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Measuring skills mismatch

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Measuring skills mismatch

This note presents indicators that can be useful for the regular monitoring of skills mismatches across EU Member States. It distinguishes three broad groups of skills mismatch indicators: indicators of macroeconomic skills mismatch, specific skills shortages, and on-the-job skills mismatch. The indicators of macroeconomic skills mismatch measure the discrepancy between employment outcomes for workers with low, medium, and high skills. This type of indicator is most useful for informing macroeconomic policy and generally identifies countries in which individuals with low skills face significant challenges in the labour market. Specific skills shortage indicators reflect shortages of very specific skills profiles, as experienced by employers trying to recruit such profiles. Indicators of on-the-job skills mismatch measure the discrepancy between the skills individual workers have and those that are needed for their job. The latter two sets of indicators are most useful to inform policy in designing and maintaining a well-functioning education and training system (including adult education) that provides high-quality education and is responsive to the needs of today's as well as tomorrow's labour market.

1. Introduction

The negative effects of the financial and economic crisis on employment outcomes, the co-existence in recent years of an increasing number of job vacancies together with high unemployment in several EU Member States, and reports of high-skilled individuals working in jobs not requiring such skills have resuscitated concern about possible skills mismatches, skills shortages and over-qualification. This analytical note aims to review a number of indicators of skills mismatch with a view to inform country surveillance.

Skills mismatch refers to a discrepancy between the demand and supply of skills in the labour market, in other words a situation in which the skills sought by employers are different from the skills offered by workers in general or job-seekers in particular. This note distinguishes between three major dimensions of mismatch. The first is **macroeconomic skills mismatch**, which relates to the gap between the skills that the working age population has and the skills needed (or used) in the economy. The main indicators presented in this note operationalise macroeconomic skills mismatch by summarising the discrepancies between the employment and unemployment rates of low, medium and high-skilled workers. The second dimension relates to **specific skills shortages** experienced by employers that are recruiting workers for occupations that require specific skills. Finally a third dimension is **on-the-job skills mismatch**, which relates to differences between a worker's skills and the skills needed for his/her job.[1]

The second section of this note focuses on **macroeconomic skills mismatch.** Every economy is likely to experience some degree of such mismatches as a result of technological and organisational change. Even when an economy is "in equilibrium", less skilled workers are likely to experience higher unemployment rates than the highly skilled (Layard et al., 2005, p. 44). Yet, having an assessment of the extent of the skills mismatch is crucial for economic policy. If unemployment increases for most groups of employees, mismatch indicators typically do not rise significantly, and unemployment is likely to be of a cyclical nature. In this case, economic policy should primarily focus on supporting the demand for labour (i.e. through supportive labour

[1] Some previous analyses used other definitions such as "quantitative" (for "macroeconomic") and "qualitative" (for "on-the-job") skills mismatch.

costs and productivity developments). If, on the other hand, high and increasing unemployment in some segments of the labour market is coupled with persistent labour shortages elsewhere, then mismatch indicators will likely rise significantly, and unemployment is likely to be at least partly structural. In this case economic policy should primarily focus on structural reforms to assist the employment of vulnerable groups (e.g., by enhancing the capacities of public employment services [PES], assisting job search, improving further education and training, improving the visibility, recognition and validation of skills and qualifications, providing targeted hiring subsidies, introducing targeted tax cuts on labour, or identifying and addressing other bottlenecks).

The analysis of the macroeconomic skills mismatch indicators updates previous work reported in European Commission (2013) and Arpaia et al. (2014). The analysis gives a number of country-specific insights. First, there are a few countries in which there is a high dispersion of both employment and unemployment rates across broad skill groups, indicating the presence of macroeconomic skills mismatches (Belgium, Bulgaria, Hungary, Ireland, Lithuania, and Malta). A few countries exhibit a high dispersion of unemployment but not of employment rates (Germany, Sweden and the UK), while a few countries exhibit the opposite pattern of high dispersion of employment but not of unemployment rates (Croatia, Italy, and Slovakia). In these country cases, a deeper analysis into the driving factors is needed to evaluate the extent of macroeconomic skills mismatches, with a particular focus on the activity rate of different groups of the population (especially the low-skilled and women).

The third section of the note focuses on **specific skills shortages**. Such skills shortages may inhibit the efficient allocation of productive resources, and as a result have a negative impact on productivity. However, as with macro-economic mismatch, the occurrence of specific skills shortages are a feature of competitive markets, and arise as a result of demographic, organisational, social and technological change (Shah and Burke, 2003). In general, they are difficult to measure (different data sources result in very different indicators). The drivers may vary from an ageing/shrinking work force; to unattractive working conditions to inadequacies in the provision of education and training and in career guidance. To take the right policy measure, a detailed country-specific exploration of the drivers of observed shortages is crucial. Very often, as wages adjust and jobs become more attractive, the supply of skills will increase without policy intervention. Policymakers can facilitate this correction by making information on labour market outcomes and wages more transparent and more easily available.

The fourth section of the note considers indicators of **on-the-job skills mismatch**, building on existing literature. Such mismatches have been linked in the literature with skills underutilisation and inefficient allocation of resources, with potentially negative impacts on wages, job satisfaction, turnover, and productivity. While there is relatively strong evidence in the literature that over-qualified workers earn less than their equally-qualified and well-matched counterparts, but more than well-matched colleagues in the same job, the evidence on job satisfaction, turnover, and productivity is less clear-cut. Also in this case, part of the observed skills mismatch is temporary (young workers are more likely to be over-qualified than older workers), and part of it is persistent. To address the latter, research has called for better career guidance services, the involvement of employers in the design of educational curricula at the upper secondary and tertiary level, and strengthened provision of adult learning opportunities.

The indicators for on-the-job skills mismatch that are relatively easy to calculate based on regularly collected data are imprecise for a number of reasons. First, skills mismatch is most often measured through qualification mismatch, although the correlation between qualifications and actual skills is imperfect. Second, even qualification mismatch is difficult to quantify as it is challenging to identify the right qualification requirement for every job based on the available data. This means that a simple indicator-based approach to quantifying on-the-job skills mismatch across countries is likely to be unreliable. Instead, more careful country-specific analysis is needed to verify the extent of "genuine" skills mismatch and its drivers to devise adequate policies.

2. Macroeconomic skills mismatch

The main indicators of macroeconomic skills mismatch calculated in this note are dispersion measures of employment and unemployment rates across skill groups. If there is a high discrepancy between the employment and unemployment rates of the high, medium, and low-skilled, this suggests that there is a large gap between the skills that the population has and the skills that the economy needs.

A practical advantage of these mismatch indicators is that they are easily calculated based on frequently (annually or even quarterly) collected EU Labour Force Survey data which become available with a short time lag (between 3-6 months after their collection). Eurostat makes available comparable high-quality data for three skill groups: those with primary or lower secondary education or less (ISCED categories 0-2), those with an upper secondary education or post-secondary non-tertiary education (ISCED categories 3-4) and those with a tertiary education (ISCED categories 5-6). In this note, they are referred to as low- medium- and high-skilled, respectively.

Weaknesses of these mismatch indicators include the fact that they disregard “unmet labour demand” (i.e. vacancies), and do not consider whether all workers are in jobs that match their qualifications. The disaggregation into three main skill levels is relatively coarse; a finer classification, typically not available in readily available data, would allow for a deeper analysis of skills mismatches. Despite these limitations, the aggregate-level indicators presented in this note are a useful first step in the analysis of skills mismatches, allowing a comparison between countries as well as tracking developments over time. At the same time, they should be complemented by other available information (e.g. on sectoral developments, vacancies, etc.) in deeper country-specific analyses.

Both indicators based on skill-specific employment rates and those based on skill-specific unemployment rates can be relevant for the analysis of skills mismatches. The dispersion of employment rates is more informative about the underlying skills mismatches if “discouragement effects” are widespread (i.e., many unemployed have stopped looking for work and become inactive). This note takes as primary indicator one based on employment rates to take account of this possibility.

2.1 Variation in employment rates across skill levels

The primary macroeconomic skills mismatch indicator presented in this note is the relative dispersion of employment rates across three main skill groups. The indicator is calculated as the sum, over the three skill groups, of the absolute difference between the share of a skill group in employment and its share in population. This is expressed by the following formula:

$$SMI_{E-RD} = \sum_{i=1}^{3} \left| \frac{E_i}{E_T} - \frac{P_i}{P_T} \right| \tag{1}$$

Here, P_i is the number of individuals in the working age population of skill group i, P_T is total working age population. Analogously, E_i is the number of workers employed of skill group i, while E_T refers to total employment.[2]

Alternatively, this indicator can be rewritten in terms of employment rates (defined as $e = E/P$ - see below) and we will henceforth refer to this indicator as **relative dispersion of employment rates (E-RD)**, following the terminology of Martin (2010) who calculates an analogous indicator to summarise regional unemployment differences:

$$SMI_{E-RD} = \frac{1}{e_T} \sum_{i=1}^{3} \left| \frac{P_i}{P_T} (e_i - e_T) \right| \tag{2}$$

In this form, the indicator is based on the absolute deviation of each group's employment rate from the national employment rate ($\boldsymbol{e_T}$); in particular, it is the weighted average of these deviations relative to the national employment rate, with the population shares of the skills groups serving as weights.

Variants of this indicator have been calculated by Estevao and Tsounta (2011) for U.S. states, ECB (2012) for the euro area as a whole and European Commission (2013, Chapter II.1) and Arpaia et al. (2014) for all EU Member States. Annex A provides some detail on statistical measures of dispersion that have been used in previous literature.

The mechanics of this indicator can be illustrated by an example in which a country is divided into two (rather than three) groups, comprising 60% and 40% of the working-age population ($P_1/P_T = 0.6$ and $P_2/P_T = 0.4$). If both groups have the same employment rate, this will mean that their share in employment will be equal to their share in population ($E_1/E_T = 0.6$ and $E_2/E_T = 0.4$), and the value of the mismatch indicator will be 0. In the other extreme case, if all employed individuals belong to, say, group 1, while none are employed in group 2, the value of the mismatch indicator will be ($|1 - 0.6| + |0 - 0.4| = 1$). In an intermediate case, if the employment rate of group 2 is higher than for group 1, then group 2 will be overrepresented in employment. For instance, it could be that both groups' share in employment becomes equal ($E_1/E_T = E_2/E_T = 0.5$). In this case, the value of the mismatch indicator becomes ($|0.5 - 0.6| + |0.5 - 0.4| = 0.2$).

Figure 1 shows the development of the indicator for all EU Member States over the past 15 years. Seen together with the auxiliary figures in Annex B (especially Figure 22 showing the components of the skills mismatch index), a number of observations can be derived from Figure 1:

- A number of countries exhibit a long-term trend of falling skills mismatch, including Eastern European Member States (BG, CZ, EE, HU, LV, PL, SK) as

[2] The difference between the share of a skill group in employment and in the overall population is in absolute value. This means that only the absolute magnitude of the difference is taken into account, not whether the employment share or the population share is larger.

well as some in the euro area "core" (AT, BE, DE).[3] Eastern European economies have been characterized by radical structural change since the transition from planned economies, including substantial job shedding in agriculture and industry (see, e.g., IMF [2001] on the Baltics), which disproportionately affected the low-skilled. Since then, demographic change (especially improving skill levels among younger cohorts) has diminished the skills mismatch (see Figure 11). In addition, other sectors employing low-skilled labour have expanded (e.g., in the service sector, see Figure 24). In AT, BE and DE, the skills mismatch decreased because the employment rate of the low-skilled remained stable (AT, BE) or even increased (DE) while, as in other countries, their share in the working age population fell (see Figure 11, Figure 19 and Figure 22 in Annex B).

- In some Southern Member States (EL, ES, IT, MT, PT), the skills mismatch was on an increasing path before the crisis, although in Greece, Italy and especially Spain, this occurred in a period of improving labour markets during which the employment rate increased for medium or high-skilled groups but not (or much less) for the low-skilled(see Figure 19).

- The crisis was accompanied by a rising mismatch in a number of countries that experienced particularly strong downturns (in particular CY, EL, ES, PT and IE). Most of these countries, especially Spain and Ireland, experienced a bust of a previous construction boom (ECB, 2012; see also Figure 24 in Annex B), with soaring unemployment and falling employment rates of low-skilled (see Figure 19 and Figure 20 in Annex B).

- The crisis was accompanied by a "hump-shaped" development in the skills mismatch indicator in several EU Member States. In some cases, the skills mismatch started to fall after a marked increase when the employment rate of low-skilled workers started to increase after the crisis (notably in IE, LT, SI and UK). While the initial shock of the crisis on the labour market of Finland and France was comparatively moderate (see Figure 14), current decreases of the skills mismatch indicator are the result of a fall in the share of low-skilled in the working age population, on the one hand, and a gradual decline in the (traditionally high) employment rate of the medium-skilled on the other.

All in all, high levels of skills mismatch often reflect low employment chances of low-skilled workers. This may occur as a result of structural changes, most often structural declines of sectors that employ low-skilled workers such as agriculture and some manufacturing industries. Part of the increase in skills mismatch may also be cyclical. While the construction sector is not expected to regain its pre-crisis weight in the economies of Member States that experienced unsustainable housing booms, some jobs in construction are expected to be created as the recovery gains strength. To the extent however that skills mismatch is structural, upskilling and re-skilling is necessary to combat mismatch unemployment, along with other policy actions that improve the employability of laid off workers.

[3] The sudden fall in the indicator in Germany in 2011, reversed in 2014, is due to a data issue related to the estimated low-skilled population (observable also in Figure 11, Figure 19, and Figure 22 in Annex B).

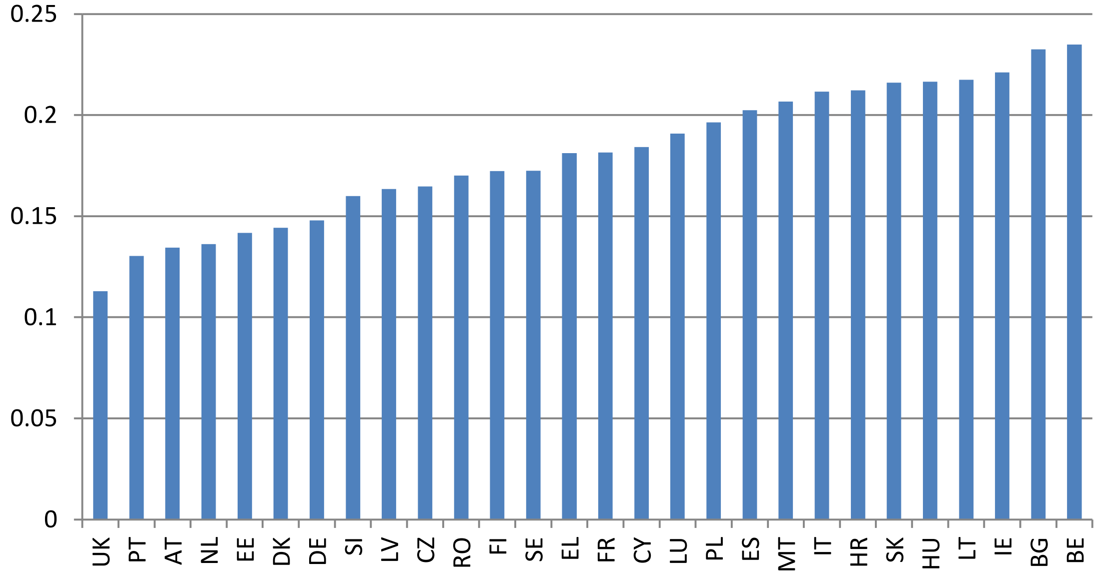
Figure 1: Relative dispersion of employment rates by skill level, 1998-2014 (country-specific scales, smoothed series)

Notes: Own calculations based on Eurostat. Quarterly data, smoothed with a moving average procedure (4-quarter window).

Figure 2 compares the level of the skills mismatch indicator in 2014 across EU Member States. A number of observations can be made:

- The relative dispersion of employment rates in the EU range from 10% to 25%. The countries with the lowest skills mismatch indicator are mostly those in which the employment rate of low-skilled workers is highest. These countries include countries from the euro area "core" like Austria, Germany, and the Netherlands, as well as Denmark, Portugal, and the UK. Portugal is an exception in this group because its workforce is characterised by a high share of low-skilled workers (over 50%, see Figure 11). Historically, employment rates of low- and medium-skilled workers have been similar in Portugal (see Figure 19). More recently, they started to diverge: the employment rate of low-skilled workers has been falling both in absolute terms and relative to medium-skilled workers. Part of this may be a compositional effect: as it is getting more and more common for individuals to obtain an upper secondary school degree, the school-to-work transition may become more difficult for the remaining early school leavers.
- Despite recent falls in the skills mismatch indicator, a number of Eastern European Member States are still among those with the highest indicators in 2014 (BG, HR, HU, LT, SK). Despite recent gains, the employment chances of low-skilled are still very low in these countries as compared to other workers: the average employment rate of low-skilled workers in Lithuania and Slovakia is below 20% (Figure 19). At the same time, the share of low-skilled workers is small in these countries compared to other EU Member States, especially in Lithuania and Slovakia (see Figure 11).
- Belgium, Ireland and Italy are among the "old" Member States with the highest skills mismatch. High skills mismatch is related, also in this case, with a relatively low employment rate of low-skilled workers, but in the case of Belgium and especially Italy coupled with a relatively high share of these workers in the working-age population (Figure 11).

Figure 2: Relative dispersion of employment rates by skill level, 2014



Notes: Own calculations based on Eurostat. Annual average based on the average of four quarters.

2.2 Variation in unemployment rates across skill levels

This section presents an alternative indicator based on unemployment, rather than employment, rates: the **relative dispersion of unemployment rates (U-RD)** across skill groups.[4]

Figure 3 shows the dispersion of unemployment rates across skill levels across EU Member States for 2014. This indicator shows a higher variance than the one based on employment rates, because there are larger relative differences between unemployment rates than between employment rates across skill groups. In particular, the relative dispersion of unemployment rates by skill level varies between 5% and 50% in 2014.

Countries with the lowest indicator include Eastern-European Member States such as Romania, Croatia and Slovenia and Southern Member States such as Cyprus, Greece, Italy and Portugal. Countries with the highest indicator include New Member States such as Bulgaria, Lithuania, and Malta, but also Belgium, Ireland, Sweden and the UK.

Figure 3: Relative dispersion of unemployment rates by skill level, 2014

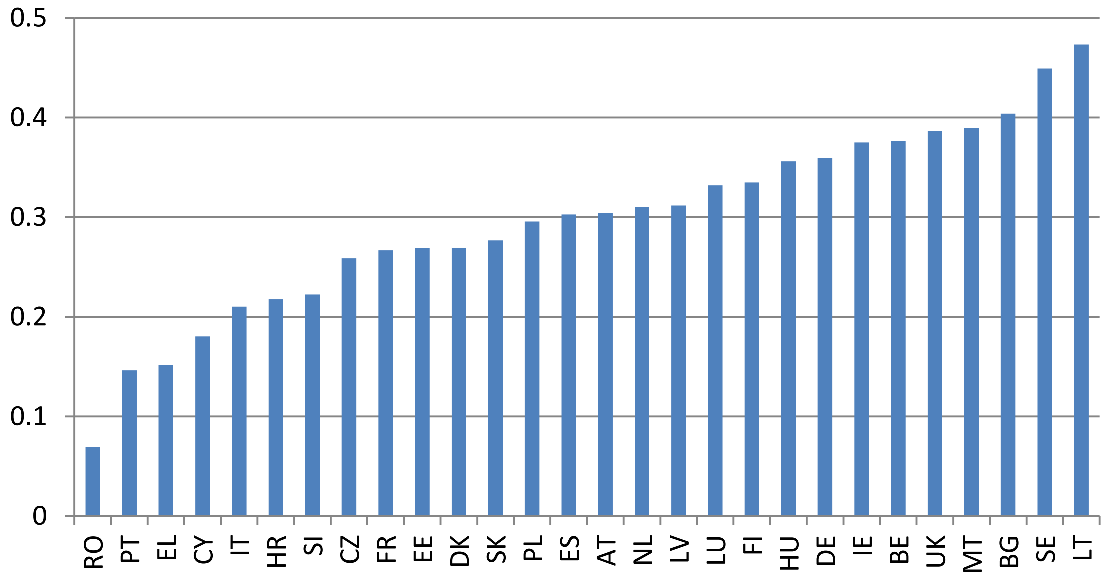


Figure 4 compares both indicators by plotting the main skills mismatch indicator based on employment rates (on the vertical axis) against the indicator based on unemployment rates. Countries with the highest skills mismatch indicators in 2014 are above the horizontal line and to the right of the vertical line included in the graph. The 7 countries with the highest dispersion of employment rates by skill level in 2014 are above the horizontal line, while the 7 countries with the highest dispersion of unemployment rates by skill level are to the right of the vertical line.

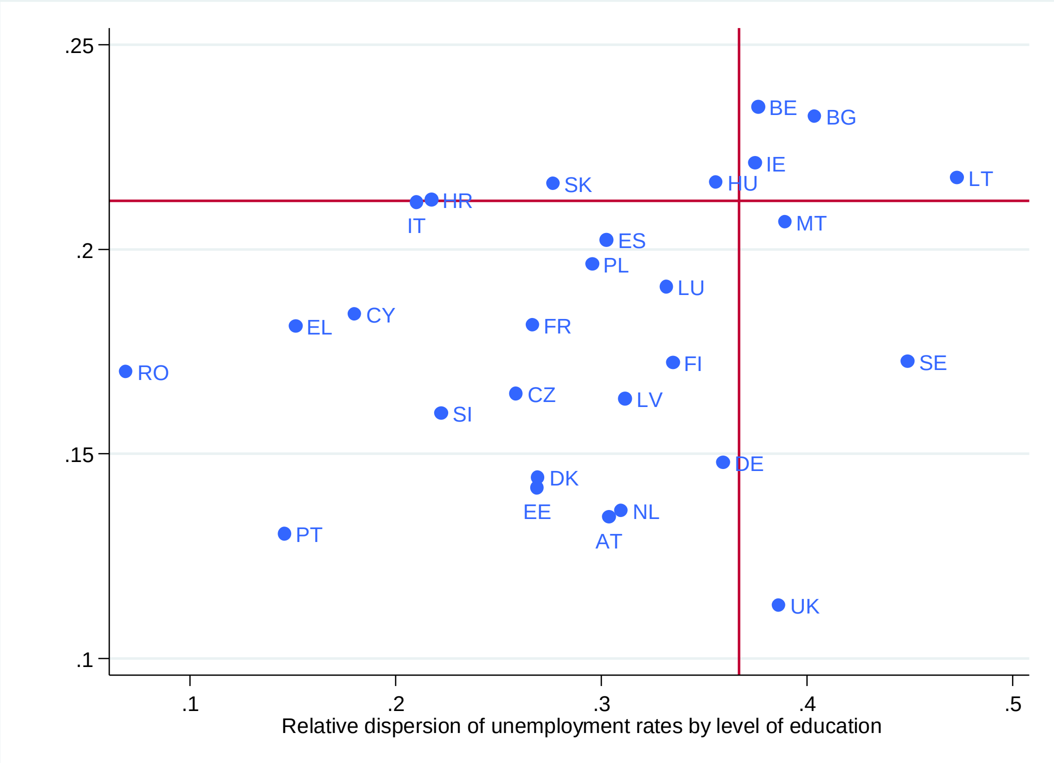
While there is variance between both indicators, some conclusions are similar. Most importantly, there is a group of countries in the top right quadrant of the graph (BE,

[4] For more detail about alternative indicators, see the Annex A.

BG, IE, LT, with HU and MT very close) that have one of the highest skills mismatches both based on employment and unemployment rates.

A few countries exhibit a high dispersion of unemployment but not employment rates (DE, SE and the UK; they are to the right of (or close to) the vertical line but far below the horizontal line), while a few countries exhibit the opposite pattern of high dispersion of employment but not of unemployment rates (HR, IT and SK; above the horizontal line but to the far-left of the vertical line). Additionally, in a few countries both indicators are close to but below the upper quartile (ES, FI, LU, PL). For these countries, a deeper analysis into the driving factors would be needed to evaluate the extent of skills mismatches on the aggregate level, with a particular focus on the activity rate of different groups of the population (especially the low-skilled and women). In general, high discrepancy of employment rates across skill groups combined with less marked differences in unemployment rates may be the result of so-called discouragement effects if some low-skilled unemployed workers have stopped looking for jobs and are thus considered as inactive rather than unemployed. The opposite case (high discrepancy of unemployment rates coupled with less marked differences in employment rates) may result if activity rates of low-skilled are relatively high (in other words, less divergent from those of medium- and high-skilled individuals than in other countries).

Figure 4: Comparison of two skills mismatch indicators, 2014



Notes: The skills mismatch indicator measured on the vertical axis is analysed in detail in Section 2.1. For more detail on related indicators, see Annex A. Horizontal and vertical lines have been added to mark the upper quartile of both indicators, i.e., the seven countries with the highest indicator are to the right of the vertical line and above the horizontal line.

2.3 Complementary indicators of macroeconomic skills mismatch

An important tool to explore labour market matching is the **Beveridge curve**, which plots aggregate unemployment against a measure of job vacancies (typically the vacancy rate – the ratio of the number of vacancies and the total number of filled and vacant posts in the economy).[5] During the normal course of the business cycle, the relationship between unemployment and vacancies is negative: good economic times are associated with a high number of vacancies and low unemployment, while the opposite applies in bad economic times. Sometimes, however, shifts of the negative-sloping Beveridge curve are observed. In the case of an "outward shift" (away from the origin), the same unemployment rate is sustained by a higher number of vacancies, suggestive of a deterioration in labour-market matching.

An outward shift of the Beveridge curve may mean that the mismatch (in terms of skill, sector or geography) between labour supply and demand has increased, but caution is in order in the interpretation of movements toward the end of the time series. In particular, it has been observed that the Beveridge curve exhibits circular movements along the business cycle: if unemployment is depicted on the horizontal axis, the typical counter-clockwise movement of the Beveridge curve means that unemployment reacts with a lag to an increase (or fall) of job vacancies (see, e.g., Arpaia et al., 2014). Therefore, an apparent outward shift in the Beveridge curve at the beginning of the recovery does not necessarily indicate that labour market mismatch has increased, as it is still possible that the curve returns to its original location at the end of the expansion (Diamond and Sahin, 2014).

Other authors have derived more detailed indicators to quantify discrepancies between unfilled vacancies and jobseekers (e.g. Nickel, 1982; Jackman and Roper, 1987). For example, the mismatch indicator proposed by Jackman and Roper is calculated as the discrepancy between the share of skill groups in unemployment and their share in the pool of available vacancies.[6] This type of indicator requires even more detailed data on vacancies than the Beveridge curve, as the level of required skill should be known for each vacancy. Such data are however not easily available, especially on a comparable basis across the EU. For this reason, such indicators are not analysed in this note.

3. Specific skills shortages

The dispersion measures discussed in the previous section are typically defined over broad categories of workers (in particular, three broad qualification levels: high, medium, and low skilled). These broad categories mask a wide diversity of different fields of training and specific skills profiles, which in reality are not perfect substitutes for each other. For example, the skills needed in the construction sector may not be exactly the same as those in manufacturing even though both are considered to belong to the medium skills group. As a result an oversupply of medium-skilled profiles in construction may co-exist with an undersupply of specific medium-skilled profiles in manufacturing, or *vice versa*.

[5] See Blanchard and Diamond (1989) for a classic exposition and Elsby et al. (2015) for a recent survey. For a recent analysis on EU Member States, see European Commission, 2013; Arpaia et al., 2014. An update of vacancy series is outside the scope of the present note.

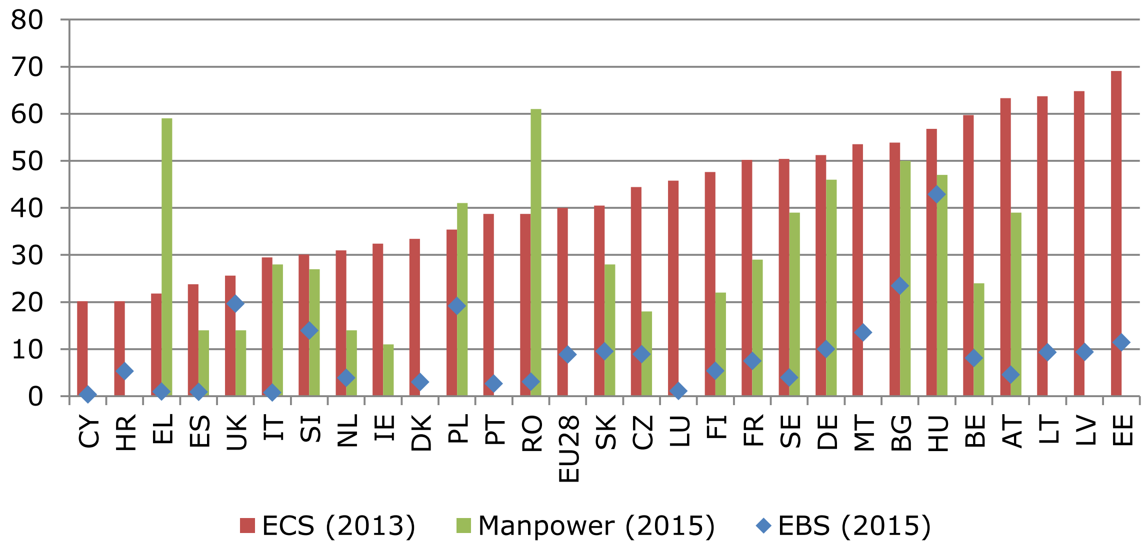
[6] The recent analysis of Sahin et al. (2014) uses an online database of vacancies to study mismatch unemployment in the U.S. across regions, sectors and occupations.

Skills shortages may occur for very specific skill profiles. To quantify such shortages, analysts usually need to rely on employer surveys on skills and/or labour shortages. The three surveys most commonly relied on are the European Business Survey (EBS, with quarterly rounds of data collection), the Manpower Talent Shortage Survey (with annual data) and the European Company Survey (ECS, carried out by Eurofound every 4 years).

It has been observed that, in some cases, employer surveys closely track the number of vacancies (European Commission, 2013; Arpaia et al., 2014). It is a question however to what extent they reflect skills shortages, and to what extent they pick up effects of the general macroeconomic environment or other factors. Their comparability across countries is also not evident. Labour shortages may have various causes, including "structural factors" like an ageing or shrinking work force and inadequacies in the labour market relevance of education and training systems, but also unattractive working conditions offered by employers or inadequacies in corporate recruitment systems (Shah and Burke, 2003; Cedefop, 2015). Employers in different countries operate in a different institutional environment, have a different distribution in terms of company size, use different hiring practices, and may have a different cultural understanding of what constitutes "difficulty in hiring".

Empirically, the results from different surveys tend to be inconsistent, leading to different rankings of EU Member States. For example, while employers in Greece report among the highest labour shortages in the Manpower survey, they report among the lowest shortages in the EBS survey (Figure 5).

Figure 5: Skills shortages reported by employers, various surveys



Notes: Countries sorted by ECS indicator. The European Company Survey (ECS) indicator reflects the share of employers who answer affirmatively to the question "Do you encounter difficulties in finding employees with the required skills?". The Manpower Talent Shortage Survey indicator measures the share of employers responding affirmatively to the question "How much difficulty are you having filling jobs due to lack of available talent?". The European Business Indicator considers the share of employers in the industry reporting that labour shortage is a major factor limiting production [Eurostat variable ei_bsin_q_r2, averaged over 4 quarters of 2015].

The questions used in these surveys are not targeted to monitor skills shortages. For example, the question asked in the EBS refers to labour shortages in general, without referring to skills. While the Manpower survey question refers to a "lack of available talent", and the ECS refers to skills directly, they do not ask which type of skills:

shortages could as well refer to attitudinal or social skills rather than vocational skills. Consequently it is difficult, solely on the basis of employer survey data, to gauge the extent of genuine skills shortages; and country-specific analysis is required (e.g. to find out which skills profiles are missing, and what are the working conditions for these skills profiles), to devise the right policy measures.

4. On-the-job skills mismatch

This section provides an overview of indicators that measure "on-the job" skills mismatch, building on earlier work by e.g. Chevalier (2003), Verhaest and Omey (2006a), Quintini (2011), and Flisi et al. (2014). Indicators are calculated in a relatively simple way based on regularly collected data that are comparable across EU Member States. In this note, skills are interpreted as "qualifications", in line with most of the existing literature in this field.[7]

4.1 Three approaches to measure on-the-job skills mismatch

Measuring skills mismatch on the job critically relies on a correct identification of the education level that is required for a job. This has proved to be challenging. Three major approaches have been taken in the literature (Tijdens and van Klaveren, 2012):

1) the subjective approach ('worker self-assessment'), where workers are asked themselves what would be the education level required for their job;

2) the objective approach ('job analysis' or 'systematic job evaluation'), where job market experts are asked to identify the education requirement based on a job description (e.g. Rumberger, 1987; McGoldrick and Robst, 1996);

3) the empirical approach ('realized matches'), where the required education level is derived from the observed mean or modal[8] education level of workers in a certain job (e.g. Verdugo and Verdugo, 1989; Kiker et al., 1997; European Commission, 2012: 360).

Each of these methodologies has its own limitations. Hartog and Jonker (1997) argue that individuals are inclined to overstate the educational requirements for their job, and that this "social desirability" effect may bias the **subjective measure** downwards. Nevertheless, in practice the subjective measure usually leads to higher instead of lower reported levels of overqualification than other measures (McGuinness, 2006). From an operational perspective, the main drawback of using the subjective measure is that it relies on data from specific surveys which are not carried out on a frequent basis.

The **objective approach** is attractive in that it relies on job market experts to define the right education level for a job, which makes it more transparent and objective, and also facilitates cross-country comparison (Flisi et al. 2014). Its major drawback is that it is only relevant if it relies on a high-quality taxonomy of job skills requirements, notably one that is up to date and sufficiently country-specific. Studies of overqualification that are considered successful in this regard include Rumberger (1987) and McGoldrick and Robst (1996) who rely on educational requirement assessments based on the US Dictionary of Occupational Titles.[9] This dictionary was

[7] Recent research work has distinguished qualification or educational mismatch from skill mismatch, arguing that qualifications are an imperfect proxy for skills.

[8] The modal education level in a given job is the education level that is most often observed among workers in that job.

[9] This dictionary was first published in 1938 as a static classification tool. With time, a more flexible database was developed to reflect the new and changing labour market needs: the Occupational

first published in 1938 as a static classification tool. With time, a more flexible database was developed to reflect the new and changing labour market needs: the Occupational Information Network (O*Net) was released at the end of the 1990s and is continuously updated (Mariani, 1999). Such a dictionary is however not always available. For cross-European analyses, no such dictionary exists as yet, but development of the European Skills, Competences, Qualifications and Occupations (ESCO) classification is in progress.[10] If EU Member States map ESCO to their national classifications, this could facilitate cross-country analysis on skill mismatch.

In the absence of a reliable dictionary, researchers have used simplified strategies to assess the incidence of overqualification. One often applied strategy uses a very simple taxonomy that crosses ISCO 1-digits job categories and ISCED 1-digit education categories and that is fixed across time and across countries. In particular, ISCO categories 1-3 are considered as "high-skilled" occupations, requiring a tertiary degree. ISCO categories 4-8 are considered as "medium-skilled" occupations, requiring an upper secondary qualification; and finally ISCO category 9 is considered as low-skilled, not requiring upper secondary education.[11] This classification was proposed by ILO (2007).

As technological progress may exert upward pressure on educational requirements for specific occupations, education requirements for specific occupations are likely to vary across countries as well as over time. For example, Livingstone (1999:74) notes the rising trend over time in employers' entry requirements (in terms of qualification) for a specific job. If one fails to account for rising skills requirements in different jobs, the measure for overqualification is likely to be upward biased.

Finally, the **empirical approach** is relatively easy to apply and draws on frequently collected data. For example, an often applied empirical measure identifies the qualification requirement for a particular occupation as the modal level of education empirically observed in that occupation (usually at the ISCO 2-digit level). Of all on-the-job skills mismatch indicators, this approach has however been criticised the most, since it implies that job skills requirements are endogenously related to the extent of overqualification in an occupation (Verhaest and Omey, 2006b; CEDEFOP, 2010: 67).

Both the objective measure and the empirical method suffer from measurement error if different jobs (with different education requirements) are clustered together in occupational categories, which usually is the case if one uses indicators at a high level of aggregation (such as ISCO 1- or 2-digit categories). This means important composition effects may be at play over time and across countries, further complicating the use of these measures.

4.2 Comparing two indicators of on-the-job skills mismatch

The discussion of the previous subsection suggests that each of the three approaches to measure on-the-job skills mismatch have strengths and limitations. It has been observed in previous analyses that the estimated extent of skills mismatch varies strongly across different measures and the correlation between different measures tends to be low (Verhaest and Omey, 2006b). This suggests that there are serious

Information Network (O*Net) was released at the end of the 1990s and is continuously updated (Mariani, 1999).

[10] A pilot version has been released in 2013; the first release of ESCO is expected by the end of 2016.

[11] ISCO 1-digit categories: 1 - Managers; 2 - Professionals; 3 - Technicians and associate professionals; 4 - Clerical support workers; 5 - Service and sales workers; 6 - Skilled agricultural, forestry and fishery workers; 7 - Craft and related trades workers; 8 - Plant and machine operators, and assemblers; 9 - Elementary occupations.

empirical challenges in identifying the extent of genuine on-the-job skills mismatch, implying that caution is needed when interpreting these indicators.

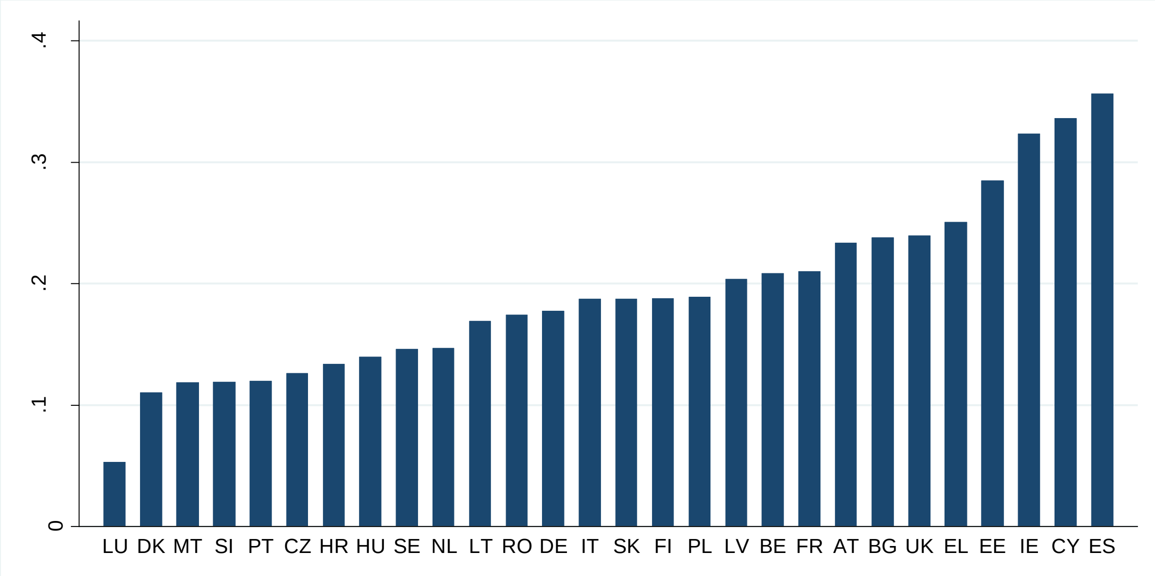
This section presents an estimate of both the objective and the empirical indicator of on-the-job skills mismatch based on the same data set, Eurostat's Labour Force Survey (2013 data).[12] The analysis focuses on possible over-qualification among tertiary graduates, as this issue has received particular attention in policy debates as well as in the academic literature. Restricting attention to the tertiary educated has two additional advantages. First, it ensures that results are not affected by composition effects.[13] Second, while some of the medium-skilled may be working in unskilled occupations, it is debatable whether any medium-skilled workers should be considered as "over-qualified" in societies that aspire to give all their students an upper secondary education to be able to successfully take part in a knowledge-based economy.

The sample used in the analysis comprises those individuals with a tertiary degree who are aged 15-64 and declare that they are working (WSTATOR = 1 or 2), ignoring those who are still studying (EDUCSTAT = 2). Individuals who do not report their education level and those who do not declare their occupational category at the ISCO-1 or 2-digit level (depending on what is required) are excluded from the analysis.

[12] The third, subjective indicator can only be estimated based on special survey data.
[13] For instance, if two countries have the same share of overqualified amongst the tertiary educated but one country has more tertiary educated than the other; we would most likely consider them as "equally good/bad performers", rather than consider the former as performing worse than the latter.

Figure 6 shows the results for the estimated share of over-qualified among high-skilled workers according to the **objective indicator.** It suggests that the highest incidence of over-qualification occurs in Spain, Cyprus, Ireland and Estonia, with shares of around 30% of the employed high-skilled population. The lowest shares of over-qualification are found in Luxembourg, Denmark, Malta and Portugal.

Figure 6: On-the-job skills mismatch, objective indicator

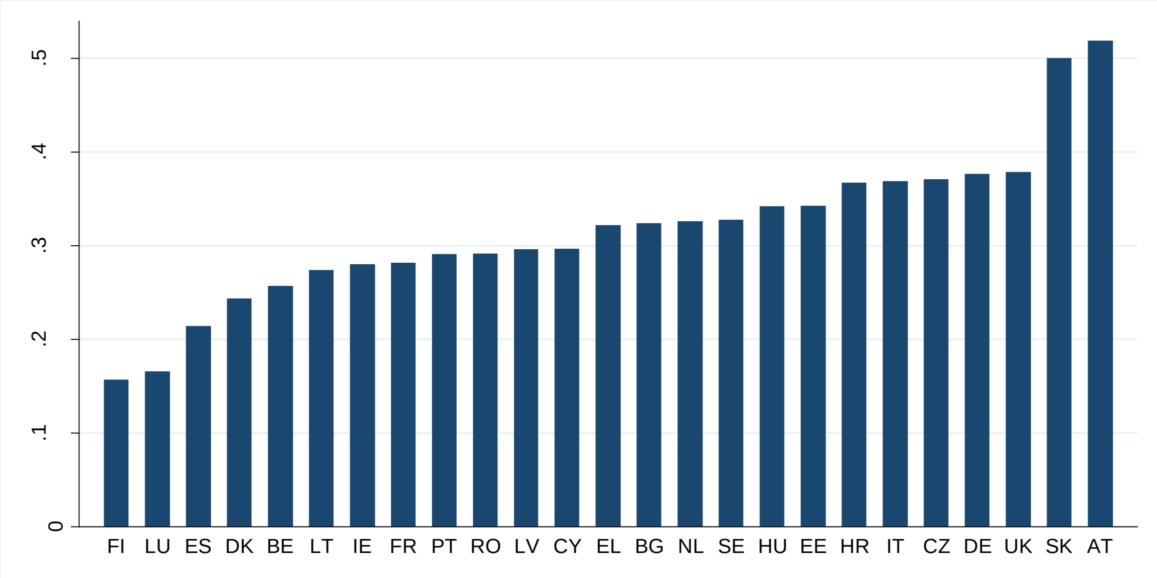


Note: Based on EU LFS data for 2013. The objective measure considers high-skilled individuals as overqualified if they work in jobs classified under ISCO4-9.

Figure 7 shows results for the estimated share of overqualified individuals among the high-skilled according to the **empirical method.** Here, the reported shares are higher – up to 50% for Slovakia and Austria. In contrast to the objective indicator shown in

Figure 6, Spain is among the Member States with the smallest share of over-qualification based on the empirical indicator, together with Finland, Luxembourg, Denmark and Belgium.

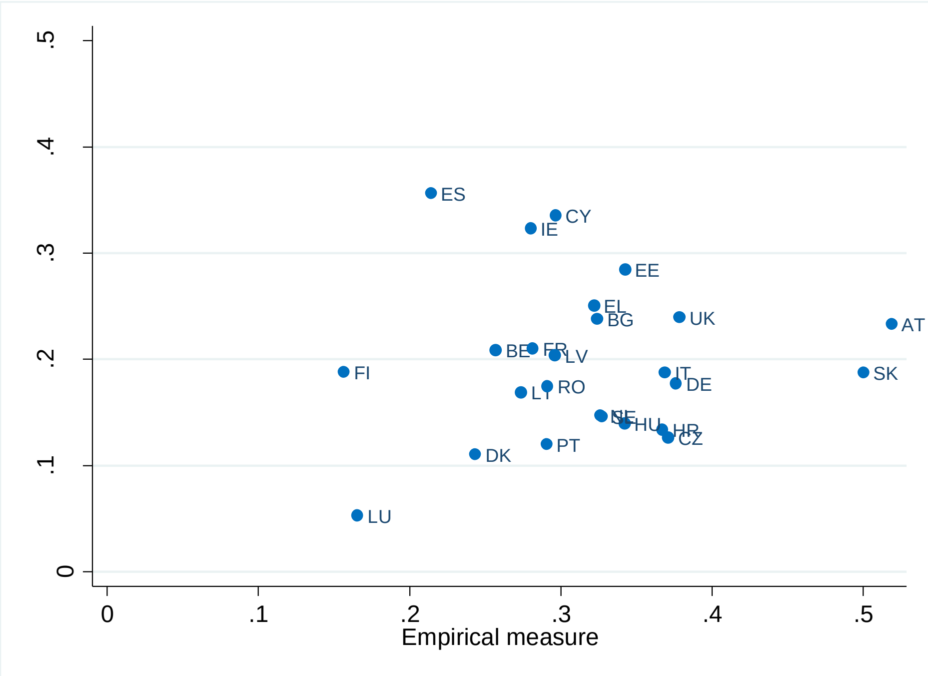
Figure 7: On-the-job skills mismatch, empirical indicator



Note: Based on the EU Labour Force Survey for 2013. The empirical measure considers high-skilled individuals as overqualified if their education level is above the modal education level observed in their ISCO 2-digit job category. MT, PL and SI are missing from this graph as the LFS data do not contain information on ISCO 2-digit job classification for these countries.

Figure 8 presents both indicators in the same scatter plot. It shows that not only the level of over-qualification varies significantly across the two measures, but also the ranking of countries is very different. The figure suggests that there is no correlation between both measures. This aligns with earlier findings by Verhaest and Omey (2006b). It suggests that there are indeed significant challenges in empirically identifying on-the-job skills mismatch, and calls for caution in the interpretation of these indicators.

Figure 8: The objective and empirical measures of on-the-job skills mismatch for high-skilled individuals, 2013



Note: Based on the EU Labour Force Survey for 2013. No information is available on ISCO 2-digit job classification (required for calculation of the empirical measure) for MT, PL and SI.

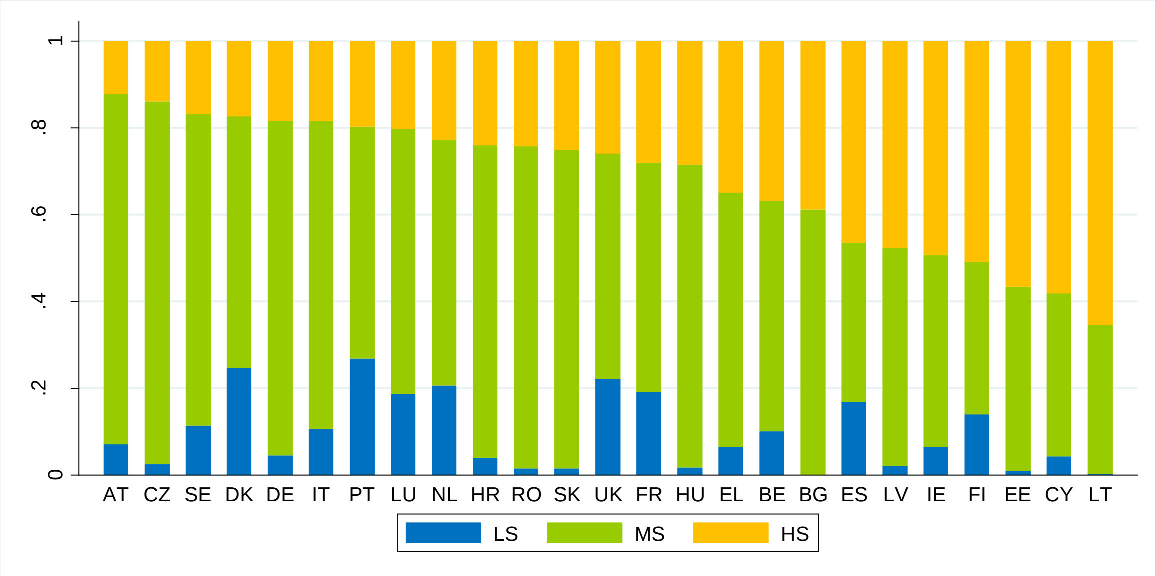
4.3 Factors influencing indicators of on-the-job skills mismatch

There are several reasons why a considerable share of the high-skilled that show up as 'overqualified' in the objective indicator should not necessarily be a concern for policy makers. First, some of the observed 'over-qualification' simply picks up differences in national education systems, where one system cannot necessarily be considered as superior to the other.

When looking in more detail at the occupations taken by individuals considered as overqualified, it is observed that 70% of them are in ISCO 1-digit categories 4 and 5, comprising "Clerical support staff" and "Services and sales staff".

Such jobs are in some EU Member States typically taken up by individuals with an upper–secondary (or post-secondary, non-tertiary) VET degree, while in other Member States they are more often taken up by individuals who follow general education at secondary education level, potentially followed by a (short) tertiary program. To illustrate this point, Figure 9 shows the educational distribution across Member States for customer service clerks, which is the ISCO 2-digit category with the highest share of over-qualified workers at the EU-level. In Lithuania, Cyprus, and Estonia, customer service clerk jobs are predominantly taken up by high-skilled individuals. In Austria, the Czech Republic, Germany and Sweden, they are more often taken up by individuals with an upper secondary qualification.

Figure 9: Educational distribution of customer service clerks (ISCO 42) across EU Member States



Note: EU Labour Force Survey 2013.

It is difficult to make a correct judgement on whether it is better to draw clerical support staff and services and sales staff from VET programs or from higher education, after general upper secondary education. On the one hand, one could argue that the former brings workers faster to the labour market, and may engender savings in the education system. On the other hand, some researchers argue that workers with more sector or occupation-specific skills are less flexible in shifting to new jobs when their own sectors or occupation is adversely affected by a cyclical downturn or a structural decline (CEDEFOP, 2010). Randstad (2012) finds that countries with lower "vertical mismatch" tend to have higher "horizontal mismatch" which means there could be a trade-off between both.[14]

Another issue that is potentially of higher policy concern is that some studies have linked the occurrence of over-qualification to heterogeneity in skills within qualification levels (Quintini, 2011). For example, Green (1999) finds, based on a longitudinal study, that pupils who scored high on a math test at the age of 16 were less likely to be overqualified later on in life. Dolton and Vignoles (2000) and Green and Zhu (2008) arrive at similar conclusions.

Some researchers have suggested that the increase in over-qualification was a result of the expansion of tertiary education. Two major arguments have been invoked in this regard, one relating to supply, another to demand. The supply argument states that the expansion of tertiary education may have lowered the standards and allowed individuals of lower ability to obtain a tertiary degree. This would result in more over-qualification if graduates turn out not to have sufficient skills for a high-skilled job. This argument is based on signalling theory (Spence, 1973) where education is considered to have mostly a signalling function, but not necessarily increases the skills of graduates. The demand argument states that the labour market can absorb only a certain number of tertiary graduates; any tertiary graduates in excess of this number will need to take up medium-skilled or even low-skilled positions. Quintini (2011)

[14] Vertical mismatch occurs when a worker's skills level is above the skills level required for his job; horizontal mismatch occurs when a worker's field of study does not match his field of work.

warns about the "lump-of-labour fallacy" in this context, an incorrect view that holds that the number of jobs in an economy is fixed. As she explains, the availability of tertiary graduates can encourage firms to move towards production technologies that require a more intensive use of high-skilled workers. An illuminating example is the emergence of innovation hubs around university campuses (Youtie and Shapira, 2008).

Figure 26 in Annex B presents the trends in the objective measure of over-qualification over the past decade alongside with trends in the share of high-skilled among employees. It shows that while in some countries, over-qualification has increased with a growing share of high-skilled (e.g. Czech Republic, Hungary, Slovakia); in many countries it has remained stable (e.g. Belgium, Spain, Finland) – and in some countries, it has even declined with a growing share of high-skilled (e.g. Germany, Lithuania).

5. Conclusion

The issue of skills mismatch has gained renewed attention in recent years. Several indicators have been used to quantify it. This note reviews three major dimensions of skills mismatch: macroeconomic skills mismatch, specific skills shortages, and on-the-job skills mismatch, together with indicators focusing on each of these dimensions.

Macroeconomic skills mismatch indicators provide useful information for macroeconomic policies. In this context, this note presents a set of dispersion measures of employment and unemployment by skill levels that are useful for the regular monitoring of macroeconomic skills mismatch. High discrepancies of the labour market outcomes of high, medium, and low skilled workers suggest that there is a significant gap between the skills of the working age population and the skills needed in the economy. The analysis provides some country specific insights. A few Member States seem to exhibit high discrepancies between both the employment and the unemployment rates of high, medium, and low-skilled workers (Belgium, Bulgaria, Hungary, Ireland, Lithuania, and Malta), indicating the presence of significant macroeconomic skills mismatches. For some other countries, a deeper country-specific analysis is needed to assess macroeconomic skills mismatches.

Measures on specific skills shortages experienced by recruiting employers are theoretically interesting to signal potential gaps in the connection between education systems and the labour market; but the various employer-survey based quantitative measures appear not to deliver consistent results across countries. This points to a need to rely more on country-specific qualitative data. It is also important to explore the drivers of the reported shortages, and whether they can be addressed through changes in the education and training system.

The indicators of on-the-job skills mismatch measure the discrepancy between the skills workers have and the skills needed to perform their job. From a theoretical perspective, these measures are also interesting in the context of ensuring quality and labour market relevance of the (higher) education system. However, this note shows that there are empirical challenges in assessing on-the-job skills mismatch based on regularly updated data sources and simple methodologies. To get at reliable assessments of genuine on-the-job skills mismatch, more detailed country-specific analysis is required (e.g. looking at labour market outcomes and wages by field of education).

The challenges encountered in measuring the labour market relevance of education should however not divert attention away from the fact that it is important to ensure that education systems are responsive to the labour market, by strengthening education and training systems (including adult education), involving employers in the design of educational curricula, and through policies that support the visibility, recognition and validation of skills and qualifications, and improve transparency of the labour market and matching efficiency. In this context, attention should be paid not only to short-term labour market requirements, but also to ensuring adaptability and flexibility to changes in the labour market structure, as labour markets are changing at an ever faster pace.

References

Allen, J., van der Velden, R. (2011): *The flexible professional in the knowledge society: New challenges for higher education.* Springer.

Arpaia, A., Kiss, A., Turrini, A. (2014): Is unemployment structural or cyclical? Main features of job matching in the EU after the crisis. European Economy Economic Papers 527. Brussels: European Commission.

Battu, H., Belfield, C.R., Sloane, P.J. (1999): Overeducation among graduates: a cohort view. *Education Economics*, 17(1): 21-38.

Blanchard, O.J., Diamond P. (1989): The Beveridge Curve, *Brookings Papers on Economic Activity*, (1): 1-76.

CEDEFOP (2010): *The skill matching challenge: Analysing skill mismatch and policy implications*. Luxembourg: Publications Office of the European Union.

CEDEFOP (2014): Skill mismatch: more than meets the eye. Briefing note, European Centre for the Development of Vocational Training.

Chevalier, A. (2003): Measuring over-education. *Economica*, 70(279): 509-531.

Diamond, P.A., Sahin, A. (2014): Shifts in the Beveridge curve. Federal Reserve Bank of New York Staff Reports, No 687.

Dixon, R. (2006): Male and female unemployment rate dispersion in a large Australian city. *Australasian Journal of Regional Studies*, 12 (2): 205-216.

Dolton, P.J., Vignoles, A. (2000): The incidence and effects of overeducation in the UK graduate labour market. *Economics of Education Review*, 19(2): 179-198.

Elsby, M.W.L., Michaels, R., Ratner, D. (2015): The Beveridge Curve: A Survey. *Journal of Economic Literature* 53 (3), 571-630.

ECB (2012): Euro Area Labour Markets and the Crisis. Occasional Paper Series No. 138. Task Force of the Monetary Policy Committee of the European System of Central Banks, European Central Bank, Frankfurt am Main.

European Commission (2013): Labour Market Developments in Europe 2013. European Economy 6.

Flisi, S., Goglio, V., Meroni, E., Rodrigues, M., Vera-Toscano, E. (2014): Occupational mismatch in Europe: Understanding overeducation and overskilling for policy making. JRC Science and Policy Reports, European Commission Joint Research Centre.

Green, F., Zhu, Y. (2008): Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. University of Kent, Department of Economics Discussion Papers KDPE 08/03.

ILO (2007): Report Meeting of Experts on Labour Statistics. Updating the International Standard Classification of Occupations (ISCO). International Labour Organization, Geneva.

IMF (2001): Labor markets in hard-peg accession countries: the Baltics and Bulgaria. IMF Country Report No. 01/100.

Jackman, R., Roper, S. (1987): Structural Unemployment. *Oxford Bulletin of Economics and Statistics,* 49(1), 9–36.

Jones, M.K., Jones, R.J., Latreille, P.L., Sloane, P.J. (2009): Training, job satisfaction and workplace performance in Britain: evidence from WERS 2004. *Labour*, 23(s1):139-175.

Kiker, B., Santos, M., Mendes de Oliveira, M. (1997): Overeducation and undereducation: evidence for Portugal. *Economics of Education Review*, 16(2): 111-125.

Layard, R., Nickell, S., Jackman, R. (2005): *Unemployment: Macroeconomic performance and the labour market.* Second Edition, Oxford University Press.

Livingstone, D.W. (1999): The education-jobs gap: Underemployment or economic democracy? Ontario: Garamond Press.

Mahy, B., Rycx, F., Vermeylen, G. (2015): Educational mismatch and firm productivity: do skills, technology and uncertainty matter? IZA DP No. 8885.

Mariani, M. (1999): Replace with a database: O*NET replaces the Dictionary of Occupational Titles. *Occupational Outlook Quarterly*, Spring 1999.

Martin, R. (1997): Regional Unemployment Disparities and their Dynamics. *Regional Studies*, 31(3): 237-252.

McGoldrick, K., Robst, J. (1996): Gender differences in overeducation, a test of the theory of differential overqualification. *American Economic Review*, 86(2): 280-284.

McGowen, M.A., Andrews, D. (2015): Labour market mismatch and labour productivity: Evidence from PIAAC data. OECD Economics Department Working Paper No. 1209.

McGuinness, S. (2006): Overeducation in the labour market. *Journal of Economic Surveys*, 20(3): 387-418.

McGuinness, S., Sloane, P.J. (2009): Labour market mismatch among UK graduates: an analysis using REFLEX data. IZA DP No. 4168.

Nickell, S. (1982): The Determinants of Equilibrium Unemployment in Britain. *The Economic Journal*, 92(367), 555–575.

Pellizzari, M., Fichen, A. (2013): A new measure of skills mismatch: theory and evidence from the survey of adult skills (PIAAC). OECD Social, Employment and Migration Working Paper 153, Paris: OECD.

Perry, G.L. (1970): Changing Labor Markets and Inflation. *Brookings Papers on Economic Activity*, 3: 411-441.

Quintini, G. (2011): Over-qualified or under-skilled: A review of existing literature. OECD Social, Employment, and Migration Working Paper 121, Paris: OECD. Randstad (2012): Into the gap: Exploring skills and mismatches. International database on employment and adaptable labour. SEO Economic Research, Randstad.

Rumberger, R. (1987): The impact of surplus schooling on productivity and earnings. *Journal of Human Resources*, 22(1): 24-50.

Sahin, A., Song, J., Topa, G., Violante, G.L. (2014): Mismatch unemployment, *American Economic Review* 104 (11): 3529-3564.

Shah, C., Burke, G. (2003) Skills shortages: concepts, measurement and implications. Working Paper No. 52, Monash University-ACER Centre for the Economics of Education and Training.

Spence, M. (1973): Job Market Signalling, *Quarterly Journal of Economics* 87: 355-374.

Tijdens, K., van Klaveren, M. (2013): A skill mismatch for migrant workers? Evidence from WageIndicator survey data. Paper presented at the Nederlandse Arbeidsmarkt Dag 2013, Den Haag.

Verdugo, R., Verdugo, N. (1989): The impact of surplus schooling on earnings, *Journal of Human Resources*, 22(4): 690-695.

Verhaest, D., Omey, E. (2006a): The impact of overeducation and its measurement. *Social Indicators Research*, 77: 419-448.

Verhaest, D., Omey, E. (2006b): Measuring the incidence of over- and undereducation. *Quality and Quantity*, 40: 783-803.

Youtie, J., Shapira, P. (2008): Building and innovation hub: a case study of the transformation of university roles in regional technological and economic development. *Research Policy*, 37(8): 118-1204.

Annex A: Statistical measures of dispersion

A.1. An overview of measures of dispersion

This section introduces four often-used measures of dispersion, applied to the example of the dispersion of employment rates. The four measures are: (a) absolute dispersion; (b) relative dispersion; (c) (weighted) standard deviation; and (d) (weighted) coefficient of variation.

The dispersion measures are defined over n skill groups indexed by $i = 1, \dots, n$. (The indicators in Section 2 are calculated over $n = 3$ skill groups.) The number of employed individuals in group i is denoted with E_i, while total employment is E_T. Analogously, the working age population in group i and overall are P_i and P_T. The employment rate is defined as $e = E/P$.

(a) The **absolute dispersion** of employment rates (*E-AD*) is the sum of skill groups' weighted absolute deviations from the overall employment rate:

$$SMI_{E-AD} = \sum_{i=1}^{n} \left| \frac{P_i}{P_T} (e_i - e_T) \right| \tag{A.1}$$

In a simple numerical example, if there are only two skill groups of equal size in the population ($n = 2$), one having an employment rate of 50% while the other 70%, the absolute deviations from the overall employment rate will be 10% each, and the indicator will have a value of 10%.

(b) The **relative dispersion** of employment rates (*E-RD*) is equal to the ratio of the absolute dispersion and the overall employment rate:

$$SMI_{E-RD} = \frac{1}{e_T} \sum_{i=1}^{n} \left| \frac{P_i}{P_T} (e_i - e_T) \right| = \sum_{i=1}^{3} \left| \frac{E_i}{E_T} - \frac{P_i}{P_T} \right| \tag{A.2}$$

In the simple numerical example described above, the absolute dispersion is equal to 10% while the overall employment rate is 60%, thus the relative dispersion is equal to 1/6.

(c) The weighted **standard deviation** of employment rates (*E-WSD*) is given by the following formula:

$$SMI_{E-WSD} = \sqrt{\sum_{i=1}^{n} \frac{P_i}{P_T} (e_i - e_T)^2} \tag{A.3}$$

In the simple numerical example above, the weighted standard deviation of employment rates is equal to their absolute dispersion (10%). More generally, the difference between both indicators is that the standard deviation gives more weight to large absolute deviations from the mean. The unweighted standard deviation is a slight variant that does not take into account the size of the skill groups.

(d) The weighted **coefficient of variation** of employment rates (*E-WCV*) is equal to the ratio of the standard deviation and the overall employment rate:

$$SMI_{E-WCV} = \frac{1}{e_T}\sqrt{\sum_{i=1}^{n} \frac{P_i}{P_T}(e_i - e_T)^2} \tag{A.4}$$

In the simple numerical example above, the weighted coefficient of variation of employment rates is equal to their relative dispersion (1/6). More generally, the difference between both indicators is that the coefficient of variation gives more weight to large absolute deviations from the mean. This indicator also has an unweighted variant that does not take into account the size of skill groups.

Analogous indicators for the **unemployment rate** are easy to define: in the equations above, the number of unemployed (U) should be substituted for employment (E), active population (L for labour force) should be substituted for working-age population (P) while the unemployment rate ($u = U/L$) should be substituted for the employment rate ($e = E/P$).

A.2. Previous applications to labour market mismatch

Variants of the *E-RD* indicator have been calculated by Estevao and Tsounta (2011), ECB (2012). The present note updates work presented in European Commission (2013) and Arpaia et al. (2014).

Many contributions in the previous literature calculated similar indicators based on unemployment rates. Perry (1970) calculates the *U-RD* indicator over age-sex groups. Layard et al. (2005, Chapter 6) calculate a variant of the (unweighted) coefficient of variation of unemployment rates (*U-CV*) by industry, occupation and region.[15] In studies focused on the regional disparities of unemployment, Martin (1997) calculates both the absolute and the relative dispersion indicator (*U-AD, U-RD*), while Dixon discusses the weighted standard deviation (*U-WSD*) besides the absolute dispersion (*U-AD*). Eurostat publishes the weighted coefficient of variation of regional unemployment rates (*U-WCV*).

Empirically, the various dispersion measures are highly correlated with each-other, especially the indicators based on employment rates.

[15] They express this indicator as $var(u_i/u_T)$, which can be shown to be equivalent to the square of U-CV.

Annex B: Auxiliary figures

B.1. Explanatory remarks

The figures in this Annex present the data series that are used to generate the skills mismatch indicators described in Section 2. They allow the reader to explore the developments that drive changes in the mismatch indicators. In general, however, country-specific conclusions can only be made based on the analysis of a broader set of indicators.

Data used are quarterly data based on the European Labour Force Survey, published by Eurostat.

In contrast to previous work reported in European Commission (2013) and Arpaia et al. (2014), structural breaks have not been corrected. The occurrence of structural breaks is natural in survey-based data. Breaks are typically related to updates of the sampling or weighting methodology by National Statistical Offices conducting the Labour Force Survey, often related to the decennial census (in Figure 10, apparent breaks occur in AT, DE, EL, IT, LT, NL, PL, RO). At other times, structural breaks are attributable to a change in the classification of national qualifications (in Figure 11, apparent breaks occur in DK, DE, LU, SE, UK).

Structural breaks are not corrected in this note for two main reasons. First, the criteria of finding and the methodology of correcting structural breaks are, by necessity, somewhat arbitrary. Second, corrections reduce the transparency and reproducibility of the results. The only corrections made were of one kind: the beginning of time series was cut if a visible structural break was near the beginning of the original series.

The existing structural breaks rarely affect the skills mismatch indicators. One exception seems to be in Germany between 2011 and 2014 and is related to the estimated low-skilled population (observable also in Figure 11, Figure 19, and Figure 22).

Time series depicted in this Annex have not been smoothed (unlike the mismatch indicator in Figure 1 in the main text). This leads to differences across countries regarding the seasonality of the data. However, trends captured by mismatch indicators are largely unaffected by the seasonal variation in the data.

B.2. Figures

Figure 10: Working-age population (age 15-64), all skill levels (million)

Figure 11: Share in working-age population by skill level (age 15-64)

Figure 12: Active population, age 15-64, all skill levels (million)

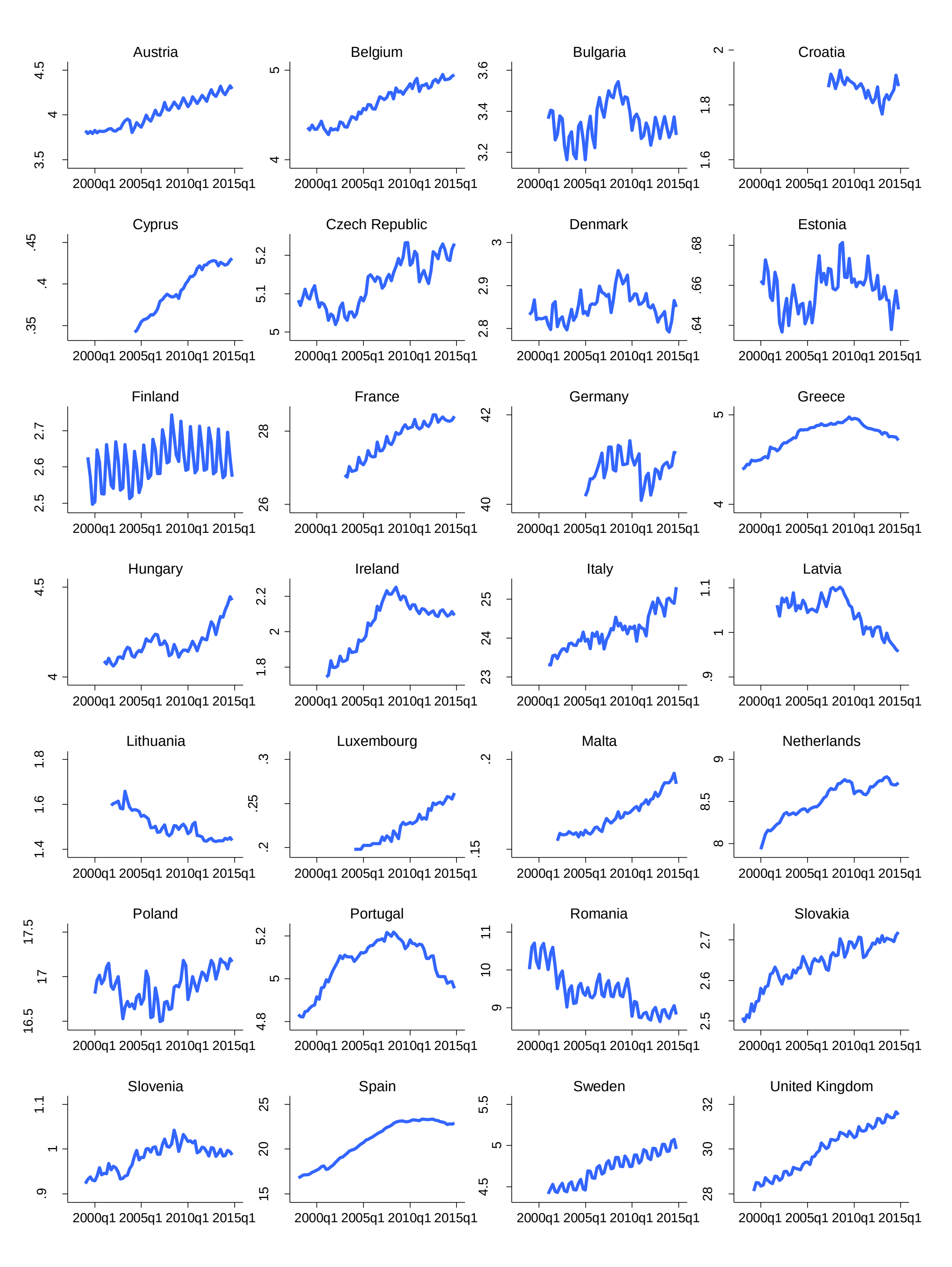


Figure 13: Share in active population by skill level (age 15-64)

Figure 14: Employment, age 15-64, all skill levels (million)

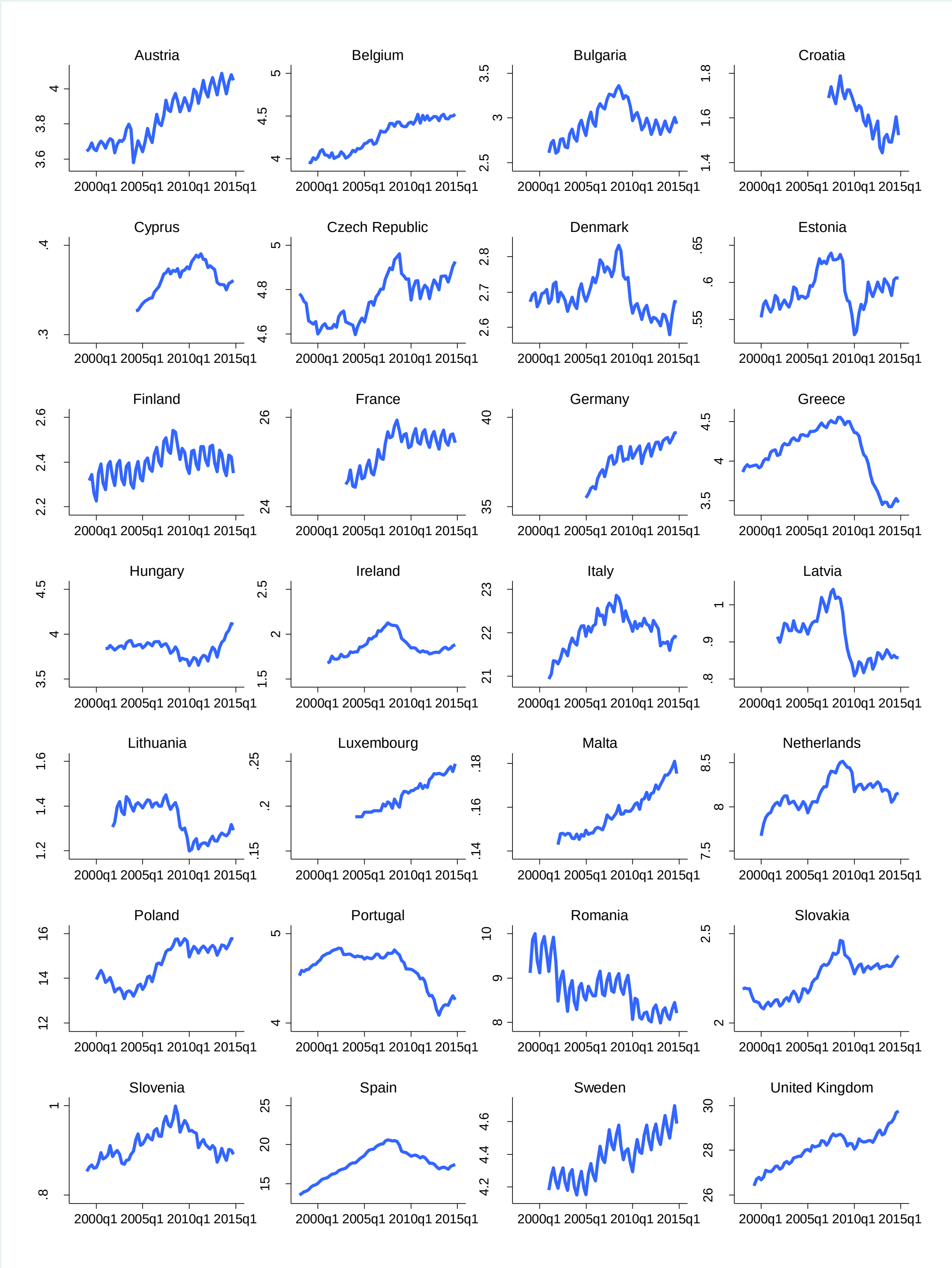


Figure 15: Share in employment by skill level (age 15-64)

Figure 16: Unemployment, age 15-64, all skill levels (thousand)

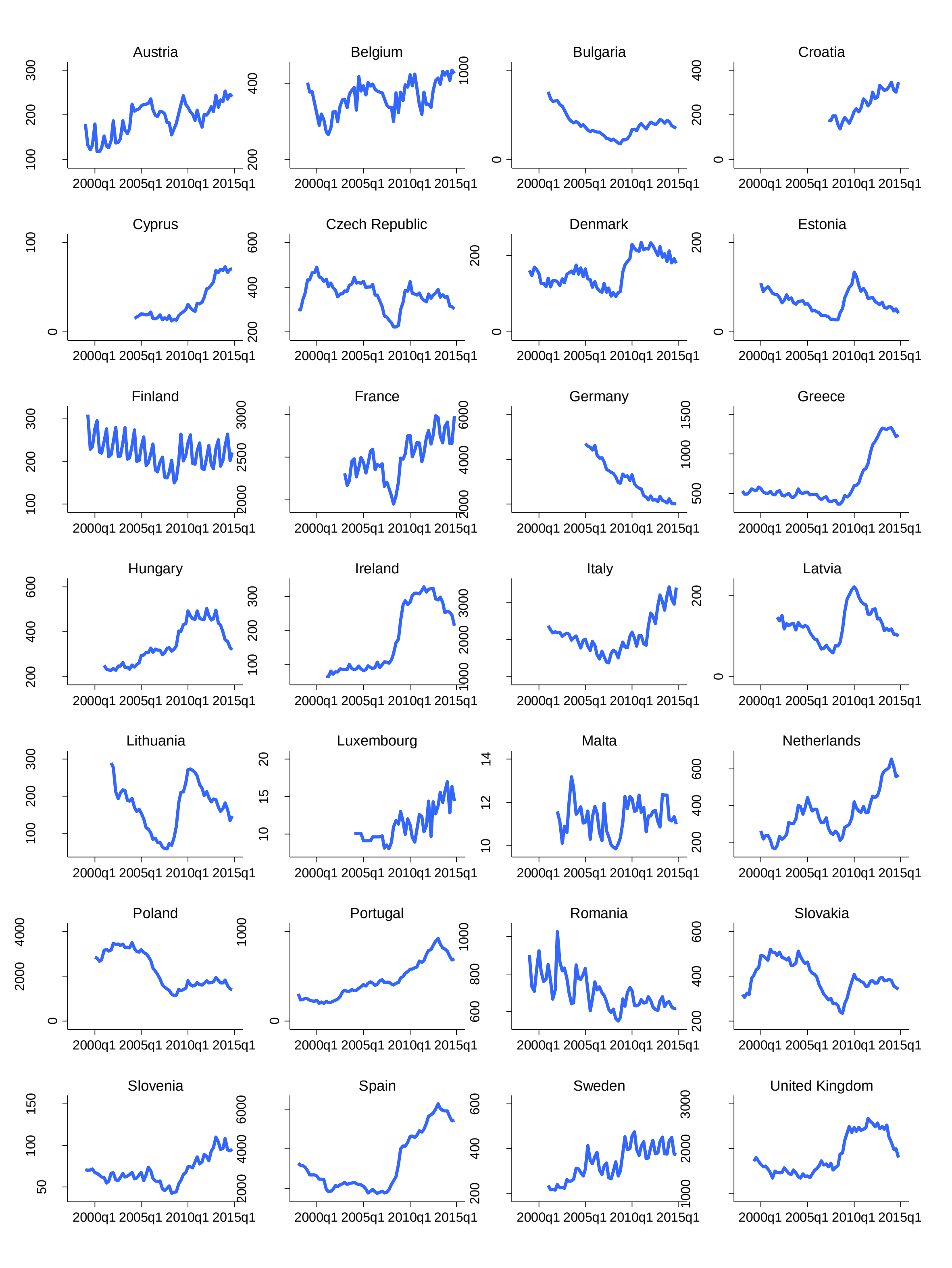


Figure 17: Share in unemployment by skill level (age 15-64)

Figure 18: Employment rate, age 15-64, all skill levels (percent)

Figure 19: Employment rate by skill level, age 15-64 (percent)

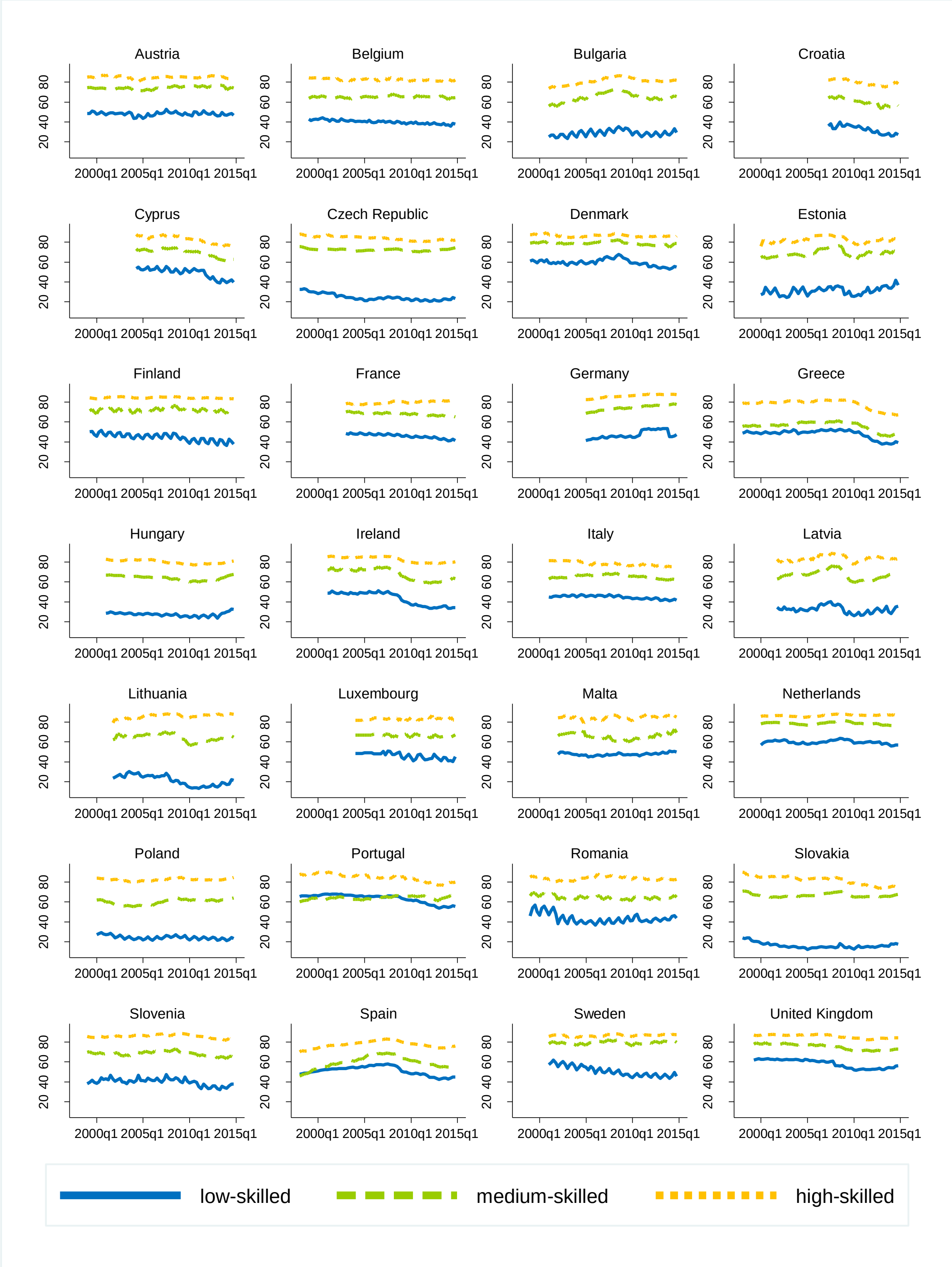


Figure 20: Unemployment rate, age 15-64, all skill levels (percent)

Figure 21: Unemployment rate by skill level, age 15-64 (percent, varying scale)

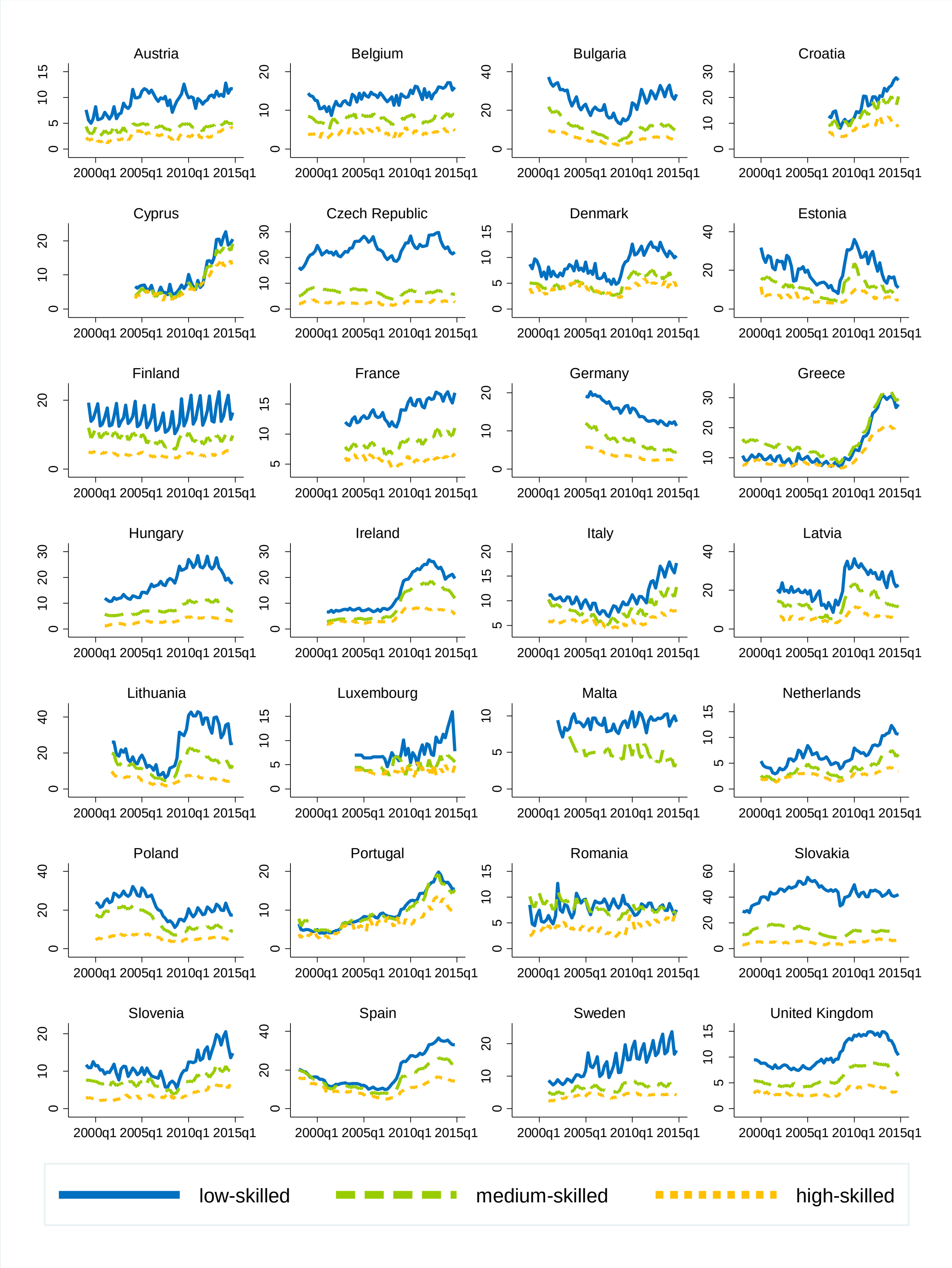
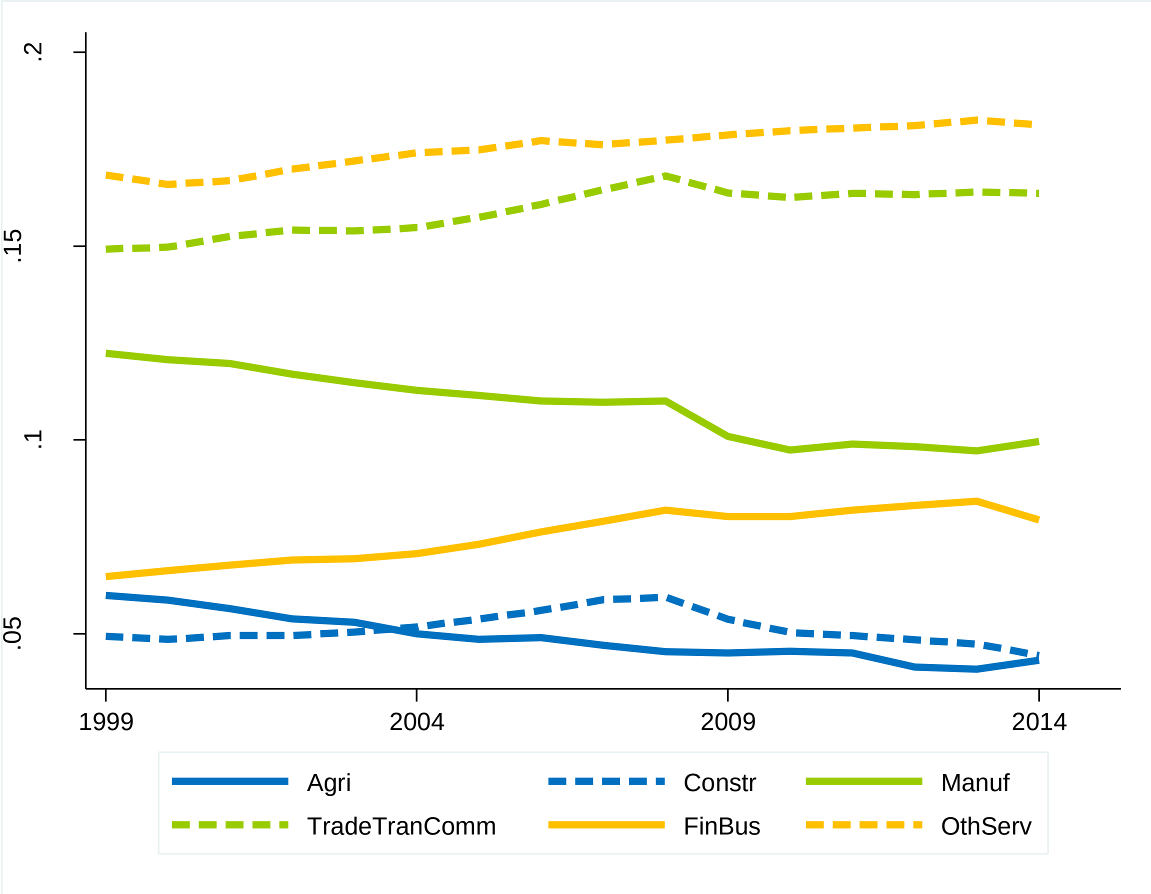


Figure 22: Components of the E-RD indicator: Deviation of skill groups' share in employment from their share in population, age 15-64

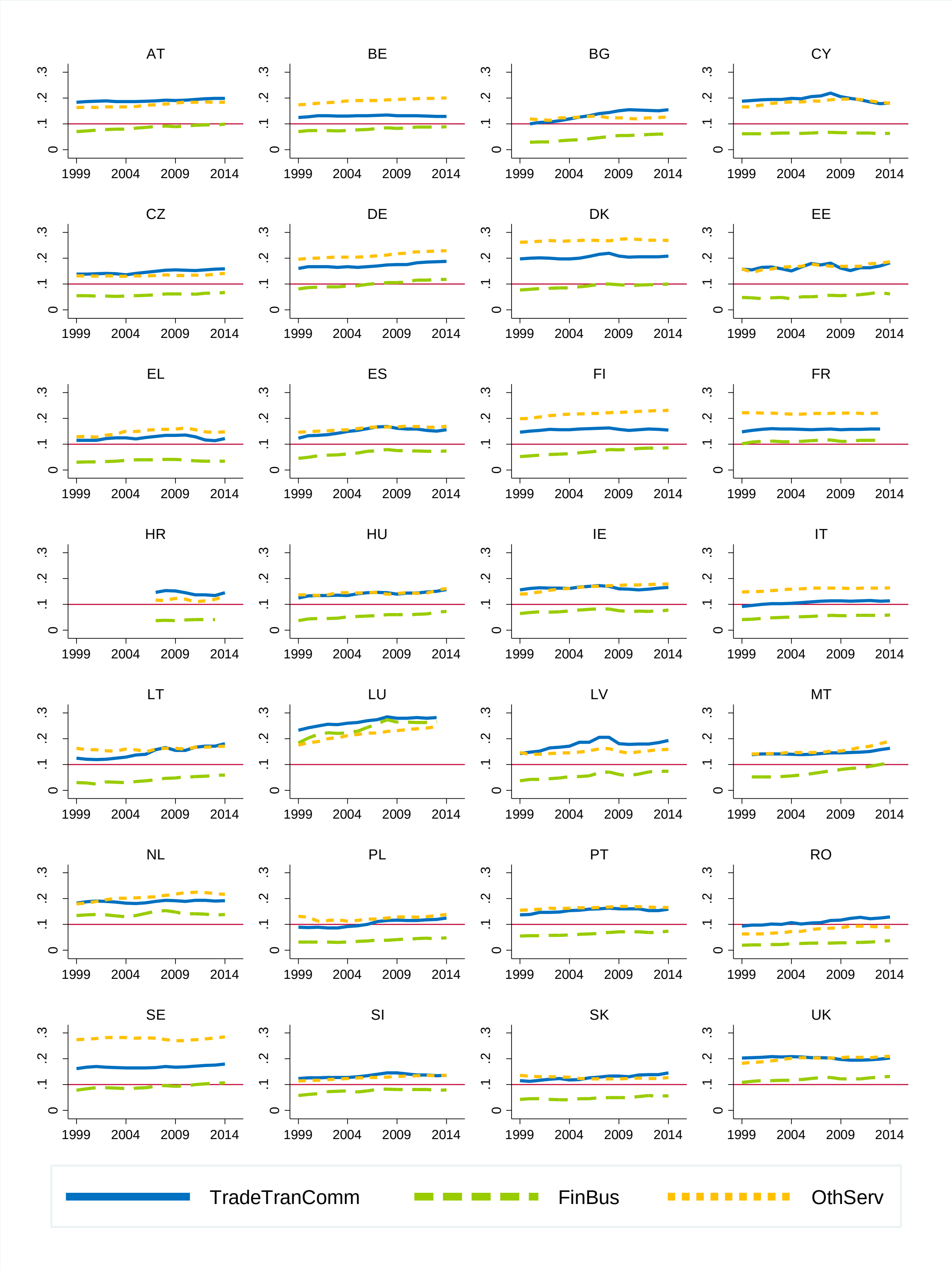
Figure 23: Employment share of sectors, all EU



Notes: The figures represent trends in EU-averages of employment shares: employment shares have first been calculated at the EU Member States level and then averaged. *TradeTranComm* stands for "Trade, Transport, Accommodation and food, Information and Communication" (NACE rev. 2 codes G-J); *FinBus* stands for "Finance and business services and professional activities" (NACE rev. 2 codes K-N); and *OthServ* stands for other services including public administration, education, health, the socio-cultural sector, personal services such as hairdressers, activities of households as employers, and activities of extraterritorial organizations (NACE rev. 2 codes O-U)

Figure 24: Employment share of agriculture, manufacturing and construction, by Member State

Figure 25: Employment share of service sectors, by Member State



Note: For a definition of the sectors, see note to Figure 21.

Figure 26: Trends in the objective measure of "overqualification" among high-skilled employees and in the share of high-skilled among employees

Note: Source: own calculations based on EU-SILC 2000-2013 data

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