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SKILLS MISMATCH AND WAGE INEQUALITY: EVIDENCE FOR DIFFERENT COUNTRIES IN EUROPE

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Abstract. This paper studies the relationship between mismatch between workers' skills and labour market requirements throughout different European Countries. It reports evidence that in several countries, over-skilled people tend to have a wage penalty and under-skilled people tend to have a premium. Interestingly, despite the typical effects of education, tenure, experience, and gender in wages being very similar, the effects of mismatch between skills and labour market requirements differ considerably across the wage distribution and the European Countries.

Keywords: education, educational mismatch, wage inequality.

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JEL Classification: I21; J31; O52.

Introduction

We study wage regressions, introducing coefficients that measure mismatch between skills and jobs features. The data used are from the European Working Conditions Survey, 2005 wave, allowing us to compare several European countries. There is a considerable body of literature on the effects of mismatch between education, skills, and job placements on wages. Muysken and Ter Weel (2000) develop a search-theoretical model of the labour market to explain the events of declining returns to schooling, over-education, and relatively higher unemployment rate of the low-skilled workers in the Netherlands. Guironnet and Peypoch (2007) find empirical evidence of over-education for low-skill French workers, while also finding a significant disequilibrium between wages and qualifications. Dolton and Silles (2008) seek evidence of over-education, and assess its main determinants in the UK. Cardoso

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(2004) found no evidence of over-education in the Portuguese labour market. McGoldrick and Robst (1996) found no evidence for differential over-education by gender. Sicherman (1991) characterizes overeducated workers. Overeducated workers are found to be younger, to have less on-the-job training, and higher rates of firm and occupational mobility. The findings suggest that over-education can be explained by the trade-off between schooling and other components of human capital and by the mobility patterns. Regarding the type of education, Robst (2007) analyses the relationship between college majors and job functions using US data. Substantial evidence of mismatch between jobs and college major was found, and this was reflected in lower wages.

As Rubb (2003) pointed out, the empirical literature until the time of his writing had presented evidence of a positive effect of over-education, less than the effect of required education and a negative effect of under-education on wages. Included in his literature review are Cohn and Kan (1995), Kiker *et al.* (1997), Sloane *et al.* (1999), and Hartog (2000), and many others. Tsai (2010) presents results for a panel data analysis of the US and argues that over-education does not cause lower earnings, as suggested in earlier studies. Instead, the significant wage differential found in those earlier studies is simply a result of ignoring the non-random assignment of workers to jobs. Ordine and Rose (2011) suggest the importance of schooling quality as a policy instrument to reduce mismatch. There is still a discussion in the literature concerning the reasons for the effects of over-education and over-skilling on wages. One of the reasons that have been argued is linked with the omission of skills variables in wage regressions. The argument is that some workers end up being lower paid than others because, despite being better educated (have more years of schooling), they do not have the skills that are well-rewarded in the market, while the others do. Thus, the underlying cause for these effects on wages would be omitted heterogeneity in the empirical frameworks.

However, more recently McGuiness and Sloane (2011) studied mismatch in the UK labour market and concluded that over-education and being over-skilled imply a wage penalty. Note that according to these authors, over-skilling has stronger negative effects on job satisfaction than over-education, which may suggest a trade-off between wage and other characteristics of the job. These authors conclude that it is over-skilling on which the policy focus should be, as this represents welfare losses to both the individual and the economy as a whole. We follow this line of thought by centring our analysis on skills (rather than education) mismatches. The different effects from mismatch in education and mismatch in skills has been addressed by Alen and Velden (2001), McGuiness and Sloane (2011), while Tsang and Levin (1985) relied on the psychology literature to argue that workers with jobs requiring more education often exhibit counterproductive behaviour in the workplace, an argument easily extended to over and under-skilled workers.

Lamo and Messina (2010) confirmed that the over-educated have lower wages in Estonia, attributing this effect to a transition period. Budria and Moro-Egido (2008) found evidence of over-skilling in the Spanish labour market. However, only strongly mismatched workers had a significant wage penalty. Moreover, these authors showed that matched workers have significantly higher returns to education than do mismatched workers.

We extend the empirical work presented so far by showing evidence from a large sample of European countries with a single methodology, and concentrate our efforts on mismatch in skills. This follows the Budria and Moro-Egido (2008:341) suggestion: "To our eyes, assessing

the impact that educational mismatches have in the European wage structure is a compelling task for future research." As these authors did, we also study the mismatch influence on wages throughout the distribution of wages, thereby examining its effect on wage inequality. Interestingly, we found that the pattern of the mismatch effect in wages differs considerably across European labour markets. We also found that the most common significant result is that under-skilling positively influences wages, while over-skilling negatively influences wages. However, this also varies across wage distributions within each country. While the finding that over-skilling negatively affects wages is relatively consistent in the literature (when compared with perfectly matched workers), the consistent finding that under-skilling positively affects wages is relatively newer, as earlier findings were that under-educated have a negative return (see e.g. Rubb 2003).

The article proceeds as follows. Section 1 presents data and the estimating model. Section 2 presents the results and is divided into three sub-sections: Section 2.1 presents the results for the usual variables (education, experience, tenure, etc.) in wage regressions; Section 2.2. details the results on the effects of over and under-skilling on wages; and Section 2.3. presents the results from a pooled regression with all the countries. The final section concludes the study.

1. Data and estimating model

We collected data from the 2005 wave of the European Working Conditions Survey[1] (EWCS) (Eurofound 2012) for 31 European countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. This survey was conducted under the supervision of the European Commission and follows the well-known survey "European Community Household Panel (ECHP)", which ended with the 2001 wave.

This survey contains personal and labour market characteristics including wage, hours worked, gender, marital status, experience, tenure, ISCED education levels and sector of the firm, among other variables. Table 1 summarizes the variables used and their respective definitions. The database also has the data that come from a question asking the respondent whether he/she has the training to deal with his/her current duties. The respondent answers if his/her skills correspond to his/her work duty ["1" I need further training to cope well with my duties; "2" My duties correspond well with my present skills; "3" I have the skills to cope with more demanding duties; "8" no opinion; "9" refuses to answer]. We eliminated answers 8 and 9 and interpret answer "1" as under-skilling and answer "3" as over-skilling, while answer "2" is a correct match between education/skills and work duties or requirements. This yields somewhat different information about mismatches from that offered by the former European Household Community Panel, which was used to study mismatches in the Spanish labour market by Budria and Moro-Egido (2008). The most important difference is that in our case (EWCS) there is no information about whether the skills that the question

[1] http://eurofound.europa.eu/ewco/surveys/

refers to were acquired through formal training and education or not. We therefore refer to mismatch in skills and not to mismatch in education.

Table 1. Variables and measurement

Variables	Variables at the regression	Definition	Measure
Wages	Wages	Monthly income measured by deciles (divided by 10 parts, each part corresponds to a group of income of each country)	"01" A; "02" B; "03" C; "04" D; "05" E; "06" F; "07" G; "08" H; "09" I; "10" J.
Education	edu0 (dummy for ISCED0); edu1 (dummy for ISCED1); edu2 (dummy for ISCED2); edu3 (dummy for ISCED3); edu4 (dummy for ISCED4); edu5 (dummy for ISCED5); edu6 (dummy for ISCED6).	International Standard Classification of Education (ISCED)	"0" ISCED0; "1" ISCED1; "2" ISCED2, "3" ISCED3, "4" ISCED4, "5" ISCED5, "6" ISCED6.
Experience	exper; exper2 (experience squared)	Number of years that respondent stopped full-time education and started a paid employment	Number of years.
Tenure	Tenure	Number of years that respondent is working at the company	"00" if less than 1 year; Number of years otherwise.
Age	Age	Age of respondent	Number of years.
Marital Status	MaritalStatus (dummy for married)	Relationship of respondent to other members of his/her household	"01" spouse/partner; "00" other.
Gender	Gender	Gender of Respondent	"1" for male; "2" for female
Firm Size	FirmSize	Company size, which is measured by number of employees that respondent's workplace has	"01" for 1 (interviewee works alone); "02" for 2–4; "03" for 5–9; "04" for 10–49; "05" for 50–99; "06" 100–249; "07" for 250–499; "08" for 500 and over.
Firm Sector	FirmSector	Sector that respondent works in	"1" private sector; "2" public sector; "3" joint private-public organization or company; "4" non-for-profit sector, NGO; "5" other.
Underskilling	mis1 (dummy for underskilling)	Respondent answers if his/her skills correspond to his/her work duty	"1" I need further training to cope well with my duties; "0" Other answers.

Continued Table 1

Variables	Variables at the regression	Definition	Measure
Over-skilling	mis3 (dummy for overskilling)	Respondent answers if his/her skills correspond to his/her work duty	"1" I have the skills to cope with more demanding duties; "0" Other answers.

Note: Non-responses, refusals, and non-opinion were deleted from the analysis

Additionally the income-related variable in ECWS is Monthly income measured by deciles (divided by 10 parts, each part corresponding to an income group for each country). EWCS justifies the earnings definition as follows. Giving the respondents a scale on which they can place themselves tends to produce higher response rates than enquiring directly about earnings. The problem facing international surveys, however, is how to make the scales meaningful in each country (by adapting them to the national pay levels) but also comparable internationally. The Foundation's approach to this issue in the fourth *European Working Conditions Survey* was to ensure that the national 10-point scales roughly matched the real distribution of earnings. Using Eurostat's European Earnings Structure Survey 2002, the earnings of each EU country were divided into 10 bands (called 'deciles', each representing 10% of the respondents), and ranked from low to high (Parent-Thirion *et al.* 2007).

This yields a better comparison between countries. Although differing substantially in the information provided, this is currently one of the most complete databases on labour information for Europe.

We estimated the following earnings equation:

$$w_i = \alpha_0 + \alpha_{\theta_1} X_i + \alpha_{\theta z} mis1 + \alpha_{\theta z} mis3, \quad (1)$$

where the subscript θ denotes the estimate at the θ^{th} conditional quantile, in which θ = 10, 25, 50, 75, and 90. The dependent variable, w_i, is the ECWS variable for wage, and X_i is a vector of explanatory variables, including education dummies, corresponding to the different ISCED levels[2], experience (and experience squared), tenure, gender, sector, and firm size. *mis*1 is a dummy variable that takes 1 if the answer to the question mentioned above was 1, i.e. 'I need further training to cope well with my duties', and mis3 is a dummy variable that takes 1 if the answer to the question mentioned above was 1, i.e. 'I have the skills to cope with more demanding duties'.

As usual in labor market studies, and in particular with the estimation of earnings equations, we use OLS estimation. To allow for assessing the effect of different determinants of earnings and specifically of mismatch on the wage distribution, we also employ quantile regressions (Koenker, Hallock 2001). In this article, we employ the design matrix bootstrap method to obtain estimates of standard errors for the coefficients, with 100 interactions. This method is robust to relatively small samples and more importantly, it is valid under many forms of heterogeneity (Buchinsky 1995, 1998). As there are no variables in the database that allows to access selection issues, we need to be clear that this model applies only to mismatch within the employed workers.

[2] In an alternative specification we introduce education levels as given in the database (from 1 to 6 in most countries) and main results do not differ. We include education as dummies thanks to a referee's suggestion.

The samples dimension for each country, as well as averages for the mismatch variables are detailed in Table 2.

2. Results

2.1. General results from countries wage regressions

Table 3 shows our results for the OLS and quantile (median) regressions, regarding the sign and statistical significance of the typical regressors. For the quantitative analysis we also refer the reader to the Tables in the Appendix that contain all of the coefficients and standard error values for all countries[3].

Table 2. Number of observations and average for overskilling and underskilling for each country

Country	Austria (1)	Belgium (2)	Cyprus (3)	Czech Rep. (4)	Germany (5)	Denmark (6)	Estonia (7)	Spain (8)
obs	610	687	551	659	839	924	446	695
Mis1 average	0.2655738	0.1201158	0.0671506	0.1198786	0.2133492	0.1374459	0.190583	0.0604317
Mis3 average	0.2114754	0.2836469	0.4065336	0.23217	0.250298	0.3203463	0.3251121	0.3482014
Country	**Finland (9)**	**France (10)**	**Greece (11)**	**Hungary (12)**	**Ireland (13)**	**Italy (14)**	**Lithuania (15)**	**Luxem-bourg(16)**
obs	955	703	801	846	797	658	801	468
Mis1 average	0.1385417	0.1026352	0.1223471	0.1134752	0.0991217	0.1458967	0.2197253	0.1374207
Mis3 average	0.2072917	0.4757282	0.4007491	0.3817967	0.3801757	0.2948328	0.2284644	0.3784355
Country	**Latvia (17)**	**Nether-lands(18)**	**Malta (19)**	**Poland (20)**	**Portugal (21)**	**Sweden (22)**	**Slovenia (23)**	**Slovakia (24)**
obs	796	823	488	706	747	994	469	814
Mis1 average	0.144802	0.0933333	0.0997963	0.1600567	0.1137885	0.0611222	0.119403	0.1191646
Mis3 average	0.3279703	0.3042424	03095723	0.3116147	0.2396252	0.4138277	0.3518124	0.3452088
Country	**UK (25)**	**Norway (26)**	**Switzer-land (27)**	**Bulgaria (28)**	**Croatia (29)**	**Romania (30)**	**Turkey (31)**	
obs	626	848	889	877	639	702	890	
Mis1 average	0.0702875	0.1450472	0.1979753	0.0558723	0.1341654	0.1434659	0.1324355	
Mis3 average	0.4376997	0.2735849	0.3104612	0.3295325	0.4477379	0.4346591	0.3445567	

[3] We present a synthesis in the main text to increase readability and in response to a referee's suggestion.

First, we wish to analyse the results of the earnings regressions for each country in the light of the usual findings for earnings regressions that are reported in the literature. In fact, our results are clearly consistent with the usual findings, pointing to positive and significant effects of tenure on wages, together with the typical non-linear effect of experience and with a clear negative effect of gender (being a woman). Our results also reflect the importance of company size to the wage performance of workers, as larger firms tend to pay higher wages. Concerning education, nearly half of the countries show a significant positive sign for some of the education dummies and another half present negative and significant signs for some of the education dummies. As expected, negative signs predominate in dummies for the lowest levels of ISCED classification[4]. Tenure also has a clear and significant effect on wages in 25 of the 31 countries (exceptions are Croatia, Estonia, Finland, Slovenia, Sweden, and Turkey), with coefficients ranging from 0.019 to 0.087, meaning that an additional year of tenure implies a 0.2% to a 0.87% increase in wages. Experience and squared experience are also significant in almost all countries (in 29 out of the 31 countries), with Slovenia and Romania as exceptions. Coefficients oscillate from 0.069 to 0.23, meaning that an additional year of experience implies a 0.69% to 2.3% increase in wages. However, after some years, experience also presents the typical negative effect. For example, in Germany, after nearly 29 years of experience, additional years tend to decrease the worker wage. In the Czech Republic, however, this occurs after 17 years of experience.

Gender has a significantly negative effect in all countries with a quantitatively important effect, as being a woman means earning from 6.4% less (in Turkey) to nearly 27% less in the Netherlands. Interestingly, countries with a lower wage penalty for female are eastern European countries (Croatia, Hungary, Romania, and Slovenia)[5] Age is less significant than the above mentioned variables, but it has a negative and significant sign in 14 of the 31 countries. When significant, its effects range from a 0.2 to 1.1% decrease in wages per additional year. Marital status tends to influence wages positively in 14 out of 31 countries, a quantitative wage premium that ranges from nearly 3% to 5% from being married.

Finally, firm size has an overall significantly positive effect on wages (exceptions are Croatia, the Czech Republic, and Slovenia), as an increase in the size class of the firm would imply an increased wage of 1% to 3.6%. Estonia, Romania, and Sweden are among the countries in which the effect of firms' size is greatest. As can be seen in Table 3, the effect of mismatch is generally the least significant of the explanatory variables in the regressions, an issue that we will address below.

Our results from the quantile regression at the median almost confirm the OLS regression results, concerning both significance and quantitative effects (Table 3)[6]. Most countries show

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[4] Had we presented an alternative specification with education measured by ISCED levels and not dummies, education would have shown a clear and significant positive effect on wages, with coefficients that range from 0.20 (in Estonia) to 1.17 (in Croatia), meaning that one additional level of education (from primary to secondary, for example) implies that wages can increase from 2.0% to 11.7% (remembering that wages are measured by deciles of the wage distribution), results that are consistent with those usually obtained for returns to education. Results are available upon request.

[5] There is an extensive literature on the wage gender gap. A survey can be found in Kunze (2000), in which one see that estimated gaps oscillate widely between 7% and 93%.

[6] Due to space considerations, we are not displaying regressions from other quantiles than the median. However, coefficients for mismatch throughout different quantiles are shown in figures below.

a significantly positive effect of tenure (exceptions are now Denmark, Finland, Greece, Poland, Slovenia, and Sweden), experience (exceptions being Croatia, Estonia, the Netherlands, Slovenia, Romania, Turkey, and the UK), and firm size (exceptions being Austria, Croatia, the Czech Republic, Malta, and Slovenia); and significantly negative coefficients of experience squared (exceptions are Croatia, Hungary, the Netherlands, Poland, Romania, and Slovenia) and gender (no exceptions). The greatest difference from OLS is the more positive and significant signs of education dummies for 19 of 31 countries, in which negative signs are more linked with lower ISCED levels, which is an intuitive result[7].

Table 3. Sign and statistical significance of typical determinants of wages (OLS, quantile – median regression)

Var	Tenure	Experience	Experience^2	Education Dummies*	Gender	Firm Size	Age	Firm Sector	Marital Status
Expected Sign	(+)	(+)	(–)	(+)	(–)	(+)	(–)	Undefined	Undefined
Austria	(+), (+)	(+), (+)	(–), (–)	(–), (+)	(–), (–)	(+), (ns)	(–), (ns)	(–), (ns)	(ns), (ns)
Belgium	(+), (+)	(+), (+)	(–), (–)	(–), (ns)	(–), (–)	(+), (+)	(–), (ns)	(ns), (ns)	(ns), (ns)
Cyprus	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (+)	(ns), (ns)
Czech Rep.	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(ns) , (ns)	(ns), (ns)	(ns), (ns)	(+), (ns)
Germany	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(–), (ns)	(–), (–)	(ns), (ns)
Denmark	(+), (ns)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(–), (ns)	(ns), (ns)	(+), (ns)
Estonia	(ns), (+)	(+), (ns)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(–), (–)	(ns), (ns)	(ns), (ns)
Spain	(+), (+)	(+), (+)	(–), (–)	(+), (–)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(ns), (ns)
Finland	(ns), (ns)	(+), (+)	(–), (–)	(–), (+)	(–), (–)	(+), (+)	(ns), (ns)	(–), (ns)	(+), (+)
France	(+), (+)	(+), (+)	(–), (–)	(–), (ns)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (+)
Greece	(+), (ns)	(+), (+)	(–), (–)	(+), (–)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (+)
Hungary	(+), (+)	(+), (+)	(–), (ns)	(–), (–)	(–), (–)	(+), (+)	(–), (ns)	(–),(ns)	(+), (ns)
Ireland	(+), (+)	(+), (+)	(–), (–)	(–), (+)	(–), (–)	(+), (+)	(–), (–)	(ns), (ns)	(ns), (ns)
Italy	(+), (+)	(+), (+)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (+)
Lithuania	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(–), (–)	(ns), (ns)
Luxembourg	(+), (+)	(+), (+)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(ns), (ns)
Latvia	(+), (+)	(+), (+)	(–), (–)	(+), (–)	(–), (–)	(+), (+)	(–), (–)	(–), (–)	(ns), (ns)
Netherlands	(+), (+)	(+), (ns)	(–), (ns)	(+), (+)	(–), (–)	(+), (+)	(ns), (ns)	(–), (–)	(+), (ns)
Malta	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (ns)	(ns), (ns)	(ns), (ns)	(+), (+)

[7] Alternative specification with education measured by ISCED levels and not dummies, education has a clear and significant positive effect on wages, as described above in footnote 5 for OLS estimations, ranged, in the case of median regression, from a 2.5% to a 12.3% wage premium by ISCED level.

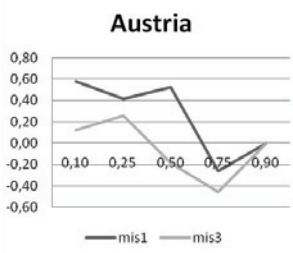
Continued Table 3

Var	Tenure	Experience	Experience^2	Education Dummies*	Gender	Firm Size	Age	Firm Sector	Marital Status
Poland	(+), (ns)	(+), (+)	(–), (ns)	(+), (+)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (ns)
Portugal	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (+)
Sweden	(ns), (ns)	(+), (+)	(–), (–)	(–), (+)	(–), (–)	(+), (+)	(ns), (ns)	(–), (–)	(ns), (ns)
Slovenia	(ns), (ns)	(ns) , (ns)	(ns), (ns)	(–), (+)	(–), (–)	(ns), (ns)	(ns), (ns)	(+), (–)	(ns), (ns)
Slovakia	(+), (+)	(+), (+)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(–), (–)	(–), (ns)	(+), (+)
UK	(+), (ns)	(+), (+)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(–), (ns)	(–), (ns)	(ns), (ns)
Norway	(+), (+)	(+), (+)	(–), (–), (–)	(+), (–)	(–), (–)	(+), (+)	(–), (–)	(–), (–)	(+), (ns)
Switzerland	(+), (+)	(+), (+)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(ns), (ns)	(+), (+)	(ns), (ns)
Bulgaria	(+), (+)	(+), (+)	(–), (ns)	(–), (+)	(–), (–)	(+), (+)	(–), (–)	(–), (–)	(ns), (ns)
Croatia	(ns), (ns)	(+), (ns)	(–), (ns)	(–), (+)	(–), (–)	(ns), (ns)	(ns), (ns)	(ns), (ns)	(ns), (ns)
Romania	(+), (+)	(ns), (ns)	(ns), (ns)	(+), (–)	(–), (–)	(+), (+)	(ns), (ns)	(ns), (ns)	(ns), (ns)
Turkey	(ns), (ns)	(+), (+)	(–), (–)	(–), (–)	(–), (–)	(+), (+)	(–), (–)	(+), (+)	(+), (ns)

Note: in the first brackets are OLS results, second brackets are quantiles results, (+) indicates positive and significant results, (–) to negative significant results and (ns) to non-significant results.
* (+) refers to a majority of dummies with positive and significant sign, (–) to a majority of dummies with negative and significant sign.

2.2. The effect of mismatch in countries regressions

The effect of mismatch between skills and labour market requirements on wages is non-significant in the majority of countries in both OLS and quantile regression on the median (Tables 3 and 4). From OLS results, we see that under-skilling (having fewer skills than required) is significant in Germany, Hungary, Slovenia, and Spain (with a positive effect of being under-skilled) and in Ireland, Latvia, and Turkey (with a negative effect of being under-skilled). Thus, we have significant results in only a quarter of the countries studied. Significant coefficients oscillate roughly from 0.5 to 1.1, meaning that, for instance, in Germany an under-skilled worker tends to earn 8.9% more than a correctly matched worker. Significantly negative coefficients are around 0.5, meaning that in Ireland under-skilled workers tend to earn nearly 6% less than a matched worker. Over-skilling appears with a positive significant effect in Hungary and Lithuania and with a negative significant effect in Denmark, Estonia, Latvia, Malta, the Netherlands, Portugal, Slovakia, and Turkey. Again, less than a third of the countries show a significant effect of mismatch. Significantly negative results oscillate from near 0.3 to near 0.5, meaning that an over-skilled worker could earn 3% to 5% less than a matched worker. Additionally, the less common positive coefficients are 0.28 in Hungary and 0.58 in Lithuania, meaning that over-skilled workers earn 2.8% more in Hungary and 5.8% in Lithuania than the respective matched counterparts.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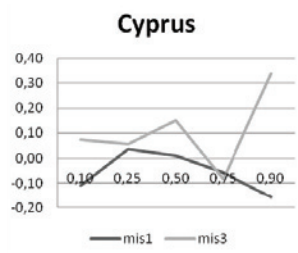
Cyprus
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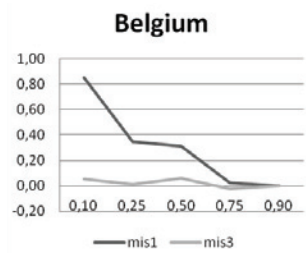
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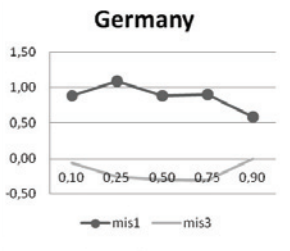
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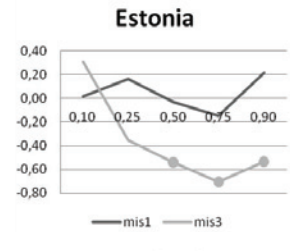
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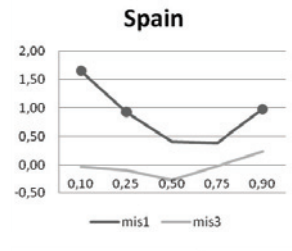
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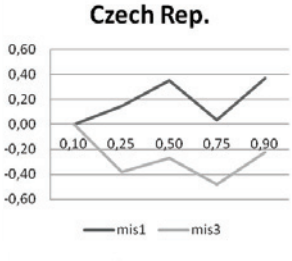
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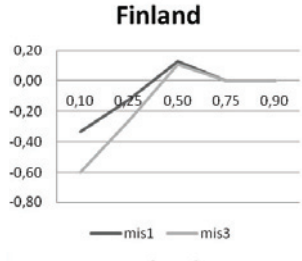
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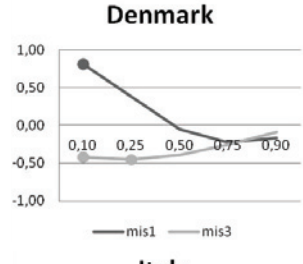
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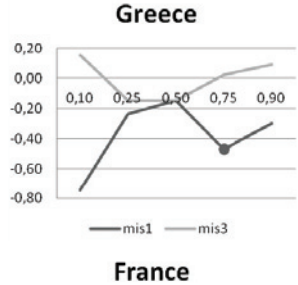
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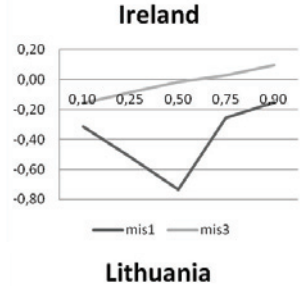
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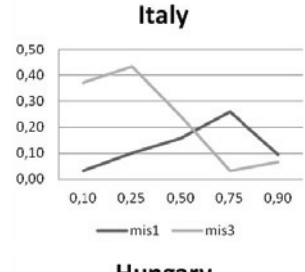
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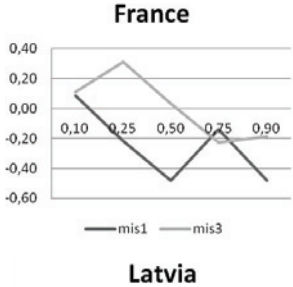
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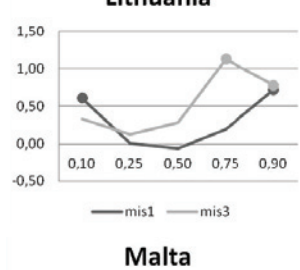
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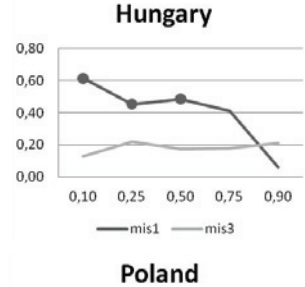
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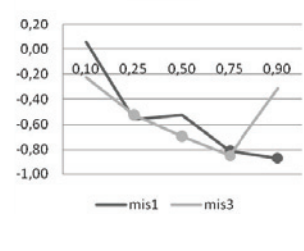
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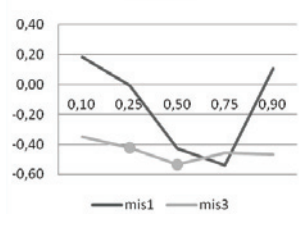
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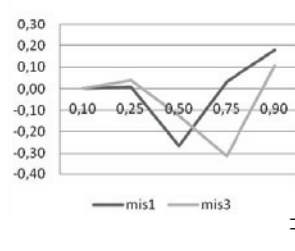
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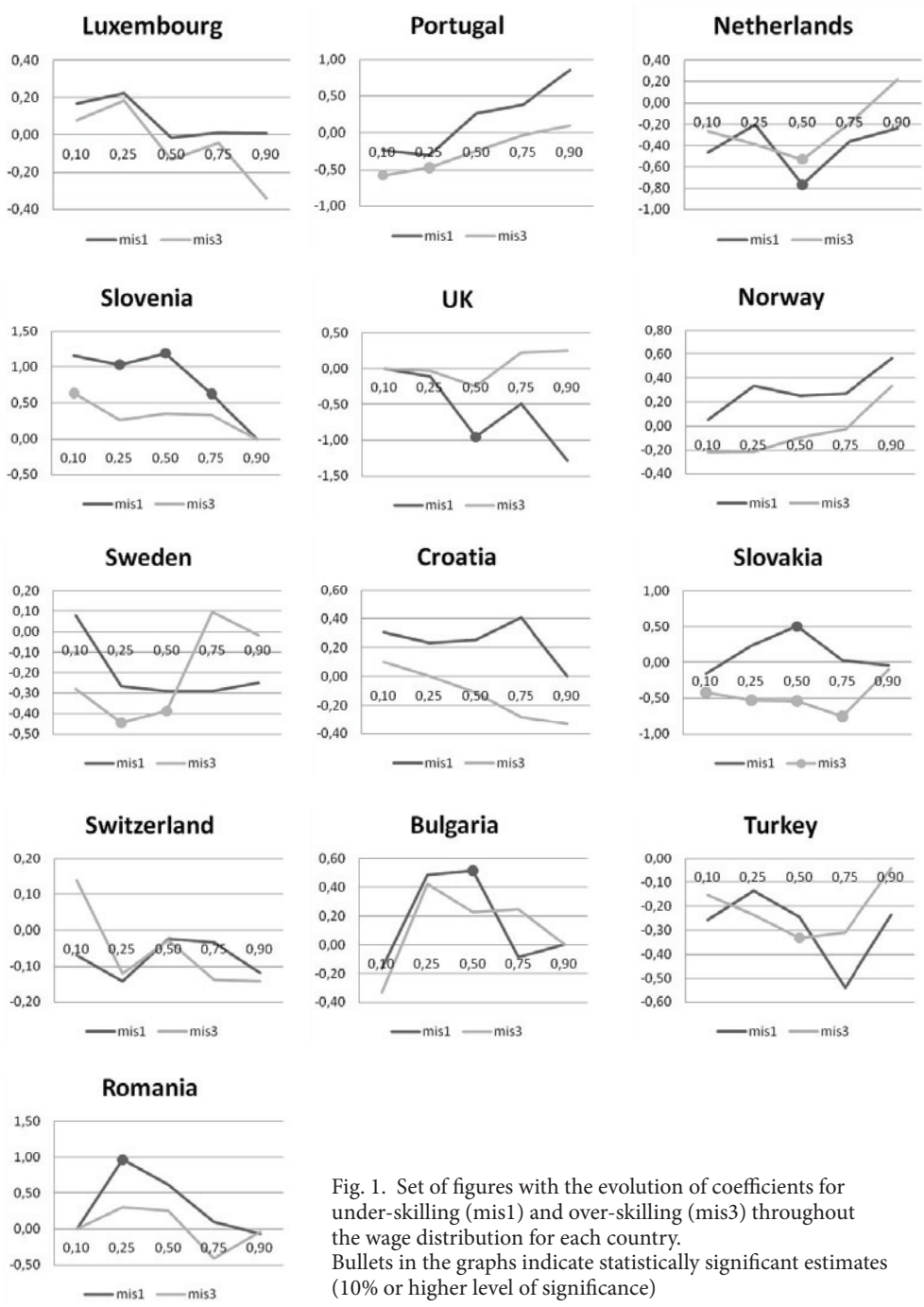

Fig. 1. Set of figures with the evolution of coefficients for under-skilling (mis1) and over-skilling (mis3) throughout the wage distribution for each country.
Bullets in the graphs indicate statistically significant estimates (10% or higher level of significance)

We may note that these results are all conditional in the sense that those premiums and penalties should be read, for the same values of the other variables. This means that, for instance, over-skilled workers in Lithuania earn 5.8% more than matched workers provided that they have the same level of education, the same years for tenure and experience, and work in firms of the same size in the same sector. The general picture is repeated when we observe results of the quantile regression on the median. In particular, Table 4 shows positive and significant under-skilling coefficients in Bulgaria, Germany, Hungary Slovakia, and Slovenia, with coefficients that oscillate between 0.5 and 1.19, and with negative and significant effects in the Netherlands and UK. There are significantly negative effects of over-skilling in Estonia, Latvia, the Netherlands, Malta, Slovakia, Sweden, and Turkey (coefficients oscillate between –0.33 to –0.69) and with no country with positive significant effects.

Quantitatively, the effects of mismatch are important, because when significant, they are routinely higher than those effects from tenure, experience, and (in some cases) education. For instance, in Germany, while being under-skilled implies a wage penalty of 8.8%, an additional year for tenure and experience implies respectively a 0.5% or 2.2% wage premium. For comparison, having the ISCED 2 education level implies a premium of 12.68% in this country.

The next step is to show and analyse the effect of mismatch (under-skilling and over-skilling throughout the distribution of wages. For this, we plot a number of figures (Fig. 1) that indicate the value of coefficients.

As expected, there are differences in the influence of mismatch (under-skilling and over-skilling) across the wage distribution. However, the most common pattern continues to be one of a positive effect of under-skilling and a negative effect of over-skilling, a pattern present in Austria, Croatia, the Czech Republic, Estonia, Denmark, Germany, Portugal, Slovakia, and Spain, at least for the majority of the quantiles analysed[8]. The pattern according to which under-skilled workers tend to have lower wages and over-skilled workers tend to have higher wages throughout the distribution is mostly present in Cyprus, France, Greece, Lithuania, and the UK. A minority of countries show positive effects of under-skilling and over-skilling, such as Belgium, Hungary, Italy, and Slovenia and even fewer show negative effects of under-skilling and over-skilling (Latvia and Sweden).

If we restrict the analysis to the most significant results, noting that under-skilling has a significant positive wage premium in Germany throughout the entire distribution, significant results that also appear in Spain (for lower wages – quantiles 0.1 and 0.25 – and for the highest quantile), for Denmark and Lithuania, just for the lowest quantile, Hungary (for the left-hand side of the wage distribution), and Slovenia (for intermediate quantiles of the wage distribution), Bulgaria and Slovakia for the median, and Romania for quantile 0.25. A significant wage penalty for under-skilling is obtained for the 0.75 quantile in Greece, 0.9 in Latvia, and 0.5 in the Netherlands and the UK. There are significant wage penalties of over-skilling in the right-hand side of the wage distribution in Estonia and in the left-hand side of the distribution in Denmark and Portugal, in

[8] We note that in most of the analysis that follows we may indicate effects that in fact are statistically non-significant. Miller and Rodgers (2008) discuss the importance of statistical significance versus economic significance. Although we will not take part in that discussion, we wish to provide information based on both statistical significance and economic significance, distinguishing between them.

quantiles 0.25, 0.5, and 0.75 in Latvia, in quantiles 0.25 and 0.5 in Malta and Sweden, 0.5 in the Netherlands and Turkey, and 0.1 in Slovenia. In Slovakia, there is a significant wage penalty for over-skilling in almost all of the wage distribution (except in the 0.9 decile). The scarce wage premiums for over-skilling occurred in the right-hand side of the wage distribution in Lithuania (quantiles 0.75 and 0.9) and in the first decile of the wage distribution in Slovenia.

2.3. Results from a pooled regression

In this section we implement a pooled regression with country dummies[9]. Table 4 shows the results. This reinforces our main finding according to which under-skilling faces a wage premium and over-skilling faces a wage penalty.

Table 4. OLS and quantile regressions

OLS						
tenure	**exper**	**exper2**	**gender**	**age**	**firm sector**	**firm size**
0.0383306***	0.1265561***	–0.0022081***	–1.701237***	–0.0269419***	–0.1793566***	0.1874068***
(0.0019479)	(0.0050703)	(0.0000811)	(0.0318051)	(0.002762)	(0.0216065)	(0.0084649)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	0.3355767*	0.8848721***	1.634418***	2.368382***	3.816538***	4.835674***
(omitted)	(0.1783907)	(0.1766723)	(0.1747487)	(0.1797852)	(0.1760404)	(0.2001004)
mis1	**mis3**	**marital status**	**_cons**	**R2**	**N**	
0.1415186***	–0.0826352**	0.2784892***	5.297743***	0.3897	22748	
(0.0479923)	(0.0341031)	(0.0339256)	(0.2243216)			
Quantile						
Q10						
tenure	**exper**	**exper2**	**gender**	**age**	**firm sector**	**firm size**
0.0321716***	0.100341***	–0.0017752***	–1.209208***	–0.0250825***	–0.1064166***	0.2364778***
(0.0029858)	(0.0060906)	(0.0000936)	(0.050102)	(0.003909)	(0.0243009)	(0.0127709)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	–0.1856663	0.1094527	0.6177948**	1.057156***	2.396798***	3.715638***
(omitted)	(0.2278249)	(0.2334774)	(0.246764)	(0.2467355)	(0.2552858)	(0.3208794)
mis1	**mis3**	**marital status**	**_cons**	**R^2**	**N**	
0.1477148**	–0.1396655***	0.1830903***	2.356181***	0.1423	22748	
(0.0676806)	(0.0468143)	(0.040315)	(0.2882447)			

[9] We thank an anonymous referee for the suggestion to include this section.

Continued Table 4

Q25						
tenure	**exper**	**exper2**	**gender**	**age**	**firm sector**	**firm size**
0.0413111***	0.1261627***	–0.0022112***	–1.664919***	–0.0296445***	–0.1133247***	0.2495299***
(0.0028079)	(0.0076901)	(0.0001337)	(0.0452171)	(0.0041729)	(0.0298882)	(0.0113195)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	0.0653056	0.5430536***	1.222429***	1.93137***	3.795588***	5.010843***
(omitted)	(.1442172)	(.1459802)	(.1468477)	(.163691)	(.1587857)	(.1894876)
mis1	**mis3**	**marital status**	**_cons**	**R^2**	**N**	
0.1384613**	–0.0631337	0.236402***	3.354734***	0.2438	22748	
(0.0644439)	(0.0471543)	(0.040569)	(0.2265432)			
Q50						
tenure	**exper**	**exper2**	**gender**	**age**	**firm sector**	**firm size**
0.0407096***	0.1300071***	–0.0022457***	–1.839469***	–0.0267553***	–0.1478047***	0.2064136***
(0.0025111)	(0.0065625)	(0.0000941)	(0.0460521)	(0.0037737)	(0.0321244)	(0.0112034)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	0.3268053**	0.999363***	1.810998***	2.691691***	4.295865***	5.224763***
(omitted)	(0.1562686)	(0.1519459)	(0.1437213)	(0.1455681)	(0.1491036)	(0.2037522)
mis1	**mis3**	**marital status**	**_cons**	**R^2**	**N**	
0.1188001**	–0.1188404***	0.2618782***	5.07478***	0.2755	22748	
(0.0602979)	(0.0438662)	(0.0390751)	(0.2320751)			
Q75						
tenure	**exper**	**exper2**	**gender**	**age**	**firm sector**	**firm size**
0.0309616***	0.1223467***	–0.002213***	–1.707621***	–0.0149946***	–.1916709***	0.1238794***
(0.0029751)	(0.0074343)	(0.0001069)	(0.0472397)	(0.0044888)	(0.0297357)	(0.0111866)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	0.5235366**	1.230001***	2.034593***	2.764888***	4.009525***	4.850638***
(omitted)	(0.2305701)	(0.230956)	(0.2293899)	(0.2233697)	(0.2259386)	(0.254467)
mis1	**mis3**	**marital status**	**_cons**	**R^2**	**N**	
0.1152762**	–0.1093143**	0.2727937***	6.939095***	0.2322	22748	
(0.0565842)	(0.043422)	(0.0405922)	(0.34563)			
Q90						

Continued Table 4

tenure	exper	exper2	gender	age	firm sector	firm size
0.023178***	0.0855561***	–0.0015764***	–1.228933***	–0.009448**	–0.1963498***	0.0409481***
(0.0028014)	(0.0087128)	(0.0001381)	(0.0463183)	(0.0047169)	(0.0302482)	(0.0124981)
edu0	**edu1**	**edu2**	**edu3**	**edu4**	**edu5**	**edu6**
0	0.6926056**	1.433658***	1.968435***	2.407889***	3.35263***	3.991848***
(omitted)	(.3365277)	(0.3275334)	(0.3221446)	(0.3216224)	(0.3083418)	(0.3445096)
mis1	**mis3**	**marital status**	**_cons**	**R^2**	**N**	
0.1671546**	0.0570462	0.2460854***	8.187674***	0.1518	22748	
(0.070113)	(0.040461)	(0.0446226)	(0.3447342)			

In these regressions, with more than 22,700 observations, all of the variables have the expected signs and with high statistical significance. An additional year of tenure implies a nearly 0.4% increase in wages (also in the quantile median regression), while an additional year of experience implies nearly a 1.3% increase in wages, but this effect tends to decrease after 57 years (with similar effects obtained in the median regression. Women tend to earn 17% less (to 18.4% when resulting from the median regression) than men. Wages decrease nearly 2.7% for every year of age, decrease 1.79% (nearly 1.48% from the median regression coefficient) when passing from the private sector to the non-private sector, increase 1.87% with the firm size (2.06% from the median regression), and increase 2.78% if married (2.62% from the median regression). Interestingly, in this pooled regression, all of the education dummies included have a positive sign, meaning that there is a positive effect of education of all ISCED levels, in both the OLS and quantile regressions. Finally, but mostly important in this paper, under-skilled workers earn 1.42% more and over-skilled earn 0.83% less. From the median regression, under-skilled workers earn almost 1.19% more, the same percentage by which the over-skilled earn less. Contrary to what we saw in most individual countries, these effects are now highly statistically significant.

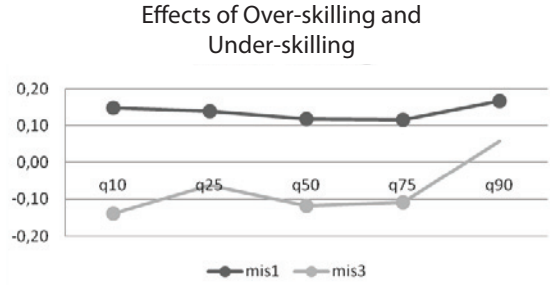

Fig. 2. Figures with the evolution of coefficients for under-skilling (mis1) and over-skilling (mis3) throughout the wage distribution for the pooled regression. Bullets in the graphs indicate statistically significant estimates (10% or higher level of significance)

From the quantile regression we can observe that variable effects on wages are almost constant throughout the distribution. The next figure (Fig. 2) shows the evolution of the effects of being over-skilled or under-skilled throughout the distribution of wages.

Conclusions

We studied the relationship between mismatch in workers' skills and labour market requirements in different European Countries. Although a vast literature reports the effects of over- and under-education on wages, the effects of mismatch in skills is less studied. We found evidence according to which over-skilled workers tend to have a wage penalty and under-skilled workers tend to have a premium. This evidence complements the prevailing evidence on the issue. However, although we obtained the typical effects of education, tenure, experience, and gender on wages, the effects of mismatch between skills and labour market requirements differ considerably across the wage distribution and countries. Quantitatively, the wage premiums and penalties due to mismatch seem to be important when compared with the effects of tenure, experience, and (even) education.

This is the first attempt to compare mismatch (under-skilling and over-skilling) across different European countries and tends to confirm an over-skilling penalty reported in papers that studied individual countries. It also reinforces a result that is rare in the literature, which is a premium for under-skilled workers. Thus, it confirms a stylized fact according to which over-skilled workers tend to have a wage penalty and under-skilled workers have a wage premium. Although it may be arguable that such a result is due to transitional phenomena, the theoretical explanation for these effects on wages are not yet well understood. This may be a path to future research. A potentially interesting way to follow up the research reported here would be to test the psychological-based approach of Tsang and Levin (1985) to explain both the effects of over-skilling and under-skilling on wages.

Acknowledgement

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APPENDIX

Table 1.A[10]: OLS Regressions with mis1 (under-skilling) and mis3 (over-skilling)

	Austria(1)		Belgium(2)		Cyprus(3)		Czech Rep0.(4)		Germany(5)	
tenure	0.0407742***	(0.0142332)	0.0740866***	(0.012806)	0.0869161***	(0.0101861)	0.0758728***	(0.0132302)	0.0645817***	(0.0114254)
exper	0.2055871***	(0.0358284)	0.1356238***	(0.0355927)	0.1347066***	(0.026657)	0.0825219**	(0.0376777)	0.2340904***	(0.0313593)
exper2	−0.0033547***	(0.0007534)	−0.0025039***	(0.0006558)	−0.0027805***	(0.0004252)	−0.0024489***	(0.0006398)	−0.0040881***	(0.0005821)
gender	−2.02435***	(0.2136721)	−1.853953***	(0.2039079)	−1.801182***	(0.1845718)	−2.312629***	(0.184416)	−2.174834***	(0.1640957)
firmsize	0.0980019*	(0.0569972)	0.1619284***	(0.0536065)	0.2565628***	(0.0548507)	0.0424298	(0.0494696)	0.1112098**	(0.0468358)
mis1	0.2393971	(0.2475181)	0.3965106	(0.3127568)	0.0321018	(0.3446031)	0.1170683	(0.2849978)	0.8985007***	(0.2103877)
mis3	−0.2060769	(0.2598744)	−0.1308987	(0.2268433)	0.2056955	(0.1759045)	−0.2823023	(0.2146553)	−0.1943033	(0.1921041)
firmsector	−0.2225813*	(0.1328325)	−0.1579474	(0.1300911)	0.1645197	(0.1082324)	−0.024457	(0.1087388)	−0.1749759*	(0.0992772)
age	−0.0405302**	(0.0191091)	−0.0633351***	(0.0228774)	−0.0090701	(0.0151277)	−0.0079502	(0.0247999)	−0.0365863**	(0.017722)
marital-status	0.0237928	(0.2118011)	−0.0017657	(0.2200209)	0.1195747	(0.2150315)	0.3561764*	(0.1973211)	0.016749	(0.1682964)
edu0	−4.183703**	(1.750623)	−1.220555	(1.679259)	(omitted)		(omitted)		(omitted)	
edu1	−3.666239***	(1.379154)	−2.84374***	(0.9872464)	0.8443858	(1.16628)	−0.1725928	(2.078331)	(omitted)	
edu2	−2.829617***	(1.043354)	−2.915728***	(0.8643763)	0.7961316	(1.184713)	−0.0737871	(1.362212)	0.7819934	(0.5609022)
edu3	−1.850781*	(1.029013)	−2.383576***	(0.7983467)	1.628626	(1.173922)	1.092841	(1.313729)	0.9882459*	(0.5491425)
edu4	−1.0923	(1.044444)	(omitted)		2.537462**	(1.185729)	(omitted)		2.447842***	(0.5949508)
edu5	−0.0444426	(1.100846)	−0.4579708	(0.7907333)	4.147516***	(1.196943)	3.532925***	(1.327609)	3.454273***	(0.5753064)
edu6	(omitted)		(omitted)		5.866545***	(1.458528)	5.904491***	(1.534256)	5.469333***	(1.425697)
_cons	10.31985***	(1.264055)	11.76248***	(1.128841)	2.133607*	(1.274986)	6.111236***	(1.492468)	5.90615***	(0.7669891)
R-squared	0.3131		0.2872		0.4955		0.4016		0.4394	

[10] * means significant at 10% level, ** means significant at 5% level, and *** means significant at 1% level.Values within parentheses are standard errors.

Continued Table A1

	Denmark(6)		Estonia(7)		Spain(8)		Finland(9)		France(10)	
tenure	0.020629*	(0.0105873)	0.0209003	(0.0128352)	0.0398556***	(0.0114444)	0.0093645	(0.008428)	0.0490623***	(0.0111104)
exper	0.1750671***	(0.0243055)	0.0944018**	(0.0396053)	0.1556479***	(0.0283664)	0.075067***	(0.0235404)	0.1189392***	(0.0285997)
exper2	−0.0027616***	(0.000317)	−0.0011899**	(0.0005726)	−0.0023005***	(0.0005302)	−0.0013507***	(0.0004668)	−0.002407***	(0.0005747)
gender	−10.587887***	(0.1539625)	−1.51437***	(0.2048393)	−1.544744***	(0.1810947)	−1.14272***	(0.1373761)	−1.361757***	(0.1505066)
firmsize	0.1591656***	(0.0392886)	0.329202***	(0.0558531)	0.1465986***	(0.0462154)	0.2581043***	(0.0382263)	0.1689153***	(0.0362754)
mis1	0.1295436	(0.2247413)	0.0153108	(0.2601366)	0.776352**	(0.3747522)	0.0839285	(0.1964484)	−0.3194402	(0.2546012)
mis3	−0.4284097**	(0.164984)	−0.3808324*	(0.2157052)	−0.1778883	(0.1899816)	−0.1379535	(0.1672786)	0.0689884	(0.1560917)
firmsector	−0.2013412	(0.1313464)	−0.056973	(0.1272781)	0.076648	(0.1741316)	−0.1504583*	(0.0877371)	−0.1626079	(0.1132862)
age	−0.0282334**	(0.012992)	−0.0928246***	(0.0313896)	−0.0221174	(0.0145287)	−0.0075105	(0.0130436)	−0.0138441	(0.0164214)
marital-status	0.4119155**	(0.169214)	0.2473723	(0.1990438)	0.2318316	(0.1974416)	0.4988099***	(0.1410245)	0.3720816**	(0.1536396)
edu0	−0.3940556	(2.467326)	(omitted)		(omitted)		−3.516634***	(1.162608)	(omitted)	
edu1	(omitted)		−5.977022***	(2.002184)	0.9727625*	(0.5386342)	−2.445456***	(0.9086873)	−2.075765*	(1.158892)
edu2	−0.9820535	(1.037547)	−4.424557***	(1.448279)	1.554949***	(0.5429892)	−2.974395***	(0.7520994)	−0.8932831	(1.126958)
edu3	−0.273684	(1.033233)	−4.037783***	(1.430929)	1.1672**	(0.5723808)	−2.273528***	(0.7321822)	−0.8366443	(1.113937)
edu4	0.7915181	(1.048153)	−3.494984**	(1.428338)	2.332837***	(0.5626576)	−1.773897**	(0.766011)	(omitted)	
edu5	1.733229*	(1.042392)	−1.923664	(1.4226)	3.641691***	(0.5476689)	−1.002699	(0.7256901)	0.2764978	(1.119536)
edu6	3.084526**	(1.313919)	(omitted)		4.442135***	(0.7636185)	(omitted)		1.335918	(1.160211)
_cons	6.504753***	(1.093957)	12.73044***	(1.734011)	4.330269***	(0.7065788)	9.271367***	(0.8755245)	6.650468***	(1.205261)
R-squared	0.4306		0.3227		0.3815		0.2436		0.3170	

Continued Table A1

	Greece(11)		**Hungary(12)**		**Ireland(13)**		**Italy(14)**		**Lithuania(15)**	
tenure	0.0318391***	(0.0105124)	0.0280627***	(0.0084158)	0.0479074***	(0.011409)	0.0449817***	(0.0134362)	0.032871***	(0.0101904)
exper	0.1602122***	(0.0260906)	0.0705877***	(0.0239777)	0.2187035***	(0.0283854)	0.2196173***	(0.0330193)	0.0998084***	(0.0311585)
exper2	−0.0032903***	(0.0004388)	-0.0010088**	(0.0004441)	−0.0030963***	(0.0005157)	−0.0031717***	(0.0005906)	−0.0016615***	(0.0005578)
gender	−1.577281***	(0.1742244)	−0.9951568***	(0.1368443)	−1.857394***	(0.2030793)	−1.642811***	(0.1969951)	−2.184383***	(0.1715689)
firmsize	0.235684***	(0.0467118)	0.129594***	(0.0343954)	0.204903***	(0.0478855)	0.1621936***	(0.0508542)	0.1725796***	(0.0516896)
mis1	−0.3543813	(0.2649292)	0.5533276**	(0.2195118)	−0.6124587*	(0.3203238)	−0.0495456	(0.2822358)	0.3173821	(0.2034893)
mis3	0.0624991	(0.1770167)	0.2815017**	(0.139591)	−0.0493213	(0.1965598)	0.2390679	(0.2133956)	0.5830011***	(0.1950527)
firmsector	0.2162335	(0.1402201)	−0.1454831*	(0.0762497)	−0.1416994	(0.1583555)	−0.1644585	(0.1459069)	−0.3537647***	(0.1090747)
age	−0.0127457	(0.0157301)	−0.0290215*	(0.015039)	−0.0710311***	(0.0167224)	−0.0256607	(0.0160613)	−0.0592432***	(0.0199852)
marital-status	0.4478142**	(0.1864191)	0.2845616**	(0.140172)	0.3292457	(0.2089437)	0.5049879**	(0.2210329)	−0.1855924	(0.1687453)
edu0	(omitted)		(omitted)		−5.9056***	(0.8189768)	(omitted)		(omitted)	
edu1	0.2829575	(0.6688954)	−2.931471***	(0.6516167)	−4.811065***	(0.4519953)	−3.440275**	(1.745536)	(omitted)	
edu2	0.5161508	(0.7144029)	−2.374441***	(0.6395793)	−4.149219***	(0.3465158)	−2.40431	(1.709128)	−0.2956715	(1.400429)
edu3	1.745404**	(0.6946383)	−1.601296**	(0.6392637)	−3.459366***	(0.3263429)	−1.630715	(1.70176)	0.5110808	(1.353901)
edu4	1.572228**	(0.7386758)	0.3597882	(0.9477519)	−2.440676***	(0.3365535)	−0.9119806	(1.780178)	1.457533	(1.359967)
edu5	2.915703***	(0.7125257)	0.4368544	(0.6451823)	−1.292787***	(0.3615131)	−0.1676265	(1.714155)	3.903928***	(1.360377)
edu6	3.940402***	(1.124759)	(omitted)		(omitted)		(omitted)		5.121823***	(1.551286)
_cons	4.585001***	(0.817165)	6.864243***	(0.8242365)	10.28101***	(0.6492009)	7.250642***	(1.78657)	8.159128***	(1.470348)
R-squared	0.3453		0.3194		0.3872		0.3858		0.4228	

Continued Table A1

	Luxembourg(16)		Latvia(17)		Netherlands(18)		Malta(19)		Poland(20)	
tenure	0.0776159***	(0.0141974)	0.0352099***	(0.0110851)	0.0560938***	(0.0100378)	0.0301202***	(0.0101682)	0.0194479*	(0.0107572)
exper	0.1053212**	(0.0424013)	0.1690028***	(0.0321891)	0.0695359**	(0.0293434)	0.1196911***	(0.0323563)	0.1117986***	(0.0324185)
exper2	−0.0020713**	(0.0008514)	−0.0021324***	(0.000485)	−0.0014899**	(0.0005971)	−0.0019729***	(0.0005447)	−0.0018105**	(0.000743)
gender	−2.150323***	(0.2177069)	−1.591283***	(0.1713375)	−2.797448***	(0.1768967)	−1.197307***	(0.1683497)	−1.659967***	(0.1830301)
firmsize	0.2501773***	(0.0517466)	0.2382085***	(0.0558975)	0.1551092***	(0.0466323)	0.0995955**	(0.0475756)	0.1128297**	(0.0446562)
mis1	0.133796	(0.3175315)	−0.5019378**	(0.2381946)	−0.4843803	(0.2963016)	−0.1858338	(0.2575346)	−0.0106122	(0.2606035)
mis3	−0.0298444	(0.2228435)	−0.4630654**	(0.178266)	−0.3106994*	(0.1877774)	−0.479739***	(0.1674271)	−0.146146	(0.2001785)
firmsector	0.1423464	(0.1339049)	−0.5358371***	(0.1313095)	−0.3667475***	(0.0763125)	0.1371665	(0.1259654)	−0.2132694	(0.1347177)
age	0.0236553	(0.0237939)	−0.1132539***	(0.0235687)	0.0181818	(0.0137461)	−0.0181622	(0.0171168)	−0.0269423	(0.0165397)
marital-status	−0.0998148	(0.2371536)	0.1157863	(0.1686568)	0.351207*	(0.1894281)	0.3944927**	(0.1898389)	0.4941398**	(0.211102)
edu0	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
edu1	−2.987041***	(0.7879837)	(omitted)		−0.3198592	(2.499906)	(omitted)		(omitted)	
edu2	−2.167605***	(0.7811383)	0.4703007	(2.298843)	0.3264086	(2.399693)	0.4577819	(0.4423022)	0.457136	(1.67736)
edu3	−1.209537	(0.7604347)	0.9618855	(2.300859)	1.529222	(2.427349)	0.9191899**	(0.3975607)	1.702536	(1.655045)
edu4	(omitted)		1.4752	(2.29894)	1.733648	(2.400236)	2.032535***	(0.4119527)	2.716896	(1.694954)
edu5	1.074787	(0.7727472)	3.064807	(2.306036)	3.358126	(2.399128)	3.56546***	(0.4292522)	4.50177***	(1.665132)
edu6	−0.4919331	(1.178586)	5.692674**	(2.370845)	4.82593**	(2.437456)	4.50074***	(0.9246038)	4.372543**	(1.845319)
_cons	6.222975***	(1.049328)	7.65965***	(2.341962)	5.442014**	(2.460872)	2.546334***	(0.5884954)	3.410331**	(1.732469)
R-squared	0.5366		0.3017		0.4579		0.4510		0.3043	

Continued Table A1

	Portugal(21)		Sweden(22)		Slovenia(23)		Slovakia(24)		UK(25)	
tenure	0.0345949***	(0.0092571)	−0.0040144	(0.0092854)	−0.0024828	(0.015075)	0.0273234***	(0.0104201)	0.0493858***	(0.0140831)
exper	0.122559***	(0.0212242)	0.1916626***	(0.0249938)	0.0188534	(0.0408241)	0.1766073***	(0.0391238)	0.1448456***	(0.0321296)
exper2	−0.0023179***	(0.0003696)	−0.0032889***	(0.0004968)	−0.0005349	(0.000805)	−0.0027578***	(0.0006553)	−0.0022158***	(0.0005426)
gender	−1.139169***	(0.1309734)	−1.636887***	(0.1609801)	−0.6896549***	(0.221325)	−1.847901***	(0.1638547)	−1.888634***	(0.2119632)
firmsize	0.1264423***	(0.0359885)	0.3485594***	(0.0429298)	0.0493843	(0.0557178)	0.1490685***	(0.042818)	0.104671**	(0.0492434)
mis1	0.0280618	(0.2095712)	−0.1582762	(0.3361502)	1.10753***	(0.3684704)	0.2616149	(0.2582809)	−0.6182267	(0.4120883)
mis3	−0.3356097**	(0.155466)	−0.1631616	(0.1615172)	0.3517938	(0.2388465)	−0.5279798***	(0.1711334)	−0.0802663	(0.2122646)
firmsector	0.1379039	(0.1315118)	−0.4211242***	(0.1133673)	0.7064884***	(0.1911262)	−0.3308217***	(0.0961763)	−0.2163133*	(0.1218497)
age	−0.0100588	(0.0109235)	−0.0163427	(0.0141491)	0.0259395	(0.029437)	−0.0645361**	(0.0281255)	−0.0458855**	(0.0190193)
marital-status	0.3129911**	(0.1465047)	0.0111296	(0.1767918)	−0.0460182	(0.240852)	0.34787*	(0.1780268)	0.3090876	(0.219808)
edu0	−2.196177***	(0.5821215)	−4.576446***	(10.35434)	(omitted)		(omitted)		−5.708084**	(2.628613)
edu1	−1.509387***	(0.4795328)	−4.164051***	(0.7572123)	−6.145342**	(2.73495)	−4.678704**	(2.306444)	(omitted)	
edu2	−0.2315203	(0.4835589)	−4.251203***	(0.6641689)	−6.372395***	(2.384975)	−5.694941***	(0.6784345)	−4.852251*	(2.558811)
edu3	0.2981553	(0.4831578)	−3.743084***	(0.6081404)	−4.179161*	(2.363371)	−3.871376***	(0.5631709)	−4.290575*	(2.529466)
edu4	(omitted)		−3.26139***	(0.607212)	(omitted)		−3.236676***	(0.6583985)	(omitted)	
edu5	2.734717***	(0.49785)	−1.488934**	(0.5917455)	−1.766606	(2.368275)	−0.7214133	(0.5732844)	−2.247558	(2.533438)
edu6	2.617299***	(0.7194381)	(omitted)		(omitted)		(omitted)		−0.7085922	(2.73573)
_cons	5.93318***	(0.5990399)	8.525792***	(0.8758486)	8.253089***	(2.572182)	11.79956***	(0.969311)	10.76149***	(2 .635318)
R-squared	0.4621		0.3378		0.3488		0.3760		0.3143	

Continued Table A1

	Norway(26)		Switzerland(27)		Bulgaria(28)		Croatia(29)		Romania(30)		Turkey(31)	
Tenure	0.0288338***	(0.0109298)	0.0339025***	(0.0087137)	0.0473053***	(0.0105731)	0.0029229	(0.0113052)	0.0190775*	(0.011521)	–0.0085225	(0.0091763)
Exper	0.2027689***	(0.0289598)	0.1600841***	(0.0240901)	0.0866739***	(0.0313013)	0.0769497**	(0.0362616)	0.0152082	(0.0239511)	0.0953078***	(0.0206283)
exper2	–0.0034072***	(0.0005598)	–0.0026573***	(0.0004087)	–0.001625***	(0.0005743)	–0.0013811*	(0.0007285)	–0.0006455	(0.0005602)	–0.0012977***	(0.0003424)
Gender	–2.064756***	(0.1788813)	–2.703626***	(0.1466797)	–1.505933***	(0.1603242)	–0.9143293***	(0.1505794)	–0.7200673***	(0.1904825)	–0.6431233***	(0.2048627)
Firmsize	0.3559237***	(0.0589986)	0.265978***	(0.0350658)	0.2331524***	(0.0440272)	0.0284612	(0.0447127)	0.2932644***	(0.0607048)	0.2190351***	(0.0420909)
mis1	0.2793244	(0.2422381)	–0.1229529	(0.1799372)	0.5659111	(0.3479395)	0.2290062	(0.2336668)	0.3621349	(0.293687)	–0.3649438*	(0.2126197)
mis3	–0.0924567	(0.1903923)	–0.0468881	(0.1551446)	0.1562391	(0.1711005)	–0.124433	(0.1587327)	0.0368925	(0.2062739)	–0.3133888**	(0.1519625)
Firm-sector	–0.7448157***	(0.1459691)	0.1903826*	(0.1022792)	–0.4692748***	(0.1166941)	0.1938258	(0.122799)	0.0276731	(0.1296361)	0.3076789*	(0.1728066)
Age	–0.038783**	(0.0153694)	–0.022529	(0.0142463)	–0.0471297***	(0.0175065)	0.0019069	(0.0212191)	0.0202197	(0.0146606)	–0.0229561*	(0.0124081)
marital-status	0.4717332**	(0.1858545)	–0.0941789	(0.1475756)	0.092044	(0.1777479)	0.2389547	(0.1698142)	0.2688109	(0.2307539)	0.4172211**	(0.1804856)
edu0	(omitted)		0.3799412	(1.204766)	–3.084005**	(1.535639)	(omitted)		(omitted)		–5.809482***	(0.8889097)
edu1	–0.3142612	(1.755529)	(omitted)		–3.893709***	(1.449537)	–7.888564***	(1.230363)	1.605635	(2.568672)	–5.453665***	(0.8499961)
edu2	–0.3318867	(1.707908)	0.4047559	(0.4470324)	–3.651226***	(1.369156)	–6.384179***	(0.7060937)	2.38478	(2.525778)	–4.603712***	(0.856031)
edu3	0.1866099	(1.695048)	1.76631***	(0.3409845)	–1.255531	(1.351424)	–4.538556***	(0.6042459)	3.187957	(2.513728)	–4.173676***	(0.8508664)
edu4	1.51191	(1.704157)	2.100297***	(0.452794)	–0.0389476	(1.383154)	–3.350265***	(0.629437)	5.042799**	(2.527193)	(omitted)	
edu5	2.933982*	(1.69143)	2.837729***	(0.3745196)	0.8245142	(1.35285)	–2.467501***	(0.6196584)	6.403716**	(2.524078)	–2.731078***	(0.8626043)
edu6	5.539016***	(1.884675)	4.220123***	(0.3718001)	(omitted)		(omitted)		7.585222***	(2.650349)	(omitted)	
_cons	5.441048***	(1.777866)	4.818372***	(0.5497397)	10.51106***	(10.502894)	9.571709***	(0.8811822)	–0.290493	(2.561285)	8.297601***	(0.9621573)
R-squared	0.4480		0.5408		0.3813		0.3235		0.3184		0.2540	

Table 2.A[11]: Quantile regression at the median (0.5) with mis1 (under-skilling) and mis3 (over-skilling)

q10	Austria(1)		Belgium(2)		Cyprus(3)		Czech Rep0.(4)		Germany(5)		Denmark(6)	
tenure	0.0539687***	(0.0187744)	0.0338778**	(0.0167927)	0.1090327***	(0.0139964)	0.0949076***	(0.0179238)	0.0527406***	(0.0156316)	0.0058004	(0.0152714)
exper	0.2056569***	(0.0620994)	0.1698102***	(0.0591727)	0.0942445***	(0.0315284)	0.0919687*	(0.0482994)	0.2206366***	(0.0470562)	0.1928615***	(0.0359423)
exper2	−0.0037956***	(0.0011223)	−0.0030057***	(0.0010273)	−0.0019848***	(0.0006492)	−0.0027442***	(0.0006756)	−0.0034962***	(0.0008598)	−0.0029674***	(0.0004757)
gender	−2.226712***	(0.3294702)	−0.9734399***	(0.2123067)	−1.791343***	(0.2290467)	−2.928667***	(0.2808714)	−2.285574***	(0.3140841)	−1.648006***	(0.1902787)
firmsize	0.0992651	(0.0794553)	0.1305421**	(0.0536469)	0.2134916***	(0.0802494)	−0.0124791	(0.0760474)	0.1754256**	(0.0684346)	0.1494243**	(0.0581556)
mis1	0.5251116	(0.384507)	0.3118616	(0.2725748)	0.0092574	(0.3843618)	0.3527376	(0.4447362)	0.8808928***	(0.2790234)	−0.0473451	(0.2063606)
mis3	−0.1836461	(0.3611569)	0.0571642	(0.2146986)	0.1509659	(0.2345615)	−0.2670092	(0.2543936)	−0.2902471	(0.3001625)	−0.3928175	(0.2427634)
firm-sector	−0.2679634	(0.2189292)	0.0214669	(0.1420523)	0.3372964**	(0.1652078)	−0.0302898	(0.1750434)	−0.3071335**	(0.1544448)	−0.2601023	(0.1708433)
age	−0.0277955	(0.0241168)	−0.0429662	(0.0483628)	−0.0108356	(0.0161034)	0.0017138	(0.0356426)	−0.0338051	(0.0285961)	−0.0219318	(0.0216191)
marital-status	−0.1445614	(0.2894137)	0.1566012	(0.2732262)	0.2037397	(0.2568443)	−0.1914276	(0.2792264)	−0.0724127	(0.2128329)	0.3786007	(0.2330418)
edu0	(omitted)		(omitted)		(omitted)		0.163524	(1.62364)	(omitted)		(omitted)	
edu1	0.445995	(1.428599)	−1.477358	(1.382178)	1.0364	(1.625089)	(omitted)		(omitted)		−0.191649	(1.378937)
edu2	1.024428	(0.9100659)	−1.411898*	(0.8192474)	0.7789317	(1.73327)	0.7007914	(1.316735)	1.268082*	(0.6548636)	−0.8319478	(1.339822)
edu3	2.00776**	(0.8198209)	−0.6419368	(0.7479455)	1.850701	(1.729769)	1.593905	(1.304196)	1.575263**	(0.6491901)	−0.0614469	(1.325242)
edu4	3.006672***	(0.8524473)	(omitted)		2.59707	(1.737779)	(omitted)		3.327752***	(0.6602673)	0.8741735	(1.333985)
edu5	4.08988***	(0.8927614)	0.8336179	(0.7059331)	4.445715**	(1.727833)	4.678606***	(1.421338)	4.145509***	(0.7371539)	2.44262*	(1.327369)
edu6	3.860923***	(1.156227)	1.641682*	(0.9574936)	6.742248***	(1.928866)	6.028963***	(1.913749)	7.280073***	(2.444286)	3.175069**	(1.380173)
_cons	6.405447***	(1.226737)	8.660008***	(1.429975)	1.827352	(1.83021)	6.374614***	(1.406184)	5.533071***	(1.062433)	6.15965***	(1.415654)
R-squared	0.2078		0.1309		0.3379		0.2896		0.2948		0.2879	

[11] * means significant at 10% level, ** means significant at 5% level, and *** means significant at 1% level. Values within parentheses are standard errors.

Continued Table A2

q25	Estonia(7)		Spain(8)		Finland(9)		France(10)		Greece(11)		Hungary(12)	
tenure	0.0450942**	(0.0190467)	0.0282076**	(0.0137513)	0.0117139	(0.0081573)	0.0402807***	(0.0133005)	0.0234879	(0.0168371)	0.0228811**	(0.0092247)
exper	0.1000567	(0.0606662)	0.1849927***	(0.0369097)	0.0685604***	(0.0251312)	0.1455734***	(0.0444507)	0.1732191***	(0.0429241)	0.0553597*	(0.0320679)
exper2	−0.0019041**	(0.0008758)	−0.0025765***	(0.0005226)	−0.001544***	(0.0004838)	−0.0028421***	(0.000785)	−0.0032799***	(0.0007834)	−0.0009317	(0.0005839)
gender	−1.696678***	(0.2506606)	−1.727206***	(0.2085576)	−1.519394***	(0.1301929)	−1.390888***	(0.2055654)	−1.536597***	(0.2533195)	−1.28429***	(0.1783941)
firmsize	0.3382797***	(0.0822133)	0.0851637*	(0.049303)	0.1286469***	(0.0398037)	0.1293712***	(0.0429762)	0.1949889***	(0.0564866)	0.1439697***	(0.0464344)
mis1	−0.0315937	(0.3320394)	0.4054133	(0.3460177)	0.126161	(0.2272401)	−0.4828322	(0.3665846)	−0.1508126	(0.2846826)	0.4857185**	(0.2382865)
mis3	−0.5397832*	(0.2765748)	−0.2579797	(0.2482552)	0.1052984	(0.1412005)	0.0314483	(0.1758326)	−0.1470967	(0.2213305)	0.1753025	(0.193403)
firmsector	0.0074926	(0.2220332)	−0.0575511	(0.2314163)	−0.0129004	(0.1022582)	−0.1070933	(0.1388598)	0.2799262	(0.177501)	−0.0705541	(0.1105973)
age	−0.0857399*	(0.0444417)	−0.028857	(0.0227601)	0.0041966	(0.0120041)	−0.0166021	(0.0291686)	−0.01514	(0.0249566)	−0.0112532	(0.0175816)
marital-status	0.1263908	(0.2728108)	0.3188441	(0.2558996)	0.3267688**	(0.1506159)	0.4562779**	(0.230659)	0.5741332*	(0.293685)	0.1829224	(0.1644467)
edu0	(omitted)		−50.420253***	(0.8091807)	(omitted)		(omitted)		−4.011876**	(1.756301)	(omitted)	
edu1	−7.472367**	(3.014828)	−40.287358***	(0.7291536)	3.089664**	(1.489816)	−1.710499*	(1.020679)	−3.269977**	(1.345443)	−30.063219***	(0.8269839)
edu2	−4.277175**	(1.966815)	−30.113613***	(0.5887258)	2.078878	(1.429551)	−0.844469	(0.8299786)	−2.937571**	(1.316316)	−20.519429***	(0.8048222)
edu3	−3.821137**	(1.934589)	−30.980739***	(0.6292295)	2.661064*	(1.364967)	−0.720622	(0.7486567)	−1.647309	(1.203476)	−1.632838**	(0.8118099)
edu4	−3.081607	(1.907046)	−20.407983***	(0.616047)	3.044506**	(1.467337)	(omitted)		−1.730432	(1.372878)	(omitted)	
edu5	−1.758106	(1.840802)	−0.8949189	(0.5620036)	3.999726***	(1.395558)	0.7062042	(0.7879315)	−0.2941244	(1.242145)	0.5334087	(0.7749238)
edu6	(omitted)		(omitted)		4.507691***	(1.637801)	1.709049**	(0.8085891)	(omitted)		−0.1639932	(1.75395)
_cons	12.77132***	(2.552603)	9.846447***	(0.8705787)	5.329358***	(1.421396)	6.558202***	(1.01783)	8.121238***	(1.619928)	6.729638***	(1.063026)
R-squared	0.1988		0.2643		0.1480		0.1828		0.2310		0.2147	

Continued Table A2

q50	Ireland(13)		Italy(14)		Lithuania(15)		Luxembourg(16)		Latvia(17)		Netherlands(18)	
tenure	0.0599744***	(0.0192476)	0.0387207**	(0.0180875)	0.0300397**	(0.0139898)	0.0897675***	(0.0199077)	0.0266582*	(0.0142023)	0.0458744***	(0.0139702)
exper	0.2674068***	(0.0453528)	0.2716473***	(0.0439539)	0.104564**	(0.0407472)	0.1152866*	(0.0590429)	0.1952185***	(0.0543448)	0.0685768	(0.0424709)
exper2	−0.0033334***	(0.0008248)	−0.0043083***	(0.0008696)	−0.0016046**	(0.0007517)	−0.0019285*	(0.0011449)	−0.0025947***	(0.0007958)	−0.0008954	(0.0009103)
gender	−1.752153***	(0.3211118)	−2.059543***	(0.286939)	−2.63712***	(0.2600758)	−2.488571***	(0.3839898)	−1.81597***	(0.2536958)	−3.098607***	(0.3371297)
firmsize	0.1687463**	(0.0697708)	0.220103***	(0.059258)	0.2210786***	(0.0642515)	0.2572816***	(0.0680632)	0.4056799***	(0.0716928)	0.1768241***	(0.0582138)
mis1	−0.7346749	(0.4888041)	0.1575485	(0.4310313)	−0.0589639	(0.2427641)	−0.0172084	(0.4580557)	−0.5219685	(0.3651496)	−0.7685533*	(0.4190198)
mis3	−0.014827	(0.3463907)	0.243159	(0.2345129)	0.2826325	(0.2540744)	−0.1335098	(0.2745099)	−0.6938466***	(0.2207841)	−0.530487*	(0.2917393)
firmsector	−0.1504088	(0.2350122)	−0.078471	(0.1617774)	−0.3432978***	(0.1226165)	0.3440189	(0.2140493)	−0.4513618**	(0.212292)	−0.3795174***	(0.1120002)
age	−0.1130525***	(0.0210124)	−0.0167719	(0.0178)	−0.0599766**	(0.0240706)	0.017401	(0.035233)	−0.1160687***	(0.0331456)	0.0024295	(0.0219431)
marital-status	0.4137105	(0.3719418)	0.5906303*	(0.3074665)	−0.2448486	(0.18272)	−0.1530404	(0.3812666)	−0.1922914	(0.2104848)	0.3605672	(0.3016701)
edu0	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
edu1	2.400865**	(1.036379)	−4.935316***	(1.788145)	(omitted)		−3.261845***	(0.6987462)	−4.792892*	(2.614234)	−0.6519403	(1.794256)
edu2	3.209871***	(1.070172)	−3.549453**	(1.769052)	0.2390086	(1.199431)	−2.347301***	(0.8233044)	−5.039592***	(1.127029)	0.3088451	(1.760964)
edu3	3.669044***	(1.11396)	−2.573827	(1.754177)	0.4692605	(1.195626)	−1.039225	(0.7728539)	−4.727368***	(1.16507)	1.869051	(1.88202)
edu4	5.192641***	(1.059721)	−2.117482	(1.729236)	1.584947	(1.177042)	(omitted)		−4.01786***	(1.133536)	2.004438	(1.738086)
edu5	6.733146***	(1.046581)	−1.310104	(1.765331)	4.668191***	(1.224211)	1.346243	(0.8165125)	−2.456025**	(1.140271)	4.003998**	(1.747263)
edu6	7.188931***	(1.054953)	(omitted)		5.385778***	(1.281727)	−0.7671016	(1.035636)	(omitted)		5.716266***	(1.843042)
_cons	3.794008***	(1.35503)	7.867486***	(1.785286)	8.475982***	(1378565)	6.316785***	(1.317176)	12.92535***	(1.432292)	6.059744***	(1.890081)
R-squared	0.2683		0.2715		00.3128		0.3946		0.1958		0.3138	

Continued Table A2

	Malta(19)		Poland(20)		Portugal(21)		Sweden(22)		Slovenia(23)		Slovakia(24)	
tenure	0.0301664**	(0.0128236)	0.0129035	(0.0140706)	0.0328827***	(0.010987)	−0.0080753	(0.0126383)	−0.0224187	(0.0211829)	0.0319516**	(0.0129241)
exper	0.0968998***	(0.0350154)	0.0913325***	(0.0335919)	0.1023173***	(0.0246787)	0.1930583***	(0.0300145)	0.0309932	(0.0790302)	0.2130076***	(0.0500343)
exper2	−0.0014374**	(0.0006579)	−0.0014061	(0.0009862)	−0.0018985***	(0.0005422)	−0.0034707***	(0.0006012)	−0.0005359	(0.0009989)	−0.0030097***	(0.0009099)
gender	−1.154735***	(0.2308942)	−1.618741***	(0.3161582)	−1.052919***	(0.1473714)	−1.732785***	(0.2479877)	−0.5696677*	(0.3048562)	−2.19713***	(0.2391986)
firmsize	0.091633	(0.0649727)	0.1536921***	(0.0546901)	0.11236***	(0.0370496)	0.4567021***	(0.0596293)	0.0183101	(0.0809595)	0.143664***	(0.0519329)
mis1	−0.4261086	(0.3306943)	−0.265508	(0.2676979)	0.2659048	(0.2914907)	−0.2887042	(0.3335651)	1.187567**	(0.4731896)	0.503329*	(0.2917378)
mis3	−0.5345248***	(0.198155)	−0.1263249	(0.198749)	−0.244912	(0.1632012)	−0.3873334*	(0.2076454)	0.3567346	(0.3463224)	−0.5336514**	(0.2550511)
firmsector	0.1535414	(0.143304)	−0.1705097	(0.185844)	0.0787841	(0.1518355)	−0.5728936***	(0.1758864)	0.7587531**	(0.2937444)	−0.283015**	(0.1106548)
age	−0.0223618	(0.0160705)	−0.0085621	(0.0132862)	−0.0125852	(0.0118439)	0.0047653	(0.0159283)	0.0381386	(0.0614702)	−0.0965334**	(0.0470482)
marital-status	0.5863834***	(0.2193243)	0.2408563	(0.2395825)	0.3261695**	(0.1492449)	0.1148783	(0.2061394)	0.2901929	(0.3739112)	0.3918851*	(0.2282612)
edu0	(omitted)		(omitted)		−1.824209	(1.275184)	(omitted)		(omitted)		(omitted)	
edu1	(omitted)		(omitted)		−1.439764	(1.153095)	−0.7522183	(1.83598)	(omitted)		−5.384384**	(2.492754)
edu2	0.5016286	(0.4950766)	0.3976812	(1.321804)	−0.1849208	(1.145944)	−1.266977	(1.77461)	−0.2822436	(2.213959)	−6.797666***	(0.6705098)
edu3	0.7365882	(0.5082205)	1.579167	(1.386814)	0.4429623	(1.173337)	−0.2140943	(1.758244)	2.444891	(2.210476)	−4.794581***	(0.6565793)
edu4	1.96568***	(0.4751233)	2.503843	(1.524986)	(omitted)		0.2828409	(1.752476)	(omitted)		−3.684379***	(0.809121)
edu5	3.453249***	(0.503476)	5.151343***	(1.430828)	3.302922***	(1.169094)	2.472128	(1.747258)	5.192658**	(2.254658)	−1.363594**	(0.6013303)
edu6	5.021788***	(1.375827)	5.413065**	(2.33854)	2.985151**	(1.187282)	4.013744**	(1.852061)	6.806627**	(3.333537)	(omitted)	
_cons	2.593863***	(0.6698614)	2.416002	(1.501696)	5.889662***	(1.23326)	3.908102**	(1.77272)	0.562433	(2.576516)	13.60481***	(1.543263)
R-squared	0.2845		0.2218		0.3164		0.2629		0.2472		0.2635	

q75

Continued Table A2

q90	UK(25)		Norway(26)		Switzerland(27)		Bulgaria(28)		Croatia(29)		Romania(30)		Turkey(31)	
Tenure	0.0364804	(0.0265208)	0.0355986**	(0.0165379)	0.0335287***	(0.0110283)	0.0309883**	(0.0128007)	0.0073978	(0.0172149)	0.0344749*	(0.0198296)	0.0014099	(0.011174)
Exper	0.136537***	(0.051236)	0.1959598***	(0.0316292)	0.1017948***	(0.0330164)	0.1490775***	(0.0503626)	0.0434777	(0.0466983)	0.0166701	(0.0359634)	0.0922151***	(0.0199252)
exper2	−0.0019984**	(0.0007931)	−0.0032682***	(0.0005888)	−0.0014828***	(0.0005437)	−0.0024924***	(0.0007469)	−0.0010052	(0.0009493)	−0.0006299	(0.0007679)	−0.0013889***	(0.0002584)
Gender	−2.4336***	(0.3541779)	−2.420923***	(0.2963506)	−3.13735***	(0.2096401)	−1.668995***	(0.1962363)	−0.7052196***	(0.2179917)	−0.7254056**	(0.3089031)	−0.8143776***	(0.2265982)
Firm-size	0.2186549***	(0.0799062)	0.4525219***	(0.0892976)	0.2458058***	(0.0428931)	0.2697202***	(0.0617927)	0.0334819	(0.0547597)	0.3787343***	(0.0869828)	0.2541893***	(0.0473878)
mis1	−0.9533209*	(0.5201806)	0.2529839	(0.2910491)	−0.0228234	(0.2315123)	0.5158532*	(0.2952897)	0.2493751	(0.2980846)	0.6214338	(0.4706024)	−0.2446248	(0.2727729)
mis3	−0.2487901	(0.3176185)	−0.0935232	(0.2702916)	−0.0282542	(0.1886693)	0.228976	(0.2004711)	−0.1096098	(0.205541)	0.2510927	(0.3005089)	−0.3314428**	(0.1669712)
firm-sector	−0.231275	(0.1597904)	−0.7767646***	(0.2076314)	0.2787188**	(0.1264462)	−0.5433853***	(0.1315316)	0.2558989	(0.1706862)	−0.0143085	(0.1849782)	0.5328681**	(0.2235103)
Age	−0.042419	(0.0259374)	−0.0412304**	(0.0163502)	−0.0161525	(0.0207778)	−0.0666929**	(0.0293312)	0.0282995	(0.0326203)	0.0191408	(0.0278945)	−0.0226408*	(0.013084)
marital-status	0.4756477	(0.3484744)	0.2545389	(0.2380196)	0.0289719	(0.198872)	−0.1131597	(0.1833967)	0.1588439	(0.237967)	0.4281462	(0.3670974)	0.3184334	(0.2182078)
edu0	−5.333051***	(1.874295)	−5.285303**	(2.203235)	−0.1604288	(0.686875)	(omitted)		(omitted)		−6.677469*	(3.832203)	−6.409361***	(0.9576642)
edu1	−0.266203	(1.262823)	−6.17998***	(0.9143491)	(omitted)		−0.7921758	(1.775433)	(omitted)		−5.905068***	(1.132752)	−6.100617***	(1.006047)
edu2	−5.160924***	(1.584544)	−6.319616***	(0.866647)	−0.2116618	(0.5561199)	−0.9530086	(1.615623)	1.430602	(1.656813)	−5.104209***	(1.135793)	−5.193098***	(1.028758)
edu3	−4.707637***	(1.549965)	−5.727446***	(0.8014509)	1.273895***	(0.4481883)	1.965122	(1.641384)	3.227114*	(1.676687)	−3.871841***	(1.104902)	−4.748328***	(1.03296)
edu4	(omitted)		−3.950201***	(0.8432889)	1.888502***	(0.5296689)	3.138205*	(1.634863)	4.521857***	(1.677677)	−1.545347	(1.099537)	(omitted)	
edu5	−1.699049	(1.545966)	−2.310198***	(0.8281242)	2.526793***	(0.5268745)	3.975964**	(1.633962)	5.076087***	(1.668328)	0.1975386	(1.058609)	−3.141161***	(1.072744)
edu6	(omitted)		(omitted)		3.896788***	(0.4850996)	3.356852*	(1.767675)	7.726407***	(1.715152)	(omitted)		(omitted)	
_cons	11.05574***	(1.878657)	11.5908***	(1.026854)	5.951956***	(0.9483251)	8.196686***	(2.018068)	0.6423004	(1.777338)	5.84607***	(1.475063)	8.446258***	(1.154706)
R-squared	0.2341		0.3249		0.3900		0.2531		0.2158		0.2174		0.1903	

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