Gender differences in skill mismatches

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Abstract

Using the Cedefop European Skills and Jobs Survey (ESJS), we analyse, by gender, to what extent skill and qualification mismatches are related. Our findings show that past skill mismatch statuses are more relevant for current over-skilling in men while qualification mismatches matter more for women. We find that labour market characteristics affect men and women differently. Finally, we also find that country differences only remain for women when controlling for other characteristics. A better understanding of the relationship among mismatches seems crucial to improve the effectiveness of policy intervention in terms of education and the labour market.

Keywords: Skill mismatch, qualification mismatch, gender differences, multilevel regression.

JEL classification: C25, J16, J24.

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1. Introduction

The literature has documented two conceptually and empirically different concepts of mismatches: skill mismatches and qualification mismatches. The growing literature on labour mismatch focuses primarily on educational mismatch rather than on skill mismatch (Mavromaras et al., 2013; McGuinness, 2018a, 2018b) and on education or skills surplus rather than deficits. As McGuinness et al. (2018b) argued, the scarce literature on human capital deficit stems from the fact that a negative effect on firm-level productivity is not clear. Therefore, it would not determine a large share of investment in the training of both employees and firms.

Both mismatches, over-education and over-skilling, can have serious consequences not only from the viewpoint of individuals, but also for society as a whole. As regards society, education accounts for one of the largest public expenditures and the return is only achieved when individuals are well matched to their jobs (Groot and Maassen van den Brink, 2000; Levin et al., 2007; Levin and Rouse, 2012). As regards individuals, there is evidence of the existence of pay penalties, job dissatisfaction and job immobility, among other effects (see, for example, Groot and Maassen van den Brink, 2000; Sloane, 2003; Robst, 2008; McGuinness and Sloane, 2011; Quintini, 2011; Montt, 2017).

However, the related literature has found a small correlation between over-education and over-skilling, suggesting they are measuring different things (Green and McIntosh, 2007; Pecoraro, 2014, among others). It has also been documented that over-education and over-skilling are distinct phenomena, work differently by gender and have different effects on labour market outcomes (Allen and van der Velden, 2001; and Mavromaras et al., 2013, among others).

Despite all these arguments, the evidence relating to the incidence of skill mismatch and the relationship with qualification mismatch is still unclear and in a very early stage. One of the main reasons may be the limited range of datasets containing information on skills and that most of the existing evidence lacks an internationally comparable and sufficiently broad assessment of skill mismatch (CEDRA, 2009; Pellizzari and Fichen, 2013; OECD, 2016; Addison et al., 2019; Brunello and Wruuck, 2019). Moreover, although skill mismatch has become an issue of particular policy concern (European Commission, 2009), policies that address the problem are rarely evident either at the national or European level.

Most importantly, gender differences in mismatches are scarcely addressed in the related literature. Most studies on mismatches, based on educational mismatch, only include gender as a possible determinant of mismatch. An exception is Addison et al. (2019) who found that women are more mismatched than men, mostly due to highly educated women. They also showed that having children leads to a greater mismatch, which can be reduced by delaying the time of childbirth, and that there is a degree of persistence in mismatch for women.

Using the Cedefop European Skills and Jobs Survey (ESJS), we contribute to the literature in different ways. Given the scarce and non-conclusive evidence on gender differences in mismatches and the evidence that there is not a one-to-one relationship between skill and qualification mismatches, we analyse, by gender, to what extent both skill and qualification mismatches are related. In particular, we test to what extent past experiences of skill mismatches (over/under) and qualification mismatches (over/under) are related to current over-skilling differently by gender. The ESJS dataset also allows us to contribute to the literature by adding the feature of international comparability as it contains information on employees from 28 European countries.

Additionally, we take advantage of multilevel techniques to control for unobserved country heterogeneity and to ascertain, by gender, the relative importance of country characteristics. Given that the ESJS is a cross-section dataset, we are not able to correct for unobserved individual heterogeneity; therefore, we will interpret our results with caution.

The paper is structured as follows. The next section provides an overview of the related literature. Section 3 presents the method of analysis. Section 4 describes the dataset and the variables used in the paper. Section 5 includes a detailed description of the regression results. Section 6 presents the concluding remarks and further discussion.

2. Background

In what follows, we review the existing theories to explain mismatches and the most common evidence regarding over-education and over-skilling. We also describe the evidence on gender differences in mismatches. Finally, we summarize the evidence on cross-country differences.

2.1 Theories of mismatch

As stated in the Introduction, most of the existing literature has focused on over-education. There are different theories to explain the existence of over-educated workers. *Human capital* theory (Becker, 1993) posits that over-education is a symptom of other human capital deficits and workers may use schooling to compensate for deficiencies in other areas of human capital. This theory assumes that accumulated human capital required for a job includes work experience and on-the-job training in addition to formal education. *Occupational mobility* theory adds to this argument that if skills deficits can be corrected with experience or on-the-job training, then over-education is a temporary phenomenon. However, if over-education reflects permanent ability differences, it will be a long-term problem for some workers. *Job completion* theory (Jovanovic, 1979) suggests that the mismatch stems from imperfect information about workers' productivity, and that this information becomes more accurate with workers' tenure and will therefore be eliminated. This theory stresses the role of search costs and imperfect information as reasons for imperfect matches. Leuven and Oosterbeek (2011) argued that over-education does not need to represent a breach of the validity of the human capital model. In fact, over-education could be conceived as the result of a lack of the work-related component of human capital, rather than a waste of human capital.

To understand the persistence of mismatches, *Job competition* theory (Thurow, 1975) brings to the debate that excess schooling is a consequence of the competition for jobs in the presence of rigidity of the demand for highly educated labour, which leads workers to accumulate education in order to get a better position in the job queue. Like human capital theory, *Assignment* theory (Sattinger, 1993) assumes that individuals are able to compete for the best jobs through investment in human capital and, like job competition theory, that available jobs are limited. Both mechanisms would cause mismatches. *Job search* theory suggests that skilled graduates have a larger reservation wage than low-skilled graduates, who tend to choose the first job offer even if it involves over-education (Pissarides, 2000). Over-education may also be explained by *career mobility* theory, which postulates that firms and workers generate matches with low earnings in the short run, but good career prospects in the long run (Galor and Sicherman, 1990).

For the case of over-skilling, theories are more scarce. Mavromaras et al. (2013) put forward different hypotheses on why individuals may become mismatched in both education and skills. Certain individuals may have low ability for their level of education compared to their peers and thus be unable to obtain a job commensurate with their educational level. Such individuals will be over-educated, but not necessarily over-skilled. Some individuals, on the other hand, may choose to accept a job for which they are overqualified given it offers them compensating advantages (less stress, shorter commuting time, etc.) In this case, such individuals may be both over-educated and over-skilled. A third possibility is that employers actually prefer over-educated workers because they are more productive and learn more quickly. Skill mismatch, and more specifically over-skilling, may result from workers being hired when the labour market is slack and jobs are hard to find. Skill mismatch might also reflect that employers do not have well-developed hiring practices. Based on the empirical literature, Congregado et al. (2016), Mavromaras et al. (2013) and Caroleo and Pastore (2018) postulated that skills under-utilization may also have a scarring effect such as unemployment and low-paying jobs.

Pecoraro (2016) provided two different explanations of how someone would be over-educated but not over-skilled. One explanation is that these workers have below-average skills for their level of education and end up in jobs for which they are over-educated. An alternative explanation is that the measure of over-education may be incorrect (at least for these workers) and any estimates of the wage return to over-education is likely to reflect a measurement error. All in all, both explanations are consistent with the human capital model in which (part of) over-education is a statistical artefact due to measurement error and merely represents unobserved heterogeneity in skills across workers (McGuinness, 2006).

Finally, in terms of gender differences, McGoldrick and Robst (1996) examined the importance of geographical constraints in explaining over-education, especially among married women with family commitments. Perhaps the best starting point for discussing the literature on gender differences in skill mismatch is Goldin (2014). The author pointed out that a gender gap in earnings exists today and differs significantly by occupation. She found that the gap still exists because hours of work in many occupations are worth more when given at particular moments and when the hours are more continuous. That is, in many occupations, earnings have a nonlinear relationship with respect to hours, and differences are based on the costs of flexibility. The main explanation has to do with the presence of good substitutes for individual workers when there are sufficiently low transaction costs of relaying information. She found evidence

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that certain features of occupations that create time demands and reduce the degree of substitution across workers are associated with larger gender earnings gaps, especially among college-educated individuals.

As seen in Addison et al. (2019), if such jobs (i.e. flexible jobs) are limited to only a few occupations, then women will experience greater mismatch when flocking into them.[2] However, this offsetting effect comes at the cost of occupational progression. Family-friendly firms employ a less-skilled workforce, offer lower wage dispersion, and reduce the scope for career development. The authors have also stated that the cost of trying out a variety of occupations to find the right skill match is costlier for women than for men. Moreover, because women have assumed a secondary role in family labour supply, they may secure worse job skill matches. However, although the labour market is less segregated by gender, an increasing number of women have entered technical and professional jobs and there has been a shift in perceived gender roles, the authors found a higher incidence of mismatches and larger negative effects on wages for women.

2.2 Over-education and over-skilling

A large number of studies, mainly using cross-sectional data, have found that the labour market mismatch, either over-education or over-skilling, is associated with negative labour market outcomes in the form of lower wages, reduced job satisfaction and higher labour turnover. At the individual level, the incidence, determinants and consequences of over-qualification have been well documented (see, for example, Duncan and Hoffman, 1981; Verdugo and Verdugo, 1989; Kiker et al., 1997; Dolton and Vignoles, 2000; Chevalier, 2003; Groeneveld and Hartog, 2004; Verhaest and Omey, 2006; McGuinness and Bennett, 2007; Dolton and Silles, 2008; McGuinness and Sloane, 2011), and various studies have provided useful reviews (e.g. Groot and Maassen van den Brink, 2000; Hartog, 2000; Rubb, 2003; Sloane, 2003; McGuinness, 2006, 2018b).

These estimations present two sources of bias: measurement error and omitted ability. Dolton and Silles (2008) and Verhaest and Omey (2012) estimated instrumental variables panel data models and concluded that the upward bias in standard OLS estimates owing to omitted fixed effects is offset by an equal downward bias resulting from measurement error. The most standard methods to control for such problems are based on panel data, fixed effects regressions and instrumental variables. Mavromaras et al.

[2] Goldin's (2014) idea has influenced family-friendly firms and the jobs literature that enable such practices as a way to reduce the motherhood wage penalty.

(2013) used panel data, Kleibrink (2016) compared the results using three different methods, fixed effects regressions, instruments and the direct inclusion of ability controls. Sellami et al. (2017) used instrumental variables in panel data. Caroleo and Pastore (2018) used a Heckman procedure to control for sample selection bias.

An alternative solution to mitigate the measurement error bias consists in refining the definition of educational mismatch to incorporate the idea that equally educated workers are not homogeneous in their human capital endowment. As stated in an excellent review of McGuinness et al. (2018b), labour market mismatches are a frequently used term in policy debates; nevertheless, the concept of skill mismatch itself is very broad and can encompass a variety of measures.

Educational mismatch has been measured in three different ways in the literature. First, through a subjective measure based on workers' responses to questions on the level of education required either to obtain or perform the current job, which is compared with their actual qualification. The second is an objective measure to determine the required level of education from a particular occupation from job analysis. The third alternative is an empirical measure which compares the worker's actual level of education with either the mean or the modal level of education in that occupation.

Skill mismatch cannot be derived in this manner as it is generally based on workers' responses to a question on the degree to which they are able to use their current skills or abilities in their present job. Recently, Pecoraro (2016) and McGuinness et al. (2018a, 2018b) stated that over-skilling is argued to be a more accurate measure of mismatch among existing workers. The argument is that over-education ignores that job entry requirements may be weakly related to job contents, and is more a reflection of qualifications inflation and credentialism, while human capital also consists of skills acquired through labour market experience and training. Moreover, the concept of perceived skill utilization has the advantage that it incorporates skills learnt in formal education and on the job. At the same time, only subjective measures allow relaxing the assumption that all jobs within a given occupation have the same requirements. Subjective measures also help to reduce the bias associated with a statistical approach and to identify whether skills of mismatched educated workers are adequate or not for the job. Thus, these measures help to verify if the statistical mismatch is genuine or apparent. Additionally, as stated above, traditional methods for measuring over-education fail to account for skills heterogeneity among workers with the same level or years of schooling. Mavromaras et al. (2013) argued that over-skilling is less likely to be contaminated by unobserved heterogeneity than over-education. Additionally, traditional methods for measuring over-education fail to account for skills heterogeneity among workers with the same level or years of schooling (Chevalier, 2003; Green and McIntosh, 2007; Green and Zhu, 2010; Quintini, 2011; Badillo-Amador and Vila, 2013; Pecoraro, 2014, 2016).

However, over-skilling also presents some shortcomings. The first is the limited range of datasets containing information on skills, which leads to unidimensional rather than multidimensional measures. Secondly, biased estimates can arise from the way the questions are phrased, as they might include skills and abilities that are totally unrelated to the workplace. Thirdly, over-skilling questions do not allow the researcher to identify the relative importance of underused skills gained from labour market experience, training, innate ability or formal schooling. Fourthly, most of the existing evidence lacks an internationally comparable and sufficiently broad assessment of skill mismatch and therefore remains a contested issue. Finally, a self-reporting bias problem regarding over-skilling also arises when measuring over-education.

Given that formal education is widely viewed as an imperfect indicator of overall skills, there have been different proposals to measure mismatches in the literature that combine both mismatches.[3] As noted in Nordin et al. (2010), most of the literature has addressed vertical mismatch (usually measured as over(under)-education and/or over(under)-skilling) and paid less attention to horizontal mismatch (in terms of field of study).[4] Some authors have incorporated the idea of real versus formal, or genuinely versus apparent, over-education according to whether or not over-education is accompanied by skill mismatch (Chevalier, 2003; Green and Zhu, 2010; Green and McIntosh, 2007; Quintini, 2011; Badillo-Amador and Vila, 2013; Pecoraro, 2014, 2016).[5] Chevalier and Lindley (2009) incorporated over-education with a mismatch in terms of job satisfaction to define genuine versus apparent mismatch.

Some literature, on the other hand, has examined over-education and over-skilling separately. Allen and van der Velden (2001) showed that while over-education has a strong negative effect on wages, over-skilling does not, although it is a better predictor of

[3] These measures can be classified into two main branches: individual-related and firm-level aggregates. We mostly focus the review on measures at the individual level. McGuiness et al. (2018b) also includes some measures at firm level.

[4] Horizontal mismatch has also been analysed in terms of measurement and determinants (McGuinness et al., 2018b; Somers et al., 2019). At the individual level, there is an increase in unemployment risks, some earning penalties, and individuals are more likely to report high job dissatisfaction (Béduwé and Giret, 2011; Bender and Roche, 2013).

[5] An excellent classification of mismatch measures is given in Table 1 in Pecoraro (2016).

job satisfaction. Mavromaras et al. (2009, 2013) found that over-education does not display negative effects on wages and job satisfaction when controlling for unobserved heterogeneity (including ability) and skill mismatch. The results suggest that policy attention should focus on over-skilling, particularly in combination with over-education. Over-skilling, whether on its own or jointly with over-education, clearly has a negative effect on the welfare of male workers and an even larger negative effect for females, and its eradication may be beneficial for employers and employees alike.

Greeen and Zhu (2010) and Nordin et al. (2010) found that over-education is weakly correlated with skills underutilization. They confirm that traditional methods for measuring educational mismatch fail to account for skills heterogeneity among workers with the same level or years of schooling. Therefore, this evidence shows that over-education does not necessarily imply skill mismatch.

2.3 Gender differences

Gender differences in mismatches have been little studied in the related literature. Most studies on mismatches focus on the educational gap between workers' level of education and years of education required for a job and only include gender as a possible determinant of education. In a survey of graduates, Cutilo and Di Prieto (2006) found that women are less likely to be over-educated than men, particularly in the fields of political science, literature and languages. However, in the fields of law, medicine, sciences, mathematics, philosophy, engineering, architecture and agriculture, the likelihood of over-education in relation to business is lower. Caroleo and Pastore (2018) showed that gender is a significant determinant of over-skilling to do the job but not of over-education to get the job. Rios-Avila and Saavedra (2019) found that women are more likely to work in jobs with greater horizontal mismatch than men, although the wage penalty is lower.

There are a few exceptions in the literature dealing specifically with gender differences. Mavromaras et al. (2013) found that females' wages are negatively affected by any mismatch (either educational or skill-based), whereas males' penalty only occurs when both types of mismatches are jointly present. They also found that over-education has no clear negative effect on welfare of either men or women, whereas over-skilling – whether on its own or jointly with over-education – does so for women. Addison et al. (2019) addressed gender disparities in match quality over a career using a multidimensional measure of skills. They found that highly educated women are more mismatched than men. Life events, such as having children and delaying the time of childbirth, evince a greater mismatch, and there is a degree of persistence in mismatch for women.

2.4 Country differences

Many studies have examined both the determinants and impacts of mismatches, particularly for over-education at the national level, but there is very little research on mismatches from a cross-national perspective (McGuinness et al., 2018a). The lack of comparative international research on this issue is, arguably, due to the lack of available datasets that measure mismatches across countries over time. Some exceptions do exist. Verhaest and Van der Velden (2013) used a multi-level model to explain cross-country variations in the incidence of graduate over-education at a single point in time. They included different variables at the country level and found that cross-country differences in over-education are related to measures that capture variations in the quality and orientations of educational systems, business cycle effects and the relative oversupply of highly skilled labour. Croce and Ghignoni (2012) reported that over-education also tends to be influenced by business cycle variables and higher in countries with a lower wage gap between graduates and workers with upper secondary education. Davia et al. (2017) also reported that over-education is higher in areas where the education labour supply exceeds demand, university enrolment levels are higher, and where the share of migrants is larger. They also found that over-education is lower for regions with a strong employment protection.

McGuinness et al. (2018a) indicated that factors such as the composition and level of demand, educational provision and business cycle effect may play a role in explaining spatial differences. They found that over-education was lower for both men and women in countries with a higher female employment share, higher female labour participation and larger shares of employment in sectors reliant on vocational skills, while labour market flexibility is a mediation factor for men. They also found that other determinants affect the likelihood of being over-educated that do not affect over-skilling, such a fall in unemployment, the percentage of employment in manufacturing, the share of skilled workers and an emphasis on vocational training. Therefore, macro-determinants of over-skilling differ from those of over-education.

Budría and Moro-Egido (2018) also found that macro-determinants of over-skilling differ from those of over-education. In particular, for the whole sample of workers, they found that individuals living in countries with a higher ratio of female workers and lower participation rate are less likely to report over-skilling, and that the share of temporary and part-time workers is significantly related with qualification mismatches. Finally, labour market participation was found to affect both forms of mismatch.

3. Econometric model

It is now common knowledge that the estimates of the determinants of mismatches may be affected by omitted heterogeneity by employment status (sample selection bias) and mismatch status (endogeneity). However, unless very good panel data or instrumental variables are available that can control for fixed effects and/or omitted heterogeneity, it is almost impossible to solve this problem (Dolton and Silles, 2008; Leuven and Oosterbeek, 2011; Kleibrink, 2016; Caroleo and Pastore, 2018). Our dataset contains cross-sectional data only for employees; therefore, we cannot fully control for these two problems. Nonetheless, we will try to control for some other issues to reduce the bias to the greatest possible extent.

Additionally, the data are structured hierarchically in two levels with individuals nested into countries. Therefore, to handle the issue of correlated observations within a country, we rely on multilevel regression. Traditional multivariate regression techniques cannot be employed with hierarchical data since the standard errors of variables at higher levels of aggregation are underestimated. This occurs because the degrees of freedom are calculated as if they were at the first level.

Specifically, using a random intercept model, we explore the information beyond clustering and analyse the effect of country-level variables.[6] Some other related papers have grouped countries following the Esping–Andersen classification. However, to fully explore the country unobserved heterogeneity and the relative role of country characteristics, multilevel techniques are more appropriate as they consider all countries separately.

Let us consider a two-level structure where individuals, i (first level), are nested into countries, c (second level). Let y_{ic} denote the response for individual i in country c.

[6] We cannot properly evaluate the effect of country-level variables in separate country regressions or with fixed effect models. Regarding the exchangeability assumption required when treating cluster effects as random, we can assume it is satisfied, as we include country-specific covariates (see Rabe-Hesketh and Skrondal, 2012). According to Bryan and Jenkins (2016), a minimum of 25 countries are necessary for linear multilevel models in order to obtain reliable results in relation to the contribution of the country effect. We fulfil this requirement.

The null model (Model 1) does not include any explanatory variables, although it gives us information on whether there are country differences in over-skilling levels.

$$y_{ic} = \beta_0 + \xi_{0c} + \varepsilon_{ic}$$

where ξ_{0c} designates the random intercept and ε_{ic} the individual-level residuals. Both residuals are assumed to be independent and to follow normal distributions with zero mean. We denote the between-country variance by $\sigma^2_{\xi_0}$ and the within-country between-individuals variance by σ^2_{ε}. Each random effect is described according to its estimated variance. If the within-country variance were zero, all the variability would be among countries. In contrast, if the between-country variance were zero, then there would only be variability among individuals of the same country. As is usual in the literature, we use the variance partition coefficient (VPC) to express the proportion of the total variance due to between-country differences,

$$VPC = \sigma^2_{\xi_0}/(\sigma^2_{\xi_0} + \sigma^2\ )$$

Formally, Model 1 for the logit transformed hazard rate for individual *i* belonging to region *c* becomes accordingly:

$$\log\left(\frac{M_{ic}}{1-M_{ic}}\right) = \beta_0 + \xi_{0c} + \varepsilon_{ic} \qquad \text{(Model 1)}$$

where $M_{ic} = P(y_{ic} = 1)$, y_{ic} is 1 if the individual *i* in region *c* is skill mismatched. We extend the null model by gradually including individual and job characteristics, $\boldsymbol{X}_{ic}$ (Model 2):

$$\log\left(\frac{M_{ic}}{1-M_{ic}}\right) = \gamma_0 + \boldsymbol{\gamma}_1'\boldsymbol{X}_{ic} + \xi_{0c} + \varepsilon_{ic} \qquad \text{(Model 2)}$$

Finally, to check whether country-level determinants have an effect over and beyond the effect of individual and job characteristics, we propose and extend the model (Model 3) to the following:

$$\log\left(\frac{M_{ic}}{1-M_{ic}}\right) = \gamma_0 + \boldsymbol{\gamma}_1'\boldsymbol{X}_{ic} + \boldsymbol{\gamma}_2'\boldsymbol{W}_c + \xi_{0c} + \varepsilon_{ic} \qquad \text{(Model 3)}$$

where $\boldsymbol{W}_c$ is a vector of country-specific characteristics.

4. Data and Variables

4.1. Dataset

The Cedefop ESJS is a state-of-the-art survey of adult employees (aged 24−65) carried out in the 28 member states of the European Union in 2014, which collects information on the match between employees' skills and skills needed on their jobs. The survey was financed and developed by the European Centre for the Development of Vocational Training (Cedefop) in collaboration with a network of experts on skills, the OECD and Eurofound (Cedefop, 2015). The ESJS is a unique dataset, as it includes a variety of mismatch measures, some of which are captured at two points in time. In particular, employees are asked about their current skill levels (at the time of survey completion), as well as their skill levels not only when they were first hired for the job, but also in the previous job. The survey also provides evidence of over-qualification measures at two points in time: getting the job and doing the job. Finally, there is an exhaustive classification of fields of education.

The ESJS contains self-reported information on both the skills required to perform the job and on the qualification needed to get the job and to do the job. It is generally accepted that an objective approach does not outperform a subjective approach. Thus, the choice of a particular approach in applied work is mostly dependent on data availability. Fairly recently, Barone and Ortiz (2011) and the European Commission (2015) performed sensitivity analyses and showed that the extent, effects and determinants of over-qualification may differ sensitively across measures.

Given that the questions are the same for all countries, the ESJS allows for cross-country comparability as well. Therefore, the ESJS data can be used to estimate the incidence of current skill mismatch affecting adult workers across countries. As pointed out in McGuinness et al. (2018b), this dataset permits identifying the relative importance of underused skills acquired through labour market experience, training, innate ability or formal schooling. We end up with 22,453 observations, of which 53.6% correspond to men.

In general, it is not easy to make comparisons with other findings of mismatch incidence since such comparisons are difficult to assess given the different measures of skills, geographical scope, temporal dimension, and more importantly due to the scarce evidence on gender differences, among other reasons. However, in the following subsections we will provide some comparisons with existing evidence of mismatch incidence.

4.2. Dependent variables: Skill mismatches

In line with the related literature, we consider the situation where workers believe that they have more skills than their current job requires. Respondents are asked to best describe, overall, their skills in relation to the skills required to do the job. We capture the response "skills are higher than required by job" at the current job (*Over-skilled*).

We observe that around 45% of men and 41% of women report that their skills are higher than required by their current job (see Table 1). Using the same dataset but with no distinction by gender, McGuinness et al. (2018b) and Budría and Moro-Egido (2018) found that 41% of employees are over-skilled.

------- Insert Table 1 around here -------

For simplicity sake, we now consider different groups of countries following Esping–Andersen's classification into *Continental, Mediterranean, Anglo-Saxon, Nordic* and *Eastern* Countries.[7] We find that the largest incidence for men and women appears in Anglo-Saxon countries and the lowest incidence occurs in Nordic countries. We find that men are more affected by all mismatches than women only in Eastern and Continental countries. The international differences reported in the table are not surprising, insofar as estimates of mismatch are typically found to differ across countries (ILO report, 2014 and Cedefop, 2015).

4.3. Independent variables

4.3.1. Past skill mismatches

The aim of including past skill mismatches is to capture the idea of persistence of skill mismatches (over-skilling in the past) and the process of skills acquisition not provided by formal education while working, as stated in occupational mobility theory and job completion theory (under-skilling in the past). Additionally, this inclusion allows us to correct endogeneity issues to some degree.

To this end, we control for past situations of over-skilling by including a four-category variable to measure if: i) the worker was neither over-skilled at starting the current job nor in the previous job (*NoStart_NoPrevious_Over*, reference category); ii) the worker was not over-skilled at starting the current job but was over-skilled in the previous job (*NoStart_Previous_Over*); iii) the worker was over-skilled at starting the current job but was not over-skilled in the previous job (S*tart_NoPrevious_Over*); and iv) the worker was over-skilled at starting the current job and in the previous job (*Start_Previous_Over*).

[7] In our sample, countries are classified as follows: UK and IE are *Anglo-Saxon*; DK, FI and SE are *Nordic*; AT, BE, DE, FR, LU and NL are *Continental* and ES, GR, IT, MT and PT are *Mediterranean*; the rest are classified as *Eastern*. All figures are included in Table S1 of the Supplemental Material.

Using the same question as in the over-skilling measure, the under-skilling measure captures the response "skills are lower than required by job". As before, we build a set of four-category variables equivalent to the previous one but for under-skilling (*NoStart_NoPrevious_Under*, *NoStart_Previous_Under*, S*tart_NoPrevious_Under* and *Start_Previous_Under*).

In terms of the unconditional incidence of past skill mismatches, we observe that men and women who were over-skilled only in the previous job represent 18% of the sample and those who were over-skilled only when starting the current job account for 13% (see Table 1, Panel A). Gender differences are only significant if both mismatches are either absent or present, showing that women are less affected by previous excess of skill. The incidence of under-skilled employees is lower (see Table 1, Panel B), with a higher impact of being only under-skilled when starting the current job. We find that women are more affected than men precisely in being only under-skilled when starting current job (around 15% for men and 18% for women)

By countries, men are more affected than women by skill mismatch in previous job in Eastern, Anglo-Saxon and Nordic countries; whereas skill mismatch when starting current job presents gender differences in Eastern and Continental countries (Table S1 in Supplemental Material). We also find that the correlation between the current job and starting the current job is larger than with the previous job for both men and women (Figure S1 in Supplemental Material).

A general finding from these unconditional averages is that women are less affected by over-skilling and more affected by under-skilling than men.

4.3.2. Qualification mismatches

We adopt the subjective approach, generally based on workers' self-assessment of the level of qualifications required "to get" or "to do" the job, which is then compared to the highest level of education actually acquired by the worker. As pointed out in Dolton and Silles (2008) and McGuinness et al. (2018b), it is important to note that the different response distributions may capture different effects. Specifically, being overqualified both "to do the job" and "to get the job" reflects surplus qualifications and skills, whereas being over-qualified "to do the job" while being matched "to get the job" may be a reflection of surplus entry requirements.

If the reported level of education required is lower (higher) than the acquired level of education, then we classified the employee as over-qualified (under-qualified). We calculate a set of dummies to account for the following possibilities: i) the worker was not over-qualified either to get or to do the job (ref. cat. *NoGet_NoDo_Over*); ii) the worker was not over-qualified to get the job but was over-qualified to do it (*NoGet_Do_Over*); iii) the worker was over-qualified to get the job but was not over-qualified to do it (*Get_NoDo_Over*); and iv) the worker was over-qualified to get and to do the job (*Get_Do_Over*). We also incorporate a categorical variable regarding under-qualification with the equivalent four possibilities (ref. cat. *NoGet_NoDo_Under*, *NoGet_Do_Under*, *Get_NoDo_Under* and *Get_Do_Under*).[8]

In terms of the unconditional incidence of educational mismatches, we observe that employees, men and women who were only over-qualified only to get the job represent 3% of the sample and those who only were over-qualified to do the job account for 8% (see Table 1, Panel C). In this respect, we do not find evidence of credentialism for any gender, that is, employers requesting a higher degree than needed at the time of hiring relative to the genuine qualification level of the job. Nevertheless, there are gender differences in over-qualification at both moments in time, with women being more affected than men (28% for men and 31% for women). The incidence is lower than that found in Dolton and Silles (2008) and in Caroleo and Pastore (2018), but they used UK data for 1998 and Italian data for 2005, respectively. Our findings on incidence are in line with Gaeta et al. (2018), who found a 35% incidence of over-education for PhD graduates for Italy. Kleibrink (2016) found that 50% of employees in Germany are in a situation of over-education. Using our dataset, Budría and Moro-Egido (2018) found that employees with over-qualification to get (to do) the job represent 25% (29%) of the sample; however, there were unconditional averages without controlling for having only one or both mismatches and without gender considerations. Addison et al. (2019) showed that, for both genders, around 50% (44%) of individuals with less (more) than 10 years of tenure are over-qualified. However, as stated before, all comparisons with other evidence should be taken with caution given the different measures, geographical scope, temporal dimension and gender considerations, among other reasons. The incidence of under-qualification at getting the job and doing the job is small and there are no gender differences (see Table 1, Panel D).

[8] As an anonymous referee pointed out, the addition of under-education might further reduce the bias of the findings.

We find some differences across countries (Table S1 and Figure S2 in Supplemental Material), with the proportion of over-qualified females (to get and to do the job) being larger than the proportion of over-qualified males in Anglo-Saxon, Continental and Mediterranean countries. The opposite occurs in Eastern and Nordic countries.

A general finding from these unconditional averages is that women are more affected than men by over-qualification and equally affected as men by under-qualification.

4.3.3. Joint incidence of mismatches

The previous analysis of mismatches shows that women are less affected by over-skilling at any point in time and more by under-skilling in the past than men. However, as shown before, women are more affected by over-qualification and equally by under-qualification than men. Therefore, an analysis of joint incidence of mismatches seems to be required.

The analysis of joint incidence of skill and qualification mismatches shows the following general findings. Among men who are over-skilled in the current job (23% of employees and 56% of over-skilled employees), we find that 57% (11%) and 51% (8%) were also over-skilled (under-skilled) at starting the current job and in the previous job, respectively (see Table 2). Among women who are over-skilled in the current job (19% of employees and 44% of over-skilled employees), we find only a significant difference in the percentage of women who were also over-skilled in the previous job, which is lower (46%). Thus, there exists persistence in over-skilling for both genders. These figures are in line with Pecoraro (2014), who found that five years after graduation 55.8% of men and 49.2% of women remain skill mismatched.

------- Insert Table 2 around here -------

The large percentage of over-skilling in the present as well as in the past provides evidence of some degree of persistence in over-skilling, while the small incidence of under-skilling in the past does not allow us, at this point of the analysis, to draw conclusions regarding the process of skills acquisition. Persistence in genuine mismatches has also been found in the literature (see, for example, Pecoraro (2014). For employees who are not over-skilled in the current job, we find that 10% (27% for men and 32% for women) and 24% (12% for men and 13% for women) were over-skilled (under-skilled) at starting the current job and in the previous job, respectively. Gender differences are significant only for under-skilling.

In terms of qualification mismatches, among the over-skilled men and women in the current job, the incidence of over-qualification (under-qualification) to get and to do the job ranges from 38% to 50%, so it is lower than the incidence of past over-skilling. In the related literature, these individuals are classified as genuine mismatched. We also find that women are more affected than men (6 p.p.). Among females who were not over-skilled, 27% (7%) and 31% (7%) were over-qualified (under-qualified) to get and to do the job, respectively. These figures are slightly, but significantly, lower for males in the case of over-qualification to get the job. Using the same dataset, McGuinness et al. (2018b) found that 60% (36%) of employees who are over-skilled (not over-skilled) in the current job are also over-educated. Our figures are far higher than the incidence rates of Gaeta et al. (2017) for Ph.D. holders in Italy in 2009 and the rates of Pecoraro (2014, 2016) for Swiss graduates in 2002 and 1999, among others. Using HILDA panel data for the period 2001–2007 and a selection of tertiary educated employees, Mavromaras et al. (2013) found that the percentage of over-educated men (women) is 14% (12%), over-skilled men (women) is 8% (7%) and men (women) with both mismatches accounts for 6% (5%). Our figures are far higher. As stated before, it is not easy to make comparisons with other findings of mismatch incidence since these comparisons are difficult to assess given the different measures of skills, geographical scope, temporal dimension and gender considerations, among other reasons.

A general finding from these joint incidence analysis is that, first, a large fraction of the population (57%–46%) is over-skilled at the current job and in the past, and, secondly, and a large fraction of the population (50%–38%) is over-skilled at the current job and over-qualified to get or to do the job. More importantly for our goal, women are more (less) affected by over-qualification (over-skilling in the past) than men, independently of the current over-skilling status. These figures give some intuition of the gravity of the mismatch incidence and the importance of gender distinction.

We provide a more detailed description of this group of individuals with excess education and skills as they are the largest group in terms of mismatching incidences. The evidence presented above supports the idea that, among men and women who are over-skilled in the current job, over-skilling when starting a job is a more widespread phenomenon than over-skilling in previous jobs and over-qualification to get or to do the job. The reverse is true for men and women who are not over-skilled in the current job: being over-skilled when starting the job turns out to be the less frequent mismatch. In this case, there exists evidence on the existence of a skill acquisition process through working.

Secondly, the incidence of over-qualification to get the job is lower than to do the job, independently of over-skilling in the current job, thus indicating that these individuals do not suffer from credentialism.

Separately by gender, we observe general patterns for over-skilled and non-over-skilled employees. Gender differences are significant only in qualification mismatches (to get and to do the job) independently of over-skilling status in current job, with women being more affected than men (6 p.p. for over-skilled and 3 p.p. for non-over-skilled). Men are more affected by over-skilling in the previous job only if they are over-skilled in the current job (5 p.p.). By group of countries, we find, in general, the same patterns as the overall case.[9]

Following the European Research Council (ERC) classification, we sort education into three fields of study: Physics & Engineering (PE), Life Sciences & Medicine (LS) and Social Sciences & Humanities (SH).[10] Regarding field of education, general finding is also confirmed with the exception of *LS* group in which there is no difference in over-qualification to get and to do the job. In both cases, if we look at men and women separately, the general findings are mostly confirmed, but the evidence is mixed by group of countries, as McGuinness et al. (2018a) also found.

Finally, to capture transitions from different states to employment in some way, we control for previous types of labour market status: employed in another job, self-employed, in education or training, unemployed and other non-working statuses. As before, the general findings of incidence are confirmed. However, there are some exceptions showing evidence of credentialism. First, among employees who are not over-skilled in the current job and had not worked before, there are no differences in over-qualification to get and to do the job. This is due to reasons other than unemployment or education. In the case of employees who are over-skilled in the current job, the incidence of over-qualification to get the job is larger than the incidence of over-qualification to do the job among those previously employed in another job, unemployed or not working for reasons other than unemployment or education. Separately by gender, the evidence is mixed.

[9] For the sake of simplicity, we relegate all tables (S2-S4) and figures (S3-S8) regarding this analysis to the Supplemental Material.

[10] Following Gaeta et al. (2018), our sample is sorted by PE (mathematics, statistics, computer sciences, engineering sciences and natural sciences), LS (agriculture, veterinary, medicine and health sciences) and SH (education, humanities, languages, arts, economics, business, law and other social sciences).

To sum up, in terms of gender differences, our findings show the following patterns. First, independently of over-skilling status in the current job, there is a larger incidence of over-qualification (to get and to do the job) for women (i) only for the over-skilled in Continental countries, for over-qualification to do the job in Eastern countries, for getting the job in Mediterranean and Anglo-Saxon countries, and only in Continental countries for those who are not over-skilled; (ii) in all fields of education for the over-skilled and in PE for women who are not over-skilled; and (iii) for those employed in another job before or self-employed if currently over-skilled and for those previously unemployed if currently not over-skilled. This would imply a larger credentialism for women. Nordic countries are an exception, since women are less affected by over-qualification than men. Secondly, the larger incidence of over-skilling when starting the job is only found for over-skilled males at the current job in (i) Eastern, Nordic and Continental countries, and the incidence of being over-skilled when starting the job is larger for men in Eastern, Anglo-Saxon and Nordic countries, although there are generally no gender differences; (ii) only for those in LS and SH if over-skilled in current job; and (iii) only for those previously working in another job or in education and training.

4.3.4. Individual, job and country characteristics

In terms of individual characteristics, we consider the most common socio-economic variables used in the related literature like age, presence of children, education, previous employment status, etc. Regarding job characteristics, we also follow the related literature and include information about whether the respondent worked in the same occupation in his/her previous job as in the current job, a similar or different occupation, the type of organization, whether they work full time or part time, the size of the firm, etc. Given the standard nature of these variables, and for the ease of reading, we relegate the descriptive statistics to the Supplemental Material (Table S5).

As presented before in the joint incidence analysis, the ESJS contains information on the field of education for those with an education higher than or equivalent to upper secondary education. As pointed out in Moore and Rosenbloom (2016), over-qualification and field-of-study mismatch are ‘actually sub-phenomena under the broader supra-phenomenon of *underemployment,* which refers to a general underutilization of the individuals’ characteristics and competencies, such as potential income (underpayment), potential job extent and permanency (work-status congruence), occupational/professional experience (skills/experience underemployment), and so on’.

We are not able to capture field mismatch in this dataset given that there are no subjective questions and occupation codes are at the one-two digit level and there is no way to objectively identify the field of education required. Therefore, we cannot account for horizontal mismatches. There have been some attempts to capture field mismatch using a subjective question that asks respondents to assess the degree to which their current job is related to the field of study of their highest qualification (Allen and de Weert, 2007; Robst, 2007, 2008; Verhaest et al., 2017). However, field mismatch could also be measured independently by comparing a field of study variable with occupation codes (Béduwé and Giret, 2011; Levels et al., 2014; Sellami et al., 2017). Rios-Avila and Saavedra (2019) proposed two indexes of education-occupation match quality based on field of education. In this paper, we only control for the field of education as a determinant of skill mismatches.

We find that, overall and by gender, the less frequent fields are agriculture and veterinary studies and the most frequent are economics, business and law. However, we find important differences in the field of education by gender, as expected. While 21% of men have a degree related to engineering sciences, only 7% of the women do. In the case of women, 14% have a degree related to medicine and the health sciences, whereas only 6% of men do. We then confirm all the evidence regarding the feminization of fields of study and occupations (see Table 3).

------- Insert Table 3 around here -------

Following McGuinness et al. (2018a), we include variables that reflect labour market demand and supply. In particular, we consider the labour force shares of working women, the employment shares of workers who are part-time or temporary, shares employed in the public administration and manufacturing sector, the unemployment rate and the participation rate. Additionally, we try to capture the degree of symmetry between labour demand and supply. We include the ratio of workers employed in professional occupations to workers in low-skilled occupations. This is intended to capture the effects of skill-biased technological change, which is generally associated with a shift in the relative demand away from high-skilled to low-skilled labour and in many countries a general hollowing out of mid-skilled occupations. In addition, we consider general economic conditions such as GDP per capita and R&D expenditures and the number of students enrolled in tertiary and vocational programmes. Again we move all the descriptive statistics to the Supplemental Material (Table S6).

5. Results

We begin the description of the results by confirming the existence of a country effect in over-skilling. To this end, we use estimations of the between-country variance ($\sigma^2_{\xi_0}$). In Model 1, the estimated between-country variance is 0.117 for men and higher for women, 0.162 (see Table 4). This implies that the country effect is larger for women.[11] We observe that, once we control for all determinants, the variability across countries is smaller for women and almost vanishes for men. Therefore, country differences only remain for women. In terms of the VPC, we find that, initially, around 3% of the unexplained variation for men in mismatches is attributable to differences between countries and slightly more for women, 5%. The relative importance of individual and job characteristics is large for women (Model 2 shows an 80% reduction in the VPC), and the one for country characteristics is similar by gender (Model 3).

------- Insert Table 4 around here -------

Now we turn to our main goals. First, we find that previous over-skilling status has by far the most relevant effect on the likelihood of being currently over-skilled.[12] In particular, not having been over-skilled before increases both males and females' likelihood of being over-skilled in the current job by about 25 p.p. Therefore, being over-skilled is not only the result of past experiences of mismatches. Moreover, having been over-skilled in the previous job (at starting current job) increases, on average, males' probability of being over-skilled in the current job by 40.8 (72.7) percentage points (Table 5 for marginal effects). For males who were over-skilled at both times, the effect increases to 83.7 p.p. The effects are lower for females (around 3–4 p.p.).

------- Insert Table 5 around here -------

Secondly, in terms of previous under-skilling status, we find that males who started the current job with under-skilling are less likely to be over-skilled (37 p.p. less). Although being under-skilled at the previous job does not have an isolated effect for either men or women, it does have an effect only for women when combined with under-skilled at starting the current job. As before, these effects are lower for women than for men (around 5–7 p.p). Therefore, previous skill mismatch statuses (over and under) have a higher effect for men.

[11] Although marked in Table 4, we do not discuss the results with significance levels higher than 0.05.
[12] Budría and Moro-Egido (2018) also reported the qualitative relevance of previous skill mismatches. However, their goal was not to focus on gender differences. They did not use our categories of one or both previous over-skilling nor control for under-skilling and qualification (over and under) mismatches.

In terms of over-qualification, we find that, overall, the effects of either being overqualified to get the job or to do the job are equivalent (41 and 45 p.p. for men and 43 p.p. for women), but lower than that of past over-skilling status. The largest effect comes from being overqualified at both moments at the same time (51.6 p.p. for men and 48.8 p.p. for women) and is far lower than past over-skilling (the previous and starting current job effect is around 80 p.p.). By gender, we observe that the effect for females is lower, with the exception of being over-qualified to get the job. There is no effect of under-qualification in getting or doing the job.

To sum up our findings concerning our main goal, we find that the likelihood of being over-skilled at the current job increases with (i) past over-skilling status (large effect for men) and (ii) with over-qualification to get and to do the job (large effect for women). Moreover, the probability of being over-skilled decreases with past under-skilling status; an effect which is larger for women. The intuition of these results is as follows. Firstly, we find a certain persistent effect of over-skilling over time, which is larger for men. Secondly, learning by doing or the acquisition of skills while working, if that is the case, reduces under-skilling status, but is not enough for employees to become over-skilled. Indeed, the fact that an employee is over-qualified denotes an inefficient hiring process in which formal education acts as a signal of skills and leads to a higher probability of being over-skilled; an effect which is larger for women.

The literature on persistence is mixed and mostly based on over-education (Ramos and Sanroma, 2011; Clark et al., 2014; Verhaest et al., 2015; among others). Our results on the persistence of over-skilling go in the direction of Mavromaras et al. (2013) and Cedefop (2015). Green and McIntosh (2007) also found a weaker correlation with over-qualification, although the evidence is scarce given that both terms are used interchangeably (Belfield, 2010). Given that under-skilling has received little attention, we cannot compare our results.

By field of education, the likelihood of being over-skilled is related to the humanities, languages and arts, economics, business and law. These fields display a similar qualitative effect for both genders, which is to increase the likelihood of being over-skilled at the current job. However, the magnitude of the effect of humanities, languages and arts for women is large (7.3 p.p.),[13] while for economics, business and law it is similar. Note that a large percentage of the population have studies related to the

[13] For the sake of simplicity, marginal effects for field of education are not reported in the tables, but are available upon request.

fields of economics, business and law (23% of the sample), hence the negative effect on the work force is significant.

Some other fields of study display a differential effect by gender. In the case of men, studies related to education, the natural sciences and computer sciences are associated with a larger probability of being over-skilled. The percentage of men studying computer sciences is 16%, which again shows a large negative incidence in the labour force. For women, this effect comes from engineering sciences and medicine and health sciences (with magnitudes of 4.7 and 3.8, respectively). The percentage of women studying medicine and health sciences is 14%, which again shows a large negative incidence in the labour force. Note that the inclusion of all fields and not the ERC classification is appropriate given that the effects are not consistent across ERC groups. Dolton and Silles (2008) only found a significant effect in humanities on over-qualification to get and to do the job for the whole sample. Caroleo and Pastore (2018) found that all fields of education are more likely to lead to over-qualification to get and over-skilling to do the job than engineering and architecture.

In terms of individual and job characteristics, we find that some effects appear only for women.[14] In particular, women whose previous labour status was self-employed, whose job involves non-routine tasks, who have a job tenure longer than 15 years and who work in a firm with 250–499 workers are more likely to be over-skilled in the current job. Dolton and Silles (2008) found this effect not only for large firms, but also for firms with 100–249 workers. Those findings evince the possible large skill acquisition process through working, which perpetuates over-skilling. However, women who are in the same occupation as the first job and whose job involves working with a team are less likely to be currently over-skilled. For men, there were some effects but they do not prevail once we control for country characteristics.

Finally, with respect to country characteristics, we also find some gender effects. Firstly, a larger share of employees in the public administration increases males' likelihood of being over-skilled. McGuinness et al. (2018a) found these results for men and over-education. For women, countries with a higher participation rate and lower percentage of women in employment increase the likelihood of being over-skilled. McGuinness et al. (2018a) and Budría and Moro-Egido (2018) reported a similar effect for all workers, not only for women, as we find. The intuition given by these authors does

[14] For ease of reading, these results have been moved to Table S6 in Supplemental Material.

not apply here, since we have shown that males' current status of over-skilling does not depend on this particular labour market characteristic.

Taking advantage of multilevel techniques, our estimation results can provide additional insight. We can rank countries by random intercept in over-skilling by gender. That is, we can calculate the level of the ξ_{0c} in the null model for any country and gender and see how it evolves when all controls are included. Graphically, we observe that the trend is flatter (see Figure 1), which corroborates that country variance has decreased. Therefore, country differences in over-skilling in the current job for both men and women are lower once we control for different individual, job and country characteristics.

Additionally, we can see a group of countries characterized by a lower average incidence of over-skilling than the sample average (those with $\xi_{0c} < 0$ in the null model), such as Estonia, Latvia and Lithuania. In those countries, initially for both genders, the average incidence of over-skilling was far below the average of the whole sample, but they converge to the average when all controls are included. On the other side, we find Germany, Spain, the United Kingdom and Greece, which show a reverse process, that is, they are initially above the average and then around it, but with differences by gender. Note that in Germany and Greece, after including all the controls, the average incidence is below the sample average and the effect is larger for men than women. In other words, after controlling for all the characteristics, the incidence of over-skilling among men is lower than the average in these two countries, and much lower compared to women. In Spain and the United Kingdom, however, there are no such gender differences. Finally, for Italy we find that males' incidence is lower than the average, while women's incidence is on the average, and that female's incidence is higher than the average in Romania.

------- Insert Figure 1 around here -------

Finally, we implement a Neumark (1988) and Oaxaca and Ransom (1994) decomposition to investigate the contribution of coefficients and endowments to the gender over-skilling gap. The aim of this exercise is primarily to examine the relevance of the components skill-mismatches – the component due to differences in the distribution of personal/individual characteristics (characteristics) and that due to the different return of these characteristics (coefficients). This is a relevant issue from the policy perspective, and different implications can be drawn depending on whether the source of the gender skill mismatch gap is the former or the latter. Table 6 presents the decomposition estimation results.

------- Insert Table 6 around here -------

We find that the raw hazard rate differentials for over-skilling are higher for women by 0.04. Around 40% of the raw differences can be explained by the different characteristics of men and women. This percentage rises to 49% when country characteristics are included in the model. Characteristics of women and the return of these characteristics reinforce the likelihood of being over-skilled for women (49% characteristics and 51% coefficients). For the case of men, the relative importance of coefficients is larger than for women (34% characteristics and 66% coefficients). Therefore, the contribution of unfair differences is lower for women than for men.

We have made some additional estimations using random slope multilevel techniques to check whether the effect of some of the relevant variables differs by country. In general, the model for the variable x_{ic} is:

$$\log\left(\frac{M_{ic}}{1-M_{ic}}\right) = \gamma_0 + \tilde{\gamma}_1 x_{ic} + \boldsymbol{\gamma}_1' \boldsymbol{X}_{ic} + \boldsymbol{\gamma}_2' \boldsymbol{W}_c + \xi_{0c} + \xi_{1c} x_{ic} + \varepsilon_{ic}$$

Therefore, we also have an estimation of between-country variance of the effect of x_{ic}, measured by $\sigma^2_{\xi_1}$. When analysing this for gender, we find no evidence of differential effects by country given that $\sigma^2_{\xi_1}$ is not significantly different from zero. If we perform the same analysis with previous over-skilling status (previous job and starting current job) and being overeducated (to get and to do the job), which are the most relevant variables, we again find that there are no differences by country.

6. Conclusions and discussion

As pointed out in McGuinness et al. (2018a, 2018b), the evidence relating to the incidence, effects and possible policy responses to skills mismatch is still unclear and in a very early stage. Nevertheless, policy interventions in this area would be beneficial for individuals, firms and the macro-economy. European governments, as part of the Europe 2020 strategy, set the target of increasing the share of the population having completed higher education to 40%. However, in light of our results, more education is not needed if it ends up in mismatches and has negative effects on individuals, firms and society as a whole. An improved understanding of some of these effects and, above all, precisely identifying the existing routes out of job mismatches seems crucial to improving the effectiveness of policy intervention in this area.

Using a unique dataset (the Cedefop ESJS), we are able to establish some findings in terms of descriptive statistics. We present here a summary of the most salient ones regarding excess qualifications and skills. First, more than 40% of workers report being over-skilled and around one third over-qualified, with women less affected by over-skilling and more affected by over-qualification. Secondly, for both genders, the incidence of over-skilling when starting the current job is larger than the incidence of over-skilling in the previous job for employees who are over-skilled, while the reverse occurs for employees who are not over-skilled. Additionally, the incidence of over-qualification to get the job is lower than to do the job, independently of over-skilling status and gender. Fourthly, independently of over-skilling status in the current job, women are more affected by over-qualification than men, whereas men are more affected by over-skilling in the previous job only if they are over-skilled in the current job. There are no gender differences in over-skilling when starting the job.

In terms of the determinants, we find that the likelihood of being over-skilled at the current job increases with (i) past over-skilling status (large effect for men) and (ii) over-qualification to get and to do the job (large effect for women). The probability of being over-skilled decreases with past under-skilling status and has a large effect for women. The intuition of these results is as follows. Firstly, we find a certain persistent effect of over-skilling over time, which is larger for men. Secondly, learning by doing or the acquisition of skills while working, if that is the case, reduces under-skilling status, but is not enough for employees to become over-skilled. Indeed, the fact that an employee is over-qualified denotes an inefficient hiring process in which formal education acts as a signal of skills and leads to a higher probability of being over-skilled; an effect which is larger for women. For the case of men, the relative importance of coefficients is larger than for women (34% characteristics and 66% coefficients). Therefore, for women the contribution of unfair differences is lower than for men.

In light of our results, the persistence in over-skilling mainly for men, as suggested by mismatches theories, would require redesigning firms' hiring processes or making the demand less rigid. As pointed out in Brunello and Wruuck (2019), employers are likely to have more accurate information about skill requirements, and the selection process should be enhanced with this information.

Moreover, the higher likelihood of ending up being over-skilled if the employee is over-qualified (mostly in women) suggests that educational institutions should redesign the supply side of their programmes, avoid feminization in certain fields of study and promote a larger degree of labour market mobility. However, from the demand side, governments should promote programmes that stimulate companies to move into higher value-added products and services and therefore increase the use of skills provided by higher education.

An additional insight of our results relies on the new skill requirements given that new sectors and jobs are emerging while others are shrinking. Even within existing occupations, the task performed and the skills needed are subject to important changes. Thus, skill demand varies with business cycles. Therefore, the excess of skills could be larger if these skills are not in line with these changes. As pointed out in Brunello and Wruuck (2019), the adoption of new technologies, and therefore the demand for new skills, are not immediately available in the labour market and in the educational sector.

Finally, in countries with larger shares employed in the public administration, we find that men have a high likelihood of being over-skilled, while this effect occurs for women in countries with a larger participation rate and lower percentage of women in employment. The intuition behind the public administration effect might reside in higher unemployment rates or job insecurity, which leads men to secure jobs in this sector, even if they are mismatched. As in McGuinness et al. (2018a), the idea that factors stimulating female labour participation may increase over-education could be interpreted as the existence of different policy approaches to facilitate effective female participation. Thus, these policies should be evaluated.

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APPENDIX

Table 1. Descriptive statistics of mismatches

	Males		Females		Diff.
Panel A: Over-skilled	Mean	Std. Dev.	Mean	Std. Dev.	
Overskilled	0.45	0.50	0.41	0.49	0.04***
Categories					
NoStart_NoPrevious_Over	0.51	0.49	0.54	0.50	-0.03***
NoStart_Previous_Over	0.18	0.39	0.17	0.38	0.01
Start_NoPrevious_Over	0.13	0.33	0.13	0.34	0.00
Start_Previous_Over	0.18	0.39	0.15	0.36	0.03***
Panel B: Under-skilled	Mean	Std. Dev.	Mean	Std. Dev.	
NoStart_NoPrevious_Under	0.75	0.43	0.72	0.45	0.03***
NoStart_Previous_Under	0.06	0.23	0.05	0.23	0.01***
Start_NoPrevious_Under	0.15	0.36	0.18	0.38	-0.03***
Start_Previous_Under	0.05	0.21	0.05	0.23	0.00
Panel C: Over-educated	Mean	Std. Dev.	Mean	Std. Dev.	
NoGet_NoDo_Over	0.61	0.49	0.58	0.49	0.03***
NoGet_Do_Over	0.08	0.27	0.08	0.27	0.00
Get_NoDo_Over	0.03	0.17	0.03	0.17	0.00
Get_Do_Over	0.28	0.45	0.31	0.46	-0.03***
Panel B: Under-educated	Mean	Std. Dev.	Mean	Std. Dev.	
NoGet_NoDo_Under	0.92	0.27	0.93	0.26	-0.01***
NoGet_Do_Under	0.02	0.14	0.02	0.13	0.00
Get_NoDo_Under r	0.02	0.13	0.02	0.13	0.00
Get_Do_Under	0.04	0.19	0.04	0.19	0.00
N. Obs.	11948		10505		

Table 2. Descriptive statistics of joint incidence

		Over-skilled					**No Over-skilled**				
		Male		Female		Diff.	Male		Female		Diff.
%		0.44		0.40			0.56		0.60		
Panel A: Excess		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Over-skilled	Start	0.57	0.50	0.56	0.50	0.01	0.10	0.30	0.10	0.30	0.00
	Previous	0.51	0.50	0.46	0.50	0.05***	0.24	0.43	0.24	0.42	0.00
Over-educated	To get	0.38	0.49	0.44	0.50	-0.06***	0.24	0.44	0.27	0.45	-0.03***
	To do	0.44	0.50	0.50	0.50	-0.06***	0.30	0.46	0.31	0.46	-0.01
Panel B: Deficit		Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Under-skilled	Current						0.10	0.29	0.09	0.29	0.01*
	Start	0.11	0.31	0.11	0.31	0.00	0.27	0.44	0.32	0.46	-0.05***
	Previous	0.08	0.27	0.08	0.27	0.00	0.12	0.33	0.13	0.33	-0.01
Under-educated	To get	0.05	0.21	0.04	0.19	0.01***	0.07	0.25	0.07	0.25	0.00
	To do	0.04	0.20	0.04	0.21	0.00	0.07	0.26	0.06	0.25	0.01***

Table 3. Descriptive statistics of field of education

	Males		**Females**		**Diff.**
	Mean	Std. Dev.	Mean	Std. Dev.	
Agriculture_Veterinary	0.02	0.12	0.02	0.13	0.00
Mathematics_Statistics	0.05	0.22	0.03	0.18	0.02***
Other_SocialSciences	0.05	0.21	0.08	0.27	-0.03***
Natural_Sciences	0.08	0.27	0.09	0.28	-0.01***
Education	0.06	0.24	0.12	0.33	-0.06***
Humanities_Languages_Arts	0.07	0.26	0.12	0.33	-0.05***
Medicine_HealthSciences	0.06	0.24	0.14	0.35	-0.08***
Computing_Sciences	0.16	0.36	0.05	0.22	0.11***
Engineering_Sciences	0.21	0.41	0.07	0.26	0.14***
Economics_Bussiness_Law	0.24	0.42	0.23	0.42	0.01
Other	0.01	0.32	0.05	0.32	-0.04***
N. Obs.	11948		10505		

Table 4. Main estimation results

	Males			Females		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Overskill: NoStart NoPrevious (Ref.)						
NoStart Previous Over		0.753***	0.749***		0.641***	0.640***
		(0.058)	(0.058)		(0.064)	(0.064)
Start NoPrevious Over		2.177***	2.175***		2.132***	2.130***
		(0.071)	(0.071)		(0.075)	(0.075)
Start Previous Over		2.853***	2.851***		2.672***	2.667***
		(0.075)	(0.075)		(0.084)	(0.084)
Underskill: NoStart NoPrevious (Ref.)						
NoStart Previous Under		0.035	0.038		0.157	0.158
		(0.094)	(0.094)		(0.102)	(0.102)
Start NoPrevious Under		-0.448***	-0.442***		-0.547***	-0.541***
		(0.065)	(0.065)		(0.069)	(0.069)
Start Previous Under		-0.210*	-0.200+		-0.423***	-0.418***
		(0.106)	(0.106)		(0.116)	(0.116)
Overqualification: NoGet NoDo (Ref.)						
NoGet Do Over		0.259**	0.266**		0.423***	0.428***
		(0.092)	(0.092)		(0.100)	(0.100)
Get NoDo Over		0.063	0.064		0.466**	0.467**
		(0.134)	(0.134)		(0.142)	(0.142)
Get Do Over		0.606***	0.616***		0.741***	0.743***
		(0.055)	(0.055)		(0.059)	(0.059)
Underqualification: NoGet NoDo(Ref.)						
NoGet Do Under		0.049	0.057		-0.028	-0.024
		(0.192)	(0.193)		(0.226)	(0.226)
Get NoDo Under		0.146	0.166		-0.305	-0.295
		(0.178)	(0.178)		(0.221)	(0.221)
Get Do Under		-0.140	-0.127		-0.207	-0.203
		(0.134)	(0.134)		(0.159)	(0.159)
Field of Education: other (ref.)						
Education		0.230*	0.231*		0.049	0.056
		(0.093)	(0.093)		(0.080)	(0.080)
Humanities Languages Arts		0.228**	0.224**		0.439***	0.441***
		(0.087)	(0.087)		(0.077)	(0.077)
Economics Bussiness Law		0.237***	0.240***		0.246***	0.254***
		(0.059)	(0.059)		(0.066)	(0.066)
Other SocialSciences		0.040	0.040		0.092	0.095
		(0.105)	(0.105)		(0.091)	(0.091)
Natural Sciences		0.200*	0.209*		-0.072	-0.071
		(0.090)	(0.090)		(0.098)	(0.098)
Mathematics Statistics		-0.177	-0.177		0.091	0.097
		(0.109)	(0.109)		(0.140)	(0.140)
Computing Sciences		0.236***	0.241***		0.052	0.060
		(0.067)	(0.067)		(0.114)	(0.114)
Engineering Sciences		0.111+	0.119+		0.279**	0.293**
		(0.061)	(0.061)		(0.102)	(0.102)
Agriculture Veterinary		-0.316+	-0.305+		-0.128	-0.122
		(0.171)	(0.171)		(0.201)	(0.201)
Medicine HealthSciences		0.209*	0.207*		0.245**	0.243**
		(0.103)	(0.103)		(0.084)	(0.084)
COUNTRY CHARACTERISTICS						
GDP			0.011			0.003
			(0.014)			(0.017)
R&D			-0.000			-0.000
			(0.000)			(0.000)
Unemp rate			0.011			-0.018
			(0.020)			(0.024)
Part rate			0.022			0.097*
			(0.031)			(0.038)
%Tertiary			-0.004			-0.001
			(0.012)			(0.015)
%Females			-0.019			-0.056+
			(0.024)			(0.029)
%Manufacturing			-0.039			-0.017
			(0.027)			(0.032)
%Parttime			0.006			0.002
			(0.004)			(0.005)
%PublicAd			0.232**			0.079
			(0.084)			(0.103)
%Temporary			-0.003			0.002
			(0.002)			(0.003)
%Vocational			0.070			0.070
			(0.059)			(0.072)
Ratio			-0.103			-0.560
			(1.004)			(1.182)
Const.	-0.374***	-1.853***	0.693	-0.529***	-1.791***	-3.835
	(0.069)	(0.290)	-2560	(0.081)	(0.320)	(3.009)
INDIVIDUAL CHARACTERISTICS	No	*Yes*	*Yes*	No	*Yes*	*Yes*
JOB CHARACTERISTICS	No	*Yes*	*Yes*	No	*Yes*	*Yes*
σ_{ε}^{2}	0.117**	0.058**	0.021+	0.162***	0.080**	0.035*
	(0.035)	(0.021)	(0.011)	(0.049)	(0.028)	(0.016)
VPC	0.03***	0.01+	0.01+	0.05***	0.01*	0.01*
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
N	11983	11983	11983	10539	10539	10539

Standard errors in parentheses. + p<0.1. * p<0.05. ** p<0.01. *** p<0.001

Table 5. Main estimation results (marginal effects in Model 3)

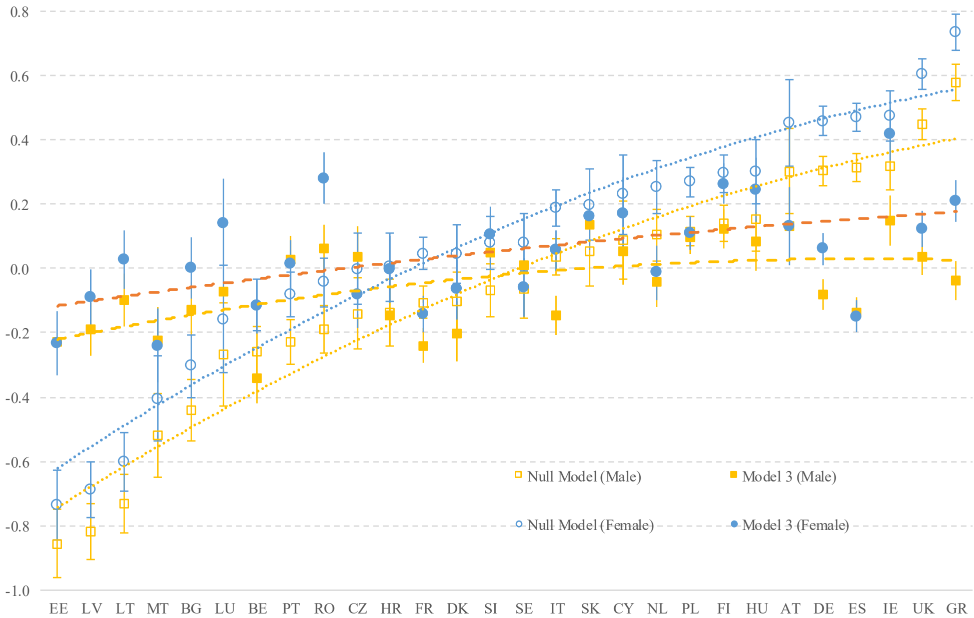
	Males	Females	Diff.
Over-Skilling			
NoStart NoPrevious	0.252 (0.008)	0.242 (0.010)	0.010***
NoStart_Previous	0.408 (0.013)	0.367 (0.015)	0.041***
Start_NoPrevious	0.727 (0.014)	0.697 (0.015)	0.030***
Start_previous	0.837 (0.010)	0.792 (0.014)	0.044***
Under-Skilling			
NoStart NoPrevious	0.452 (0.007)	0.419 (0.009)	0.033***
NoStart_Previous	0.459 (0.017)	0.448 (0.019)	0.011***
Start_NoPrevious	0.376 (0.011)	0.328 (0.012)	0.048***
Start_previous	0.417+ (0.019)	0.348 (0.020)	0.069***
Over-qualification			
NoGet NoDo	0.405 (0.007)	0.356 (0.009)	0.049***
NoGet_Do	0.452 (0.017)	0.430 (0.019)	0.022***
Get_NoDo	0.416 (0.023)	0.437 (0.026)	-0.020***
Get_Do	0.516 (0.010)	0.488 (0.012)	0.028***
Under-qualification			
NoGet NoDo	0.438 (0.007)	0.402 (0.008)	0.036***
NoGet_Do	0.448 (0.034)	0.398 (0.038)	0.050***
Get_NoDo	0.467 (0.032)	0.353 (0.036)	0.114***
Get_Do	0.416 (0.023)	0.368 (0.026)	0.048***

Standard errors in parentheses. + p < 0.1. * p < 0.05. ** p < 0.01. *** p < 0.001

Table 6. Main estimation results (Oxaca-Blinder decomposition in Model 3)

		Mismatches	*Mismatches +field of education*	*Model 2*	*Model 3*
Females	*Characteristics*	-0.02***	-0.02**	-0.02**	-0.02**
	St.dev	(0.00)	(0.01)	(0.01)	(0.01)
	%	0.42	0.38	0.40	0.49
	Coefficients	-0.02***	-0.03***	-0.02**	-0.02**
	St.dev	(0.01)	(0.01)	(0.01)	(0.01)
	%	0.58	0.62	0.60	0.51
Males	*Characteristics*	-0.02***	-0.01**	-0.01*	-0.01**
	St.dev	(0.00)	(0.00)	(0.00)	(0.00)
	%	0.43	0.33	0.26	0.34
	Coefficients	-0.02***	-0.03***	-0.03***	-0.03***
	St.dev	(0.01)	(0.01)	(0.01)	(0.01)
	%	0.57	0.67	0.74	0.66
	Raw	-0.04***			
	St.dev	(0.01)			
	%	1.00			

Figure 1: Over-skilling to do the job (evolution of country residuals)



Note: Austria (AT). Belgium (BE). Bulgaria (BG). Croatia (HR). Cyprus (CY). Czech Republic (CZ). Denmark (DK). Estonia (EE). Finland (FI). France (FR). Germany (DE). Greece (GR). Hungary (HU). Ireland (IE). Italy (IT). Latvia (LV). Lithuania (LT). Luxembourg (LU). Malta (MT). Netherlands (NL). Poland (PL). Portugal (PT). Romania (RO). Slovakia (SK). Slovenia (SI). Spain (ES). Sweden (SE) and United Kingdom (UK).