidence of skills mismatches, such as high unemployment rates (especially for youth), differences in unemployment by education level, high NEET rates in all countries, suggesting structural and institutional problems in the labour market and shortcomings in the educational system leading to problematic school-to-work transitions. Over-education is also a common issue in most countries analysed, where one in four employees are often over-educated, especially men. In most of the countries object of our analysis instead, women are more likely than men to be under-educated, suggesting the existence of a gender gap in access to the education system. Horizontal mismatch also seems to be high and persistent over time in all the countries. Despite the magnitude of the indicator, the data should not be interpreted too strictly due to methodological constraints (particularly in the definition of education fields and matched occupational areas) as well as specific country contexts.

Similar indicators of horizontal mismatches, such as the occupational mismatch and the indicator of over-education, pointed in similar directions and usually followed similar dynamics. A more reliable comparative review of the mismatch indicator’s reliability and outcomes can be done as soon as more countries are included.

VET-based training showed mixed success in overcoming the skills mismatch problem. In some countries, the indicators prove easier matches of VET-based workers relative to non-VET graduates. However, it should be noted in this context that the identification of VET remains problematic in the data. VET training is only provided for very specific qualifications or occupations, depending on both the fields and levels of education. The interpretation of skills mismatch should be sensitive enough to the country context, economic structures, economic outputs, demographic context, and migration.

The biggest challenges in comparing the skills mismatch indicators across countries are due to the different coding of occupations: ISCO-88, ISCO-08 or a national classification was used. The specific field of education was classified using either ISCED-F 1997, ISCED-F 1997, or a national classification. Even classifying the level of education is not straightforward. We aggregated where possible the education categories, but in some countries, it was not possible to distinguish between vocational training and upper-secondary education. This study harmonized these variables across countries to ensure the highest possible degree of cross-country comparability.

Data availability was quite homogeneous across countries. LFSs are collected in all partner countries, regularly updated, and include (in most countries) all the relevant variables for the skills mismatch indicators. The data accessibility was heterogeneous across countries. In a few cases, we had direct access to the LFS. In most cases, the NSOs provided us with data samples, codebooks, and questionnaires to prepare the scripts to calculate the indicators. The NSOs could also calculate the indicators and send us the analysis output.

In this study, we constructed and analysed the skills mismatch indicators for the population above 15 years old and according to some dimensions that allow us to provide insights on specific groups to allow for more specific policy recommendations. Next to age, which identifies the difficult school-to-work transition, education level and gender are crucial dimensions to analyse. In many countries, both labour market participation and access, especially in SEMED countries, are very different for men and women. In some countries, many youths are enrolled in VET secondary education. Breaking down the indicators according to these dimensions should help policymakers to shape better policy responses.

Additional dimensions that could be explored in future studies are the formality/informality of labour markets and urban/rural labour markets. These differences might help understand cross-country differences in the skills mismatch indicators and provide a new angle to interpreting the results. However, these dimensions are not consistently (across countries) captured in the LFS surveys, and complementary data sources would be needed to include them in another study. It would also be interesting to do some econometric analysis and look at the factors (e.g. socio-demographic, job characteristics, labour market and education policies) influencing different types of mismatches, as well as the effect of mismatches on wage levels in ETF partner countries.

Innovation practices in data management, interpretation, and selection of indicators

The project involved some novelties in communication, data-management cooperation, and knowledge sharing that would increase the chances of participation by national statistics offices, but that should also increase the knowledge sharing and sustainability of using skills mismatch indicators in the national context.

The project involved some novelties in data management and analysis introduced to alleviate the burden on the national statistics offices and increase the willingness to participate. Unlike what we did in previous projects, and as described above, in this study, we attempted to analyse the data through three main avenues:

The first option was to gain direct access to microdata from the national statistics offices. It can be a simple process (e.g. Georgia allows anonymized microdata to be downloaded). Sometimes, it involved a long administrative process (fulfilling certain standards and describing the research project and organisation, including the IT environment).

The second option was to provide scripts or programs for the statistical processing within the national statistics offices, which we refer to as assisted remote execution. This process involved the transfer of a small sample of the microdata-set (about 100 observations) along with codebooks or questionnaires for each wave of the data used. A script (in SPSS or Stata) was developed based on this sample. The NSO could then run the script with little difficulty. Depending on the set-up of the NSO's data access and the sample's representativeness, this process mostly ran smoothly, although in some cases, it called for some iterations to make improvements to the script before the output was generated successfully.

The final access option used data aggregators like Eurostat or the Economic Research Forum (ERF).

One key aim of the current project was to extend the reach toward as many ETF countries as possible by simplifying the process and reducing the potential overhead burden on the NSO involved. Both sides' explicit involvement encouraged knowledge sharing in the calculation and interpretation of the mismatch indicators. By providing the scripts for the statistical software used in the NSO, follow-up calculations and analyses in subsequent years should also be possible by the NSOs.

In addition, an exemplary analysis of the various indicators was shared with the NSOs, which provided them with the interpretation of each national outcome of the indicator. While the interpretation is indicator-based and does not provide additional qualitative or quantitative inputs from other national sources, it should help the NSO understand the process of generating the results and provide a meaningful context. It also allowed for feedback on the results of the outcomes by the NSO that should systematically flag outcomes that are not reliable or wrong because of calculation errors.

Another innovative practice regarding the selection of the indicators was that the indicators selected for our analysis were extended to include horizontal mismatch following the definitions used by Eurostat based on the work by Wolbers (2003). It required, as described before, the mapping of fields of education in relation to occupations for various countries. This approach is likely to represent only the first step towards a better and deeper analysis of horizontal mismatch, and it serves to initiate the discussion of the existence of horizontal mismatch in ETF partner countries. The partner countries provide – in many cases – the first analysis of the indicator, which facilitates national efforts to build upon our first comparative approach using both this methodology and the scripts freely at the national level.

Finally, another innovation in this project concerns the design of the indicators. In this study, the indicators were calculated separately (disaggregated) for either narrow groups of individuals or employees such as those with VET and non-VET qualifications, age groups, inactive versus unemployed (NEET rates), and employed versus all workers (CVAR).

These innovations in selecting the indicators and their design allowed us to provide more accurate analytical inputs to policy design.

Recommendations

Skills mismatch is important to consider and monitor because its incidence reflects changes in the labour market, some at a rapid pace, and it is interconnected with human capital. The literature shows that the level and profile of education, qualifications, or skills of many workers across geographical regions and countries do not match their jobs. It is likely to cause labour shortages and affect businesses negatively, as well as the career prospects of the young and adult workforce. Understanding skills mismatches is an important topic for the ETF Partner Countries and the Member States of the European Union (EU). It also links to EU priorities to enhance the relevance of education and training and provide further learning opportunities, 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 the supply and demand and to assess the effectiveness of their level of skills and employment policies.

Datasets development and usage

One of the key challenges of this project was having access to LFSs microdata, which are the most available, reliable, and updated labour market data across the ETF countries. In most cases, not having access to the microdata and working remotely with the NSOs took longer than if we had direct access to them and was sometimes subject to a long bureaucratic process. Developing national analytical capacity is crucial. Access to microdata for researchers, ministries, and similar institutions is an important prerequisite to fully developing and using the information that exists in the microdata.

Working closely with the NSOs and involving them in constructing the skills mismatch indicators is beneficial to exchange feedback on harmonising the variables across countries and directly contribute to capacity building in the ETF partner countries. In addition, receiving short feedback in the comment on the skills mismatch indicators from the NSOs would provide us with the valuable points of view of country experts who are best qualified to understand the data underlying the analysis.

Countries should consider strengthening their data collection in several ways. In particular, the sample size in small countries remains small, often too small to allow analysis along several dimensions. In small countries, it could be useful to increase the sampling. Some countries had few observations on key groups, e.g. unemployed or young people, especially when splitting these up into other dimensions (education, age, gender). A scoping exercise with detailed information on the cell sizes of key dimensions helps to optimally determine age groups, for example, to include as many observations as possible.

Cross-country comparisons still prove difficult within a particular education level and across occupations. National education systems do not always easily correspond to the international ISCED standards. The national classifications of occupations do not always easily correspond to the ISCO classification and fields of education in the ISCED-F classification, which represents challenges for cross-country and cross-survey wave comparability. While countries have already taken measures to harmonise their statistical products with international standards and to update them, in certain cases, labour force surveys still need to be properly synchronised with the new standards in the ISCED and ISCO classifications.

Given that VET and non-VET disaggregation were found to be impractical or unavailable in many cases, we recommend better coverage of VET programmes in labour force and skills surveys. Current data are not always fully capable of demonstrating the effect of VET on students and graduates, such as their labour market outcomes.

In a nutshell, countries could consider improving their statistics in relation to skills measurement as follows:

- Standardise the education field's classification to the latest ISCED-F (ISCED-F 2013) for all education levels.
- Use the occupation codes at the 3-digit level (ISCO classification).
- Where possible, keep the education classification consistent over time.
- Specify which level of education is VET/higher education.
- Improve survey design of the LFS and explore consistent utilisation of other data sources, such as skills surveys, tracer studies, administrative data sources (registers), and online vacancy datasets.

Policy implications of skills mismatches

Joblessness remains a key challenge in all countries analysed in this report. The impact of the Covid-19 pandemic, digital and green transition, as well as global challenges related to energy, food insecurity and armed conflicts, will most likely worsen the employment and wellbeing of young people and adults and impede the improved performance of education and training systems.

Even if this analysis captures labour market and skills trends in the pre-Covid period, it shows that unemployment and inactivity incidence run high, affecting in particular women, young people, and people with lower levels of education (although, strikingly, several countries are confronted with increased rates of joblessness among people with tertiary education attainments).

The study results show that, in 2019, at least one in four tertiary graduates held jobs requiring lower formal qualifications in most countries. The evidence also shows that the incidence of the skills mismatch for upper/post-secondary graduates is lower than that of tertiary graduates. Young tertiary graduates had a higher incidence of over-skilling in all countries with data available, confirming the finding that being highly skilled has not always led to better employment prospects, and in some countries, holding a university degree does not always mean being employed and/or job-matched (ETF, 2020).

This shows that education systems face many challenges in responding to changing skill demands. It may also suggest that many higher-skilled graduates have to accept positions below their level of formal qualifications. High unemployment levels and limited opportunities in the labour market are forcing especially more highly-educated individuals to accept such positions.

The labour and social contexts of selected countries, in particular the informality and migration impact on skills demand and supply, also proved to be a limiting factor. In labour markets with a significant proportion of informal workplaces, some indicators (e.g. those proxying skills using the qualification level) were less meaningful as on-the-job training and apprenticeships usually provide the necessary skills. Additionally, migration may lead to an underestimation of mismatch magnitude and characteristics. Generally, an interpretation of the skills mismatch results should be sensitive enough to the country context, the economy's structure and its outputs, as well as the demographic context and migration factors.

All these call for consolidated skills development and matching policies which cover large proportions of the young and adult population and are responsive to learners' and companies' needs. A system capable of continuously updating skills-sets, with well-funded and relevant (re)skilling programmes accessible to all youth and adults, becomes crucial in a dynamic economic context with significant technological and environmental transformations (ETF, 2021b).

The relatively high incidence of over-qualified tertiary graduates in most countries included in this analysis indicates that graduation does not necessarily always lead to a matched integration in the labour market and could signal a human capital loss. There could be many reasons to explain this, and further country-specific studies are necessary to identify the determinants of such imbalances and the most effective solutions to prevent them. What emerges clearly is that education systems are in part generating such imbalances. This could be through insufficiently forward-looking enrolment policies, the poor quality and relevance of educational programmes, or failures in addressing social inclusiveness goals. Career guidance and career education from early schooling onwards, effective matching services and work-experience programmes during the transition phase from school to work are also essential (ETF, 2021c).

Youth transition is seen to be increasingly linked to the existence of various imbalances in the labour market. During their transition from school to the labour market, young people often gain practical experience by accepting jobs requiring lower levels of skills. Together with low labour mobility, this leads to a higher level of observed overqualification. Young people face more challenges than adults in entering the labour market, owing to their lack of work experience and the mismatch between the skills they offer and those required by employers (ETF, 2021b).

When planning national education provision, countries could particularly focus on the school-to-work transition. They should develop policies that focus more on outcomes for VET education vs general education at the upper secondary level and the real work outcomes for more highly educated graduates. Efforts must be made to tackle both NEETs and gender gaps.

Therefore, in terms of policy implications and actions to address the high mismatch incidence, the ETF underlines the need to improve labour market matches for youth and adult workers through more effective enrolment education policies, (re)skilling programmes, as well as efforts to diversify employment opportunities and economic policies to enable technological progress and value-added activities.

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Appendix A: Additional results

Variance of relative unemployment rates

VARIANCE OF RELATIVE UNEMPLOYMENT RATES (BY EDUCATION)

This indicator shows how unemployment deviates within education levels from the average of the entire country. The higher the value of the variance, the higher the level of mismatches. While education levels are generally used as our indicator, the methodology would also apply to sub-groups such as age, age and gender, and (previous) occupation (ETF, 2012).

Table A1: Variance of relative unemployment rates between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Variance of relative (un)employment rates (optional)	*Bosnia and Herzegovina* ▪ The variance of relative employment rates significantly reduced overtime while that of unemployment rates remained stable ▪ Within the country, the variance of relative (un)employment rates among three age groups was the highest, followed by those among education levels and between genders *Northern Macedonia* ▪ Suggests a slight improvement in labour market matches across education levels. ▪ Within the country, the variance of relative unemployment rates among three age groups was the highest, followed by those among education levels and between genders	*Palestine* ▪ The indicator suggests a slight improvement of labour market matches across education levels ▪ The variance of employment and unemployment rates fluctuated between 2016 and 2019 *Tunisia* ▪ The variance of relative unemployment rates between education levels and gender increased over time, while the variance	*Belarus* ▪ The variance of relative unemployment rates decreased slightly, suggesting an improvement in skills matching. *Georgia* ▪ Improved. It decreased over time, especially between men and women *Ukraine* ▪ Suggested a slight improvement in labour market matches across	*Kyrgyzstan* ▪ The variance of relative unemployment rates was stable over time, but it slightly increased between gender, and it significantly increased between age groups

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	Kosovo ▪ Stable over time across education levels ▪ Decreasing across gender ▪ Increasing across age groups *Montenegro* ▪ Slightly decreasing between age groups and education levels *Albania* ▪ Low and reduced gradually from 2016 to 2019 *Serbia* ▪ Variance of relative employment rates gradually increased while one of the unemployment rates significantly reduced ▪ In 2019, the magnitude of the variance among age groups was relatively higher than between genders or among education levels *Turkey* ▪ Low variance of relative employment rates and gradually reduced between 2016 and 2019. In addition, the aggregate for variance of employment was highest between gender, followed by among age groups and education levels ▪ There was a low and stable variance of relative unemployment rates (except between age groups which significantly increased in 2019) ▪ Over time, the variance of relative employment rate between males and females decreased while the variance of unemployment rates between males and females slightly increased	between age groups decreased *Egypt* ▪ The variance of relative unemployment rates between 2016 and 2017 decreased over time, across age groups, while it increased across education levels *Jordan* ▪ The variance of relative unemployment rates was higher between education levels than between age groups or gender	both education levels, gender and age groups *Armenia* ▪ The variance of relative unemployment rates across education levels decreased over time. The variance of relative unemployment rates across age groups increased, while between men and women it remained stable between 2016 -2019. *Moldova* ▪ It was stable over time. In 2019 the variance of relative unemployment rates was slightly higher between age groups than between education levels or gender	

Coefficient of variation by the level of education

COEFFICIENT OF VARIATION BY LEVEL OF EDUCATION

The indicator compares the distribution of skills within different groups while correcting for the overall size of the underlying statistic. The difference in the skill composition of employed and unemployed is expressed in one number, which measures the overall extent of mismatch. The higher the number, the greater the difference between the skills possessed by people employed in the labour market and those who wish to enter the labour market. Therefore, the extent to which the distributions are different can be interpreted as a measure of the ineffectiveness caused by the matching process of supply and demand of skills in the labour market (ETF, 2012).

Table A2: Coefficient of variation by level of education between 2016 and 2019

Indicator	SEE countries	SEMED countries	EaP	Central Asia
Coefficient of Variation (CVAR) (optional)	*Bosnia and Herzegovina* ▪ Stable *Northern Macedonia* ▪ Decreased over time, also suggesting an improvement in labour market matches across education levels *Kosovo* ▪ CVAR between employed and population slightly increased from 45,2% in 2016 to 50,6% in 2019 *Montenegro* ▪ Slightly decreased over time, especially for 15-24 year old group ▪ A significant high share of CVAR among women compared to men	*Palestine* ▪ Slightly reduced (both CVAR employed vs unemployed and CAVR employed vs population) *Tunisia* ▪ The CVAR (employment vs unemployment) slightly decreased over time *Egypt* ▪ It was stable between 2016 and 2017 *Jordan* ▪ No trends available ▪ In 2016, higher for men than for women and for	*Belarus* ▪ It slightly increased ▪ CVAR (employed vs population) was highest among the youth between 15-24 years old *Georgia* ▪ It slightly improved for the youngest age group (15-24 years old) *Ukraine* ▪ It slightly decreased over time, especially for men *Armenia* ▪ Was stable over time	*Kyrgyzstan* ▪ It was stable over time and slightly increased only among 15-24 years old

Indicator	SEE countries	SEMED countries	EaP	Central Asia
	Albania ▪ CVAR (employed vs population) was around 10% and decreased slightly over time *Serbia* ▪ In 2019, it was significantly higher for women than men and considerably higher for the younger age group (15-24 years old) *Turkey* ▪ The CVAR between employed and unemployed shows an improvement over time while the CVAR between employed and the whole population remained stable ▪ The CVAR (employed/population) among male workers was significantly lower than among female workers, and higher for employed youth aged 25-49 years old	those 15-24 years old and above 50	*Moldova* ▪ It increased over time, especially for women	

Appendix B: Education classification

Table B1: Georgia (LFS survey, 2016/2017-2019)

Aggregated level*	Level of educational attainment (2017-2019)	Level of educational attainment (2016)
Low	Illiterate	Illiterate
	Has no education but can read and write	Does not have primary education but can read and write
	Pre-primary education	Primary education
	Basic general education (lower secondary)	Lower education
Medium - General (Internediate - non VET)	Secondary general education (upper secondary)	Upper secondary education
Medium - VET (Internediate - VET)	Vocational education without secondary general education	Vocational programme
	Vocational education on the base of lower secondary education with secondary general education certificate	Secondary professional program
	Vocational education on the base of secondary general education (except higher professional education)	
High	Higher professional education or equivalent	Higher professional education or equivalent
	Bachelor or equivalent	Bachelor or equivalent
	Master or equivalent	Master or equivalent
	Doctor or equivalent	Doctor or equivalent

Table B2: Palestine (HLFS Palestine, 2016/2017-2019)

Aggregated level (2016)	Country Palestine (national classification 2016)	Country Palestine (national classification 2017-2019)	ISCED-97 level
Low	Illiterate	Illiterate	
	Read and write	Can read and write	0, 1
	Primary	Elementary	
	Preparatory	Preparatory	
Intermediate	Secondary	Secondary	2, 3

Aggregated level (2016)	Country Palestine (national classification 2016)	Country Palestine (national classification 2017-2019)	ISCED-97 level
High	Post-secondary or equivalent	Associate diploma	
	High diploma	Higher diploma	4
	University	BA/BSc	5, 6
	Masters	Master's degree	
	PhD	PhD	

Table B3: Kosovo (LFS survey, 2016-2019)

Aggregated level	Country	ISCED-97 level
	Kosovo (national classification)	
Low	*1 – No school *2 – (Primary) Elementary education (classes I-IV or I-V)	0, 1
Intermediate – non-VET	* 3 – 8/9-years school (classes V-VIII or V-IX)	
	* 6 – Upper Secondary – general (gymnasium)	
	* 7 – High – school	2, 3
Intermediate – VET	* 4 – Upper secondary - vocational 2-3 years * 5 – Upper secondary - vocational 4-5 years	4
High	* 8 – Tertiary / University	
	* 9 – Post university / Master	5, 6
	* 10 – Doctorate	

Table B4: Bosnia and Herzegovina (LFS survey, 2016/2017-2019)

Aggregated level	Bosnia and Herzegovina (national classification) 2016	Bosnia and Herzegovina (national classification) 2017-2019
Low	No education	No education
	1 to 4/5 grades of elementary school,	1 to 3 grades of eight-year program elementary school
	5/6 to 7/8 grades of elementary school	1 to 4 grades of nine-year program elementary school
	Completed elementary school (ISCED 2)	4 to 7 grades of eight-year program elementary school
		5 to 8 grades of nine-year program elementary school
		Completed elementary school (ISCED 2)
Intermediate – non-VET	Completed secondary school-Four - five years (Only: Field of education = General education programme)	Completed secondary school-duration 4 years and more (Only: Field of education = General education programme)
Intermediate –VET	Completed secondary school -One year	Completed secondary school: duration from 1 or 2 years
	Completed secondary school -Two year	Completed secondary school-duration 3 years
	Completed secondary school-Three year	Completed secondary school-duration 4 years and more (Excluding field of education General education programme)
	Completed secondary school-Four - five year (Excluding field of education General education programme)	10 - Specialization after secondary school (ISCED 4)
	Specialization after secondary school (ISCED = 4)	
High	Completed high school (ISCED 5)	Completed high school or first stage of college (ISCED 5)
	University education - Bachelor	University education - duration 4-4,5 years, study of I cycle
	University education (old programme 4-4.5 years),	University education - duration 5-6 years, specialist and master's studies, integrated I and II cycles and II cycle studies
	University education (old programme 5-6 years),	PhD studies or studies of the III cycle
	Postgraduate studies (M.A., master),	
	Doctorate	

Table B5: North Macedonia (LFS survey, 2016-2019)

Aggregated level	Country North Macedonia (national classification)
Low	Without education
	1-5 grades of primary education
	6-8 grades of primary education
	Primary
Intermediate – non-VET	2 years of secondary education
	3 years of secondary education
	4 years of secondary education
Intermediate – VET	Higher vocational education Post-secondary non-tertiary education
High	Tertiary education, faculty, academy
	Master´s degree
	Doctorate

Table B6: Belarus (LFS survey, 2016-2019)

Aggregated level	Country Belarus (national classification)
Low	No education
	Primary
	Basic
Intermediate – VET	Medium (technical)
High	Higher

Table B7: Ukraine (LFS Survey, 2016-2019)

Aggregated level	Country Ukraine (national classification)
Low	Basic secondary
	Primary education or no education
Intermediate – non-VET	Complete secondary

Aggregated level	Country Ukraine (national classification)
Intermediate – VET	Vocational
	Complete Higher
High	Basic higher
	Incomplete higher

Table B8: Montenegro (LFS survey, 2016-2019)

Aggregated level	Country
	Montenegro (national classification)
Low	0 No formal education
	1 Less than 6 years of primary school
	2 At least 6 years of school, but not completed primary education
	3 Primary education
Intermediate – non-VET	6 Secondary general
Intermediate – VET	4 Vocational school after basic school lasting 2 years
	5 Vocational school after basic school lasting 3 years
	7 Secondary vocational school
	8 After basic educ., completed voc. or other lasting 2 or more (post-secondary non-tertiary education)
High	9 First level of professional tertiary education (2 years)
	10 Faculty, academy/university
	11 Master's degree
	12 Doctor's degree
	13 Academic higher education (3 years)
	14 Academic higher education (4 years)
	15 Academic higher education (5-6 years)
	16 Undergraduate studies at the applied degree programs
	17 Postgraduate specialist studies
	18 Master studies
	19 Doctoral studies

Table B9: Armenia (LFS survey, 2016/2017-2018/2019)

Aggregated level	Armenia (national classification) 2016/2017	Armenia (national classification) 2018-2019
Low	Illiterate	No primary
	No primary	Primary
	Primary	Basic
	Basic	Secondary/high school
	Secondary	
Intermediate – non-VET	Secondary specialized	Secondary specialized
Intermediate –VET	Vocational	Vocational
High	Tertiary	Bachelor´s degree
	Post-graduate	Master´s degree
		Certified specialist
		Post-graduate (PhD)

Table B10: Egypt (LFS survey, 2016/2017)

Aggregated level	Country
	Egypt (national classification)
Low	None
	Illiterate
	Read only
	Read and write
	Literacy
	Never attended school
	Primary
	Preparatory
Intermediate – non-VET	Academic secondary
	Post-secondary or equivalent
Intermediate – VET	Professional/Vocational
High	University
	Post-graduate

Table B11: Jordan (LFS survey, 2016)

Aggregated level	Country
	Jordan (national classification)
Low	Illiterate
	Read and write
	Primary
	Preparatory
	Lower secondary
Intermediate – non-VET	Academic secondary
	Post-secondary or equivalent
Intermediate – VET	Professional/vocational
	University
High	High diploma
	Masters
	PhD

Table B12: Tunisia (LFS survey, 2016-2019)

Aggregated level	Country
	Tunisia (national classification)
Low	Koutteb
	Course d`Alphab
	De Base (up to 9 years)
	Primaire
	Neant
Intermediate	Secondaire (up to 4 years)
	Secondaire Ancien regime (up to 7 years)
	Professionnel (up to 9 years)
High	Superieur (up to 9 years)

Table B13: Serbia (LFS survey, 2016-2019)

Aggregated level	Country Serbia (national classification)
Low	Without education
	1-3 grades of primary education
	4-7 grades of primary education
	Primary education (eight years)
Intermediate – non-VET	Grammar school
Intermediate – VET	Lower secondary education lasting 1-2 years
	Lower secondary education lasting 3 years
	Upper secondary education lasting 4 years
	Specialisation after secondary education, school for highly qualified workers
	High education, first level of faculty (old programme)
High	Faculty, academy, undergraduate academic studies, high applied education school, specialised academic studies
	Master academic studies, integrated studies (medicine, pharmacy, stomatology and veterinary science)
	Doctoral academic studies

Table B14: Albania (LFS survey, 2016-2019)

Aggregated level	Country Albania (national classification, LFS 2016/2017)	Country Albania (national classification, LFS 2018/2019)
Low	No school	No school
	Primary	Preschool
		Primary (4-5 years)
Intermediate – non-VET	8/9-years school (classes V-IX)	Lower secondary (classes VI-IX of 7/8/9 years school)
	Upper Secondary - general	Upper secondary general
		Upper secondary socio-cultural (3 years, as artistic or foreign languages)

Aggregated level	Country Albania (national classification, LFS 2016/2017)	Country Albania (national classification, LFS 2018/2019)
Intermediate –VET		Upper secondary vocational, 2+1 years
	Upper secondary - technical 2-3 years	Upper secondary vocational, 2+1+1 years
	Upper secondary - vocational 4-5 years	Upper secondary vocational, 2+2 years
		Upper secondary vocational, 4 years
		Upper secondary technical, 2 years
		Post-secondary not tertiary (2 years)
High	University, first stage - Bachelor	Bachelor
	University second stage - First Master Level	Master or equivalent (here is classified also university old system)
	University old system	Doctorate
	Post university Second Master Level	
	Doctorate	

Table B15: Turkey (HLFS survey, 2016-2019)

Aggregated level	Country
	Turkey (national classification, LFS 2016/2019)
Low	Literate but not completed any educational institution
	Primary school (5 year)
	Lower secondary, Vocational, and technical secondary school or Primary education
Intermediate – non-VET	Upper secondary school (High school)
Intermediate –VET	Vocational and technical high school
High	2- or 3-years of higher education or faculty or 4 years higher education or faculty
	Master's degree (5- or 6-years faculty included) or Doctorate

Table B16: Kyrgyzstan (LFS survey, 2016-2019)

Aggregated level	Country
	Kyrgyzstan (national classification)
	Cannot read
Low	No primary education
	Primary general education
	Basic secondary
Intermediate – non-VET	Full (completed) secondary
Intermediate – VET	Basic professional (w/o secondary) Basic professional (with secondary education)
	Intermediate professional
High	Incomplete higher
	Higher

Table B17: Moldova (LFS survey, 2016-2019)

Aggregated level	Country
	Moldova (national classification)
	No education
Low	Primary education
	Gymnasium education
Intermediate – non VET	High education, secondary general
Intermediate – VET	Secondary vocational education
	Secondary professional education
High	Higher education
	Master's degrees
	Doctoral studies

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

Table C1: Field of education ISCED-F 2013

ISCED-F 1997	ISCED-F 2013
0-General programs	00 – Generic programmes and 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 (NA). International Standard Classification of Education (ISCED).

Table C2: Summary of horizontal mismatch matching method

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

Country	Matching method
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*
Turkey	ISCO 08 2-ISCED F 13*

Source: Authors' own compilation; (*)the national education classification was converted to ISCED-F.

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

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

Source: Authors' own compilation

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

ISCED-F 1997	ISCO-08
1 – Education	231; 232; 234; 234; 234; 235; 235; 235; 235; 315; 342; 343; 516;
2 – Humanities and arts	216; 232; 233; 243; 262; 263; 264; 265; 341; 342; 343; 522; 524;
3 – Social sciences, business and law	111; 112; 121; 121; 121; 122; 122; 131; 132; 132; 132; 133; 133; 133; 134; 134; 141; 141; 142; 142; 143; 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 compilation

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

ISCED-F 2013	ISCO-08
01_Education	23; 34, 53
02_Arts and humanities	23; 26; 34; 52;
03_Social sciences, journalism and information	23; 26; 33; 34;
04_Business, administration and law	11; 12; 13; 14; 24; 33; 35; 41; 42;
05_Natural sciences, mathematics and statistics	13; 21; 23; 31; 33; 75; 81;
06_Information and Communication Technologies (ICTs)	13; 25; 35;
07_Engineering, manufacturing and construction	21; 31; 72; 71; 74; 75; 73; 81; 82; 83
08_Agriculture, forestry, fisheries and veterinary	22; 32; 61; 62; 92;

ISCED-F 2013	ISCO-08
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 compilation

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

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

Source: Authors' own compilation

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

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

Source: Authors' own compilation

Table C8: 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

ISCO 88 3-Digit (used by Wolbers 2013)	ISCO 08 3-Digit
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

ISCO 88 3-Digit (used by Wolbers 2013)	ISCO 08 3-Digit
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

ISCO 88 3-Digit (used by Wolbers 2013)	ISCO 08 3-Digit
814	313; 817
815	313; 813
816	313; 818
817	312; 313
821	312; 722; 811
822	312; 812; 813
823	312; 814
824	312; 752
825	312; 732; 814
826	312; 815
827	312; 816
828	312; 821
829	312; 818; 821
831	831; 831
832	832; 833
833	834
834	835
911	521; 524; 952
912	951
913	911; 912; 941
914	515; 912
915	541; 962
916	961; 962
921	921
931	931
932	932; 961
933	933

Sources: Authors' compilation based on ILO (2012)
(*): Only available in Wolbers (2013), not available for ILO ISCO-88 3 digits, to represent general occupations

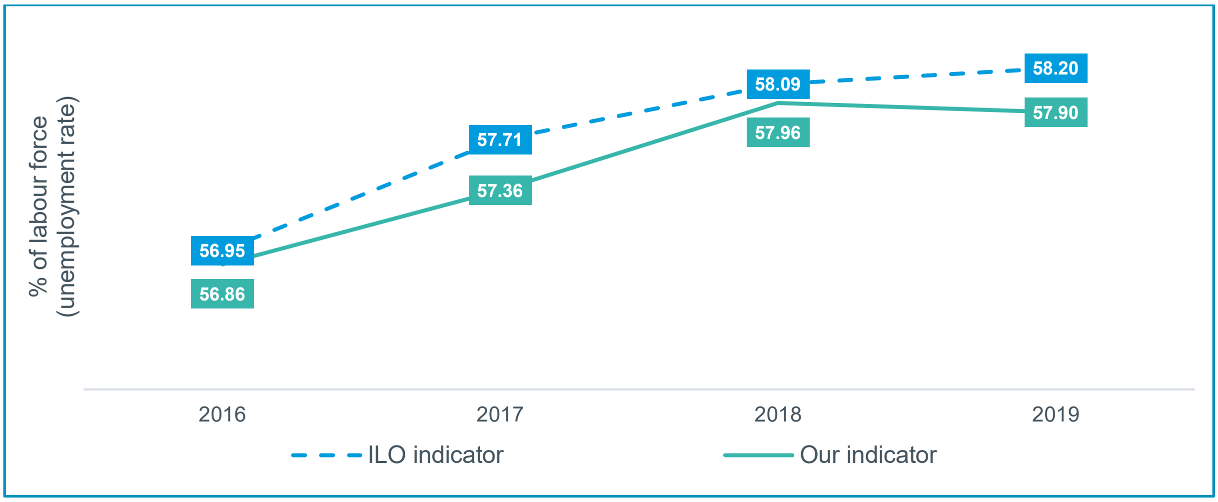
Appendix D: Comparison with ILO indicators

The figures below provide skills mismatch indicators taken from the ILO database. These can be compared to those calculated for the same countries (Bosnia and Herzegovina, and Palestine). The method used to calculate the indicators is similar yet not always identical. Still, these measures represent a good external comparison for our analysis and show high correlations with our indicators presented in Section 4. It also allows us to understand what alternate data-source could provide for countries unable to calculate the indicator on their microdata within the project (e.g., Albania).

Unemployment and inactivity rates

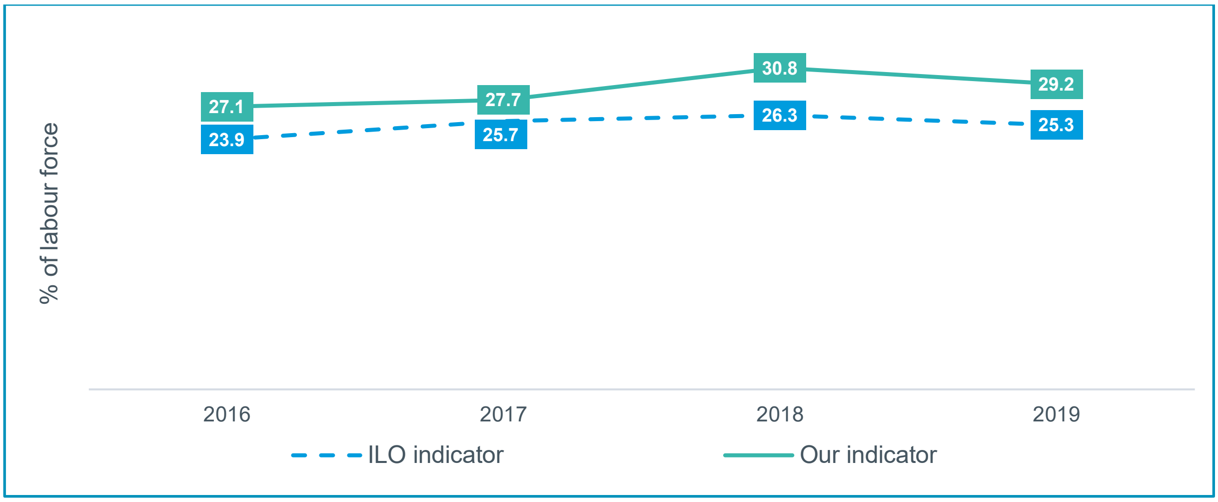
In Bosnia and Herzegovina and North Macedonia, the unemployment rate calculated by ILO coincide with the one we calculated for this study. Our indicators almost coincide with the ILO ones for Palestine, North Macedonia, and Montenegro (Figure D1-D3).

Figure D1: Inactivity rate (Bosnia and Herzegovina)



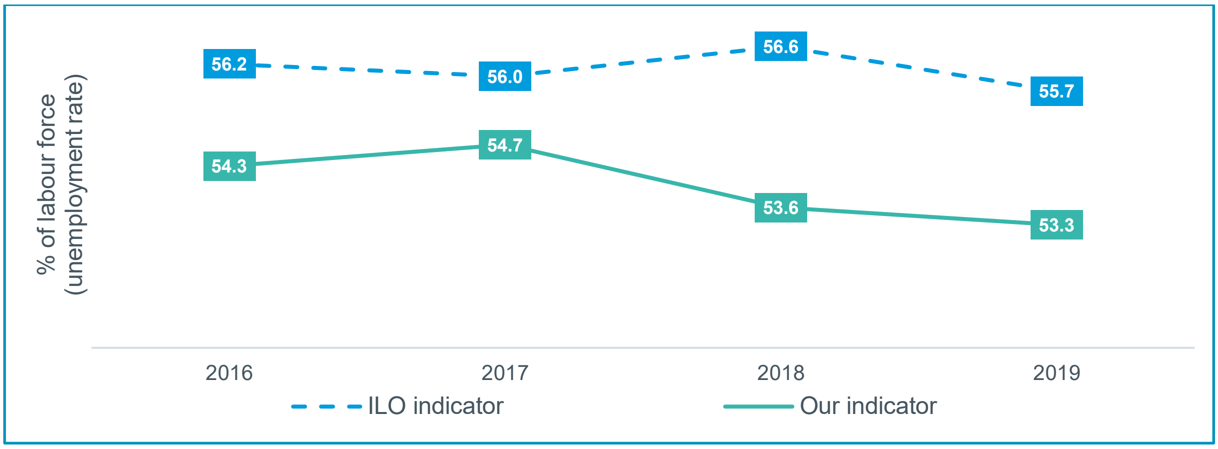
Source: LFSs and https://ilostat.ilo.org/data/

Figure D2.A: Unemployment rate (Palestine)



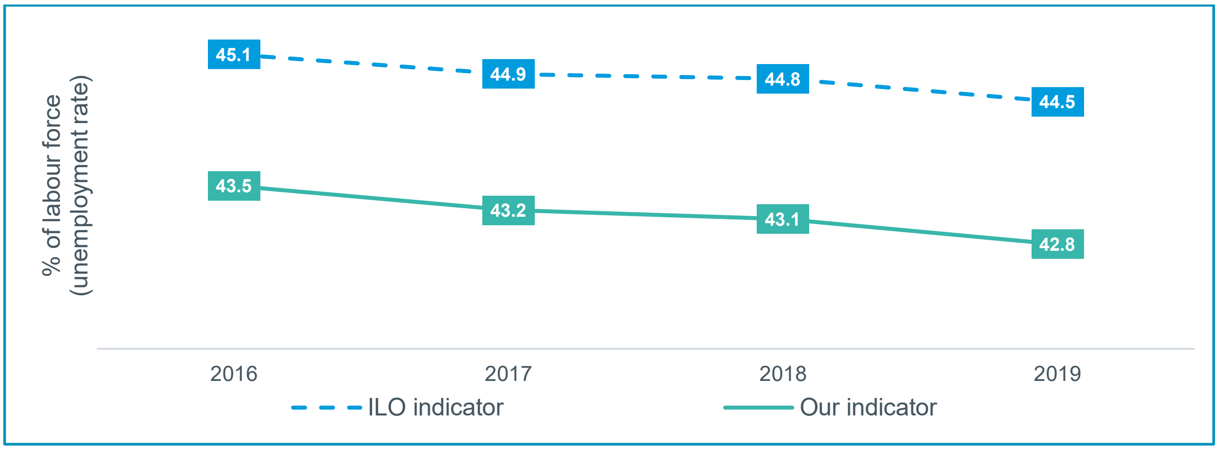
Source: LFSs and https://ilostat.ilo.org/data/

Figure D2.B: Inactivity rate (Palestine)



Source: LFSs and https://ilostat.ilo.org/data/

Figure D3: Inactivity rate (North Macedonia)

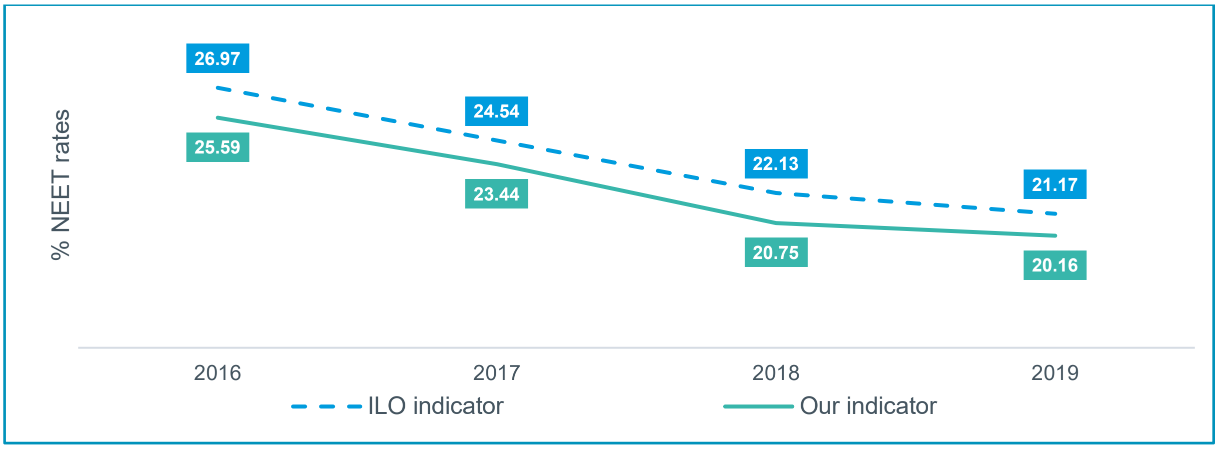


Source: LFSs and https://ilostat.ilo.org/data/

NEET rates (15-24)

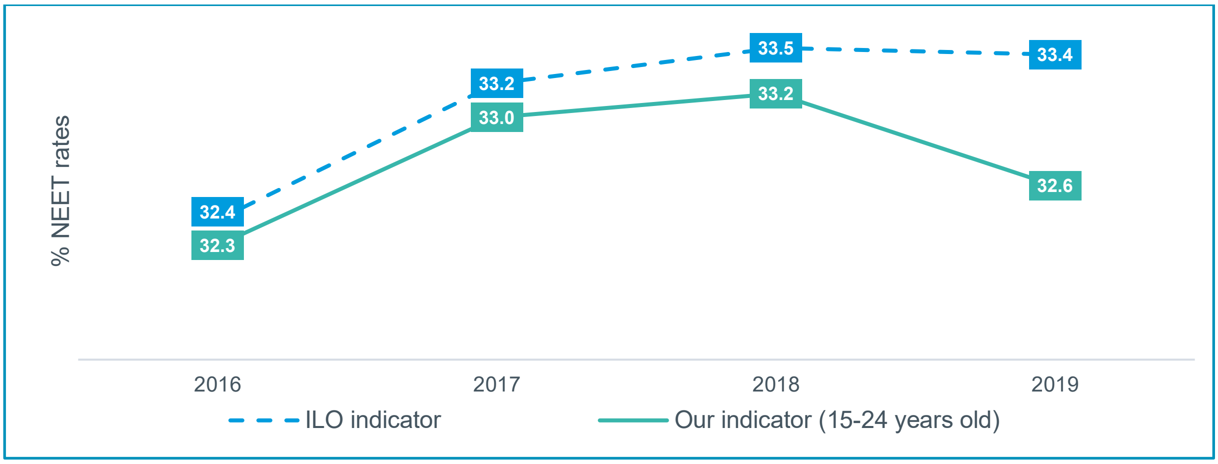
The NEET rates (15-24) calculated by the ILO almost coincide with those we calculated for this study (Figures D4-D7).

Figure D4: NEET rate (15-24 years old) (Bosnia and Herzegovina)



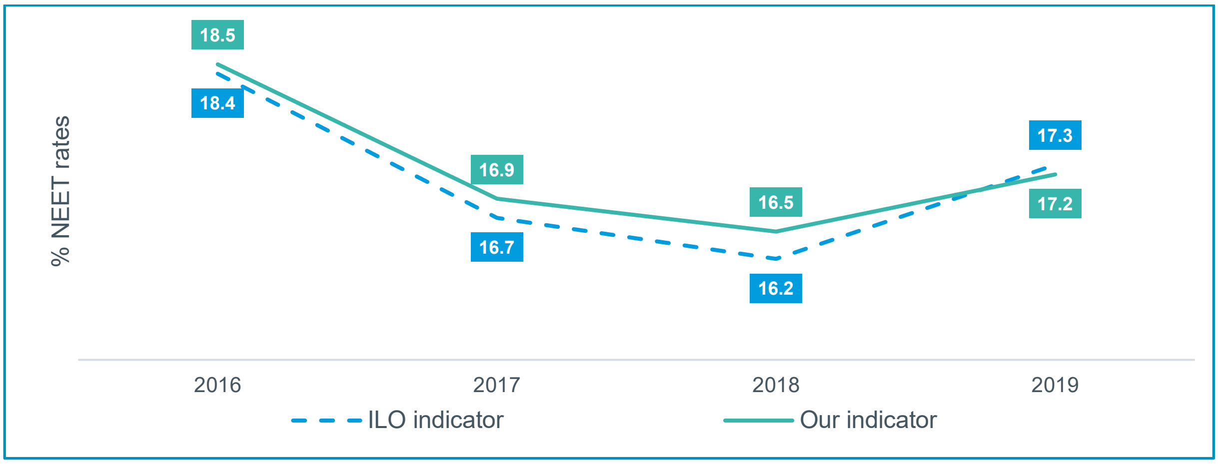
Source: LFSs and https://ilostat.ilo.org/data/

Figure D5: NEET rate (15-24 years old) (Palestine)



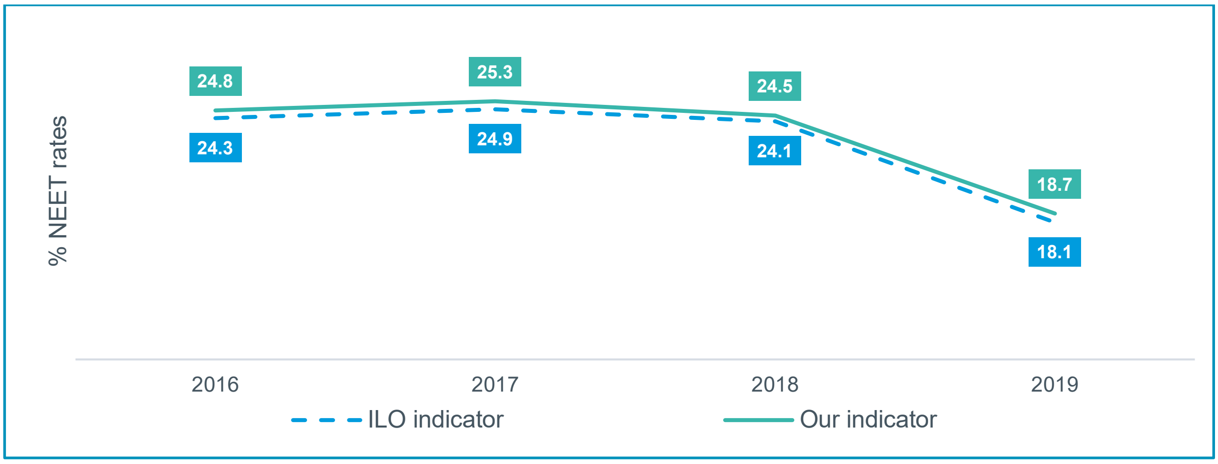
Source: LFSs and https://ilostat.ilo.org/data/

Figure D6: NEET rate (15-24 years old) (North Macedonia)



Source: LFSs and https://ilostat.ilo.org/data/

Figure D7: NEET rate (15-24 years old) (Montenegro)

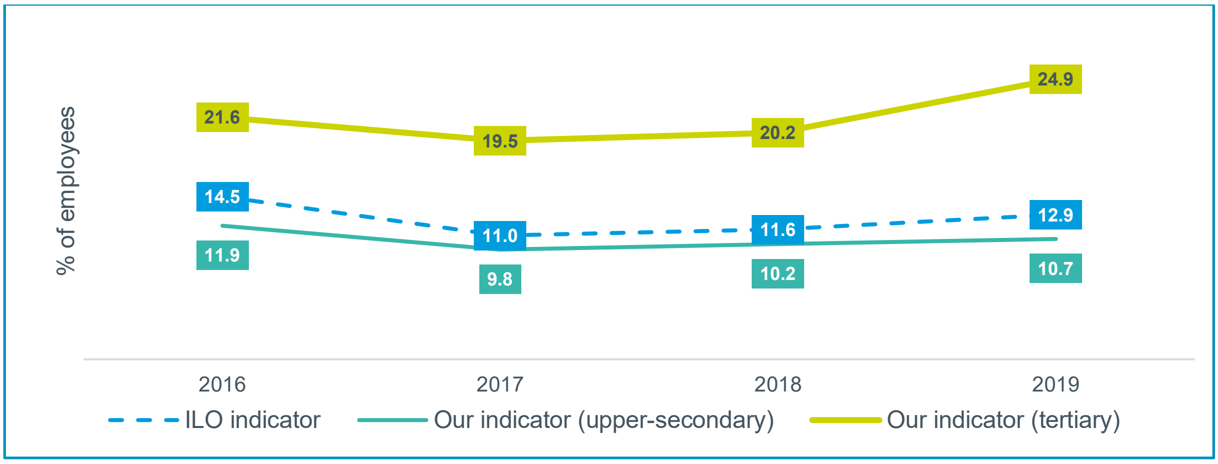


Source: LFSs and https://ilostat.ilo.org/data/

Occupational mismatch

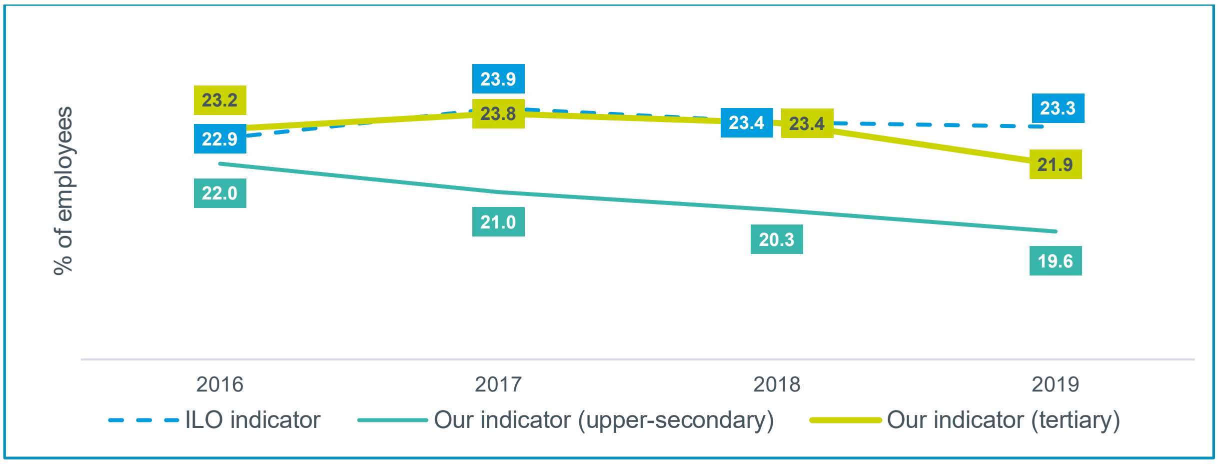
The ILO calculated the occupational mismatch without distinguishing the over-educated with medium or high qualifications, which was done in this project. In any case, the ILO indicators are similar to the average between the two groups, or one of the two groups for Bosnia and Herzegovina, Palestine and Montenegro (Figures D8-D11).

Figure D8: Occupational mismatch (normative method) (Bosnia and Herzegovina)



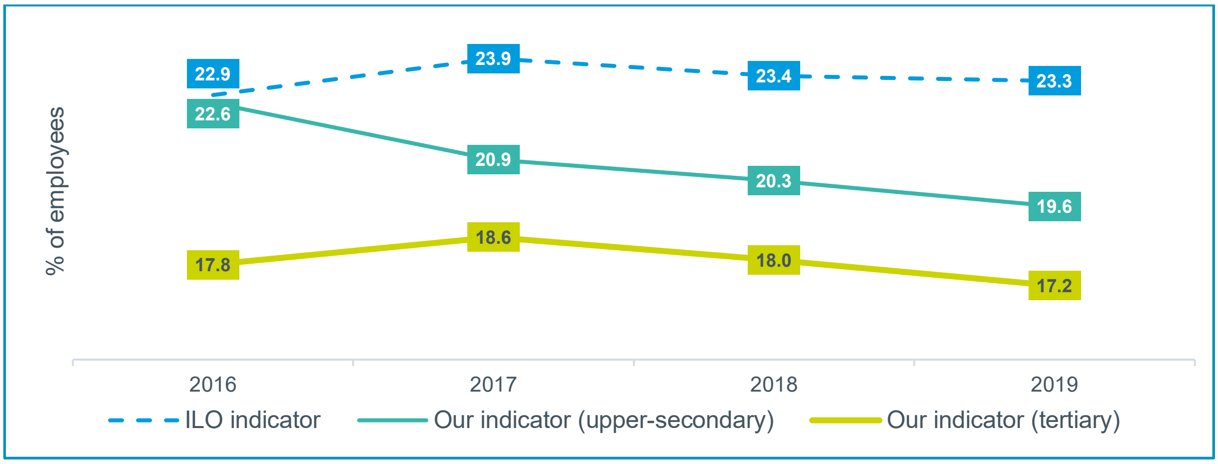
Source: LFSs and https://ilostat.ilo.org/data/

Figure D9: Occupational mismatch (normative method) (Palestine)



Source: LFSs and https://ilostat.ilo.org/data/

Figure D10: Occupational mismatch (normative method) (Montenegro)

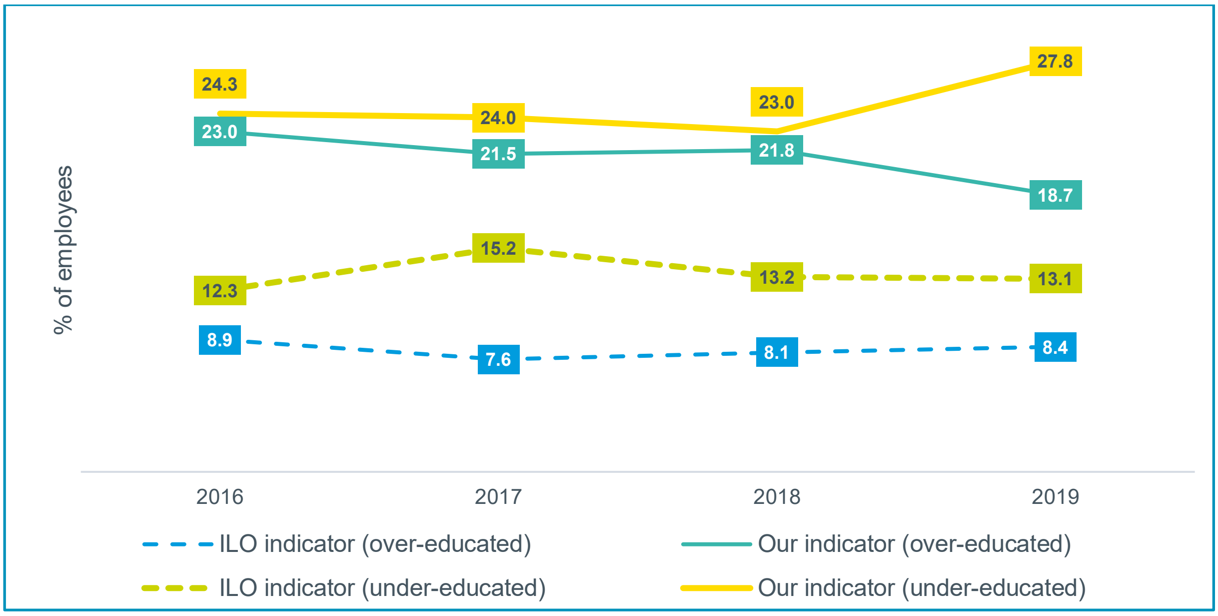


Source: LFSs and https://ilostat.ilo.org/data/

Vertical mismatch

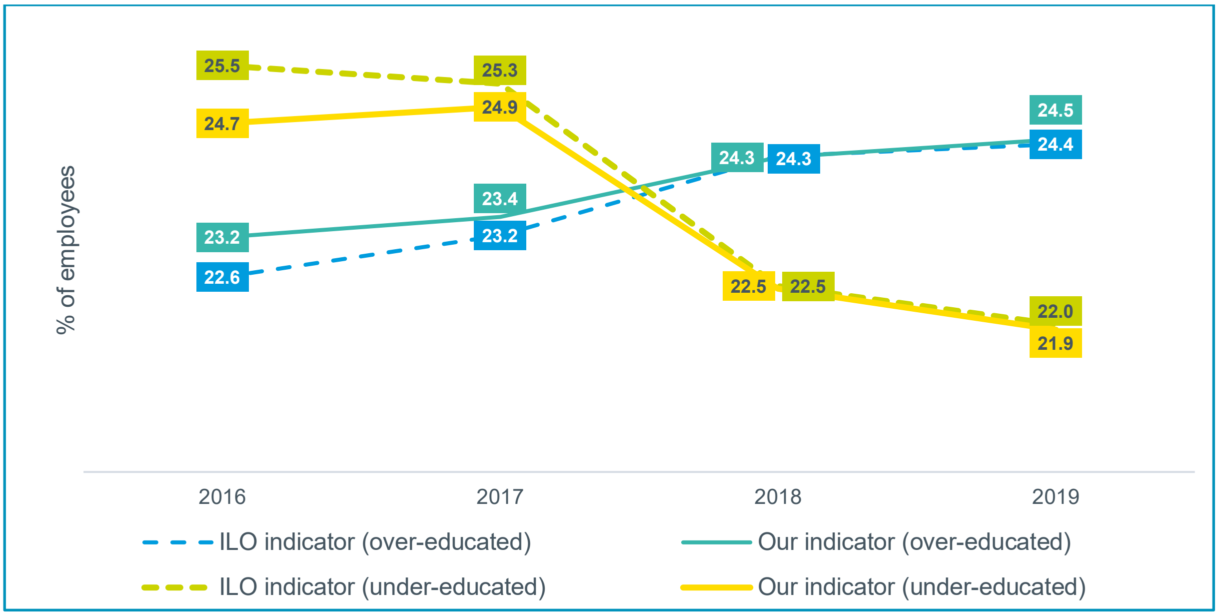
While the ILO indicator shows a very similar vertical mismatch indicator to the one we calculated for Palestine (Figure D12), a bigger difference can be found in the vertical mismatch using the empirical method for Bosnia and Herzegovina and Montenegro (Figures D11 and D13). The reason for the differences could be the definition of occupation categories or the distinction of the levels of education. However, the trends of the indicators are similar.

Figure D11: Vertical mismatch (empirical method) (Bosnia and Herzegovina)



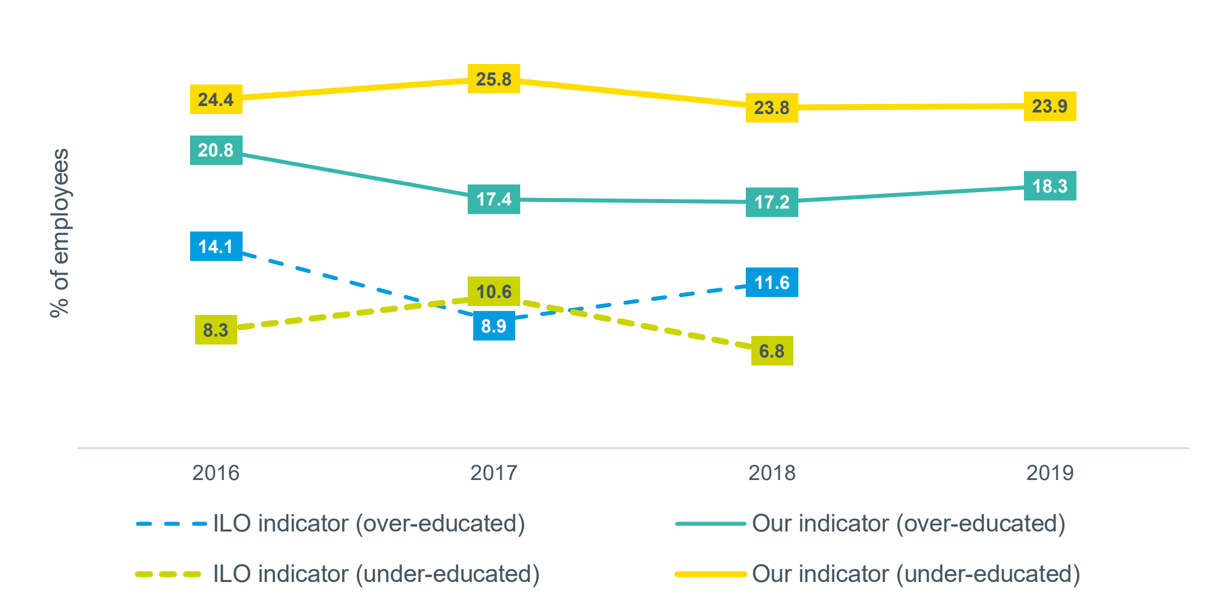
Source: LFSs and https://ilostat.ilo.org/data/

Figure D12: Vertical mismatch (empirical method) (Palestine)



Source: LFS and https://ilostat.ilo.org/data/

Figure D13: Vertical mismatch (empirical method) (Montenegro)



Source: LFSs and https://ilostat.ilo.org/data/

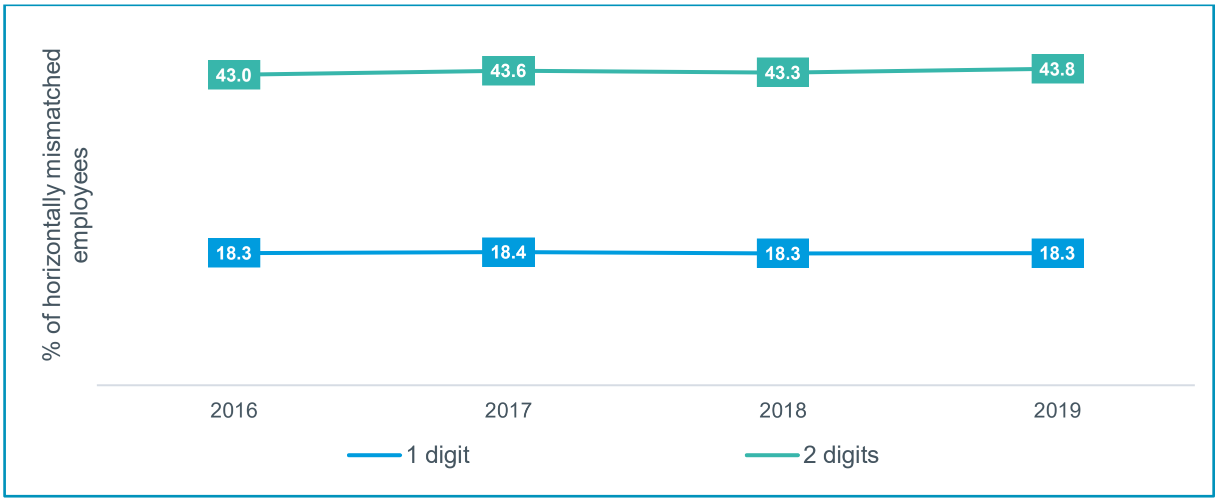
Appendix E: Sensitivity analysis

Horizontal mismatch

The ISCO classification at different digit levels

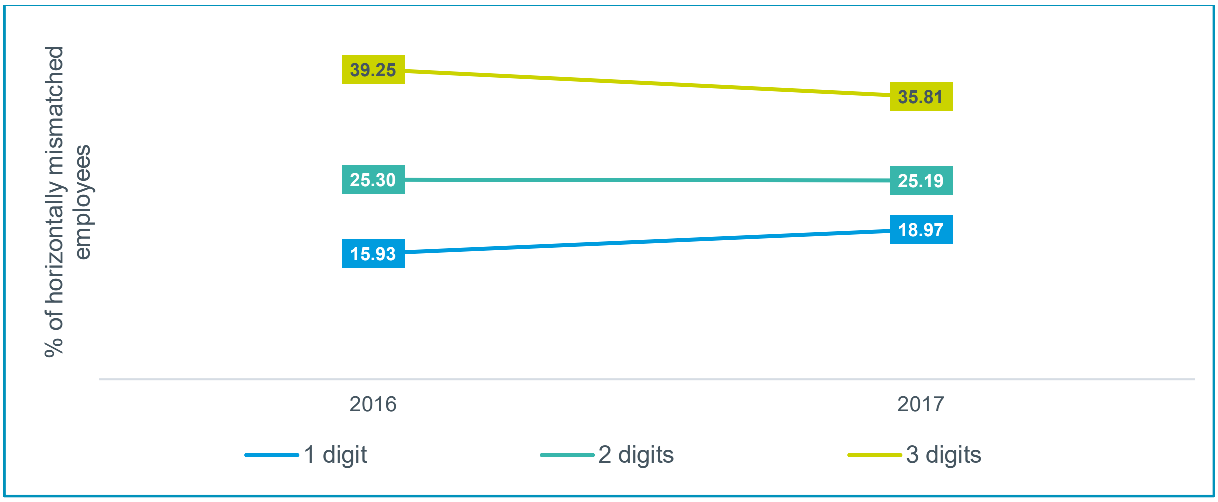
How does the horizontal mismatch indicator change when using the ISCO classification for occupations at different digit levels? We run sensitivity checks for the horizontal mismatch indicator using the occupation at the 1-, 2- and 3-digit level for some countries. We have the occupation coded according to the ISCO classification available at the three-digit level (Turkey and Egypt). Figure E1 and Figure E2 show that the indicator is higher in magnitude when the number of digits is higher as the matching rule between occupation and field of education are stricter. As the results using the ISCO classification at the one-digit level underestimate the magnitude of horizontal mismatch, we included in our analysis only the results obtained using the ISCO code at either the two or at the three digits level.

Figure E1: Horizontal mismatch (15+ years old, tertiary education level)



Source: Turkish Household Labour Force Survey (HLFS).

Figure E2: Horizontal mismatch (15+ years old, tertiary education level)

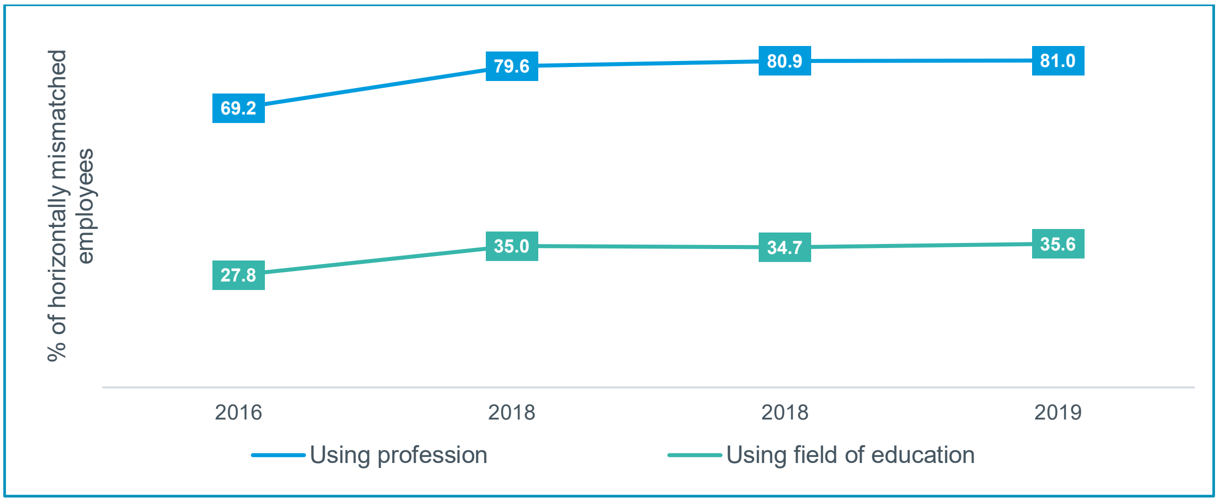


Source: Egyptian LFS 2016-2019.
Notes: Occupation is classified according to the ISCO-88 categories, the field of education according to ISCED-F 1997.

Matching profession and occupation directly

Figure E3 shows that matches found using the field of education retrieved from profession lead to lower matches. This latter matching method may be less precise than the direct matching between profession and occupation but it has the advantage of allowing to account for the fact that those who attended general education cannot be considered as mismatched.

Figure E3: Horizontal mismatch differences in methodology (15+ years old, any education level)



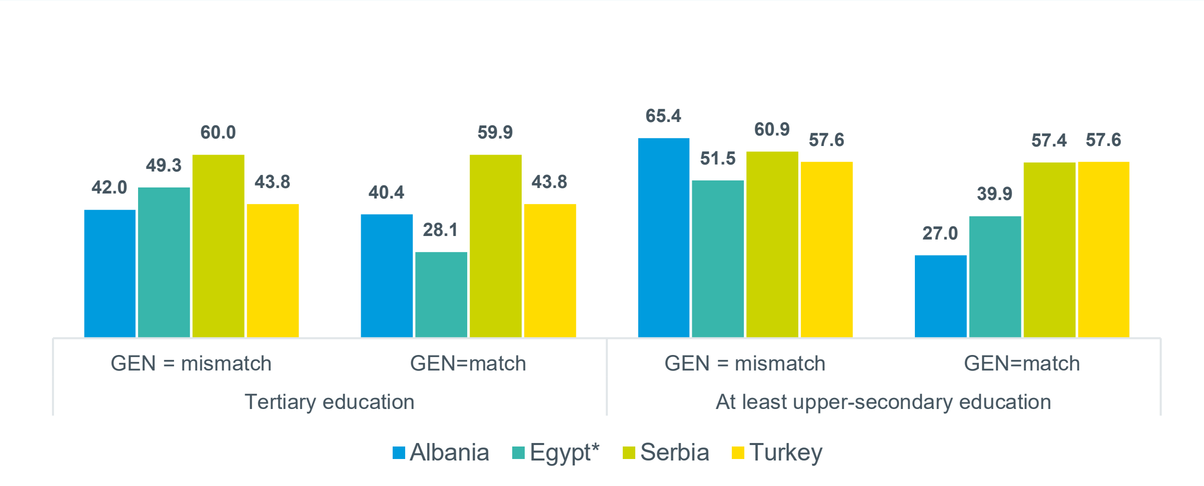
Source: Georgian LFS 2016-2019

Considering people with a general field of education as matched

In this sensitivity analysis, employees with a general field of education are considered as matched when calculating the horizontal mismatch indicator. The assumption is that they acquired competences that are relevant for many different occupations. The sensitivity of the results is calculated separately for employees with tertiary education and for those with at least upper-secondary education.

Figure E4 shows the analysis for horizontal mismatch across countries including Albania, Egypt, Serbia, and Turkey for employees. The graph compares the changes in horizontal mismatch rates when the matching method changes, i.e. people who attended general education are assumed to be matched. The graph shows the extent of such changes both for people with tertiary education and for those with at least upper-secondary education. The results show that considering people with general education as matched reduces the share of horizontal mismatch. However, the changes were more significant among people with at least upper-secondary education degrees, where most people have general education qualification, and in some countries (e.g. Albania and Egypt).

Figure E4: Horizontal mismatch across countries, 2019 (15+ years old, employees) (%)



Source: LFS survey 2016-2019
(*) Latest data in 2017

Comparisons across alternative methods of calculating horizontal mismatch

Table C9 below shows using the Albanian LFS survey that there are two effects that drive down the mismatch considerably: (i) excluding lower education levels; (ii) considering those with a general field of education as a match, but mostly only when looking at the sample of those with at least upper secondary education, because they are more likely to have a "general field of education" than those with tertiary education in the country and therefore drive up the number if matches considerably. On tertiary education alone, this assumption does not have a big effect.

Table C9: Alternative calculations of horizontal mismatch (Albania)

	all education levels, employees only, general Field of Education no automatic match	only upper secondary and tertiary, employees only, general Field of Education no automatic match	only tertiary, employees only, general Field of Education no automatic match	only upper secondary and tertiary, general Field of Education = match	only tertiary, general Field of Education = match
2016	66,9	66,9	44,3	28,5	42,6
2017	66,3	66,3	43,9	28,9	42,9
2018	70,4	68,5	44,6	28,1	42,5
2019	65,3	65,4	42	27	40,4

Source: Albanian LFS survey 2016-2019

Occupational mismatch

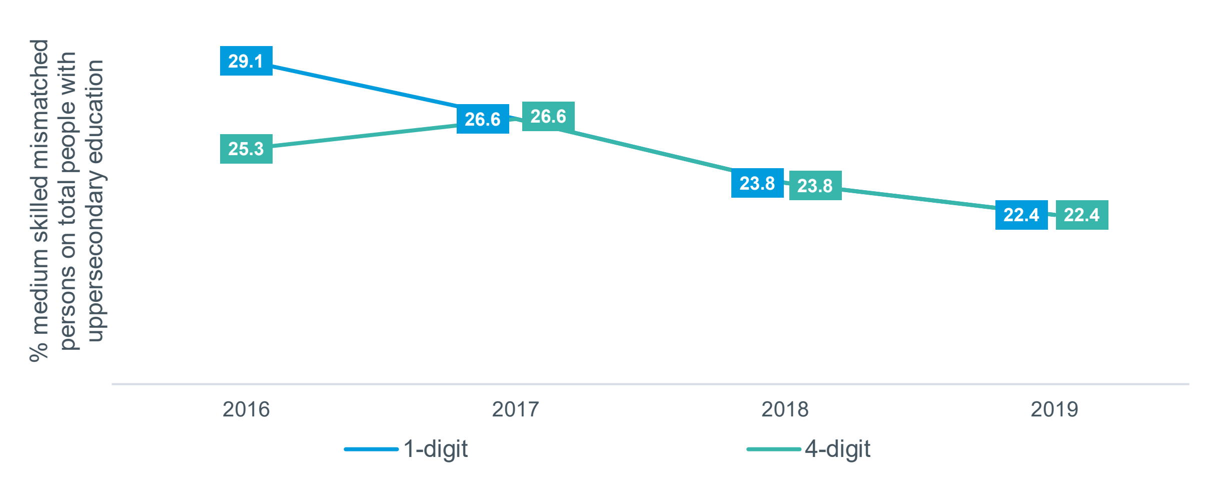
Using secondary education rather than upper-secondary education

In Turkey, the medium occupational mismatch was identical when calculated using either a strict definition of upper-secondary education or a more general definition of secondary education.

Using occupation at the one-digit level rather than the ILO definition at the four-digit level (definition according to ETF (2012))

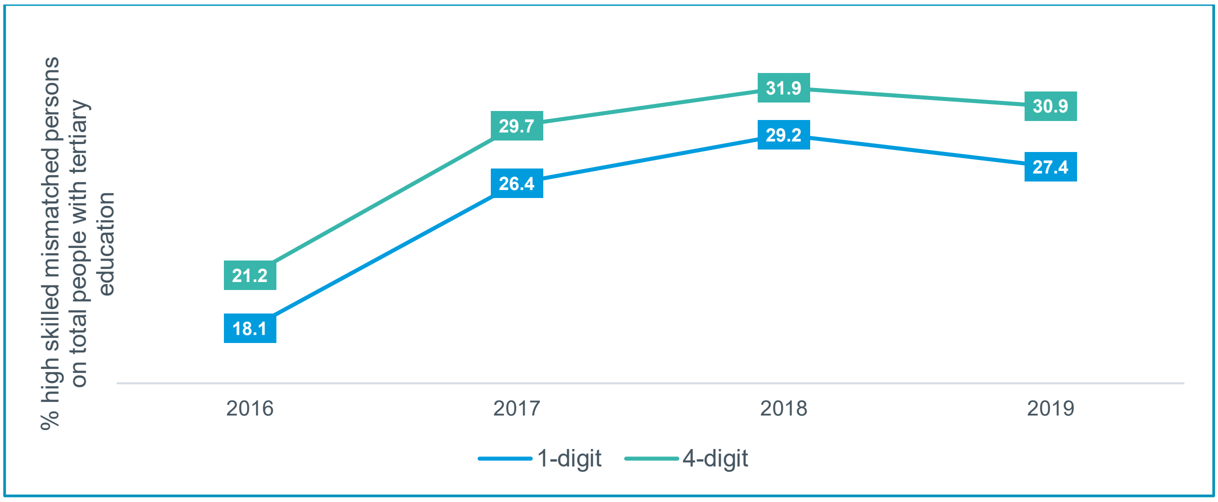
We used the ISCO at 1-digit level instead of 4-digit level to calculate the occupational mismatch indicators in Georgia. The results show that the difference in the definition of elementary and semi-skilled occupations according to ETF (2012) and OECD (2010) lead to the same share of medium occupational mismatch, but slightly different shares of high occupational mismatch (Figure E5 and Figure E6). The increase in the number of digits increased the magnitude of the high occupational mismatch indicator.

Figure E5: Occupational mismatch- medium education: comparing ETF (2012) and OECD (2010) definitions (Georgia)



Source: Georgian LFS survey.
Notes: The share of high mismatched was defined using the ISCO occupation codes using both the ETF (2012) definition at the one-digit level (elementary occupations have ISCO-08 code equal to 9 and semi-skilled ones have ISCO-08 code between 4 and 8) and the OECD (2010) definition at the four-digit level (elementary occupation have ISCO-08 code between 9000 and 9900 and semi-skilled ones have ISCO-08 code between 4000 and 9500).

Figure E6: Occupational mismatch – high education: comparing ETF (2012) and ILO definition (Georgia).



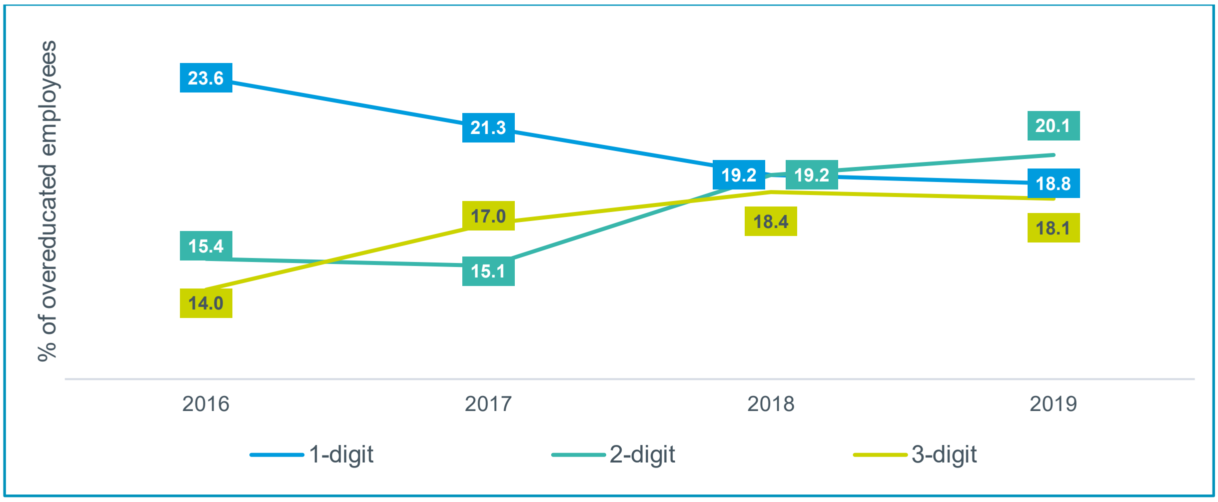
Source: Georgian LFS survey.
Notes: The share of high mismatched was defined using the ISCO occupation codes using both the ETF (2012) definition at the one-digit level (elementary occupations have ISCO-08 code equal to 9 and semi-skilled ones have ISCO-08 code between 4 and 8) and the OECD (2010) definition at the four-digit level (elementary occupation have ISCO-08 code between 9000 and 9900 and semi-skilled ones have ISCO-08 code between 4000 and 9500).

Empirical method

How does the share of over-educated and under-educated employees change when occupation is defined at a 1-, 2-, or 3-digit level when calculating the indicator using the empirical method methodology?

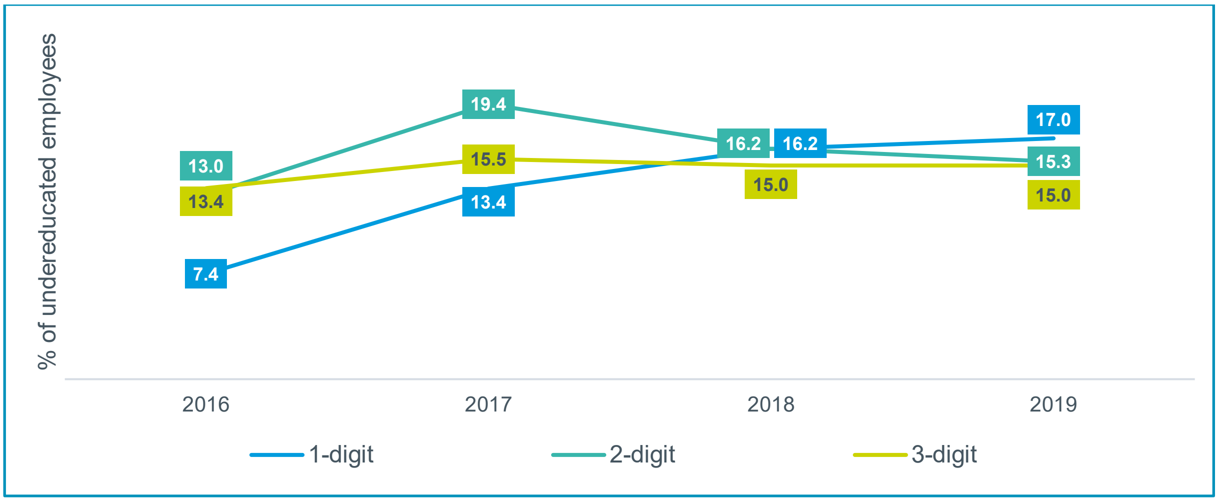
Figure E7 and Figure E8 below show how the empirical mismatch indicator for over- and under-education changes according to the number of digits available to define the occupation in Georgia. The differences were small and increased when the number of digits of the occupation classification increased, but the differences were very small (a few percentage points).

Figure E7: Overeducation outcomes (Georgia – any education level)



Source: Georgian LFS survey
Notes: Occupation is defined according to the ISCO-88 classification to the 1,2,3-digit level

Figure E8: Undereducation outcomes (Georgia – any education level)



Source: Georgian LFS survey
Notes: Occupation is defined according to the ISCO-88 classification to the 1,2,3-digit level

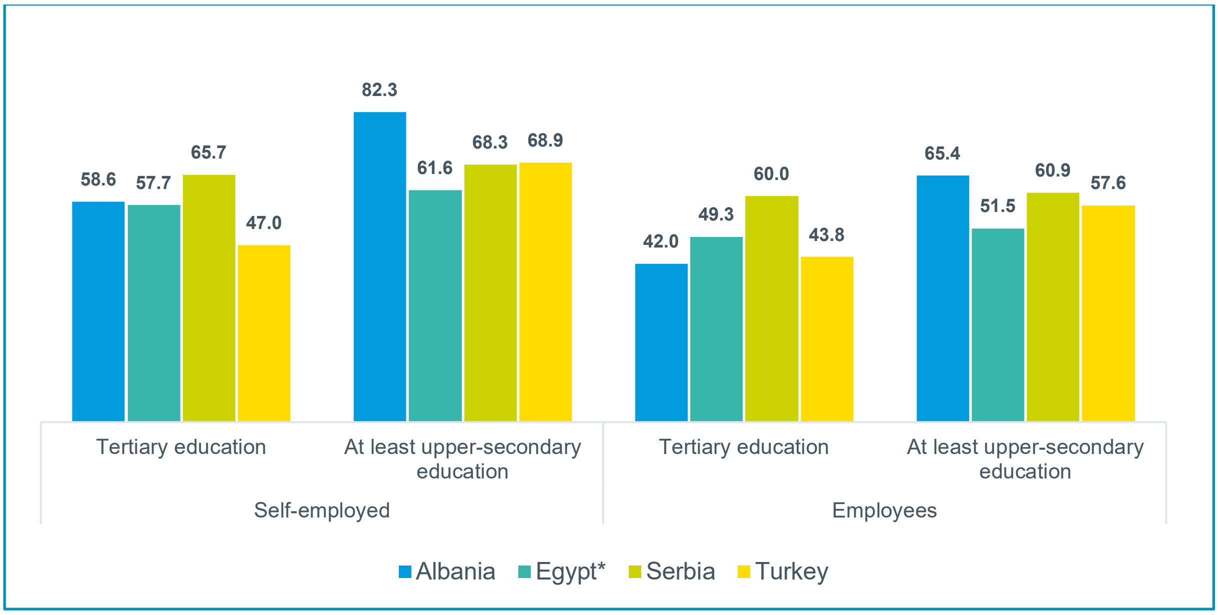
Appendix F: Skills mismatch comparisons between employees and self-employed workers

In our main analysis we excluded from the sample self-employed workers. We show below how sensitive the skills mismatch indicators are when they are calculated for the sample of self-employed workers.

Horizontal mismatch

The additional analysis confirms the fact that self-employed people are more likely than employees to work in occupations that do not match with the field of education that they were studying, both when they have more than upper secondary education and when they have tertiary education (Figure E9). Also, self-employed workers with at least upper-secondary education were more likely to be mismatched compared to those with tertiary education than employees.

Figure E9: Horizontal mismatch across countries (15+ years old, self-employed) (%)

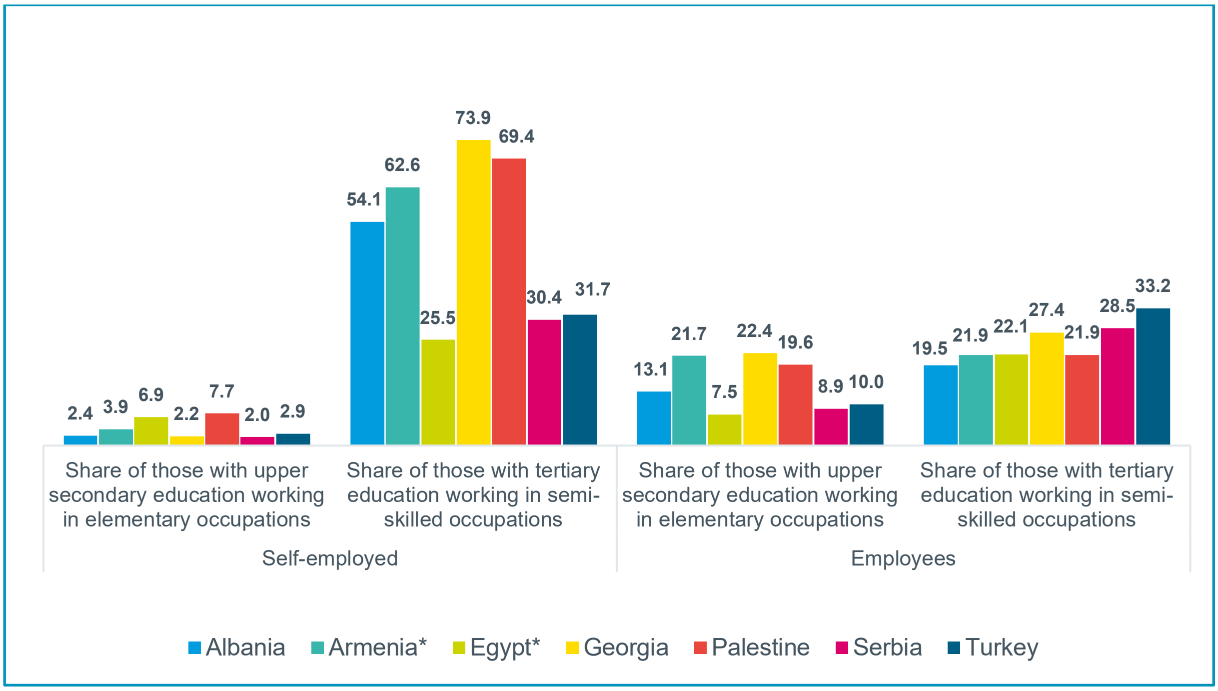


Source: LFS survey 2016-2019
(*) Latest data in 2017

Occupational mismatch

Figure E10 shows that self-employed workers with tertiary education were more likely to experience (high education) occupational mismatch compared to employees. On the other hand, self-employed workers were less likely to experience (medium education) occupational mismatch.

Figure E10: Occupational mismatch between self-employed and employee in 2019 across countries (%)



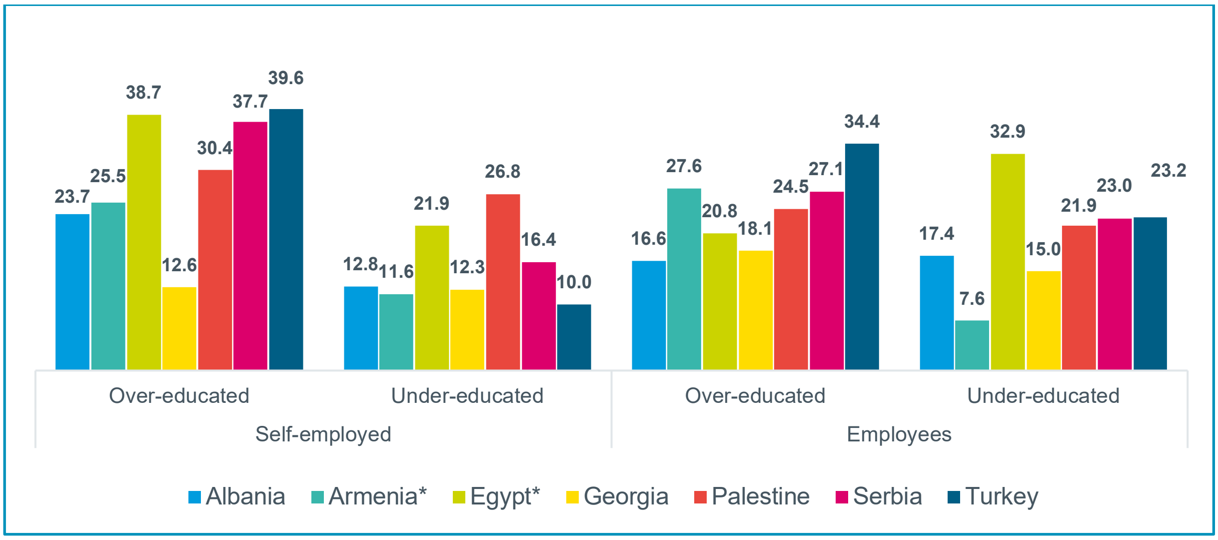
Source: Own calculations

Notes: (*) Latest data for Armenia and Egypt are in 2019

Vertical mismatch (empirical method)

The results are shown in Figure E11 for both self-employed and employee across countries in 2019 and suggest that those who were self-employed were more likely to be over-educated compared to employees. At the same time, they were less likely to experience under-education issues compared to employees.

Figure E11: Vertical mismatch (empirical method) across countries in 2019 (%)



Source: Authors' own calculations

Notes: (*) The latest data for Armenia and Egypt are in 2019.

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