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Graduate labor mismatch in Central and Eastern Europe[1]

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RESUM

Utilitzant l'enquesta REFLEX/HEGESCO, aquest article explora la probabilitat de desajustament entre educació i treball a l'Europa de l'Est i Central. Classifiquem els països en dos grups segons la transparència dels títols educatius al mercat de treball. Polònia, la República Txeca i Eslovènia formen el grup amb més transparència, i Hongria, Lituània i Estònia formen el grup amb més opacitat. Analitzem tres tipus de desajustaments: el vertical (infra-, sobre-educació), l'horitzontal (desajustament del camp d'estudi) i el desajust en habilitats. Focalitzem l'anàlisi en l'efecte dels camps d'estudi i les competències dels individus en el desajustament del mercat laboral en aquests països. Els resultats mostren important diferències entre els dos grups de països estudiats.

ABSTRACT

Using cross-section data from the REFLEX/HEGESCO surveys, this paper explores the likelihood of education-job mismatch in Central and Eastern Europe. We classify countries in two groups according to the signaling strength of their educational credentials: the occupational labor market group (Poland, Czech Republic and Slovenia) and the internal labor market group (Hungary, Lithuania and Estonia). We analyze three types of mismatch: the vertical mismatch (under-/over-education), horizontal mismatch (inadequacy of the field of study) and, finally, skills mismatch. We are particularly interested in studying how fields of study and individual competencies affect mismatch in the labor market in these economies. Results indicate that fields of study and individual competencies both significantly affect the likelihood of various types of mismatch. There are important differences between occupational and internal labor market structures in terms of mismatch determinants.

Keywords: Eastern Europe, education-labor mismatch, occupational labor market, internal labor market, competencies, fields of study, over-education.

JEL Codes: J24, J44, I23, I28

1. Introduction

There is a large literature on education-job mismatch in Western European countries and the US from both a theoretical (Charlot and Decreuse 2010; Sattinger 1993; Sicherman 1991; Sicherman and Galor 1990; Tsang and Levin 1985) and an empirical perspective (Duncan and Hoffman 1981; Groot and Brink 2000; Halaby 1994; Hartog 2000; McGuinness 2006). Three main dimensions of education-job mismatch have been analyzed in these studies: education level mismatch (most of these studies deal with over-education), field of study mismatch (Allen and Velden 2001; Robst 2007) and skills mismatch (Allen and Velden 2001; Chevalier and Lindley 2009; McGuinness and Sloane 2010).

The goal of this paper is to examine the determinants of education-job mismatch in the Central and Eastern European countries (CEE). Studying the transition from university to work in these countries is particularly important because of two reasons chiefly associated with their economic transition. First of all, the job matching process became more ambiguous due to the economic transformation and the associated economic crisis. Secondly, a significant educational expansion took place and the number of graduates increased rapidly. While the school-to-work transition in the CEE countries has been investigated by some sociologists (Kogan and Unt 2005; Saar *et al*. 2008), there is hardly any research on university graduate mismatch in these countries. There are only two recent studies on vertical education-job mismatch using general population surveys, one on Hungary, Slovenia and Estonia by Kogan and Unt (2005) and another on Estonia (Lamo and Messina 2010).

In order to investigate the determinants of vertical, horizontal and skills mismatches in the CEE countries, we divide the sample into two groups of countries: those with strong educational signal comprising of Poland, Czech Republic and Slovenia, and those with relatively weak educational signal composed by Lithuania, Estonia and Hungary (Kogan, Gebel and Noelke 2008). This division enables us to control for one of the major institutional characteristics affecting mismatch in the labor market, namely the strength of the connection between education and the labor market.

We use the REFLEX/HEGESCO data. Interviews using the standard questionnaire of the REFLEX project were carried out in 2005 and 2008 for the REFLEX and HEGESCO samples respectively, five years after graduation of the respondents. Thus, interviewees represent cohorts of graduates from 2000 and 2003 with a number of retrospective questions on their career experience during five years since graduation, giving a quasi-longitudinal character to the data.

In the course of the paper, we investigate how fields of study and competencies affect the likelihood of each type of mismatch. Workers' competencies comprise of their knowledge and learning abilities, their executive skills, organizational skills, entrepreneurial skills, communication skills and the knowledge of a foreign language. Both fields of study and competencies have been shown previously in the literature to have strong impacts on the job matches of graduates (Garcia-Aracil and Van der Velden 2008; Werfhorst 2002).

The importance of the topic of mismatch cannot be underestimated in the light of new evidence demonstrating its detrimental influence on workers' cognitive condition (de Grip et al. 2008) and its steady growth in the UK leading to enlarging dispersion in the returns to higher education (Green and Zhu 2010).

The paper is organized as follows. Next section provides a theoretical basis to our analysis describing the transition period of the Central and Eastern Europe and its relation to labor mismatch. Section 3 describes data and methods used in the analysis. Next we present the results of the econometric analysis and section 5 concludes the paper.

2. Theoretical discussion

In this section we first discuss the role of the transition process from the socialist regime to a market economy in the labor mismatch dynamics in Central and Eastern European countries. Later we classify the countries in two groups according to the strength of the connection between education and the labor market, which adds a new dimension to the analysis of mismatch.

2.1. Mismatch in the East

Most of the research on mismatch has concentrated on Western countries (Chevalier 2003; Handel 2003; Kucel 2011; McGuinness 2006). So far, however, almost no studies have looked at the Central and Eastern European economies. The notable exception is the work of Kogan and Unt (2005) who investigated the likelihood of under-/over-education in the first significant jobs for individuals in Hungary, Slovenia and Estonia. Their investigation reveals significant impacts of gender, job market experience and parental level of education on the likelihood of over-education. Another study, Lamo and Messina (2010), examines the wage penalties of being mismatched in Estonia in the years 1997-2003 and finds significant penalties to over-education.

The scarcity of studies on mismatch in the Eastern Europe is chiefly a result of the lack of adequate data. Notwithstanding, this does not mean that transition economies of the post-Soviet bloc have not been investigated in terms of their labor markets. Several recent studies on the transition from centrally planned economy towards market economy shed important insights on how the mismatch could have developed in these countries (Diewald, Solga and Goedicke 2002; Jeong, Kejak and Vinogradov 2008; Roberts 1998).

After the fall of state-socialism in 1989, Eastern European countries entered a path of transition towards a market economy. Soviet bloc economies before 1989 were characterized by a large industrial sector, while the service sector was rather underdeveloped. This situation at the early stages of transition led to massive unemployment due to layoffs in the industrial companies (Diewald, Solga and Goedicke 2002; Jeong, Kejak and Vinogradov 2008; Solga and Diewald 2001). At the same time skilled labor became scarce for the emerging service sector. This duality led to large unemployment of skilled labor from the industrial sectors and increased employment of often under-educated workers in the service sector (Kogan and Unt

2005). Domanski (2005) observes an important growth of returns to education in Poland and postulates that similar processes occurred in other CEE countries during the transition (see Galasi 2003 for Hungary). Educational systems in the CEE countries responded with a large educational expansion to the increased demand for skilled labor for the service sector. But economies did not keep the pace of development and the increase in demand for skilled labor halted (Cazes and Nesporova 2003; Helemäe and Saar 2000; Kertesi and Köllö 2002; Saar, Unt and Kogan 2008). In consequence, an excess of skilled labor flowed the labor markets inflating the entry credentials to skilled jobs and producing over-education.

These two processes led to a sizable increase of both, under-education in the early phase of transition, and over-education in the later, more matured phase of transition (Slomczynski et al. 2007). Finally, but not less importantly, large pools of more vulnerable groups (youth, elderly workers, women) in CEE countries have suffered economic hurdles from the transition chiefly due to the skills mismatch (the heavy industry sector) and fierce competition in the labor market in the second phase of the transition (Plessz 2009).

Our paper aims at identifying which fields of study and which competencies lead to various types of mismatch in Czech Republic, Hungary, Poland, Lithuania, Estonia and Slovenia in the second half of 2000s.

2.2. Classification of countries

We classify countries based on the connection between their education system and the labor market. This classification was developed and has been widely used in sociology for the Western economies (Gangl 2001; Maurice, Sellier and Silvestre 1986; Shavit and Muller 1998). It distinguishes between two types of labor markets: the occupational and the internal labor market (OLM/ILM). The OLM, also called qualificational space, is characterized by a strong linkage between education and the labor market, which facilitates the school-to-work transition of graduates (Allmendinger 1989; Witte and Kalleberg 1995). Conversely, in the internal labor markets, otherwise called organizational space, the school-to-work transition is troublesome due to low quality signal from educational credentials (Rosen 1972; Spence 1973). Nevertheless, firms use these credentials to discriminate between more or less able individuals in these countries (Kalleberg and Sorensen 1979; Thurow 1974).

In our classification we follow those authors who elaborated on this distinction for the CEE countries (Kogan, Gebel and Noelke 2008; Saar, Unt and Kogan 2008). Four of the countries studied here (Czech Republic, Hungary, Slovenia and Poland) used to have a school structure very similar to the German school system, characterized by a strong vocational specificity, standardization of the curriculum and high level of education signalling. Estonia and Lithuania, instead, as former Soviet Union states, used to be part of the Soviet educational structure. As Saar describes the Estonian system (Saar 2005), some features like standardised curriculum and tracking system looked similar to the German case, though the main features (also in Lithuania) were centralisation and state control from Soviet government. In these two countries, the strong link between school and work used to be less the outcome of a qualificational mobility space but more a sign of the command economy where school leavers were centrally directed to jobs.

During transition, the general OLM character of the school to work linkage changed to a different extent in each of these countries. The OLM features remained the strongest in Slovenia, and they are still characteristic for the Czech Republic and Poland. Yet they weakened significantly in Estonia and Lithuania, but also in Hungary (Bukodi and Robert 2002), which are now considered countries with weak educational signalling (ILM). Therefore, we classify countries as follows: the occupational group comprises of the Czech Republic, Poland and Slovenia, and the organizational group entails Lithuania, Estonia and Hungary.

3. Data and methods

3.1. Data description

In our empirical analyses we resort to a combined dataset of REFLEX and HEGESCO higher education graduates' surveys. Data for Czech Republic and Estonia come from the REFLEX survey, which refers to graduates from 1999/2000 interviewed five years later in 2005. Data for Hungary, Poland, Lithuania, and Slovenia come from the HEGESCO survey which captured information on graduates from 2002/2003 interviewed in 2008. The survey contains roughly 1000-1500 observations per country with an exception for the Czech Republic with nearly 7000 cases and Slovenia with close to 3000 cases. To avoid that results being driven by some particular countries, we use a random sample of no more than 2000 cases per country in all our analysis. We exclude from our analysis all individuals who were self-employed and all part-time workers (those who worked less than 20 hours per week).[1]

As mentioned above, we have grouped the country samples in two groups: the OLM countries consisting of Poland, Czech Republic and Slovenia and the ILM countries comprised of Hungary, Lithuania, and Estonia. Our effective samples once all missing cases are deleted are 3204 individuals for the OLM group and 1459 individuals for the ILM group. The complete set of variables and their descriptive statistics for both groups can be found in Tables A and B in the Appendix.

3.2. Mismatches

We use three dependent variables measuring different types of labor mismatch. Vertical mismatch refers to three possible categories: under-educated if the respondent considered his/her job required more education than s/he currently possessed, over-educated if the s/he

[1] The self-employed and part-time workers are very specific groups. Different reasons can explain why individuals become self-employed or prefer a part-time job. Explaining them is beyond the scope of this paper.

had more education than required by the job, and matched otherwise. Horizontal mismatch is a dichotomous variable which takes value 0 if own or related field was the most appropriate for the present job and 1 when completely other or no specific field was required. The third dependent variable measures the level of skill mismatch and comprises of three categories: over-skilled if the respondent considers that his/her skills are little utilized in his/her current job; under-skilled if the the current work demands more skills than s/he can offer; and matched otherwise.

The OLM markets in the Eastern Europe resemble to some extent their counterparts in the West. Their strong education-labor market linkages facilitate efficient allocation of graduates to jobs, which consequently reduce the observed levels of mismatch. Contrary to that, in the ILM space, where markets are weakly connected with the educational systems, we observe higher incidence of mismatch (Wolbers 2003). The proportion of graduates that are over-educated is 12% in the OLM group and as much as 18% in the ILM space. Interestingly, the levels of under-education are fairly similar in both groups (around 15%). The levels of horizontal mismatch are again similar across both groups (13% for the OLM group and 16% for the ILM group) with slightly better matching situation in the OLM group. Finally, although over-skill levels are exactly the same in both groups (7%), around 30% of graduates in the ILM group are under-skilled, while only 23% are under-skilled in the OLM group.

3.3. Competencies

We construct six indexes of competencies based on a battery of questions regarding individuals' self-perception of their competence in 19 facets spanning from knowledge of their own field to knowledge of a foreign language (see Table 1). Every facet of competency was measured on a 7-level Likert-type scale. Table 1 reports the groupings of all 19 facets into indexes based on a factor analysis and their corresponding Cronbach's alpha coefficients of reliability. Each index was later standardized to mean 0 and variance 1.

Insert here Table 1.

3.4. Methodology

Given the categorical nature of the dependent variables we employ multinomial logistic models for vertical and skills mismatch and a logistic model for the horizontal mismatch.

We estimate three models for each type of mismatch. In model 1 we introduce fields of study, model 2 has instead competency indexes and, finally, model 3 introduces both fields and competencies. Additionally all models have as explanatory variables individual and job characteristics (gender, age, relative grade in tertiary studies, education level, control if student strived for the highest possible marks (goodstu) and whether s/he participated in an internship, tenure and firm size) as well as occupation, sector and country dummies.

Table 2 presents the results for multinomial logistic estimation for vertical mismatch in OLM and ILM groups of countries. Similarly, table 3 reports the coefficients of the multinomial logistic estimation for skills mismatch for each group of countries. Finally, table 4 presents the results of a logistic estimation for horizontal mismatch in each group of countries.

4. Results

As mentioned above, we employ multinomial logistic models for vertical and skills mismatch and a logistic model for the horizontal mismatch. For the sake of clarity of our argument we discuss first the effect of fields of study and competency indexes on each type of mismatch, and provide a general overview of the effect of other explanatory variables on labor mismatch in the end.

4.1 Vertical mismatch

Table 2 provides results on vertical mismatch for OLM and ILM country groups. For the OLM group results reveal that both, fields of study and competency indexes, matter for vertical mismatch.[2] For the ILM group, only the education field is significant, while several competency indexes matter for vertical mismatch. The likelihood-ratio test on joint significance of fields of study rejects that their effect is jointly zero.

Insert here Table 2

Educational mismatches, unlike skills mismatches, are directly a product of inadequacy of educational credentials to job requirements. Therefore in countries belonging to the OLM group one could anticipate that fields like education or health should decrease the likelihood of mismatch, because their target jobs are clearly defined and their skills more transparent. Alternatively, we should observe higher levels of mismatch associated with wide disciplines as their target jobs are less clearly defined. In the ILM countries, fields of study should have a weaker explanatory power on educational mismatch. The intuition is that both narrow and wide disciplines have weak signal in the ILM markets, and therefore, their effects on mismatch get diffused. Our results support this view. Fields of study have a bigger role in explaining vertical mismatch within the OLM countries than within the ILM group of countries. We obtain that Education, Social Sciences, Sciences and Health lead to less over-education and more under-education than Engineering. We can conclude that these fields are better than Engineering in terms of vertical mismatch if we consider over-education a "bad mismatch" (the worker could have obtained a better job) and under-education a "good mismatch" (the worker is performing better than expected by his/her education level). Among these fields of study there are those narrow and focused towards particular occupations (Education, Health) and those broader and more demanded in transition economies (Social Sciences and Sciences),

[2] Both Akaike's information criterion and adjusted McFadden's R^2 support Model 3. Also the likelihood-ratio tests reject that the effects of all fields on one hand and competencies on the other are jointly zero.

which facilitate a better education-labor match.[3] In contrast, the only field that comes out significant in the ILM group is Education and it does so only at the 0.10 significance level (Table 2). Notwithstanding, Education leads to higher probability of over-education and lower probability of under-education as compared to Engineering, which is not consistent with the idea that narrow fields (such as Education) should lead to less mismatch.

While educational credentials and fields of study signalize not only level of human capital but also its type (Kalmijn and Lippe 1997; Werfhorst 2002), individual competencies do not necessarily have to be associated neither with the level of education nor with the field of study. They form, at least to some extent, a separate group of explanatory factors in the mismatch literature (Chevalier and Lindley 2009; Green and McIntosh 2007; Handel 2003; Werfhorst 2002). Our expectation is that those competencies more demanded and easier to demonstrate through educational credentials should improve match in the OLM countries and have no effect in the ILM countries. On the other hand more general competencies, like knowledge of foreign language or communication skills (which Werfhorst (2002) labels “cultural skills”), which can be detected through personal interview, should be rewarded in both OLM and ILM countries.

We find that several competency indexes improve matching (decrease over-education and increase under-education) in the OLM group of countries. Among them, some are related to formal education, such as ‘executive’ and ‘resourceful’, while some are more general skills, such as ‘eloquence’ and ‘language’. In contrast, in the ILM group only ‘language’ increases under-education (Table 2).

Somewhat surprisingly organizational skills lead to worse mismatch (less under-education in both groups and more over-education in the OLM group). A tentative explanation could be

[3] A good example where Social sciences or Science graduates could apply their skills and be highly valued are the banking and insurance sectors. Both require high quantitative skills which could be obtained in the aforementioned fields of study.

that organizational skills are more rewarded in secretarial-type jobs, where university graduates may feel that they are clearly over-educated.

4.2. Skill mismatch

Results on skill mismatch are reported in Table 3. Since ILM/OLM countries differ in how skills learned in the school are known or linked to employer's needs, we should find similar (if not stronger) results than those obtained for vertical mismatch.

Insert here Table 3

We find strong evidence that fields of study do not matter at all to explain skill mismatch in ILM countries, as expected. The likelihood-ratio test of fields effects being jointly zero cannot be rejected. In contrast, in the OLM group, Agriculture and Health have significant coefficients. Agriculture field increases both, the likelihood of being over-skilled and under-skilled with respect to the field Engineering. Health instead increases the likelihood of being under-skilled and decreases the chances of being over-skilled with respect to Engineering. The second result might be explained by a dramatic change in the health system since the communist times, by the introduction of new technology, which may induce workers in this sector to feel more under-skilled than workers in other sectors of the economy. This may be especially strong if adaptation of curricula for the studies was slow and lagged behind due to the rising costs that universities in the region were unable to cover.

As with regards to competencies, there are two competency indexes that behave similarly in both groups of countries, 'knowledge' and 'executive' (Table 3). Having strong knowledge about your or other fields, facility in acquiring new knowledge and good analytical skills decreases the probability of being under-skilled. In contrast, executive skills (such as negotiation ability and leadership) decrease the probability of being over-skilled in the job.

While in the ILM group no other competency appears to be significant, there are additional competencies that explain skill mismatch in the OLM group. Good organizational skills decrease the likelihood of being under-skilled, while communication skills ('eloquent' competency index) decrease the likelihood of over-skilling. Finally, enterprising skills (as signalized by the competency index 'resourceful') increase chances of under-skill in the OLM countries.

4.3. Horizontal mismatch

Table 4 presents the results for the logistic estimation of horizontal mismatch in the OLM and ILM groups of countries.

Insert here Table 4

We expect that fields matter more in OLM countries, where they provide information to employers on workers' productivity, than in ILM countries, where differences across fields of study are more diffuse. We find that in the OLM group Agriculture and Services lead to larger horizontal mismatch, while studying Health leads to less horizontal mismatch than studying Engineering. In the ILM group only Humanities have larger likelihood of horizontal mismatch than Engineering. Therefore, results support our expectations.

Competencies do not have any effect on horizontal mismatch (as indicated by likelihood-ratio test of joint significance). We find that competencies are not important in explaining horizontal mismatch in any group of countries, even though we had expected general skills (such as language and eloquence) to help individuals get a matched job, especially in the ILM countries.

4.4. Effects of other explanatory variables on mismatch

Relative grade (our measure of ability) decreases probability of over-education and over-skilling in the OLM group only. Moreover, it decreases horizontal mismatch in OLM countries, although it increases horizontal mismatch in the ILM group. More able individuals even after graduating from fairly non-marketable fields such as humanities may be able to find jobs outside their field domain. Cases like anthropologists obtaining successful positions in high consultancy are not alien to the ILM countries.

Internship and tenure are significant in the ILM countries, decreasing probability of under-education. They provide a better signal of worker's productivity than education credentials in these countries. Moreover, tenure has a negative effect on being under-skilled (as you get experience you learn on the job). In contrast, tenure turns out significant to explain horizontal mismatch in the OLM countries: the longer the tenure, the more likely to be horizontally matched. This last result is consistent with job mobility theory, whereby workers change job to get better matched. If they remained long in the job, it is likely they are horizontally matched.

Those workers that report to have strived for the highest marks in their studies ('goodstu' variable) are more likely to be under-educated in the OLM group. Surprisingly though, they are more likely to be over-educated in the ILM group. We also find that striving for the highest marks helps in getting better skills match in both groups of countries, while improves chances of horizontal match for ILM countries. These results are consistent with considering this variable a measure of personal motivation.

Firm size has an effect on labor mismatch only in the ILM group: the larger the firm, the higher the likelihood of being under-educated, most likely due to internal promotion schemes (workers enter initially in low positions and become under-educated and may rise to higher levels with time). Firm size does not matter nor for skill mismatch, neither for horizontal match.

The only gender difference is that females are in general less likely to be under-educated than men in the OLM group. Age affects similarly both groups. It increases the likelihood of being under-skilled in the ILM group and decreases the likelihood of being over-skilled in the OLM group. It does not affect the other types of mismatch.

5. Conclusions

The purpose of this paper was to investigate on the determinants of education-job mismatches in the Central and Eastern European countries. We have used six countries and grouped them along their education to labor market connection into organizational labor markets (OLM) and internal labor markets (ILM). The first group comprised of Czech Republic, Poland and Slovenia, while the ILM category grouped Estonia, Lithuania, and Hungary. We have distinguished three types of mismatch: vertical (under-/over-education), skills (under-/over-skilled) and horizontal (wrong field for the job performed).

We find that the OLM countries experience fewer mismatches than the ILM countries due to their better connection between education and the labor market. When looking for the determinants of mismatch in the two groups, we find that for vertical and horizontal mismatch fields of study have stronger predicting power in the OLM than in the ILM countries. There is no effect of fields on the likelihood of skills mismatch in the ILM group.

We have also investigated the influence of competencies on the likelihoods of the three dimensions of mismatch. We demonstrate that they predict better vertical and skills mismatch in the OLM than in the ILM countries. As regards horizontal mismatch we find that competencies do not play any role.

Labor mismatches in the CEE countries are found to be similar to the Western economies. Yet there are two main differences which stem from historical reasons. Firstly, the transition lived in the CEE countries created a larger pool of under-educated individuals than commonly found in Western countries. Secondly, fields of study such as Social Science and Sciences, which tend to increase mismatch in Western countries, are found to improve vertical mismatch in the OLM group of countries.

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Appendix

Table A. Variable definitions.

Variable	Definition
medu	1=under-educated, 2=matched, 3=over-educated
mskill	1=under-skilled, 2=matched, 3=over-skilled
hmismatch	0=matched (own or related field or strictly own field required), 1=mismatched (completely other field or no particular field required)
Education	Field of study: Education
Humanities	Field of study: Humanities and arts
Social	Field of study: Social Sciences, Business and Law.
Science	Field of study: Science, Mathematics and Computing.
Engineer	Field of study: Engineering, Manufacturing and Construction.
Agricult	Field of study: Agriculture and Veterinary
Health	Field of study: Health and Welfare
Services	Field of study: Services
Relgrade	Relative grade at university studies: 1=below average, 2=average, 3=above average.
edulvlG_2	Current level of education: dummy variable= 1 if isced 5a long programme providing direct access to doctorate or above, 0 otherwise (isced5a not providing direct access to doctorate).
knowledge	Competency index on knowledge (see Table 1).
executive	Competency index on executive skills (see Table 1).
organize	Competency index on organizational skills (see Table 1).
resourceful	Competency index on enterprising ability (see Table 1).
eloquent	Competency index on communication skills (see Table 1).
language	Competency index on knowledge of a foreign language (see Table 1).
goodstu	1 if the respondent strived for the highest possible marks, 0 otherwise.
internship	1 if the respondent participated in internships during studies, 0 otherwise.
female	1 if female, 0 otherwise.
age	Age of the respondent when interviewed.
tenure	Number of months working with the current employer.
firmsizeG_1	Firm with less than 50 employees
firmsizeG_2	Firm with more than 50 and less than 250 employees
firmsizeG_3	Firm with more than 250 employees
isco88G_1	Legislators, senior officials and managers and professionals
isco88G_2	Technicians and associate professionals and armed forces
isco88G_3	Clerks and lower occupations
nace08G_1	Agriculture, mining, manufacturing and construction
nace08G_2	Distribution, hotels, transportation and communications
nace08G_3	Services and public

Table B. Descriptive statistics.

	Group 1: PL+CZ+SI (OLM) N=3204				Group 2: HU+LT+EE (ILM) N=1459			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
medu	1.982	0.516	1	3	2.029	0.583	1	3
mskill	1.841	0.531	1	3	1.777	0.568	1	3
hmatch	0.870	0.336	0	1	0.838	0.369	0	1
field_1	0.132	0.339	0	1	0.165	0.371	0	1
field_2	0.043	0.204	0	1	0.097	0.297	0	1
field_3	0.380	0.485	0	1	0.353	0.478	0	1
field_4	0.061	0.240	0	1	0.086	0.281	0	1
field_5	0.186	0.389	0	1	0.154	0.361	0	1
field_6	0.045	0.207	0	1	0.023	0.149	0	1
field_7	0.102	0.302	0	1	0.090	0.287	0	1
field_8	0.051	0.220	0	1	0.032	0.175	0	1
relgrade	2.415	0.532	1	3	2.459	0.551	1	3
edulvlG_2	0.530	0.499	0	1	0.425	0.495	0	1
knowledge	5.357	0.818	2	7	5.082	0.770	2.5	7
executive	5.077	0.968	1.17	7	5.125	0.842	2	7
organize	5.664	0.909	1.33	7	5.460	0.915	1	7
resourceful	5.786	0.844	1	7	5.478	0.853	2	7
eloquent	5.240	1.194	1	7	5.000	1.228	1	7
language	4.748	1.718	1	7	4.803	1.582	1	7
goodstu	0.552	0.497	0	1	0.655	0.475	0	1
internship	0.535	0.499	0	1	0.737	0.441	0	1
female	0.589	0.492	0	1	0.665	0.472	0	1
age	31.298	5.034	23	61	29.918	3.462	24	64
tenure	53.682	56.497	0	416	45.350	33.249	0	420
firmsizeG_1	0.287	0.452	0	1	0.330	0.471	0	1
firmsizeG_2	0.289	0.454	0	1	0.316	0.465	0	1
firmsizeG_3	0.424	0.494	0	1	0.354	0.478	0	1
isco88G_1	0.823	0.382	0	1	0.733	0.443	0	1
isco88G_2	0.144	0.351	0	1	0.175	0.380	0	1
isco88G_3	0.033	0.180	0	1	0.092	0.289	0	1
nace08G_1	0.219	0.413	0	1	0.166	0.372	0	1
nace08G_2	0.094	0.292	0	1	0.135	0.342	0	1
nace08G_3	0.687	0.464	0	1	0.699	0.459	0	1

Table 1. Indexes of competencies and competence facets comprising each index.

Index	Competence facets	Cronbach's alpha
knowledgeable	• mastery of own field or discipline • knowledge of other field or disciplines • ability to acquire new knowledge • analytical thinking	α=0.71
executive	• ability to negotiate effectively • ability to perform well under pressure • alertness to new opportunities • ability to mobilize the capacities of others • ability to make your meaning clear to others • ability to exert authority	α=0.79
organize	• ability to coordinate activities • ability to use time efficiently • ability to work productively with others	α=0.73
resourceful	• ability to use computers and internet • ability to come up with new ideas and solutions • willingness to question your own and others' ideas	α=0.67
eloquent	• ability to present products, ideas or reports to an audience • ability to write reports, memos or documents	α=0.65
language*	• ability to write and speak in a foreign language	--

Note: *language was left as a sole facet since it did not fit into any other index in the course of factor analysis.

Table 2. Education vertical mismatch. Coefficients from a multinomial logistic estimation.

	OLM group of countries						ILM group of countries					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	undered	overed	undered	overed	undered	overed	undered	overed	undered	overed	undered	overed
Education	-0.373	-0.575**			-0.273	-0.561**	-0.636*	0.529*			-0.681*	0.522*
	(0.268)	(0.256)			(0.271)	(0.259)	(0.340)	(0.295)			(0.348)	(0.297)
Humanities	0.187	0.088			0.107	0.049	0.029	0.251			-0.162	0.271
	(0.319)	(0.306)			(0.330)	(0.309)	(0.345)	(0.326)			(0.356)	(0.329)
Social Sc.	0.023	-0.352**			0.010	-0.376**	-0.121	-0.427			-0.222	-0.404
	(0.202)	(0.170)			(0.203)	(0.174)	(0.260)	(0.260)			(0.266)	(0.264)
Sciences	0.644**	-0.415			0.543**	-0.490	0.297	0.043			0.131	-0.009
	(0.261)	(0.296)			(0.267)	(0.300)	(0.335)	(0.338)			(0.341)	(0.341)
Agric. & vet	-0.029	0.143			0.092	0.069	-0.040	0.553			0.066	0.537
	(0.388)	(0.252)			(0.394)	(0.257)	(0.682)	(0.495)			(0.690)	(0.501)
Health	0.769***	-1.408***			0.954***	-1.540***	0.190	0.296			0.183	0.282
	(0.249)	(0.345)			(0.255)	(0.351)	(0.377)	(0.336)			(0.387)	(0.339)
Services	0.103	-0.078			0.198	-0.064	-0.801	0.112			-0.746	0.109
	(0.327)	(0.261)			(0.331)	(0.263)	(0.592)	(0.486)			(0.595)	(0.487)
sknowledge			0.088	-0.061	0.071	-0.047			0.083	-0.000	0.075	0.020
			(0.084)	(0.078)	(0.084)	(0.079)			(0.103)	(0.101)	(0.104)	(0.102)
sexecutive			-0.142	-0.303***	-0.111	-0.296***			-0.231*	-0.063	-0.207	-0.073
			(0.096)	(0.086)	(0.097)	(0.087)			(0.129)	(0.122)	(0.131)	(0.124)
sorganize			-0.249***	0.139*	-0.275***	0.147*			-0.260**	-0.054	-0.265**	-0.070
			(0.087)	(0.080)	(0.089)	(0.081)			(0.113)	(0.104)	(0.114)	(0.106)
sresourceful			0.123	-0.101	0.144*	-0.130*			0.129	-0.024	0.111	-0.004
			(0.083)	(0.075)	(0.085)	(0.077)			(0.103)	(0.101)	(0.105)	(0.103)
seloquent			0.235***	-0.004	0.260***	-0.033			0.170	0.024	0.186*	0.022
			(0.082)	(0.073)	(0.082)	(0.074)			(0.106)	(0.098)	(0.107)	(0.100)
slanguage			0.269***	0.052	0.265***	0.067			0.201**	-0.111	0.200**	-0.066
			(0.071)	(0.066)	(0.073)	(0.067)			(0.092)	(0.089)	(0.095)	(0.091)
relgrade	0.160	-0.323***	0.140	-0.236**	0.124	-0.275**	-0.114	-0.237	-0.181	-0.243	-0.148	-0.238
	(0.119)	(0.116)	(0.119)	(0.116)	(0.121)	(0.117)	(0.149)	(0.152)	(0.149)	(0.152)	(0.150)	(0.154)
edulvlG_2	-3.413***	1.972***	-3.501***	2.025***	-3.582***	2.026***	-1.595***	2.207***	-1.675***	2.187***	-1.726***	2.235***

	(0.176)	(0.206)	(0.178)	(0.209)	(0.182)	(0.211)	(0.209)	(0.197)	(0.215)	(0.196)	(0.217)	(0.201)
internship	-0.020	0.144	0.072	0.042	-0.025	0.120	-0.437**	0.206	-0.384**	0.250	-0.347*	0.211
	(0.141)	(0.138)	(0.134)	(0.132)	(0.142)	(0.139)	(0.189)	(0.190)	(0.186)	(0.186)	(0.193)	(0.192)
female	-0.384***	0.035	-0.301**	-0.143	-0.303**	0.011	-0.345*	0.148	-0.311*	0.149	-0.245	0.161
	(0.137)	(0.130)	(0.131)	(0.125)	(0.140)	(0.134)	(0.176)	(0.180)	(0.177)	(0.174)	(0.184)	(0.185)
age	0.007	0.018	0.012	0.016	0.014	0.023	0.023	-0.041	0.036	-0.036	0.036	-0.042
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)	(0.024)	(0.028)	(0.024)	(0.028)	(0.024)	(0.028)
tenure	-0.002*	-0.001	-0.001	-0.001	-0.002	-0.001	-0.005**	0.001	-0.005*	0.001	-0.004*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
goodstu	0.468***	-0.064	0.472***	-0.049	0.432***	-0.027	0.299*	0.423**	0.295	0.434**	0.274	0.454**
	(0.131)	(0.122)	(0.132)	(0.123)	(0.134)	(0.124)	(0.181)	(0.183)	(0.182)	(0.182)	(0.184)	(0.185)
firmsizeG_2	0.194	-0.150	0.147	-0.133	0.153	-0.166	0.495**	-0.271	0.477**	-0.244	0.460**	-0.256
	(0.162)	(0.155)	(0.162)	(0.155)	(0.164)	(0.156)	(0.210)	(0.198)	(0.210)	(0.197)	(0.213)	(0.199)
firmsizeG_3	0.335**	-0.198	0.352**	-0.215	0.257	-0.200	0.745***	-0.095	0.768***	-0.153	0.712***	-0.068
	(0.155)	(0.144)	(0.154)	(0.144)	(0.157)	(0.146)	(0.208)	(0.189)	(0.207)	(0.187)	(0.211)	(0.192)
PL	0.296	0.917***	0.146	1.029***	0.289	0.921***						
	(0.182)	(0.177)	(0.176)	(0.170)	(0.184)	(0.179)						
SI	-2.531***	1.770***	-2.686***	1.845***	-2.731***	1.818***						
	(0.200)	(0.222)	(0.204)	(0.224)	(0.209)	(0.228)						
LT							1.264***	0.785***	1.387***	0.655***	1.381***	0.766***
							(0.251)	(0.205)	(0.248)	(0.203)	(0.256)	(0.209)
EE							0.626**	0.435*	0.682***	0.399*	0.668***	0.436*
							(0.253)	(0.222)	(0.243)	(0.220)	(0.256)	(0.223)
_cons	0.166	-3.842***	0.147	-4.321***	0.102	-4.196***	-1.553*	-2.448**	-2.074**	-2.461***	-1.960**	-2.447**
	(0.647)	(0.608)	(0.638)	(0.614)	(0.667)	(0.624)	(0.871)	(0.956)	(0.862)	(0.939)	(0.892)	(0.970)
N	3204		3204		3204		1459		1459		1459	
AIC	3993.761		3974.667		3934.644		2172.242		2172.528		2172.378	
BIC	4273.081		4241.842		4286.829		2415.375		2405.090		2478.938	
r2_mfadj	0.185		0.189		0.197		0.150		0.150		0.150	
chi2	997.027		1012.122		1080.144		474.261		469.975		498.125	

OLM Group: PL+CZ+SI, ILM group: HU+LT+EE.
Dependent variable: medu. Reference category for field of study: Engineering. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other controls: occupation and sector.

Table 3. Skills mismatch. Coefficients from a multinomial logistic estimation.

	OLM group of countries						ILM group of countries					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	underskill	overskill	underskill	overskill	underskill	overskill	underskill	overskill	underskill	overskill	underskill	overskill
Education	0.194	-0.229			0.233	-0.232	-0.038	0.076			-0.006	0.119
	(0.184)	(0.314)			(0.185)	(0.317)	(0.236)	(0.414)			(0.240)	(0.417)
Humanities	-0.211	-0.183			-0.186	-0.139	-0.156	0.389			-0.102	0.490
	(0.262)	(0.395)			(0.265)	(0.401)	(0.265)	(0.440)			(0.272)	(0.446)
Social Sc.	0.007	-0.213			0.008	-0.214	-0.321	0.047			-0.251	0.130
	(0.137)	(0.215)			(0.139)	(0.220)	(0.201)	(0.347)			(0.205)	(0.349)
Sciences	0.260	-0.048			0.213	-0.134	-0.427	0.406			-0.396	0.364
	(0.200)	(0.341)			(0.202)	(0.347)	(0.274)	(0.450)			(0.278)	(0.454)
Agric. & vet	0.455**	0.864***			0.489**	0.782**	0.365	0.089			0.297	0.100
	(0.227)	(0.301)			(0.228)	(0.308)	(0.443)	(0.653)			(0.450)	(0.661)
Health	0.357*	-1.556***			0.400**	-1.712***	0.352	0.282			0.357	0.330
	(0.190)	(0.505)			(0.193)	(0.511)	(0.271)	(0.503)			(0.276)	(0.507)
Services	0.262	0.182			0.290	0.195	0.013	0.167			0.027	0.147
	(0.221)	(0.314)			(0.222)	(0.317)	(0.374)	(0.633)			(0.378)	(0.633)
sknowledge			-0.105*	-0.087	-0.107*	-0.073			-0.351***	-0.051	-0.335***	-0.048
			(0.059)	(0.093)	(0.060)	(0.094)			(0.079)	(0.139)	(0.080)	(0.139)
sexecutive			-0.010	-0.190*	-0.005	-0.179*			-0.006	-0.324**	-0.023	-0.318*
			(0.068)	(0.106)	(0.068)	(0.107)			(0.098)	(0.164)	(0.099)	(0.164)
sorganize			-0.096	0.024	-0.110*	0.034			0.044	0.173	0.025	0.174
			(0.062)	(0.096)	(0.063)	(0.098)			(0.085)	(0.144)	(0.086)	(0.144)
sresourceful			0.116*	0.003	0.120**	-0.022			0.086	0.164	0.111	0.168
			(0.059)	(0.090)	(0.060)	(0.093)			(0.078)	(0.142)	(0.079)	(0.143)
seloquent			-0.038	-0.167**	-0.028	-0.203**			-0.054	0.050	-0.052	0.048
			(0.057)	(0.085)	(0.057)	(0.087)			(0.078)	(0.131)	(0.079)	(0.131)
slanguage			0.052	-0.074	0.069	-0.053			-0.054	-0.165	-0.033	-0.170
			(0.050)	(0.079)	(0.051)	(0.081)			(0.069)	(0.121)	(0.070)	(0.123)
relgrade	-0.051	-0.489***	-0.017	-0.374***	-0.025	-0.419***	-0.068	0.235	-0.026	0.230	-0.023	0.248
	(0.086)	(0.142)	(0.086)	(0.142)	(0.087)	(0.144)	(0.116)	(0.204)	(0.117)	(0.204)	(0.118)	(0.206)
edulvlG_2	0.016	-0.036	0.026	0.050	0.003	-0.042	0.021	-0.148	0.114	-0.053	0.099	-0.072

	(0.125)	(0.210)	(0.124)	(0.208)	(0.126)	(0.214)	(0.130)	(0.232)	(0.132)	(0.234)	(0.134)	(0.237)
internship	-0.122	-0.237	-0.040	-0.279*	-0.132	-0.253	-0.033	0.202	0.058	0.191	-0.013	0.227
	(0.104)	(0.167)	(0.098)	(0.159)	(0.104)	(0.168)	(0.147)	(0.272)	(0.144)	(0.271)	(0.149)	(0.277)
female	-0.187*	0.102	-0.151	-0.020	-0.157	0.114	0.060	0.055	0.015	0.078	0.016	0.034
	(0.099)	(0.159)	(0.094)	(0.155)	(0.101)	(0.165)	(0.138)	(0.242)	(0.137)	(0.238)	(0.143)	(0.250)
age	-0.012	-0.053**	-0.007	-0.055**	-0.008	-0.050*	0.038**	0.052	0.047**	0.045	0.042**	0.046
	(0.013)	(0.026)	(0.013)	(0.026)	(0.013)	(0.026)	(0.019)	(0.035)	(0.019)	(0.036)	(0.019)	(0.036)
tenure	-0.002*	-0.001	-0.001	-0.002	-0.002	-0.001	-0.006***	-0.003	-0.006***	-0.003	-0.006***	-0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
goodstu	-0.002	-0.458***	0.023	-0.425***	0.010	-0.389**	0.031	-0.536**	0.099	-0.524**	0.097	-0.527**
	(0.093)	(0.151)	(0.093)	(0.152)	(0.094)	(0.153)	(0.138)	(0.233)	(0.140)	(0.234)	(0.141)	(0.237)
firmsizeG_2	0.094	-0.241	0.088	-0.203	0.091	-0.225	0.129	0.005	0.148	-0.009	0.154	-0.020
	(0.116)	(0.199)	(0.116)	(0.199)	(0.117)	(0.201)	(0.152)	(0.282)	(0.153)	(0.283)	(0.154)	(0.285)
firmsizeG_3	0.132	0.145	0.127	0.156	0.122	0.187	0.195	0.216	0.228	0.251	0.255*	0.255
	(0.111)	(0.172)	(0.111)	(0.171)	(0.112)	(0.175)	(0.152)	(0.261)	(0.152)	(0.260)	(0.155)	(0.265)
PL	1.363***	0.830***	1.291***	0.977***	1.371***	0.845***						
	(0.132)	(0.220)	(0.126)	(0.213)	(0.133)	(0.222)						
SI	0.588***	0.345	0.532***	0.465*	0.559***	0.367						
	(0.157)	(0.258)	(0.155)	(0.254)	(0.158)	(0.263)						
LT							1.356***	0.312	1.207***	0.286	1.326***	0.275
							(0.178)	(0.279)	(0.175)	(0.276)	(0.181)	(0.284)
EE							0.862***	-0.190	0.743***	-0.166	0.840***	-0.172
							(0.178)	(0.300)	(0.175)	(0.294)	(0.181)	(0.302)
_cons	-1.067**	0.348	-1.270***	-0.161	-1.294***	-0.033	-2.140***	-4.911***	-2.684***	-4.639***	-2.489***	-4.878***
	(0.472)	(0.875)	(0.466)	(0.856)	(0.479)	(0.882)	(0.677)	(1.246)	(0.663)	(1.247)	(0.687)	(1.278)
N	3204		3204		3204		1459		1459		1459	
AIC	4808.905		4804.496		4788.941		2384.293		2359.320		2375.498	
BIC	5088.224		5071.671		5141.126		2627.426		2591.883		2682.057	
r2_mfadj	0.046		0.047		0.050		0.036		0.046		0.039	
chi2	326.309		326.718		370.273		179.919		200.892		212.714	

OLM Group: PL+CZ+SI, ILM group: HU+LT+EE.
Dependent variable: medu. Reference category for field of study: Engineering. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other controls: occupation and sector.

Table 4. Horizontal mismatch. Coefficients from a logistic estimation.

	OLM group of countries			ILM group of countries		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Education	0.044		0.044	0.163		0.147
	(0.241)		(0.242)	(0.282)		(0.286)
Humanities	0.399		0.372	0.612**		0.540*
	(0.293)		(0.295)	(0.299)		(0.303)
Social Sc.	0.265		0.250	-0.383		-0.429*
	(0.172)		(0.173)	(0.247)		(0.250)
Sciences	0.092		0.051	-0.171		-0.113
	(0.280)		(0.282)	(0.337)		(0.340)
Agric. & vet	0.875***		0.852***	0.522		0.528
	(0.247)		(0.248)	(0.454)		(0.457)
Health	-1.698***		-1.715***	-0.176		-0.190
	(0.424)		(0.425)	(0.363)		(0.367)
Services	0.604**		0.597**	0.393		0.441
	(0.245)		(0.245)	(0.417)		(0.421)
sknowledge		0.016	0.022		0.001	0.018
		(0.074)	(0.075)		(0.097)	(0.098)
sexecutive		-0.112	-0.107		0.217*	0.223*
		(0.085)	(0.086)		(0.120)	(0.121)
sorganize		-0.007	0.012		-0.034	-0.052
		(0.078)	(0.079)		(0.103)	(0.104)
sresourceful		-0.040	-0.054		-0.141	-0.122
		(0.073)	(0.075)		(0.096)	(0.097)
seloquent		0.089	0.062		-0.150	-0.157*
		(0.071)	(0.073)		(0.093)	(0.094)
slanguage		0.019	0.015		0.174**	0.178**
		(0.062)	(0.063)		(0.086)	(0.088)
relgrade	-0.264**	-0.233**	-0.257**	0.257*	0.283*	0.266*
	(0.109)	(0.108)	(0.110)	(0.145)	(0.146)	(0.148)
edulvlG_2	-0.351**	-0.302**	-0.364**	-0.393**	-0.418**	-0.424**
	(0.154)	(0.151)	(0.155)	(0.166)	(0.168)	(0.170)
internship	0.078	-0.029	0.078	0.034	0.014	0.032
	(0.130)	(0.124)	(0.130)	(0.187)	(0.184)	(0.191)
female	0.108	0.058	0.099	-0.137	-0.162	-0.132
	(0.123)	(0.119)	(0.126)	(0.170)	(0.166)	(0.175)
age	0.018	0.013	0.019	-0.016	-0.011	-0.011
	(0.017)	(0.017)	(0.017)	(0.027)	(0.027)	(0.027)
tenure	-0.003**	-0.004**	-0.003**	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
goodstu	-0.171	-0.222*	-0.169	-0.427**	-0.441***	-0.436**
	(0.117)	(0.116)	(0.117)	(0.168)	(0.167)	(0.170)
firmsizeG_2	-0.147	-0.130	-0.153	0.140	0.101	0.148

	(0.149)	(0.148)	(0.149)	(0.191)	(0.190)	(0.192)
firmsizeG_3	0.002	-0.016	-0.001	0.122	-0.021	0.101
	(0.136)	(0.134)	(0.137)	(0.188)	(0.185)	(0.191)
PL	0.338**	0.540***	0.336**			
	(0.160)	(0.154)	(0.160)			
SI	-0.697***	-0.548***	-0.709***			
	(0.196)	(0.192)	(0.197)			
LT				0.682***	0.634***	0.703***
				(0.211)	(0.207)	(0.214)
EE				0.362*	0.352	0.349
				(0.220)	(0.214)	(0.221)
_cons	-1.800***	-1.634***	-1.814***	-2.206**	-2.342**	-2.369**
	(0.597)	(0.589)	(0.604)	(0.938)	(0.918)	(0.951)
N	3204	3204	3204	1459	1459	1459
AIC	2277.710	2331.711	2286.507	1216.548	1224.030	1218.614
BIC	2417.369	2465.299	2462.600	1338.115	1340.311	1371.894
r2_mfadj	0.078	0.056	0.074	0.060	0.055	0.059
chi2	238.471	182.469	241.674	124.151	114.669	134.085

OLM Group: PL+CZ+SI, ILM group: HU+LT+EE.
Dependent variable: hmismatch. Reference category for field of study: Engineering.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other controls: occupation and sector.