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Skills mismatch and productivity in the EU

Written by Anneleen Vandeplas and Anna Thum-Thysen
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Abstract

This paper analyses different dimensions of skills mismatch (notably 'macro-economic skills mismatch', 'skills shortages', and 'on-the-job skills mismatch') and their empirical relationship with labour productivity. Macro-economic skills mismatch arises when the skills distribution differs between the available workers and those that get hired. Skills shortages occur when employers encounter difficulties to fill their vacancies. On-the-job skills mismatch (overqualification or underqualification) refers to a discrepancy between the qualification level of a jobholder and the requirements for that particular job.

Our data suggest that certain types of skills mismatch are indeed on the rise in the EU, notably skills shortages and overqualification. Other types are on a long-term declining trend (e.g. underqualification) or follow more complex patterns over time (e.g. macro-economic skills mismatch). There are also significant differences across EU Member States in the levels of these indicators. We further suggest that theoretical predictions on the relationship between skills mismatch and productivity depend on the dimension of skills mismatch considered. Our empirical analysis suggests a negative relationship between macro-economic skill mismatch and labour productivity and – as a sign of a buoyant economy - a positive relationship between skills shortages and labour productivity. With regard to on-the-job skills mismatch, our data confirm earlier findings from the economic literature: when comparing a mismatched with a well-matched worker within the same occupation, overqualification raises and underqualification reduces productivity. When comparing a mismatched with a well-matched worker within the same qualification level, overqualification reduces and underqualification increases productivity.

Our results imply a positive link between skills supply and productivity. However, to realise the full potential of higher skills, skills should be labour market relevant and skilled workers need to be matched with jobs that use these skills. Therefore upskilling policies should ideally be accompanied by policies that assure quality and labour market relevance of acquired skills, policies that foster a general upgrading of jobs such as business regulations allowing for firm entry, growth, sectoral reallocation and policies supporting labour mobility and innovation.

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Contact:

Anneleen Vandeplas, European Commission, Directorate-General for Economic and Financial Affairs, anneleen.vandeplas@ec.europa.eu; Anna Thum-Thysen, European Commission, Directorate-General for Economic and Financial Affairs, anna.thum-thysen@ec.europa.eu

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Unit ECFIN B2 – Assessment and benchmarking of national reforms

Contact: Anneleen Vandeplas, Anna Thum-Thysen

E-mail: anneleen.vandeplas@ec.europa.eu
anna.thum-thysen@*ec.europa.eu*

European Commission
B-1049 Brussel

European Commission
Directorate-General for Employment Social Affairs and Inclusion
Directorate A

1. INTRODUCTION

Human capital is a major driver of inclusive growth. As a consequence of ongoing trends such as progressive globalization, demographic change, technological change and digitalisation, jobs are becoming increasingly skills-intensive. Innovation, which heavily relies on advanced knowledge, is a key contributing factor to productivity growth, the main source of growth for EU Member States today. These developments underline the increasing importance of human capital, and the need to foster a good match between the demand for and the supply of skills.

Some have argued that there are increasing mismatches between the skills or qualifications the work force has on the one hand and the skills or qualifications required by the economy, as the demand for skills is changing rapidly as a result of the ongoing processes of structural change listed above.[1] There is also a concern that the onset of the economic crisis in 2008-2009 has exacerbated skills mismatch, as previously rapidly expanding sectors employing less-skilled labour - such as the construction sector - experienced severe difficulties.[2] Moreover, there are concerns that these mismatches are hampering productivity growth, which has been sluggish since the mid-1990s.[3]

This note reviews different dimensions of skills mismatch (at the aggregate level) and describes how they vary across EU Member States, as well as over time. It then explores the empirical relationship between these skills mismatch measures and labour productivity. The note highlights that the relationship between skills mismatch and productivity is not as clear-cut as it may seem at first sight: the various different concepts of skills mismatch that are being discussed in the literature and by policymakers imply very different theoretical and empirical conclusions on both the sign and the size of their relationship with productivity. We find a positive relationship between skills shortages and labour productivity, and a negative relationship between macro-economic skill mismatch and labour productivity, while controlling for the output gap. With regard to on-the-job skills mismatch, our data seem to confirm earlier findings from the economic literature. Notably, when comparing with well-matched workers in the same occupation, overqualification raises productivity and underqualification reduces it. When comparing with well-matched workers with the same qualification level, however, overqualification reduces and underqualification increases productivity. Our work goes beyond earlier work by McGowan and Andrews (2015a) by being more comprehensive in the dimensions of skills mismatch considered. Moreover, in contrast with their paper, ours concentrates on aggregate labour productivity.

To enhance a positive link between skills and productivity, the note argues in favour of policies aiming at upskilling of the workforce, which should ideally be accompanied by a general upgrading of jobs in order to put these higher skills in their best use.

The note is organised as follows: Section 2 provides an overview of the different concepts or dimensions of skills mismatch which have been described and analysed in the economic literature. Section 3 explores the relationship (across countries and over time) between labour productivity and a set of four different measures of skills mismatch that can be easily constructed based on data readily available through Eurostat. It first discusses our prior expectations on the sign and size of the relationship with productivity based on economic theory, and then the observed empirical results. Finally, Section 5 concludes and provides a set of general policy implications.

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[1] For example, Toner (2011) argues, that economies of today need workers with a combination of technical competences and generic or transferable/trans-occupational skills, such as problem-solving, creativity, teamwork and communication skills. Durbin (2004) argues that raising productivity requires entrepreneurial skills (to identify and respond to market and innovation opportunities); managerial skills (to provide leadership and organise production processes in the most effective way); and technical skills (to increase the effectiveness of production and take advantage of technological improvements).

[2] see e.g. ECB (2012), European Commission (2016)

[3] e.g. McGowan and Andrews (2015a) or Mavromaras et al. (2009)

2. SKILLS MISMATCH IN THE EU: AN OVERVIEW OF DIFFERENT MEASURES

Skills mismatch is a broad concept that is meant to reflect a suboptimal match between workers and jobs in terms of skills and/or qualifications. While qualifications relate to formally certified undertaken education and training, skills are the abilities an individual actually possesses and may have been acquired through informal learning processes. Notwithstanding the important distinction between skills and qualifications, for the purpose of this note we will refer to "skills mismatch" rather than "qualification mismatch" for reasons of brevity but also because the former is a more standard term in the research literature. Some degree of mismatch naturally occurs as a result of labour market frictions in the short term (Kiss and Vandeplas, 2015). When mismatch is more broad-based and persistent, it becomes a stronger concern to policymakers.

Two major approaches have been used in the literature. On the one hand, the literature has considered mismatches between individuals available for work and the available jobs. Such mismatches give rise to the coexistence of unemployed individuals and vacancies. On the other hand, there is a proliferating literature on mismatches between those individuals who have a job, and the job they are in. In the latter approach, no attention is paid to individuals who are out of work.

This note will focus on two indicators that belong to the first approach, notably macro-economic skills mismatch and skills shortages; and two indicators that rather fit under the second approach (underqualification and overqualification).[4] The considered indicators have been used for some time by now for EU-related policy analysis. Kiss and Vandeplas (2015) provide a more detailed justification of the choice of these indicators. An important criterion is the availability of cross-country comparable data for EU-28 countries over a sufficiently long time period. In what follows, we discuss the specific definitions and indicators that will be used.

2.1. Macro-economic skills mismatch

Macro-economists have typically looked at skills mismatches between individuals available for work (the unemployed) and the available jobs (vacancies) and have compared them across time and across countries at the macro-level.[5] For the purpose of this note, this type of skills mismatch is referred to as "macro-economic skills mismatch". It may result in a persistent coexistence of a pool of unemployed workers (of a certain skills type) with a relatively high vacancy rate (suggesting demand for workers of a different skills type) and can therefore reflect structural labour market matching inefficiencies, leading to structural unemployment or inactivity. As this measure of skills mismatch only accounts for whether or not individuals of a certain skill type are (un)employed (or not), it does not take into account whether, if they are employed, their job is in line with their skills.

Several inter-related measures are available to assess macroeconomic skills mismatch.[6] For reasons of data availability, skills are in this context usually proxied by qualifications. While the term "macroeconomic qualifications mismatch" would arguably be more

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[4] Several researchers have argued that overskilling measures are more significantly associated with several economic variables than overqualification measures (see e.g. Quintini, 2011; Sloane, 2014; Mavromaras et al., 2012; Budria and Moro-Egido, 2014), and that the former type of measures are therefore more relevant for analysis. However, data on the latter type of measures are typically more easily available, which explains why they have been used more frequently, including in our own analysis. The PIAAC and the European Skills and Jobs Survey, which currently provide the best measures on skills (including subjective reports of overskilling and underskilling) consist of only one data round. While it offers unique data on direct measures of skills, PIAAC currently covers an incomplete set of European Member States: BG, HR, HU, LU, LV, MT, PT and RO are missing.

[5] See e.g. Kiss and Vandeplas (2015), Sahin et al. (2014), Arpaia et al. (2014), Estevão and Tsounta (2011), and ECB (2012).

[6] See for instance Kiss and Vandeplas (2015), Arpaia et al. (2014), Estevão and Tsounta (2011), European Commission (2008:119); Peters (2000), ECB (2012:73). Similar indicators can be derived for regional or sectoral mismatch.

correct, the term "skills mismatch" remains more commonly used in the macroeconomic literature. If data are available, one can compare directly the composition of vacancies (in terms of qualification levels) with that of (un)employment (see e.g. Şahin *et al*., 2014). As vacancy data are not always available or reliable, simplified measures can be used that compare the composition of employment in terms of qualifications (as a proxy for labour demand) with that of the population of working age (as a proxy for supply); or the composition of unemployment (as a proxy for the lack of demand) with that of the labour force (as a proxy for supply).

The use of dispersion indicators to measure mismatch in the labour market dates back to Lipsey (1960), who argued that such mismatch can influence the trade-off between unemployment and inflation. By now, their use for macro-economic analysis is widespread. One can consider absolute or relative dispersion measures; one can look at sums of squares or at sums of absolute values of deviations from the mean; one can weight different categories considered or not. Differences between the resulting measures can generally be explained based on the selected methodology, and different methodologies can be defended based on the purpose of the analysis.

For the purpose of this paper, the following specification is proposed for *macro-economic skills mismatch*, measured as the relative dispersion of employment rates across three population groups with different educational attainment:

$$SMI = \sum_{i=L,M,H} \left|\frac{E_i}{E_t} - \frac{P_i}{P_t}\right| = \frac{1}{e_t} \sum_{i=L,M,H} \left|\frac{P_i}{P_t}(e_i - e_t)\right|$$

where i stands for the three different qualification groups *L*, *M* and *H*,[7] E_i, P_i and e_i for total employment, the working age population and the employment rate of group *i* respectively; and E_t, P_t and e_t for aggregate (or total – indicated by the subscript t) employment, the aggregate population and the aggregate employment rate respectively.[8]

We selected this specification following Dixon (2006) who argues that a simple dispersion indicator is easier to interpret than e.g. a standard deviation or a coefficient of variation; we divide it however by aggregate employment to obtain a relative dispersion indicator that is more easily comparable across countries and years with considerable variations in employment rates. This measure quantifies the differences in employment rates between qualification groups, weighted by their importance in the working age population. It will be 0 if the employment rates of all qualification groups are equal to each other and hence to the aggregate employment rate. It will converge to its upper limit if the employment rate is extremely low (0%) in two out of three qualification groups, and extremely high (100%) in the third group, and if the size of the third group converges to 0 such that the aggregate employment rate converges to 0 as well. In general, a relatively high mismatch will be observed if employment rates of low- and/or medium-qualified workers are low as compared to those of high-qualified workers, while the former make out a substantial share of the working age population.

Macro-economic skills mismatch can reflect both cyclical and structural dynamics. On the one hand, as low-qualified (un)employment tends to be more sensitive to the cycle than high-qualified (un)employment, the difference in (un)employment rates between qualification groups typically increases in economic downturns. As a result, mismatch typically increases during an economic downturn, and declines again during the recovery.

However, as there are also structural reasons underlying broader dynamics in (un)employment rate differences between education groups, mismatch dynamics can

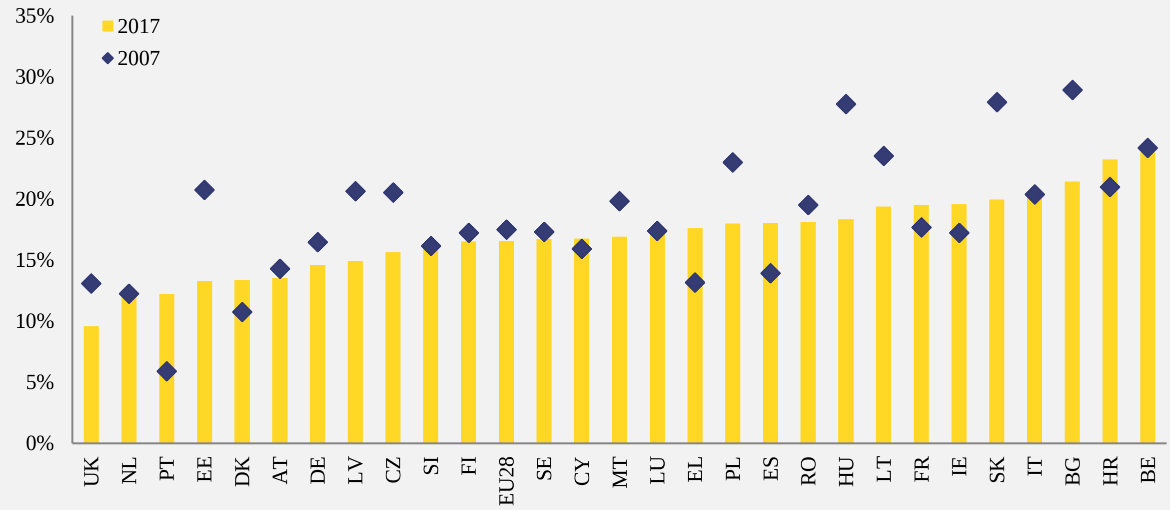
[7] Notably *low-qualified* individuals (with educational attainment at most at ISCED 0-2 level); *medium-qualified* individuals (with attainment at most at ISCED 3-4 level); and *high-qualified* individuals which hold a tertiary degree (ISCED 5-8 level)

[8] As a relative indicator, this measure takes on a value between 0 and 2. The 2 refers to n - 1 where n = 3 as three groups of workers are considered (L, M, and H)

also reflect those. Examples include a changing relative demand for low- versus high-qualified workers or differences in the impact of changing institutional settings and of demographics across education groups (e.g. if the increasing generosity of benefit systems affects low-qualified workers more than high-qualified ones; or if ageing is proceeding faster among low-qualified workers than among high-qualified ones). Some of these reasons are more concerning than others are, which underlines the importance of deeper investigation to assess the policy implications of a deterioration of mismatch.

Figure 1 shows that in terms of macro-economic skills mismatch, Belgium, Croatia, Bulgaria, Italy and Slovakia show differences in employment rates across qualification levels of 20% and above. These countries generally combine substantial employment gaps (between low- and high-qualified workers, and/or between medium- and high-qualified workers) with substantial shares of low- and/or medium-qualified workers in their population. At the other end of the spectrum, the best performer is the United Kingdom, the where employment rates differ by below 10% across workers of different qualification levels, suggesting that supply and demand for workers of different qualification levels are more in line with each other.

Figure 1: Comparison of macro-economic skills mismatch in terms of employment (%) across EU Member States



Source: Own calculations based on EU LFS according to methodology proposed by Kiss and Vandeplas (2015). Annual average based on the average of four quarters.

Over the last decade, macro-economic skills mismatch has followed largely a countercyclical pattern on average in the European Union: rising with the economic downturn, and declining again during the recovery (see Figure 1 and Figure 3). At the individual Member State level, patterns vary considerably.

Fifteen Member States saw a reduction of mismatch. The largest (relative) declines over the past decade are observed in Estonia, Hungary, Slovakia and Bulgaria. In these countries, employment rates of medium- and high-qualified workers have been structurally converging to the aggregate employment rate over recent decades, while the latter have been growing in importance as a share of the working age population. The opposite applies to the employment rate of low-qualified workers, who however make out a shrinking part of the working-age population. These dynamics have led to lower employment rate dispersion and have not been visibly interrupted by the crisis.

On the other hand, skills mismatch has gone up in some of the countries that were particularly hit by the crisis (such as Portugal, Spain, Greece, or Ireland) but also in

France, Croatia and Denmark. It remained relatively stable in Belgium, Cyprus, Italy, Luxemburg, the Netherlands, Slovenia and Sweden.[9]

While there is no significant correlation between macro-economic skills mismatch and the educational attainment of the working age population or the *sectoral* or *occupational* composition of employment in a cross-country section, some interesting correlation patterns can be distinguished over time within countries. A first observation is that macro-economic skills mismatch has increased particularly in countries where the building sector saw a strong decline in 2008 (Figure A2.7). Since then, employment in the construction sectors has not returned to these levels.[10] Macro-economic skills mismatch is increasing in the share of high-skilled occupations (ISCO 1-3) in employment, suggesting that the process of occupational upgrading is associated with an increased challenge of integrating less-qualified workers in the labour market (Figure A2.8). Finally, macro-economic skills mismatch is declining in the share of tertiary graduates in the population, highlighting the negative relationship between mismatch and rising educational attainment of the workforce (Figure A2.9).[11]

A related mismatch indicator can be calculated based on the dispersion of unemployment (rather than employment) rates across qualification groups (Figure 2). In general, unemployment dispersion rates are more volatile than employment dispersion rates. Figure 2 shows that unemployment rates have diverged across qualification groups on average in the EU-28 over the period 2007-17, with important contributions from Portugal, the Baltic countries, Spain, Poland, but also Malta and Sweden. Unemployment rates became more similar across qualification groups in Bulgaria, Cyprus, the Czech Republic, Denmark, Slovakia, the United Kingdom, and the Netherlands.

While relative dispersion of employment rates increased on average in the EU-28 over the crisis period (roughly from 2008-2014) and declined since then, relative dispersion of unemployment rates has seen a steady increase, which started even before the crisis (Figure 3).

In the case of the employment-based indicator, this reflects the crisis-related divergence in employment rates. The recovery brought a halt and a partial reversal to this process of divergence. The decline in the relative size of the low attainment group (as a share of the working age population) put further downward pressure on the indicator. As a result, by 2017 the indicator has returned to its 2007 level for EU-28.

In the case of the unemployment-based indicator, similar patterns can be discerned. Unemployment rate dispersion was already increasing before the onset of the crisis on account of an increasing deviation of the unemployment rate of low-qualified vis-à-vis other educational groups (in spite of the fact that their population share was already steadily declining).[12] This effect was reinforced by the crisis. The coincidence of convergence in employment rates with divergence of unemployment rates can be explained by the underlying dynamics in activity rates – it can reflect either a widening gap in activity rates or a general rise in activity rates (denominator effect).

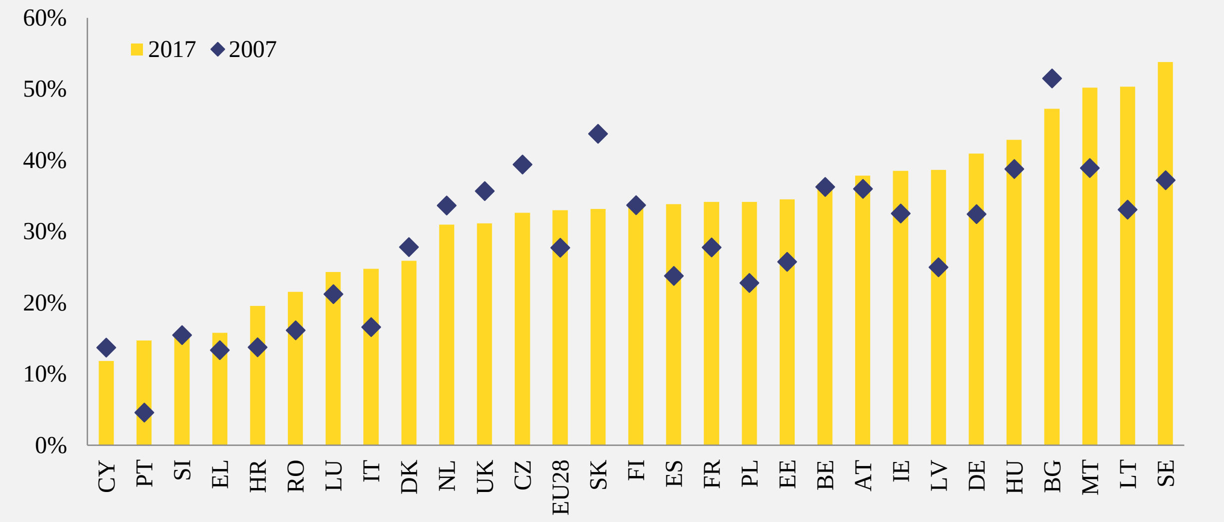
[9] Time trends by country are provided in **Figure A2.5**.

[10] One could of course wonder whether it would be desirable for employment in construction to fully recover to the 2008 levels, as this was widely considered an unsustainable construction boom in many countries.

[11] Note that the macro-economic mismatch uses population weights of different qualification groups. If the group with more problematic labour market outcomes shrinks, mismatch will improve.

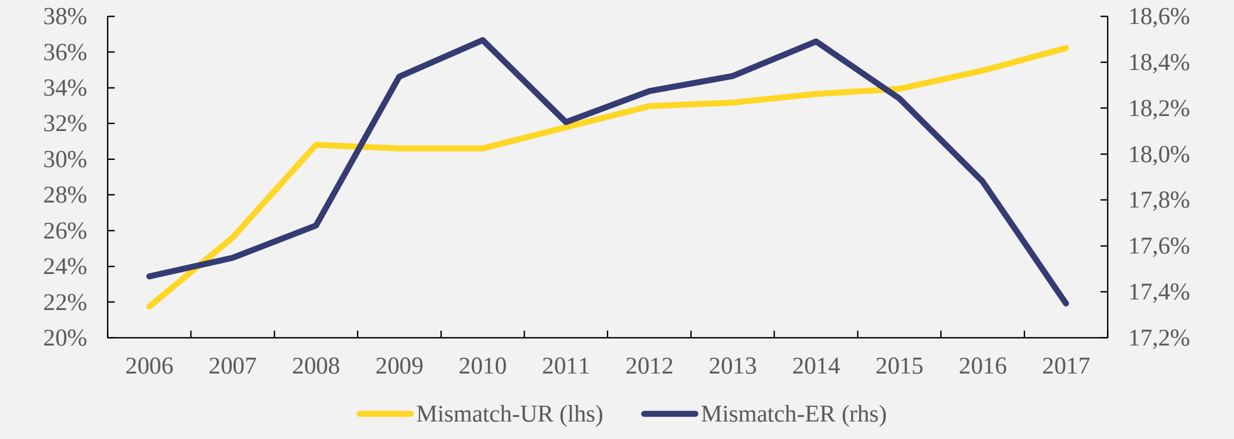
[12] Note that even if the unemployment rate for low-qualified workers reached an all-time low in 2007, its relative performance was still weaker than other education groups (who saw a stronger relative decline in unemployment rates in the "economic boom" period).

Figure 2: Comparison of macro-economic skills mismatch in terms of unemployment (%) across EU Member States



Source: Own calculations based on EU LFS according to methodology proposed by Kiss and Vandeplas (2015). Annual average based on the average of four quarters.

Figure 3: Evolution of macro-economic skills mismatch over time, EU-28



Note: Mismatch-ER measures employment rate dispersion; Mismatch-UR measures unemployment rate dispersion across educational attainment groups.
Source: Own calculations based on EU LFS according to methodology proposed by Kiss and Vandeplas (2015). Annual average based on the average of four quarters.

2.2. Skills shortages

A related dimension of labour market mismatch is when employers encounter difficulties filling their vacancies (*skills shortages*). This also reflects an imbalance between demand and supply on the labour market, as there are seemingly no suitable workers for the jobs to be occupied.

Skills shortages can be cyclical and/or structural (European Parliament, 2015). Employers typically encounter more challenges to recruit the "right" workers at times of economic growth (Green and Ashton, 1992; Desjardins and Rubenson, 2011) and technological or organisational change (Bosworth and Dutton, 1990). Empirical evidence supports the view that employers adjust wages upwards and/or recruitment standards down (such as minimum qualification levels for hiring) during economic upturns when job applicants become scarcer (Reder 1955; Mortensen 1970; Devereux, 2002; Büttner et al., 2010).

At present, there is no perfect way to measure skills shortages. Three surveys collect data from employers on their difficulties to fill vacancies, but the sampling methodologies, the questions that are asked, and the results are different. First, Eurofound's European Company Survey (ECS) asks employers whether they "encounter difficulties in finding employees with the right skills". Second, the Manpower Talent Shortage Survey indicator identifies employers with difficulties filling jobs "due to lack of available talent". Both questions refer directly to skills or talent, but at the same time they do not exclude difficulties arising from some other sources (see further). Also, ECS data are not collected on a frequent basis. Finally, the European Business and Consumer Surveys (EU-BCS) collects (depending on the sector) quarterly or monthly data on employers in manufacturing, services and construction reporting whether labour shortages are a major factor limiting their production.

Recently, the OECD has started to develop new indicators for skills shortages ("Skills for jobs") based on more objective data (such as employment growth, wage pressure etc.). These are currently publicly available as a single year-cross-sectional dataset (OECD.Stat, 2018).

For our analysis, we construct a measure of skills shortages drawing on data from the EBCS on the share of employers in manufacturing, services and construction reporting that labour shortages are a major factor limiting their production. The major advantage of this survey is that it produces regular, cross-country comparable data (on a quarterly or monthly basis) and covers a relatively long time span. The main disadvantage is that it does not directly allow us to distinguish skills shortages from more general labour shortages (e.g. as a result of a shrinking or ageing population).

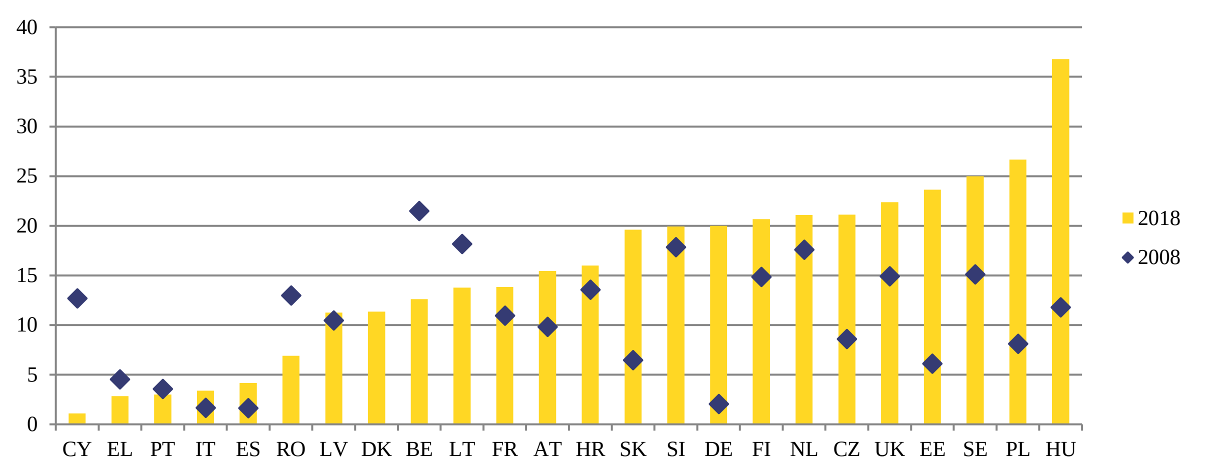
A composite measure of shortages was constructed as the weighted average of three sectors (construction, industry and services), weighting each sector by its share in value added. Unfortunately, data are missing for Bulgaria, Ireland, Luxembourg, and Malta.

Figure 4 provides an overview of the indicator, showing that shortages are reportedly most imminent in countries such as Hungary and Poland with the incidence of skills shortages is reported to be above 35% and 25%, respectively, and least problematic in Cyprus, Greece, Portugal, Italy and Spain where the incidence of skill shortages is reported to be lower than 5%. Interestingly, countries with higher levels of educational attainment (such as Finland, the United Kingdom, Sweden, Lithuania and Estonia) tend to be located near the right side of the figure, implying that they are more likely to encounter skills shortages, not less.[13]

An important caveat applies in interpreting data from employer surveys, as difficulties to fill vacancies can result from unattractive working conditions offered, inefficiencies in recruitment practices, or broader "labour shortages" following from a general decline of the labour force currently observed in several EU countries, rather than from skills mismatch as such (see e.g. CEDEFOP, 2015; Shah and Burke, 2003). It is also important to note that even if employers are looking out for specific skills, these are not necessarily technical skills that relate to specific qualifications. For instance, Capelli (2015) reports that only a third of employer reports of talent shortages in the Manpower data for the US related to a lack of hard skills that can be learned in school.

[13] A notable exception is Cyprus, which combines one of the highest rates of educational attainment with one of the lowest rates of skills shortages.

Figure 4: Comparison of skills shortages (%) across EU Member States



Source: Own calculations based on European Business Survey and AMECO
Notes: Skills shortages data are missing for IE and LU and value added data missing for BG and MT.

For reasons of data availability, the added value of sectors G-N is used as weight for the EBCS services sector which covers sectors H-N and R-S. This implies the assumption that the added value of the wholesale and retail sector (G) is reasonably close to the added value of the arts and other service activities sector (R-S).

Our data on shortages are however more strongly correlated with the availability of high-qualified labour than with that of low-qualified labour, suggesting that they do not merely reflect labour shortages in most countries. In particular, our indicator for skills shortages is negatively and statistically significantly correlated with unemployment rates of medium- and high-qualified workers, and less so with unemployment of low-qualified workers (see Figure A2.15 - Figure A2.17).

A potential explanation could be that, while worker reallocation rates tend to be higher in those jobs and industries that generally offer lower wages and more difficult working schedules[14] firms tend to find new hires relatively easily for these types of jobs. In other words, the least productive firms hire as frequently as the most productive ones, but their separation rates are considerably higher as well (more often because of quits than because of layoffs). Vacancies tend to persist longer for firms that are more productive and/or follow higher-end product strategies, and for jobs that require higher qualification or more experience (Galenianos et al., 2015; Bennett and McGuinness, 2009; UKCES, 2012). Interestingly, countries with higher levels of educational attainment (such as Finland, the United Kingdom, Sweden, Lithuania and Estonia) tend to be located near the right side of the figure, implying that they are more likely to encounter skills shortages, not less.[15]

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[14] For example, OECD (2009) presents data on worker reallocation rates by industry, showing that rates are generally higher in the hotels and restaurants sector, wholesale and retail, and construction. Note that worker reallocation means that a different worker is hired for an existing job. If a worker is hired for a new job, this is usually referred to as job reallocation. Usually job reallocation is (more so than worker reallocation) associated with productivity increases. Worker reallocation can for example be the result of worker quits, involving recruitment and training costs for the employer; a new worker with lower tenure may be less productive than a worker with longer tenure and more experience.

[15] A notable exception is Cyprus, which combines one of the highest rates of educational attainment with one of the lowest rates of skills shortages.

2.3. Measures of on-the-job mismatch

On-the-job mismatch indicators reflect a complementary dimension of labour market mismatch that has received ample attention in the micro-economics literature. It considers the discrepancies between the skills and qualifications of individuals who have a job and the skills/qualifications requirements of their job. It does not take into account the unemployed.

The difficulty in pinning down the appropriate skills/qualifications requirements for a job in practice has resulted in a wide range of different indicators in this area that are often only weakly correlated with each other.

On-the-job mismatch indicators may look at mismatches between the skills a worker possesses and those that are needed for his/her job; or rather at qualifications, he/she has and those needed for his/her job. Differences between skills and qualifications can arise for instance as a result of differences in the skills content (or the quality) of qualifications, skills developed through non-formal or informal training (e.g. training on-the-job, which raises one's skills beyond his/her qualifications) or skills depreciation over the lifetime (e.g. because of changes in skills demands or insufficient maintenance or use of skills, which can reduce one's skills as compared to his/her qualifications).

For each of these dimensions, the literature has proposed a variety of measures[16] based on different data sources[17], often producing diverging results.[18] Workers experiencing a mismatch with their jobs might either have too few skills/qualifications (underskilling/ underqualification) or too many skills/qualifications (overskilling/overqualification) as compared to what their job requires or allows them to use. Workers may as well in some cases experience underskilling at the same time as being overqualified (or vice versa); see e.g. Perry and Maehler (2017). Another dimension of on-the-job mismatch is horizontal mismatch, referring to a mismatch between an individual's field of study and the area (s)he is working in. This topic remains beyond the scope of this paper – not only because of challenges in measurement,[19] but also because it is considered less problematic from a policy perspective than vertical mismatch (see e.g. Sellami et al., 2018 and Montt, 2017 for a discussion).

This note considers two measures of on-the job *qualification* mismatch that can be calculated based on regularly available and cross-country comparable data from Eurostat's Labour Force Survey (LFS), by comparing the qualification level of a particular worker with the required qualification level of his/her job, based on the occupational classification of that job.

ILO (2007) proposes that jobs classified at ISCO levels 1-3 require workers that are high-qualified, jobs at ISCO levels 4-8 require workers that are medium-qualified; and elementary jobs (ISCO level 9) do not require workers to have any qualification.[20,21] As a result, a high-qualified worker will be considered as overqualified if (s)he has a job at ISCO levels 4-9. A medium qualified worker will be considered as overqualified if (s)he

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[16] E.g., qualification mismatch can be measured based on direct or indirect self-assessment, job analysis, or mean or modal empirical analysis. Similarly, skills mismatch can be measured based on self-assessment or on empirical analysis; and within these, there are still different methodological options available.

[17] Such as Eurostat's Labour Force Survey (LFS) and Adult Education Survey (AES), OECD's survey of adult skills PIAAC, CEDEFOP's European Skills and Jobs Survey (ESJ) and so on

[18] see e.g. for a fairly comprehensive overview Ramos (2014) on qualification mismatch; Perry *et al*. (2014) on skills mismatch

[19] EUROSTAT has recently initiated work on the development of indicators of horizontal mismatch based on the EU-LFS, but as yet, the available indicators remain experimental due to the remaining challenges in the underlying methodology.

[20] ISCO 1-digit categories are specified as follows: 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.

[21] ECB (2012: 74) proposes a slightly different classification, notably assuming that jobs at ISCO levels 7-9 do not require any qualification.

has a job at ISCO level 9, and as underqualified if (s)he has a job at ISCO level 1-3. A low-qualified worker will be considered as underqualified if (s)he has a job at ISCO levels 1-8.

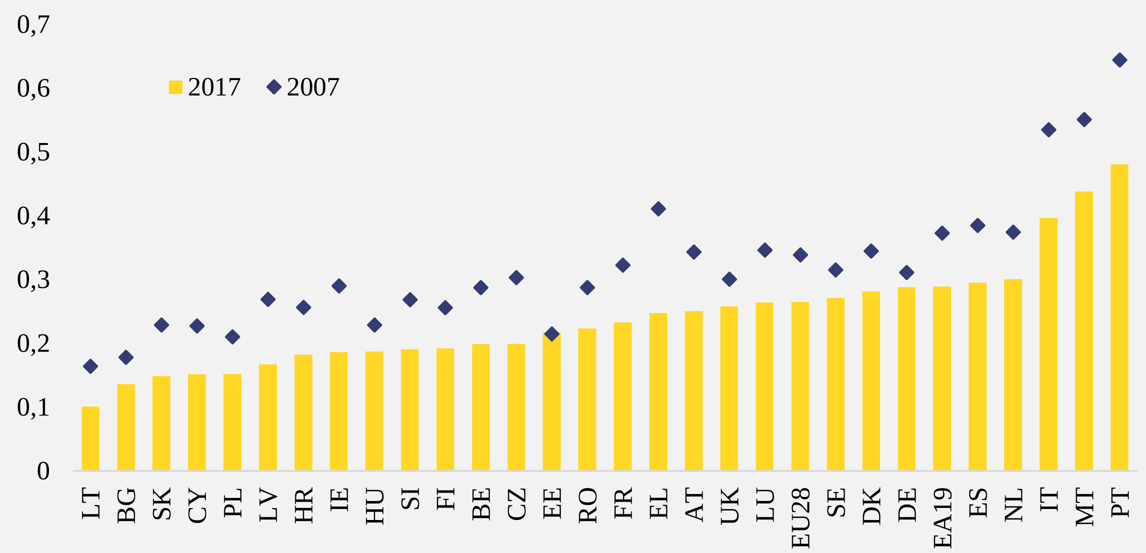
Several researchers have argued that overskilling measures are more significantly associated with several economic variables than overqualification measures (see e.g. Quintini, 2011; Sloane, 2014; Mavromaras et al., 2012; Budria and Moro-Egido, 2014), and that the former type of measures are therefore more relevant for analysis. However, qualification-based data are typically more easily available, which explains why they have been used more frequently, including in our own analysis.[22] Unfortunately, the link between skills and qualification mismatch is rather weak. Quintini (2011) shows that only about 36% of overqualified workers report being overskilled. Similarly, only about 12% of underqualified workers report being underskilled. Hence, a majority of over- and under-qualified workers report that their skills match their jobs' requirements well. Flisi et al. (2017) even find a negative correlation between qualification and skills mismatch based on an analysis of PIAAC data.

A. Underqualification

Underqualification measures the number of low- and medium-qualified workers that hold a job for which they are underqualified, as a share of total employment. Therefore, underqualification is not only determined by the probability that a low- (or medium-) qualified worker is underqualified, but also by the share of low- and medium-qualified workers in total employment.

As shown in Figure 5, Portugal, Malta, and Italy have the highest incidence of underqualification (with above 30% of total employment), most likely as a result of the general low level of educational attainment in the working-age population. The lowest incidence of underqualification is found in Lithuania, Bulgaria and Slovakia (at below 15% of total employment). Of these, Lithuania and Slovakia are amongst the countries with the lowest share of low-qualified individuals in the population.

Figure 5: Underqualification as a % of total employment



Source: Own calculations based on EU LFS data

[22] The PIAAC and the European Skills and Jobs Survey, which currently provide the best measures on skills (including subjective reports of overskilling and underskilling) consist of only one data round. While it offers unique data on direct measures of skills, PIAAC currently covers an incomplete set of European Member States: BG, HR, HU, LU, LV, MT, PT and RO are missing.

Over time, underqualification has declined across all EU Member States, with the exception of Estonia, where it has remained relatively stable. Estonia is one of the EU Member States that have made the least progress in reducing low attainment over the past decade. On the other hand, it also has one of the lowest shares of low attainment across the EU.

In cross-country comparison and after controlling for educational attainment, underqualification is positively correlated with the share of jobs with high skills requirements (Figure A2.21). This is intuitive: if job skills requirements increase and educational attainment remains the same, underqualification will increase. As expected, it declines with rising educational attainment, when taking job skills requirements as given (Figure A2.22).

Underqualification can be the result of skills shortages, notably the non-availability of workers with the right qualifications; but it can as well be the result of inefficient recruitment strategies (e.g. employers not investing sufficient efforts in searching for the right workers, unattractive wage policies, and so on). Finally, it could as well reflect some measurement error, in the sense that workers may have the correct skills for the job, but this is not reflected by their qualification level (e.g. because they have relevant work experience or undertook additional non-formal training in a different way).

B. Overqualification

Overqualification measures the number of medium- and high-qualified workers holding a job for which they are overqualified, as a share of total employment. As a natural consequence, overqualification is not only determined by the probability that a high- (or medium-) qualified worker is overqualified, but also by the share of high- and medium-qualified workers in total employment.

As shown in Figure 6, the countries with the highest level of overqualification is Cyprus with above 20% overqualification in total employment, followed by Ireland, Spain and Lithuania (with above 18% overqualification), all countries with above-average tertiary attainment. The lowest level of overqualification is found in Luxembourg, Malta and Portugal – even if tertiary attainment in Luxembourg is relatively high (higher than for Spain). Over the last decade, overqualification has increased significantly in Greece, Cyprus, Ireland, Latvia and Austria.[23]

Overqualification and underqualification are negatively correlated with each other (see Figure A2.20). A remarkable exception is Spain, which combines a high rate of overqualification with a high rate of underqualification. Cyprus and Ireland also have much higher rates of underqualification than what one would expect based on the incidence of overqualification in these countries.

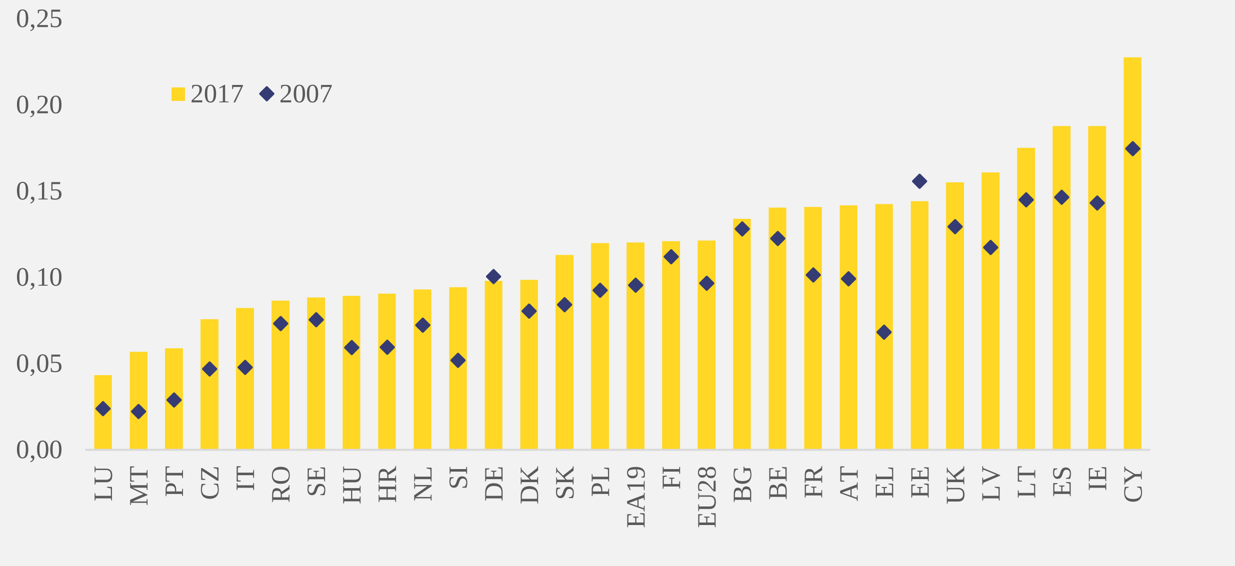
Overqualification declines with the share of jobs with high skills requirements (when keeping educational attainment constant) and increases with educational attainment (when controlling for jobs' skills requirements (Figure A2.23 and Figure A2.24).

Some have argued that the expansion of higher education necessarily leads to higher rates of overqualification. Interestingly, however, the positive correlation between overqualification and tertiary attainment is driven by those countries with very low tertiary attainment and hardly any overqualification as a result. Among the countries with high tertiary attainment (for instance above 30% as in Figure A2.19), there no longer is a significant correlation between tertiary attainment and overqualification. The reason is that in some countries, growing tertiary attainment has coincided with a correspondingly strong growth in jobs with higher skills requirements, while in other countries the

[23] Most of the increase in overqualification in Austria was due to a methodological change, where several post-secondary qualifications (ISCED level 4) were reclassified as tertiary qualifications (ISCED level 5) as of 2014.

growing number of tertiary graduates has seemingly not been absorbed into higher skilled jobs, resulting in overqualification. Different factors may be at play here, including policy-related ones such as quality assurance institutions in education, policies that promote the alignment between education and training systems and the labour market, but also business regulations allowing for firm entry, growth, sectoral reallocation and policies supporting labour mobility and innovation.

Figure 6: Overqualification as a % of total employment



Source: Own calculations based on EU LFS data

To a certain extent, overqualification can be the result of rational decision-making at the individual or the household level. For example, Frank (1978)'s "differential overqualification theory" argues that women are often constrained in their job search by their husband's job choice.[24] By facing a "smaller" labour market than men, they have a higher chance of being overqualified. These predictions have been empirically tested by McGoldrick and Robst (1996) and Büchel and Battu (2002). While the former rejected its validity, the latter did find some evidence that higher commuting distances strongly reduce the probability of being overqualified; and that individuals living in rural areas run a higher risk of being overeducated. The argument that spatial mobility constraints lead employees to accept a job with lower formal requirements has broadly been accepted in the economic literature (e.g. Reichelt and Abraham, 2017). Furthermore, Sicherman (1991) suggests that some workers may accept jobs for which they are overqualified with a view to receiving on-the-job training and experience needed for future jobs. Similarly, recent immigrants or mobile workers might accept jobs with lower formal requirements temporarily whilst building up the necessary language skills for a more requiring job. Some employers may prefer to hire overqualified workers,[25] as they want to promote innovation and decentralized decision-making.[26] Individuals tend to undertake education not only to expand their labour market opportunities, but also to

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[24] Notably, Frank (1978) argues that women are often "tied stayers" or "tied movers", as they have to stay in a certain area or to move to a certain area where their husband has found a job. Note that at the time of his writing, men were typically better educated and had higher earning power than women. This difference is slowly fading away by now. Still, optimizing job decisions in a couple is bound to be subject to more constraints than optimizing individual job decisions.

[25] See e.g. Verhaest et al. (2018)

[26] See e.g. Blundell et al. (2016) who consider decentralized decision-making as a skills-biased innovation.

some extent for personal development and fulfilment.[27] Some reports of overqualification can also result from measurement error: there is some evidence that workers with lower levels of skills than the average for their qualification level are more likely to be overqualified for their jobs (LaRochelle-Côté and Hango 2016; Erdsiek 2017; Reichelt and Abraham, 2017).

However, if overqualification is widespread, it tends to occur in environments where labour market demand for high-qualified individuals is weak. Furthermore, it tends to be even weaker for lower-qualified individuals, suggesting that high-qualified individuals mostly take up jobs with lower qualification requirements because there are no other jobs available that would allow them to fully exploit their skills; and that low labour market returns to low- and medium qualification levels strengthen incentives for tertiary educational attainment (Figure A2.27).

2.4. Are mismatches increasing over time in the EU?

Over the last decade, *macro-economic skills mismatch* has largely followed a countercyclical pattern in the EU-28, with a notable uptick over the crisis years (Figure 7: Evolution of macro-economic skills mismatch and skills shortages in the EU-28Figure 7, Figure 8). As noted earlier in Section 2.2, the aggregate picture hides diverging evolutions at the Member State level. On the one hand, a strong declining trend is observed in EU-13 countries.[28] On the other hand, in EU-15 countries, a growing trend in macro-economic skills mismatch is observed, with a remarkable acceleration over the crisis period, and a slight improvement after 2014 (see Figure A2.10).

Figure 7: Evolution of macro-economic skills mismatch and skills shortages in the EU-28

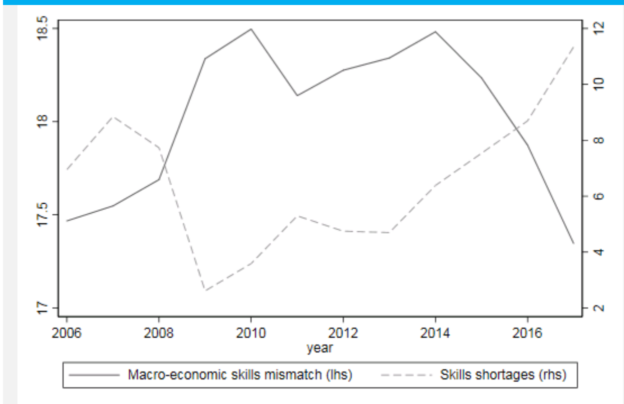
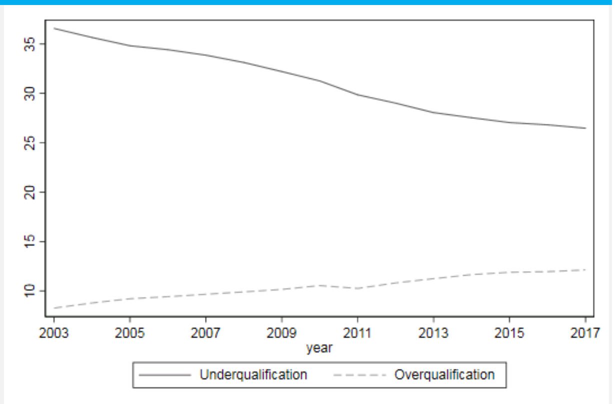


Figure 8: Evolution of underqualification and overqualification in the EU-28



Note: The EU-28 aggregate reflects population-weighted averages. In the case of skills shortages, these averages take into account the countries for which data are available in each respective year.

For most of the EU-13 countries, the high level of mismatch is a legacy from transition (Figure A2.10): the collapse of the Soviet Union generated macro-economic skills mismatch at a large scale, as economic production systems were being thoroughly

[27] See e.g. Green and Henseke (2016)

[28] In this paper, EU-13 comprises the EU Member States that joined the EU as of 2004 (Bulgaria, Cyprus, Czech Republic, Estonia, Croatia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovenia, and Slovakia). EU-15 comprises those countries which were already EU Member States before 2004, notably Austria, Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden, and the United Kingdom.

disrupted. Typically, activation support and adult learning policies in these countries are rather weak, resulting in relatively little support being given to lower-qualified persons for labour market reintegration. Throughout the process of transition, however, macroeconomic mismatch is gradually declining in EU-13 countries. In contrast, the EU-15 countries saw a strong upsurge in macroeconomic mismatch since the crisis in 2008, albeit from a much lower starting level.

Skills shortages are also observed to move broadly with the economic cycle (Figure 7), and particularly so in EU-13 countries. They increase during economic recoveries, and decline in times of economic slack. Skills shortages reached a peak in 2007 and a trough in 2009. In other words, this mismatch indicator does not seem to show a consistent upward or downward structural trend over time.

Underqualification (overqualification) is on a long term declining (increasing) trend, mostly driven by upward trends in educational attainment (Figure 8). The reduction in underqualification is driven by a decline of the population share with low educational attainment; the increase in overqualification is driven by an increase of the population share with tertiary attainment. In some countries, however, the increase in tertiary attainment is not (e.g. Germany, Estonia, Luxembourg) or hardly (e.g. Denmark) significantly related with overqualification (See Figure A2.6).[29]

3. RELATIONSHIP BETWEEN SKILLS MISMATCHES AND PRODUCTIVITY

The question of how human capital in general and skills mismatch in particular is related with productivity has been explored previously in the literature (see Section 3.1). Most of these studies have considered skills mismatch in terms of on-the-job mismatch (under- or over-qualification or under- or over-skilling); and some studies have looked at skills shortages. The question of how macro-economic skills mismatch and productivity are related is a relatively novel question, which has not yet attracted significant attention in the literature, possibly because the link is more indirect than for other dimensions of skills mismatch.

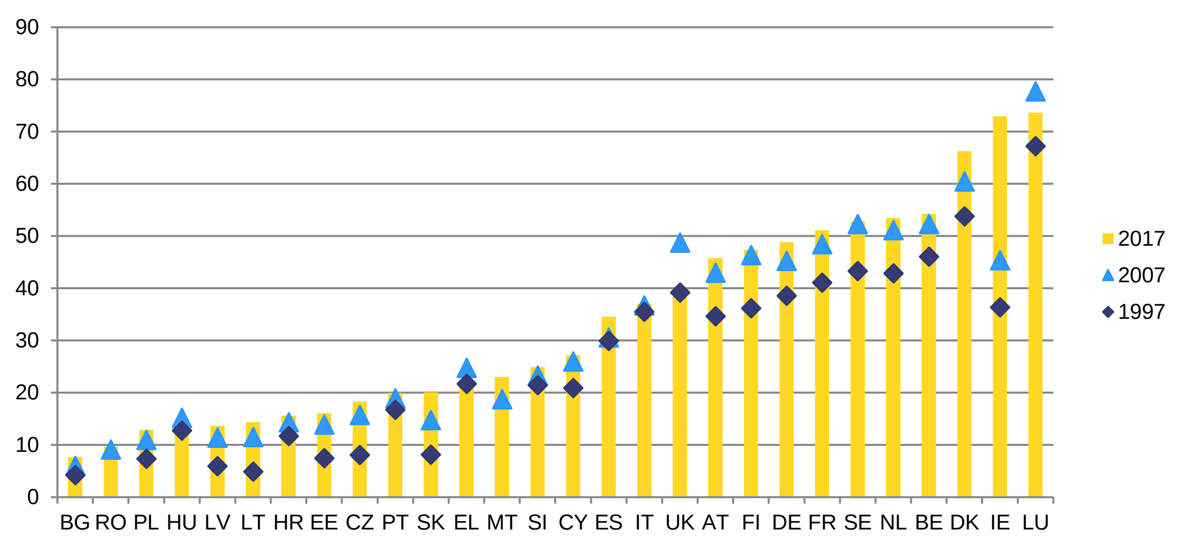
Our analysis looks at labour productivity, a productivity measure that is easy to calculate, and intuitively closely related to per capita GDP levels and living standards (per capita GDP can be decomposed into labour productivity (GDP per hour worked) and labour resource utilization (hours worked per capita)). Figure 9 presents a view of how EU Member States compare against each other in terms of labour productivity levels. The best performing Member States are Luxemburg, Ireland and Denmark. At the other end of the spectrum are Bulgaria, Romania and Poland. As can be seen, labour productivity increases were considerably larger over the period 1997-2007 than over the most recent decade, reflecting the recent slowdown in productivity growth. Figure 10 provides a longer time perspective on labour productivity trends in the EU, showing that labour productivity has been considerably affected by the economic crisis (as of 2009).

3.1. Framework for analysis

This section will describe the relationship between various measures of skills mismatch and productivity based on (i) a review of theoretical arguments that can be derived from or have been put forward in the literature, (ii) descriptive evidence, and (iii) a set of panel data regressions that allow us to exploit both cross-country and cross-time variation. As the regression methods used may not suffice to allow for a causal interpretation (e.g. there may be important omitted variables or issues of non-stationarity), we will interpret our results as correlations, and refrain from drawing overly strong conclusions on causality.

[29] This is all the more remarkable, as it implies that overqualification among tertiary graduates must decline to allow the share of overqualified in employment to remain stable while tertiary attainment increases.

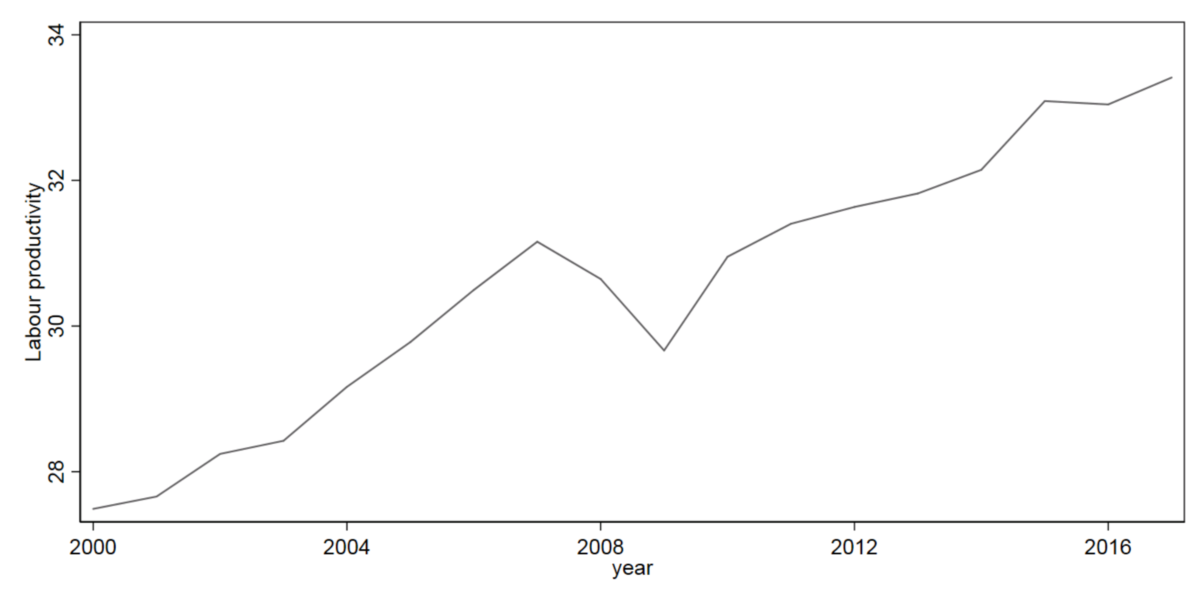
Figure 9: Labour productivity (€ per hour worked) across EU Member States



Source: AMECO

Note: Labour productivity is measured as GDP per hour worked, expressed in Euro and in constant 2010 prices.

Figure 10: Trend over time in labour productivity – EU-28



Note: Labour productivity is measured as GDP per hour worked, expressed in Euro per hour worked in constant 2010 prices.

Estimates from both random- and fixed-effects panel regressions will be discussed, taking into consideration between- and within-country variation. The estimated country-level regressions are of the following (reduced) form:

$$LP_{i,t} = \beta H_{i,t} + \gamma S_{Hi,t} + \delta X_{i,t} + c_i + \varepsilon_{i,t}$$

with *LP* denoting labour productivity (measured as GDP per hour worked, expressed in log levels based constant 2010 prices), *H* reflecting the level of human capital in the economy, and S_H denoting skills mismatch in country *i* at time ***t***. In some specifications of the regression model, human capital is measured by educational attainment of the population at working age (25-64) (notably the % of tertiary qualified individuals in the population); in others it is measured by the skills intensity of jobs in the economy (notably the % of high-skilled jobs in total employment, according to the ILO (2007) assumption).[30] *X* comprises additional variables such as the output gap[31] to control for cyclical influences, and c_i includes country fixed effects. Dependent variables are expressed in logs and independent variables in percentages.[32]

This reduced form model can be derived from a production function expressed in labour productivity terms as in $\left(\frac{Y}{L}\right)_{it} = A_{it}\left(\frac{K}{L}\right)_{it}^{\alpha}$ or, in logs $\ln y_{it} = \ln A_{it} + \alpha \ln k_{it}$, where $\frac{Y}{L}$ denotes GDP per hour worked, A denotes total factor productivity (TFP), $\frac{K}{L}$ denotes capital intensity and α denotes the factor elasticity of capital. To account for the possibility that human capital (and as a result also skills mismatch) is related with labour productivity through capital accumulation and through innovation and total factor productivity, we use the following theoretical framework to underpin our regression analysis: we assume that both $\ln A_{it}$ and $\ln k_{it}$ depend on H_{it} (human capital), S_{it} (skills mismatch) and possible other covariates (X_{it}). The regressions reported in Annex 4 (regression TFP levels on H, S and X) and Annex 5 (regressing capital intensity on H, S and X)) test the validity of these assumptions and suggest that human capital and skills mismatch indeed correlate with both TFP and capital intensity in a similar way as with labour productivity. As ln $k_{it} = f_1(H_{it}, S_{it}, X_{it})$ and $\ln A_{it} = f_2(H_{it}, S_{it}, X_{it})$, this implies that labour productivity can be written as $y_{it} = f(H_{it}, S_{it}, X_{it})$, the empirical specification of which is described by the equation above.

The literature examining the way human capital accumulation may sustain growth and motivating as such the positive correlation between labour productivity and the level of education (see e.g. Schultz, 1962) supports the setup of our model above. Human capital can have a positive impact on labour productivity both by raising TFP and by fostering physical capital accumulation. The positive relationship between human capital and TFP - implied in our reduced form model by our assumption that $\ln A_{it} = f_2(H_{it}, S_{it}, X_{it})$ - arises from increasing knowledge raising the capacity to innovate and to adapt and operate new technologies (e.g. Benhabib and Spiegel, 1994; Miller and Upadhyay, 2000).

Complementarities between human and physical capital, which we imply in our reduced form model by our assumption that ln $k_{it} = f_1(H_{it}, S_{it}, X_{it})$, have also been frequently emphasised. For example, Acemoglu (1996) argues that firms are willing to invest more in physical capital if the workforce is raising its education and skills levels. Lucas (1990) hypothesizes that lower stocks of human capital restrict capital inflow (and as such, growth) in poor countries. Barro (1991) discusses that if human capital has positive

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[30] Unfortunately, it is not possible to control for educational attainment and the skills intensity of jobs at the same time, as these are too strongly correlated to allow for proper estimation.

[31] The output gap is measured as the deviation from potential GDP, in other words, it will be positive in economic upturns and negative in economic downturns.

[32] Note that correcting the standard errors for heteroscedasticity and within-cluster correlation at the country level yields similar results in terms of significance in most cases. However, for the on-the-job skills mismatch indicators significance levels decrease. Since robust standard errors may be overestimated with less than 40 clusters (see Angrist and Pischke 2008), we conclude that there is still evidence for significant results.

spillover effects (as hypothesized in Lucas (1988)), upskilling will lead to higher rates of investment, both in human and in physical capital, and as a result, to higher per capita growth. Goldin and Katz (1998) conclude that the complementarity between physical and human capital is not a new phenomenon, as it was already observed in the early 20th century. It can even be argued that human capital, in a form or another, is behind any source of growth, whether it has been explicitly accounted for or not.[33] The complementarities between physical and human capital underlie our choice not to add capital intensity as a control variable, as this would possibly cover up some of the relationship between human capital (and skills mismatch) and productivity in the reduced form equation.

Productivity regressions are run in levels, following the approach taken (amongst others) by McGowan and Andrews (2015) and in Acemoglu et al. (2014). Education (and therefore also skills mismatch) may generally affect economic and productivity growth through different channels (see Lucas, 1988 or Barro, 2001), for instance by increasing the innovation capacity and the general quality of the workforce, which also leads to higher absorption of new techniques and technologies. Consequently, a country's level of human capital (and therefore also skills mismatches) can have an impact on productivity levels (referred to as a "level-level" effect) and/or on the rate of productivity growth (a "level-growth" effect). In turn, the "level-growth" literature emphasises the interaction between the human capital stock and technological change (see for instance Benhabib and Spiegel 1994). The major difference between the two strands relates to the actual transmission channels at work: while the first emphasises the productivity-enhancing effects of schooling (and the associated skill-upgrading of the labour force), the second strand stresses the adoption and innovation channels (shifting the boundaries of the production possibilities outwards due to technological progress). Both channels work in parallel. Which one tends to be more conducive to growth appears to be country-specific.[34]

The reduced form model described in this section allows estimating the unconstrained direct relationship between education and mismatch on the one hand, and productivity on the other hand, but is little informative about the channels of these relationships. To test empirically the channels at play in determining the relationship between education and mismatch with productivity, one could resort to specific structural models. The education and growth literature has proposed different types of models that integrate human capital in standard production functions (see De la Fuente 2011 for a brief review). These models could be adjusted to incorporate the relationship with skills mismatch. Developing a structural model is however beyond the scope of this exploratory note and left for future work.

In what follows, we discuss for each of the four measures of skills mismatch described in Section 2, their expected relationship with labour productivity, some descriptive results, and then the results of our regressions.

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[33] For instance, in models of embodied technical progress (e.g. Greenwood et al., 1997) the increasing quality of equipment goods could well be interpreted to be the result of the increasing degree of sophistication of engineering. Models of expanding product variety (e.g. Grossman and Helpman, 1991) consider that R&D in product innovation uses growing human capital to create new and better varieties.

[34] We tested level-growth and growth-growth relationships but did not find evidence for significant relationships. Note that concerning the level-level relationship one might say that, since the variables in question are in levels with a trending behaviour - indicating non-stationarity, their relationship may be spurious if there is no co-integrating relationship. However, we somewhat control for possible residual non-stationarity by adding educational attainment or occupation indicators, which are typically also trending variables.

3.2. Macro-economic skills mismatch

3.2.1. Theoretical arguments

Macro-economic skills mismatch points at the presence of substantial differences in employment rates between different qualification groups. In practice, this implies that employment rates of low- and/or medium-qualified individuals are low compared to those of other groups, while they make out a substantial share of the population; in other words, that there is a significant composition bias towards high-qualified workers in employment. Usually this is associated with generally low aggregate employment rates.

From a theoretical perspective, it is not straightforward to relate this type of mismatch to labour productivity. In a growth accounting framework, it would link more directly to labour utilization than to labour productivity (see for example European Commission, 2008:117). At the same time, the exclusion of low-qualified workers from employment can raise labour quality and as such raise labour productivity, as high-qualified workers are expected to be more productive than low- or medium-qualified workers (see e.g. European Commission, 2008: 44). Given the stronger link with labour utilization than with labour productivity, the relationship between macro-economic skills mismatch and GDP per capita is expected to be negative.

However, other factors may be at play simultaneously, adding "noise" to the relationship between labour productivity and macro-economic skills mismatch. First there is a possible concern about reverse causality. Past literature has argued that productivity growth tends to be associated with aggregate employment growth (see e.g. Saltari and Travaglini 2009; Chirinko 1995; Christiano et al 2003). If technological progress is skill-biased[35] and wages show downward rigidities, productivity growth will reinforce the composition bias of employment towards high-qualified workers, hence increasing skills mismatch (Moreno-Galbis and Sneessens 2007). This would strengthen the positive correlation between productivity and skills mismatch, but lead to an over-estimation of the relationship between skills mismatch and productivity.

In addition, there may be some cyclical factors at play. Macro-economic skills mismatch behaves to some extent countercyclically. As low-qualified employment is more sensitive to the cycle than high-qualified employment, macro-economic skills mismatch will increase during economic downturns. Economic studies that have looked specifically into the cyclicality of labour productivity find striking discrepancies between theoretical predictions and empirical observations. Notably, theory would predict that in perfectly competitive markets, profit-maximizing firms will produce according to a production function with decreasing marginal returns. As a result, during an economic upturn, firms expand production and hire marginally less productive workers, with a negative impact on average labour productivity. During an economic downturn, less productive workers are fired first, increasing average labour productivity.[36] This implies that labour productivity should show countercyclical movements (see e.g. Aizcorbe 1992).

Interestingly, however, most economists have observed that labour productivity moves with the cycle instead (see e.g. Baily et al., 2001).[37] The most popular explanation for why labour productivity moves with the cycle is the labour hoarding hypothesis, which argues that in the presence of transaction costs for hiring and firing, firms adjust factor utilization during downturns (e.g. by letting employees work less intensively), resulting in lower output production with the same staff – while the intensity of factor utilization is

[35] See e.g. Bound and Johnson (1995), Berman et al. (1994); Johnson (1997), Machin and Van Reenen (1998); Akerman et al. (2015)

[36] Along the same lines, Devereux (2002) finds that new hires are more qualified during economic downturns than during economic upturns; and Pollmann-Schult (2005) provides evidence of crowding out of low-qualified workers during economic downturns.

[37] However, focussing mainly on the US, a number of scholars finds this pro-cyclicality of labour productivity to have become more subdued since the early 1980s (see for instance Blanchard and Watson, 1986, Galí and van Rens, 2014 or Stiroh, 2009).

difficult to observe (see e.g. Oi, 1962; Solow, 1964; Rotemberg and Summers, 1990; Bernanke and Parkinson, 1991; Burnside, Eichenbaum and Rebelo, 1993, Basu, 1996; Wen, 2004; Barnichon, 2014). Some scholars have suggested as well that a drop in the speed of production (and an associated drop in employment at the firm level) leads to a decline in the degree of specialization (as the remaining workers are reorganised along the assembly line), resulting in lower labour productivity (Aizcorbe 1992). These theoretical arguments would not establish a causal link between macro-economic skills mismatch and productivity, but they could offer an explanation for a possible negative correlation between productivity (which is procyclical) and skills mismatch (which is countercyclical, as low-skilled employment is more sensitive to the cycle (Maré and Hyslop 2008; Abraham and Haltiwanger 1995; Saint-Paul 1993). In our regressions, we try to filter out these cyclical elements by controlling for the output gap.

There could as well be some dynamic impacts on productivity, through different channels. First, long unemployment spells may lead to human capital depreciation or skill loss, including because the unemployed lose opportunities to learn by doing (Martin and Rogers, 2000), leading to a permanent loss of productivity and potential output (hysteresis) (Blanchard and Summers, 1986). On the other hand, a wider dispersion in employment outcomes between workers of different qualifications may increase the incentive to invest in education. Some scholars have argued that economic downturns may reduce incentives to drop out of school prematurely and raise educational attainment as such (see e.g. Dellas 2003; Alessandrini et al., 2015). There is some evidence that this has indeed happened in the countries where the 2008 economic crisis hit hardest (Quarina 2017; European Commission 2015). These issues could as well contribute to a positive hysteresis with a more skilled labour force, lower macro-economic skills mismatch, and higher productivity when the economy picks up.

Finally, there is a strand of economic literature arguing that recessions have positive impacts on productivity when the crisis unwinds and recovery takes hold. Saint-Paul (1993) provides a brief review of these effects, including the "lame duck" effect (less productive firms being less likely to survive recessions); "discipline effects" (the recession would put pressure on firms to reorganise and raise productivity); and "intertemporal substitution effects", where firms allocate a larger share of their labour force to productivity-improving activities (such as training or reorganization) during a recession, when the opportunity cost of doing so is lower than during upturns. Our analysis however focuses on contemporary links between mismatch and productivity, without considering dynamic relationships.

As a result, our hypothesis on the link between mismatch and productivity is as follows:

> *Macro-economic skills mismatch is expected to be positively related with productivity, after controlling for cyclical elements.*

3.2.2. Empirical findings

The data however show a relatively strong negative correlation between macro-economic skills mismatch and productivity, both in a cross-section comparison and when considering variation within countries over time, even after controlling for the output gap (Figure 11). This negative relationship is mostly driven by EU-13 countries. With only a few exceptions such as Estonia and Latvia, these countries combine a relatively high level of skills mismatch with a relatively low level of labour productivity – but while skills mismatch is on a structural downward trend (mostly as a result of upskilling), labour productivity is on a structural upward trend as a result of catching up effects. When zooming in on EU-15 countries, we do find the expected positive relationship between labour productivity and macro-economic skills mismatch (Figure 12).

Regression results, controlling for cyclical elements by the output gap, educational attainment or occupation levels and country-specific effects, confirm the observed negative relationship both for the cross-sectional and the within-country dimensions. They suggest that an increase of 10 ppt in macro-mismatch[38] is associated with a reduction of 19% in labour productivity (or of 23% in the fixed effects regression model). The magnitude of the relationship is similar in size (but opposite in sign) to the relationship between raising the level of high-skilled jobs or of tertiary attainment in the economy by 10 ppt and labour productivity. The sign of the output gap is positive, suggesting that labour productivity behaves as a pro-cyclical variable (fitting for instance the labour hoarding hypothesis). The Hausman test suggests that the fixed effects model is the preferred one, in other words that time-invariant country-specific variables are correlated with labour productivity, and that it is therefore better to control for these in the regression.

Figure 11: Fixed effects correlation between labour productivity and macro-economic skills mismatch (all MS), controlling for output gap (2000-17)

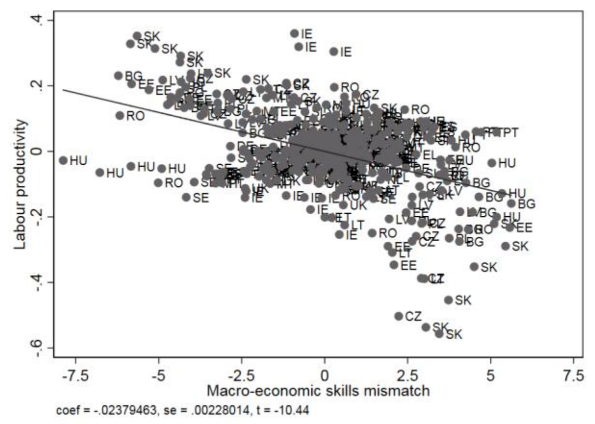
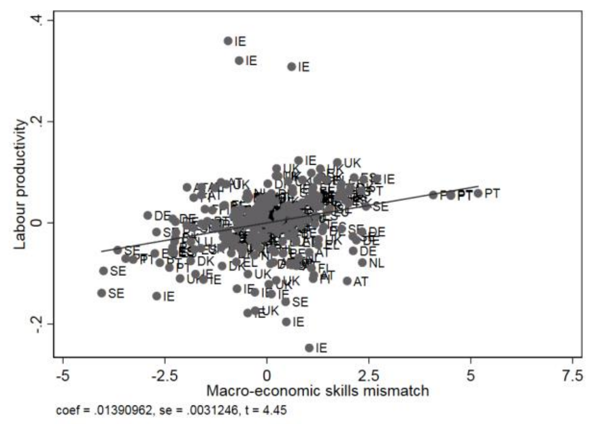


Figure 12: Fixed effects correlation between labour productivity and macro-economic skills mismatch (EU-15 only), controlling for output gap (2000-17)



Source: Labour productivity data are taken from AMECO and measured as GDP per hour worked, expressed in log levels based on constant 2010 prices. Macro-economic skills mismatch data are based on own calculations drawing on LFS data.
Note: In the Figures above, all countries appear 18 times – once for each year included in the sample.

If the sample is split between EU-15 and EU-13 countries, a positive relationship is revealed for EU-15 countries, fitting more closely our prior expectations (either because mismatch is positively related with productivity or because of skills-biased technological change). In EU-13 countries, however, the negative relationship remains, possibly reflecting other time-variant factors (omitted variables) that lead both to reducing macroeconomic skills mismatch and improving labour productivity.[39] It is beyond the scope of this paper, however, to go deeper into these issues.

[38] A 10 percentage-point difference in macro-mismatch is roughly equivalent to the difference in mismatch between RO and UK in 2017 or to the rise observed in ES observed over 2007-17.
[39] Possible contributing factors could be FDI inflows or business regulations supporting firm entry and growth.

Table 1a: Random-effects regressions of labour productivity and macro-economic skills mismatch[40]

VARIABLES	(1) re	(2) re	(3) re-EU-15	(4) re-EU-15	(5) re-EU-13	(6) re-EU-13
Output gap	0.001	0.005***	0.004**	0.008***	0.007***	0.007***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
% High-skilled jobs	0.019***		0.011***		0.021***	
	(0.002)		(0.002)		(0.003)	
Macro-economic skills mismatch	-0.025***	-0.017***	0.010***	0.010***	-0.035***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
% Tertiary attainment		0.017***		0.009***		0.021***
		(0.001)		(0.001)		(0.002)
Constant	2.935***	3.083***	3.147***	3.330***	2.582***	2.511***
	(0.109)	(0.112)	(0.076)	(0.077)	(0.157)	(0.150)
Observations	493	489	267	263	226	226
R-squared	0.608	0.436	0.735	0.531	0.472	0.234
Number of geo	28	28	15	15	13	13
Wald chi2	258.587	437.729	81.302	159.167	243.368	313.327
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1b: Fixed-effects regressions of labour productivity and macro-economic skills mismatch

VARIABLES	(1) fe	(2) fe	(3) fe-EU-15	(4) fe-EU-15	(5) fe-EU-13	(6) fe-EU-13
Output gap	0.001	0.005***	0.003*	0.008***	0.007***	0.007***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
% High-skilled jobs	0.018***		0.008***		0.021***	
	(0.002)		(0.001)		(0.003)	
Macro-economic skills mismatch	-0.024***	-0.017***	0.009***	0.009***	-0.035***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
% Tertiary attainment		0.017***		0.009***		0.022***
		(0.001)		(0.001)		(0.002)
Constant	2.956***	3.065***	3.267***	3.321***	2.573***	2.477***
	(0.076)	(0.050)	(0.063)	(0.042)	(0.138)	(0.115)
Observations	493	489	267	263	226	226
R-squared	0.344	0.486	0.179	0.385	0.528	0.597
Number of geo	28	28	15	15	13	13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[40] The reported R² value for this and other random-effects regressions in this paper is the overall-R². Note that this does not have the same properties as the usual OLS R².

3.3. Skills shortages

3.3.1. Theoretical arguments

Skills shortages generally reflect the lack of availability of (skilled) labour. Several scholars have assessed the relationship between skills shortages and productivity. From a theoretical perspective, one would expect skills shortages to be negatively related with productivity, as they may lead to loss of production due to unfilled jobs for a certain period of time; or to the recruitment of workers with lower skills or qualifications than what their vacancies would ideally require, resulting in underskilling and underqualification (Bennett and McGuinness, 2009). Another argument that is commonly made is that skills shortages inhibit investment and the adoption of new technologies, reducing productivity growth (e.g. Foley and Watts, 1994). By raising labour costs (e.g. because firms need to spend more on training, recruitment or wages), they could distort the optimal allocation of resources. Some scholars have argued as well that skills shortages put workers in a better bargaining position, allowing them to demand an easier pace at work (Haskel and Martin, 1993a).[41]

Empirical evidence on the magnitude of these relationships has however produced mixed results. On the one hand, Forth and Mason (2004) and McGuinness and Bennett (2006) identified no clear link between productivity and unfilled vacancies based on their analysis of firm-level data. On the other hand, Haskel and Martin (1993a) find that skills shortages have reduced productivity growth in the United Kingdom by around 0.7 percentage-points per year over the period 1983-86. Furthermore, Nickell and Nicolatsis (1997) argue that a 10% increase in the number of firms reporting a skills shortage leads to a (permanent) 10% reduction in fixed capital investment and a (temporary) 4% reduction in spending on research and development. Tang and Wang (2005) find a negative impact on the performance of small- and medium-sized companies; and Bennett and McGuinness (2009) find, after controlling for selection bias arising from the fact that more productive firms are more likely to experience skills shortages, a substantial impact of those shortages on firm-level productivity.

A complicating factor pertains to cyclical elements: while skills shortages may prevail during economic expansions, as more firms will be hiring new workers, we have seen above that economic expansions are typically associated with higher productivity. This relationship may mitigate the observed negative relationship of skills shortages with labour productivity and underlines the importance of controlling for the cyclical elements.

As a result, our hypothesis on the link between skills shortages and productivity is as follows:

> *Skills shortages are expected to be negatively related with productivity, after controlling for cyclical elements.*

3.3.2. Empirical findings

When we look at the data, however, we do not observable any relevant link between labour productivity and skills shortages in a cross-sectional comparison. The apparently negative link in Figure 13 is entirely driven by an outlier (Hungary) and not statistically significant. In the fixed effects correlation plot shown in Figure 14 (which considers the variation over time within countries), a faint (but significant) positive correlation can be observed, even after controlling for cyclical elements; driven in particular by EU-15 countries.

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[41] On the other hand, a paper by the same authors finds that firms often adapt to shortages by adjusting overtime – especially when shortages are perceived as cyclical - which would have the opposite effect on the pace of work of workers in shortage positions (Haskel and Martin, 1993b)

Figure 13: Labour productivity in relation to skills shortages, cross-sectional comparison (2017)

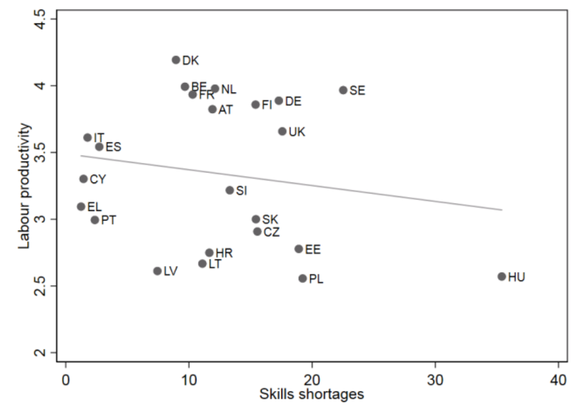
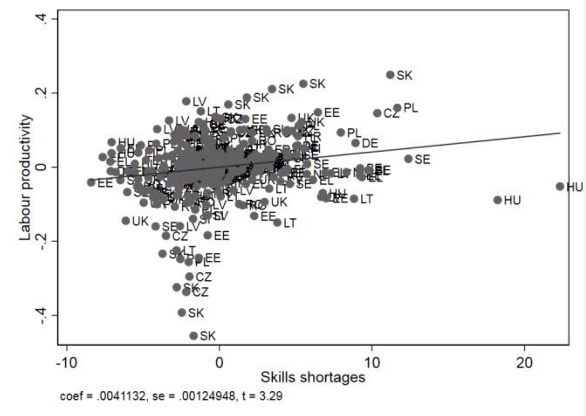


Figure 14: Fixed-effects correlation between labour productivity and skills shortages (2000-17)



Source: Labour productivity data are taken from AMECO and measured as GDP per hour worked, expressed in log levels based on constant 2010 prices. Macro-economic skills mismatch data are based on own calculations drawing on LFS data.
Note: In Figure 14, all countries appear 18 times – once for each year included in the sample.

Our best explanation of this counter-intuitive positive correlation is possible endogeneity as a result of omitted variables or even reverse causality; with countries who are performing better in terms of labour market outcomes (on a structural basis)[42] and have higher labour productivity, also exhibiting higher needs for high-skilled labour, and running into shortages when supply is insufficient.[43] This relationship seems to outweigh the potentially negative relationship between skills shortages and labour productivity.

Countries with the highest skills shortages in EU-15 are Germany, Sweden, and the United Kingdom. These have good labour market conditions in general – not only for high-qualified workers. The countries with the lowest skills shortages in EU-15 are Greece, Spain, Italy, and Portugal. These combine low productivity with high unemployment among high-qualified individuals (as well as among the general population).[44] As a matter of fact, in none of the countries with the highest skills shortages (Hungary, the United Kingdom, Sweden, Poland, Germany, and Estonia), the unemployment rate of high-skilled workers exceeds 4%.[45]

[42] Figure A2.18 shows that skills shortages are strongly correlated with the cyclically adjusted unemployment rate measured as the non-accelerating wage rate of unemployment (NAWRU) (Havik et al., 2014).
[43] E.g. because there is a time lag between new needs arising in the economy and adequate labour supply response (e.g. because new training programs need to be developed, students need to be trained).
[44] These countries have aggregate unemployment rates above 10% and unemployment rates of at least 8% for high-qualified workers.
[45] Interestingly, unemployment of high-qualified workers has no link with tertiary attainment in the population: while HU, PL and DE have less than 30% tertiary attainment and are therefore on the lower side within the EU; UK, SE and EE are amongst the EU countries with the highest tertiary attainment (around 40% or more).

Table 2a: Random-effects regressions of labour productivity and skills shortages

VARIABLES	(1) re	(2) re	(3) re-EU-15	(4) re-EU-15	(5) re-EU-13	(6) re-EU-13
Output gap	-0.000	0.005***	0.002*	0.004***	-0.001	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
% High-skilled jobs	0.014***		0.005***		0.022***	
	(0.002)		(0.001)		(0.004)	
Skills shortages	0.004***	0.000	0.004***	0.003***	0.004*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
% Tertiary attainment		0.014***		0.004***		0.025***
		(0.001)		(0.001)		(0.002)
Constant	2.675***	2.849***	3.466***	3.580***	1.846***	2.065***
	(0.115)	(0.118)	(0.074)	(0.068)	(0.173)	(0.102)
Observations	323	322	174	173	149	149
R-squared	0.362	0.213	0.596	0.385	0.164	0.168
Number of geo	24	24	13	13	11	11
Wald chi2	49.735	145.870	56.745	67.554	29.614	162.918
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2b: Fixed-effects regressions of labour productivity and skills shortages

VARIABLES	(1) fe	(2) fe	(3) fe-EU-15	(4) fe-EU-15	(5) fe-EU-13	(6) fe-EU-13
Output gap	-0.001	0.005***	0.002*	0.004***	-0.001	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
% High-skilled jobs	0.012***		0.004***		0.022***	
	(0.002)		(0.001)		(0.005)	
Skills shortages	0.004***	0.000	0.004***	0.003***	0.005**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
% Tertiary attainment		0.014***		0.004***		0.025***
		(0.001)		(0.001)		(0.002)
Constant	2.734***	2.850***	3.523***	3.589***	1.835***	2.060***
	(0.083)	(0.032)	(0.054)	(0.024)	(0.164)	(0.047)
Observations	323	322	174	173	149	149
R-squared	0.130	0.326	0.264	0.302	0.172	0.544
Number of geo	24	24	13	13	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression results also provide evidence for a positive relationship between labour productivity and skills shortages. The positive relationship persists when controlling for educational attainment and high-skilled occupations, and, as can be seen from split sample regressions, is mostly driven by results for EU-15 countries.[46] The size of the relationship is not large, however, as an increase in skills shortages by 10 percentage-points is associated with an increase of about 4% in labour productivity (both in random and fixed-effects regressions). These results can also be turned around, to say that relatively small increases in labour productivity can already go hand in hand with a sizeable relationship with the perception of skills shortages in an economy.

Note that our results do not imply that skills shortages have a positive impact on labour productivity. Rather, we are not able to isolate the potentially negative impact of skills shortages based on our analysis at the aggregate level. Micro-econometric analyses based on firm-level data may be more adequate to measure this impact. The correct interpretation of our findings would be that skills shortages tend to occur in an environment of economic expansion and growing productivity.

3.4. Measures of on-the-job skills mismatch

We now turn to our two measures of on-the-job skills mismatch: underqualification and overqualification.

3.4.1. Theoretical arguments

In the existing literature, inferences on the productivity of workers have mostly been drawn from observations on their wages – which are considered as proxies for labour productivity. Workers with higher qualifications tend to fetch higher wages than workers with lower qualifications. Wages also tend to grow with the occupational status of someone's job: managers, professionals and technicians tend to earn more than clerks, sales workers, and artisans. If wages correctly reflect productivity, this implies that productivity is increasing with a worker's qualification level and with the occupational level of his/her job. Aggregate data indeed suggest a positive correlation between labour productivity and the share of high-skilled jobs on the one hand (Figure 15) and between labour productivity and the share of tertiary attainment on the other hand (Figure 16).

Countries with a higher share of high-skilled occupations typically also have a higher labour productivity. The relationship between the share of high-qualified individuals in the working population and productivity is a bit less strong. In countries such as Lithuania and Cyprus, where, as we will see in subsequent analysis, the degree of overqualification is relatively high, labour productivity is below what one would expect in a country with such a high share of tertiary educated workers.

A. Underqualification

Underskilling or underqualification implies that workers do not have the skills or qualifications, which would allow them to attain the highest possible productivity in their jobs. The argument that skilled workers are more capable of using new technologies has been made earlier by Katz and Autor (1999), Acemoglu (2002) and Link and Siegel (2003). Acemoglu and Zilibotti (2001) argue that less developed countries, which import technologies developed by more advanced countries, are unable to achieve the same productivity levels, resulting in considerable output gaps. They attribute this to "skills scarcity", implying that in less-developed countries, unskilled workers perform the tasks that are carried out by skilled workers in developed countries.

[46] The results are impacted by outliers HU and EL; if these outliers are dropped, the results become stronger and more robust across different regression specifications.

Figure 15: Linear fit between productivity and employment share of high-skilled occupations (2017)

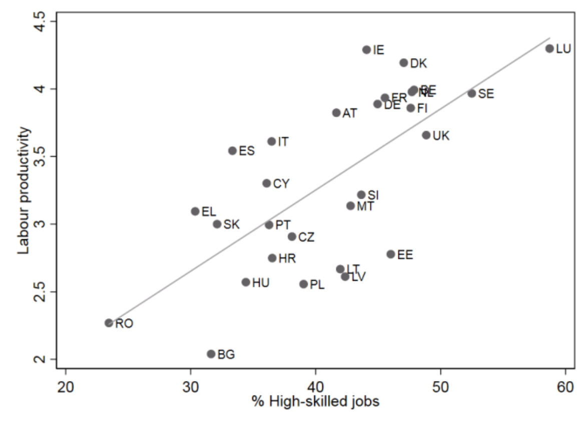
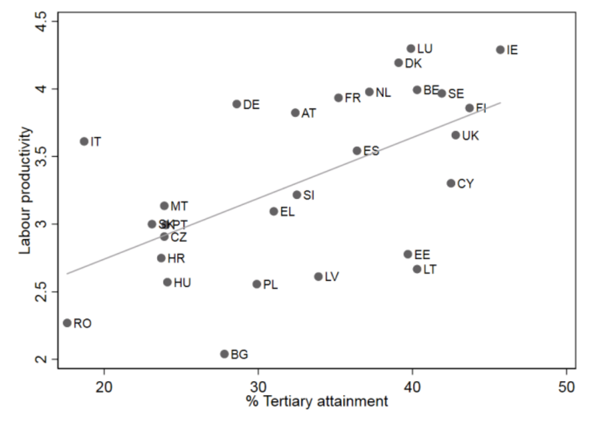


Figure 16: Linear fit between productivity and qualification level of the population (2017)



Note: High-skilled jobs are occupations with ISCO 1-digit codes 1-3. Tertiary attainment is measured as the share of individuals holding a tertiary degree (ISCED levels 5-8) in age group 25-64. The R^2adj-values of the linear models are respectively 0.47 and 0.30.

Empirical studies on the contribution of workers' human capital to productivity find that workers with higher educational attainment achieve higher sales per worker (e.g. Abowd and Kramaz, 2005) and contribute to raising total factor productivity (e.g. Ilmakunnas et al., 2004). Based on an analysis of PIAAC data, both McGowan and Andrews (2015a) and Zira (2016) find a negative relationship between underskilling and firm-level productivity. Based on linked employer-employee panel data, similar results have been found for underqualification (Kampelmann and Rycx, 2012; Grunau, 2016).

The relationship between underqualification and aggregate productivity depends on the perspective taken. If one compares productivity of underqualified workers with productivity of workers with the right (higher) educational attainment in a similar job, it is clear that underqualification leads to lower aggregate productivity. On the other hand, if one compares the productivity level of underqualified workers with the productivity level of workers with similar educational attainment in a well-matched job (in other words, a job with lower skills requirements), the underqualified worker will have a higher labour productivity as jobs with higher skills requirements tend to be more productive. It is also important to mention that underqualification might actually be a sign of the successful labour market integration of low-qualified workers, strengthening effective labour resource utilization, and as such be positively related with aggregate output. Figure A2.25 and Figure A2.26 in Annex 2 show the positive correlation between underqualification and employment outcomes for low-qualified workers. See also e.g. Maré et al. (2015) for a paper considering the impact of "skills dilution" as a result of strong employment growth for workers with relatively low skills on firm-level productivity growth.

B. Overqualification

Overqualification implies that workers have a higher qualification level than their job requires, or than they can use in their jobs. The literature has identified several theoretical channels through which overqualification (or the related – albeit not identical – phenomenon of overskilling) can be related with productivity of workers. On the one hand, as mentioned in Section 3.1 human capital theory predicts that education and skills have a positive impact on productivity – and this would apply even beyond the qualifications or skills that are strictly required for a job (although at a lesser rate).[47] On the other hand, overqualification has been argued to reduce job satisfaction and motivation and increase turnover, reducing productivity (Tsang, 1987; Tsang et al., 1991; Hersch 1991).[48] Over time, overqualification may as well lead to cognitive decline (De Grip et al., 2008). These relationships mitigate the positive relationship between overqualification and productivity at the micro-level.

Empirical work suggests that overqualified workers typically earn more than workers with a similar job and matching qualifications; but less than workers with a similar qualification level and a matching job (see e.g. Sicherman, 1991; Sloane et al., 1999; Cohn and Ng, 2000; Dolton and Silles, 2008; Levels et al., 2014). Hence, if wages reflect productivity,[49] overqualification raises productivity compared to the case where a worker would have a lower qualification in the same job; but reduces productivity compared to the case where a worker would have the same qualification level but a more requiring job.

Some researchers have directly assessed the impact of overqualification on firm-level productivity. For example, Rycx and co-authors find that overeducation has a positive impact on productivity (implicitly controlling for jobs' skills requirements); and in particular so for firms with a higher share of high-skilled jobs, in high-tech industries, and in a more uncertain economic environment (Kampelmann and Rycx, 2012; Mahy et al., 2015).

McGowan and Andrews (2015a) argue that, while firm-level productivity may indeed increase with overqualification, there may still be a negative association between aggregate productivity of an economy and overqualification as a result of a suboptimal allocation of resources (referring to the "potential productivity" higher-skilled workers could have if they were in well-matched jobs). Their main argument is that if (less productive) firms recruit highly qualified workers for jobs that do not require such qualifications; while other firms face a shortage of or have difficulties accessing highly qualified workers for the (more productive) jobs they offer, such misallocation of resources constrains entry and expansion of more productive firms and as such reduces aggregate productivity.[50] Potential causes include policy variables such as rigid labour market regulations, barriers to competition and to firm entry and exit, but also structural factors (such as housing policies etc.) leading to low geographic labour mobility (McGowan and Andrews, 2015b).

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[47] Note that some scholars have argued against the human capital theory, arguing that the positive correlation between education and productivity reflects to a certain extent the signalling value of education for individuals who already had a higher innate ability (and hence productivity) before undertaking education (e.g. Arrow, 1973; Spence, 1973; 1974). Brown and Sessions (1999) and by Psacharopolous (1979) found some evidence in favour of this hypothesis; however, a substantial number of studies refute these results and point at a substantial impact of education on productivity (e.g. Chevalier et al., 2004; Layard and Psacharopolous, 1974; Groot and Oosterbeek, 1994; Kroch and Sjoblom, 1994; Johnes, 1998; Dickson, 2013). An interesting argument in this context is made by Pericles Rospigliosi et al. (2014), who argue that most (40-70%) graduate job vacancies are open to graduates of any subject; implying that employers are not interested in subject-specific knowledge per se (see as well Roberts 2006) as it rapidly becomes outdated; but rather in the fact that they are "specialists in the practice of learning", reflecting a strong ability and willingness to "learn on-the-job". In their view, the propensity to learn benefits graduates (who earn higher wages), employers, as well as economies at large (who benefit from increased resilience if the workforce has a higher capacity to adapt to rapid change).

[48] Some counterevidence is however provided by Büchel (2002).

[49] Human capital theory asserts that wage differentials reflect differences in productivity (Becker, 1964). Labour market regulations and bargaining institutions can however generate a mismatch between productivity and wages in the short run (see e.g. Weeden, 2002). A recent study by Rycx et al. (2015) argues that qualifications have a stronger impact on productivity than on wages; as productivity dispersion tends to exceed wage dispersion.

[50] This argument is also used by Berton et al. (2017) as a starting point for their analysis of the impact of deregulation of employment protection legislation on skills mismatch and productivity.

The ensuing hypotheses on the sign of the relationship between on-the-job mismatch and productivity are as follows:

> *Underqualification is expected to be negatively related with productivity, after controlling for jobs' qualification requirements in the economy (in which case the counterfactual consists of those with the right – and hence higher - qualification in the same job).*
>
> *Underqualification is expected to be positively related with productivity, after controlling for educational attainment in the economy (in which case the counterfactual considers those with similar qualifications in less-requiring jobs).*
>
> *Overqualification is expected to be positively related with productivity, when controlling for jobs' skills requirements in the economy (in which case the counterfactual consists of those with the right – and hence lower - qualification in the same job.*
>
> *Overqualification is expected to be negatively related with productivity, when controlling for educational attainment in the economy (in which case the counterfactual considers those with similar qualifications in more-requiring jobs).*

3.4.2. Empirical findings

Figure 17 shows that there is a positive cross-country correlation between underqualification and labour productivity. The correlation becomes even stronger when outliers such as Italy, Malta and Portugal are dropped from the plot. Again, the relationship seems strongly influenced by divergences between EU-15 and EU-13 countries. While the former generally have higher labour productivity, they also have more underqualification. The difference in underqualification results from the fact that EU-13 countries have on average lower shares of low-qualified individuals (and higher levels of medium attainment).[51] Moreover, those who are low-qualified are significantly less likely to be employed (given high levels of macro-economic skills mismatch in EU-13 countries), again reducing the extent of underqualification (as the latter only accounts for those individuals who hold a job).

Fixed-effects correlations in Figure 18 suggest that, as one would expect, the relationship between labour productivity and underqualification over time is negative, once controls for job skills requirements are included. If one controls for educational attainment instead, the relationship becomes insignificant, suggesting that the relationship between underqualification and labour productivity mostly coincides with the relationship between educational attainment and the latter.

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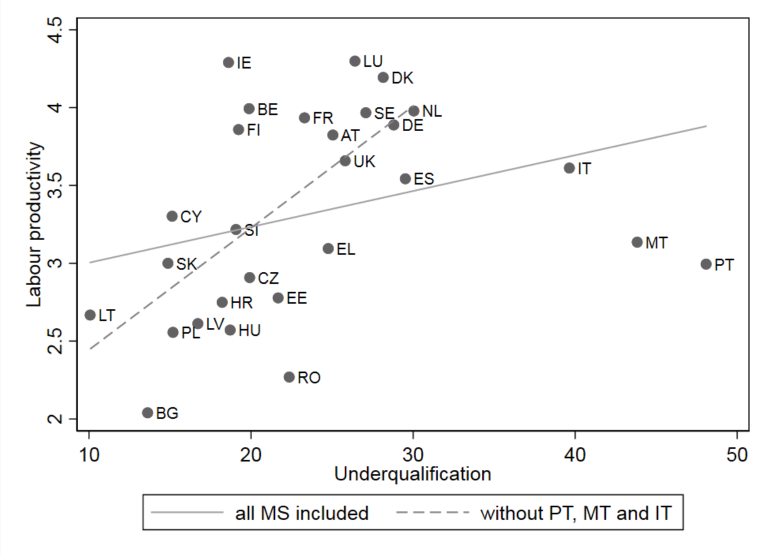
[51] The share of individuals with low educational attainment in the New Member States is 13%, as compared to 20% in 2016 in the Old Member States (excluding Portugal, Malta, Italy and Spain).

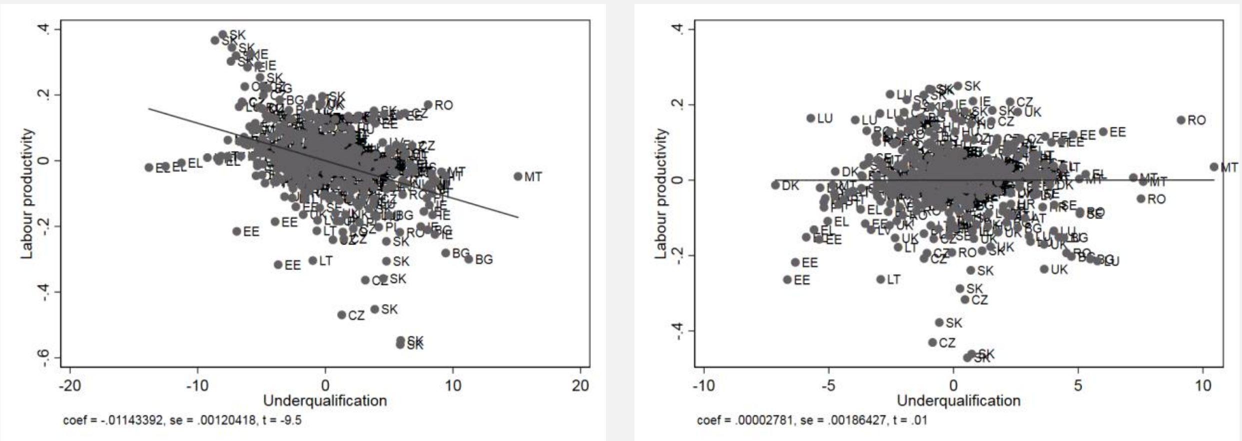
Figure 17: Linear fit between labour productivity and underqualification (2017)



Source: Own calculations based on LFS. The R^2adj-values of the linear models are respectively 0.06 (all MS included) and 0.37 (without PT, MT, and IT).

Figure 18: Fixed-effects correlations between labour productivity and under-qualification (2000-17)

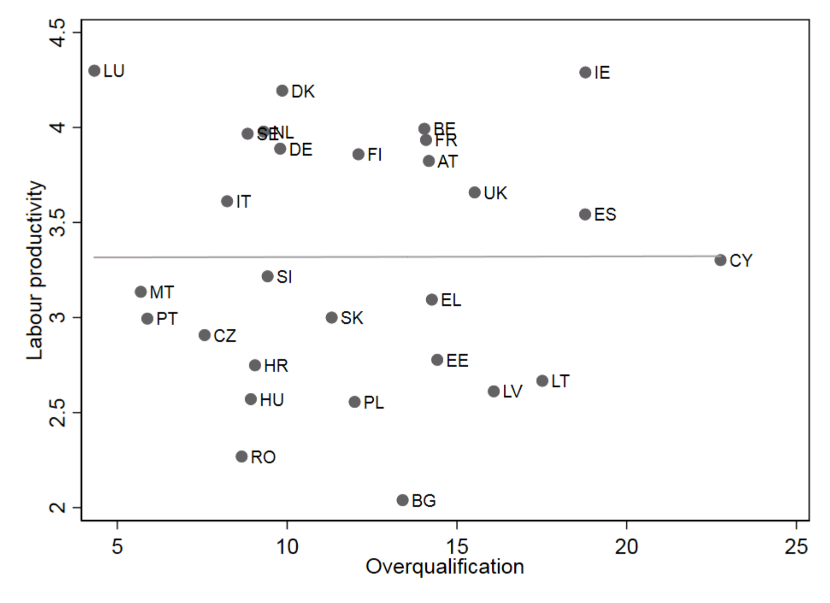
(a) controlling for % high-skilled jobs **(b) controlling for tertiary attainment**



Note: In the Figures above, all countries appear 18 times – once for each year included in the sample.

As Figure 19 shows, there is no significant cross-country correlation between labour productivity and overqualification. This could be related to the fact that overqualification relates positively to tertiary attainment (which relates positively with labour productivity) on the one hand, and it relates negatively to the share of high-skilled jobs in the economy (which relates positively with labour productivity as well).

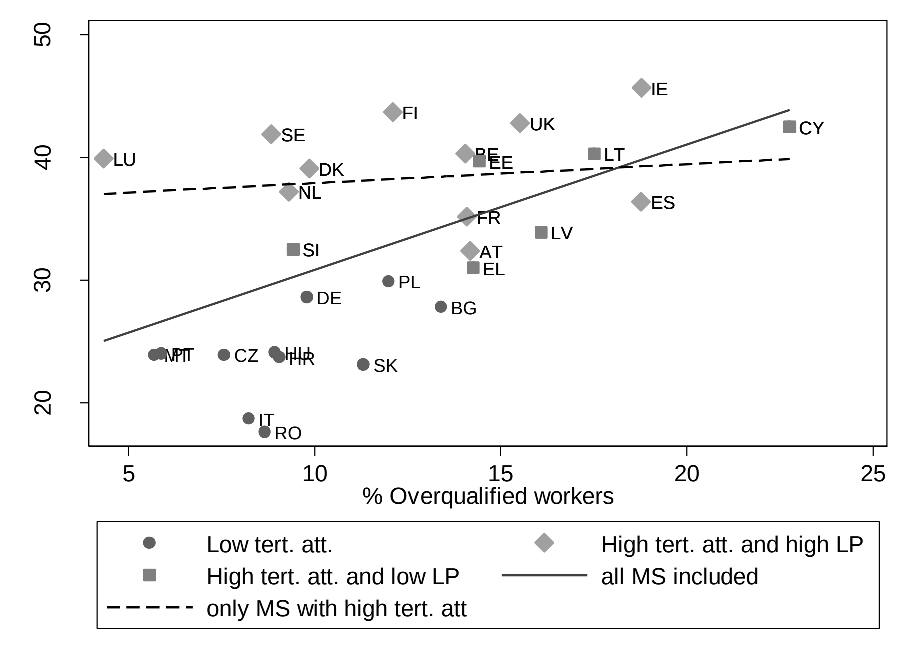
Figure 19: Linear fit between labour productivity and overqualification (2017)



Source: Own calculations based on LFS

We noted earlier the positive correlation between countries with high tertiary attainment and overqualification. Countries that combine high tertiary attainment with low overqualification clearly have a higher labour productivity on average than those countries combining high tertiary attainment with high levels of overqualification (Figure 20).

Figure 20: The relationship between tertiary attainment, overqualification and labour productivity (2017)

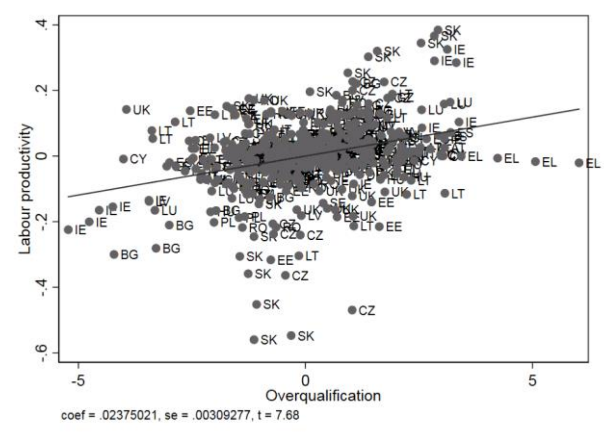


The R^2adj-values of the linear models are respectively 0.28 (all MS included) and ± 0 (only MS with high tertiary attainment).

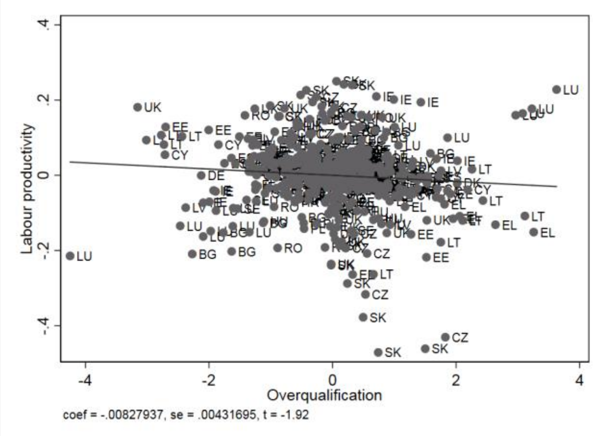
When exploiting within country variation over time, we find a positive relationship with overqualification when controlling for job skills requirements; and a negative relationship when controlling for educational attainment, in line with what one would expect.

Figure 21: Fixed- effects correlations between labour productivity and overqualification (2000-17)

(a) controlling for % high-skilled jobs



(b) controlling for tertiary attainment



Note: In the Figures above, all countries appear 18 times – once for each year included in the sample.

Regression results in Table 3a and 3b confirm the expected relationships outlined above, i.e. overqualification is positively correlated with labour productivity when controlling for occupation levels and negatively when controlling for educational attainment. In terms of the size of the relationship, an increase of 10 percentage-points in overqualification will increase labour productivity by 24%, if we keep the share of high-skilled jobs equal. Note that this implicitly means that attainment is increased, while no additional jobs are generated that require a higher degree. If on the other hand one keeps the share of tertiary attainment equal, however, an increase of 10 percentage-points in overqualification will reduce productivity by 11%.[52] Note that this implicitly means that jobs' skills requirements are reduced.

The relationship between underqualification and productivity has the opposite sign. An increase in underqualification by 10 percentage-points reduces productivity by 10-12%, when controlling for jobs' skills intensity. When controlling for attainment, however, this relationship loses significance, even if it has the expected positive sign. This again aligns with our earlier finding that the relationship between underqualification and productivity works mainly through the channel of educational attainment.

[52] These results refer to the random-effects regression estimations. The size of the relationship is similar (resp. +25% and -10% according to the fixed-effects regression estimations.

Table 3a: Random-effects regressions of labour productivity and on-the-job mismatch indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	re	re	re	re	re	re	re
Overqualification	0.023***	-0.012***			0.005	-0.012**	
	(0.003)	(0.004)			(0.005)	(0.005)	
Underqualification			-0.010***	0.002	-0.009***	0.000	
			(0.001)	(0.002)	(0.002)	(0.002)	
Output gap	0.008***	0.008***	0.009***	0.008***	0.009***	0.008***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
% High-skilled jobs	0.012***		0.009***		0.009***		
	(0.002)		(0.002)		(0.002)		
Tertiary attainment		0.022***		0.020***		0.022***	0.018***
		(0.002)		(0.002)		(0.002)	(0.001)
Constant	2.531***	2.760***	3.167***	2.615***	3.073***	2.745***	2.748***
	(0.113)	(0.101)	(0.129)	(0.133)	(0.157)	(0.141)	(0.119)
Observations	586	581	586	581	586	581	585
R-squared	0.124	0.317	0.005	0.298	0.010	0.327	0.217
Number of geo	28	28	28	28	28	28	28
Wald chi2	237.698	448.552	261.698	435.802	260.751	442.572	453.796
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3b: Fixed-effects regressions of labour productivity and on-the-job mismatch indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	fe	fe	fe	fe	fe	fe	fe
Overqualification	0.024***	-0.010**			0.003	-0.011**	
	(0.003)	(0.004)			(0.005)	(0.005)	
Underqualification			-0.012***	0.001	-0.011***	-0.001	
			(0.001)	(0.002)	(0.002)	(0.002)	
Output gap	0.008***	0.008***	0.009***	0.009***	0.009***	0.008***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
% High-skilled jobs	0.011***		0.007***		0.007***		
	(0.002)		(0.002)		(0.002)		
Tertiary attainment		0.021***		0.019***		0.020***	0.018***
		(0.002)		(0.002)		(0.002)	(0.001)
Constant	2.593***	2.798***	3.325***	2.728***	3.276***	2.867***	2.790***
	(0.053)	(0.022)	(0.096)	(0.094)	(0.131)	(0.110)	(0.021)
Observations	586	581	586	581	586	581	585
R-squared	0.303	0.450	0.340	0.444	0.341	0.450	0.448
Number of geo	28	28	28	28	28	28	28

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4. Conclusion and policy implications

In conclusion, we have provided theoretical considerations on the relationship between skills mismatch and productivity and have shown a correlational analysis thereof. These considerations have shown the complexity of this relationship and the need for further work in terms of developing a structural model.

In terms of skills mismatch developments our data suggest that certain types of skills mismatch are indeed on the rise in the EU, notably skills shortages (especially in those countries with good labour market performances) and overqualification (especially in those countries where tertiary attainment has expanded considerably, without being accompanied by a commensurate rise in high-skilled jobs). Other types are on a long-term declining trend (e.g. underqualification) or follow more complex patterns over time (e.g. macro-economic skills mismatch). Nevertheless, there are significant differences across EU Member States in the levels of these indicators as well as in their evolutions over time.

In terms of the relationship between skills mismatch and productivity, our analysis suggests that it is not as clear-cut as it may seem.

Table 1 presents a schematic overview of our findings.

Table 1: Overview of our findings

Skills mismatch indicator	Expected relationship	Empirical relationship
Macro-economic skills mismatch	(+) as high macro-economic skills mismatch is associated with low employment rates of lower qualified individuals and labour productivity is expected to be higher if employment is biased towards the higher-qualified	(-) for the full sample, possibly due to strong correlation with economic growth (+) for the EU-15
Skills shortages	(-)	(+) possibly due to strong correlation with economic growth
Overqualification	(+) within a given job category, (-) within a given qualification	(+) within a given job category, (-) within a given qualification
Underqualification	(-) within a given job category, (+) within a given qualification	(-) within a given job category, (+) within a given qualification

In the case of macro-economic skills mismatch and skills shortages, our results contradict our prior hypotheses – potentially pointing to other factors at play that may require some further investigation. In the case of macro-economic skills mismatch, the results should not entirely surprise us as similar inconsistencies between what theory predicts under common assumptions have been found in the existing literature at the level of the cyclical behaviour of productivity, where it has for example been explained by the labour hoarding hypothesis. The hypothesis that higher macro-economic skills mismatch (i.e. a right-skewed distribution of employment towards higher qualified workers) is correlated with higher productivity is, however, confirmed for EU-15 countries.

For skills shortages, while one would theoretically expect a negative relationship with productivity, across countries and across time, we mostly observe that those countries doing better in terms of economic growth (beyond what is captured by the output gap) generally combine labour productivity growth with a higher incidence of skills shortages. This by no means implies that skills shortages are a desirable feature. It rather means that they are often an undesirable side effect of an otherwise positive phenomenon (economic expansion). To accurately analyse their relationship with productivity, micro-level analysis based on firm-level data might be more appropriate than the type of macro-level analysis we have pursued.

Finally, in the case of on-the-job mismatch indicators, our macro-level findings align closely with earlier findings from micro-level studies. They imply that educational expansion is positively related with productivity, but to be exploited to its full potential, it needs to be accompanied by a general upgrading of jobs in order to put these higher skills to their best use. Important framework conditions are quality assurance in education, policies that promote the alignment between education and training systems and the labour market, and a policy setting that encourages the creation of higher value-added jobs.

What options are available to policymakers wanting to address skills mismatch?

Macro-economic skills mismatch is typically caused by a weak integration in the labour market of less-skilled workers, while they still make out a substantial share of the population. Skills mismatch can decline through a **reduction in the share of less-skilled workers** – e.g. through prevention of early school leaving, by making available appropriate means to allow individuals to upskill and reskill themselves (including through work-based learning) and fight skills obsolescence (active labour market policies, the accessibility of vocational training and higher education for adults and so on).

When not caused by general labour shortages, *skills shortages* often reflect the lack of specific skills or profiles among individuals available for work. To some extent, skills shortages may result from inertia in wage adjustment (for certain types of shortages wage increases can raise labour supply) and/or reflect the unavoidable lag between emerging labour market demands (e.g. as a result of the development of new sectors) and the response of labour supply (as education and training programs typically take a few years). It may be solved through market mechanisms. Economists argue indeed that the **demand side issues such as wage setting practices** are also important responses to mismatch (Rathelot and van Rens 2017). In view of the important role of wages, **also the wider policy context such as labour market and welfare policies should be considered**. However, to address structural skills shortages, **measures that allow individuals to upskill and reskill themselves**, including through "Upskilling pathways"[53] and work-based learning, are crucial here too.[54] In this context, the European Commission has been promoting the European Pillar of Social Rights[55] since 2017 – with as first principle that "Everyone [should have] the right to quality and inclusive education, training and life-long earning in order to maintain and acquire skills that enable them to participate fully in society and manage successfully transitions in the labour market". Furthermore, the "New Skills Agenda for Europe"[56], proposed by the European Commission in 2016, aims at improving training, skills and support available to people in the EU as well as enhancing the skill matching process and proposes ten actions ("Upskilling Pathways" is one of them). It includes dimensions related to improving skills matching, also by developing labour market intelligence and by better

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[53] See EC (2016) Council Recommendation of 19 December 2016 on Upskilling Pathways: New Opportunities for Adults (2016/C 484/01).

[54] For a more detailed review of some policy options, see e.g. EP (2015)

[55] See https://ec.europa.eu/commission/priorities/deeper-and-fairer-economic-and-monetary-union/european-pillar-social-rights_en

[56] See SWD(2016) 195 final.

aligning skills to labour market needs (such as for instance the "Europass"[57] framework, the "European Alliance for Apprenticeships (EAfA)[58]" or the "European multilingual classification of Skills, Competences, Qualifications and Occupations (ESCO)[59]"). **Labour market intelligence and skill governance** are measures that inform prospective students about labour market outcomes of specific training programs (based for instance on graduate tracking surveys), reports on expected skills needs by growing sectors, the involvement of social partners in the development and update of education and training curricula or effective tools for workforce planning in specific sectors (such as healthcare). **Effective immigration policies** for specific higher skills profiles can also help address skills shortages in a relative short-term. [60]

When it comes to *overqualification,* some degree of overqualification can be acceptable. However, if overqualification is widespread, persistent, involuntary, and results from gaps in the quality of education or from a lack of labour demand (of graduates of a specific type), it is an important reason for policy concern. Strategies to address it include **ensuring the quality and labour market relevance of education and training programs** (e.g. if graduates are lacking specific skills indispensable to employers),[61] and **broader initiatives to promote regional development of skills-intensive industries[62] and reduce possible barriers to firm entry, exit and growth[63]** to foster the creation of jobs that can effectively exploit available human capital. Reducing overqualification by restricting access to tertiary attainment may in the end not be an optimal policy response, given that our results suggest a positive relationship between higher attainment and productivity, even in case of overqualification, where it is attenuated. Moreover, upskilling of the population can reduce macro-economic skills mismatch, address skills shortages, and reduce underqualification and may have a positive relationship with productivity and/or output through these channels as well.

Likewise, *underqualification* can be a sign of successful labour market integration of less-skilled workers, for example through non-formal vocational training courses that are not necessarily leading to higher formal qualifications. It is certainly more desirable to have underqualified workers than to have high unemployment or inactivity rates among less-skilled workers. On the other hand, underqualification can be mitigated by **reducing the share of low-qualified workers** in the population by preventing early school leaving and providing adequate "Upskilling pathways" (see above). A considerable share of the underqualified are workers that left school without at least an upper secondary school degree. However, upper secondary education is nowadays generally considered as the minimum qualification for a successful integration in the labour market and in society more generally. Educational requirements can be expected to strengthen further due to ongoing societal trends of globalization, skill-biased technological change, and the need to raise productivity to counteract demographic challenges in Europe. This is attested by the observation that employment expansion in occupations with higher skills requirements has outpaced employment growth in other occupations over recent decades.

[57] See SWD(2016) 320 final

[58] See https://ec.europa.eu/social/main.jsp?catId=1147

[59] See https://ec.europa.eu/esco/portal/home

[60] See European Migration Network, EMN (2015)

[61] For example, Erdsiek (2017) finds that overqualification persistence is partly attributable to ability and choice of study field. The negative impact of ability on the probability of overqualification has been highlighted before by Büchel and Pollmann-Schult (2004) and Chevalier and Lindley (2009). Erdsiek (2014) has found social capital to play a role as well.

[62] For example by strengthening local knowledge conditions (Roper et al., 2017)

[63] See e.g. McGowan and Andrews (2015b) on firm entry and exit regulations and mismatch. There are different reasons why barriers to firm growth may constrain the knowledge intensity of the economy. For example, large firms may invest more in R&D due to their easier access to external capital (Czarnitzki and Hottenrott, 2011). Moreover, growth options can mitigate the R&D investment dampening effect of uncertainty (Czarnitzki and Toole, 2013)

Note that in this paper, we have not looked explicitly at *horizontal* skills mismatches, notably that a mismatch can exist between workers' fields of study and the field of their jobs. The main reason is we have not been able to identify a robust indicator of horizontal mismatch that covers all or most EU countries, and can be calculated on a yearly basis. As mentioned above in Section **Error! Reference source not found.**, horizontal mismatch is more difficult to measure than vertical mismatch (Sellami et al., 2018), and arguably less problematic from a policy perspective as horizontally mismatched workers are less likely to suffer from a wage penalty than overqualified workers (Montt, 2017). Yet, in terms of policy implications, **reskilling workers** is often as important as upskilling them. Reskilling often involves shorter and more flexible training programs, and is of particular importance for workers who have left initial education and are seeking to update their skills or reorient their skills set towards new demands of the labour market.

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ANNEX I: DATA SOURCES AND COVERAGE

The table below presents in more detail the sources and coverage of the data used in the analysis in this paper.

Table A1.1: Data sources and coverage

Indicator	**Data source**	**Description**
Productivity		
Labour productivity (LP) – GDP per hour worked	AMECO (no sectoral information)	Definition: GDP in Euros and constant prices at 2010 reference level per hours worked Frequency: Annual data Member states covered: all Time coverage: EU15: 1970-2018; EU12: 1995-2018
Total factor productivity (TFP)	DG ECFIN-B3 based on AMECO (no sectoral information)	Definition: TFP is calculated as the Solow residual i.e. the residual of a log-linearized Cobb-Douglas production function with assumed factor elasticities of 0.65 for labour and 0.35 for capital and employment is expressed in terms of hours worked. European Economy Forecast Frequency: Annual data Member states covered: all Time coverage: EU15: 1961-2018; EU12: 1995-2018
Capital intensity	AMECO (no sectoral information)	Definition: Net capital stock in 1000 Euros and constant prices at 2010 reference level per hours worked Frequency: Annual data Member states covered: all Time coverage: EU15: 1970-2018; EU12: 1995-2018
Mismatch variables		
Macro-economic skills mismatch (mismatch_macro) – based on employment rates	DG EMPL calculations based on LFS data	Definition: relative dispersion of employment rates (Eurostat code: lfsa_ergaed) by educational attainment, weighted by their importance in the working age population (Eurostat code: lfsq_pgaed) Frequency: quarterly or annual data Member States covered: all Time coverage: as of 2007q2 for HR, as of 2005q1 for all others; as of 1998q1 for some; up to 2017Q4 (last update 07.12.2017)
Macro-economic skills mismatch (mismatch_macro) – based on unemployment rates	DG EMPL calculations based on LFS data	Definition: relative dispersion of unemployment rates (Eurostat code: lfsa_urgaed) by educational attainment, weighted by their importance in the active population (Eurostat code: lfsq_agaed) Frequency: quarterly or annual data Member States covered: all Time coverage: as of 2007q2 for HR, as of 2005q1 for all others; as of 1998q1 for some; up to 2017Q4 (last update 07.12.2017)
Overqualification, normative measure (overqual)	DG EMPL calculations based on LFS	Definition: Share of overqualified medium- and high-qualified workers (as percentage of employment) (Eurostat code for employment

	data	by occupation: lfsa_egised; Eurostat code for population by educational attainment level: edat_lfse_03) Frequency: quarterly data Member States covered: all Time coverage: as of around 2005 for quarterly data; as of around 2000 for annual data.
Underqualification, normative measure (underqual)	DG EMPL calculations based on LFS data	Definition: Share of underqualified low- and medium-qualified workers (as percentage of employment) (Eurostat code for employment by occupation: lfsa_egised; Eurostat code for population by educational attainment level: edat_lfse_03) Frequency: quarterly data Member States covered: all Time coverage: as of around 2005 for quarterly data; as of around 2000 for annual data.
Skills shortages – industry	Business & Consumer Surveys; Eurostat	Definition: % companies in industry sector reporting that labour is a factor constraining their production (Eurostat code: ei_bsin_q_r2) Frequency: Quarterly data Member States covered: all except for IE Time coverage: for some MS as of 1982; as of 1996 for all except for 5 (IE, HR, CY, LV, MT), for all except IE as of 2008
Skills shortages – services	Business & Consumer Surveys; Eurostat	Definition: % companies in services sector reporting that labour is a factor constraining their production (Eurostat code: ei_bsse_q_r2) Frequency: Quarterly data Member States covered: all except for IE and LU Time coverage: as of around 2003
Skills shortages – construction	Business & Consumer Surveys; Eurostat	Definition: % companies in construction sector reporting that labour is a factor constraining their production (Eurostat code: ei_bsse_q_r2) Frequency: Monthly data Member States covered: all except for IE Time coverage: for some MS already as of 1985. At EU level: as of 1993
Skills shortages (LS_tot)	Business & Consumer Surveys; Eurostat and AMECO	Weighted average of the three sectoral skills shortages indicators above. Weights are constructed based on sectoral gross value added figures in 2010 prices from AMECO.
Possible control variables		
Educational attainment (ISCED_58, ISCED_02)	EU-LFS	Definition: % of 25-64 year old population with tertiary educational attainment (as measured by ISCED[64] levels 5-8) or with low educational attainment (as measured by ISCED levels 0-2) (Eurostat code for population by educational attainment level: edat_lfse_03) Frequency: Annual data

[64] http://uis.unesco.org/en/topic/international-standard-classification-education-isced

		Member states covered: all Time coverage: EU15: around 1992-2017; EU12: around 2000-2017
Share of occupations requiring high skills (ISCO_high)	EU-LFS	Definition: % of employed population with an occupation requiring tertiary educational attainment according to ILO (2007), notably occupations in ISCO levels 1-3. (Eurostat code for employment by occupation: lfsa_egised) Frequency: Annual data Member states covered: all Time coverage: EU15: around 1992-2017; EU12: around 2000-2017
Output gap (OG)	DG ECFIN-B3 calculations based on AMECO data	Definition: % difference between actual GDP and potential GDP (for calculations of potential GDP see Havik et al. 2014) Frequency: Annual data Member states covered: all Time coverage: EU15: around 1965-2018; EU12: around 1997-2018

ANNEX II: DESCRIPTIVE STATISTICS AND GRAPHS

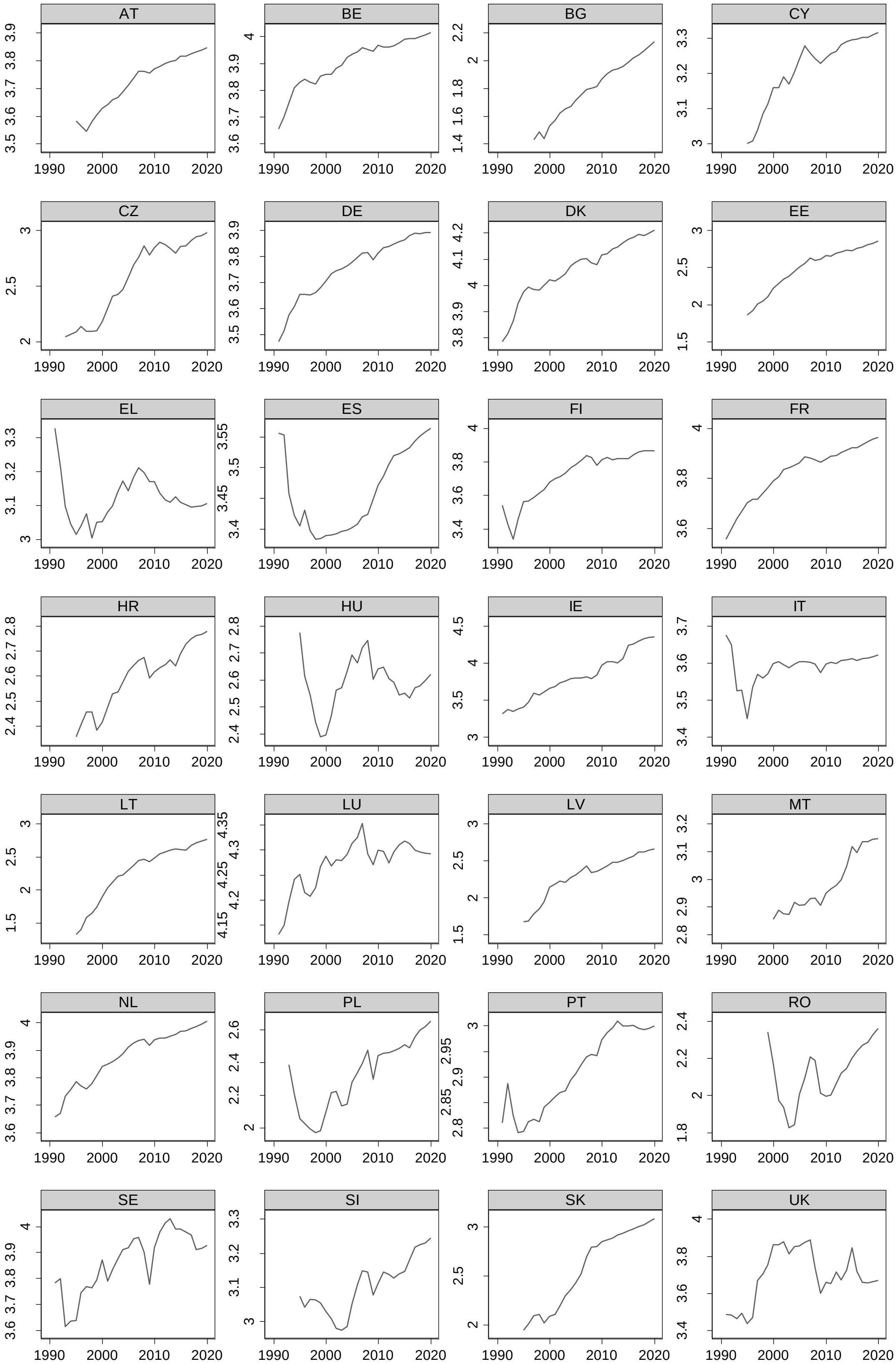
Table A2.1: Summary statistics

	Obs	Mean	St. Dev.	Min.	Max.
Log(Labour productivity)	1052	3.267	0.637	1.322	4.353
Log(Total factor productivity)	1065	-7.285	0.377	-8.329	-6.375
Log(Capital intensity)	1054	-2.777	0.789	-4.849	-1.632
Output gap	1133	-0.226	2.966	-15.810	16.868
Overqualification	590	9.150	4.444	0.000	22.763
Underqualification	590	31.661	12.158	10.071	73.794
Macro-economic skills mismatch	521	18.364	5.202	4.307	33.307
Skills shortages	347	7.549	6.558	0.162	36.800
% High-skilled jobs	600	37.264	7.289	16.248	62.834
% Medium-skilled jobs	600	53.243	7.099	30.719	77.477
% Low-skilled jobs	600	9.493	2.534	4.591	18.015
% Tertiary attainment	588	24.522	8.982	5.400	45.900
% Upper secondary attainment	592	46.880	15.638	9.500	76.900
% Lower attainment	592	28.527	16.938	5.200	82.200

Table A2.2. Correlation table

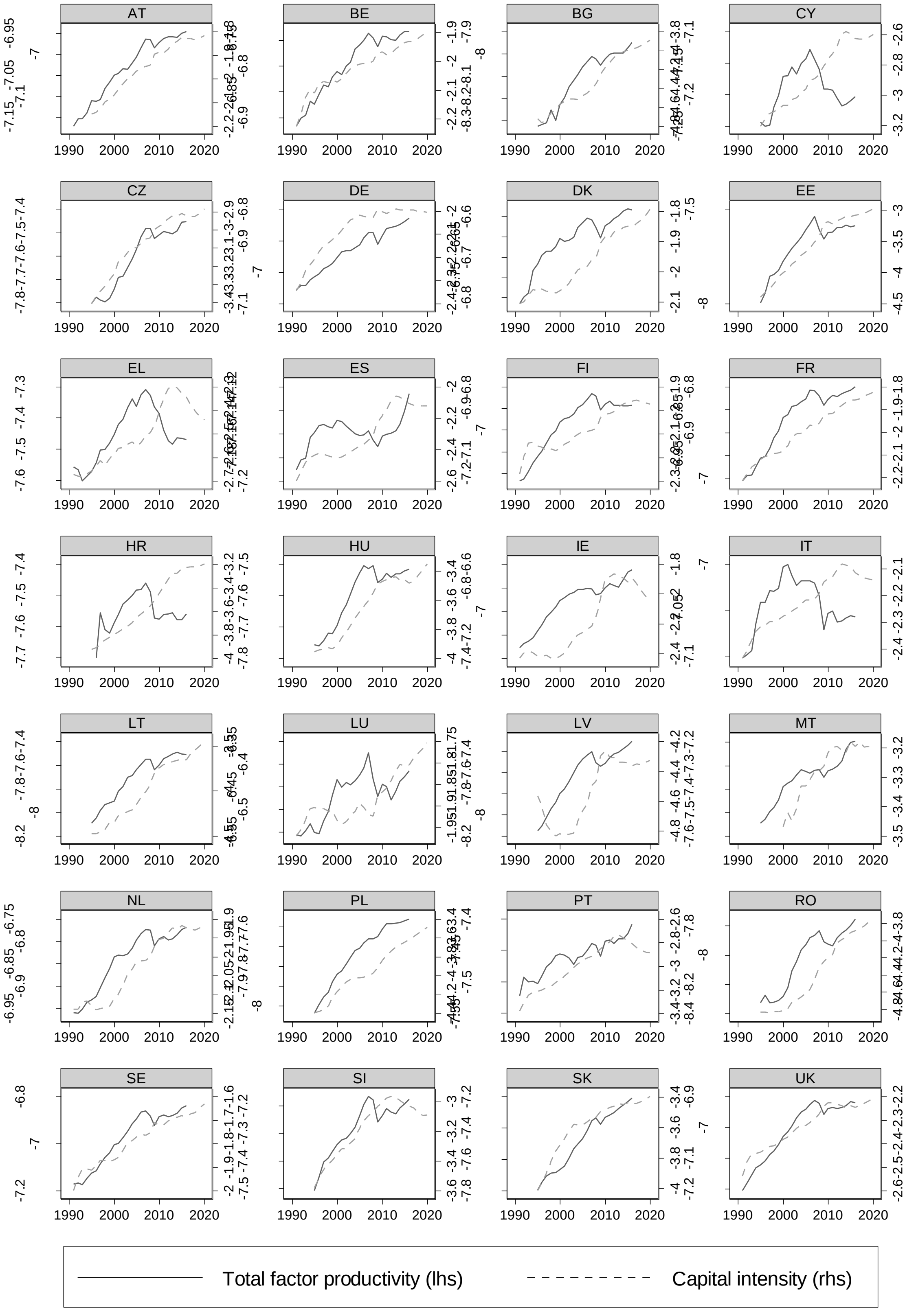
	Log (Labour prod.)	Log (Total factor prod.)	Log (Capital intensity)	Output gap	Overqualification	Underqualification	Macro-economic skills mismatch	Skills shortages	% High-skilled jobs	% Medium-skilled jobs	% Low-skilled jobs	% Tertiary att.	% Upper secondary att.	% Lower att.
Log(Labour productivity)	1,00													
Log(Total factor productivity)	0,87 *	1,00												
	0,00													
Log(Capital intensity)	0,89 *	0,89 *	1,00											
	0,00	0,00												
Output gap	0,01	0,07 *	-0,07 *	1,00										
	-0,82	-0,02	-0,02											
Overqualification	-0,03	-0,01	-0,02	-0,10 *	1,00									
	-0,45	-0,73	-0,60	-0,02										
Underqualification	0,23 *	0,16 *	0,25 *	0,08 *	-0,65 *	1,00								
	0,00	0,00	0,00	-0,04	0,00									
Macro-economic skills mismatch	-0,46 *	-0,40 *	-0,46 *	-0,05	0,14 *	-0,49 *	1,00							
	0,00	0,00	0,00	-0,30	0,00	0,00								
Skills shortages	0,06	0,12 *	-0,04	0,55 *	0,13 *	-0,25 *	-0,07	1,00						
	-0,29	-0,03	-0,51	0,00	-0,02	0,00	-0,20							
% High-skilled jobs	0,62 *	0,68 *	0,57 *	-0,05	0,18 *	-0,27 *	-0,08	0,28 *	1,00					
	0,00	0,00	0,00	-0,19	0,00	0,00	-0,08	0,00						
% Medium-skilled jobs	-0,61 *	-0,69 *	-0,54 *	0,03	-0,31 *	0,24 *	0,12 *	-0,25 *	-0,94 *	1,00				
	0,00	0,00	0,00	-0,45	0,00	0,00	-0,01	0,00	0,00					
% Low-skilled jobs	-0,09 *	-0,02	-0,14 *	0,07	0,35 *	0,13 *	-0,10 *	-0,11	-0,25 *	-0,10 *	1,00			
	-0,03	-0,71	0,00	-0,10	0,00	0,00	-0,02	-0,05	0,00	-0,01				
% Tertiary attainment	0,47 *	0,48 *	0,43 *	-0,12 *	0,69 *	-0,52 *	-0,17 *	0,27 *	0,70 *	-0,73 *	0,04	1,00		
	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,36			
% Upper secondary attainment	-0,42 *	-0,36 *	-0,43 *	0,02	0,09 *	-0,68 *	0,46 *	0,09	0,01	0,13 *	-0,39 *	-0,14 *	1,00	
	0,00	0,00	0,00	-0,57	-0,04	0,00	0,00	-0,10	-0,89	0,00	0,00	0,00		
% Lower attainment	0,16 *	0,10 *	0,18 *	0,04	-0,44 *	0,90 *	-0,35 *	-0,28 *	-0,37 *	0,26 *	0,34 *	-0,40 *	-0,85 *	1,00
	0,00	-0,02	0,00	-0,30	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Figure A2.1 Trends in labour productivity across the European Union



Note: Labour productivity is expressed as logarithm (GDP in EUR (2010 prices) per hour worked).

Figure A2.2 Trends in total factor productivity and capital intensity across the European Union



Note: Total factor productivity is expressed as lograrithm. Capital intensity is expressed as logarithm (1000 EUR (2010 prices) per hour worked).

Figure A2.3 Trends in the output gap across the European Union

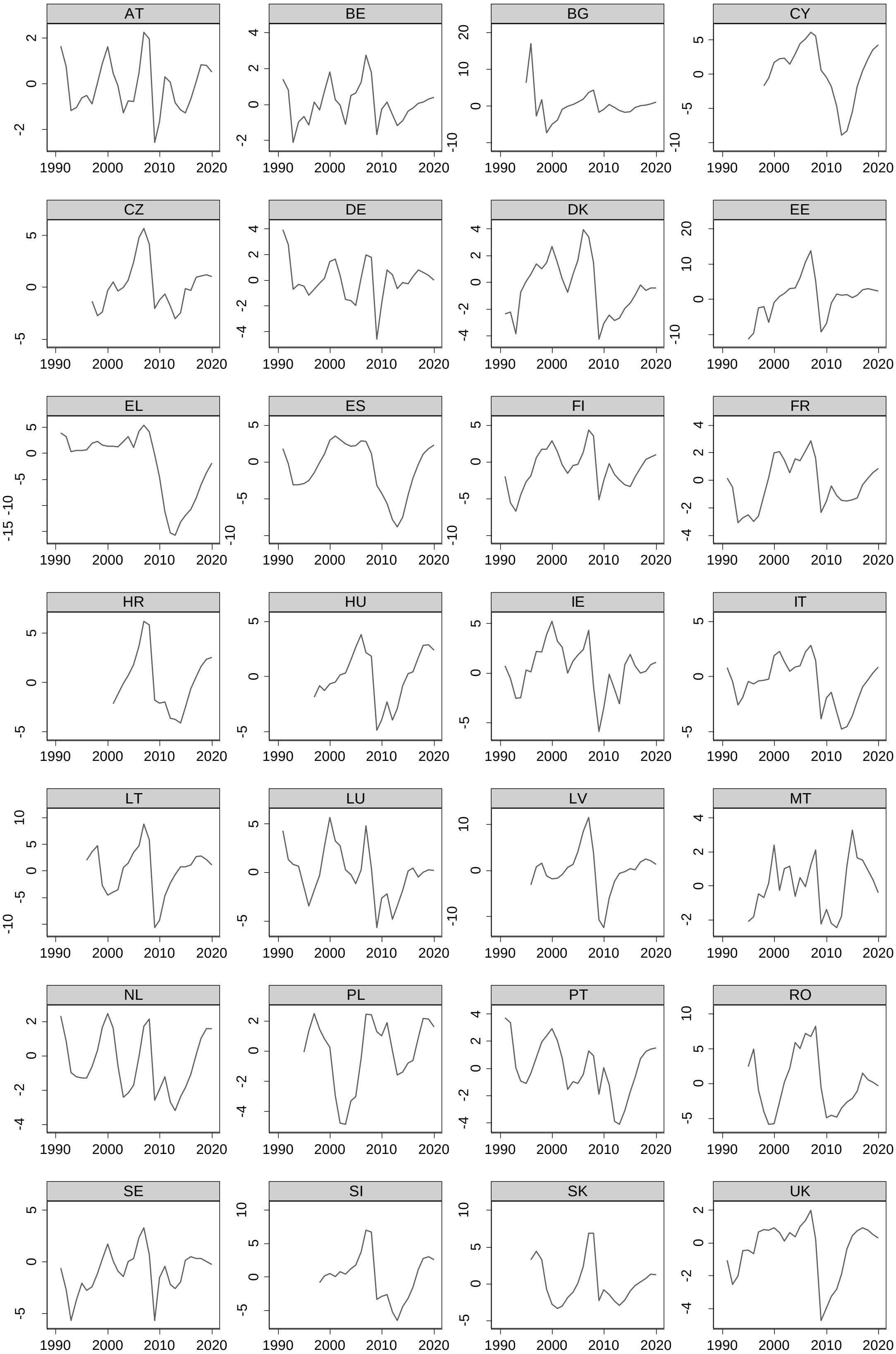


Figure A2.4 Trends in jobs' skills requirements and tertiary attainment across the European Union

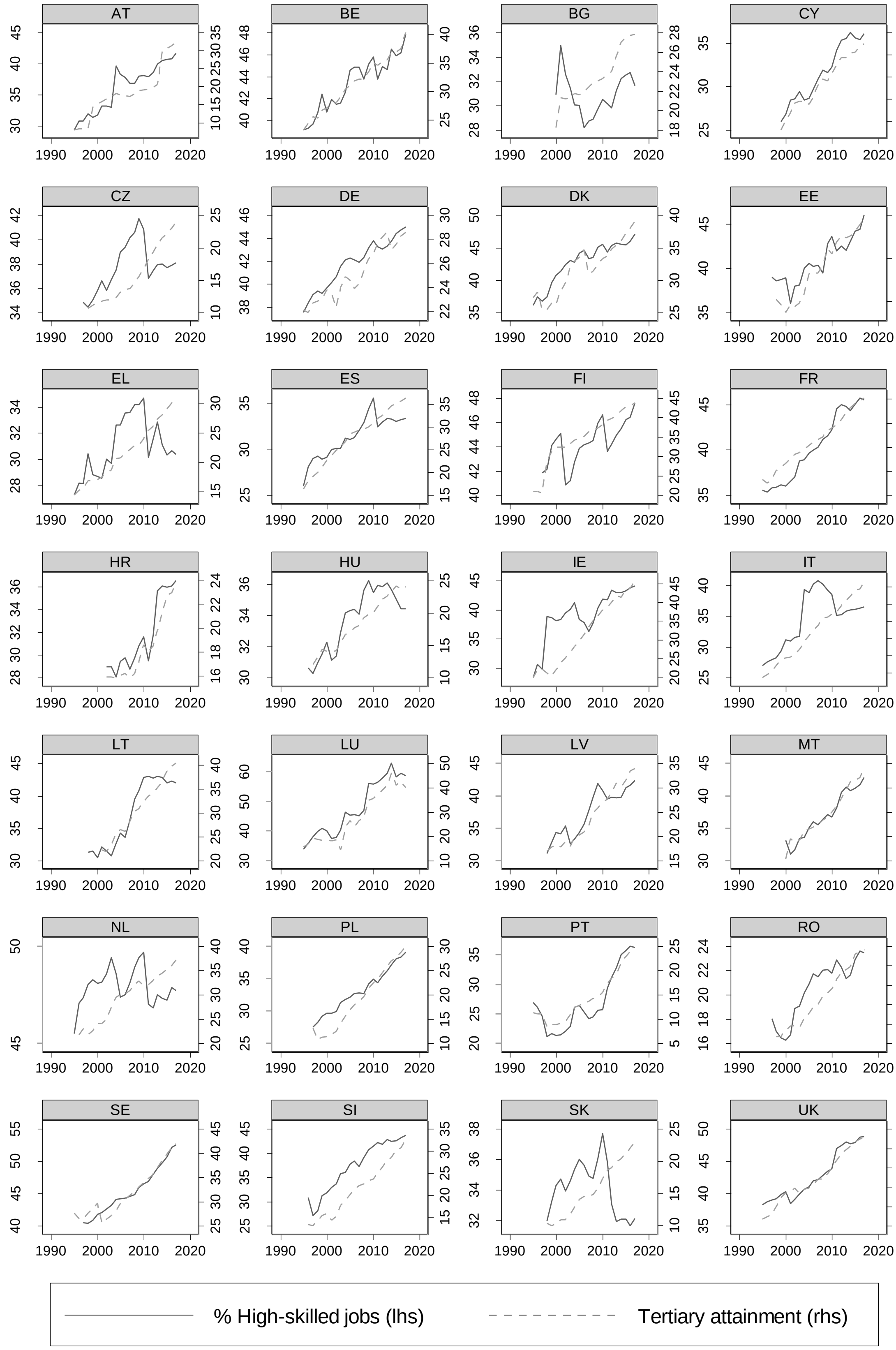


Figure A2.5 Trends in macro-economic skills mismatch and skills shortages across the European Union

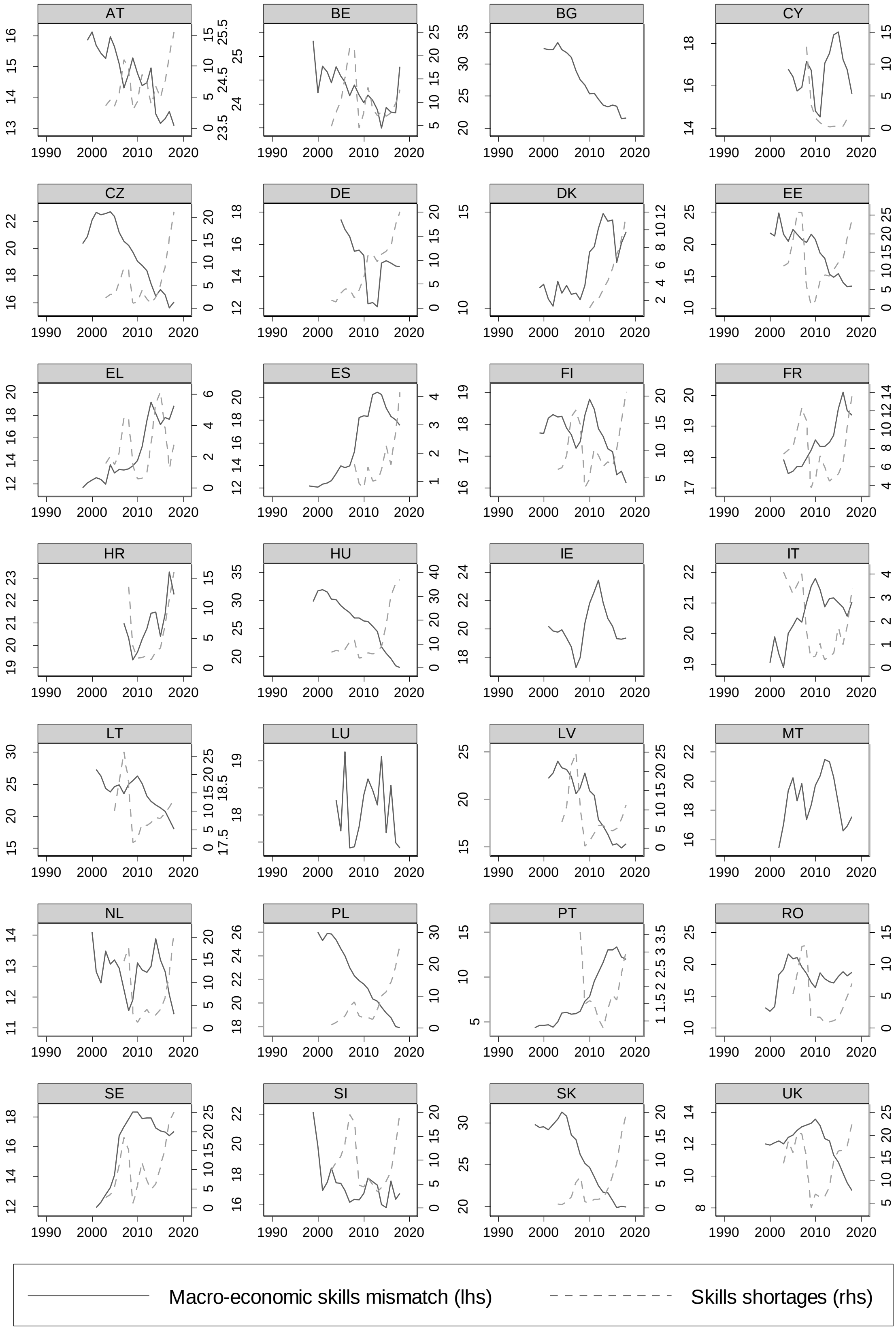
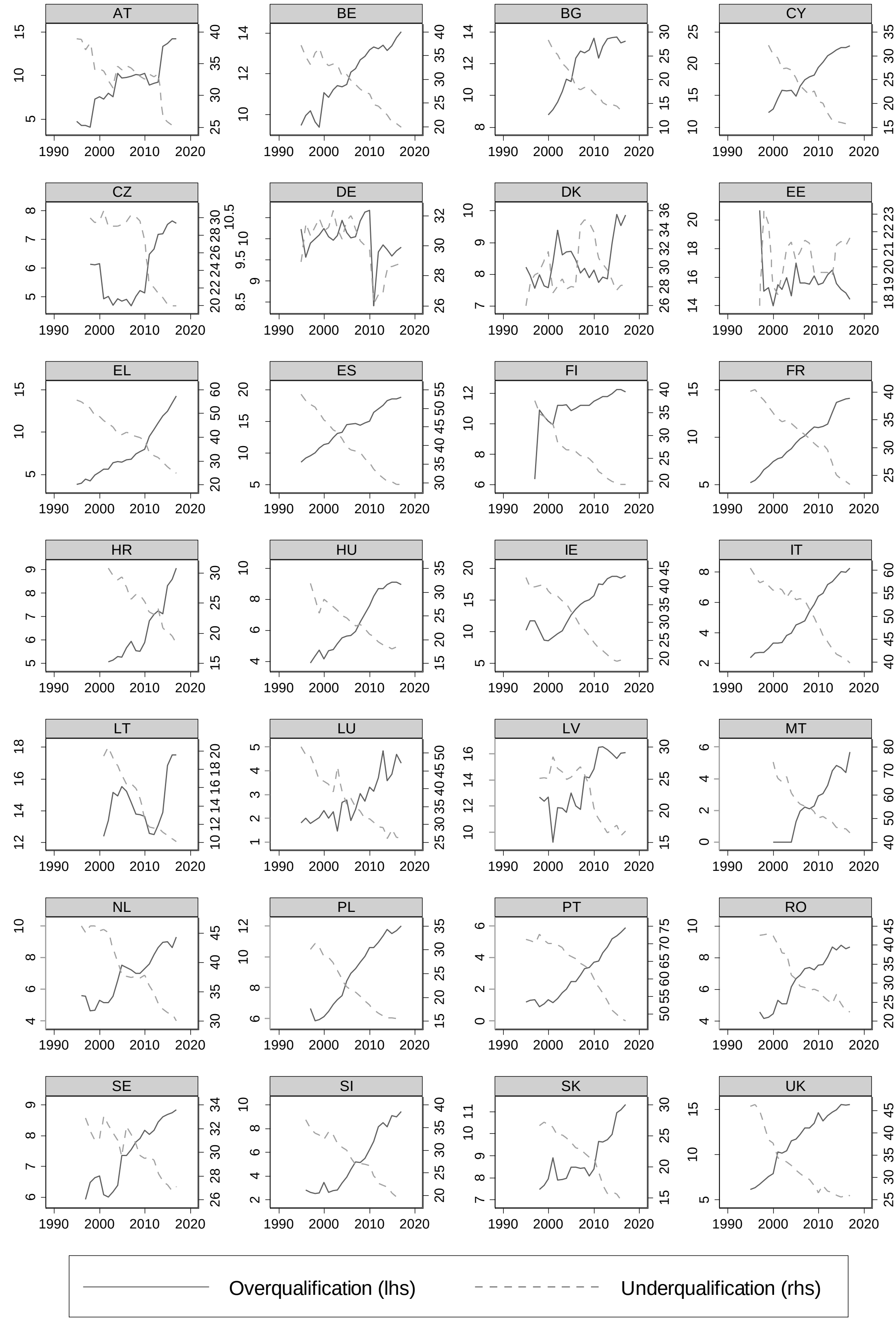


Figure A2.6 Trends in overqualification and underqualification across the European Union



Additional graphs on macro-economic skills mismatch

Figure A2.7 Fixed-effects correlation between macro-economic skills mismatch and employment in the construction sector (2000-17)

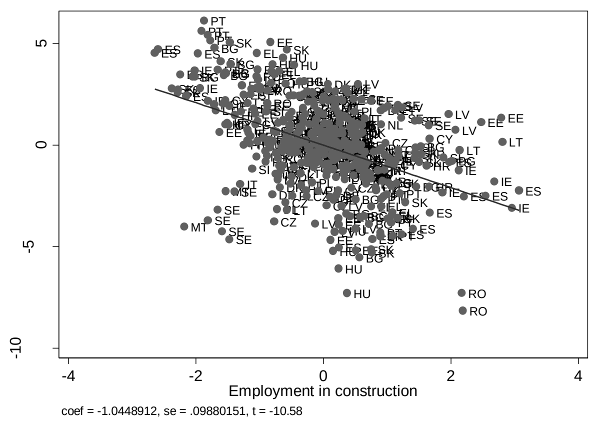


Figure A2.8 Fixed-effects correlation between macro-economic skills mismatch and employment in high-skilled occupations (2000-17)

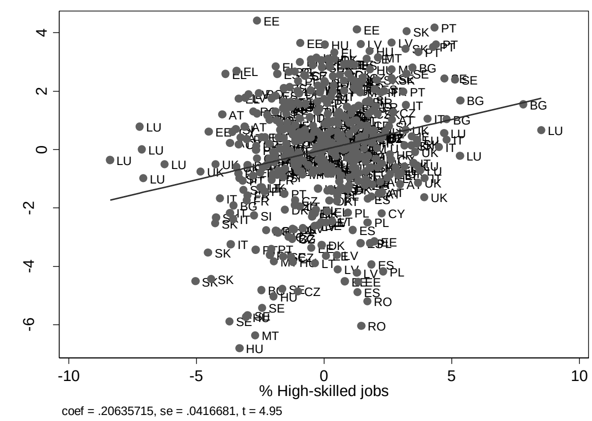
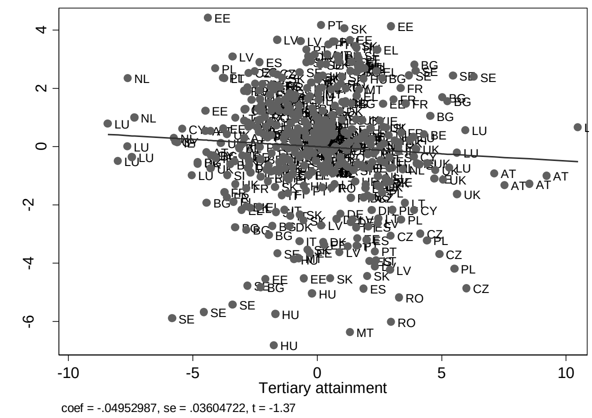


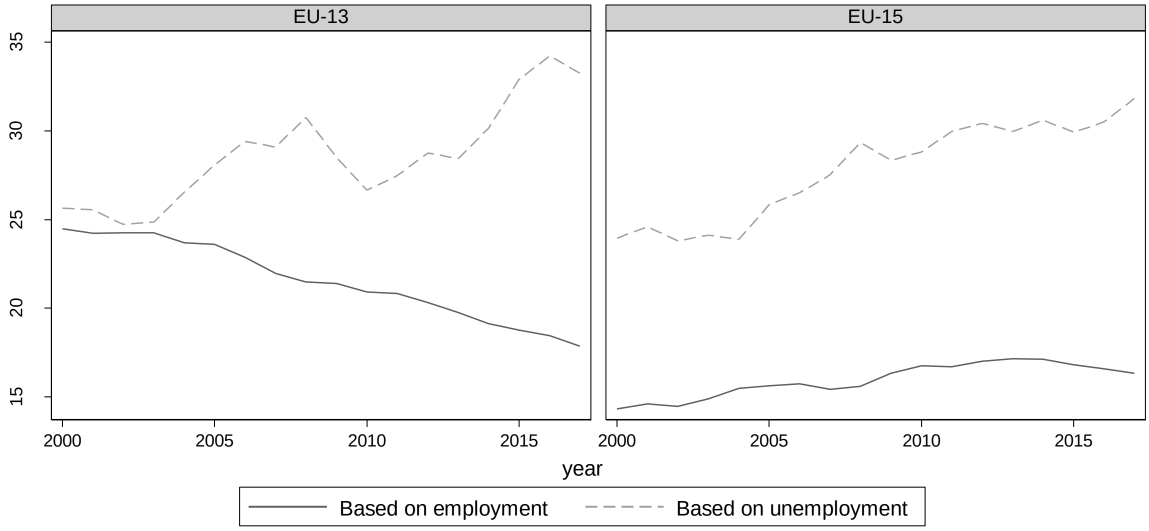
Figure A2.9 Fixed- effects correlation between macro-economic skills mismatch and the share of tertiary graduates in the working age population (2000-17)



Source: Own calculations based on Kiss and Vandeplas (2015), LFS

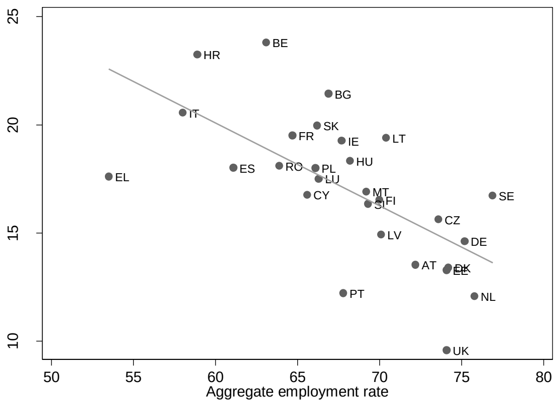
Note: The fixed-effects correlation reflects an added-value plot of the considered variable based on a regression with independent variables: the employment share in agriculture, in construction, and in services, country dummies. For Figure A2.7 and Figure A2.8 Fixed-effects correlation between macro-economic skills mismatch and employment in high-skilled occupations the regression also includes the share of tertiary graduates in the working age population; for Figure A2.9 Fixed- effects correlation between macro-economic skills mismatch and the share of tertiary graduates in the working age population includes the employment share in high-skilled occupations instead. The share of tertiary graduates and of high-skilled occupations could not be included in the same regression due to their high degree of multicollinearity.

Figure A2.10 Broad trends in macro-economic skills mismatch for EU-13 and EU-15 countries



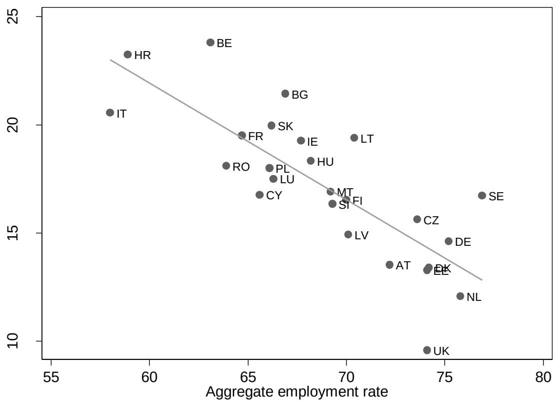
Macro-economic skills mismatch reflects weaknesses in labour resource utilization. This is reflected in the figures below through a negative correlation (in cross-country comparison) between macro-economic skills mismatch and the aggregate employment rate, and a positive one between macro-economic skills mismatch and the cyclically adjusted unemployment rate measured as the non-accelerating wage rate of unemployment (NAWRU) (Havik et al. 2014).

Figure A2.11 Linear fit between macro-economic skills mismatch and aggregate employment rate, all Member States (2017)



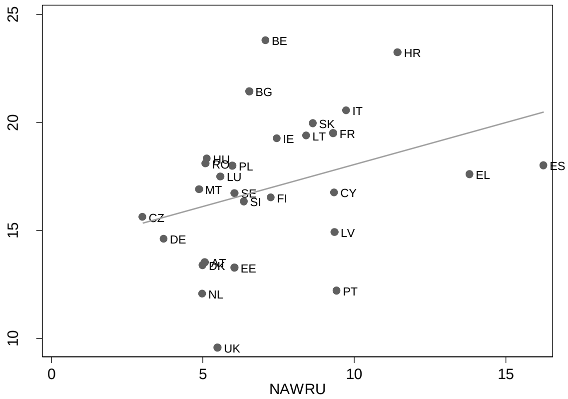
Note: R^2 adj of linear regression= 0.40

Figure A2.12 Linear fit between macro-economic skills mismatch and aggregate employment rate, excl. ES, PT, EL (2017)



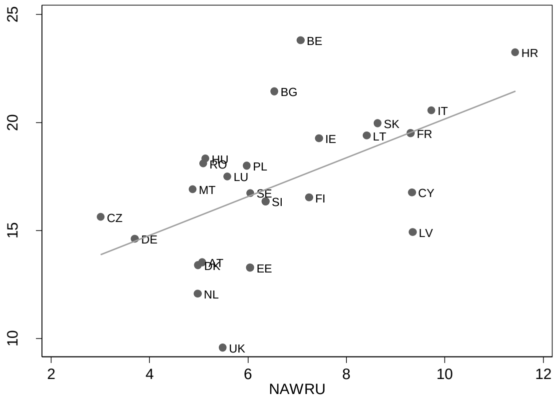
Note: R^2 adj of linear regression= 0.62

Figure A2.13 Linear fit between macro-economic skills mismatch and NAWRU, all Member States (2017)



Note: R^2 adj of linear regression= 0.09

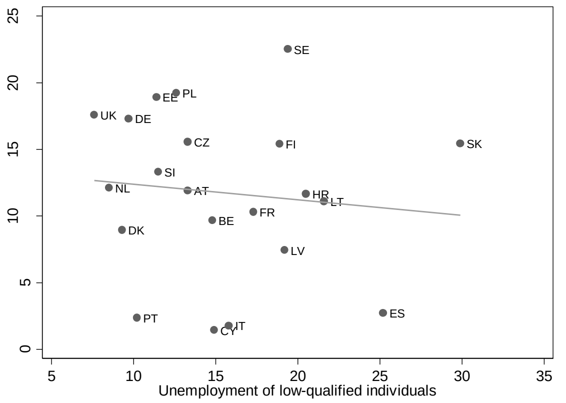
Figure A2.14 Linear fit between macro-economic skills mismatch and NAWRU, excluding ES, PT, EL (2017)



Note: R^2 adj of linear regression= 0.27

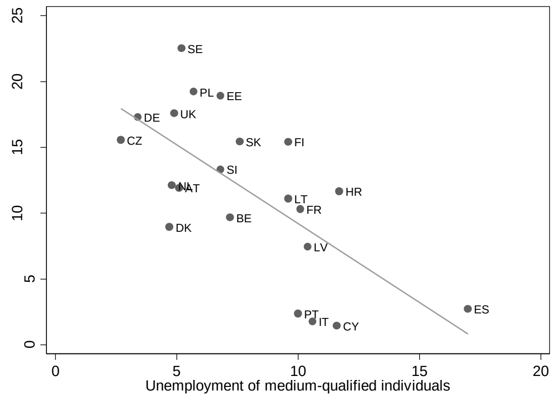
Additional graphs on skills shortages

Figure A2.15 Linear fit between composite measure of skills shortages and unemployment among low-qualified individuals (2017)



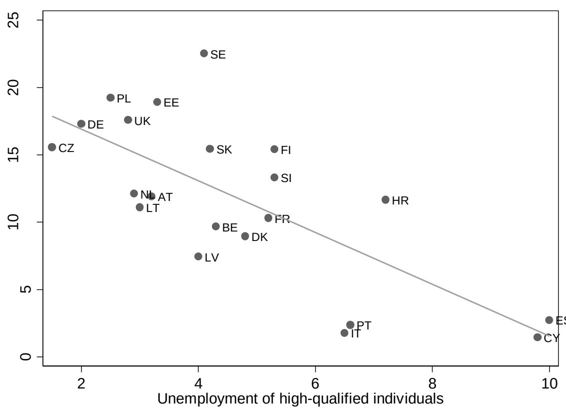
Note: R^2 adj of linear regression ± 0

Figure A2.16 Linear fit between composite measure of skills shortages and unemployment among medium-qualified individuals (2017)



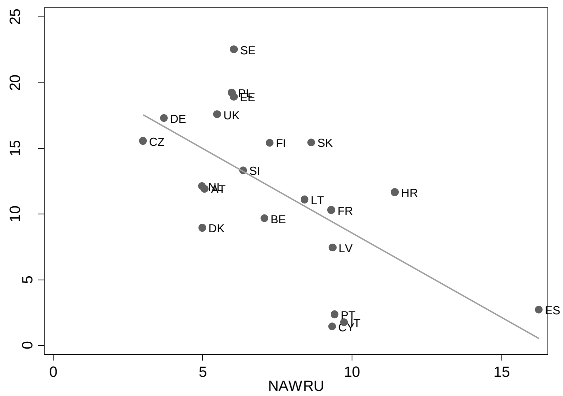
Note: R^2 adj of linear regression = 0.43

Figure A2.17 Linear fit between composite measure of skills shortages and unemployment among high-qualified individuals (2017)



Note: R^2 adj of linear regression = 0.50

Figure A2.18 Linear fit between composite measure of skills shortages and the NAWRU (2017)

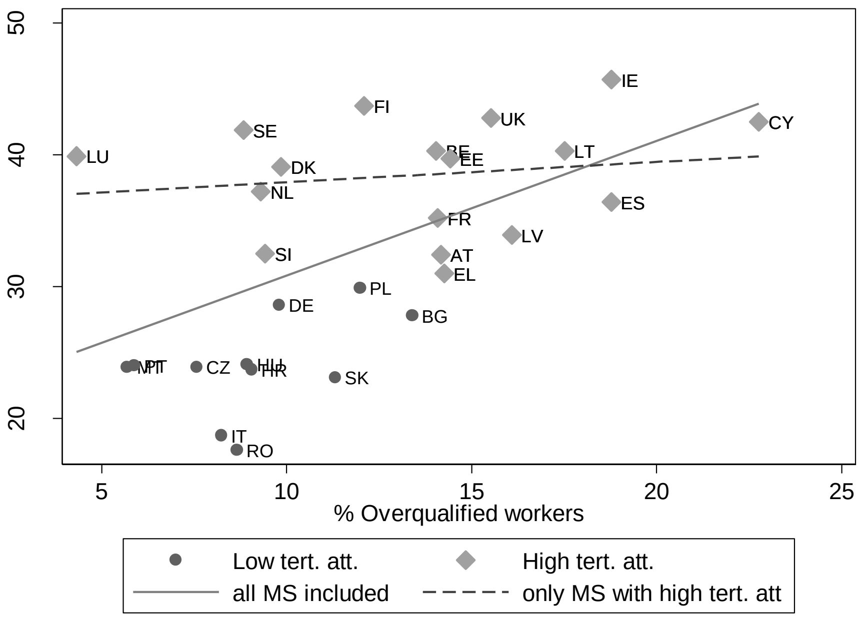


Note: R^2 adj of linear regression = 0.37

Source: Own calculations based on European Business Survey and AMECO

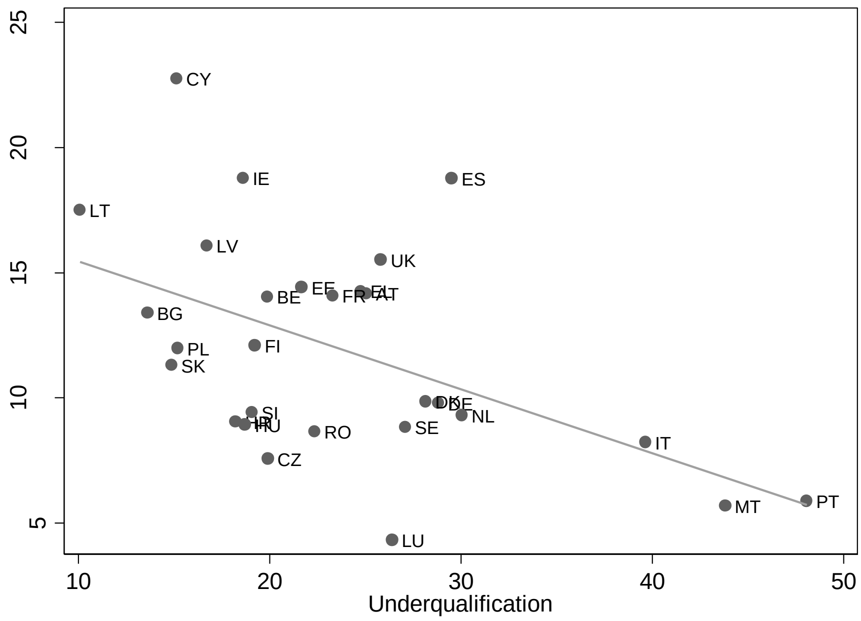
Additional graphs on on-the-job mismatch

Figure A2.19 Cross-country correlation between tertiary attainment and overqualification (2017)



Note: "High" tertiary attainment is defined as exceeding a share of 30% of the population in age group 25-64.
Source: EC own elaborations based on EUROSTAT-LFS data

Figure A2.20 Linear fit between overqualification and underqualification (2017)



Source: Own calculations based on Eurostat-LFS data
Note: R^2 adj. = 0.23

Figure A2.21 Linear fit between underqualification and ISCO after controlling for ISCED (2017)

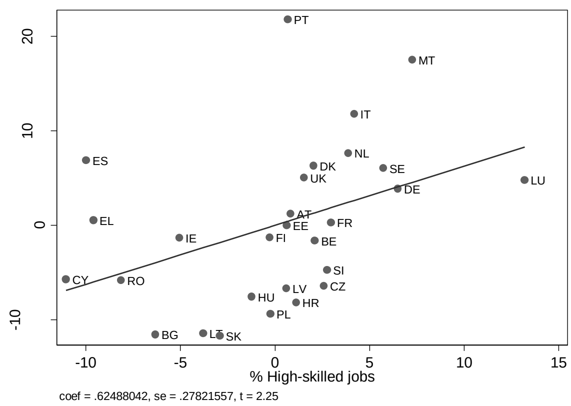


Figure A2.22 Linear fit between underqualification and ISCED after controlling for ISCO (2017)

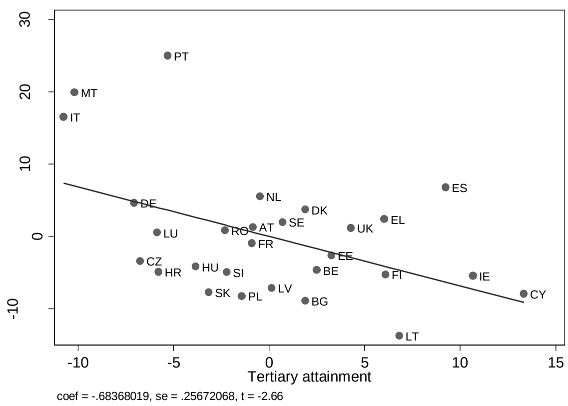


Figure A2.23 Linear fit between overqualification and ISCO after controlling for ISCED (2017)

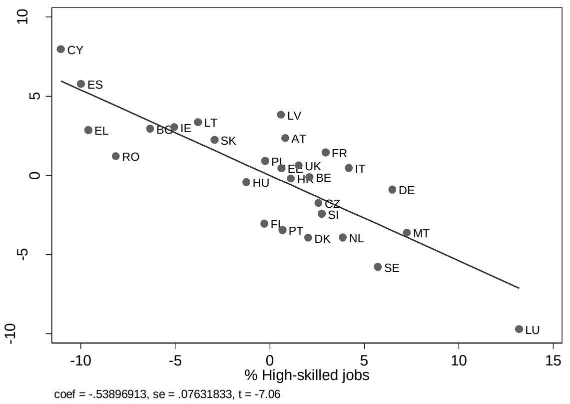


Figure A2.24 Linear fit between overqualification and ISCED after controlling for ISCO (2017)

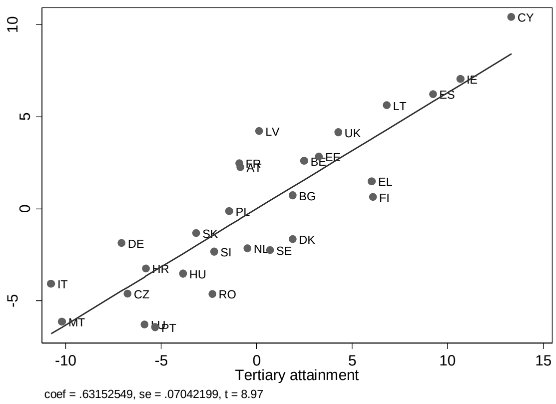
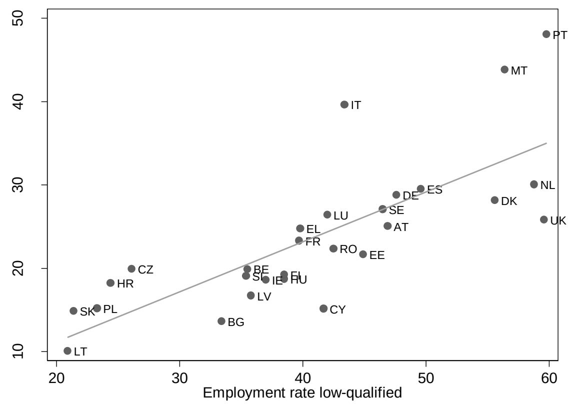
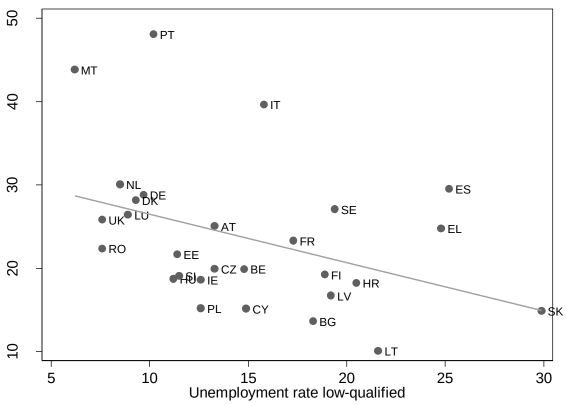


Figure A2.25 Linear fit between underqualification and employment rates of low-qualified (2017)



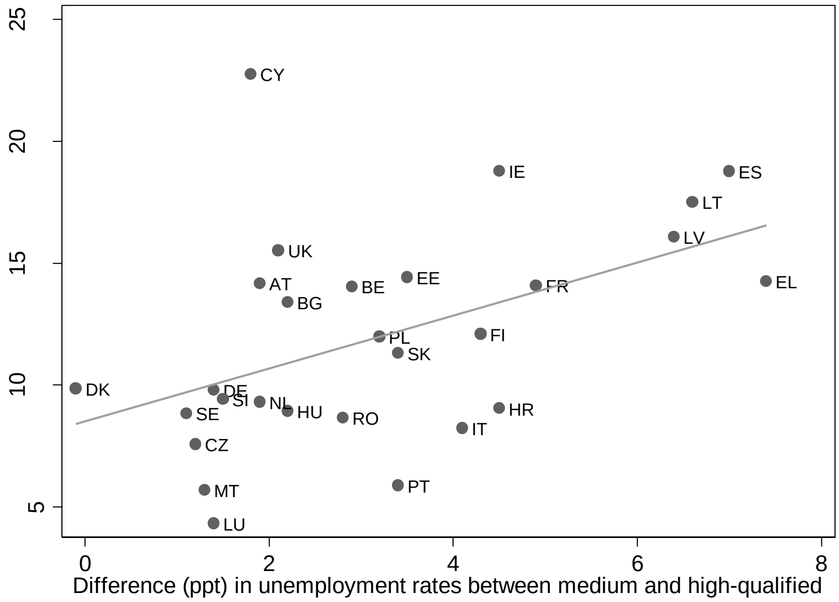
Note: R² adj of linear regression= 0.57

Figure A2.26 Linear fit between underqualification and unemployment rates of low-qualified (2017)



Note: R² adj of linear regression= 0.12

Figure A2.27 Linear fit between overqualification and the difference (in percentage-points) between unemployment rates for medium and for high-qualified individuals (2017)



Note: R^2 adj of linear regression= 0.20. Source: Eurostat, based on LFS

ANNEX III: THEORITICAL APPROACHES TO MODELLING THE RELATIONSHIP BETWEEN SKILLS MISMATCH AND PRODUCTIVITY

The literature has proposed several approaches that integrate human capital in production functions for growth accounting, or as a basis for the development of more structural models. These approaches typically start out from a simple Cobb-Douglas production function framework:

$$Y_{it} = A_{it}K_{it}^{\alpha}L_{it}^{(1-\alpha)} \tag{1}$$

with Y_{it}, K_{it}, L_{it} and A_{it} denoting respectively GDP, the capital stock, hours worked and total factor productivity (TFP) in country i and time t. α denotes the factor elasticity of capital. If both sides of the equation are multiplied by L_{it}^{-1}, we obtain

$$\left(\frac{Y}{L}\right)_{it} = A_{it}\left(\frac{K}{L}\right)_{it}^{\alpha} \tag{2}$$

or, in logs:

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} \tag{3}$$

implying that labour productivity (y = Y/L) is a function of TFP[65] (A_{it}) and capital intensity (k = *K/L*). Human capital has been integrated in these equations in several ways, including by considering it as a labour-augmenting factor in the following way:

$$Y_{it} = A_{it}K_{it}^{\alpha}(H_{it}L_{it})^{(1-\alpha)} \text{ such that } \ln y_{it} = \ln A_{it} + (1-\alpha)\ln H_{it} + \alpha \ln k_{it} \tag{4}$$

where H_{it} denotes human capital, or as a separate production factor (next to capital and labour):[66]

$$Y_{it} = A_{it}K_{it}^{\alpha}H_{it}^{\beta}L_{it}^{(1-\alpha-\beta)} \text{ such that } \ln y_{it} = \ln A_{it} + \beta \ln h_{it} + \alpha \ln k_{it} \tag{5}$$

where $h_{it} = H_{it}/L$ is a measure of skills intensity. In both of these cases, human capital accumulation has a direct positive relationship with labour productivity as well as an indirect positive relationship through its complementary with physical capital accumulation. Using more generalized versions of the production function such as a constant elasticity of substitution (CES) specification allows assuming even stronger complementarities between human and physical capital accumulation (see e.g. Duffy et al., 2004). TFP – denoted by A_{it} – is assumed to be exogenous, in the sense of not being affected by human capital accumulation.

Alternatively, human capital can also enter more simply as a determinant of total factor productivity (or TFP growth – as in De La Fuente (2011) and in Benhabib and Spiegel (1994)[67]), in which case the complementarity between human and physical capital accumulation becomes less explicit.

Skills mismatch could be incorporated in these models as a factor correcting human capital (upwards or downwards, depending on the type of mismatch and the measure of human capital), for instance as follows (based on equation (5) above):

$$Y_{it} = A_{it}{K_{it}}^{\alpha}{(SH)_{it}}^{\beta}(L_{it})^{1-\alpha-\beta} \tag{6}$$

resulting in labour productivity

$$\left(\frac{Y}{L}\right)_{it} = A_{it}\left(\frac{K}{L}\right)_{it}^{\alpha}\left(\frac{SH}{L}\right)_{it}^{\beta} \quad \text{or, in logs,} \quad \ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + \beta(\ln h_{it} + \ln s_{it}) \tag{7}$$

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[65] Total factor productivity measures the efficiency of all inputs used in the economy by capturing the growth contribution of disembodied[65] technological change (stemming e.g. from general knowledge, spillovers or organizational structures (OECD 2001)). It is harder to measure than labour productivity and as it is typically measured as a residual of a production function estimate it includes measurement errors. The choice of the productivity measure to be used depends on the purpose of the analysis and on data availability.

[66] See e.g. Mankiw et al. (1992) or De La Fuente (2011)

[67] Note that the equations below represent a simplified and at the same time slightly extended version of Benhabib and Spiegel's (1994) model.

In this setting s_{it} (measured as overqualification) could act as a factor correcting H_{it} (measured as educational attainment) downwards as those with high qualifications are in a job that does not allow them to make full use of their skills.

Given that we prefer not to impose many restrictions on our model at this stage, we take a more ad-hoc approach in this paper (see Section 3.1).

ANNEX IV: EMPIRICAL RELATIONSHIPS BETWEEN TFP AND SKILLS MISMATCH

A4.1 Macro-economic skills mismatch

Table A4.1: Random-effects regressions of TFP and macro-economic skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	re	re	re-EU-15	re-EU-15	re-EU-13	re-EU-13
Output gap	0.007***	0.010***	0.006***	0.008***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% High-skilled jobs	0.013***		0.006***		0.018***	
	(0.001)		(0.001)		(0.002)	
Macro-economic skills mismatch	-0.011***	-0.006***	0.002	0.003**	-0.015***	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
% Tertiary attainment		0.011***		0.006***		0.018***
		(0.001)		(0.000)		(0.001)
Constant	-7.514***	-7.384***	-7.220***	-7.125***	-7.858***	-7.909***
	(0.061)	(0.067)	(0.045)	(0.055)	(0.092)	(0.092)
Observations	465	461	252	248	213	213
R-squared	0.644	0.390	0.758	0.498	0.443	0.106
Number of geo	28	28	15	15	13	13
Wald chi2	309.822	527.980	98.885	216.242	248.414	404.609
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.1: Fixed-effects regressions of TFP and macro-economic skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	fe	fe	fe-EU-15	fe-EU-15	fe-EU-13	fe-EU-13
Output gap	0.007***	0.010***	0.005***	0.008***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% High-skilled jobs	0.013***		0.005***		0.018***	
	(0.001)		(0.001)		(0.002)	
Macro-economic skills mismatch	-0.011***	-0.006***	0.002	0.003**	-0.015***	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
% Tertiary attainment		0.011***		0.006***		0.018***
		(0.001)		(0.000)		(0.001)
Constant	-7.501***	-7.396***	-7.196***	-7.138***	-7.863***	-7.927***
	(0.042)	(0.027)	(0.032)	(0.021)	(0.080)	(0.062)
Observations	465	461	252	248	213	213
R-squared	0.405	0.549	0.282	0.484	0.552	0.674
Number of geo	28	28	15	15	13	13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A4.2 Skills shortages

Table A4.2: Random-effects regressions of TFP and skills shortages

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	re	re	re-EU-15	re-EU-15	re-EU-13	re-EU-13
Output gap	0.004***	0.007***	0.006***	0.008***	0.002	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
% High-skilled jobs	0.008***		0.005***		0.009***	
	(0.001)		(0.001)		(0.002)	
Skills shortages	0.002***	-0.000	0.001***	0.000	0.003**	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
% Tertiary attainment		0.008***		0.004***		0.013***
		(0.001)		(0.000)		(0.001)
Constant	-7.524***	-7.426***	-7.182***	-7.070***	-7.859***	-7.811***
	(0.059)	(0.065)	(0.041)	(0.042)	(0.088)	(0.059)
Observations	300	299	161	160	139	139
R-squared	0.396	0.225	0.649	0.439	0.170	0.113
Number of geo	24	24	13	13	11	11
Wald chi2	106.594	310.487	326.365	422.048	32.578	254.872
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.3: Fixed-effects regressions of TFP and skills shortages

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	fe	fe	fe-EU-15	fe-EU-15	fe-EU-13	fe-EU-13
Output gap	0.004***	0.007***	0.006***	0.008***	0.002	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
% High-skilled jobs	0.007***		0.005***		0.009***	
	(0.001)		(0.001)		(0.002)	
Skills shortages	0.002***	0.000	0.001***	0.000	0.003***	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
% Tertiary attainment		0.008***		0.004***		0.013***
		(0.001)		(0.000)		(0.001)
Constant	-7.497***	-7.428***	-7.171***	-7.068***	-7.846***	-7.812***
	(0.040)	(0.015)	(0.023)	(0.010)	(0.080)	(0.021)
Observations	300	299	161	160	139	139
R-squared	0.283	0.531	0.722	0.762	0.202	0.670
Number of geo	24	24	13	13	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A4.3.Measures of on-the-job skills mismatch

Table A4.4: Random-effects regressions of TFP and on-the-job skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	re	re	re	re	re	re	re
Overqualification	0.016***	-0.001			0.002	-0.006*	
	(0.002)	(0.002)			(0.003)	(0.003)	
Underqualification			-0.008***	-0.002**	-0.007***	-0.003***	
			(0.001)	(0.001)	(0.001)	(0.001)	
Output gap	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% High-skilled jobs	0.009***		0.007***		0.007***		
	(0.001)		(0.001)		(0.001)		
Tertiary attainment		0.012***		0.010***		0.011***	0.012***
		(0.001)		(0.001)		(0.001)	(0.001)
Constant	-7.708***	-7.517***	-7.238***	-7.387***	-7.269***	-7.328***	-7.521***
	(0.063)	(0.059)	(0.073)	(0.081)	(0.089)	(0.085)	(0.070)
Observations	560	554	560	554	560	554	558
R-squared	0.183	0.257	0.028	0.128	0.031	0.146	0.238
Number of geo	28	28	28	28	28	28	28
Wald chi2	385.781	541.428	450.714	554.327	449.216	554.611	579.835
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.5: Fixed-effects regressions of TFP and on-the-job skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	fe	fe	fe	fe	fe	fe	fe
Overqualification	0.017***	-0.000			0.001	-0.005*	
	(0.002)	(0.002)			(0.003)	(0.003)	
Underqualification			-0.008***	-0.003***	-0.008***	-0.004***	
			(0.001)	(0.001)	(0.001)	(0.001)	
Output gap	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% High-skilled jobs	0.008***		0.005***		0.005***		
	(0.001)		(0.001)		(0.001)		
Tertiary attainment		0.012***		0.009***		0.010***	0.012***
		(0.001)		(0.001)		(0.001)	(0.001)
Constant	-7.673***	-7.497***	-7.147***	-7.322***	-7.159***	-7.258***	-7.499***
	(0.031)	(0.013)	(0.054)	(0.056)	(0.073)	(0.065)	(0.013)
Observations	560	554	560	554	560	554	558
R-squared	0.426	0.511	0.483	0.520	0.483	0.524	0.521
Number of geo	28	28	28	28	28	28	28

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ANNEX V: EMPIRICAL RELATIONSHIPS BETWEEN CAPITAL INTENSITY AND SKILLS MISMATCH

A5.1 Macro-economic skills mismatch

Table A4.6: Random-effects regressions of capital intensity and macro-economic skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	re	re	re-EU-15	re-EU-15	re-EU-13	re-EU-13
Output gap	-0.013***	-0.008***	-0.013***	-0.006***	-0.005**	-0.006***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
% High-skilled jobs	0.031***		0.014***		0.044***	
	(0.002)		(0.001)		(0.003)	
Macro-economic skills mismatch	-0.022***	-0.011***	0.012***	0.014***	-0.028***	-0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)
% Tertiary attainment		0.023***		0.013***		0.034***
		(0.001)		(0.001)		(0.002)
Constant	-3.595***	-3.196***	-2.874***	-2.696***	-4.559***	-4.286***
	(0.134)	(0.140)	(0.071)	(0.068)	(0.191)	(0.196)
Observations	493	489	267	263	226	226
R-squared	0.533	0.335	0.646	0.489	0.349	0.094
Number of geo	28	28	15	15	13	13
Wald chi2	557.230	727.363	456.422	1128.614	471.314	432.642
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.7: Fixed-effects regressions of capital intensity and macro-economic skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	fe	fe	fe-EU-15	fe-EU-15	fe-EU-13	fe-EU-13
Output gap	-0.013***	-0.008***	-0.013***	-0.007***	-0.005**	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
% High-skilled jobs	0.031***		0.013***		0.044***	
	(0.002)		(0.001)		(0.003)	
Macro-economic skills mismatch	-0.022***	-0.011***	0.012***	0.013***	-0.028***	-0.004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)
% Tertiary attainment		0.023***		0.013***		0.035***
		(0.001)		(0.001)		(0.002)
Constant	-3.589***	-3.213***	-2.854***	-2.711***	-4.578***	-4.311***
	(0.076)	(0.052)	(0.055)	(0.030)	(0.131)	(0.121)
Observations	493	489	267	263	226	226
R-squared	0.544	0.614	0.642	0.820	0.688	0.673
Number of geo	28	28	15	15	13	13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A5.2 Skills shortages [68]

Table A4.8: Random-effects regressions of capital intensity and skills shortages

VARIABLES	(1) re	(2) re	(3) re-EU-15	(4) re-EU-15	(5) re-EU-13	(6) re-EU-13
Output gap	-0.018***	-0.011***	-0.014***	-0.010***	-0.018***	-0.011***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
% High-skilled jobs	0.023***		0.009***		0.039***	
	(0.002)		(0.001)		(0.004)	
Skills shortages	0.005***	0.000	0.003***	0.001*	0.007***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
% Tertiary attainment		0.018***		0.009***		0.028***
		(0.001)		(0.001)		(0.002)
Constant	-3.665***	-3.248***	-2.497***	-2.360***	-4.985***	-4.217***
	(0.141)	(0.158)	(0.072)	(0.071)	(0.211)	(0.173)
Observations	323	322	174	173	149	149
R-squared	0.322	0.179	0.334	0.130	0.133	0.101
Number of geo	24	24	13	13	11	11
Wald chi2	281.622	445.349	335.309	849.113	189.507	309.230
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.9: Fixed-effects regressions of capital intensity and skills shortages

VARIABLES	(1) fe	(2) fe	(3) fe-EU-15	(4) fe-EU-15	(5) fe-EU-13	(6) fe-EU-13
Output gap	-0.018***	-0.011***	-0.014***	-0.010***	-0.018***	-0.011***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
% High-skilled jobs	0.022***		0.009***		0.040***	
	(0.002)		(0.001)		(0.004)	
Skills shortages	0.005***	0.000	0.003***	0.001*	0.007***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
% Tertiary attainment		0.018***		0.008***		0.028***
		(0.001)		(0.001)		(0.002)
Constant	-3.647***	-3.247***	-2.476***	-2.349***	-5.019***	-4.222***
	(0.081)	(0.032)	(0.043)	(0.014)	(0.150)	(0.050)
Observations	323	322	174	173	149	149
R-squared	0.495	0.600	0.684	0.845	0.583	0.693
Number of geo	24	24	13	13	11	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[68] Data are missing for IE and LU (in EU-15) and BG and MT (in EU-13)

A5.3 Measures of on-the-job skills mismatch

Table A4.10: Random-effects regressions of capital intensity and on-the-job skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	re	re	re	re	re	re	re
Overqualification	0.033***	0.011**			0.016***	0.008	
	(0.003)	(0.004)			(0.005)	(0.005)	
Underqualification			-0.013***	-0.004**	-0.008***	-0.002	
			(0.001)	(0.002)	(0.002)	(0.002)	
Output gap	-0.004***	-0.005***	-0.004***	-0.005***	-0.004**	-0.005***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% High-skilled jobs	0.017***		0.015***		0.015***		
	(0.002)		(0.002)		(0.002)		
Tertiary attainment		0.019***		0.019***		0.018***	0.022***
		(0.002)		(0.002)		(0.002)	(0.001)
Constant	-3.788***	-3.401***	-2.982***	-3.183***	-3.284***	-3.282***	-3.376***
	(0.143)	(0.134)	(0.152)	(0.158)	(0.176)	(0.167)	(0.152)
Observations	588	582	588	582	588	582	586
R-squared	0.109	0.122	0.010	0.094	0.027	0.092	0.182
Number of geo	28	28	28	28	28	28	28
Wald chi2	565.571	700.657	566.444	690.329	583.689	690.882	688.948
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.11: Fixed-effects regressions of capital intensity and on-the-job skills mismatch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	fe	fe	fe	fe	fe	fe	fe
Overqualification	0.034***	0.012***			0.015***	0.008	
	(0.003)	(0.004)			(0.005)	(0.005)	
Underqualification			-0.014***	-0.005***	-0.010***	-0.003*	
			(0.001)	(0.002)	(0.002)	(0.002)	
Output gap	-0.004***	-0.005***	-0.004**	-0.005***	-0.004**	-0.004***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% High-skilled jobs	0.017***		0.013***		0.013***		
	(0.002)		(0.002)		(0.002)		
Tertiary attainment		0.018***		0.017***		0.016***	0.022***
		(0.002)		(0.002)		(0.002)	(0.001)
Constant	-3.725***	-3.355***	-2.849***	-3.062***	-3.125***	-3.160***	-3.325***
	(0.054)	(0.023)	(0.099)	(0.100)	(0.134)	(0.117)	(0.022)
Observations	588	582	588	582	588	582	586
R-squared	0.508	0.564	0.520	0.564	0.528	0.566	0.553
Number of geo	28	28	28	28	28	28	28

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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