J Labour Market Res (2016) 49:15–42
DOI 10.1007/s12651-016-0196-y

ARTICLE

Imbalanced Job Polarization and Skills Mismatch in Europe

Theo Sparreboom · Alexander Tarvid

Published online: 2 March 2016

Abstract This paper considers the education of the labour force based on an analysis of trends in and the relationships between job polarization and skills mismatch. Both job polarization and skills mismatch have become topics of increasing interest, but relationships between the two have been relatively neglected in the literature. We argue that the relationship between polarization and skills mismatch is an empirical matter, which we analyse at both the macroeconomic and microeconomic level in European countries. A novel job polarization index (JPI) is proposed to measure imbalanced job polarization. It takes into account not only the change in the share of medium-level jobs, as is typical for measuring pure polarization, but also the imbalance between the change in high-level and low-level jobs. Skills mismatch at macro-level is measured by a skills mismatch index (SMI), while traditional measures of undereducation and overeducation are used at the microeconomic level. At the macroeconomic level, we estimate a system of two equations, one for each of the country-level variables gauging polarization and mismatch, respectively. Imbalanced job polarization measured by the JPI negatively affects skills mismatch at the macroeconomic level (SMI), but there is no significant reverse effect. Thereafter we consider the microeconomic level and study the determinants of mismatch using multi-level mixed effects logistic models. The effect of imbalanced job polarization on individual-level mismatch was arguably favourable for individuals in non-crisis time, decreasing overeducation risk although also increasing the chances of undereducation, both gauged using the normative measure, but unfavourable during the global financial crisis of 2008–2009 and the following two years.

Keywords Job polarization · Imbalanced polarization · Skills mismatch · Job polarization index · Skills mismatch index · Overeducation · Undereducation

1 Introduction

An adequately educated and trained labour force is essential for economic growth. Education and training raise the productivity of workers and create capacity to innovate and adopt new technologies. Conversely, shortages of educated and skilled workers, or workers with education and skills that do not match labour market needs, lower the potential for growth and may raise unemployment. However, translating 'adequate' into concrete education and training policies is a challenging task, not least because jobs are continuously changing. Structural change, technological change, globalization and trade have a bearing on the tasks and duties performed in our economies, which are to an important extent reflected in differential changes in job growth across occupations. These changes in the occupational structure, by implication, affect the economy-wide requirements in terms of education and skills of workers. Furthermore, various im-

Electronic supplementary material The online version of this article (doi:10.1007/s12651-016-0196-y) contains supplementary material, which is available to authorized users.

Responsibility for opinions expressed in this paper rests solely with the authors and does not constitute an endorsement by the ILO.

T. Sparreboom (✉)
Statistics Department, International Labour Office,
Route des Morillons 4, CH-1211 Geneva 22, Switzerland
e-mail: sparreboom@ilo.org

A. Tarvid
Faculty of Economics and Management, University of Latvia,
5 Aspazijas blvd., Riga, LV-1050, Latvia
e-mail: atarvid@inbox.lv

perfections in labour markets give rise to skills mismatch, and this issue has risen on policy agendas because of the skills-intensive nature of much economic and technological change, as well as the impact of the economic crisis (Cedefop 2010; European Commission 2012; World Economic Forum 2014).

This paper considers the education and training of the labour force based on an analysis of trends in and the relationships between job polarization and skills mismatch. Both job polarization and skills mismatch have become topics of increasing interest, but most of the literature has focused either on skills mismatch or on job polarization, and not on possible relationships between the two. Nevertheless, such relationships have been suggested in the literature on job polarization (Goos and Manning 2007).

Job polarization means that the share of high- and low-skill jobs grow at the expense of medium-skill jobs, and such trends have been linked to the decline in the demand for routine or codifiable tasks, including both manual and cognitive tasks (Acemoglu and Autor 2011; Goos et al. 2014, 2013). Starting from a hypothetical steady state in the labour market in which the supply of education and skills perfectly matches demand, and all jobs are fulfilled by adequately trained workers, polarization would have several effects that could increase skills mismatch. In particular, in the absence of a supply response, underqualification could be expected to rise among workers performing the growing share of high-skill jobs, while overqualification would rise for workers performing low-skill jobs, if these jobs are increasingly taken by workers previously employed in medium-skill jobs.

Whether such trends would materialize is uncertain for at least three reasons. Firstly, the supply of educated workers in many countries is on an upward trend, which may or may not be in accordance with the increasing share of high-skill jobs. Secondly, the literature suggests that labour markets are often characterized by a certain extent of skills mismatch, and different starting positions with regard to current or past levels of skills mismatch will clearly affect how polarization at the demand side will play out. In theory, if the supply of educated workers is polarized (in the sense of relatively high shares of workers with low and high levels of education), polarization at the demand side could lead to a reduction of measured levels of skills mismatch. Finally, job polarization may interact with unemployment, which adds to the uncertainty with regard to labour market outcomes if workers with different levels of education are affected differently by unemployment.

Therefore, the relationship between polarization and skills mismatch seems an empirical matter. We analyse the relationships between imbalanced job polarization and skills mismatch at two levels in European countries. At the country-level, we estimate a system of two equations, one for each of the country-level variables gauging imbalanced polarization and mismatch, respectively. The main result is that imbalanced job polarization decreases mismatch between skills demand and skills supply proxied by level of educational attainment, but there is no statistically significant effect from skills mismatch to imbalanced job polarization. Thereafter we consider the individual-level and study the determinants of mismatch by running multi-level mixed effects logistic models. Determinants are divided into two categories: individual-level and macro-level, and imbalanced job polarization is one of the macro-level determinants. The main result is that the effect of imbalanced job polarization on individual-level mismatch was arguably favourable for individuals in non-crisis time (it decreases overeducation risk although it increases the chances of undereducation, both gauged using the normative measure) but unfavourable during the global financial crisis of 2008–2009 and the following two years. The effect on overeducation gauged by the statistical measure is the opposite to the effect based on the normative measure, but we demonstrate that these results nevertheless allow for a coherent view on the interaction between job polarization and skills mismatch in Europe.

The paper contributes to the literature by an analysis of the relationship between job polarization and skills mismatch in a large group of European economies based on a job polarization index, which allows for the measurement of the extent of imbalanced job polarization in a single number for a given country and year. Similarly, we use a recently introduced measure of skills mismatch at the macroeconomic level, alongside traditional measures of skills mismatch at the individual level.

The remaining structure of the paper is as follows. We start with a review of the literature on job polarization and skills mismatch in Sect. 2. Subsequently, we define measures of polarization and skills mismatch (at macro- and micro-levels) and review trends in Sect. 3. Section 4 first analyses the relationships between imbalanced job polarization and macro-level skills mismatch, and thereafter between imbalanced job polarization and individual-level skills mismatch. The last section concludes.

2 Determinants of Job Polarization and Skills Mismatch

The trend in job polarization (Goos and Manning 2007) has been observed in many countries. The most common explanation is technological change, which leads to the replacement of routine tasks undertaken by workers by tasks performed by computers and associated technologies (the 'routinization hypothesis'). For example, bank services available online have increasingly replaced traditional banking offices, which limits the demand for clerks and increases the demand for technicians and professionals to maintain online systems. But other factors discussed in the literature include international trade and outsourcing of routine tasks to countries with lower labour costs (Goos et al. 2009). In the United States, polarization of jobs has also been linked to growing wage inequality. Based on census data, it was found that the growing share of incomes going to high-skilled workers has increased demand for non-tradeable time-intensive services that are difficult to automate – such as food preparation and cleaning – provided by low-skilled workers (the 'consumption hypothesis') (Mazzolari and Ragusa 2013). Based on data for 16 countries, strong evidence for the routinization hypothesis was found in Europe, and only weak evidence for the effects of offshoring and inequality on job polarization (Goos et al. 2009).

The relationship between job polarization and business cycles is the subject of intense debate based on apparently mixed evidence. According to some authors, job polarization is intrinsically related to economic cycles. Jaimovich and Siu (2012) find that in the US, much or all of the job loss in medium-skill occupations occurs during economic downturns, while jobless recoveries are also accounted for by the disappearance of such jobs. On the contrary, high- and low-skill occupations, if they experience contractions, tend to rebound in accordance with trends in output during upswings. Jaimovich and Siu, therefore, consider job polarization to be a key driver of recent business cycles, but others are less convinced. Another US-based study (Foote and Ryan 2013) found that recessions were synchronized across workers with different levels of skills, and even high-skilled workers were far from immune. Finally, Tüzemen and Willis (2013) suggest that job polarization can best be seen as a structural phenomenon. Polarization accelerates during recessions and contributes to jobless recoveries, but is not causing them.

Job polarization has been linked to skills mismatch by Goos and Manning (2007), who argue that the scarcity of medium-skill jobs may force educated workers to take low-skill jobs. Polarization was found to be associated with increasing overqualification in Germany between the mid 1980s and the mid 2000s (Rohrbach-Schmidt and Tiemann 2011). A framework where several types of mismatch between vacancies and job seekers can help explain unemployment is developed by Şahin et al. (2014). To capture the effects of job polarization on mismatch, the authors examine the behaviour of groups of routine occupations that have become less important, and find a strong relationship with unemployment.

Much research has been devoted to skills mismatch in relation to macro-level demand factors. Overeducation behaves counter-cyclically: the highly-educated crowd out the lower-educated during economic downturns (Croce and Ghignoni 2012; Kiersztyn 2013). Higher shares of temporary contracts increase overeducation via lowering the selectivity of employers and workers, while higher long-term unemployment decreases it by keeping less-able workers out of labour force (Croce and Ghignoni 2012). A larger shadow economy does not affect the mismatch likelihood of the locally-born, but decreases the chances of overeducation of immigrants by easing the job search process for the lower-skilled; finally, employment protection legislation increases undereducation (Aleksynska and Tritah 2013). Macro-level supply factors also play a role: overeducation on a particular education level increases with the share of population having that education level (Di Pietro 2002).

Individual characteristics may be more important than macro-level factors (Ghignoni and Verashchagina 2014). At the microeconomic level, five categories of factors have been found to affect the risk of overeducation: (1) ability, academic performance, and personality; (2) gender and age; (3) immigrant background; (4) labour market and job characteristics; and (5) characteristics of education.

Although an individual's ability or academic performance has proven to be difficult to capture in empirical work, research, using various approximations, suggests that graduates with lower ability face a higher risk of overeducation (Barone and Ortiz 2011; Chevalier 2003; Lianos et al. 2004; Tarvid 2012; Verhaest and Omey 2010). Personality traits also affect the risk of overeducation and frequently are more important than ability (Blázquez and Budría 2012; Tarvid 2013). Empirical evidence about gender effects has been mixed, with roughly equal number of studies concluding that women have a higher skills mismatch risk than men (Aleksynska and Tritah 2013; Baert et al. 2013; Betti et al. 2011; Karakaya et al. 2007; Ramos and Sanromá 2013; Tani 2012; Verhaest and Omey 2010; Verhaest and Van der Velden 2013) as those finding no difference across sex (Blázquez and Budría 2012; Büchel and van Ham 2003; Chevalier 2003; Chevalier and Lindley 2009; Frei and Sousa-Poza 2012; Frenette 2004; Støslashren and Wiers-Jenssen 2010; Wirz and Atukeren 2005); a few studies result in men being at a relative disadvantage (European Commission 2012; Kiersztyn 2013).[1] The literature disagrees on the effect on overeducation from age[2]. Some studies show that overeducation decreases with age (Aleksynska and Tritah 2013; Jensen et al. 2010; Robst 2008; Sutherland 2012) or has a U-shaped

[1] See also Quintini (2011) and European Commission (2012, p. 371 Footnote 17).

[2] The effect from labour market experience is similar to the effect from age, as the two differ approximately by a constant representing the duration of childhood and compulsory education.

relationship with it (Tarvid 2012), while others report that age is irrelevant (Blázquez and Budría 2012; Chevalier and Lindley 2009; Frei and Sousa-Poza 2012; Kiersztyn 2013; Wirz and Atukeren 2005). Overall, these results imply that the young may still have a comparatively higher probability of mismatch after controlling for other relevant factors. First- and second-generation immigrants face higher risk of mismatch (Aleksynska and Tritah 2013; Tarvid 2012) and residence duration seems to have no effect on it (Aleksynska and Tritah 2013; Fernández and Ortega 2008). Where overeducation decreases with the length of stay, it was interpreted as immigrants preferring unemployment (Støren and Wiers-Jenssen 2010), may be affected by the country's skill-based immigration policy (Tani 2012), or happens only for specific types of education (Beckhusen et al. 2013). Immigrating to a close country or having more knowledge about it dampens the risk of overeducation (Aleksynska and Tritah 2013; Tani 2012). Higher-quality education system in the home country increases the chances of undereducation (Aleksynska and Tritah 2013), but foreign education – even for the locally-born – is not perfectly transferable to the local labour market, as reflected by higher overeducation risk than for the locally-educated (Støren and Wiers-Jenssen 2010). The type of mismatch after migration also strongly depends on that before migration (Piracha et al. 2012; Tani 2012).

Studies also found that overeducation risk decreases with tenure (Büchel and van Ham 2003; Frei and Sousa-Poza 2012; Jensen et al. 2010; Karakaya et al. 2007; Wirz and Atukeren 2005), which allows to conclude that labour market experience acts as a substitute for formal education. Finding a good match in a larger labour market should be easier, and in Europe, the risk of overeducation in big cities is indeed substantially smaller than elsewhere (Ramos and Sanromá 2013; Tarvid 2012), although the reverse is observed in the US (Beckhusen et al. 2013). Working without a contract substantially increases the risk of overeducation, and this result is stable across European country groups (Tarvid 2012). Research also shows that graduates in economics, law and arts & humanities face higher overeducation risk (Barone and Ortiz 2011; Betti et al. 2011; Chevalier 2003; Cutillo and di Pietro 2006; Jauhiainen 2011; Ortiz and Kucel 2008; Støren and Wiers-Jenssen 2010). Studies disagree on the sign of the effect from educational attainment (in terms of years or level). While some find that the risk decreases with attainment (Barone and Ortiz 2011; Büchel and van Ham 2003; Jensen et al. 2010), others report that higher years of education (Fernández and Ortega 2008; Jauhiainen 2011) or a university degree (Frei and Sousa-Poza 2012; Wirz and Atukeren 2005) increase the risk of overeducation.

3 Measures of and Trends in Job Polarization and Skills Mismatch

3.1 Job Polarization

3.1.1 Measures

Job polarization typically reflects a declining share of "medium-level" occupations in the occupational structure, and increasing shares of "low-level" and "high-level" occupations. Different studies then define these three groups differently, e.g., based on mean wages by ISCO minor (two-digit) groups (Fernández-Macías 2012; Goos et al. 2009) or on the extent of cognitive, routine and manual tasks (Autor and Dorn 2013; Jaimovich and Siu 2012). Typically, studies do not provide a single measure of polarization and instead attempt to explain changes in the employment shares in different occupations as such. An exception is Dauth (2014), who proposes to regress employment growth rates in occupations on their rank according to average log wage and rank-squared and then use the t-ratio of rank-squared to measure the extent of polarization. While this measure allows to gauge the curvature along many occupation groups, it is difficult to decompose it in a meaningful way. The measure we propose later in this section is defined for three occupation groups only, but is more transparent and decomposable into clear subcomponents.

Several measures of polarization were proposed in the income polarization literature, but all of these have drawbacks. For instance, the measure of Wolfson (1994),

$$2(1 - 2L(0.5) - \text{Gini}) \times (\text{mean}/\text{median}), \tag{1}$$

requires to specify mean and median levels of the underlying variable and, in addition, $L(0.5)$, which (in its original application) is the income share of the bottom half of the population – but it does not make sense to specify the "mean" or "median" job category in a given labour market, not even speaking about defining $L(0.5)$ for jobs. Similarly, in the proposal of Tsui and Wang (1998):

$$\frac{\theta}{N}\sum_{i=1}^{K}\pi_i\left|\frac{\text{mean}_i - \text{median}}{\text{median}}\right|^r, \tag{2}$$

where θ and r are parameters, N is the total number of observations and K is the number of groups, it again does not make sense to consider mean and median values of job category. An alternative proposal (Esteban and Ray 1994) is

$$K\sum_i\sum_j\pi_i^{1+\alpha}\pi_j|y_i - y_j|, \tag{3}$$

where K and α are parameters and $(\pi, \mathbf{y})$ is a distribution over different values of vector $\mathbf{y}$, where π_i is the number of observations with $y = y_i$ (although it can be easily reformulated into a probability). In our case, this measure could be applied, in principle, because the three job levels can be represented as y_1, y_2 and y_3 with respective probabilities, but such approach does not allow for country idiosyncrasies and assumes instead that all countries should ideally have the same occupational structure.

Because the existing measures are inapplicable, we propose a new measure of job polarization. We need a single measure that would show the extent of polarization at a point in time. Ideally, this measure should distinguish between two situations: *skill upgrading*, when the share of "high-level" jobs grows, that of "medium-level" jobs declines, but that of "low-level" jobs stays constant, and *true polarization*, a similar situation but where the share of "low-level" jobs also grows.

Before constructing this measure, it is important to define polarization. In other words, when we say that the occupational structure is polarized, which comparison is made? In this paper, we consider polarization for a given country at a *concrete point in time* to be higher (lower) if the share of "medium-level" jobs relative to its *average value in the previous five years* in the same country is lower (higher). Thus, the measure should compare the current occupational structure of a country to the typical recent occupational structure of the same country. Comparing it to one specific year (e.g., previous year) could make the measure too unstable and subject to business cycle effects, while taking a longer period over which to measure the average might no longer reflect the typical occupational structure of the country (in addition, using a longer period may be difficult in view of the availability of consistent data for the 1990s).

To be more specific, this measure should be zero if the share of "medium-level" jobs has not deviated from its typical value, positive when it decreased and negative when it increased. Furthermore, given a change in the share of "medium-level" jobs, the measure should be sensitive to the relative changes in the share of "low-level" and "high-level" jobs. The larger the increase in one of these shares relative to the increase in the other, the larger should be the measure. For instance, the measure should be larger if the share of "high-level" jobs increases 15 percentage points and that of "low-level" jobs increases 5 percentage points than if both shares increase 10 percentage points.

Before we show the expression for such a measure, we define an operator $\overline{\Delta_5}$. For time series x_t, the operator is defined as follows:

$$\overline{\Delta_5} x_t \equiv x_t - \frac{1}{5}(x_{t-1} + x_{t-2} + x_{t-3} + x_{t-4} + x_{t-5}) \,. \quad (4)$$

Now we are ready to propose *job polarization index* (JPI) as a measure of job polarization based on the division of occupations into three groups:

$$p = \frac{1}{2} \times \underbrace{\left(\overline{\Delta_5} l + \overline{\Delta_5} h\right)}_{\text{change in medium-level jobs reversed}} \times \overbrace{\left(1 + \left|\overline{\Delta_5} h - \overline{\Delta_5} l\right|\right)}^{\text{imbalance in high-/low-level jobs}} \times 100, \quad (5)$$

where $\overline{\Delta_5} l$ is change in the share of "low-level" jobs from the average level in the last five years and $\overline{\Delta_5} h$ is defined accordingly for "high-level" jobs, and $|\cdot|$ denotes the absolute value. Time subscripts are suppressed for p, l and h for readability. The sum in the first brackets is the reverse of the change in the share of "medium-level" jobs. It determines the main magnitude and direction of the index. The expression in the second brackets takes into account the imbalance between the change in "high-level" and "low-level" jobs and grows linearly[3] with this difference. If that expression consisted only of $\left|\overline{\Delta_5} h - \overline{\Delta_5} l\right|$, it would be zero if $\overline{\Delta_5} h = \overline{\Delta_5} l$, regardless of how large the change in "medium-level" jobs is, and, as a result, p would also be zero. Because this is not the behaviour we want the index to have, we add one to the linear term in the second brackets. Hence, if $\overline{\Delta_5} h = \overline{\Delta_5} l$, the expression in the second brackets is one and p equals to $1/2 \times \left(\overline{\Delta_5} l + \overline{\Delta_5} h\right) \times 100$. The multiplier 1/2 constrains the index to be in the interval $[-100, 100]$.[4]

The dependence of the JPI on two components may confuse the reader. Indeed, if we see an increase in the index, is it due to a drop in the share of "medium-level" jobs only or is there also an imbalanced change at the high and low ends? We can't say, unless we decompose. This confusion, however, arises from the expectation that the index will show only *pure* polarization – i.e., a change in the share of "medium-level" jobs. The JPI measures what can be called *imbalanced* polarization. The second component does not immediately allow for a distinction between a skill upgrading case and a true polarization case, as defined above. However, holding

[3]In principle, one can specify a quadratic dependence here, $\left(\overline{\Delta_5} h - \overline{\Delta_5} l\right)^2$. We did that and found that the following results of the paper remain qualitatively similar. The drawback of the quadratic dependence is that it results in very low values of the expression $\left(\overline{\Delta_5} h - \overline{\Delta_5} l\right)^2$ and, hence, the whole term in the second brackets in (5) is only slightly different from 1.0, making its presence in the equation questionable.

[4]It is straightforward to show that, under three restrictions, max $p = 100$ and min $p = -100$. These restrictions follow from the nature of the parameters of function p (a change in a share cannot be larger than 1 and smaller than -1) and are as follows: (1) $\overline{\Delta_5} l \in [-1, 1]$, (2) $\overline{\Delta_5} h \in [-1, 1]$ and (3) $\overline{\Delta_5} l + \overline{\Delta_5} h \in [-1, 1]$. Because the function is fully symmetric, it is sufficient to prove the upper border. It is clear from the expression in the first brackets that the maximum is reached when that expression equals one. Then the maximum of the second expression is attained when one of the parameters is one and the other is zero, and this maximum is $(1 + |1 + 0|) = 2$. Then $p = 1/2 \times 1 \times 2 \times 100 = 100$.

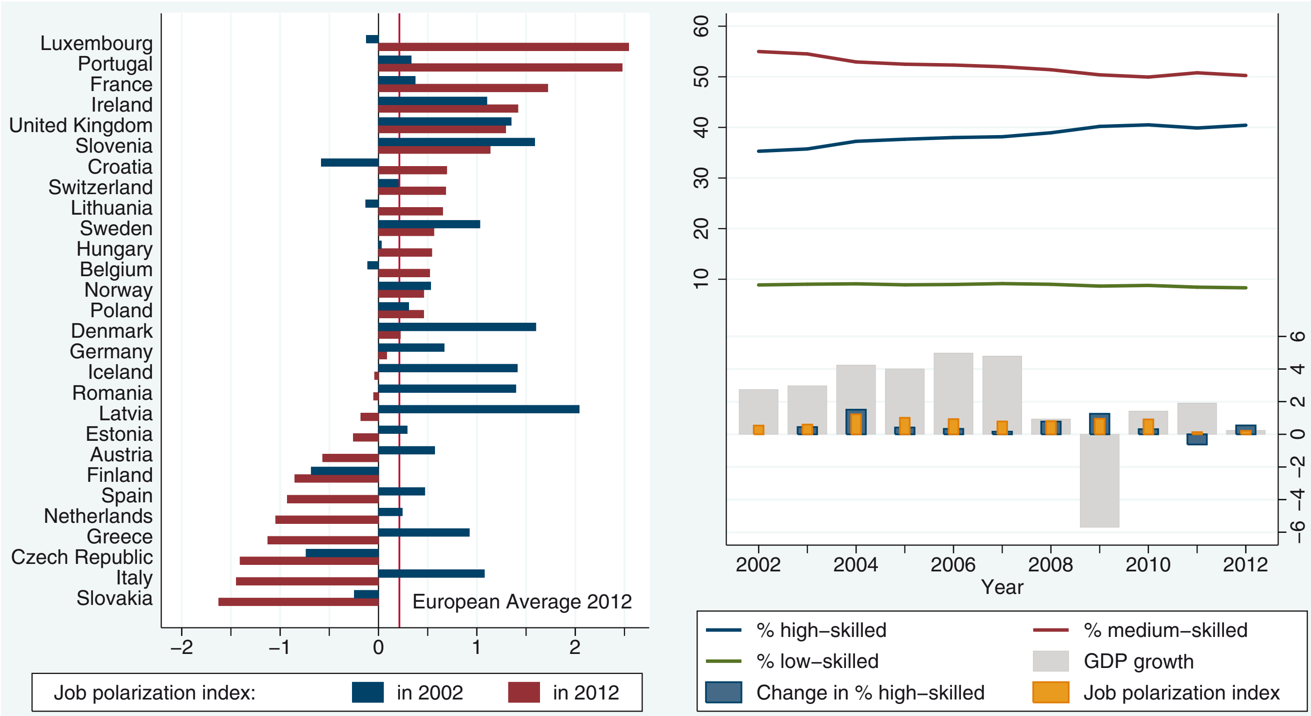

Fig. 1 Job Polarization Index and Occupational Distribution in Europe by Level of Skills. *Source:* Authors' calculations based on ILO (2013c). The right panel of the figure shows unweighted averages based on data from the following 28 countries: Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom. High-skill occupations comprise ISCO major groups 1–3, medium-skill occupations include ISCO major groups 4–8 and low-skill occupations are elementary occupations (ISCO major group 9). The value of the index for a given country and year was determined from (5). E.g., the JPI for 2002 is based on the occupational structure in 2002 compared to the average occupational structure in 1997–2001.

the first component constant, the JPI will be higher in case of skill upgrading than in case of true polarization, because the imbalance in the changes in the ends is higher in the former case than in the latter.

In this paper, we will use the JPI over three groups of occupations based on skill requirements defined by the International Standard Classification of Occupations (ISCO, ILO 2013c). Thus, high-skill occupations constitute ISCO major groups 1–3, medium-skill occupations include all occupations from ISCO major groups 4–8 and low-skill occupations consist of elementary occupations (ISCO major group 9).

3.1.2 Trends

Figure 1 shows how the index performs on European data. In Europe, the share of high-skill occupations increased on average 5.5 percentage points between 2002 and 2012, with a similar decrease in medium-skill occupations, while the share of low-skill occupations remained flat throughout the period. As expected from this behaviour, average JPI was positive in 2002–2012, although it fell to 0.13 in 2011 and rebounded to only 0.21 in 2012.

Its pattern was not strongly related to economic growth, as accelerations in growth sometimes resulted in an acceleration in the pace of increase in the JPI (e.g., in 2004) and sometimes in a deceleration (e.g., in 2006–2007). At the height of the economic crisis in 2009, the share of high-skill occupations and the JPI both increased, which confirms the conclusion by Eurofound (2013) regarding the polarizing effects of the recession and the greater resilience of higher-paid jobs during the crisis in Europe.[5]

Nevertheless, according to Cedefop (2012) projections, job polarization is likely to continue to be important in Europe in the coming years, as most new jobs will be created at the high-skill and low-skill ends of the spectrum, which means that the JPI will remain positive.

As the left panel of Fig. 1 shows, although the average European value of the JPI is close to zero, countries are highly heterogeneous with respect to the values of the JPI in 2012 (in 2002, the index was positive in almost all countries). Luxembourg and Portugal are leading the list with the index being around 2.5, while Slovakia, Italy and Czech Republic are in the bottom with their indices being around −1.5. Germany,

[5] Eurofound (2013) uses a far more detailed categorization of jobs than the broad categories distinguished in this paper, which is based on occupations, sectors, as well as wages.

Iceland and Romania have almost no polarization in 2012: their indices are close to zero.

3.2 Macro-Level Skills Mismatch

3.2.1 Measures

Labour markets around the world continuously demonstrate various types of "mismatch," including mismatch between the number of job seekers and employment opportunities, which is reflected in unemployment. In contrast to unemployment, however, which is measured according to international standards, a uniform typology or measurement framework regarding skills mismatch and related issues, such as skills shortages, is lacking.

As skills and competencies *per se* are not measured by the regular statistical programmes of most countries, skill proxies are used such as qualifications and years of education at the supply side, and occupations at the demand side. The literature offers several overviews of types, strengths and weaknesses of skills mismatch measures (Johansen and Gatelli 2012; Quintini 2011; Sparreboom and Powell 2009; Wilson et al. 2013).

At the macro level, we focus on skill shortage and surplus in this paper, which seems appropriate for the analysis at hand. According to ISCO, low-skill occupations are matched with primary education, medium-skill with secondary and high-skill with tertiary education. For the labour market to be in equilibrium, a shift to high-skill occupations should, therefore, be accompanied by a similar shift to tertiary education at the supply side. The latter is clearly what has been happening for decades in European countries. The proportion of persons with tertiary education in the EU has been steadily rising from 17 per cent in 2000 to 25 per cent in 2012 (Eurostat data). Nevertheless, this is insufficient to match the polarization trend, which resulted in 40 per cent of all employment in the EU in 2012 being in high-skilled occupations, according to Eurostat.[6]

This apparent shortage of highly educated workers helps explain the inverse relationship between unemployment risk and education level. In Europe as a whole (EU-27, Eurostat data), individuals with primary education saw their unemployment risk gradually increase relative to that of the tertiary-educated from 2.4 times in 2000 to 3.0 times in 2013. The risk of unemployment for the secondary-educated was around twice higher than for the tertiary-educated in 2000, but this ratio dropped to 1.5 by 2013.

Differences in unemployment rates by level of education of workers signal skills mismatch, as such differences indicate that the level of educational attainment of workers is an important determinant of the probability of finding a job besides the overall level of unemployment. These differences can be summarized in a *skills mismatch index* (SMI), which was introduced by ILO (2013a, 2013b), based on a comparison of the structure of educational attainment of the employed and the unemployed.

The index is defined as follows:

$$m = \frac{1}{2}\sum_{i=1}^{3}\left|\frac{E_i}{E} - \frac{U_i}{U}\right|, \qquad (6)$$

where i is an indicator for the level of education (primary or less, secondary or tertiary), $|\cdot|$ denotes the absolute value, E_i/E is the proportion of the employed with education level i and U_i/U is the proportion of the unemployed with education level i.

It should be emphasized that this index captures one dimension of mismatch, namely mismatch between skills demand (defined by the skills of the employed) and skills supply (defined by the skills of the unemployed), both proxied by level of educational attainment. The index does not capture mismatch at more detailed levels of skills or mismatch between the skills of the employed and their job requirements.

Apart from being a measure of mismatch between skills supply and demand, the SMI can be interpreted as a summary measure of the relative position of labour market groups with different levels of education (that is, a measure of inequality). If primary, secondary and tertiary graduates all have the same unemployment rate, the index will have a value of zero (no dissimilarity between groups), while the index would reach a value of 1 or 100 per cent (complete dissimilarity) if, for example, all those with primary and tertiary education are employed and all those with secondary education are unemployed.

3.2.2 Trends

A wide range of skills mismatch is observed across the sample of 31 European countries (see Fig. 2). In 2012, the SMI ranged from 4.3 per cent in Romania to 24.6 per cent in Lithuania. In most countries, the index increased, compared to its value in 2000. Nevertheless, it dropped in 11 out of 31 countries, with the largest decrease observed in Romania (−15.5 percentage points) and Luxembourg (−8.7 percentage points). The largest increase during these 12 years happened in Spain (12.8 percentage points), Malta (11.9 percentage points) and Latvia (9.9 percentage points). In case of Spain, such a spike occurred because unemployment doubled for the primary-educated, increased 75 per cent for the secondary-educated, but rose only 37 per cent for the tertiary-educated in this time period (Eurostat data).

[6]Europe 2020, which is the EU's growth strategy, aims to raise tertiary educational attainment to at least 40 per cent of the population aged 30 to 34 by 2020 (according to Eurostat, this proportion was 36 per cent in 2012).

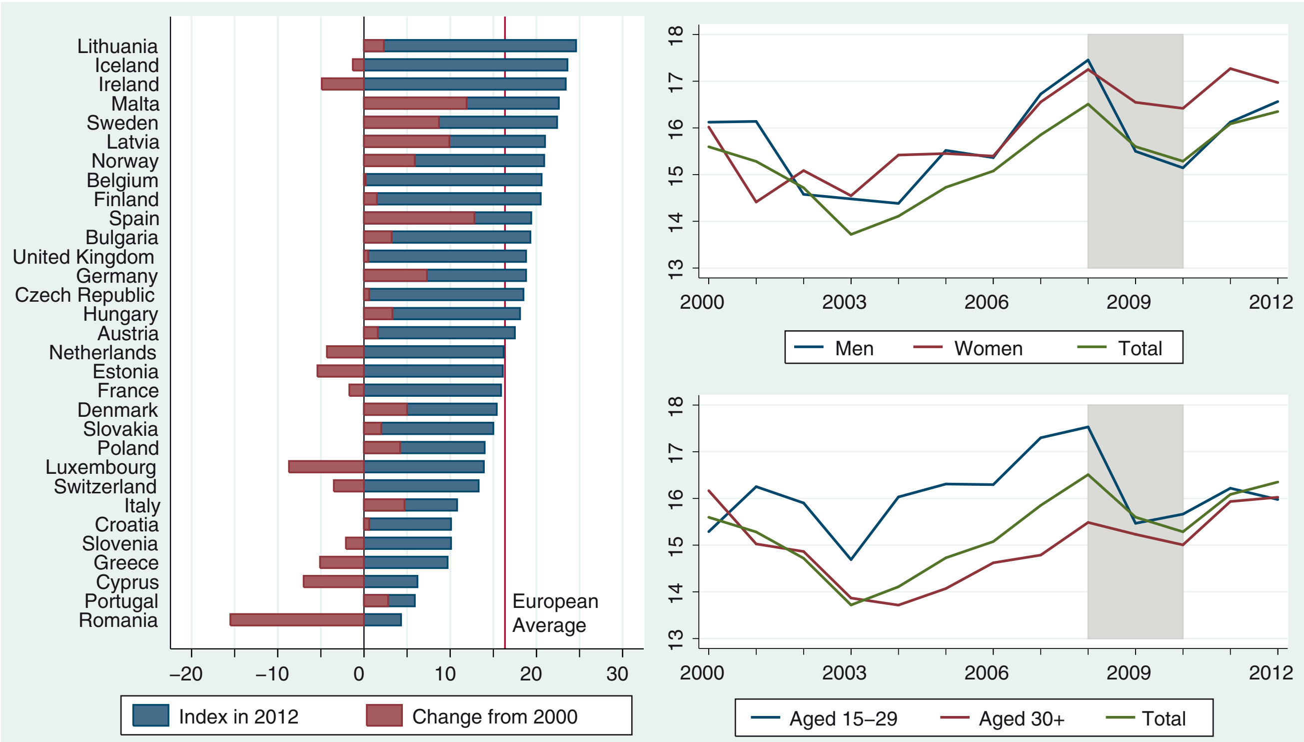

Fig. 2 Mismatch Index in Europe in 2012 (Left) and Its Trends in 2000–2012 (Right). *Source:* based on data from ILO (2013c). Trends based on simple averages of country values. There are no observations for Croatia in 2000–01; thus, mismatch index in 2012 is compared with its value in 2002 for Croatia in the left panel.

It should be noted that mismatch between supply and demand measured on the basis of unemployment rates by level of educational attainment is not an indication of the quality or responsiveness of education and training systems as such. High-quality education and training improves the employability of workers, and in this way contributes to low unemployment. However, among those who are unemployed, there are likely to be many workers who did not benefit from the education system to the same extent as the employed. In Austria, Germany and Finland, for example, the SMI was above the European average in 2012, despite low unemployment rates and well-regarded education and training systems.

The right panels of Fig. 2 show that after sliding down in 2000–2003, the average SMI rebounded and started growing until the peak in 2008, when the global financial crisis started. This reflects that while unemployment rates for workers with primary, secondary and tertiary education all decreased during this period, the relative decrease was larger for those with secondary and tertiary education. The crisis dampened the mismatch, as the relative increase in the unemployment rates for workers with secondary and tertiary education became larger than that for workers with primary education.[7] The crisis, thus, resulted in less skills mismatch on this measure, which may appear counter-intuitive. However, it should be borne in mind that the SMI is constructed in such a way that it is independent from the level of unemployment and reflects how different groups of workers are affected in relative terms. The decrease in the index demonstrates that the relative position of better educated workers deteriorated in comparison with their position in 2008.

The average index primarily decreased for men and the young (aged 15–29), whose average indices dropped around 2 percentage points each. On the contrary, the average mismatch for women and adults (aged 30 and above) lost only around 0.5 percentage points by the end of the crisis. After the crisis, the growth in average mismatch index resumed.

3.3 Micro-Level Skills Mismatch

3.3.1 Measures

We complement the measure of skills mismatch at the macro level with measures of overeducation and undereducation at the individual level. The concept of overeducation (undereducation) means having more (less) education than required by the job, but the measurement has proven to be quite controversial. Four different approaches exist in the literature

[7]The change in percentage points was larger for workers with primary education, which has often been used as an argument that these workers were hit "relatively hard" during the crisis (ILO 2012; OECD 2012).

Table 1 Measurements of Mismatch.

	Idea	Advantages	Disadvantages
Normative	Use a pre-determined mapping between the job and the required education level	Easily measurable Objective	Assumes constant mappings over all jobs of a given occupation Costly to create and update the mapping
Statistical	The overeducated are those with education level higher by some ad-hoc value than the mean or mode of the sample within a given occupation	Easily measurable Objective Always up-to-date	Assumes constant mappings over all jobs of a given occupation Sensitive to cohort effects Results depend on the level of aggregation of occupations
Self-assessment	Respondents are asked about their perceptions of the extent their education or skills are used in their job	Always up-to-date Corresponds with requirements in the individual firm	Subjective bias: respondents may overstate job requirements, inflate their status or reproduce actual hiring standards
Income-ratio[a]	Overeducation is a continuous variable measured by comparing actual and potential income	Reflects that one of the goals of investment in education is maximising income	Indirect measure, can be influenced by many other factors

Source: Authors' elaboration; (Hartog 2000; Quintini 2011)
[a] This measure is not typically discussed in the literature; it connects overeducation to another failure in the labour market – underpayment. See Guironnet and Peypoch (2007) or Jensen et al. (2010) for examples.

(see Table 1) with their own advantages and disadvantages, and there is no agreement on a single "correct" measure. Moreover, different measures may lead to very different results, and this also leads to differences in model estimates in which overeducation is used.

In this paper, we use the normative measure based on ISCO alongside a statistical measure,[8] which allows for a categorisation of workers that is consistent with the macro level measure (following ILO (2013c, 2014)). The normative measure starts from the division of major occupational groups (first-digit ISCO levels) into the three groups used in previous sections and assigns a level of education to each group in accordance with the International Standard Classification of Education (ISCED). Workers in a particular group who have the assigned level of education are considered well matched: workers with tertiary education match high-skill jobs, the secondary-educated match medium-skill jobs and those with primary education match low-skill jobs. Those who have a higher (lower) level of education are considered overeducated (undereducated). For instance, a university graduate working as a clerk (a medium-skill occupation) is overeducated, while a secondary school graduate working as an engineer (a high-skill occupation) is undereducated.

An advantage of the ISCO-based measure is that the definition of mismatch does not change over time and the results are, therefore, strictly comparable. A possible disadvantage of this method is that it does not take the actual distribution of educational attainment into account. Therefore, in high-attainment countries, the proportion of the overeducated might be higher. Another disadvantage of this measure is that, by construction, it does not allow for either overeducation in major groups 1 to 3 or undereducation in major group 9.[9]

The statistical measure is constructed based on the years of full-time education of workers and their occupation code. For each 2-digit ISCO group in each country and year, the mean number of years of education, as well as its standard deviation, is measured. Then the over- (under-) educated are respondents who have education years above (below) the mean level by one standard deviation. An advantage of this method is that there is less heterogeneity among groups of jobs compared with the three groups according to the normative method. In addition, this method is less sensitive to the average level of educational attainment in a country, as this will be reflected in higher mean levels of education. But this is also a disadvantage in the sense that mean levels may or may not be driven by job requirements.[10]

We will use data from the European Social Survey (ESS), rounds 1 through 6 (European Social Survey 2002, 2004, 2006, 2008, 2010, 2012). ESS is a biennial survey covering over 30 countries, although country coverage differs by round: only 16 out of 36 countries appear in all six rounds. This data source was selected because it has rich individual-level data, including data on individual's personality, which can be used as explanatory variables in the models of mismatch.[11]

[8] European Social Survey data, which we use for running models of over-/undereducation, do not allow to construct a measure of mismatch based on self-assessment.

[9] Workers in advanced economies usually have at least a completed primary education.

[10] In countries with very low levels of educational attainment, the mean level of education may be a poor indicator of job requirements, and the statistical method may be inappropriate (Sparreboom and Nübler 2013).

[11] ISCO sub-major groups with less than five observations in a particular country and round of ESS will be excluded from the analysis of mean-based mismatch measure.

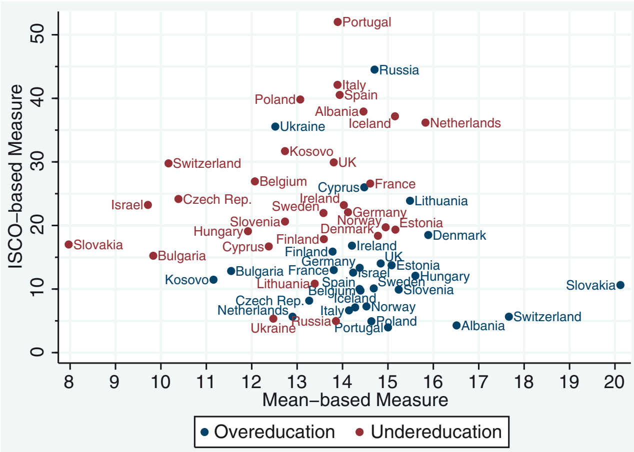

Fig. 3 Incidence of Mismatch in Europe, 2012. *Source:* Authors' calculations based on ESS Round 6 data. Design weights applied.

3.3.2 Trends

Countries differ markedly in mismatch patterns (Fig. 3). The ISCO-based measure shows that across all workers, overeducation in 2012 ranged from below 5 per cent in Portugal to above 25 per cent in Cyprus, Ukraine and Russia, while undereducation was below 10 per cent in Russia and Ukraine and exceeded 40 per cent in Spain, Italy and Portugal. The range in mismatch according to the statistical measure is smaller: from around 11 per cent in Kosovo to above 20 per cent in Slovakia for overeducation and from 8 per cent in Slovakia to above 15 per cent in Iceland, Estonia and the Netherlands for undereducation.

Considering stable recent country-specific trends in skills mismatch in countries with sufficient data to assess trends (ILO 2014), we find that in the majority of countries (16 out of 26) overeducation increased on at least one measure, while it increased on both measures in Cyprus. Seven countries experienced a downward trend in overeducation by at least one measure (Finland, Greece, Ireland, Israel, Poland, Slovenia and Ukraine). Undereducation decreased on at least one measure in the majority of countries (18 out of 26), and decreased on both measures in Bulgaria, Israel, Poland, Portugal, Russia and Slovakia. However, in five countries it was growing (Denmark, Greece, Lithuania, the Netherlands and Switzerland).

In countries covered in all six ESS rounds, the average incidence of overeducation is increasing and the average incidence of undereducation is decreasing from 2002 to 2012 (Fig. 4). According to the ISCO-based measure, the increase was 3.2 percentage points, while the mean-based measure shows a U-shaped pattern in 2002–2010 followed by a 0.4 percentage point drop in 2012. As was noted before, the ISCO-based measure in part reflects an increase in the educational attainment levels of workers. However, the sharp rise in the average incidence of overeducation according to both the ISCO- and mean-based measures during 2008–2010 (by 1.5 and 0.8 percentage points, respectively) is likely to also reflect increased competition for jobs associated with the employment crisis.

Undereducation dropped 8.2 percentage points in 2002–2012 on the ISCO-based measure, which again partly reflects an increase in workers' educational attainment levels, and by 0.5 percentage points, according to the statistical measure. Similarly to overeducation, the downward trend in undereducation accelerated in 2010, decreasing by 2.9 and 0.14 percentage points, according to the ISCO- and mean-based measures, respectively, which is again consistent with stronger competition for jobs between 2008 and 2010.

Women are more frequently overeducated and less frequently undereducated than men of their age group, according to the ISCO-based measure, and both results are stable over time (Fig. 5). However, the statistical measure leads to the opposite conclusion for overeducation: not only are women less frequently overeducated, but gender differences also decrease over time. There is no contradiction between these seemingly contrasting results, however. The normative measure shows that women are more frequently working in jobs where their education level is, from the normative point of view, not necessary. The statistical measure reflects that, at the same education level, women have less years of education than men[12], which is why they are less likely than men to have more years of education than the mean years of education in their occupation. For undereducation, the statistical measure produces intertwined dynamics for both sexes. According to both measures, workers aged 15–29 face higher overeducation risk and lower undereducation risk than workers aged 30 and above.

Disaggregation of average mismatch dynamics by skill level of jobs (Fig. 6) mostly shows clear trends for the ISCO-based measure but more complicated dynamics of the mean-based measure. ISCO-based overeducation was increasing and undereducation was decreasing during 2002–2012.[13] Similarly, mean-based undereducation on high- and medium-skill jobs shows a general downward trend – this time, with the exception of the undereducation on high-skill jobs, which jumped in 2012 to the level it had in 2002–2004. On low-skill jobs, mean-based undereducation dropped three percentage points in 2004 and then started increasing in circa 1.5 percentage point jumps (in 2006 and 2010, resting somewhat in 2008 and 2012). Mean-based overeducation on high-skill jobs returned in 2010–2012 back to its level in 2002

[12]As shown by a two-level regression with country-level random effects controlling for ESS round (not reported), women on average have 0.15 less years of education then men with the same education level. Among the tertiary-educated, the effect from being a female is −0.26 years of education.

[13]Undereducation has a slightly more complex dynamics, rebounding in 2008 and 2012, but the overall downward direction was kept.

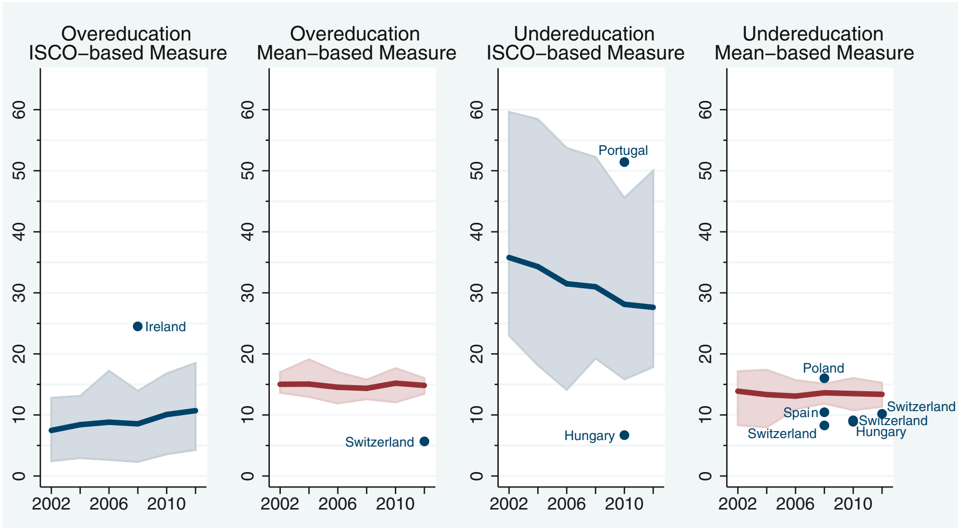

Fig. 4 Average Incidence of Over-/Undereducation in Europe. *Source:* Authors' calculations based on ESS data. The figure shows unweighted averages based on data from countries appearing in all six ESS rounds (Belgium, Denmark, Finland, France, Germany, Hungary, Ireland, the Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland and the UK). The shaded area shows the range of incidence across countries. Labelled points outside shaded areas represent countries with a significantly different incidence of skills mismatch from other countries in a particular round. These outliers have an incidence outside the interval $[p_{25} - 1.5 \times IQR, p_{75} + 1.5 \times IQR]$, where p_i is ith percentile of the incidence distribution in a given round and IQR is the interquantile range. The outliers are excluded from the average values.

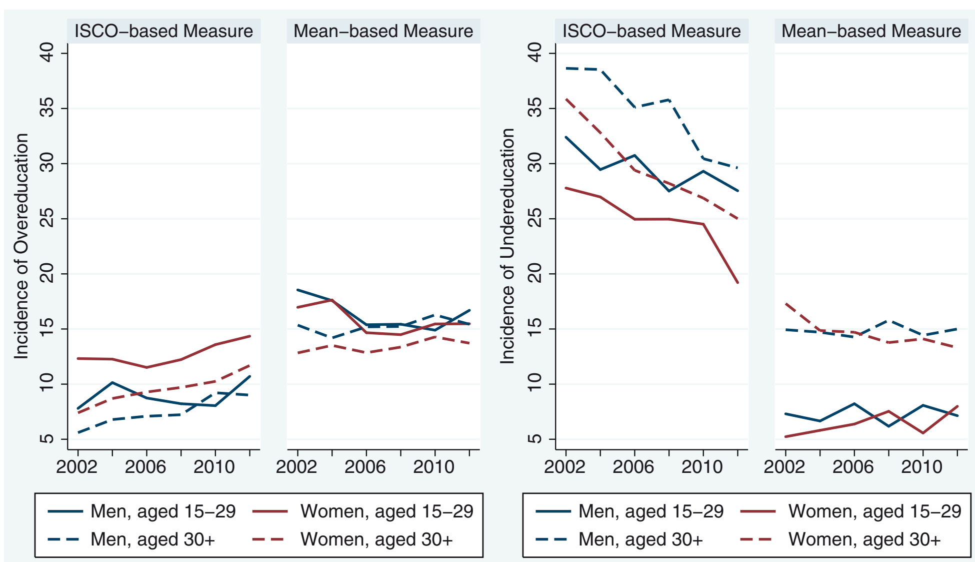

Fig. 5 Average Incidence of Over-/Undereducation in Europe by Sex and Age Group. *Source:* Authors' calculations based on ESS data. The figure shows unweighted averages over same countries as in Fig. 4. Countries that have significantly different (as defined in the notes to Fig. 4) skills mismatch incidence from other countries in a round in at least one of four sex–age group pairs are excluded from the calculation of the averages in that round.

after jumping one percentage point in 2004 first and then immediately dropping 1.5 percentage points in 2006 and resting there in 2008. The value of this indicator on medium-skill jobs was relatively stable in 2002–2008, which was followed by a one percentage point jump in 2010 and a slight further increase in 2012. For low-skill jobs, mean-based overeducation jumped more than one percentage point in 2004, fluctuated near 15 per cent until 2008 and started gradually dropping in the following years, in 2012 falling below its level in 2002.

4 Results

In this section, we first discuss the relationship between the JPI and the SMI. Then we move to studying the effects from the JPI on individual-level mismatch. Summary statistics of the variables used in this section are available in the Appendix, Table 11 for macro-level models and Tables 12 and 13 for multi-level models.

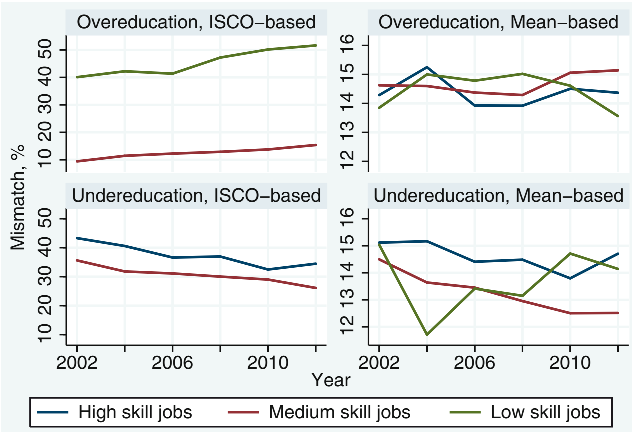

Fig. 6 Average Incidence of Over-/Undereducation in Europe by Skill Level of Jobs. See notes to Fig. 4. Recall that overeducation in high-skill jobs and undereducation in low-skill jobs is undefined when the ISCO-based measure of mismatch is used.

Table 2 Results of Single-Equation Models of the SMI and the JPI

Dep. Var.	SMI	JPI	
		(1)	(2)
JPI	−0.232		
SMI		−0.021	−0.019
EPL	−4.830***		
GDP growth	0.126*		
log(GDP per capita)		0.587**	
Population growth			0.583***
Crisis (2008–09)	1.475***		
Aftercrisis (2011–12)		−0.690***	−0.641***
Constant	27.823***	−0.809	0.818***
Random Effects:			
Constant	3.008	0.407	0.420
	(0.486)	(0.084)	(0.086)
N	264	264	264
LR test, p-value	0.000	0.000	0.000
Residual ICC	0.512	0.200	0.219
	(0.085)	(0.069)	(0.074)
AIC	1392	684	674
BIC	1417	705	695

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ EPL is employment protection legislation. Most data on EPL were taken from OECD. EPL data for Estonia (2002–2007) and Slovenia (2002–2007) were taken from Tarvid (2011, p. 96). EPL data for Iceland and Luxembourg in 2002–2007 were set equal to the available data for 2008–2012. EPL data for Sweden in 2005 and 2006 were set equal to the available data in the surrounding years. All other data taken from ILO (2013c). Random effects computed at country-level. Parentheses contain standard errors. ICC is intra-class correlation.

4.1 Polarization and Macro-Level Skills Mismatch

We first estimate the models of the SMI and the JPI separately. We use a linear model with country-level random intercepts based on a panel of 24 countries[14] observed in 2002–2012. The results (see Table 2) suggest that there is no relationship between the two indices. The SMI is inversely related to employment protection legislation (EPL) and pro-cyclical. The JPI increases with per capita income and population growth.

Single-equation results, however, may be biased, as they do not take into account possible inter-relationship between the two equations. Theoretically, one would expect that job polarization increases the demand for workers at certain levels of education, and in the absence of a supply response this will lead to more mismatch, unless the supply of educated workers was already polarized to a larger extent than available jobs. On the other hand, high levels of skills mismatch in groups of occupations may also influence the pace of job polarization, again abstracting from a supply response.

Simultaneous equations where endogenous variables appear on both sides of equations are typically estimated using three-stage least squares (3SLS) (Zellner and Theil 1962). We run a 3SLS-like simultaneous equations model for the JPI and the SMI with country-level random effects correlated across equations:

$$\begin{cases} m_{it} = \gamma_0 + \gamma_1 p_{it} + \boldsymbol{\delta}\mathbf{x}_{it} + \boldsymbol{\varphi}\mathbf{y}_{it} + \kappa_i + \varepsilon_{it} \\ p_{it} = \alpha_0 + \alpha_1 m_{it} + \boldsymbol{\beta}\mathbf{x}_{it} + \boldsymbol{\psi}\mathbf{z}_{it} + \lambda_i + \xi_{it}, \end{cases} \quad (7)$$

where i is country index and t is year index. We use conditional mixed process estimator with multilevel random effects and coefficients (Roodman 2011) for that purpose. Table 3 shows that the JPI negatively and statistically significantly affects the SMI, but the reverse effect is close to zero and not significant. The size of the effect from the JPI on the SMI is close to −1.8.

Further analysis[15] shows that the SMI is related to the low-skill occupation parameter ($\overline{\Delta_5 l}$) of the JPI more strongly than to its high-skill occupation parameter ($\overline{\Delta_5 h}$), although both are highly significant.

None of SMI components is significantly correlated with $\overline{\Delta_5 h}$. At the same time, all three components of the SMI are significantly correlated with $\overline{\Delta_5 l}$.[16] To get a clearer picture of the relationship between the components of both indices, we run the following three-equation seemingly unrelated regressions (indices denoting observations suppressed for readability):

$$\left|\frac{E_i}{E} - \frac{U_i}{U}\right| = \alpha_i + \beta_i \overline{\Delta_5 h} + \gamma_i \overline{\Delta_5 l} + \varepsilon_i, \quad i = 1, 2, 3. \quad (8)$$

[14]Austria, Belgium, Czech Rep., Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the UK. Only in these 24 countries was it possible to define employment protection legislation, which is one of the independent variables in the model discussed below.

[15]Model (7) without country-level random effects and with the two JPI components included on the right-hand side of the SMI equation instead of the JPI itself estimated by seemingly unrelated regression, not reported.

[16]The correlations are −0.17, −0.11 and −0.21 for the primary-, secondary- and tertiary-education components of the SMI, respectively.

Table 3 Results of Simultaneous Equations Models for the JPI and the SMI

	(1)		(2)	
Dep. Var.	SMI	JPI	SMI	JPI
JPI	−1.798***		−1.789***	
SMI		−0.029		−0.048
EPL	−4.116***		−4.057***	
GDP growth	0.176		0.163	
log(GDP per capita)		0.689**		
Population growth				0.590***
Crisis (2008–09)	2.023		2.009	
Aftercrisis (2011–12)		−0.694***		−0.621**
Constant	26.892***	−1.030	26.759***	1.258*
Random Effects:				
Constant	2.813	0.398	2.826	0.391
	(0.469)	(0.102)	(0.479)	(0.082)
Correlation	−0.171		0.058	
	(0.563)		(0.610)	
N	264		264	
Residual CEC	0.545**		0.602***	
AIC	2070		2058	
BIC	2123		2112	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ See notes under Table 2. CEC is cross-equation correlation.

Table 4 Results of Seemingly Unrelated Regressions of SMI Components on JPI Parameters

Dep. Var.	$\left\lvert \frac{E_1}{E} - \frac{U_1}{U} \right\rvert$	$\left\lvert \frac{E_2}{E} - \frac{U_2}{U} \right\rvert$	$\left\lvert \frac{E_3}{E} - \frac{U_3}{U} \right\rvert$
$\overline{\Delta_5}h$	−0.489***	0.046	−0.513***
$\overline{\Delta_5}l$	−1.292***	−0.143	−1.152***
R^2	0.0470	0.0024	0.0657

Breusch–Pagan test of independence of equations has a p-value of 0.0000.

Table 4 shows that changes in low-skill occupation share have a more than twice larger effect on the components of the SMI than changes in high-skill occupation share. At the same time, the low-skill component of the JPI most strongly affects the primary-education component of the SMI, and the high-skill component of the JPI most strongly affects the tertiary-education component of the SMI, although the effect size from $\overline{\Delta_5}h$ is nearly the same on both the primary- and tertiary-education components of the SMI.

The results, thus, suggest that labour markets have a greater difficulty in accommodating changes in the share of low-skill occupations, which are more strongly related to skills mismatch, which can be explained by several factors. Given that the supply of high-skill workers is in general on an upward trend, this may mitigate the effects of job polarization on skills mismatch for high-skill occupations. It may also be that education systems are relatively responsive at higher levels of education, in part because the upward trend is supported by policies in many countries. Other explanations are related to the behaviour of workers, which will be discussed in the next subsection.

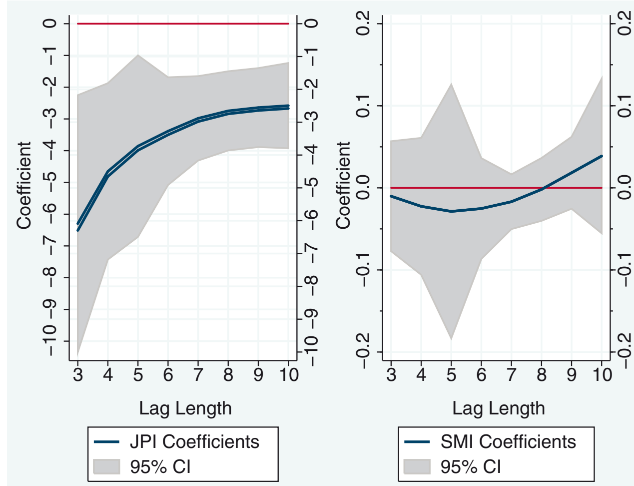

Fig. 7 Sensitivity of JPI–SMI Relationship Depending on the Lag Length in JPI Definition. Each point on the lines represents the value of the coefficient of the JPI or the SMI in the respective equation of (7). The system (7), in the specification (3) as shown in Table 3, was estimated on a subset of countries where it was possible to include all lags from 3^{rd} to 10^{th} in 2002–2012. These countries are Denmark, Estonia, France, Germany, Greece, Iceland, Ireland, Italy, the Netherlands, Portugal, Spain, Switzerland and the United Kingdom. Because it was not possible to include all countries that were included in the model whose results were discussed above due to data unavailability, the values of the coefficients shown in the figure are different from those shown in Table 3.

We will now analyse how sensitive the above results are to alternative definitions of the JPI. Recall that we used the $\overline{\Delta_5}$ operator, that is, five lags of data in (5). We will now analyse how the coefficients in (7) depend on whether the JPI was defined using operators $\overline{\Delta_3}$, $\overline{\Delta_4}$, ... $\overline{\Delta_{10}}$ defined analogously to (4) – that is, from three lags (reference to short-term average) through ten lags (reference to long-term average). The dataset does not allow us to go beyond 10 lags (as there are no data before 1992), and we continue estimating (7) on years 2002–2012. The dataset also does not contain data for all countries in 1992–1997, so to keep the following analysis consistent, we take only those countries where we have data from 1992 through 1997 on which to compute longer lags in JPI definition (see the list of countries in the note to Fig. 7).

Figure 7 shows that the effect from the JPI on the SMI is the strongest when compared to short-term averages (lag lengths of 3–4), but the closer we move to the long-term reference value, the less pronounced the relationship becomes. Even when the JPI has 10 lags, however, its effect on the SMI remains significant. The effect from the SMI on the JPI increases somewhat with lag length, but remains modest (as compared to the reverse effect) and insignificant.

4.2 Polarization and Individual-Level Skills Mismatch

Overeducation and undereducation may be related to job polarization in various ways. For example, if the growth of high-skill occupations outpaces the supply of workers at this level of skills, undereducation can be expected to rise. On the other hand, overeducation may rise if high-skilled workers cannot find appropriate jobs and increasingly compete for jobs usually taken by those with a lower level of education.

In this section, we will study how the risk of mismatch at individual level depends on the polarization of the occupational structure. We will use the nominal (ISCO-based) and the statistical (mean-based) definitions of mismatch of both overeducation and undereducation that were introduced before.

Several methods are possible in studying the determinants of over- and undereducation on cross-sectional data, such as that available from ESS. The simplest is to run logit/probit models separately for two dummies representing overeducation and undereducation, respectively. A more elaborate method is to create a three-category variable and run a multinomial logit/probit model with a base category of full match between the individual and the job.

We will use multi-level mixed effects logistic model. This model allows for intra-cluster correlation of observations by assuming that they share common cluster-level random effects. The model allows for several levels of nested clusters, and we will use two levels: individuals (the first level) will be nested inside countries (the second level). This model also allows for cluster-level random coefficients, i.e., separate random effects of the variable within each cluster. We will include random coefficients on the sex dummy in aggregate (i.e., not sex-specific) models. All models will be estimated by adaptive Gaussian quadrature with seven integration points. The models will be estimated on 30 countries: 24 used in Sect. 4.1, Bulgaria, Croatia, Cyprus, Latvia, Lithuania and Romania. The dependent variables will be overeducation and undereducation defined by ISCO-based and mean-based measures.

Accounting for unobserved heterogeneity is important for micro-level models of mismatch. There might be unobserved individual- or job-specific factors that, together with the observed factors, make the worker a perfect candidate for his or her job. Not controlling for such unobserved factors might make results biased. For cross-sectional data[17], unobserved heterogeneity can be approximated by using a proxy for ability (Cainarca and Sgobbi 2012; Chevalier 2003; Korpi and Tåhlin 2009), splitting the sample into more homogeneous (e.g., in terms of earnings) sub-samples (Budría 2011; McGuinness and Bennett 2007) or controlling for the environment where the individual was raised (Korpi and Tåhlin 2009). Personality is another important source of unobserved heterogeneity, but it was used by only two studies in the context of mismatch (Blázquez and Budría 2012; Tarvid 2013). Tarvid (2013) showed that personality is an important predictor of overeducation and frequently performs better than ability.

Data on respondent's personality are included in ESS data. We will use it to control for unobserved heterogeneity.[18] ESS data contain 12 variables describing respondent's personality. Each of them measures the extent to which the respondent believes he/she resembles the description of a given trait. We created 12 dummies indicating respondents who were "very much like" the respective description. We then ran factor analysis, which allowed us to combine these dummies in three summated scales created by taking the average value of the relevant dummies:

- Social orientation (important to be treated equally, follow rules, help people and be loyal to friends)
- Achievement orientation (important to be rich, show abilities, get respect and be successful)
- Openness to experience (important to be creative, try new things, make decisions freely and seek adventures)

Each scale runs from 0 to 1, where larger values indicate better representation of particular composite trait in the respondent. Principal-component factor, iterated principal factor and maximum-likelihood factor methods all gave the same grouping after rotation, whether orthogonal or oblique. KMO measure is between 0.80 and 0.90 for the whole sample and each of the twelve dummies individually; Cronbach's alphas are between 0.60 and 0.65.

Other individual-level explanatory variables in the current model were shown to be related to mismatch in other studies (see Sect. 2) or are otherwise related to it. These can be grouped into three categories. Personal characteristics, besides personality variables, include general demographics (age and its square, sex dummy), dummies for being a student or a disabled, immigrant background and education level (only where mismatch is measured by the mean-based criterion). Family characteristics include the number of children, partner employment status, parental and partner's education level and whether one of the parents is responsible for supervising other employees (dummy). Finally, labour-market characteristics include the type of domicile, firm size, whether the respondent is responsible for supervising other employees (dummy), unemployment experience with a duration up to 3 months or up to 1 year (in a lifetime in both cases, dummies) and working without a contract.

[17]There are more options if panel data are available, but because ESS is a cross-sectional dataset, these are not reviewed here.

[18]Ideally, we would also include the ability variable defined by Tarvid (2013), but it is impossible to construct it in all rounds due to conflicting measures of respondent's income in different rounds.

The model also includes two macro-level country-specific explanatory variables: the JPI and total unemployment. Time fixed effects are represented by ESS rounds.

We will now analyse the effects from the variables of main interest: the JPI, unemployment, sex and ESS rounds, which are shown in Tables 5 (for overeducation) and 6 (for undereducation). Four models are compared:

1. $y_{ict} = \alpha + \beta p_{ct} + \boldsymbol{\gamma t} + (\delta + \xi_c) f_{ict} + \zeta_c + \varepsilon_{ict}$
2. $y_{ict} = \alpha + \boldsymbol{\beta}(p_{ct} \times \boldsymbol{t}) + (\delta + \xi_c) f_{ict} + \zeta_c + \varepsilon_{ict}$
3. $y_{ict} = \alpha + \beta p_{ct} + \boldsymbol{\gamma t} + (\delta + \xi_c) f_{ict} + \zeta_c + \boldsymbol{\kappa}\mathbf{x} + \varepsilon_{ict}$
4. $y_{ict} = \alpha + \boldsymbol{\beta}(p_{ct} \times \boldsymbol{t}) + (\delta + \xi_c) f_{ict} + \zeta_c + \boldsymbol{\kappa}\mathbf{x} + \varepsilon_{ict}$,

where y is mismatch state (overeducation or undereducation, depending on the model), p is the JPI, f is the female dummy (note that it has both a fixed coefficient, δ, and a country-level random coefficient, ξ_c), $\boldsymbol{t}$ denotes ESS rounds, vector $\mathbf{x}$ contains all individual-specific variables other than sex and the unemployment rate of a country in the given ESS round, and ζ_c are country-level random intercepts. Indices i, c and t denote individuals, countries and ESS rounds, respectively. This set-up, thus, allows to compare the effect on individual's mismatch coming purely from the JPI (controlling for sex and time fixed effects) and the changes in the effect after controlling for other relevant variables included in vector $\mathbf{x}$. The same four models are also run separately for men and women (without the sex dummy, of course). Of these models, model (3) is the main model.

At first, the results from model (3) seem to say that the JPI is irrelevant for individual-level mismatch: the only significant effect on the total sample is the positive effect on mean-based overeducation. Model (1), however, shows all effects from the JPI on the total sample as not significant, so the significant effect in the mean-based overeducation model appeared only after including other explanatory variables.

We hypothesise that there in fact is an effect, but it is different for subgroups of individuals and, thus, cancels out. We, thus, set two hypotheses: (1) the effect is different for men and women and (2) it differs across ESS rounds. Sex-specific models and models with interactions between the JPI and ESS rounds (models (2) and (4)) on the total sample allow us to investigate this issue further.

The first hypothesis does not hold in case of undereducation: Table 6 shows that there is no effect for males or females in models (1) and (3) for both mismatch measures. However, we find support for this hypothesis in case of overeducation (Table 5). The JPI increases the risk of overeducation of males but does not affect it for females. Note that adding other explanatory variables decreases the odds ratio of ISCO-based overeducation but increases it for mean-based overeducation, but the changes are certainly not radical. Summing up the results from both measures, we can conclude that a one-point increase in the JPI increases the risk of overeducation for males by 4 to 5 per cent, depending on the measure.

The second hypothesis generally holds in case of ISCO-based mismatch measure. In both models (2) and (4), we can see that the effect from the JPI was arguably positive to the individual in the first three rounds (i.e., in 2002–2007) in the sense that in countries with a higher JPI the probability of overeducation was lower but that of undereducation was higher. The absolute size of the effect, however, was much smaller in the second and third rounds (2004–2007) than in the first round (2002–2003). In contrast, the fourth round (2008–2009) and, to some extent, the fifth round (2010–2011) have a contrasting effect: countries with a higher JPI can be associated with a generally *higher* overeducation. The situation with undereducation was somewhat different: the effect is still positive in the fourth round (in model (4)), but then in the fifth round, it went down to being insignificant (in model (4)) or negative (in model (2)). Most likely, these effects come from the crisis, but note that in model (4), we do control for unemployment rate, which should accommodate some of the effects from the crisis on mismatch.

In case of mean-based mismatch measure, the second hypothesis also holds but to a smaller extent, because most effects on undereducation are not significant. For overeducation, effects become significant only after non-sex individual-level controls are added (note that unemployment is not significant). Again, we can observe that in the first two rounds, the JPI increased mean-based overeducation, but the effect disappeared in the following two rounds, then became risk-decreasing in the fifth round (2010–2011) and finally, in the most recent round (2012–2013), it turned back to be risk-increasing. This is the reason why the overall effect from the JPI on mean-based overeducation is positive and significant.

As just noted, the effect of the JPI on mean-based overeducation is generally positive, and its behaviour during the global financial crisis (2008–2009) and immediately afterwards (2010–2011) appeared to be a temporary deviation, which ended in 2012–2013. Can we see similar behaviour in the effect of the JPI on ISCO-based overeducation? We would answer in the affirmative, as the overall effect peaked in the crisis years and afterwards started diminishing and moving to below one. The same cannot be said about the effect on ISCO-based undereducation: no clear indication of future moving directions can be inferred from the effects shown in Table 6.

Tables 5 and 6 also enable us to combine both hypotheses and see how sex-specific effects from the JPI change over time. The overall effects on ISCO-based overeducation are clearly driven by the effect on females, as once we control for individual-level factors and unemployment rate, the only significant effect for males is observed during the crisis.

Table 5 Odds Ratios After Multi-Level Mixed Effects Logit of Overeducation: Key Effects

	Total, ISCO-Based Measure				Male, ISCO-Based Measure				Female, ISCO-Based Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
JPI	1.020		1.010		1.067***		1.047**		0.980		0.978	
× ESSR1		0.790***		0.821***		0.873**		0.918		0.717***		0.736***
× ESSR2		0.964*		0.979		1.011		1.026		0.911***		0.925**
× ESSR3		0.916***		0.909***		0.958		0.950		0.880***		0.876***
× ESSR4		1.108***		1.071***		1.186***		1.130***		1.057*		1.033
× ESSR5		1.089***		1.044		1.095**		1.019		1.087**		1.067*
× ESSR6		1.031		0.976		1.082**		1.000		0.994		0.964
Unempl.			10.065***	46.582***			55.834***	296.734***			2.403	9.175***
ESS Round (rel. to Round 1)												
ESSR2	1.153***		1.120***		1.150**		1.101		1.152**		1.139**	
ESSR3	1.114***		1.092**		1.065		1.038		1.162***		1.153**	
ESSR4	1.242***		1.194***		1.247***		1.174***		1.247***		1.223***	
ESSR5	1.350***		1.261***		1.319***		1.182***		1.387***		1.348***	
ESSR6	1.452***		1.409***		1.442***		1.359***		1.469***		1.481***	
Female	1.273***	1.275***	1.192***	1.193***								
Constant	0.072***	0.090***	0.086***	0.099***	0.070***	0.087***	0.071***	0.078***	0.094***	0.120***	0.109***	0.133***
Random Effects												
Female	0.243	0.244	0.247	0.246								
	(0.039)	(0.039)	(0.040)	(0.040)								
Const.	0.508	0.493	0.491	0.490	0.519	0.502	0.497	0.499	0.508	0.490	0.505	0.492
	(0.069)	(0.067)	(0.067)	(0.067)	(0.071)	(0.069)	(0.068)	(0.069)	(0.069)	(0.067)	(0.069)	(0.068)
N	121731	121731	121731	121731	62980	62980	62980	62980	58751	58751	58751	58751
LR test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	75421	75465	74072	74099	36282	36313	35824	35840	39168	39174	38224	38230
BIC	75518	75562	74519	74546	36355	36386	36222	36238	39240	39246	38619	38625
	Total, Mean-Based Measure				Male, Mean-Based Measure				Female, Mean-Based Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
JPI	1.015		1.034**		1.036**		1.042**		0.993		1.023	
× ESSR1		1.029		1.185***		1.069		1.214***		0.983		1.142***
× ESSR2		1.002		1.048***		1.020		1.059***		0.978		1.036
× ESSR3		0.990		1.012		1.042		1.053		0.927**		0.963
× ESSR4		1.023		0.969		1.005		0.945		1.041		0.991
× ESSR5		1.033		0.942**		0.998		0.899***		1.072**		0.980
× ESSR6		1.038*		1.051**		1.080***		1.059*		1.007		1.037
Unempl.			0.714	1.054			2.221	2.203			0.286	0.587
ESS Round (rel. to Round 1)												
ESSR2	0.984		0.926**		0.943		0.878***		1.030		0.993	
ESSR3	0.947*		0.846***		0.923*		0.821***		0.979		0.884**	
ESSR4	0.965		0.820***		0.919**		0.771***		1.024		0.888**	
ESSR5	1.006		0.822***		0.930*		0.743***		1.101**		0.924	
ESSR6	1.010		0.907***		0.975		0.834***		1.058		1.002	
Female	0.874***	0.873***	0.723***	0.723***								
Constant	0.181***	0.178***	0.172***	0.150***	0.185***	0.177***	0.176***	0.148***	0.153***	0.157***	0.111***	0.102***
Random Effects												
Female	0.056	0.053	0.070	0.072								
	(0.022)	(0.022)	(0.025)	(0.025)								
Const.	0.065	0.061	0.253	0.251	0.069	0.064	0.264	0.262	0.077	0.067	0.224	0.223
	(0.014)	(0.014)	(0.035)	(0.035)	(0.016)	(0.016)	(0.037)	(0.036)	(0.019)	(0.019)	(0.033)	(0.033)
N	114869	114869	114869	114869	59079	59079	59079	59079	55790	55790	55790	55790
LR test	0.088	1.000	0.000	0.000	0.129	1.000	0.000	0.000	0.086	1.000	0.000	0.000
AIC	95072	95075	81510	81526	50583	50584	43461	43474	44491	44485	38073	38077
BIC	95168	95171	81974	81990	50655	50656	43874	43888	44562	44557	38484	38488

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ Subset of results shown. Likelihood ratio (LR) test compares the given models with the corresponding models fit by standard logistic regression; its p-value is reported. ESSR is ESS round. ESS round 1 was fielded in 2002–2003, round 2 in 2004–2005, round 3 in 2006–2007, round 4 in 2008–2009, round 5 in 2010–2011 and round 6 in 2012–2013. As stated in the main text, models (2) and (4) include the interaction between the JPI and ESS rounds but do not include the respective main effects.

Table 6 Odds Ratios After Multi-Level Mixed Effects Logit of Undereducation: Key Effects

	Total, ISCO-Based Measure				Male, ISCO-Based Measure				Female, ISCO-Based Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
JPI	0.994		0.985		0.988		0.981		1.004		0.992	
× ESSR1		1.285***		1.297***		1.191***		1.199***		1.410***		1.429***
× ESSR2		1.041***		1.056***		1.027*		1.043**		1.063***		1.077***
× ESSR3		1.022		1.065***		1.003		1.049*		1.048		1.089***
× ESSR4		0.974		1.059***		1.011		1.118***		0.935**		1.001
× ESSR5		0.874***		0.985		0.865***		0.994		0.882***		0.976
× ESSR6		0.982		0.977		0.956**		0.945**		1.010		1.010
Unempl.			0.924	0.019***			0.353*	0.012***			2.174	0.028***
ESS Round (rel. to Round 1)												
ESSR2	0.889***		0.903***		0.919**		0.947		0.852***		0.853***	
ESSR3	0.836***		0.863***		0.881***		0.919**		0.786***		0.800***	
ESSR4	0.806***		0.837***		0.875***		0.929**		0.731***		0.740***	
ESSR5	0.696***		0.721***		0.726***		0.777***		0.659***		0.658***	
ESSR6	0.667***		0.513***		0.740***		0.582***		0.590***		0.442***	
Female	0.815***	0.815***	0.842**	0.841**								
Constant	0.540***	0.426***	0.889	0.752**	0.514***	0.429***	0.910	0.812	0.467***	0.343***	0.797	0.625***
Random Effects												
Female	0.348	0.347	0.372	0.367								
	(0.047)	(0.047)	(0.050)	(0.049)								
Const.	0.535	0.527	0.532	0.529	0.543	0.539	0.542	0.546	0.475	0.469	0.478	0.464
	(0.070)	(0.069)	(0.070)	(0.069)	(0.071)	(0.071)	(0.071)	(0.072)	(0.063)	(0.062)	(0.064)	(0.062)
N	121731	121731	121731	121731	62980	62980	62980	62980	58751	58751	58751	58751
LR test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	141545	141753	136313	136903	74725	74799	71771	71997	66821	66962	64393	64766
BIC	141642	141850	136759	137350	74797	74872	72169	72395	66893	67034	64789	65161
	Total, Mean-Based Measure				Male, Mean-Based Measure				Female, Mean-Based Measure			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
JPI	1.012		1.014		1.008		1.026		1.016		1.003	
× ESSR1		1.068**		0.942*		0.995		0.880**		1.154***		1.016
× ESSR2		1.009		0.974		0.985		0.958*		1.042**		0.991
× ESSR3		1.007		1.035		0.983		1.043		1.033		1.033
× ESSR4		0.977		1.039		0.983		1.051		0.969		1.032
× ESSR5		1.011		1.086***		1.027		1.105**		0.988		1.071
× ESSR6		1.017		1.025		1.033		1.073*		0.997		0.982
Unempl.			2.959	2.605			1.080	1.444			5.801*	3.387
ESS Round (rel. to Round 1)												
ESSR2	0.932**		0.989		0.958		1.037		0.910**		0.943	
ESSR3	0.940*		1.068*		0.982		1.145***		0.896**		0.989	
ESSR4	0.930**		1.087**		0.993		1.180***		0.862***		0.994	
ESSR5	0.929**		1.106***		0.998		1.212***		0.854***		1.003	
ESSR6	0.928**		1.084**		1.031		1.267***		0.826***		0.919	
Female	0.995	0.994	1.192***	1.192***								
Constant	0.156***	0.147***	0.032***	0.035***	0.148***	0.149***	0.036***	0.042***	0.165***	0.145***	0.034***	0.034***
Random Effects												
Female	0.121	0.121	0.169	0.168								
	(0.025)	(0.025)	(0.031)	(0.031)								
Const.	0.154	0.153	0.382	0.377	0.172	0.174	0.397	0.394	0.130	0.129	0.372	0.365
	(0.024)	(0.024)	(0.051)	(0.051)	(0.027)	(0.028)	(0.054)	(0.053)	(0.022)	(0.022)	(0.051)	(0.050)
N	114869	114869	114869	114869	59079	59079	59079	59079	55790	55790	55790	55790
LR test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	88695	88697	73005	73004	45669	45669	37279	37286	43019	43026	35721	35721
BIC	88791	88793	73469	73468	45741	45741	37693	37699	43091	43097	36131	36132

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$ Subset of results shown. Likelihood ratio (LR) test compares the given models with the corresponding models fit by standard logistic regression; its p-value is reported. ESSR is ESS round. ESS round 1 was fielded in 2002–2003, round 2 in 2004–2005, round 3 in 2006–2007, round 4 in 2008–2009, round 5 in 2010–2011 and round 6 in 2012–2013. As stated in the main text, models (2) and (4) include the interaction between the JPI and ESS rounds but do not include the respective main effects.

Note that this contradicts the overall effect direction for males and females, which was positive and significant for the former but not significant for the latter. The overall effect for males, thus, seems to be purely driven by the crisis, while the absence of the overall effect for females by the pre-crisis and after-crisis (round 5) effects cancelling out. The overall effects on mean-based overeducation for males and females, in contrast, are in line with what is observed over time: the interactions are mostly significant for men, while only the round-one effect is significant for women.

ISCO-based undereducation analysed by sex shows that most interactions are significant for both males and females, so the insignificance of their overall effects stems purely from the dynamics over time wiping out the average effect. The situation with mean-based undereducation somewhat resembles that with ISCO-based overeducation, with two differences: interactions in case of men (but not women) are mostly significant but neither for the male nor for the female sub-sample does it lead to a significant overall effect.

Two sensitivity checks are required at this point. Firstly, we ran sex-specific models with *general* JPI, studying how the general level of polarization affects the situation with each sex. Would the situation change if in sex-specific models, we instead use *sex-specific* JPI? As Tables 9 and 10 in the Appendix show, making this change indeed changes the results somewhat. Firstly, sex-specific JPI no longer affects the risk of ISCO-based overeducation for men. Secondly, it now decreases the chances of ISCO-based undereducation for females and increases the chances of mean-based undereducation for males. Overall, however, the directions and sizes of effects in general JPI and sex-specific JPI models are similar. Moreover, the values of their information criteria are very close, so we cannot conclude that using a sex-specific JPI improves the explanatory power of models.[19] It this case, we would argue, the effects of sex-specific JPI should be treated as a scientific fact of general interest, while economic policy should be based on the models using general JPI. Otherwise, we would effectively consider the male labour market and the female labour market as two non-intersecting markets guided by their own mechanisms, which, we believe, does not reflect the true situation, at least regarding mismatch and job polarization. Further research would add clarity to this issue.

Secondly, the same check for sensitivity to JPI lag length is required, as we did in Sect. 4.1. Figure 8 shows its results on the subset of 13 countries where the JPI with up to 10 lags can be defined. These results are in line with our above observations. While the effect from the JPI on ISCO-based mismatch is not significant for most lag lengths, it quickly moves away from 1.0 with lag lengths increasing and are close to being significant when the JPI is defined with 10 lags (i.e., the current situation in the labour market is compared to the average long-term situation there). As we stated above, these nearly-significant effects are negative for overeducation and positive for undereducation. The effect on mean-based overeducation is positive and significant for any lag length from 3 to 10, while that on mean-based undereducation is not significant.

5 Conclusions and Discussion

In this paper, we have argued that the relationship between polarization and skills mismatch is an empirical matter, which is dependent on the prevailing levels of skills mismatch, supply responses to changes in the demand for educated workers and the pace of imbalanced job polarization – the extent to which the share of high-skill jobs and low-skill jobs grow relatively to each other at the expense of medium-skill jobs. We analysed the relationship between imbalanced polarization and skills mismatch at both the macroeconomic and the microeconomic level. We introduced a job polarization index, and used a skills mismatch index at the macroeconomic level alongside traditional measures of overeducation and undereducation at the microeconomic level.

Descriptive evidence showed that polarization has been slowing down recently (as shown by a near-zero or negative JPI in half of European countries, although the heterogeneity in JPI values is high), while skills mismatch at the macroeconomic level rebounded after a decline during the crisis. Skills mismatch at the microeconomic level reflects a stable tendency in many European countries for overeducation to rise and undereducation to fall.

The main result of the regression analysis at the macroeconomic level is that imbalanced job polarization negatively affects the mismatch between skills demand and skills supply proxied by level of educational attainment, but there is no statistically significant reverse effect. In other words, job polarization seems to be the principal force in the labour market, which influences the extent of skills mismatch alongside supply trends such as the increase in workers with higher levels of education. The negative relationship reflects that skills mismatch is to an important extent driven by what happens to low-skill occupations. The trend towards a growing share of high-skill occupations by itself raises the SMI, but the SMI is more strongly related to changes in the share of low-skill occupations as captured in the JPI. Our interpretation of these results is that labour markets have greater difficulty in accommodating changes in the share of low-skill occupations. This may be due to the upward trend in the supply of educated workers, the responsiveness of education systems at different levels of education, as well as microeconomic ex-

[19] This holds not only for models (3) and (4), but also for models (1) and (2), whose results are not reported in case of sex-specific JPI.

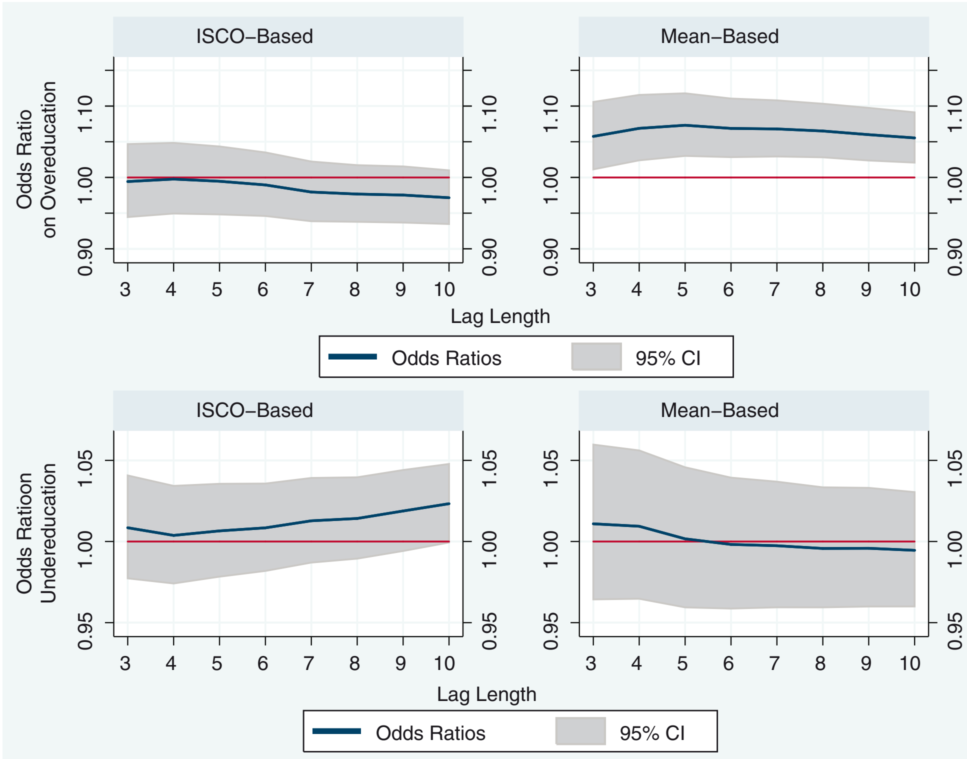

Fig. 8 Sensitivity of the Effects from JPI on Individual-Level Mismatch on the Lag Length in JPI Definition. Each point on the lines represents the value of the odds ratio of JPI on overeducation or undereducation, measured by the ISCO- or mean-based measure. Model (3) was estimated with Laplace approximation. Same 13 countries as in Fig. 7 were used for the same reason and with the same implications as stated in the notes to Fig. 7.

planations based on the options of workers at different levels of education.

At the microeconomic level, results from multi-level logistic models show that imbalanced job polarization has no overall effect on ISCO-based mismatch or mean-based undereducation, but increases mean-based overeducation. A closer analysis identified that the lack of statistical significance in the models of ISCO-based mismatch came from a reversal of the relationship during the global financial crisis of 2008–2009 and the following two years. In non-crisis years, the JPI decreases ISCO-based overeducation and increases ISCO-based undereducation. The same effect directions were shown by further sensitivity analysis.

The results are consistent for both macro-level and individual-level mismatch in that higher or more imbalanced job polarization (i.e., stronger upgrading) tends to dampen mismatch. Note that when we claim that polarization dampens mismatch at the individual level, we focus on ISCO-based overeducation.

One could then ask two questions. Firstly, why not take into account the effect on *under*education? While in principle undereducation is a type of mismatch similar to overeducation, undereducation may be less problematic to the extent that it can be remedied by additional education and training, does not lead to depressive symptoms as opposed to overeducation (Bracke et al. 2013) and to lower job satisfaction as opposed to overeducation (Peiró et al. 2010).[20] When the JPI decreases the risk of ISCO-based overeducation (in non-crisis years), even if it also increases the exposure to ISCO-based undereducation, the exposure to mismatch with negative consequences to the individual becomes lower.

Secondly, the effect on ISCO-based overeducation is the opposite of the effect on mean-based overeducation, so why are we focusing on the former? ISCO-based mismatch is conceptually closer to the SMI (and the JPI) in that it also considers three education levels. In contrast, the statistical (in this case, the mean-based) measure operates on the basis of

[20]The effects on earnings have more nuances and controversies. For instance, the standard result is that the wages of the over-(under-)educated are lower (higher) than for the well-matched at the same education level, but higher (lower) than for the well-matched in the same job (Korpi and Tåhlin 2009; Rubb 2003; Verhaest and Omey 2012), although lack of the difference in the effect magnitude and significance was also reported (Tsai 2010). There is some evidence that the overeducated have higher wage growth than the undereducated (Rubb 2006), but this finding is again not universal (Groeneveld and Hartog 2004; Korpi and Tåhlin 2009).

years, and not levels, of education. Different directions of the JPI effects can be explained as follows. In case of the ISCO-based measure, higher levels and/or greater skewness of polarization allow the secondary-educated to move to higher-level positions (for which they might be undereducated), as demand increases, instead of moving to elementary occupations (which require primary education only). In case of the mean-based measure, higher levels and/or greater skewness of polarization foster investment in further education (which takes time, but not necessarily leads to a change in education level), which increases the proportion of the employees with too many years of education in a given occupation group. At the same time, there is no effect on mean-based undereducation, showing that upward mobility is more restricted for workers with lower values of years of education than the average in their occupation group. There is, thus, no contradiction in these results – they merely allow for a consideration of the labour market from different angles.

There are several limitations of this work. One of them is the definition of the JPI, which consists of a pure polarization and an imbalance component, so that a change in the JPI cannot be readily attributed to one of these. Although we argued that this is not problematic, there might be some relationship between both components that is hidden in the current set-up. Secondly, there are drawbacks in each of the individual-level mismatch measures. By construction of the ISCO-based measure, for instance, overeducation is undefined for high-skill positions. The mean-based measure, in turn, endogenises the changing skill composition of the population, which makes the interpretation of trends less transparent. Thirdly, jobs are classified into only three categories – low-, medium- and high-skill – while a more elaborate classification might yield additional insights.

Acknowledgments We would like to thank Patrick Belser, Catherine Saget, Carlos Andre da Silva Gama Nogueira and two referees for excellent comments.

Appendix

The remaining results of the multi-level models are shown in Tables 7 and 8. These will be discussed along the three groups of variables: personal characteristics, family characteristics and labour-market factors.

There is weak dependence of overeducation on age, while undereducation has a U-shaped relationship with it. A more careful analysis (not reported) shows that individuals aged 25–34 are hurt most by mismatch, having both higher overeducation risk and lower undereducation chances on both measures. Disability and the student status increase both types of mismatch on the ISCO-based measure, while on the mean-based measure they increase only the exposure to overeducation but not undereducation. Of migrants, the highest (lowest) risk of overeducation (undereducation) is faced by those from former Soviet Union countries followed by Latin American, Asian and African and Central and Eastern European immigrants. Being an ethnic minority or a second-generation immigrant has less pronounced effects on mismatch – but note how minorities are *more* exposed to undereducation than the fully natives. Achievement orientation is a beneficial personality trait, because it decreases the risk of ISCO-based overeducation and increases the chances of ISCO-based undereducation. Openness to experience decreases ISCO-based overeducation risk but increases mean-based overeducation risk, while social orientation is not significant in any model but is close to the border of significance for ISCO-based overeducation. Finally, a tertiary degree increases the risk of becoming overeducated at the expense of the chances of becoming undereducated, according to the mean-based measure.

Having one child decreases overeducation on the ISCO-based measure, and this is the only strong effect from the number of children. Having a partner with any employment status has a positive effect on the labour market status of the respondent on the ISCO-based measure (lower overeducation, higher undereducation); the effects on the mean-based measure of mismatch are more limited, especially for undereducation. Higher education of parents or partner generally tends to increase overeducation and decrease undereducation (again, limited effects are observed for mean-based undereducation). The likely mechanisms behind that are intergenerational mobility of education level and homophily (McPherson et al. 2001) (in case of partner). As the effects from partner's higher education are stronger, the effects from homophily tend to be stronger. A similar effect is from a parent supervising others in their job, except that it does not affect the risk of ISCO-based overeducation.

Larger labour markets do not necessarily lead to better match – they do decrease ISCO-based undereducation, but do not affect ISCO-based overeducation risk and increase mean-based mismatch. ISCO-based mismatch generally decreases with firm size, but the effect on mean-based mismatch is U-shaped in case of overeducation and inverse U-shaped in case of undereducation. Respondents supervising other employees benefit from lower exposure to overeducation and higher chances of undereducation. Unemployment experience (in a lifetime) has different effects depending on its length. Three-month unemployment experience raises the risk of overeducation and decreases the exposure to undereducation. Twelve-month (long-term) unemployment experience also increases the risk of overeducation, but less strongly than three-month unemployment, and *increases* the exposure to ISCO-based undereducation but does not affect mean-based undereducation. Working without a written contract generally increases overeducation risk, but has limited effects on undereducation.

Table 7 Odds Ratios After Multi-Level Mixed Effects Logit of Overeducation: Non-Key Effects

	ISCO-Based Measure			Mean-Based Measure		
	Total	Men	Women	Total	Men	Women
Personal Characteristics						
Age	1.003	1.006	1.005	0.990*	0.993	0.991
Age^2/100	0.987*	0.987	0.980**	1.001	1.001	0.998
Student	1.192***	1.153*	1.210***	1.900***	1.773***	2.009***
Disabled	1.072**	1.073*	1.070*	1.087***	1.085**	1.091**
Immigrant Background (rel. to Native)						
Minority	0.977	0.979	0.975	1.027	1.066	0.989
Parent-immigrant	0.998	0.944	1.048	1.045	1.016	1.075
Both parents immigrants	1.038	0.954	1.128	1.169**	1.062	1.290***
Immigrant from Central and Eastern Europe	2.071***	1.643***	2.531***	1.809***	1.657***	1.949***
Immigrant from former Soviet Union	2.178***	1.775***	2.520***	1.677***	1.535***	1.784***
Immigrant from Latin America/Africa/Asia	2.122***	1.936***	2.337***	2.096***	1.974***	2.298***
Immigrant from other European countries	1.209***	1.048	1.372***	1.341***	1.249***	1.447***
Immigrant from other countries	1.455**	1.465	1.453*	1.175	1.237	1.106
Personality Traits						
Social orientation	1.098	1.153	1.055	1.044	1.033	1.055
Achievement orientation	0.855***	0.808**	0.907	0.971	1.007	0.943
Openness to experience	0.885**	0.945	0.830**	1.135**	1.099	1.165**
Education (rel. to Secondary education)						
Primary				0.132***	0.137***	0.121***
Tertiary				4.457***	4.432***	4.534***
Family Characteristics						
Number of Children (rel. to No children)						
1	0.917***	0.915*	0.912**	1.026	1.043	1.011
2	0.965	0.937	0.989	1.009	1.035	0.981
3+	1.022	1.043	1.016	1.019	0.996	1.048
Partner Employment Status (rel. to No partner)						
Unemployed	0.814***	0.753***	0.909*	0.936**	0.909**	0.917
Employed	0.887***	0.850***	0.889***	0.923***	0.868***	0.971
Supervising others	0.869***	0.849***	0.877***	0.956	0.890**	1.001
Parental and Partner Effects						
Higher education, mother	0.944	0.984	0.917	1.046	1.042	1.038
Higher education, father	1.095***	1.136**	1.050	1.080***	1.039	1.130***
Higher education, partner	1.139***	1.192***	1.097**	1.106***	1.096***	1.122***
Parent supervises others	1.028	1.000	1.053	1.107***	1.101***	1.114***
Labour-Market Factors						
Domicile (rel. to Rural)						
Big city	0.971	0.947	1.003	1.107***	1.037	1.209***
Small city	0.967	0.941*	1.000	0.978	0.965	1.011
Firm Size (rel. to $<$ 10 employees)						
10–24	0.989	1.019	0.973	0.800***	0.826***	0.772***
25–99	0.957	1.077*	0.872***	0.773***	0.824***	0.721***
100–499	0.916***	0.940	0.906**	0.789***	0.819***	0.756***
500+	0.814***	0.838***	0.801***	0.865***	0.859***	0.877***
Works as supervisor	0.665***	0.703***	0.613***	0.961**	0.910***	1.026
Was unemployed for 3 months	1.297***	1.185***	1.412***	1.206***	1.121***	1.314***
Was unemployed for 1 year	1.160***	1.172***	1.131***	1.157***	1.137**	1.171***
No written contract	1.166***	1.089	1.241***	1.098**	1.098	1.083

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ Subset of results from model (3) shown.

Table 8 Odds Ratios After Multi-Level Mixed Effects Logit of Undereducation: Non-Key Effects

	ISCO-Based Measure			Mean-Based Measure		
	Total	Men	Women	Total	Men	Women
Personal Characteristics						
Age	0.976***	0.976***	0.971***	1.009*	1.000	1.017**
Age^2/100	1.044***	1.040***	1.054***	1.026***	1.035***	1.019**
Student	1.300***	1.270***	1.345***	0.877**	0.741***	1.022
Disabled	1.075***	1.099***	1.048*	1.021	1.051	0.995
Immigrant Background (rel. to Native)						
Minority	1.155***	1.184***	1.123**	1.123***	1.076	1.171**
Parent-immigrant	1.067**	1.116**	1.020	0.987	1.011	0.968
Both parents immigrants	1.085*	1.160**	1.008	0.991	0.903	1.100
Immigrant from Central and Eastern Europe	0.873***	1.050	0.697***	0.883	0.945	0.818*
Immigrant from former Soviet Union	0.671***	0.800*	0.579***	0.835*	0.954	0.775**
Immigrant from Latin America/Africa/Asia	0.814***	0.932	0.685***	0.918	0.975	0.829
Immigrant from other European countries	0.885***	1.041	0.719***	1.146**	1.214**	1.045
Immigrant from other countries	0.615***	0.547**	0.689*	0.991	0.826	1.139
Personality Traits						
Social orientation	0.997	0.980	1.013	0.934	0.892	0.966
Achievement orientation	1.107**	1.142**	1.057	1.097	1.046	1.137
Openness to experience	0.982	0.983	0.981	1.076	1.210**	0.966
Education (rel. to Secondary education)						
Primary				6.126***	6.587***	5.634***
Tertiary				0.232***	0.182***	0.280***
Family Characteristics						
Number of Children (rel. to No children)						
1	1.007	0.988	1.041	0.997	1.007	1.009
2	0.950**	0.953	0.957	0.957	0.964	0.967
3+	0.947	0.951	0.950	0.939	0.953	0.939
Partner Employment Status (rel. to No partner)						
Unemployed	1.316***	1.324***	1.386***	1.102***	1.065	1.163***
Employed	1.170***	1.247***	1.137***	1.005	0.995	1.019
Supervising others	1.283***	1.362***	1.246***	1.012	0.951	1.050
Parental and Partner Effects						
Higher education, mother	0.673***	0.742***	0.601***	0.906*	0.994	0.822**
Higher education, father	0.610***	0.594***	0.631***	0.992	1.019	0.981
Higher education, partner	0.439***	0.416***	0.458***	0.995	1.025	0.962
Parent supervises others	0.915***	0.925***	0.902***	0.892***	0.893***	0.888***
Labour-Market Factors						
Domicile (rel. to Rural)						
Big city	0.837***	0.810***	0.862***	1.057**	1.107***	1.010
Small city	0.917***	0.892***	0.943**	1.066***	1.063*	1.067*
Firm Size (rel. to < 10 employees)						
10–24	0.851***	0.844***	0.858***	1.105***	1.061	1.149***
25–99	0.746***	0.721***	0.774***	1.084***	1.086**	1.084**
100–499	0.782***	0.684***	0.912***	1.023	1.011	1.047
500+	0.714***	0.634***	0.833***	1.053	1.028	1.099*
Works as supervisor	1.182***	1.199***	1.165***	1.399***	1.496***	1.294***
Was unemployed for 3 months	0.882***	0.900***	0.861***	0.914***	0.952	0.871***
Was unemployed for 1 year	1.092***	1.128***	1.068*	1.004	1.053	0.979
No written contract	1.012	1.112**	0.913**	0.998	1.056	0.947

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ Subset of results of model (3) shown.

Table 9 Odds Ratios After Multi-Level Mixed Effects Logit of Overeducation: Key Effects, Sex-Specific JPI

	ISCO-Based Measure				Mean-Based Measure			
	Male		Female		Male		Female	
	(3)	(4)	(3)	(4)	(3)	(4)	(3)	(4)
JPI	0.994		1.025		1.030*		1.015	
× Round 1		0.863***		0.885***		1.178***		1.058
× Round 2		1.012		0.974		1.054***		1.032
× Round 3		0.893**		0.957		1.035		0.947
× Round 4		1.131***		1.038		0.926*		0.977
× Round 5		0.977		1.119***		0.893***		0.978
× Round 6		0.957		1.057**		1.043		1.024
Unemployment rate	77.176***	464.951***	1.630	6.155**	2.459	1.607	0.293	0.604
ESS Round (rel. to Round 1)								
Round 2	1.126**		1.108*		0.887***		0.995	
Round 3	1.035		1.146**		0.827***		0.881**	
Round 4	1.170***		1.211***		0.777***		0.884**	
Round 5	1.191***		1.331***		0.748***		0.925	
Round 6	1.330***		1.503***		0.832***		0.998	
Constant	0.073***	0.078***	0.107***	0.129***	0.177***	0.151***	0.111***	0.103***
Random Effects								
Constant	0.496	0.505	0.509	0.500	0.264	0.260	0.224	0.223
	(0.068)	(0.069)	(0.070)	(0.069)	(0.037)	(0.036)	(0.033)	(0.033)
N	62980	62980	58751	58751	59079	59079	55790	55790
LR test, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	35828	35830	38223	38255	43462	43479	38074	38080
BIC	36226	36228	38618	38650	43876	43893	38484	38490

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ Subset of results shown.

Table 10 Odds Ratios After Multi-Level Mixed Effects Logit of Undereducation: Key Effects, Sex-Specific JPI

	ISCO-Based Measure				Mean-Based Measure			
	Male		Female		Male		Female	
	(3)	(4)	(3)	(4)	(3)	(4)	(3)	(4)
JPI	1.009		0.973**		1.034*		0.995	
× Round 1		1.235***		1.213***		0.873***		1.034
× Round 2		1.034**		1.057***		0.970		0.975
× Round 3		1.056*		1.048**		1.073		1.014
× Round 4		1.136***		0.998		1.112**		1.017
× Round 5		1.010		0.964		1.107**		1.070
× Round 6		0.994		0.961**		1.070*		0.990
Unemployment rate	0.327*	0.008***	2.475	0.033***	1.103	1.875	6.202*	3.084
ESS Round (rel. to Round 1)								
Round 2	0.929**		0.868***		1.036		0.948	
Round 3	0.918***		0.808***		1.153***		0.991	
Round 4	0.930**		0.747***		1.190***		0.995	
Round 5	0.771***		0.664***		1.214***		1.006	
Round 6	0.587***		0.440***		1.272***		0.917	
Constant	0.894	0.828	0.803	0.635***	0.035***	0.041***	0.035***	0.034***
Random Effects								
Constant	0.538	0.549	0.481	0.468	0.397	0.395	0.372	0.366
	(0.071)	(0.072)	(0.064)	(0.062)	(0.054)	(0.053)	(0.051)	(0.050)
N	62980	62980	58751	58751	59079	59079	55790	55790
LR test, p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	71772	71993	64388	64818	37278	37281	35721	35720
BIC	72171	72391	64783	65214	37691	37695	36131	36131

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ Subset of results shown.

Table 11 Summary Statistics for Macro-Level Models

	Mean	Std.Dev.	Min	Max
$\overline{\Delta_5 h}$	0.015	0.019	−0.048	0.099
$\overline{\Delta_5 l}$	−0.001	0.008	−0.031	0.028
Change in medium-level jobs	1.370	1.874	−4.220	9.380
Imbalance in high/low-level jobs	1.021	0.018	1.000	1.130
JPI	0.707	0.982	−2.224	5.068
SMI	15.630	5.060	1.200	30.100
EPL	2.593	0.442	1.677	4.095
GDP growth	1.797	3.327	−14.100	10.500
log(GDP per capita)	3.360	0.347	2.496	4.304
Population growth	0.526	0.554	−0.700	2.300

Table 12 Summary Statistics for Multi-Level Models, Categorical Variables (%)

	ISCO-Based Models			Mean-Based Models		
	Total	Male	Female	Total	Male	Female
Number of kids:						
0	67.89	68.56	67.19	67.77	68.42	67.07
1	16.45	15.45	17.52	16.56	15.56	17.62
2	12.30	12.35	12.25	12.34	12.42	12.26
3+	3.35	3.64	3.05	3.34	3.61	3.05
Partner employment status:						
No partner	32.16	30.69	33.74	32.05	30.60	33.59
Partner, not working	15.40	20.96	9.43	15.37	20.98	9.42
Partner, employed	39.26	39.02	39.52	39.36	39.12	39.60
Partner, supervisor	13.18	9.33	17.31	13.23	9.29	17.39
Type of domicile:						
Big city	33.36	32.38	34.40	33.47	32.50	34.49
Town/small city	30.37	29.86	30.92	30.37	29.90	30.87
Rural	36.27	37.76	34.68	36.16	37.60	34.65
Firm size:						
< 10	33.97	34.32	33.59	34.01	34.41	33.60
10–24	18.23	17.61	18.89	18.23	17.60	18.90
25–99	22.50	21.33	23.75	22.59	21.42	23.84
100–499	14.78	15.31	14.21	14.72	15.25	14.15
500+	10.53	11.44	9.56	10.44	11.33	9.50
Immigrant background:						
Fully native	80.15	80.17	80.14	80.44	80.46	80.41
Minority, no immigrant background	4.89	5.00	4.76	4.80	4.88	4.70
Local born, 1 parent-immigrant	4.89	4.77	5.02	4.86	4.74	4.98
Local born, 2 parents-immigrants	2.03	2.06	2.00	2.02	2.04	2.00
Immigrant from Central and Eastern Europe	1.75	1.73	1.76	1.75	1.76	1.73
Immigrant form former Soviet Union	1.07	0.87	1.27	1.07	0.87	1.28
Immigrant from Latin America/Africa/Asia	2.08	2.19	1.97	2.01	2.11	1.91
Immigrant from other European countries	2.87	2.98	2.76	2.80	2.90	2.69
Immigrant from other countries	0.27	0.23	0.31	0.26	0.23	0.30

Table 13 Summary Statistics for Multi-Level Models, Binary and Continuous Variables

	ISCO-Based Models			Mean-Based Models		
	Total	Male	Female	Total	Male	Female
Overeducation	0.098	0.087	0.109	0.145	0.153	0.137
	(0.297)	(0.282)	(0.311)	(0.352)	(0.360)	(0.343)
Undereducation	0.298	0.316	0.278	0.130	0.131	0.130
	(0.457)	(0.465)	(0.448)	(0.337)	(0.337)	(0.336)
Age	41.946	42.012	41.877	41.882	41.935	41.825
	(12.018)	(12.275)	(11.736)	(12.010)	(12.266)	(11.733)
Female	0.483			0.486		
	(0.500)			(0.500)		
Works as supervisor	0.323	0.386	0.256	0.319	0.381	0.254
	(0.468)	(0.487)	(0.436)	(0.466)	(0.486)	(0.436)
Student	0.037	0.032	0.043	0.037	0.031	0.043
	(0.190)	(0.175)	(0.204)	(0.188)	(0.173)	(0.203)
Disabled	0.142	0.134	0.152	0.141	0.133	0.151
	(0.349)	(0.340)	(0.359)	(0.349)	(0.339)	(0.358)
Was unemployed for 3 months	0.278	0.272	0.284	0.278	0.273	0.283
	(0.448)	(0.445)	(0.451)	(0.448)	(0.446)	(0.451)
Was unemployed for 1 year	0.095	0.085	0.106	0.095	0.085	0.106
	(0.294)	(0.280)	(0.308)	(0.294)	(0.280)	(0.308)
No written contract	0.052	0.050	0.054	0.052	0.050	0.054
	(0.222)	(0.218)	(0.226)	(0.221)	(0.217)	(0.226)
Social orientation	0.187	0.181	0.193	0.186	0.181	0.193
	(0.225)	(0.226)	(0.224)	(0.225)	(0.226)	(0.224)
Achievement orientation	0.087	0.091	0.083	0.088	0.092	0.083
	∗(0.192)	(0.198)	(0.185)	(0.192)	(0.199)	(0.186)
Openness to experience	0.178	0.177	0.180	0.178	0.176	0.179
	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)
Higher education, mother	0.082	0.078	0.085	0.082	0.078	0.085
	(0.274)	(0.269)	(0.279)	(0.274)	(0.269)	(0.279)
Higher education, father	0.120	0.119	0.121	0.119	0.118	0.121
	(0.325)	(0.324)	(0.326)	(0.324)	(0.323)	(0.326)
Higher education, partner	0.170	0.173	0.167	0.170	0.173	0.167
	(0.376)	(0.378)	(0.373)	(0.375)	(0.378)	(0.373)
Parent supervises others	0.294	0.299	0.289	0.293	0.298	0.289
	(0.456)	(0.458)	(0.453)	(0.455)	(0.457)	(0.453)
Unemployment rate	0.044	0.047	0.040	0.044	0.047	0.040
	(0.256)	(0.031)	(0.024)	(0.026)	(0.031)	(0.024)
JPI	0.725	0.630	0.811	0.725	0.630	0.811
	(0.980)	(0.988)	(1.173)	(0.980)	(0.988)	(1.173)

Mean values reported, standard deviation in brackets. Unemployment rate calculated from ESS data over country–round pairs.

References

Acemoglu, D., Autor, D.: Skills, tasks and technologies: Implications for employment and earnings. In: Card, D., Ashenfelter, O.. (eds.) Handbook of labor economics, vol. 4, Part B, pp. 1043–1171. Elsevier, Amsterdam (2011). doi:10.1016/S0169-7218(11)02410-5

Şahin, A., Song, J., Topa, G., Violante, G.L.: Mismatch unemployment. Am. Econ. Review. **104**(11), 3529–3564 (2014). doi:101257aer.104.11.3529

Aleksynska, M., Tritah, A.: Occupation–education mismatch of immigrant workers in Europe: context and policies. Econ. Educ. Rev. **36**, 229–244 (2013). doi:10.1016/j.econedurev.2013.06.001

Autor, D.H., Dorn, D.: The growth of low-skill service jobs and the polarization of the US labor market. Amer. Econ. Rev. **103**(5), 1553–1597 (2013). doi:10.1257/aer.103.5.1553

Baert, S., Cockx, B., Verhaest, D.: Overeducation at the start of the career: stepping stone or trap? Lab. Econ. **25**, 123–140(2013). doi:10.1016/j.labeco.2013.04.013

Barone, C., Ortiz, L.: Overeducation among European university graduates: a comparative analysis of its incidence and the importance of higher education differentiation. High. Educ. **61**(3), 325–337 (2011). doi:10.1007/s10734-010-9380-0

Büchel, F., van Ham, M.: Overeducation, regional labor markets, and spatial flexibility. J. Urban Econ. **53**(3), 482–493 (2003). doi:10.1016/S0094-1190(03)00008-1

Beckhusen, J., Florax, R.J., Poot, J., Waldorf, B.S.: Attracting global talent and then what? Overeducated immigrants in the United States. J. Reg. Sci. **53**(5), 834–854 (2013). doi:10.1111/jors.12030

Betti, G., D'Agostino, A., Neri, L.: Educational mismatch of graduates: a multidimensional and fuzzy indicator. Soc. Indic. Res. **103**(3), 465–480 (2011). doi:10.1007/s11205-010-9712-6

Blázquez, M., Budría, S.: Overeducation dynamics and personality. Educ. Econ. **20**(3), 260–283 (2012). doi:10.1080/09645292.2012.679338

Bracke, P., Pattyn, E., von dem Knesebeck, O.: Overeducation and depressive symptoms: diminishing mental health returns to education. Sociol. Health Ill. **35**(8), 1242–1259 (2013). doi:10.1111/1467-9566.12039

Budría, S.: Are educational mismatches responsible for the 'inequality increasing effect' of education? Soc. Indic. Res. **102**(3), 409–437 (2011). doi:10.1007/s11205-010-9675-7

Cainarca, G.C., Sgobbi, F.: The return to education and skills in Italy. Int. J. Manpower **33**(2), 187–205 (2012). doi:10.1108/01437721211225444

Cedefop: Skill mismatch in Europe. Briefing Note No. 9023 EN, European Centre for the Development of Vocational Training, Luxembourg (2010)

Cedefop: Future skills supply and demand in Europe. Forecast 2012. Research Paper No. 26, European Centre for the Development of Vocational Training, Luxembourg (2012)

Chevalier, A.: Measuring over-education. Economica **70**(279), 509–531 (2003). doi:10.1111/1468-0335.t01-1-00296

Chevalier, A., Lindley, J.: Overeducation and the skills of UK graduates. J R Stat Soc: Series A (Statistics Society) **172**(2), 307–337 (2009). doi:10.1111/j.1467-985X.2008.00578.x

Croce, G., Ghignoni, E.: Demand and supply of skilled labour and overeducation in Europe: a country-level analysis. Compar. Econ. Stud. **54**(2), 413–439 (2012). doi:10.1057/ces.2012.12

Cutillo, A., di Pietro, G.: The effects of overeducation on wages in Italy: a bivariate selectivity approach. Int. J. Manpower **27**(2), 143–168 (2006). doi:10.1108/01437720610666182

Dauth, W.: Job polarization on local labor markets. Iab discussion paper no. 18/2014, Leibniz Information Centre for Economics (2014)

Di Pietro, G.: Technological change, labor markets, and 'low-skill, low-technology traps'. Technol. Forecast. Soc. Change **69**(9), 885–895 (2002). doi:10.1016/S0040-1625(01)00182-2

Esteban, J.M., Ray, D.: On the measurement of polarization. Econometrica. **62**(4), 819–851 (1994)

Eurofound: Employment polarisation and job quality in the crisis: European jobs monitor 2013. Report. Eurofound, Dublin (2013)

DG Employment, Social Affairs and Inclusion: Employment and social developments in Europe 2012. Tech. rep., European Commission (2012)

Fernández, C., Ortega, C.: Labor market assimilation of immigrants in Spain: employment at the expense of bad job-matches? Spanish Econ. Rev. **10**(2), 83–107 (2008). doi:10.1007/s10108-007-9032-4

Fernández-Macías, E.: Job polarization in Europe? Changes in the employment structure and job quality, 1995–2007. Work Occup. **39**(2), 157–182 (2012). doi:10.1177/0730888411427078

Foote, C.L., Ryan, R.W.: Labor-market polarization over the business cycle. Public Policy Discussion Paper No. 12-8, Federal Reserve Bank of Boston, Boston (2013)

Frei, C., Sousa-Poza, A.: Overqualification: permanent or transitory? Appl. Econ. **44**(14), 1837–1847 (2012). doi:10.1080/00036846.2011.554380

Frenette, M.: The overqualified Canadian graduate: the role of the academic program in the incidence, persistence, and economic returns to overqualification. Econ. Educ. Rev. **23**(1), 29–45 (2004). doi:10.1016/S0272-7757(03)00043-8

Ghignoni, E., Verashchagina, A.: Educational qualifications mismatch in Europe. Is it demand or supply driven? J. Compar. Econ. **42**(3), 670–692 (2014). doi:10.1016/j.jce.2013.06.006

Goos, M., Manning, A.: Lousy and lovely jobs: the rising polarization of work in Britain. Rev. Econ. Stat. **89**(1), 118–133 (2007). doi:10.1162/rest.89.1.118

Goos, M., Manning, A., Salomons, A.: Job polarization in Europe. Am. Econ. Rev.: Papers & Proceedings **99**(2), 58–63 (2009). doi:10.1257/aer.99.2.58

Goos, M., Manning, A., Salomons, A.: Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. **104**(8), 2509–2526 (2014). doi:doi:10.1257/aer.104.8.2509

Goos, M., Salomons, A., Vandeweyer, M.: Job polarization during the Great Recession and beyond. Euroforum policy paper 2, KU Leuven (2013)

Groeneveld, S., Hartog, J.: Overeducation, wages and promotions within the firm. Lab. Econ. **11**(6), 701–714 (2004). doi:10.1016/j.labeco.2003.11.005

Guironnet, J.P., Peypoch, N.: Human capital allocation and overeducation: A measure of French productivity (1987, 1999). Econ. Model. **24**(3), 398–410 (2007). doi:10.1016/j.econmod.2006.09.003

Hartog, J.: Over-education and earnings: where are we, where should we go? Econ. Educ. Rev. **19**(2), 131–147 (2000). doi:10.1016/S0272-7757(99)00050-3

ILO: Global employment trends for youth 2012. Report, International Labour Office, Geneva (2012)

ILO: Global employment trends 2013: Recovering from a second jobs dip. Report, International Labour Office, Geneva (2013a)

ILO: Global employment trends for youth 2013: A generation at risk. Report, International Labour Office, Geneva (2013b)

ILO: Key indicators of the labour market, 8th edition: (2013c)

ILO: Skills mismatch in Europe. Report, International Labour Office, Geneva (2014)

Jaimovich, N., Siu, H.E.: The trend is the cycle: job polarization and jobless recoveries. Working Paper No. 18334, National Bureau of Economic Research (2012)

Jauhiainen, S.: Overeducation in the Finnish regional labour markets. Pap. Reg. Sci. **90**(3), 573–588 (2011). doi:10.1111/j.1435-5957.2010.00334.x

Jensen, U., Gartner, H., Rässler, S.: Estimating German overqualification with stochastic earnings frontiers. AStA Adv. Stat. Anal. **94**(1), 33–51 (2010). doi:10.1007/s10182-009-0121-6

Johansen, J., Gatelli, D.: Measuring mismatch in ETF partner countries: a methodological note. Report, European Training Foundation, Turin (2012)

Karakaya, G., Plasman, R., Rycx, F.: Overeducation on the Belgian labour market: evaluation and analysis of the explanatory factors through two types of approaches. Comp. J. Comp. Int. Educ. **37**(4), 513–532 (2007). doi:10.1080/03057920701366317

Kiersztyn, A.: Stuck in a mismatch? The persistence of overeducation during twenty years of the post-communist transition in Poland. Econ. Educ. Rev. **32**, 78–91 (2013). doi:10.1016/j.econedurev.2012.09.009

Korpi, T., Tåhlin, M.: Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974—2000. Lab. Econ. **16**(2), 183–193 (2009). doi:10.1016/j.labeco.2008.08.004

Lianos, T.P., Asteriou, D., Agiomirgianakis, G.: Foreign university graduates in the Greek labour market: employment, salaries and overeducation. Int. J. Financ. Econ. **9**(2), 151–164 (2004). doi:10.1002/ijfe.238

Mazzolari, F., Ragusa, G.: Spillovers from high-skill consumption to low-skill labor markets. Rev. Econ. Stat. **95**(1), 74–86 (2013). doi:10.1162/REST_a_00234

McGuinness, S., Bennett, J.: Overeducation in the graduate labour market: a quantile regression approach. Econ. Educ. Rev. **26**(5), 521–531 (2007). doi:10.1016/j.econedurev.2005.12.003

McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: homophily in social networks. Ann. Rev. Sociol. **27**, 415–444 (2001). doi:10.1146/annurev.soc.27.1.415

Norwegian Social Science Data Services: European social survey round 1 data. Data file edition 6.3. (2002)

Norwegian Social Science Data Services: European social survey round 2 data. Data file edition 3.3. (2004)

Norwegian Social Science Data Services: European social survey round 3 data. Data file edition 3.4. (2006)

Norwegian Social Science Data Services: European social survey round 4 data. Data file edition 4.2. (2008)

Norwegian Social Science Data Services: European social survey round 5 data. Data file edition 3.1. (2010)

Norwegian Social Science Data Services: European social survey round 6 data. Data file edition 2.0. (2012)

OECD: How has the global economic crisis affected people with different levels of education? Education indicators in focus 2012/01, OECD (2012)

Ortiz, L., Kucel, A.: Do fields of study matter for over-education?: the cases of Spain and Germany. Int. J. Comp. Sociol. **49**(4–5), 305–327 (2008). doi:10.1177/0020715208093079

Peiró, J.M., Agut, S., Grau, R.: The relationship between overeducation and job satisfaction among young Spanish workers: the role of salary, contract of employment, and work experience. J. Appl. Soc. Psychol. **40**(3), 666–689 (2010). doi:10.1111/j.1559-1816.2010.00592.x

Piracha, M., Tani, M., Vadean, F.: Immigrant over- and under-education: the role of home country labour market experience. IZA J. Migr. **1**, 3 (2012). doi:10.1186/2193-9039-1-3

Quintini, G.: Over-qualified or under-skilled: A review of existing literature. OECD Employment and Migration Working Paper No. 121, OECD Publishing (2011). doi:10.1787/5kg58j9d7b6d-en

Ramos, R., Sanromá, E.: Overeducation and local labour markets in Spain. Tijdschr. Econ. Soc. Ge. **104**(3), 278–291 (2013). doi:10.1111/j.1467-9663.2012.00752.x

Robst, J.: Overeducation and college major: expanding the definition of mismatch between schooling and jobs. Manch. Sch. **76**(4), 349–368 (2008). doi:10.1111/j.1467-9957.2008.01064.x

Rohrbach-Schmidt, D., Tiemann, M.: Mismatching and job tasks in Germany – rising over-qualification through polarization? Empir. Res. Vocat. Educ. Train. **3**(1), 39–53 (2011)

Roodman, D.: Estimating fully observed recursive mixed-process models with cmp. Stata J. **11**(2), 159–206 (2011)

Rubb, S.: Overeducation in the labor market: a comment and re-analysis of a meta-analysis. Econ. Educ. Rev. **22**(6), 621–629 (2003). doi:10.1016/S0272-7757(02)00077-8

Rubb, S.: Educational mismatches and earnings: Extensions of occupational mobility theory and evidence of human capital depreciation. Educ. Econ. **14**(2), 135–154 (2006). doi:10.1080/09645290600622905

Sparreboom, T., Nübler, J.: Productive transformation, employment and education in Tanzania. Paper presented at the 2013 UNU-WIDER Development Conference on Learning to Compete: Industrial Development and Policy in Africa, 24–25 June, Helsinki (2013)

Sparreboom, T., Powell, M.: Labour market information and analysis for skills development. ILO Employment Working Paper No. 27, International Labour Office, Geneva (2009)

Støren, L.A., Wiers-Jenssen, J.: Foreign diploma versus immigrant background: determinants of labour market success or failure? J. Stud. Int. Educ. **14**(1), 29–49 (2010). doi:10.1177/1028315308327951

Sutherland, J.: Qualifications mismatch and skills mismatch. Educ. Train. **54**(7), 619–632 (2012). doi:10.1108/00400911211265666

Tani, M.:Does immigration policy affect the education-occupation mismatch? Evidence from Australia. Australian Bull. Lab. **38**(2), 111–140 (2012)

Tarvid, A.: Field of higher education and unemployment risk in European countries. In: New Socio-Economic Challenges of Development in Europe – 2010, pp. 87–96. University of Latvia, Riga (2011)

Tarvid, A.: Effects of the field of higher education on the prevalence of over-education in European countries. In: Kesner, J. (ed.) Education: Evaluation, Reform and Policy, pp. 167–184. Athens Institute for Education and Research, Athens (2012)

Tarvid, A.: Unobserved heterogeneity in overeducation models: Is personality more important than ability? Proced. Econ. Financ. **5**, 722–731 (2013). doi:10.1016/S2212-5671(13)00084-1

Tsai, Y.: Returns to overeducation: A longitudinal analysis of the U.S. labor market. Econ. Educ. Rev. **29**(4), 606–617 (2010). doi:10.1016/j.econedurev.2010.01.001

Tsui, K.Y., Wang, Y.: Polarisation ordering and new classes of polarisation indices. Tech. rep., The Chinese University of Hong Kong, Hong Kong (1998)

Tüzemen, D., Willis, J.L.: The vanishing middle: job polarization and workers' response to the decline in middle-skill jobs. Economic Review **First Quarter**, 5–32 (2013)

Verhaest, D., Omey, E.: The determinants of overeducation: different measures, different outcomes? Int. J. Manpower **31**(6), 608–625 (2010). doi:10.1108/01437721011073337

Verhaest, D., Omey, E.: Overeducation, undereducation and earnings: further evidence on the importance of ability and measurement error bias. J. Lab. Res. **33**(1), 76–90 (2012). doi:10.1007/s12122-011-9125-6

Verhaest, D., Van der Velden R.: Cross-country differences in graduate overeducation. Eur. Sociol. Rev. **29**(3), 642–653 (2013). doi:10.1093/esr/jcs044

Wilson, R., Tarjáni, H., Rihova, H.: A practical guide on anticipation and matching of skills at sector level. Report, European Training Foundation, Warwick Institute for Employment Research and International Labour Office (2013)

Wirz, A., Atukeren, E.: An analysis of perceived overqualification in the Swiss labor market. Economic Bulletin. **9**(2), 1–10 (2005)

Wolfson, M.C.: When inequalities diverge. Am. Econ. Rev. **84**(2), 353–358 (1994)

Global Agenda Council on Employment: matching skills and labour market needs: building social partnerships for better skills and better jobs. Tech. rep., World Economic Forum (2014)

Zellner, A., Theil, H.: Three-stage least squares: simultaneous estimation of simultaneous equations. Econometrica. **30**(1), 54–78 (1962)