UNIVERSIDADE DA BEIRA INTERIOR
Ciências Sociais e Humanas

Education, Educational Mismatch, and Wage Inequality
Evidence for Different European Countries

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Dissertação para obtenção do Grau de Mestre em
Economia
(2º ciclo de estudos)

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Resumo

Neste trabalho, estuda-se o efeito do desajustamento entre a educação dos trabalhadores e os requisitos do seu trabalho no seu nível salarial, em diferentes países europeus. Encontraram-se indícios, em vários países, de que trabalhadores com sobre-educação tendem a ter uma penalização no salário enquanto os trabalhadores com sub-educação tendem a ter um prémio salarial. Esta situação contradiz alguns estudos sobre o tema. No entanto, apesar dos efeitos típicos da educação, do tempo de trabalho na empresa, experiência e género nos salários, os efeitos do desajustamento entre a educação dos trabalhadores e os requisitos do seu trabalho variam bastante ao longo da distribuição dos salários e dos países europeus. O trabalho evidencia ainda o que parece ser um novo facto estilizado na relação entre educação e desigualdade do salário: uma forma de U invertido na relação entre educação e salário.

Palavras-chave: Educação, Desajustamento Educacional, Desigualdade Salarial

Resumo alargado

Nesta dissertação é feito um estudo empírico acerca dos efeitos de diferentes variáveis nos salários dos trabalhadores. Foi recolhido um conjunto de dados levada a cabo pelo questionário europeu para as condições de trabalho (European Working Conditions Survey) que envolveu cerca de 30 países em 2005 com uma informação bastante completa no que toca a informação do mercado de trabalho europeu permitindo, para além da comparação entre países, fazer uma análise precisa de cada país.

Inicialmente é feita uma regressão (OLS) com o intuito de se captar os efeitos de diversas variáveis que achámos importantes para o estudo, são elas: educação, nº de anos na empresa, experiência, género, tamanho da empresa, sub-educação, sobre-educação e sector de atividade. Mais tarde efetuou-se uma regressão de quantis (SQReg) usando as mesmas variáveis mas sendo possível verificar os seus efeitos ao longo da distribuição salarial, sendo esta distribuição dividida em: 0,1 (incluídos nos que recebem menos do país), 0,25 (incluídos na classe média-baixa de salários), 0,5 (incluídos na classe média de salários), 0,75 (incluídos na classe média-alta de salários), e 0,9 (incluídos na classe alta de salários).

Através dos resultados obtidos foi possível chegar a variadas conclusões, de acordo com a regressão OLS, ter maior nível de educação significa salários melhores em todos os países, o nº de anos a trabalhar para a mesma empresa implica também um aumento de salário em 27 dos 31 países, quanto maior a dimensão da empresa maior a tendência em auferirem salários mais altos, a experiência tem um efeito positivo e significativo em 25 dos 31 países e um efeito negativo em apenas dois países e, por último, verificamos que o facto de se ser mulher significa obter salários mais baixos em todos os países do estudo.

Com os resultados obtidos na regressão de quantis podemos constatar de que a sobre-educação tende a penalizar os salários dos trabalhadores enquanto a sub-educação tende a premiá-los (evidências encontradas na Áustria, Bélgica, Republica Checa, Alemanha, Dinamarca, Espanha, Portugal, Eslováquia, Noruega e Croácia). Verificámos ainda de que os efeitos da educação ao longo da distribuição salarial variam bastante, tendendo a crescer antes da mediana e a decrescer depois desta, concluindo então que os retornos na educação estão a aumentar a desigualdade salarial na primeira parte da distribuição mas também a contribuir para uma diminuição desta desigualdade na segunda parte (as exceções a esta relação são a Hungria, Turquia, Bélgica, Finlândia e Croácia). Esta relação parece evidenciar um novo facto estilizado, a forma de um “U” invertido.

Abstract

In this dissertation, we study the relationship of mismatch between workers' education and labor market requirements throughout different European countries. We found evidence in several countries that overeducated people tend to have a wage penalty and undereducated people tend to have a wage premium. This evidence contradicts the few existing evidence on the issue. However, despite the typical effects of education, tenure, experience, and gender in wages, the effects of mismatch between education and labor market requirements differ a lot throughout the wage distribution and European countries. Meanwhile, we also found a potentially new stylized fact on the relationship between returns to education and wage inequality: an inverted U-shaped relationship between returns to education and wage.

Key-Words: Education, Educational Mismatch, Wage Inequality.

JEL Codes: I21; J31; O52

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Chapter 1

Introduction

It is known that investment on education brings more qualified employees, more productivity, more R & D and, therefore, economic growth. Nevertheless, in spite of a Country having high or low levels of education, the labor market produces some interesting phenomena. Some of these phenomena are wage inequality and educational mismatch which could be effects of education and also of labor markets gaps. But what are the real effects of education on these variables? And what are the effects of educational mismatch on salaries?

In this dissertation, we study wage regressions in which we introduce coefficients that measure mismatch between education and job characteristics. The data used is from the European Working Conditions Survey, 2005 wave, comprising around 30 countries, and this allows us to compare several European countries.

The previous work on the issue is extremely scarce and is divided between theoretical and empirical work and is devoted to the analysis of a single country. Muysken and Ter Weel (2000) develop a search-theoretical model of the labor market to explain the events of declining returns to schooling, overeducation, and relatively higher unemployment rate of the low-skilled workers in the Netherlands. Guironnet and Peypoch (2007) find empirical evidence of overeducation for low-skill French workers, while also finding a significant disequilibrium between wages and qualifications. Dolton and Silles (2008) besides trying to find evidence of overeducation, also try to assess its main determinants in the UK. Cardoso (2004) found no evidence of overeducation in the Portuguese labor market, while Budria and Moro-Egido (2008) found evidence of overeducation in the Spanish labor market. However, only strongly mismatched workers found themselves with a significant wage penalty. Moreover, these authors showed that matched workers have significantly higher returns to education when compared with mismatched workers. Regarding the type of education, Robst (2007) analyzed the relationship between college majors and job functions using US data. Substantial evidence of mismatch between jobs and college major was found, being this reflected in lower wages.

We extend the empirical work presented so far by showing evidence from a large sample of European countries with a single methodology. As Budria and Moro-Egido (2008) we also study the mismatch influence on wages throughout the distribution of wages thus analyzing its effect on wage inequality. Interestingly, we found that the pattern of the mismatch effect in wages differs a lot across European labor markets. Also, we found that the most common significant result is that undereducation positively influences wages, while overeducation negatively influences wages. However this also changes a lot across wages distributions within each country. Meanwhile, we found a new stylized fact between returns to education and the

distribution of wages: an inverted U-shaped relationship between returns to education and the wage distribution.
This study is structured in over three chapters, in addition to this one, discriminated by the following way. On Chapter 2 we present and clarify the data set and the models used on our estimations. Chapter 3 is divided by three subchapters, on the first one we expose the first findings on wage regressions and analyze the results, second one we focus on relationship between education and wage distribution and on the third one we show and analyze the effects of mismatch throughout the distribution of wages. At the Chapter 4 we take our final findings about this study.

Chapter 2

Data and Estimating the Model

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

This survey contains personal and labor market characteristics of workers including wage, hours worked, gender, marriage status, experience, tenure, education years, sector of the firm, among other variables. The survey also includes one question that asks the respondent whether he/she has the training to deal with his/her current duties. In particular, the respondent answers if his/her skills correspond to his/her work duty choosing one of the following options: "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" if refuses to answer. We have eliminated answers 8 and 9 and interpret answer “1” as undereducation and answer “3” as overeducation, while answer “2” is a correct match between education/skills and work duties or requirements. This gives somewhat different information about mismatches from the one offered by the former European Household Community Panel, used e.g. to study mismatches in the Spanish labor market by Budria and Moro-Egido (2008). The most important difference is that in this case (EWCS), there is not information whether the skills that the question refers to were acquired through formal training and education or not. Additionally the income-related variable in EWCS is monthly income measured by decilees (divided by 10 parts, each part corresponds to a group of income of each country). Here is the description the EWCS makes of its earnings variable: “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 ‘decilees’, each representing 10% of the respondents), and ranked from low to high.” Parent-Thirion et al (2007).

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

Although substantially different in the provided information, this is one of the currently most complete databases on labor information for Europe. This work aims to extract relevant information from it, to correctly derive labor policies in Europe.

We have estimated the following earnings equation:

$$w_i = \alpha_0 + \alpha_{\theta 1} X_i + \alpha_{\theta 2} mis1 + \alpha_{\theta 3} mis3 \qquad (1)$$

Where the subscript θ denotes the estimate at the θth 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 experience (and experience squared), tenure, gender, sector, and firm size. $mis1$ 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 3, i.e. 'I have the skills to cope with more demanding duties'. We experimented an alternative specification:

$$w_i = \alpha_0 + \alpha_{\theta 1} X_i + \alpha_{\theta 2} mis1 + \alpha_{\theta 3} mis2 \qquad \text{and}$$

$$w_i = \alpha_0 + \alpha_{\theta 1} X_i + \alpha_{\theta 2} mis3 + \alpha_{\theta 3} mis2 \qquad (2)$$

in which $mis2$ is a dummy variable that takes the value 1 when the answer was 'My duties correspond well with my present skills'. These results are available upon request, and they would not change the conclusion that can be drawn from our first specification.

As usual in labor market studies and in particular with the estimation of earnings equations, we use OLS estimation. To allow an assessment of the effect of different determinants of earnings and specifically of mismatch on the wage distribution, we also employ quantile regressions Koenker and Hallock (2001). In this dissertation, 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). We have used STATA® for the regressions estimations.

The samples dimension for each country is detailed in Table 1.

Table 1: Number of observations for each country

Country	Number of obs	Country	Number of obs	Country	Number of obs	Country	Number of obs
		Spain(8)	677	Luxembourg(16)	474	Slovakia(24)	669
Austria(1)	613	Finland(9)	871	Latvia(17)	827	UK(25)	615
Belgium(2)	650	France(10)	756	Netherlands(18)	625	Norway(26)	826
Cyprus(3)	544	Greece(11)	770	Malta(19)	436	Switzerland(27)	717
Czech Rep.(4)	578	Hungary(12)	743	Poland(20)	702	Bulgaria(28)	874
Germany(5)	828	Ireland(13)	797	Portugal(21)	738	Croatia(29)	703
Denmark(6)	786	Italy(14)	636	Sweden(22)	1012	Romania(30)	727
Estonia(7)	327	Lithuania(15)	752	Slovenia(23)	459	Turkey(31)	815

Chapter 3

Results

3.1. General Results from Wage Regressions

Table 2 presents results for our benchmark OLS regression.

Table 2[◊]: OLS Regressions with mis1 (undereducation) and mis3 (overeducation)

Country	edu	Tenure	exper	exper2	gender	Companysize	mis1	mis3	companysec~r	_cons	R-squared
1	.8325227 ***	.0395029 ***	.1645545 ***	-.003266 ***	-2.109801 ***	.1226489 **	.2321153	-.2800303	-.2392762 *	5.126946 ***	0.3077
	(.1058961)	(.0135743)	(.0336709)	(.0007921)	(.2074746)	(.0566985)	(.2361407)	(.2461821)	(.132515)	(.6715981)	
2	.3738457 ***	.0768928 ***	.0677442 **	-.0023659 ***	-2.113816 ***	.1433128 **	.3515697	-.2119962	-.0307875	6.904546 ***	0.2718
	(.0605677)	(.0144684)	(.0337687)	(.0007245)	(.2062664)	(.0576754)	(.3295602)	(.2259139)	(.1555931)	(.6371324)	
3	.8369603 ***	.0877397 ***	.1175574 ***	-.0024952 ***	-1.805267 ***	.262542 ***	-.1285688	.1662161	.2011044	1.380857 ***	0.4668
	(.0773099)	(.0113034)	(.0233023)	(.0004422)	(.1762753)	(.0569158)	(.3281489)	(.1818574)	(.1268918)	(.5013418)	
4	.8384081 ***	.0737621 ***	.1095651 ***	-.0032651 ***	-2.581018 ***	.0624993	.0716614	-.4138378 *	-.0747007	3.62197 ***	0.4173
	(.0644038)	(.0144374)	(.0266225)	(.0006132)	(.187143)	(.0524089)	(.3019211)	(.2140328)	(.1141723)	(.5659071)	
5	.3035381 ***	.0655605 ***	.1910144 ***	-.0038084 ***	-2.260495 ***	.0947132 *	1.000465 ***	-.162607	-.1083071	4.773417 ***	0.4234
	(.0281427)	(.0123421)	(.0265348)	(.0006073)	(.1700319)	(.048363)	(.2242049)	(.1930315)	(.1038369)	(.4827285)	
6	.4181348 ***	.0292872 ***	.1308764 ***	-.0021283 ***	-1.567613 ***	.0956476 **	.2718448	-.4104466 **	-.1369338	4.288141 ***	0.3858
	(.0443597)	(.0110041)	(.0160596)	(.0001974)	(.1719891)	(.0460514)	(.2134564)	(.1835433)	(.1360934)	(.4739696)	

[◊] * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

7	.1802987 ***	.0147249	-.0119318	-.0005425	-1.501161 ***	.3312853 ***	.0746035	-.0422327	-.0453117	5.875786 ***	0.2277
	(.0599192)	(.0151941)	(.0308277)	(.0006512)	(.2370222)	(.06877)	(.3174928)	(.2454043)	(.169293)	(.6391671)	
8	.5989313 ***	.0415888 ***	.1448164 ***	-.0023433 ***	-1.619723 ***	.1446758 ***	.8373057 ***	-.2088774	.0559402	2.894284 ***	0.3633
	(.0560102)	(.0115922)	(.0219452)	(.0004614)	(.1786582)	(.0466177)	(.3161414)	(.1902132)	(.1598911)	(.4529486)	
9	.3786758 ***	.0108271	.0771994 ***	-.001431 ***	-1.2431 ***	.2580629 ***	.1529173	-.091748	-.1331934	5.43692 ***	0.2084
	(.0403586)	(.0088582)	(.0219145)	(.0004931)	(.1481818)	(.0407923)	(.209325)	(.185228)	(.1004163)	(.4068889)	
10	.4545465 ***	.056784 ***	.0974993 ***	-.0022087 ***	-1.485959 ***	.1491574 ***	-.3055863	.0725207	-.1078531	4.021385 ***	0.2972
	(.0549023)	(.0108291)	(.0250687)	(.000667)	(.1453415)	(.0366468)	(.246159)	(.157002)	(.1107264)	(.4438344)	
11	.4337936 ***	.0323809 ***	.1645294 ***	-.003605 ***	-1.650573 ***	.234155 ***	-.4290868	.0639143	.2271957	4.151275 ***	0.3348
	(.04457)	(.0114956)	(.0211264)	(.0003989)	(.17664)	(.0473891)	(.2682307)	(.1819097)	(.1595699)	(.4398809)	
12	.5282949 ***	.026535 ***	.0252406	-.0005326	-1.039208 ***	.1321308 ***	.6432381 ***	.2539488 *	-.1458597 *	1.531624 ***	0.2672
	(.0523123)	(.0078416)	(.0224078)	(.0004757)	(.1426223)	(.036108)	(.240625)	(.1523369)	(.0772419)	(.4236266)	
13	.9664488 ***	.0429727 ***	.1626527 ***	-.0030876 ***	-2.212223 ***	.2397638 ***	-.60517 **	-.0496626	-.1708623	2.060285 ***	0.3766
	(.0622934)	(.0119231)	(.022515)	(.0004834)	(.1894666)	(.0484744)	(.3020788)	(.1973307)	(.1670957)	(.5236885)	
14	.4541213 ***	.040207 ***	.2241427 ***	-.003534 ***	-1.656925 ***	.1727257 ***	.0009581	.1766584	-.269828 *	2.958226 ***	0.3808
	(.0615177)	(.0149127)	(.0295742)	(.0006683)	(.1996296)	(.0518435)	(.2971945)	(.2118445)	(.139484)	(.5061376)	
15	1.083802 ***	.0300083 ***	.0192876	-.0009522 *	-2.095367 ***	.22102 ***	.4523326 **	.7200503 ***	-.3467507 ***	1.971148 ***	0.3748
	(.0715215)	(.0104452)	(.0247644)	(.0005304)	(.1856926)	(.0584631)	(.2211974)	(.2139423)	(.1292861)	(.6014966)	
16	.3091632 ***	.0683174 ***	.1407907 ***	-.0023986 ***	-2.05497 ***	.2194858 ***	.1930769	.0309509	.1425553	2.980999 ***	0.5267
	(.0206047)	(.0133212)	(.0382111)	(.0009153)	(.2232496)	(.0501844)	(.3088052)	(.2180554)	(.1634367)	(.5967498)	
17	.8451068 ***	.031262 ***	.0470803 **	-.0018145 ***	-1.654375 ***	.244121 ***	-.4328338 *	-.4177829 **	-.4571882 ***	2.898909 ***	0.2471
	(.0900364)	(.0101373)	(.0217406)	(.0004389)	(.1743287)	(.0576337)	(.2303414)	(.1825443)	(.1247126)	(.5988432)	
18	.5013788 ***	.063659 ***	.0784112 **	-.0015983 **	-2.937346 ***	.1867344 ***	-.500093	-.3783541 *	-.2988763 ***	4.608272 ***	0.4690
	(.0371448)	(.0124791)	(.031372)	(.0007168)	(.2106285)	(.0519405)	(.36121)	(.2084643)	(.091037)	(.6043392)	

19	.4956047 ***	.0272432 ***	.1090268 ***	-.0019081 ***	-1.065826 ***	.1072651 **	-.2313637	-.3551027 **	.0864651	1.013148 **	0.3979
	(.0453591)	(.0105384)	(.0236352)	(.0005095)	(.168586)	(.05257)	(.2226384)	(.1769679)	(.1274729)	(.4462182)	
20	1.020105 ***	.0163191	.1205652 ***	-.0024159 ***	-1.837894 ***	.1045735 **	-.0448584	-.2160138	-.2856994 **	.428801	0.3144
	(.0769812)	(.0113596)	(.0278099)	(.0007606)	(.188352)	(.0458483)	(.2718889)	(.1987159)	(.1343048)	(.4727645)	
21	.8064611 ***	.0322421 ***	.1248758 ***	-.0025389 ***	-1.141806 ***	.1260237 ***	.1375072	-.3170535 **	.1366162	2.872809 ***	0.4457
	(.0457482)	(.0095724)	(.0185609)	(.0003576)	(.1335246)	(.0365814)	(.250385)	(.1588624)	(.1284265)	(.3598552)	
22	.8984165 ***	-.0057557	.163501 ***	-.0028474 ***	-1.650045 ***	.37656 ***	-.007137	-.1685038	-.417862 ***	.8931806 *	0.3213
	(.0750112)	(.0101095)	(.0218764)	(.0005071)	(.1623067)	(.0450114)	(.307029)	(.1631595)	(.1076092)	(.5226153)	
23	1.024864 ***	-.0065749	.0633654 *	-.0007285	-.8129075 ***	.0388179	.9484408 ***	.2239795	.6672365 ***	-.0577099	0.3574
	(.0873786)	(.0157326)	(.0323717)	(.0007693)	(.2217593)	(.0597036)	(.3528872)	(.236822)	(.2193786)	(.6568983)	
24	.7250393 ***	.034724 ***	.1310325 ***	-.0031462 ***	-2.449634 ***	.1049313 **	.3072548	-.6169247 ***	-.2950779 ***	4.119287 ***	0.3405
	(.0639885)	(.0111851)	(.0316806)	(.000716)	(.176128)	(.04558)	(.342947)	(.1777338)	.0996174	(.5496471)	
25	.605046 ***	.0499815 ***	.0992495 ***	-.002124 ***	-2.083033 ***	.1297821 **	-.5187584	.000805	-.1478135	2.771557 ***	0.2709
	(.0851564)	(.0152947)	(.0252853)	(.0005129)	(.2116517)	(.0514459)	(.4240205)	(.2157573)	(.1207455)	(.7041958)	
26	.7636232 ***	.0309901 ***	.1644723 ***	-.0031542 ***	-2.180038 ***	.3689616 ***	.3505523	-.1645992	-.8535178 ***	2.320383 ***	0.4333
	(.0485714)	(.0115566)	(.0234186)	(.0005544)	(.1772284)	(.0690242)	(.24683)	(.195636)	(.161798)	(.4843961)	
27	.4122466 ***	.0348222 ***	.1512847 ***	-.0027544 ***	-2.881562 ***	.2647631 ***	-.03649	.0443237	.207917 *	3.806897 ***	0.5191
	(.0407488)	(.0097982)	(.0220624)	(.0004421)	(.1592302)	(.0400611)	(.1957603)	(.1699613)	(.1187519)	(.4699925)	
28	1.128849 ***	.0533475 ***	.0384033	-.0017017 ***	-1.443076 ***	.2674388 ***	.5765616 *	.194052	-.5364871 ***	3.38993 ***	0.3473
	(.0731982)	(.0102754)	(.0260147)	(.0006067)	(.1640315)	(.0463939)	(.3373991)	(.1777794)	(.112247)	(.5168308)	
29	1.153226 ***	.0004321	.1131338 ***	-.0021317 ***	-.9344345 ***	.0338844	.4322354 *	.0169935	.1019424	.4382154	0.3021
	(.0751055)	(.0116736)	(.0236143)	(.0006287)	(.1492276)	(.0448724)	(.2272166)	(.1544372)	(.1223727)	(.4812201)	
30	.9229513 ***	.0268401 **	.0222876	-.000214	-.7630892 ***	.2703817 ***	.2618902	.0949025	-.0110079	-.2579858	0.3040
	(.0588051)	(.0114883)	(.022902)	(.0005524)	(.1889219)	(.058668)	(.2876752)	(.2017913)	(.1389823)	(.553501)	

31	.4674541 ***	.0021616	.0799592 ***	-.0014388 ***	-.5676861 ***	.2166133 ***	-.3972323 *	-.2357418	.3442066 **	1.079056 **	0.2082
	(.0500473)	(.0094481)	(.0175883)	(.0003117)	(.2054025)	(.0449309)	(.2237492)	(.1613506)	(.1682914)	(.4650397)	

First of all, we want to analyze the results of the earnings regressions for each country in the light of the usual results for earnings regressions that were previously obtained in the literature. In fact, our results are clearly consistent with the usual results, pointing out for positive and significant effects of education and 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 bigger firms tend to pay higher wages. According to our OLS results, education has a clear positive effect on wages, with coefficients that range from 0.18 (in Estonia) to 1.15 (in Croatia), meaning that one additional level of education (from primary to secondary, for example) implies that wages can increase from 1.8% to 11.5% (since wages are measured by decilees of the wage distribution). Tenure has also a clear and significant effect on wages on 27 out of the 31 countries (exceptions are Finland, Sweden, Slovenia, and Turkey), with coefficients from 0.026 to 0.087, meaning that an additional year of tenure imply a 0.26% to a 0.87% increase in wages. Experience and squared experience are also significant in almost all countries (in 26 out of the 31 countries). Lithuania and Bulgaria show a significantly (linear) negative effect of experience on wages. Estonia, Hungary, and Romania present non-significant results on the coefficients for experience and experience squared. Gender has a significantly negative effect in all countries with a quantitatively important effect as being a woman means earning 5.6% less (in Turkey) to nearly 30% less in Netherlands. However, countries with a lower wage penalty for female are Eastern European countries (as Hungary, Slovenia, Croatia, and Romania).[2] Finally, firm size has an overall significantly positive effect on wages (exceptions are Czech Republic and Slovenia), as an increase in the size class of the firm implies an increased wage of 1% to 3.7%. Sweden, Romania, and Estonia are among the countries in which the effect of firms size is higher. As it can be observed in Table 2, the effect of mismatch is generally the least significant of the explanatory variables in the regressions, an issue that we will detail below.

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

Table 3[◊]: Quantile regression at the median (0.5) with mis1 (undereducation) and mis3 (overeducation)

q50											
Country	edu	tenure	exper	exper2	gender	companysize	mis1	mis3	companysec~r	_cons	R-squared
1	.9143045 ***	.054607 ***	.1745491 ***	-.003774 ***	-2.355892 ***	.102398	.5014894	-.3104903	-.2528183	5.267808 ***	0.2089
	(.1339811)	(.0162933)	(.0397907)	(.0008946)	(.2593682)	(.0737528)	(.3065252)	(.3159843)	(.2289113)	(.8447255)	
2	.3600748 ***	.0501955 **	.1300947 ***	-.0032434 ***	-1.267251 ***	.0783475	.6417098 **	.068427	.0156659	6.137761 ***	0.1269
	(.0650544)	(.0193871)	(.0399439)	(.0008195)	(.21548)	(.0563432)	(.2674095)	(.2029922)	(.1250042)	(.6461619)	
3	.8786279 ***	.1006531 ***	.0841433 ***	-.0016009 ***	-1.797277 ***	.2504033 ***	-.0660813	.0774562	.459251 **	.8154179	0.3148
	(.0938554)	(.0135893)	(.0281032)	(.0005523)	(.2407783)	(.0895146)	(.5268376)	(.243413)	(.2135988)	(.6768214)	
4	.8631128 ***	.0802029 ***	.0874657 ***	-.0029388 ***	-3.048397 ***	.0739568	.3372817	-.4792264	-.0081483	4.21097 ***	0.2912
	(.108625)	(.0193977)	(.0323547)	(.0007427)	(.2282752)	(.076953)	(.4071745)	(.3280624)	(.1553516)	(.8125887)	
5	.340107 ***	.0608478 ***	.1917132 ***	-.0033945 ***	-2.358541 ***	.1750484 ***	.7619403 ***	-.2818698	-.1652267	4.421728 ***	0.2846
	(.0364994)	(.0150285)	(.0352941)	(.0008651)	(.2897799)	(.0645912)	(.2837836)	(.2601488)	(.1517547)	(.5976683)	
6	.5409313 ***	.0091069	.178905 ***	-.0026396 ***	-1.53577 ***	.1028916	-.059194	-.5621947 **	-.2042743	3.437079 ***	0.2437
	(.0757615)	(.014604)	(.0267068)	(.0003321)	(.2598425)	(.0626897)	(.3132873)	(.2638213)	(.1734983)	(.8138484)	
7	.2229229 **	.0315863	-.0127069	-.0005249	-1.826913 ***	.4113776 ***	.099861	-.2662022	-.3603846	6.296174 ***	0.1515
	(.0888375)	(.0222468)	(.0417317)	(.0009095)	(.327899)	(.0957193)	(.4416131)	(.3380271)	(.2581828)	(.7570459)	
8	.6650645 ***	.0335133 ***	.1768028 ***	-.0029448 ***	-1.683171 ***	.1164779 **	.524265	-.1684401	.0517912	2.711063 ***	0.2504
	(.0583984)	(.0121086)	(.0221784)	(.000489)	(.1996325)	(.0578069)	(.4352179)	(.2626853)	(.2103643)	(.4698091)	
9	.3807839 ***	.0098882	.0854268 ***	-.0017066 ***	-1.393199 ***	.1575722 ***	.1306588	.11784	-.0663216	6.318691 ***	0.1255
	(.0451672)	(.0110971)	(.0231076)	(.0005256)	(.1564465)	(.0509355)	(.2945485)	(.1812745)	(.1259836)	(.4035596)	
10	.526613 ***	.0479473 ***	.1189629 ***	-.0024742 ***	-1.308799 ***	.1437719 ***	-.3995287	-.196585	-.0753321	3.429226 ***	0.1665
	(.0926615)	(.0131053)	(.0302522)	(.0007887)	(.1648416)	(.0503922)	(.3500672)	(.1873163)	(.1401901)	(.589788)	

[◊] * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

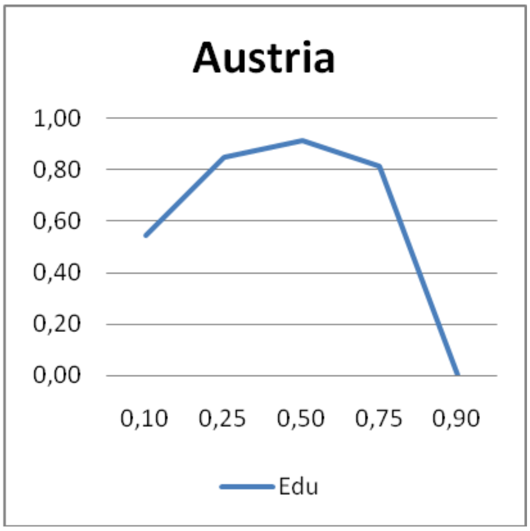
11	.3974701 ***	.0277242	.177225 ***	-.0038339 ***	-1.820114 ***	.1765868 ***	-.3600568	-.0831463	.4014566 **	4.705654 ***	0.2278
	(.0464131)	(.0169588)	(.0287319)	(.0005418)	(.245317)	(.0638894)	(.2438037)	(.2333319)	(.1601417)	(.592818)	
12	.6054389 ***	.0319918 ***	.0378074	-.0006553	-1.127824 ***	.1654928 ***	.4437337	.2027026	-.0890235	.6101209	0.1794
	(.0550082)	(.0100867)	(.029966)	(.0006532)	(.1827773)	(.0405587)	(.3539456)	(.1889601)	(.09675)	(.7181249)	
13	1.14316 ***	.0542244 ***	.2101257 ***	-.0039002 ***	-2.237626 ***	.1993078 **	-.3016868	.0378054	-.1816328	.878757	0.2477
	(.1048365)	(.0182719)	(.0387083)	(.0008073)	(.3520622)	(.078285)	(.6432795)	(.3549416)	(.2965238)	(.8723744)	
14	.4830863 ***	.0398756 ***	.2789793 ***	-.0045824 ***	-2.108007 ***	.2109981 ***	.1502282	.0446576	-.1251162	2.750114 ***	0.2631
	(.0758476)	(.014772)	(.0400235)	(.0008828)	(.2294988)	(.0626646)	(.3979164)	(.2598768)	(.1386564)	(.6667979)	
15	1.136538 ***	.0335576 ***	.0336459	-.0013055	-2.359648 ***	.2912543 ***	.2279622	.6762894 ***	-.3731701 ***	1.776749 **	0.2649
	(.0935048)	(.0122833)	(.0354552)	(.0008302)	(.2779757)	(.0697626)	(.2579269)	(.2279387)	(.1386615)	(.7005415)	
16	.342437 ***	.072567 ***	.143685 ***	-.002018	-2.421967 ***	.2627919 ***	-.0343423	-.040845	.2409983	2.557996 ***	0.3847
	(.0320737)	(.018256)	(.0539636)	(.0012661)	(.3380954)	(.0642075)	(.4738425)	(.2977497)	(.2452506)	(.822333)	
17	1.052411 ***	.0193456	.0502675 *	-.0017597 ***	-1.748748 ***	.4461251 ***	-.5352944 **	-.8477894 ***	-.4876835 **	1.33193 *	0.1682
	(.1452168)	(.0135797)	(.0281874)	(.0006096)	(.217614)	(.0582203)	(.2408287)	(.2067945)	(.2124102)	(.7930772)	
18	.5722763 ***	.0512602 ***	.061532	-.0008974	-3.765013 ***	.1558958 ***	-.2916247	-.347578	-.2748435 **	5.387653 ***	0.3386
	(.0501754)	(.0127906)	(.0449982)	(.0009901)	(.2854407)	(.0524531)	(.3534611)	(.2425132)	(.1105265)	(.7933156)	
19	.5382529 ***	.026638 **	.0535041 *	-.0005948	-1.027554 ***	.035689	-.2395388	-.4428133 **	.1000884	1.197504 *	0.2408
	(.0719902)	(.0123389)	(.0306014)	(.0007527)	(.1891855)	(.0879428)	(.3077952)	(.1982209)	(.116983)	(.6572938)	
20	1.058323 ***	.024772	.0901243 **	-.0016273	-1.623914 ***	.16604 **	-.0882305	-.0844706	-.2353708	-.7485627	0.2193
	(.1166079)	(.0173306)	(.0434026)	(.0010982)	(.3262967)	(.065504)	(.3850185)	(.2352819)	(.1655309)	(.8082506)	
21	.892704 ***	.0265001 **	.1053879 ***	-.002108 ***	-1.04533 ***	.0916618 **	.2637525	-.2454753	.2101907	2.550679 ***	0.3018
	(.0415809)	(.010845)	(.0197628)	(.0004801)	(.1473218)	(.0388372)	(.2673804)	(.1624701)	(.1461617)	(.3461907)	
22	1.195509 ***	-.0129592	.1919872 ***	-.0032016 ***	-1.734573 ***	.4802713 ***	-.1068922	-.3614175 *	-.5644998 ***	-.8683755	0.2540
	(.0932339)	(.0110468)	(.0242799)	(.0005387)	(.2089353)	(.0552596)	(.3082029)	(.2130261)	(.1619326)	(.6529261)	

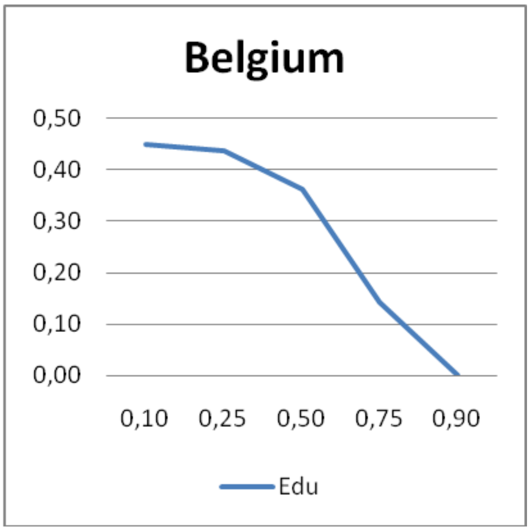
23	1.152728 ***	-.0306434	.0815661	-.0006001	-.9595948 ***	.0699149	1.327515 **	.165262	.7283683 ***	-1.07721	0.2438
	(.0955441)	(.026425)	(.0554611)	(.0013986)	(.3042785)	(.0896526)	(.516215)	(.3342573)	(.2679471)	(.9033467)	
24	.8059231 ***	.0561691 ***	.1090326 **	-.0027944 **	-2.793133 ***	.1190454 **	.7204484	-.5660687 **	-.2295937 **	3.94075 ***	0.2298
	(.084096)	(.0156636)	(.0507711)	(.0012215)	(.2345498)	(.0603923)	(.4377467)	(.2837648)	(.1137068)	(.770757)	
25	.8875458 ***	.0652415 **	.0876605 *	-.0017282 *	-2.863931 ***	.1757271 **	-.6250657	.0647363	-.1541147	1.821455	0.1950
	(.1490894)	(.0275381)	(.0446856)	(.0010458)	(.4585492)	(.0864771)	(.5655712)	(.3190919)	(.1788579)	(1.198428)	
26	.9412748 ***	.0367897 **	.1455888 ***	-.002518 ***	-2.461143 ***	.3987052 ***	.3047253	-.1911711	-.9885815 ***	1.932586 **	0.3129
	(.0662481)	(.0177154)	(.0310205)	(.0007563)	(.237258)	(.094604)	(.3353665)	(.2443962)	(.2183242)	(.8044993)	
27	.4122253 ***	.0401453 ***	.1004273 ***	-.0017399 ***	-3.376993 ***	.2916102 ***	.1149349	.018627	.2692603 *	4.693997 ***	0.3770
	(.0576796)	(.0112595)	(.0293246)	(.0005965)	(.2139029)	(.0462542)	(.274961)	(.1918193)	(.1591198)	(.6469699)	
28	1.173319 ***	.0521278 ***	.0765645 **	-.002694 ***	-1.605913 ***	.2742158 ***	.4253484	.2709846	-.7332327 ***	3.73367 ***	0.2191
	(.0837407)	(.0136645)	(.0344891)	(.0008394)	(.2192382)	(.0677492)	(.3561776)	(.2712729)	(.172538)	(.7607479)	
29	1.192067 ***	.0069083	.087511 ***	-.0014151 *	-.6562763 ***	.0675079	.5076278 *	.1371421	.196151	-.6506375	0.1983
	(.1026815)	(.0177089)	(.0293844)	(.0007727)	(.194416)	(.0864808)	(.2840848)	(.2321794)	(.2121927)	(.6254606)	
30	1.130087 ***	.0344922 **	.0388348	-.0004537	-.814871 ***	.3383118 ***	.4991732	.1311565	-.040256	-1.681519 ***	0.2053
	(.0718101)	(.0164317)	(.0346306)	(.0007386)	(.2579713)	(.0683246)	(.4295014)	(.2448455)	(.1866086)	(.6542252)	
31	.5176838 ***	.0122546	.0633973 ***	-.0012336 ***	-.4811645 **	.2702662 ***	-.2473394	-.2473394 *	.5213715 **	.2245238	0.1600
	(.0664793)	(.0096234)	(.0190853)	(.0003309)	(.2198408)	(.0492625)	(.2139994)	(.1429938)	(.256582)	(.4943059)	

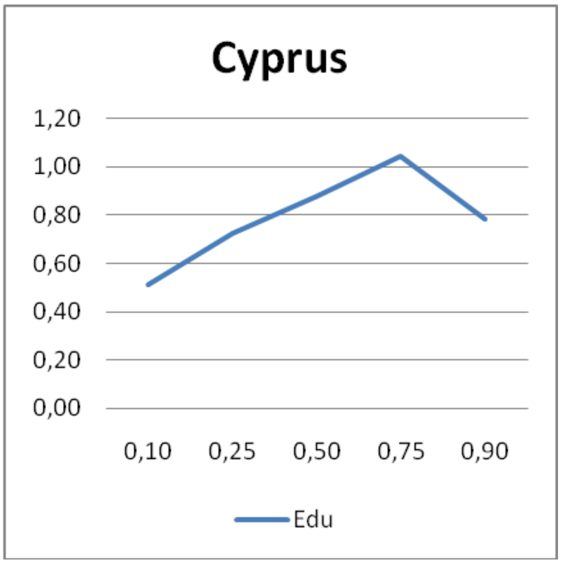
Our results from the quantile regression at the median almost confirm the OLS regression results, in what concerns significance and quantitative effects (see Table 3). For education and gender all the countries present highly significant results. However, exceptions for significant results occur more in tenure, experience, and firm size. Denmark, Estonia, Finland, Greece, Latvia, Poland, Sweden, Slovenia, Croatia, and Turkey present non-significant coefficients for tenure, which mean 1/3 of the countries with non-significant results for this variable. For experience, Estonia, Hungary, Lithuania, Netherlands, Slovenia, and Romania present non-significant results and Luxembourg, Malta, and Poland present linear significantly positive results. For company size there are non-significant results on Austria, Belgium, Czech Republic, Denmark, Malta, Slovenia, and Croatia.

3.2. Returns to Education

There are several papers that dealt with the relationship between returns to education and the wage distribution. In particular, Machado and Mata (2001), Hartog et al. (2001), and Fersterer and Winter-Ebmer (2003) also used quantile regressions to estimate wage regressions and conclude that typically returns to education tend to be higher in the right tail of the distribution. Martins and Pereira (2004), for example, in an article that covered 15 European countries and the USA, showed that, for most of them, returns to education are higher for the right-hand tail of the wages distribution. A comparison between the first and the ninth decilee would entail that the unique exception to that rule was Greece. However some of the countries showed a slight decrease in the returns coefficient between the eighth and the ninth decilees, which were the case of Ireland, Germany and Spain. In this section we address this relevant issue, using the results of the wage regression presented so far.



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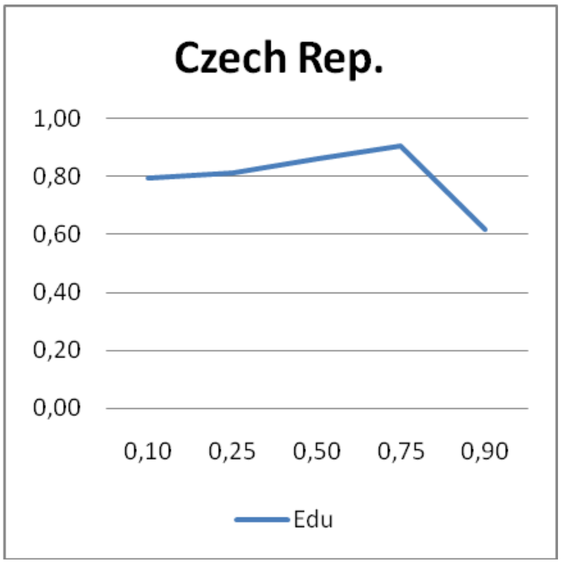
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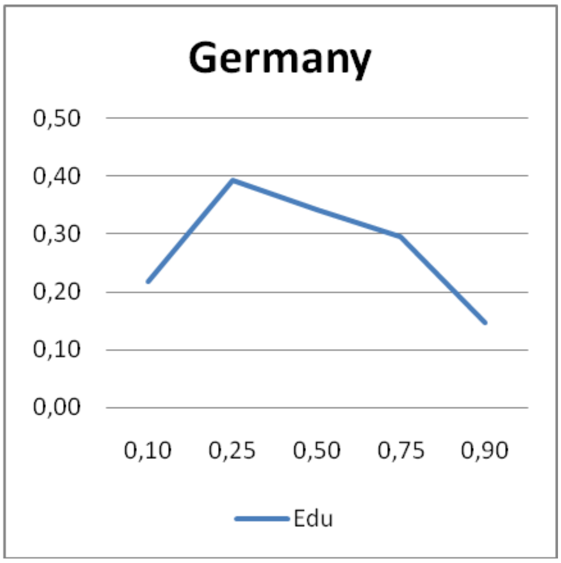
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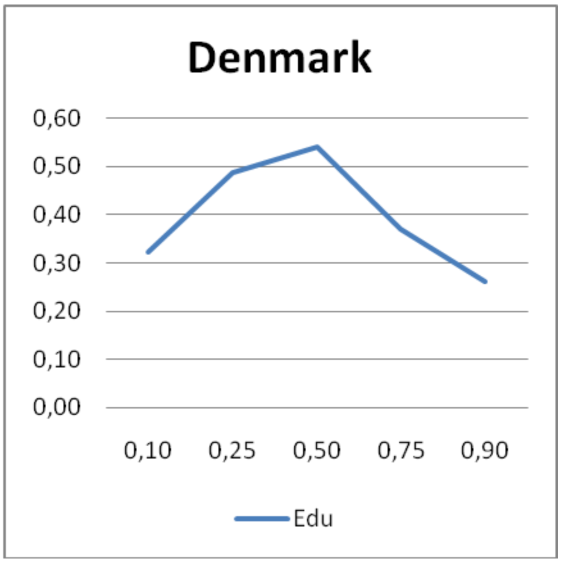
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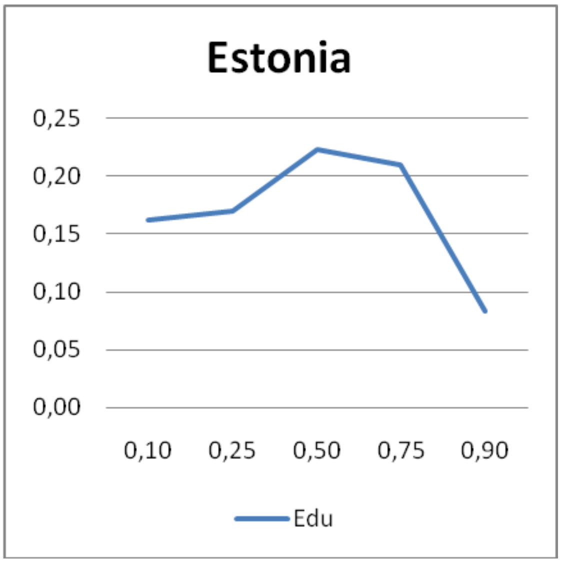
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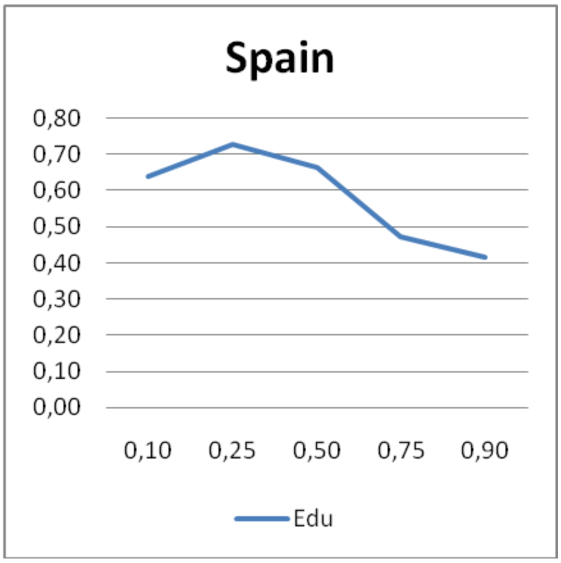
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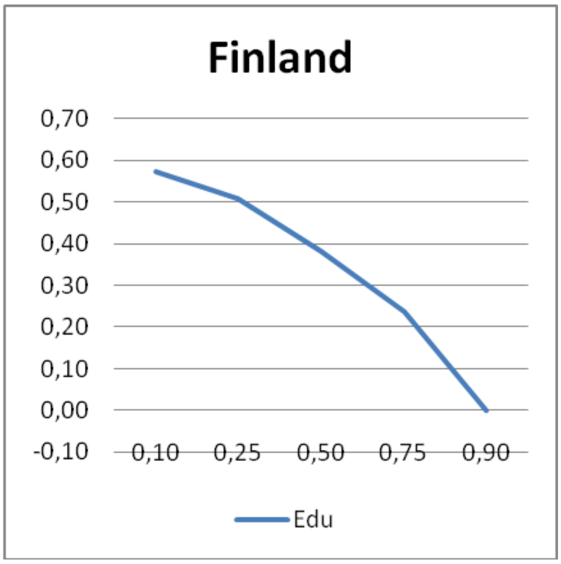
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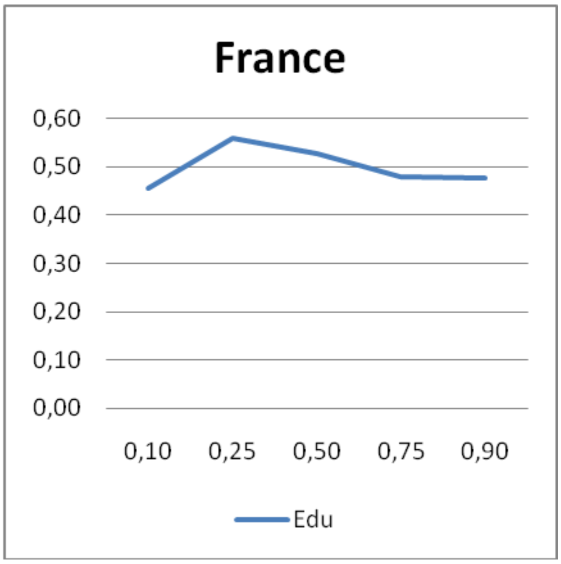
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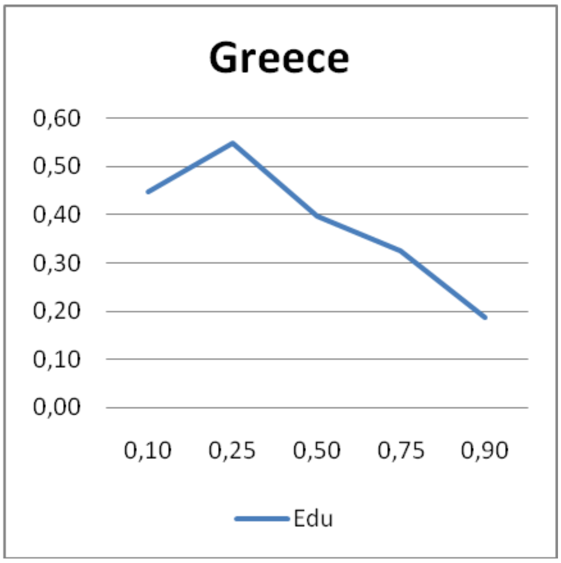
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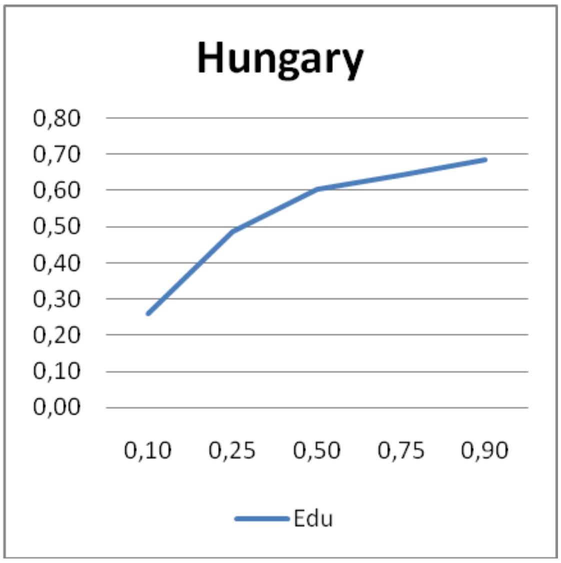
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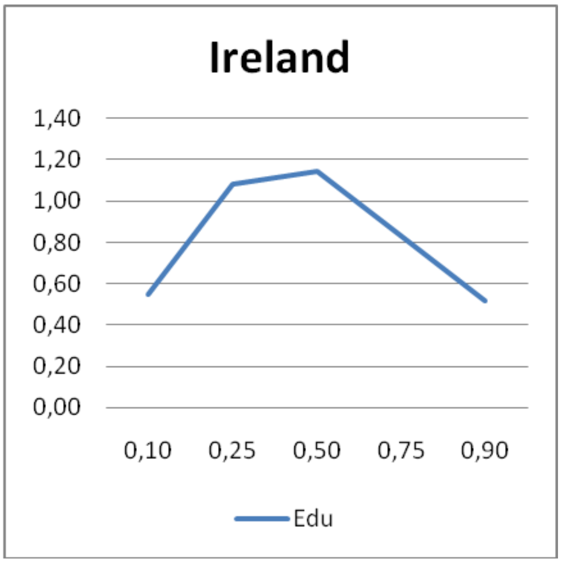
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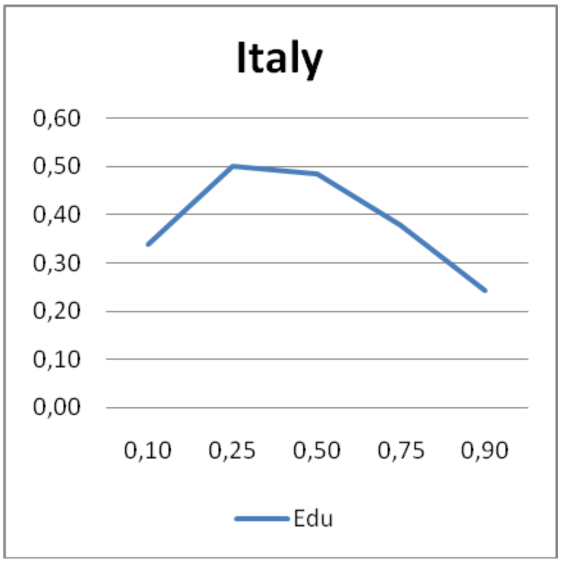
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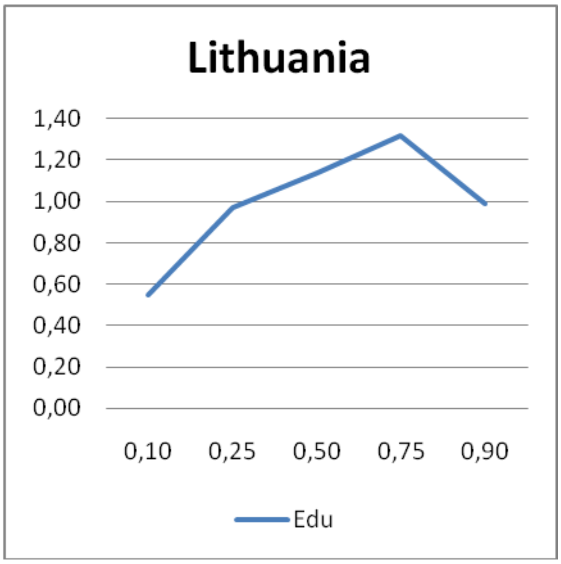
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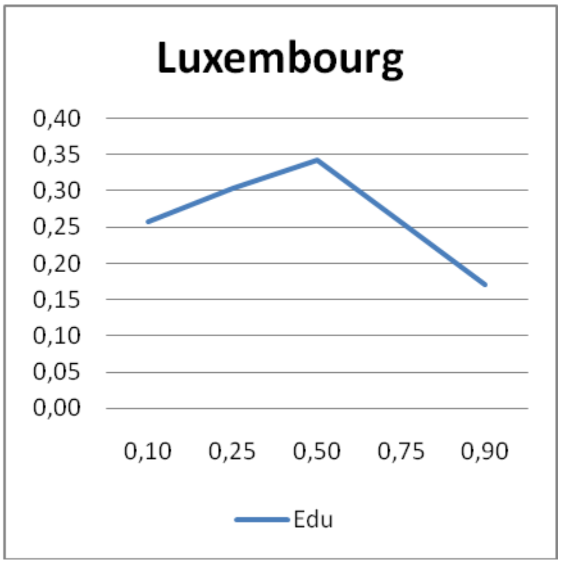
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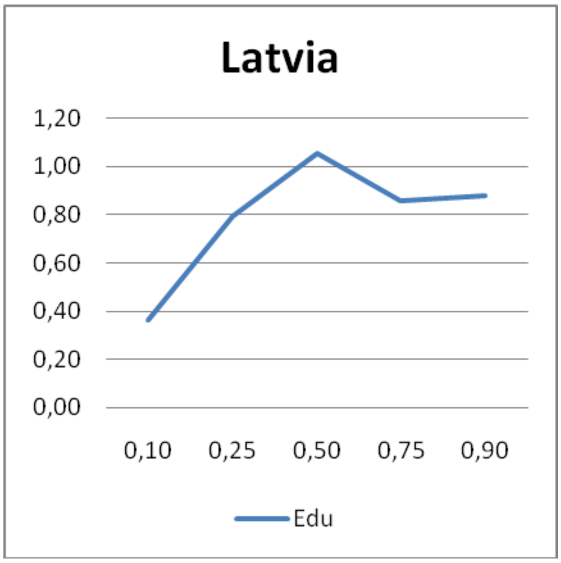
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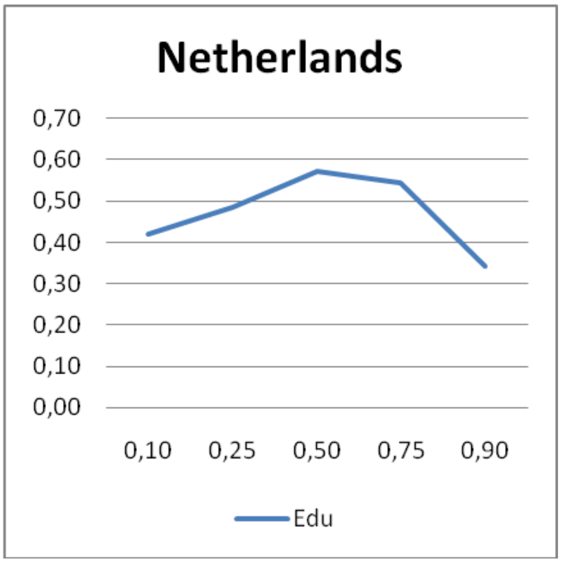
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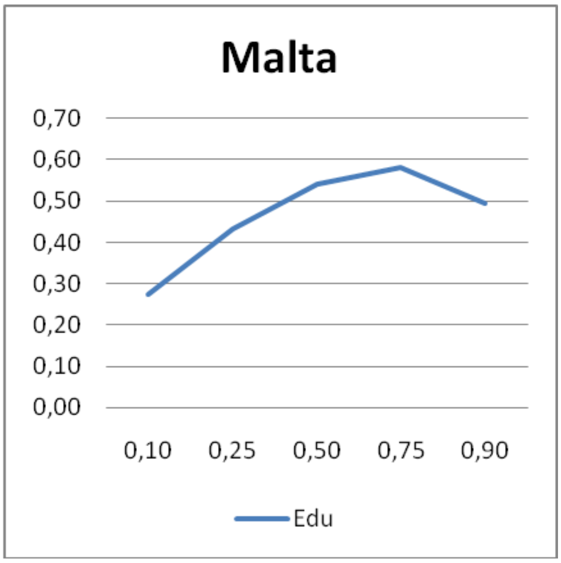
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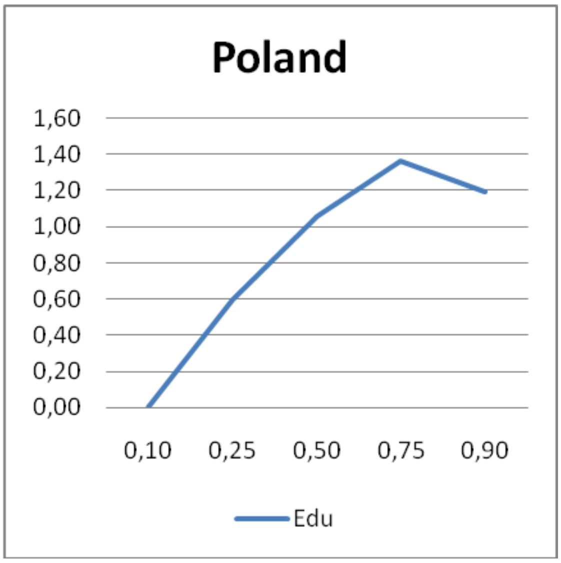
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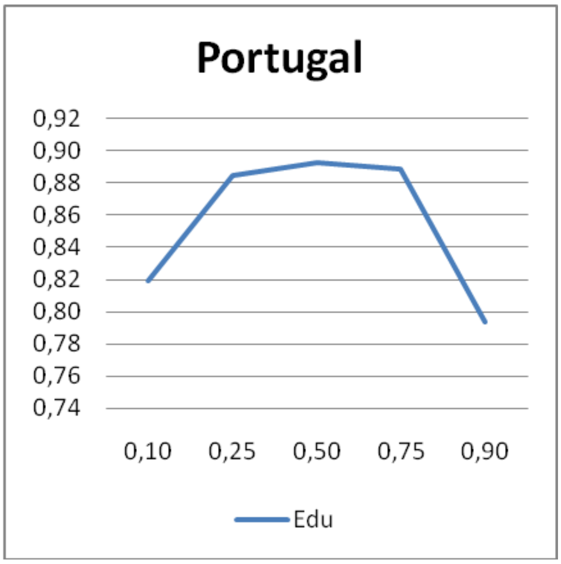
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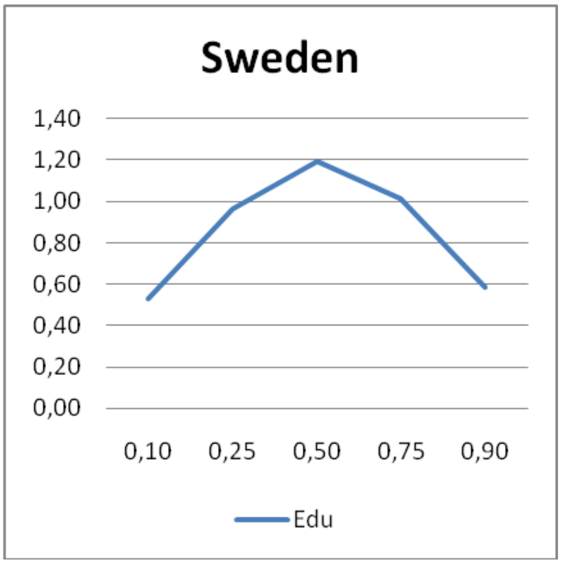
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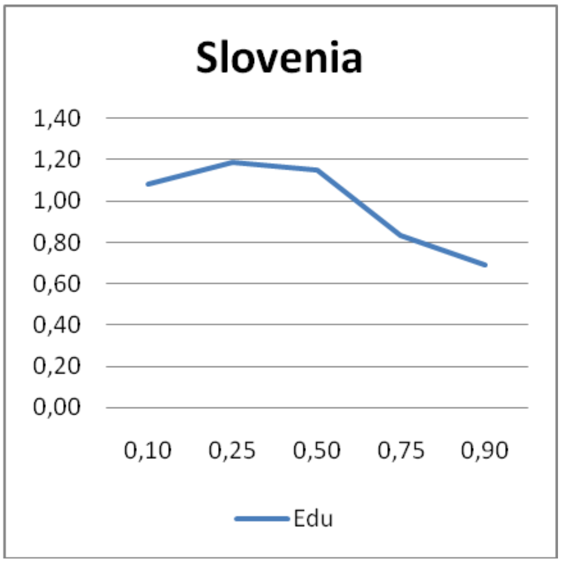
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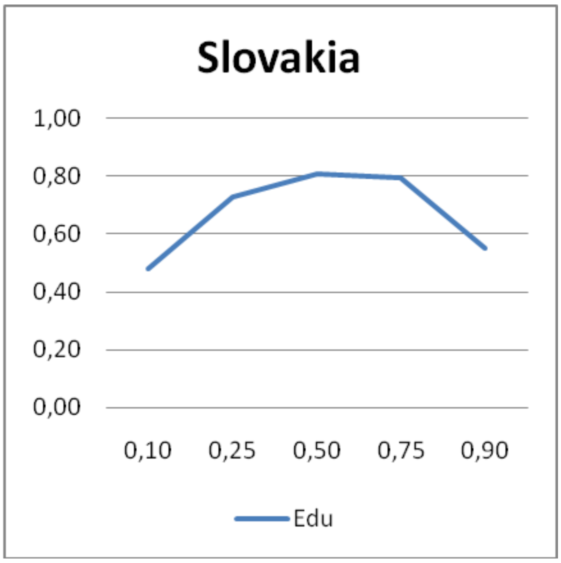
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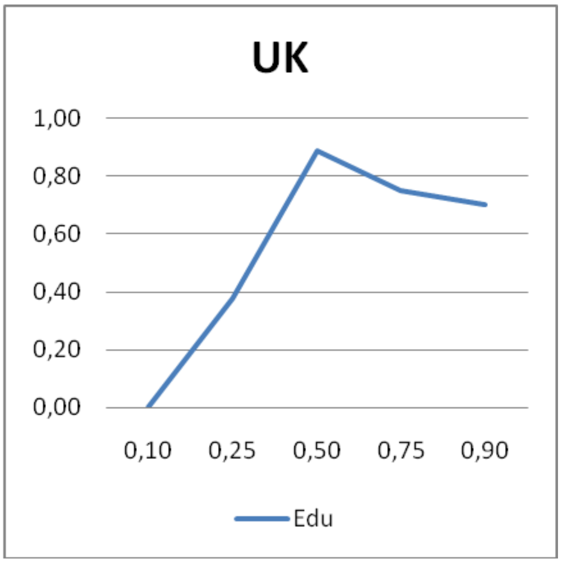
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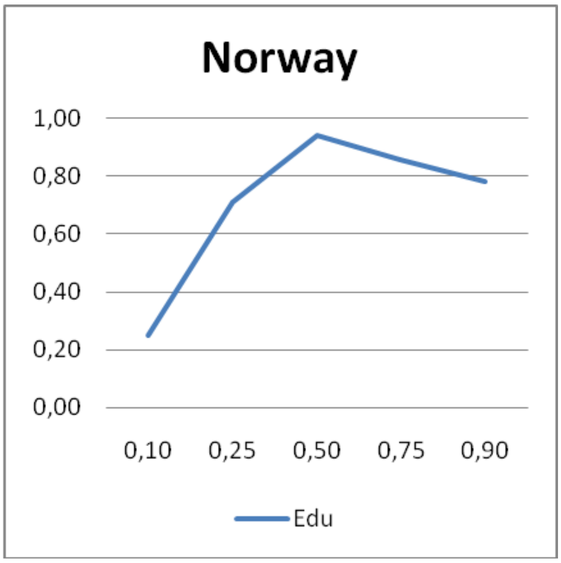
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0,10 0,25 0,50 0,75 0,90
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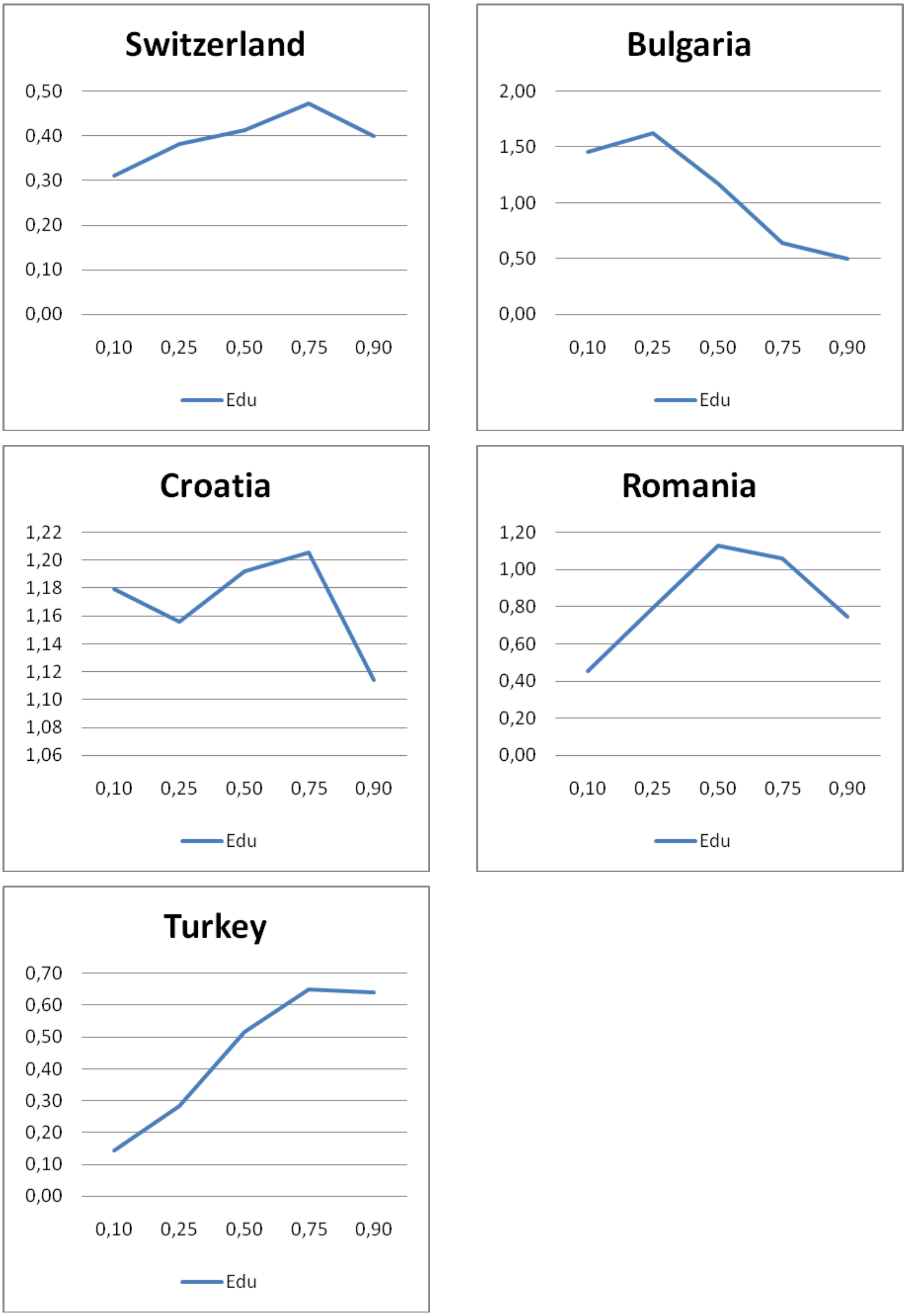


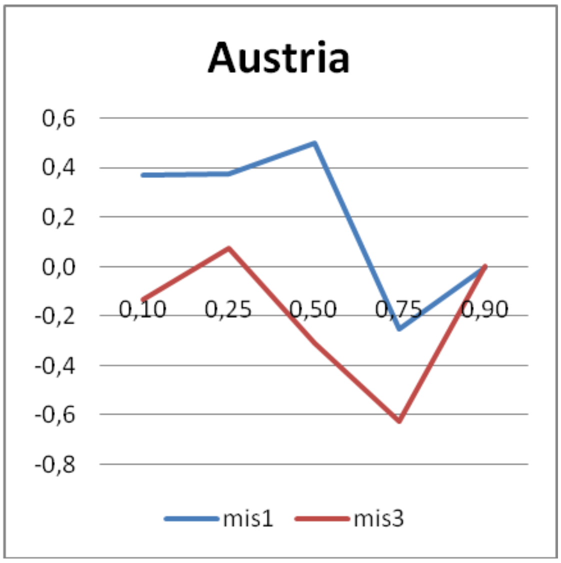
Figure 1: Set of graphs with the evolution of coef. for education throughout the wage distribution for each country.

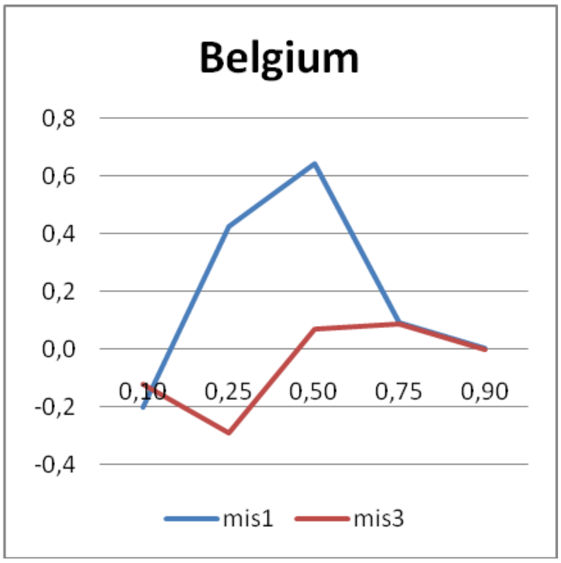
From the figure, we note that several countries showed a common pattern which we name as an inverted U-shaped relationship between returns to education and wage decilees, meaning that returns to education tend to rise with the wage distribution until a certain point of that distribution and then decrease. This implies that returns to education are contributing to the wage inequality in the first part of the distribution tail but are also contributing to the decrease of the wage inequality for the right side of the wage distribution. This pattern is common to 26 out of the 31 countries, which mean that it can be a candidate to a stylized fact. Exceptions are Hungary and Turkey (with a positive relationship), Belgium and Finland (with a negative relationship), and Croatia.

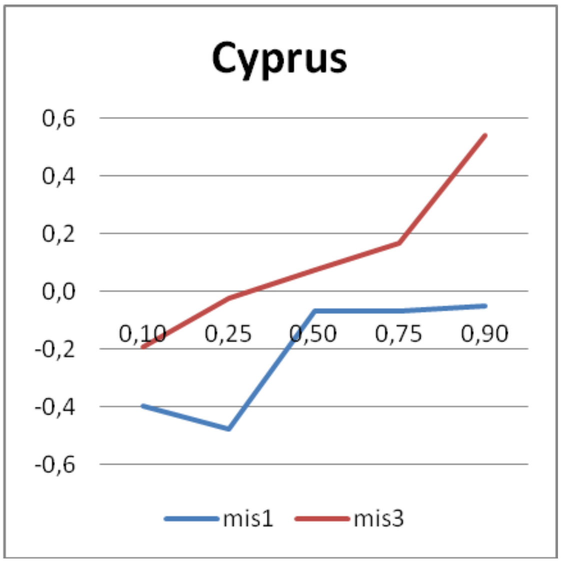
3.3. The effect of Mismatch

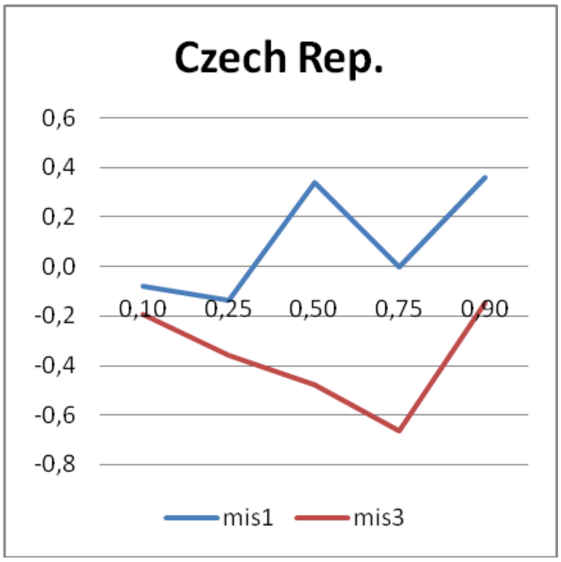
The effect of mismatch between skills and labor market requirements on wages is non-significant in the great majority of countries both in OLS and quantile regression on the median (see Table 2 and 3). From OLS results, we can observe that undereducation (having less skills than the required) is significant in Germany, Spain, Hungary, Lithuania, Slovenia, Bulgaria, and Croatia (with a positive effect of being undereducated) and in Ireland, Latvia, and Turkey (with a negative effect of being undereducated). Thus, we have significant results in only 1/3 of the studied countries and only 10% of the countries with the most expected result of a negative effect of undereducation on wages. Significant coefficients oscillate from 0.5 to 1, which mean that, for instance, in Germany an undereducated worker tends to earn 10% more than a correctly matched worker. Significantly negative coefficients are around 0.5, meaning that in Ireland undereducated workers tend to earn 6% less than a matched worker. Overeducation is even less significant, appearing with a positive significant effect on Hungary and Lithuania and with a negative significant effect on Czech Republic, Denmark, Latvia, Netherlands, Malta, Portugal, and Slovakia. Again, less than 1/3 of the countries present a significant effect of mismatch and only two of them with a significantly positive effect. Significantly negative results oscillate from near 0.4 to near 0.6, meaning that an overeducated worker could earn less 4 to 6% less than a matched worker. Additionally, the less common positive coefficients are 0.25 in Hungary and 0.72 in Lithuania, meaning that overeducated workers earn more 2.5% in Hungary and 7.2% in Lithuania than the respective matched counterparts. We may note that these results are all conditional in the sense that those premiums and penalties should be read as holding for the same values of the other variables. This means that, for instance, overeducated workers in Lithuania earn more 7.2% than matched workers provided that they have the same degree of education, the same years for tenure and experience, work in firms of the same size in the same sector and that we are comparing workers of the same gender. The general picture is repeated when we observe results of the quantile regression on the median. In particular, Table 3 shows positive and significant undereducation coefficients on Belgium, Germany, Slovenia, and Croatia, with coefficients that oscillate between 0.5 and 1.32, and with negative and significant effects just on Latvia. There are significantly negative effects of overeducation on Denmark, Latvia, Malta, Sweden, Slovakia, and Turkey (coefficients oscillate between -0.25 to -0.85) and significantly positive effects just on Lithuania.

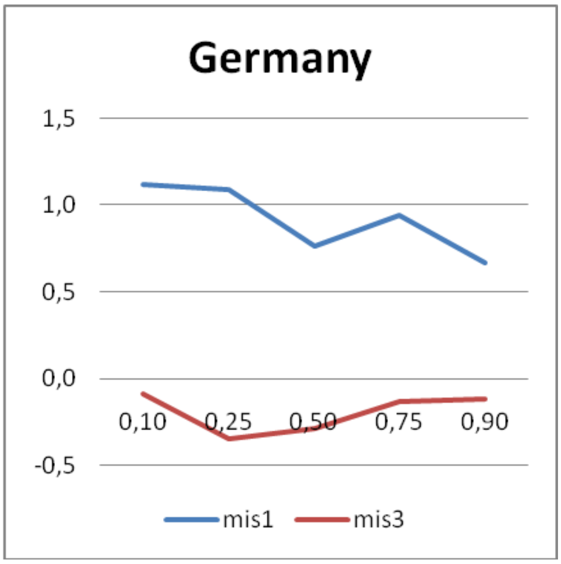
The next step is to show and analyze the effect of mismatch (under and overeducation) throughout the distribution of wages. To this end, we plot a number of figures that indicate the value of coefficients of under and overeducation throughout the wage distribution.







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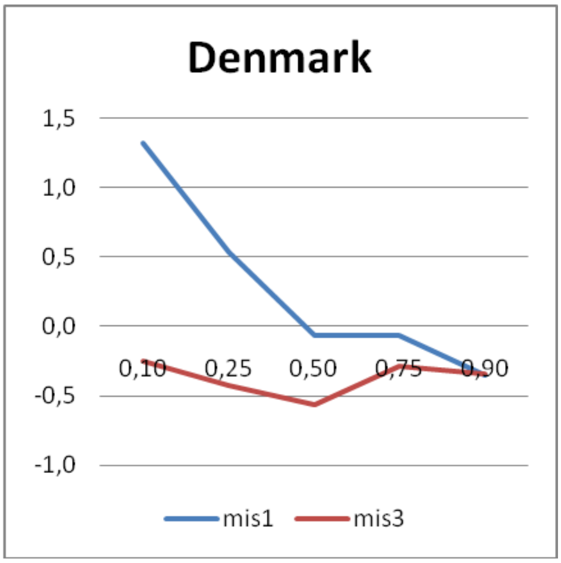
1,5
1,0
0,5
0,0
-0,5
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Denmark
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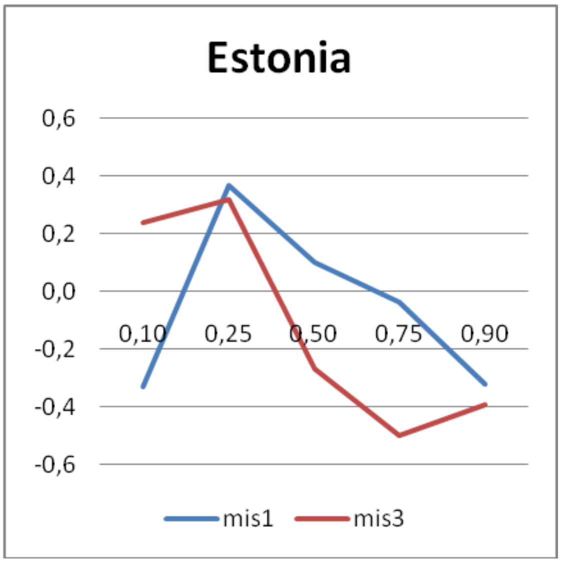
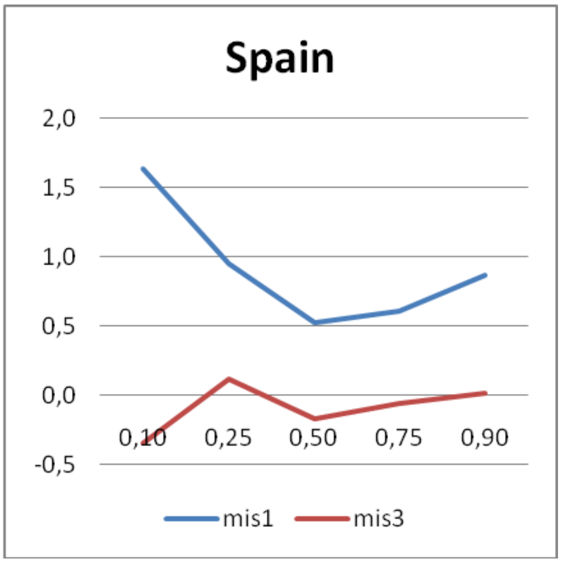
1,0
0,5
0,0
-0,5
-1,0
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Estonia
0,6
0,4
0,2
0,0
-0,2
-0,4
-0,6
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Spain
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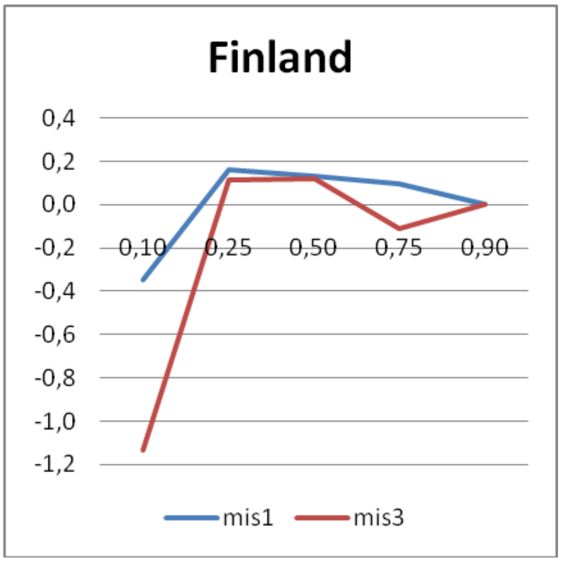
1,5
1,0
0,5
0,0
-0,5
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Finland
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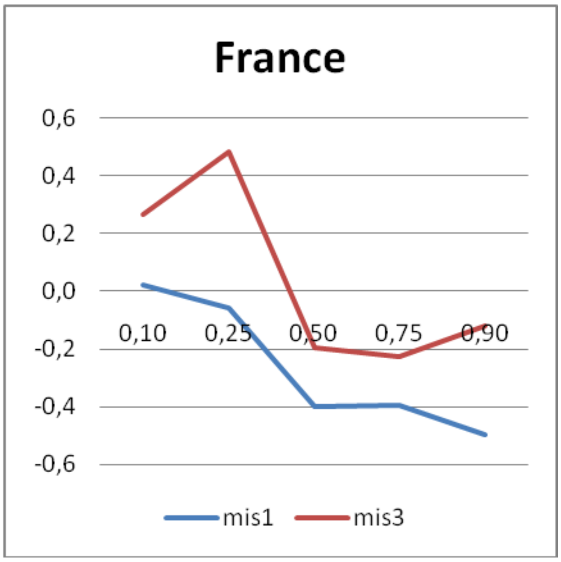
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
-1,2
0,10 0,25 0,50 0,75 0,90
mis1 mis3


France
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0,4
0,2
0,0
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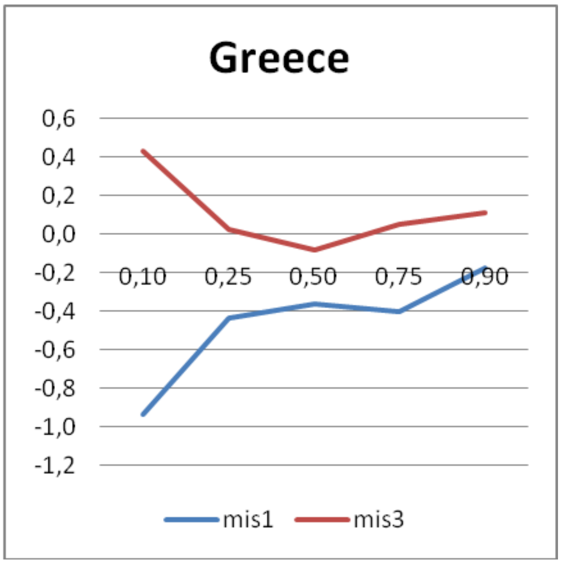
-0,4
-0,6
0,10 0,25 0,50 0,75 0,90
mis1 mis3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0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
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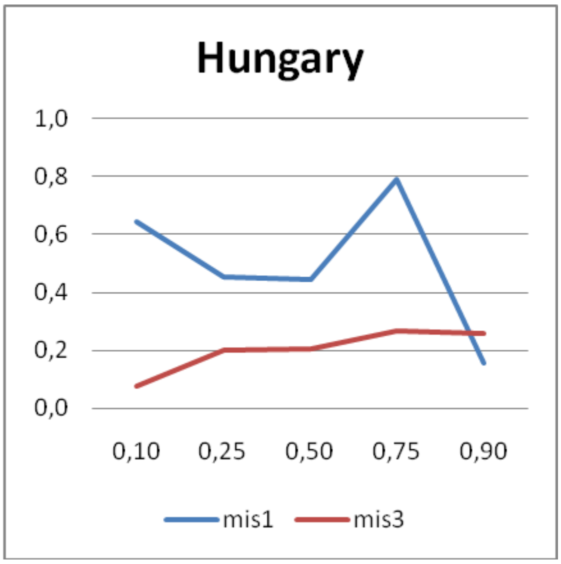
0,10
0,25
0,50
0,75
0,90
mis1
mis3


Hungary
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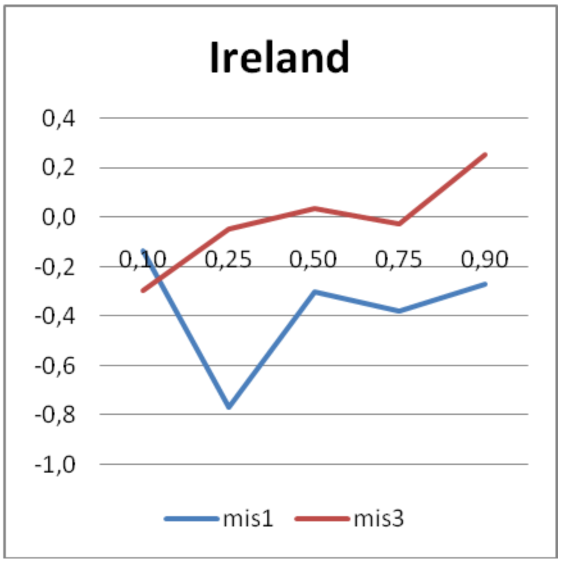
0,25
0,50
0,75
0,90
mis1
mis3


Ireland
0,4
0,2
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
0,10
0,25
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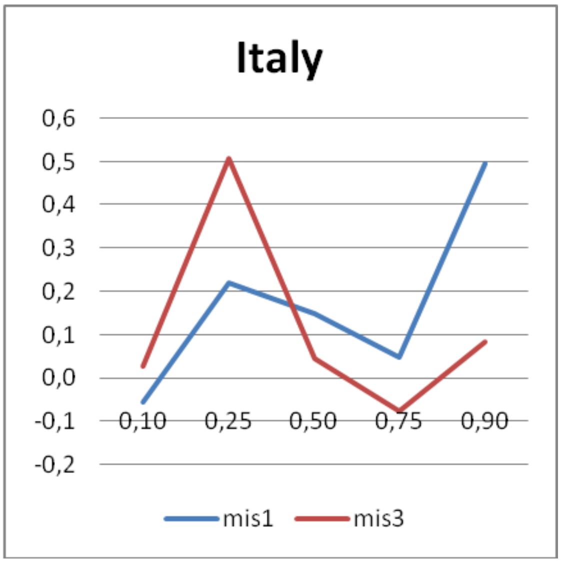
0,90
mis1
mis3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0,5
0,4
0,3
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0,1
0,0
-0,1
-0,2
0,10
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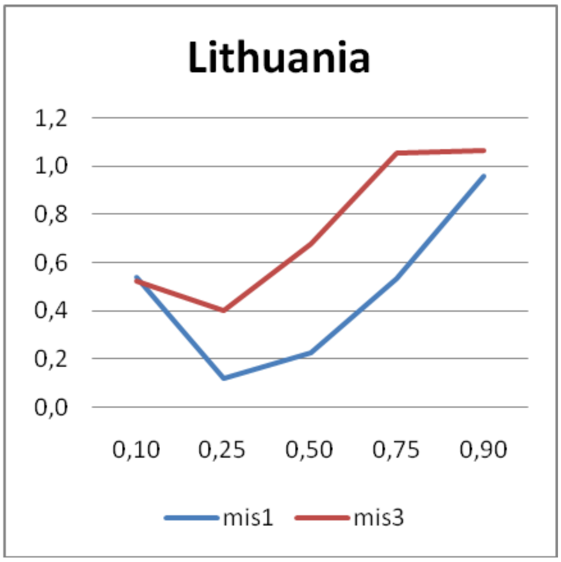
0,90
mis1
mis3


Lithuania
1,2
1,0
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0,6
0,4
0,2
0,0
0,10
0,25
0,50
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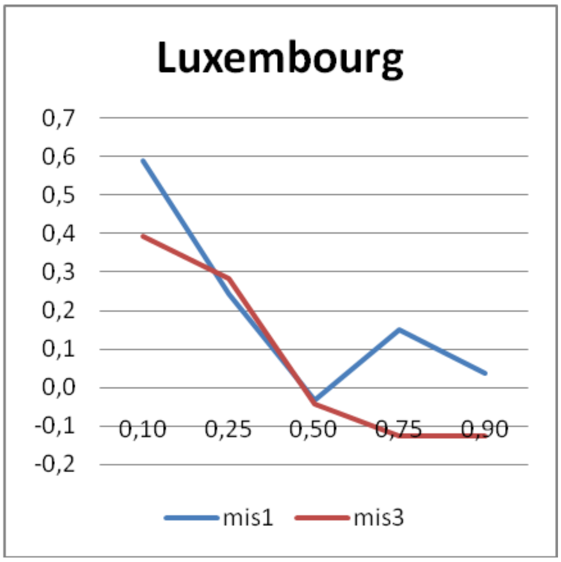
0,90
mis1
mis3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0,6
0,5
0,4
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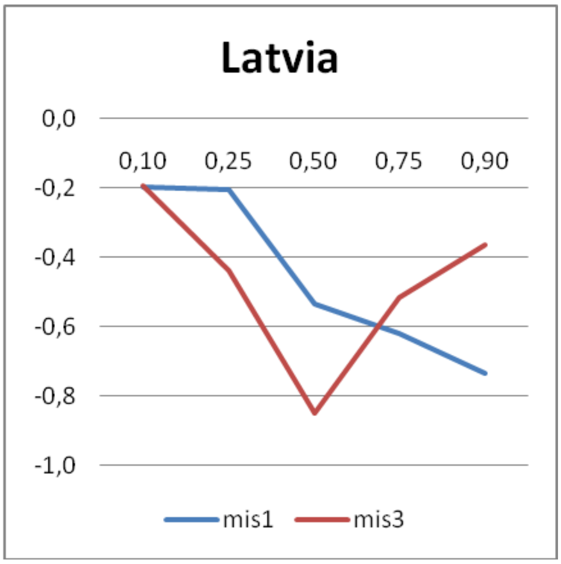
0,90
mis1
mis3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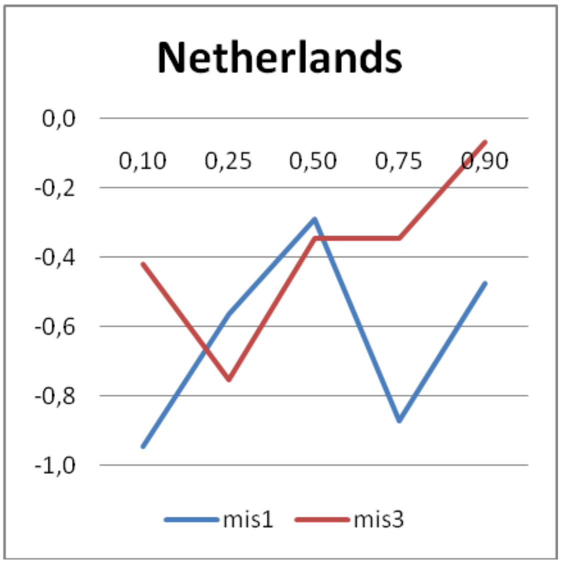
mis1 mis3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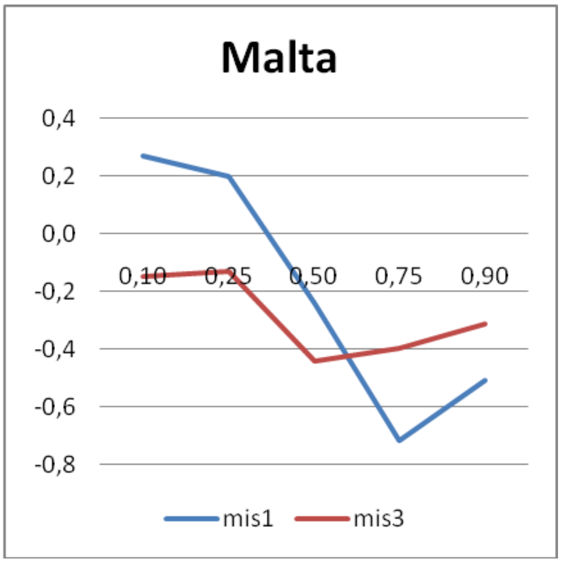
mis1 mis3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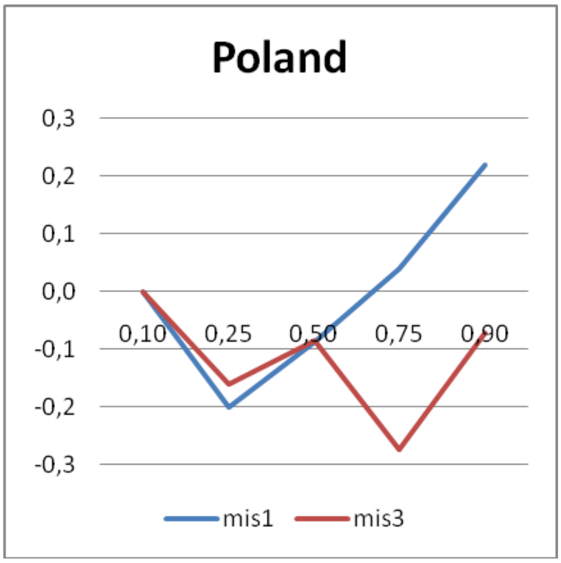
mis1 mis3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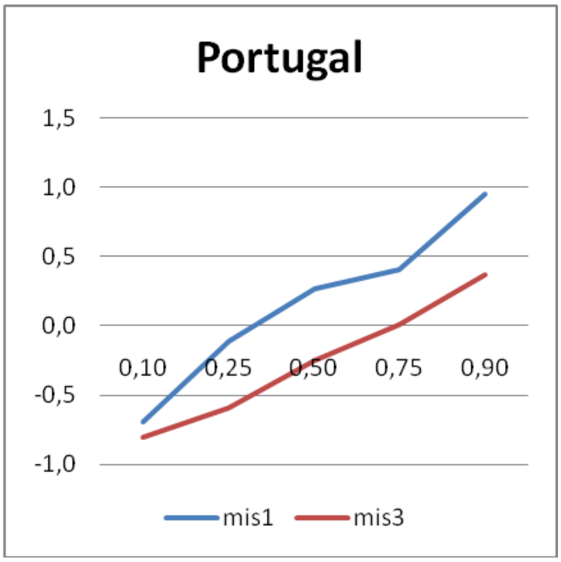
mis1 mis3


Portugal
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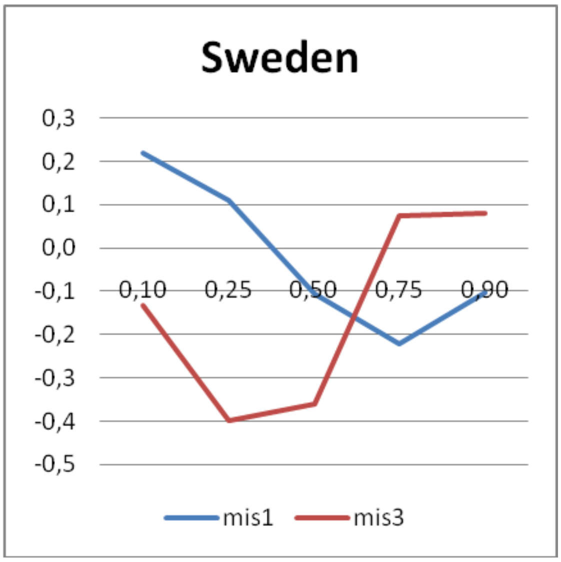
-1,0
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Sweden
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0,2
0,1
0,0
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-0,2
-0,3
-0,4
-0,5
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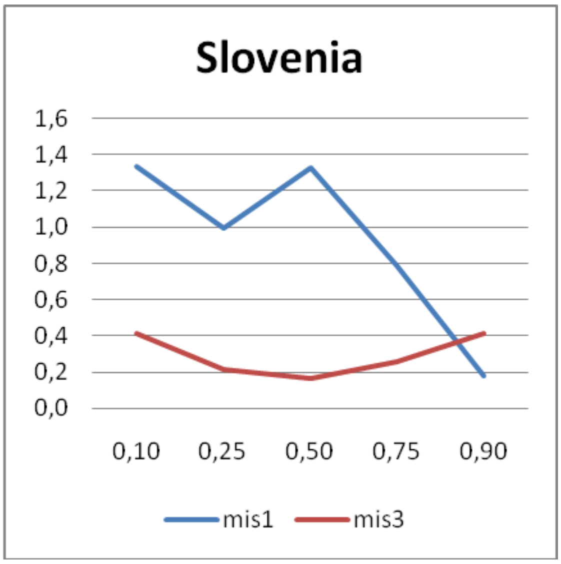
mis1 mis3


Slovenia
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0,8
0,6
0,4
0,2
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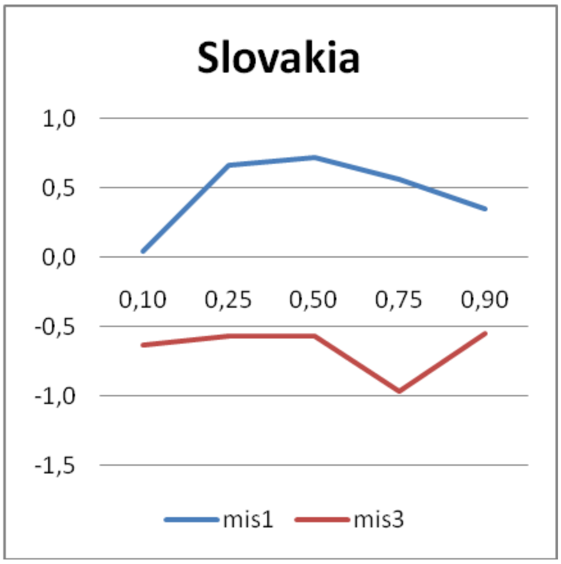
mis1 mis3


Slovakia
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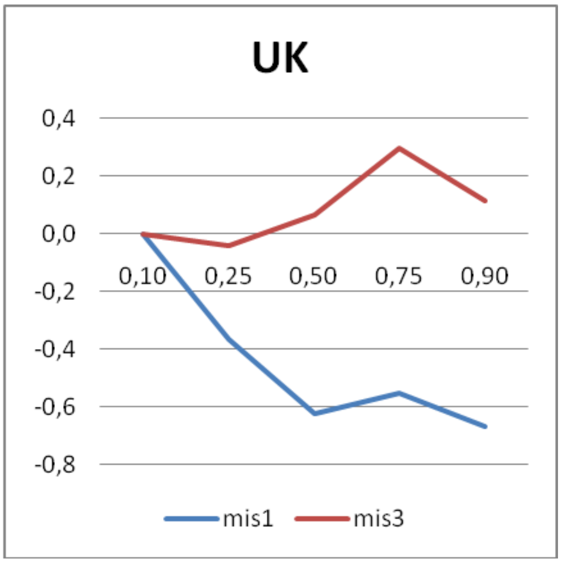
0,0
-0,5
-1,0
-1,5
0,10 0,25 0,50 0,75 0,90
mis1 mis3


UK
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0,2
0,0
-0,2
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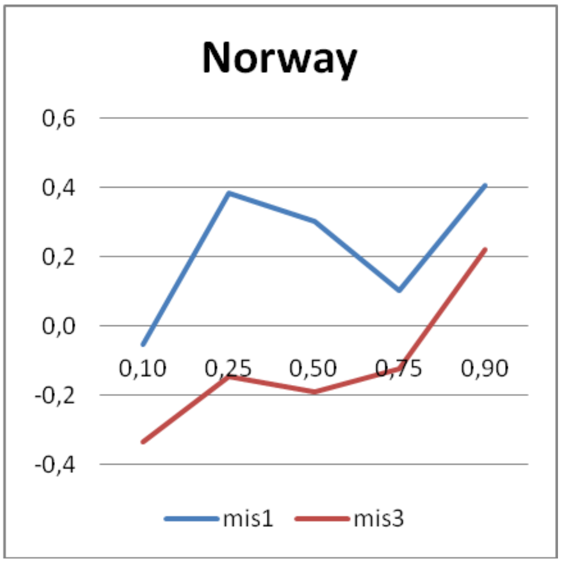
mis1 mis3


Norway
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0,4
0,2
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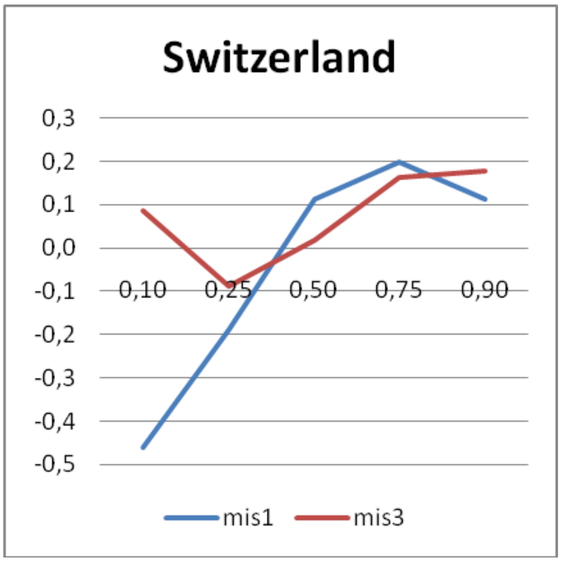
0,10 0,25 0,50 0,75 0,90
mis1 mis3


Switzerland
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0,1
0,0
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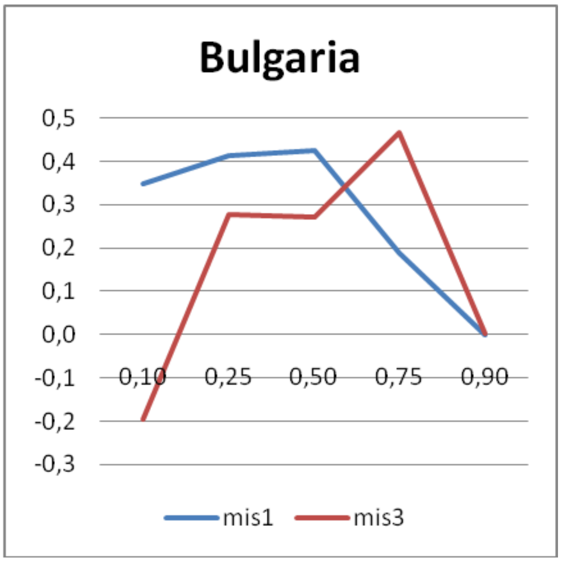
-0,2
-0,3
-0,4
-0,5
0,10 0,25 0,50 0,75 0,90
mis1 mis3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-0,3
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mis1 mis3

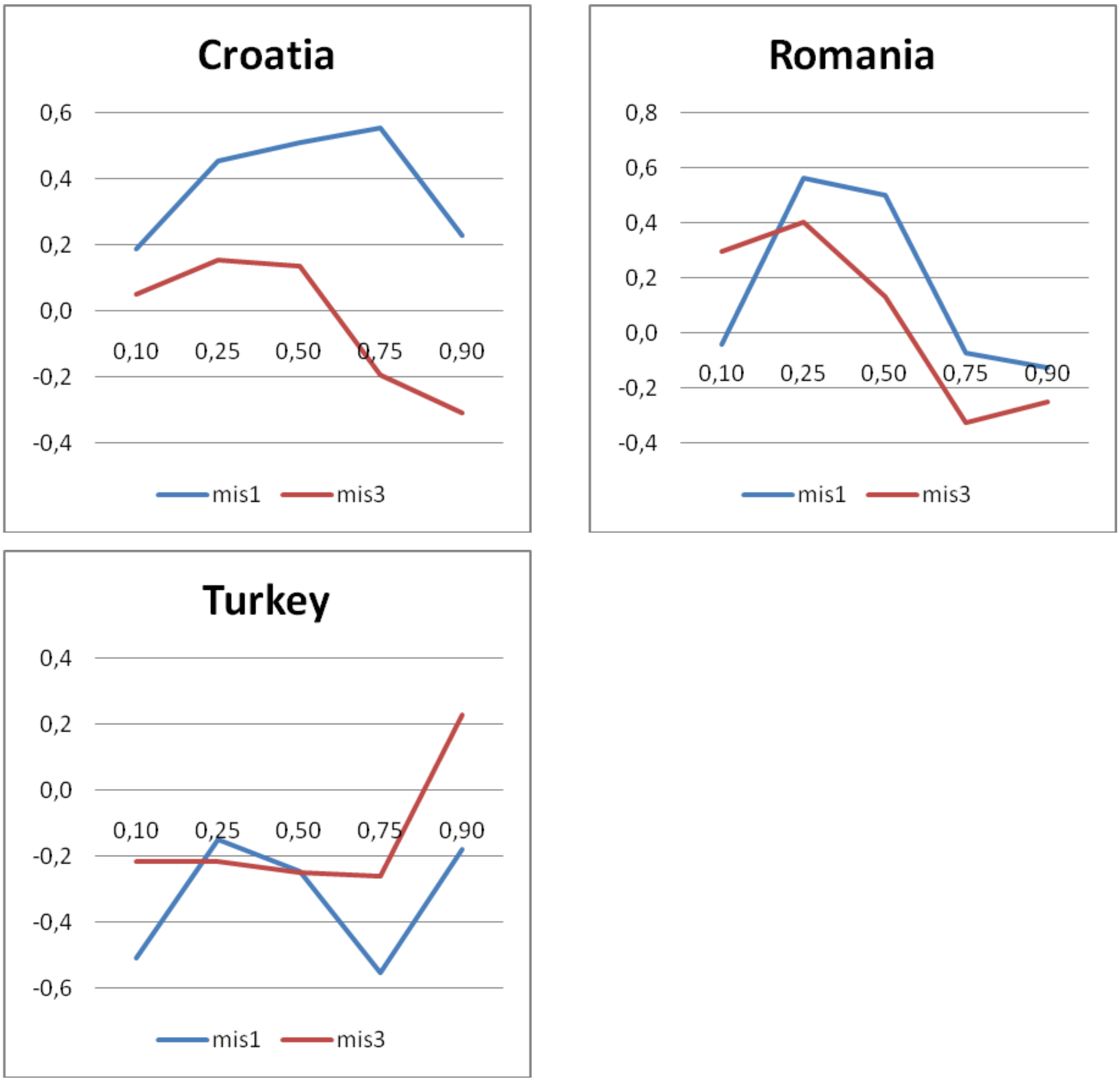

Figure 2: Set of graphs with the evolution of coef. for undereducation (mis1) and overeducation (mis3) throughout the wage distribution for each country.

As expected, there are differences in the influence of mismatch (under and overeducation) across the wages distribution.[3] However, the most common pattern continues to be one of a positive effect of undereducation and a negative effect of overeducation, a pattern present in Austria, Belgium, Czech Republic, Germany, Denmark, Spain (in this case overeducation has a nearly null effect on wages), Portugal (although with a negative impact of undereducation on the left-hand side of the distribution until the median), Slovakia, Norway, and Croatia (in this case overeducation has a nearly null effect for low levels of wages). The pattern according to which undereducated workers tend to have lower wages and overeducated workers tend to have higher wages throughout the distribution is mostly present in Cyprus (after the first quartile of the wage distribution), France (in this case overeducation began to have a negative effect after the median of the wage distribution), Greece, Ireland (although in this case overeducation has a nearly null effect). The effects on the other countries are clearly mixed between positive and negative effects of under and overeducation, from which we will analyze a sample, which we think are the most interesting. For example, in Italy, there is a positive effect of overeducation in low wages until the median, which is higher than a positive effect of undereducation. In the median the effects are inverted and undereducation began to have a higher effect than those of overeducation, a difference that is maximized in the right-hand side of the distribution. In Sweden, we note positive effects of undereducation and negative effects of overeducation until the wage median, after that the signs of the effects are inverted. In Finland, both effects of under and overeducating present low positive values after the first quartile of the wage distribution, while in the first decile, both effects are negative with overeducation having a stronger negative effect. In Switzerland, there is a negative effect of undereducation together with a positive effect of overeducation in the first decile of the wage distribution and after that the undereducation effect overcomes the overeducation effect and both become positive. In the last decile, overeducation has again a higher effect than that of undereducation. In Poland, both effects are close to zero in the first half of the wage distribution and after that undereducation becomes positively related to wage and overeducation remains negatively related to wage. Finally, we focus on the analysis of the effects on Turkey, in which both effects of under and overeducation are negative until the last wage decile in which overeducation has a positive effect and undereducation remains with a negative effect.

[3] 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) discusses the importance of statistical significance versus economic significance. Although we will not take part on that discussion, we want to provide information based both on statistical significance and economic significance.

Chapter 4

Conclusion

This dissertation studied for the first time the effects of workers's educational mismatch in several European countries, showing comparable results between countries. To this end, several wage regressions were implemented, through OLS and quantile estimators. A stronger (and positive) effect of undereducation than the effect of overeducation (which in fact tended to be negative) was the main result of this dissertation. Although this is somewhat contradictory to some previous country studies on the issue, this also asks for an interesting theoretical answer to the question: why overeducated workers seem to suffer a wage penalty and/or why undereducated workers seem to benefit from a wage premium? This pattern is not dismissed when all the wage distribution is analyzed through quantile regressions. We also pointed out a possible candidate to a new stylized fact: an inverted U relationship between returns to education and the distribution of the wage.

References

- Brudia, S. and A. Moro-Egido (2008). “Education, educational mismatch and wage inequality: Evidence for Spain”. Economics of Education Review 27, 332-341.
- Buchinsky, M. (1995). “Estimating the asymptotic covariance matrix for quantile regression models: a Monte Carlo study”. Journal of Econometrics 65, 109–54.
- Buchinsky, M. (1998). “Recent advances of quantile regression: a practical guideline for empirical research”. Journal of Human Resources XXXIII, 88–126.
- Cardoso, A. R. (2004). “Jobs for Young University Graduates: Is It Worth Having a Degree?”. IZA Discussion Papers 1311, Institute for the Study of Labor (IZA).
- Dolton, P. and Silles, M. (2008). “The Effects of Overeducation on earnings in the graduate labor market”. Economics of Education Review 27, 125-139.
- Fersterer, J., Winter-Ebmer, R. (2003). “Are Austrian returns to education falling over time?”. Labour Economics 10, 73–89.
- Guironnet, J. P. and Peypoch, N. (2007). “Human Capital Allocation and overeducation: A measure of French Productivity”. Economic Modelling 24, 398-410.
- Hartog, J., Pereira, P. and Vieira, J.A. (2001). “Changing returns to education in Portugal during the 1980s and early 1990s: OLS and quantile regression estimators”. Applied Economics 33, 1021–1037.
- Koenker, R. and Hallock, K. (2001). “Quantile regression: an introduction”. Journal of Economic Perspectives 15, 143–56.
- Kunze, A. (2000). “*The Determination of Wages and the Wage Gender Gap: a Survey*”. IZA DP 193, August.
- Machado, J. and Mata, J. (2001). “Earnings functions in Portugal 1982–1994: evidence from quantile regressions”. Empirical Economics 26, 115–134.
- Martins, P. and Pereira, P. (2004). Does education reduce wage inequality? Quantile regressions evidence from fifteen European countries. Labour Economics, 11(3), 355 – 371.
- Miller, J. and Rodgers, Y. (2008). “Economic Importance and Statistical Significance: Guidelines for communication Empirical Research”. Feminist Economics 14(2), 117-149.
- Muysken, J. and Ter Weel, B. (2000). "Overeducation and crowding out of low-skilled workers”. in: Lex Borghans and Andries de Grip (eds.), *The Overeducated Worker? The Economics of Skill Utilization*, Edward Elgar Publishers, 109-132.
- Parent-Thirion, A., Macías, E. F., Hurley, J. and Vermeylen, G. (2007). “Fourth European Working Conditions Survey”. Dublin: European Foundation for the Improvement of Living and Working Conditions.
- Robst, J. (2007). “Education and Job Match: the relatedness of College Major and work”, Economics of Education Review 26, 397-407.

Appendix

A.1: Table with the variables used and their measures

Variable Code	Variable Name	Name used at the regression	Measure
ef5	Income	income	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; "88" no opinion; "99" if refuses to answer]
ef1	Education Level	edu	Measures the highest level of education that respondent successfully completed ["1" No education; "2" Primary education; "3" Lower secondary education; "4" Upper secondary education; "5" Post-secondary including pre-vocational or vocational education but not tertiary; "6" Tertiary education – first level; "7" Tertiary education - advanced level; "9" if refuses to answer]
q2d	Years in Company	tenure	Number of years that respondent is working at the company ["00" if less than 1 year; "77" not applicable; "88" no opinion; "99" if refuses to answer]
q2c	Working Years	exper	Number of years that respondent stopped full-time education and started a paid employment ["77" if still a full-time student; "99" if refuses to answer]
q27	Skills in work	mis1(for answer 1) and mis3(for answer 3)	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" if refuses to answer]
hh2a	Gender	gender	Gender of Respondent ["1" for male; "2" for female]
q5	Company Sector	companysec~r	Sector that respondent works ["1" private sector; "2" public sector; "3" joint private-public organization or company; "4" non-for-profit sector, NGO; "5" other; "8" no opinion; "9" if refuses to answer]
q6	Company Size	companysize	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; "88" no opinion; "99" if refuses to answer]

A.2[◊]: Quantile regression at the (0.1) with mis1 (undereducation) and mis3 (overeducation)

q10											
Country	edu	tenure	exper	exper2	gender	companysize	mis1	mis3	companysec~r	_cons	R-squared
1	.5465134 ***	.0420689 *	.1750413 ***	-.0036089 **	-2.711537 ***	.1612361 *	.3698415	-.135367	-.1861262	3.384891 ***	0.2143
	(.1912203)	(.0222117)	(.0572571)	(.0015313)	(.3861123)	(.0929437)	(.3737281)	(.3720031)	(.134571)	(1.277525)	
2	.4482676 ***	.1043918 ***	.1131811 *	-.0039615 **	-3.991591 ***	.3419599 **	-.2027129	-.118064	-.1917759	4.898188 ***	0.2347
	(.171415)	(.0337788)	(.0625717)	(.0016914)	(.5248546)	(.1331377)	(.798281)	(.4925076)	(.3156954)	(1.568038)	
3	.5109481 ***	.0413897 ***	.0888228 ***	-.0020326 ***	-1.861575 ***	.2723489 ***	-.3950728	-.1904686	.0031385	1.252649 *	0.1605
	(.1132043)	(.0138168)	(.018935)	(.0004342)	(.2205296)	(.0545198)	(.3955056)	(.215481)	(.1481964)	(.6710906)	
4	.7979458 ***	.0447107 **	.108498 ***	-.003 ***	-1.476894 ***	.1324204 *	-.081936	-.1946128	-.1410869	-.7596051	0.1122
	(.1477676)	(.0222757)	(.0397416)	(.0010204)	(.277083)	(.0705641)	(.4225168)	(.2095579)	(.1672478)	(.9204562)	
5	.2170784 ***	.0774995 ***	.2997753 ***	-.0063652 ***	-3.068383 ***	.0764033	1.121747 **	-.0870849	-.0356278	2.494477 ***	0.2420
	(.0748305)	(.0162337)	(.0492997)	(.0011144)	(.302272)	(.0952529)	(.4653131)	(.2655396)	(.1666553)	(.7217117)	
6	.3230744 ***	.0452655 **	.1136554 ***	-.0017162 ***	-1.665715 ***	.0615964	1.323074 ***	-.2463854	.2820203	1.168086 *	0.1354
	(.0657619)	(.0222797)	(.0196429)	(.0002814)	(.2774809)	(.0774043)	(.2952935)	(.3756818)	(.2182828)	(.6136486)	
7	.1614604	.0314521	-.0454749	.0006744	-.2802838	.3610498 ***	-.3295977	.2385363	-.1543166	1.001966	0.1245
	(.1153444)	(.0219648)	(.0497652)	(.0010553)	(.4199246)	(.0823112)	(.7406821)	(.375579)	(.2056874)	(1.283111)	
8	.6371377 ***	.0719348 ***	.109866 ***	-.0019531 ***	-1914896 ***	.1721524 *	1.634822 ***	-.3408811	.2733279	.0059774	0.1696
	(.1173606)	(.023593)	(.0256202)	(.0006396)	(.36236)	(.0913921)	(.4921948)	(.2860522)	(.2305846)	(.8373526)	
9	.5723821 ***	.0237776	.0992042 **	-.0018677 *	-.9414126 ***	.5430082 ***	-.3458182	-1.134455 **	-.1676112	-.0695236	0.1538
	(.1057894)	(.0217315)	(.0464191)	(.0010125)	(.3576241)	(.0876954)	(.5216558)	(.4636757)	(.2522571)	(.8422197)	
10	.4561336 ***	.104508 ***	.0844103 *	-.0025866 **	-2.139278 ***	.2285051 ***	.0203531	.2642901	-.2558263	2.134503 **	0.2315
	(.0997836)	(.0223925)	(.0482161)	(.0012)	(.3442886)	(.0812302)	(.4324918)	(.3051656)	(.2202749)	(.8784514)	

[◊] * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

11	.447234 ***	.0291312	.1279265 ***	-.0029286 ***	-1.969888 ***	.5242699 ***	-.9335069	.4304715	.0300917	.9897065	0.1685
	(.1516575)	(.0260203)	(.042673)	(.00104)	(.4845872)	(.116111)	(.6211313)	(.4064017)	(.3734431)	(.982017)	
12	.2597551 ***	.043336 ***	.0005452	-.0002463	-.2935602 **	.2153502 ***	.6449466	.0754584	-.0725076	-.3837404	0.1109
	(.0827952)	(.0078044)	(.0245297)	(.0005654)	(.1338635)	(.0378416)	(.3074201)	(.1466559)	(.0636227)	(.5546105)	
13	.5470455 ***	.0228678	.1087271 ***	-.0022171 **	-1.607494 ***	.2489254 ***	-.1344828	-.2957936	-.141874	.1125299	0.0824
	(.1579489)	(.0219081)	(.0346337)	(.000894)	(.3587341)	(.0860793)	(.4115273)	(.3019468)	(.2323677)	(.7691028)	
14	.3385762 ***	.0702368 **	.2003273 ***	-.0039478 ***	-1.309239 ***	.2551073 ***	-.0543171	.0282918	-.3315421	-.0457062	0.1462
	(.1236114)	(.0270161)	(.0362421)	(.0007631)	(.3258542)	(.0898902)	(.5997377)	(.337909)	(.2379846)	(.7590453)	
15	.5475168 ***	.0288004 ***	.0367145	-.0009231	-1.034106 ***	.2550795 ***	.5390345 *	.5247965 **	-.2636654	-.4123208	0.1176
	(.1551931)	(.010216)	(.0493465)	(.0010185)	(.275345)	(.0761155)	(.277746)	(.2631066)	(.1612136)	(.7445066)	
16	.2579746 ***	.0748792 **	.137652 *	-.0029611	-2.296111 ***	.3206568 ***	.5888612	.3922286	-.4971204	1.427979	0.2817
	(.0449987)	(.0303345)	(.0715173)	(.0020191)	(.3676041)	(.1016278)	(.5185306)	(.3942154)	(.329507)	(.8760876)	
17	.3658814 ***	.0208917 *	.010735	-.0004986	-.5253304 ***	.175229 ***	-.197343	-.1921949	-.1356103	.1412043	0.0405
	(.1189324)	(.0117046)	(.0237874)	(.000536)	(.1738141)	(.0646389)	(.2108131)	(.163365)	(.1181603)	(.6614872)	
18	.4201499 ***	.0554329 ***	.1010339 **	-.0024096 **	-2.746223 ***	.2652195 ***	-.9466678	-.4212291 *	-.2419063 **	1.623033 ***	0.1122
	(.0751435)	(.0172499)	(.0470611)	(.0010963)	(.3386737)	(.0656753)	(.7025521)	(.2324951)	(.101665)	(.6182788)	
19	.2747363 ***	.0239591 ***	.0843257 ***	-.0015581 **	-.6466068 ***	.0963361 **	.270049	-.1466419	.2503052 **	-.246456	0.2096
	(.067372)	(.0085647)	(.0272752)	(.0006074)	(.1684943)	(.0425423)	(.1826956)	(.1635751)	(.1216424)	(.3874508)	
20	0	0	0	0	0	0	0	0	0	1	-0.0000
	(.1370064)	(.0058166)	(.0224077)	(.0005327)	(.2054372)	(.0418289)	(.1430644)	(.1061761)	(.0534405)	(.6821161)	
21	.8191001 ***	.0360558 **	.1255356 ***	-.0026344 ***	-.7702157 ***	.2177724 ***	-.6933062	-.8031069 ***	.1694632	.0230924	0.2122
	(.1023653)	(.0182169)	(.0405529)	(.0007816)	(.2878725)	(.0686826)	(.540883)	(.2878144)	(.2789063)	(.7285271)	
22	.5301794 ***	-3.04e-10	.1193583 ***	-.002447 ***	-1.39043 ***	.3322458 ***	.2196846	-.1326808	-.0984231	-.7286569	0.0854
	(.1229693)	(.017062)	(.0326505)	(.0006393)	(.2587483)	(.0588492)	(.6043104)	(.2037558)	(.1275818)	(.6937566)	

23	1.082165 ***	.0281894	.0258411	-.000362	-.6161355 *	.093281	1.335013	.4109044	.9515776 **	-4.017322 ***	0.1794
	(.1678983)	(.025208)	(.0479425)	(.0011385)	(.3397058)	(.0895678)	(.9013847)	(.3269585)	(.4392333)	(1.153908)	
24	.4808025 ***	.0349552 **	.0513	-.0014778 *	-1.312555 ***	.1695486 ***	.0399908	-.628455 ***	-.1751635	1.137818 *	0.1334
	(.0838385)	(.0141321)	(.0383945)	(.0008701)	(.2531493)	(.0565356)	(.7351011)	(.1924159)	(.1347169)	(.6651733)	
25	0	0	0	0	0	0	0	0	0	1 *	-0.0000
	(.0520065)	(.0064538)	(.0064776)	(.000252)	(.3961183)	(.0082426)	(.2605307)	(.0279018)	(.0499217)	(.6047079)	
26	.2483399 ***	.0245538 **	.076254 ***	-.0018629 ***	-.7402843 ***	.2581163 ***	-.0508974	-.334086 *	-.3227478 **	.2808282	0.0426
	(.0745975)	(.0111646)	(.019548)	(.0004976)	(.1793082)	(.0821509)	(.2745081)	(.1762356)	(.1348226)	(.5168028)	
27	.3102139 ***	.0273847 *	.159715 ***	-.0031462 ***	-2.778442 ***	.2501885 ***	-.4617262	.0854706	-.0365915	2.312758 ***	0.2420
	(.0650589)	(.0140998)	(.039019)	(.0007653)	(.2179412)	(.0549532)	(.306178)	(.2259225)	(.1687219)	(.5385165)	
28	1.450583 ***	.0548183 ***	-.0112247	-.0002729	-.9758598 ***	.3272292 ***	.3488723	-.1973379	-.1301837	-2.399897 ***	0.2202
	(.1675311)	(.0148758)	(.0404288)	(.0008336)	(.2526683)	(.0805675)	(.8992044)	(.3285823)	(.2074677)	(.9025912)	
29	1.179177 ***	-.00748	.0927648 **	-.00199 *	-.8134608 ***	.1143696 *	.1895332	.0523602	.1460248	-2.221733 **	0.1468
	(.1525346)	(.0211324)	(.0388786)	(.0010315)	(.2389954)	(.0667076)	(.4028544)	(.2063501)	(.1993519)	(.9637055)	
30	.4540371 ***	.0083874	.0099903	-.0000373	-.0048088	.1520913 **	-.0428316	.2982554	.0587117	-1.739767 *	0.0250
	(.1426784)	(.0127277)	(.024211)	(.0005403)	(.1548457)	(.0611819)	(.2884239)	(.1999487)	(.0930892)	(.8894812)	
31	.1449804 *	.0068101	.0382891 *	-.0007213 **	-.2477259	.1815941 **	-.5091017	-.2168652	-.0361511	.4725945	0.0337
	(.0779652)	(.0105231)	(.0212921)	(.0003478)	(.2579591)	(.0762766)	(.3280001)	(.1882377)	(.3594386)	(.9154927)	

A.3◊: Quantile regression at the (0.25) with mis1 (undereducation) and mis3 (overeducation)

q25											
Country	edu	tenure	exper	exper2	gender	companysize	mis1	mis3	companysec~r	_cons	R-squared
1	.8477736 ***	.0591564 ***	.2278276 ***	-.0045813 ***	-2.690782 ***	.2221786 ***	.3755851	.072382	-.479645 **	3.362807 ***	0.2368
	(.1377066)	(.0209156)	(.0430346)	(.0010903)	(.3484701)	(.0835669)	(.3387616)	(.390924)	(.205515)	(.961307)	
2	.4348657 ***	.1072926 ***	.0490364	-.0026328 **	-3.78631 ***	.1076218	.422461	-.2876557	-.0708941	7.709454 ***	0.2320
	(.1100483)	(.0317269)	(.0619196)	(.0012423)	(.6177356)	(.1084141)	(.5274186)	(.4495645)	(.2938454)	(1.164465)	
3	.7223686 ***	.0952995 ***	.1261241 ***	-.0029373 ***	-1.916912 ***	.3017789 ***	-.4749404	-.0209571	.0976681	.6068128	0.2455
	(.1267592)	(.0200244)	(.0329434)	(.0007195)	(.2126852)	(.0617402)	(.4909355)	(.2634983)	(.2557575)	(.6694566)	
4	.8143989 ***	.0601057 ***	.0834709 **	-.0023943 **	-2.34148 ***	.1609974 **	-.1390357	-.3576618	-.0652246	1.538144 *	0.2117
	(.0993501)	(.0218976)	(.0404283)	(.0009468)	(.2894241)	(.0687475)	(.5548795)	(.2276636)	(.1854036)	(.9197676)	
5	.3920856 ***	.0824809 ***	.2120007 ***	-.0046375 ***	-2.905159 ***	.1744099 **	1.094841 ***	-.3422275	-.2016498	3.356229 ***	0.3190
	(.0377104)	(.0159672)	(.0365885)	(.0007857)	(.2443599)	(.0719364)	(.3820636)	(.2888698)	(.1588414)	(.8432678)	
6	.4878347 ***	.0433766 **	.1162499 ***	-.0018285 ***	-1.569291 ***	.1959706 **	.5346422 *	-.4272786 *	.185567	1.533079 **	0.2672
	(.0794814)	(.0182576)	(.0248075)	(.0003084)	(.2707274)	(.0818942)	(.3020321)	(.2580891)	(.2033671)	(.7686233)	
7	.1700663 *	.008011	-.0084178	-.000368	-1.267016 **	.3340428 ***	.3656138	.3171779	-.1218373	3.938423 ***	0.0937
	(.0932146)	(.0215369)	(.0417098)	(.000924)	(.5084982)	(.1080571)	(.4673982)	(.4254262)	(.1995331)	(1.462762)	
8	.7267991 ***	.0513669 ***	.1568134 ***	-.0022885 ***	-2.224087 ***	.1864836 ***	.9520097 **	.1190741	.0078297	1.145666	0.2840
	(.0973499)	(.0181673)	(.0333952)	(.00067)	(.3488795)	(.0629814)	(.3852912)	(.3340993)	(.2620594)	(.96425)	
9	.5086852***	.014679	.1273555 ***	-.0024463 **	-1.506758 ***	.3790931 ***	.1624968	.1121723	-.1453996	2.954691 ***	0.1415
	(.0670417)	(.0144402)	(.0429422)	(.0009587)	(.2274665)	(.0651026)	(.4140744)	(.3717707)	(.1674476)	(.600152)	
10	.559797 ***	.0685512 ***	.1212521 ***	-.0027684 ***	-1.869525 ***	.2160803 ***	-.0586614	.483918	.017582	1.847386 ***	0.1961
	(.0926293)	(.0133257)	(.0285072)	(.0007444)	(.2074053)	(.0534828)	(.3739812)	(.2295)	(.2085263)	(.607449)	

◊ * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

11	.5485921 ***	.023126	.174004 ***	-.0038667 ***	-1.800722 ***	.4059615 ***	-.4328147	.0227354	.2732877	1.834653 ***	0.2579
	(.0642879)	(.016694)	(.0402828)	(.0009181)	(.2680098)	(.0687266)	(.4331882)	(.2724369)	(.2616881)	(.6649149)	
12	.4890953 ***	.0314075 ***	.0221058	-.0005106	-.5968465 ***	.2540689 ***	.4529256 *	.201191	-.0899172	-.8130736 **	0.1554
	(.0532863)	(.0079948)	(.0145945)	(.0003295)	(.1277673)	(.0344751)	(.2715622)	(.1727522)	(.0660564)	(.4573085)	
13	1.083577 ***	.0662885 ***	.1556066 ***	-.0029346 ***	-2.469491 ***	.2908931 ***	-.766846 **	-.0482139	.0361851	-.5319919	0.2592
	(.0808969)	(.0168345)	(.0262733)	(.0006462)	(.2493155)	(.0709417)	(.3208724)	(.2723268)	(.2115241)	(.6708956)	
14	.4994981 ***	.0832234 ***	.2423502 ***	-.0043662 ***	-1.722197 ***	.204144 **	.2206481	.5078864	-.1521795	.4283051	0.2720
	(.111034)	(.0288879)	(.0401494)	(.0008563)	(.2680051)	(.0916659)	(.4769383)	(.3389775)	(.219831)	(.7040084)	
15	.9702611 ***	.0222411	-.0055603	-.0001862	-1.995001 ***	.2561165 ***	.1193344	.4002828	-.2765809	.9030455	0.1627
	(.1122663)	(.0154663)	(.0356034)	(.0008204)	(.3501795)	(.0830291)	(.2610921)	(.3712239)	(.183428)	(.9762031)	
16	.3039656 ***	.0832834 ***	.1605488 ***	-.0031412 **	-2.507273 ***	.2401144 ***	.2429951	.2823524	.3589221	1.546189 **	0.3626
	(.0338912)	(.0214564)	(.0536299)	(.0014406)	(.3353583)	(.0617877)	(.368813)	(.3331986)	(.2216197)	(.7302452)	
17	.7935385	.0470155 ***	.0311811	-.0013887 **	-1.275105 ***	.2848799 ***	-.2059878	-.4363932 *	-.1827919	.1442233	0.1172
	(.1139272)	(.0153567)	(.0291943)	(.0006045)	(.2461823)	(.0640835)	(.4256285)	(.2499501)	(.2038792)	(.7391286)	
18	.4850165 ***	.0520141 ***	.0813906 *	-.0016242	-3.548854 ***	.2421945 ***	-.5669058	-.7520627 **	-.2932779 **	3.88987 ***	0.3108
	(.0696317)	(.0193319)	(.0457628)	(.0011772)	(.295443)	(.059602)	(.6097187)	(.3011252)	(.1268441)	(.9093678)	
19	.4303978 ***	.0346373 ***	.0557217 *	-.0008256	-.7315166 ***	.0986292 **	.1999878	-.1309454	.2276542 **	-.204303	0.2244
	(.0541274)	(.0107434)	(.0285645)	(.0006507)	(.1673787)	(.0482123)	(.2131636)	(.1662858)	(.1127216)	(.4066375)	
20	.5973506 ***	.0149808	.0771309 ***	-.0017363 ***	-.9227901 ***	.1157086 ***	-.2013411	-.1606509	-3.43e-09	-.6332979	0.1337
	(.1081578)	(.0101205)	(.022728)	(.0005518)	(.1948453)	(.0431506)	(.2968128)	(.1393252)	(.1137836)	(.5031428)	
21	.8843236 ***	.0334227 **	.1315795 ***	-.0029056 ***	-.9760672 ***	.1461942 ***	-.1091058	-.5862543 ***	-.0489698	1.680738 ***	0.2575
	(.0535555)	(.0139915)	(.0229187)	(.0004502)	(.1722796)	(.041354)	(.3847099)	(.1814575)	(.14528)	(.4115643)	
22	.9643403 ***	.016025	.1259734 ***	-.0024514 ***	-1.801758 ***	.4650079 ***	.11115	-.3994656 *	-.3803623 ***	-1.007765	0.1840
	(.1105959)	(.0141922)	(.0304007)	(.0007081)	(.2404937)	(.0683849)	(.5066084)	(.2334519)	(.1461685)	(.7899354)	

23	1.188533 ***	.016462	.0526054	-.0008792	-.7936455 ***	.0830005	.9930617 **	.2174304	.8978476 ***	-3.069568 ***	0.2739
	(.102854)	(.0175642)	(.0364095)	(.0008677)	(.2097898)	(.063553)	(.4521614)	(.2754766)	(.2943987)	(.7502042)	
24	.7254665 ***	.0403225 ***	.1192216 ***	-.0029377 ***	-2.229045 ***	.1513426 ***	.668149	-.5613278 ***	-.1813192	1.924035 ***	0.2132
	(.097599)	(.0135571)	(.0351941)	(.0008239)	(.2270144)	(.0555428)	(.6556338)	(.2063335)	(.1571114)	(.628834)	
25	.376339 ***	.0470963 **	.0035518	-.000326	-2.382247 ***	.1120331 *	-.3668715	-.0425375	-.0937468	3.462716 ***	0.1270
	(.1617738)	(.0198173)	(.0188228)	(.0005395)	(.3278554)	(.0581405)	(.4510851)	(.1422379)	(.0884139)	(1.26905)	
26	.7123041 ***	.0305247 *	.1312175 ***	-.002779 ***	-1.765174 ***	.4283562 ***	.3832111	-.145716	-.3513668	-.3173676	0.2021
	(.0953875)	(.0157578)	(.035454)	(.0008128)	(.3215446)	(.114795)	(.3227945)	(.3043643)	(.2820226)	(.8889719)	
27	.3812361 ***	.0372618 **	.1457753 ***	-.002513 ***	-3.281525 ***	.2198737 ***	-.1873844	-.0880171	.3321517 *	3.241133 ***	0.3311
	(.079065)	(.0163308)	(.0330466)	(.0006777)	(.2344668)	(.0635728)	(.3257551)	(.2284655)	(.1753208)	(1.007521)	
28	1.62082 ***	.0519554 ***	.0681805	-.0020889 **	-1.594228 ***	.3197436 ***	.4149523	.2763417	-.5848238 ***	-.6926971	0.2766
	(.1146049)	(.0193637)	(.0414767)	(.0010064)	(.2822843)	(.0847077)	(.6014157)	(.2892906)	(.2099974)	(.9069985)	
29	1.155874 ***	.0128029	.0871228 **	-.0017865	-.5865907 ***	.0211526	.4545888 *	.1556745	.3152327 **	-1.524256 ***	0.1723
	(.1002406)	(.0137534)	(.0369569)	(.0011345)	(.2057151)	(.0727057)	(.2734555)	(.2195766)	(.1591697)	(.5680428)	
30	.7935999 ***	.0376342 **	.0326513	-.0005383	-.3540021	.3035076 ***	.5619363	.4036326	.1662987	-2.896656 ***	0.1520
	(.0918896)	(.0174469)	(.0264052)	(.0006363)	(.2444369)	(.0815156)	(.4686074)	(.2934519)	(.1795277)	(.5153439)	
31	.2836054 ***	.00265	.0377106 **	-.0006664 **	-.7626994 ***	.1881906 ***	-.1507428	-.2157415	.8962058 **	.372012	0.0794
	(.0646393)	(.0079498)	(.0183255)	(.0003186)	(.2258753)	(.0600822)	(.2508024)	(.1721742)	(.3530375)	(.5537619)	

A.4[◊]: Quantile regression at the (0.75) with mis1 (undereducation) and mis3 (overeducation)

q75											
Country	edu	tenure	exper	exper2	gender	companysize	mis1	mis3	companysec~r	_cons	R-squared
1	.8167158 ***	.0162266	.1607192 ***	-.003128 ***	-1.5433 ***	.0541155	-.250408	-.6255782 **	-.1694358	6.7798 ***	0.1222
	(.1252963)	(.0183095)	(.0464517)	(.0011544)	(.3503887)	(.0746684)	(.3181827)	(.3157304)	(.1264081)	(.7372199)	
2	.1429244 ***	.0228544 ***	.0671323 ***	-.0014304 ***	-.5090135 ***	.0031396	.0922385	.0871685	.0018625	8.504279 ***	0.0663
	(.0335658)	(.007179)	(.0241046)	(.000515)	(.132261)	(.0244574)	(.1224572)	(.1054562)	(.0692869)	(.4211709)	
3	1.042291 ***	.0999587 ***	.1272227 ***	-.0025244 ***	-1.893367 ***	.1816966 *	-.0672478	.167914	.3033495 *	1.994807 **	0.2954
	(.1334973)	(.0220207)	(.0430128)	(.0007151)	(.3026069)	(.0934117)	(.6537511)	(.3241332)	(.173379)	(.839559)	
4	.9070007 ***	.0954815 ***	.1022412 ***	-.0033719 ***	-2.977855 ***	.0222155	-.0052559	-.6662471	.0271128	5.283565 ***	0.2776
	(.1169282)	(.0253811)	(.0358885)	(.0008686)	(.2927704)	(.0737836)	(.3771287)	(.3366949)	(.1581264)	(.782458)	
5	.2943441 ***	.0398063 ***	.1820804 ***	-.0031271 **	-1.651912 ***	.0487756	.9427169 ***	-.1288121	-.1991167	6.052275 ***	0.2224
	(.0453479)	(.0108908)	(.0374956)	(.0007407)	(.2188814)	(.0612511)	(.337915)	(.2375207)	(.1312799)	(.8022674)	
6	.3698041 ***	.0125971	.1431317 ***	-.0024568 ***	-1.34065 ***	.0832786 *	-.0650872	-.2845821	-.6306684 ***	6.763522 ***	0.2169
	(.052253)	(.0125404)	(.0202909)	(.0002441)	(.2013794)	(.0487922)	(.2486835)	(.2541848)	(.1738371)	(.6011728)	
7	.2096357 ***	.005596	-.0206176	-.0002853	-2.036902 ***	.2606062 ***	-.0368774	-.4987436 *	.1326034	8.320717 ***	0.1766
	(.0780054)	(.02122)	(.0392694)	(.0008731)	(.3126236)	(.0966508)	(.3647286)	(.2975437)	(.2101998)	(.8482588)	
8	.4735756 ***	.020444	.1397259 ***	-.0022589 ***	-.9067838 ***	.0305602	.6047069	-.0516309	-.0382217	4.911919 ***	0.1420
	(.0751188)	(.0130909)	(.0334743)	(.0006865)	(.279762)	(.0578992)	(.5151747)	(.2455743)	(.2259036)	(.5775604)	
9	.235803 ***	.0097639	.0517289 **	-.001026 **	-1.359516 ***	.0867213 **	.095249	-.1118378	-.079534	8.794015 ***	0.1120
	(.0343277)	(.0087115)	(.0251894)	(.0004864)	(.1549125)	(.0421563)	(.1627576)	(.179075)	(.0954444)	(.4933498)	
10	.4800736 ***	.0335292 **	.0635774 *	-.0012056	-1.19034 ***	.0582054	-.3921332	-.22637	-.1227986	5.741853 ***	0.1684
	(.0607267)	(.0150047)	(.0353659)	(.0009351)	(.1847635)	(.0406504)	(.3106695)	(.2003541)	(.1142424)	(.5934493)	

[◊] * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

11	.3250638 ***	.0192229	.1437453 ***	-.003041 ***	-1.241288 ***	.0565343	-.4019228	.048357	.183619	6.662941 ***	0.1264
	(.0456394)	(.0139975)	(.0362699)	(.0007078)	(.265158)	(.046128)	(.2860474)	(.1953059)	(.1636863)	(.521155)	
12	.6446663 ***	.0162085	.0454627	-.0007754	-1.579399 ***	-.0123795	.7910652 **	.2664747	-.2643281 **	3.372294 ***	0.1663
	(.0533421)	(.0133164)	(.0420145)	(.0009108)	(.2500414)	(.0513934)	(.3681882)	(.2689215)	(.1023883)	(.5976973)	
13	.8361949 ***	.0234838 *	.1647986 ***	-.0030064 ***	-1.824274 ***	.2024614 ***	-.3806755	-.0248094	-.2675519	4.460211 ***	0.2146
	(.0706027)	(.0125644)	(.031773)	(.0007678)	(.2295505)	(.0552013)	(.3128584)	(.2151825)	(.2205038)	(.6191499)	
14	.3768945 ***	.0154827	.219393 ***	-.0027647 ***	-1.494633 ***	.1090958 *	.0478823	-.0768051	-.399921 **	5.337568 ***	0.2120
	(.0835378)	(.0170522)	(.0488546)	(.0010605)	(.319504)	(.060237)	(.3987745)	(.2715331)	(.1789829)	(.8485939)	
15	1.317728 ***	.030027	.0227907	-.0007768	-2.006135 ***	.2567218 **	.5354136 *	1.054081 ***	-.5900552 ***	2.011266 **	0.2543
	(.0879996)	(.0188168)	(.0438381)	(.0008536)	(.2796007)	(.1033536)	(.293003)	(.3604697)	(.2002655)	(.9944256)	
16	.2582624 ***	.0585023 ***	.172726 ***	-.0031013 **	-1.469928 ***	.1392399 *	.1497758	-.1246735	.4050007	4.194461 ***	0.2395
	(.0427283)	(.0190567)	(.0632635)	(.0013639)	(.316863)	(.084086)	(.4271267)	(.2820334)	(.2841513)	(1.090397)	
17	.8595802 ***	.0265069 *	.0428639	-.0018604 **	-2.317972 ***	.0430445	-.6181847 **	-.5150987 *	-.6174947 ***	6.919312 ***	0.1727
	(.1271761)	(.014091)	(.0414665)	(.0008795)	(.2522737)	(.0987185)	(.3130789)	(.2653587)	(.2005036)	(.9340944)	
18	.5444658 ***	.0569571 ***	.0919255	-.0018581	-2.466951 ***	.1263442 *	-.8729925 *	-.3477759	-.2901283 *	5.475819 ***	0.2622
	(.0506389)	(.0166162)	(.0578972)	(.0012948)	(.4288607)	(.0757254)	(.4854475)	(.3242819)	(.1493333)	(1.072376)	
19	.5798061 ***	.0336557 *	.1320019 ***	-.0024727 ***	-1.454155 ***	.1356284	-.7158307	-.3972688	-.0984101	2.071226 ***	0.2628
	(.0624118)	(.0177997)	(.0454525)	(.0009421)	(.2840878)	(.0859218)	(.4592585)	(.2785594)	(.1881008)	(.7150646)	
20	1.365343 ***	.0171815	.0961333 **	-.0014566	-2.806536 ***	.0874688	.038627	-.2745465	-.4267142 *	1.878663 ***	0.2442
	(.0938908)	(.0181201)	(.045047)	(.0011326)	(.2982725)	(.0672979)	(.5094416)	(.292659)	(.2351299)	(.7072188)	
21	.888863 ***	.0234932 *	.1184219 ***	-.0019466 ***	-1.369455 ***	.0807729 *	.4009503	.0067972	.0555366	4.047148 ***	0.3274
	(.0406429)	(.0126839)	(.020228)	(.0004048)	(.1787839)	(.0421591)	(.3150712)	(.2476093)	(.1689435)	(.3709282)	
22	1.013426 ***	-.0156316	.192368 ***	-.003145 ***	-1.71026 ***	.2924096 ***	-.22274	.0731718	-.3886959 ***	2.160734 ***	0.1819
	(.1070494)	(.0103675)	(.036539)	(.0008657)	(.2190396)	(.0471154)	(.3866238)	(.1732448)	(.1436947)	(.7031274)	

23	.8318788 ***	-.0310246	.103829 *	-.0010601	-.6444078 *	-.0796771	.7909389 **	.256067	.5038472 *	2.909485 ***	0.1722
	(.1232703)	(.0211937)	(.0587183)	(.0015035)	(.3364238)	(.0867244)	(.3498364)	(.4367211)	(.2683614)	(.8653172)	
24	.7938822 ***	.0315644	.1233281 *	-.0031039 **	-2.848764 ***	-.0128265	.5664639	-.9674044 ***	-.3346655 **	6.769008 ***	0.1982
	(.0908949)	(.0211911)	(.0629481)	(.0014755)	(.3236784)	(.0823987)	(.5220405)	(.2940463)	(.1556749)	(.998159)	
25	.7478118 ***	.0485138 **	.1554369 ***	-.003062 ***	-1.98145 ***	.1032336	-.5537087	.2981551	-.1888239	3.205482 ***	0.1689
	(.118192)	(.0209378)	(.0446085)	(.0009608)	(.3548097)	(.1049075)	(.665155)	(.364212)	(.2388888)	(1.20236)	
26	.8564233 ***	.0235522	.1917389 ***	-.0032503 ***	-2.450284 ***	.2656594 ***	.1031429	-.123431	-1.257854 ***	4.540549 ***	0.3102
	(.0653441)	(.0193879)	(.0349757)	(.0008207)	(.2721369)	(.0906845)	(.3715276)	(.2681801)	(.2689113)	(.7157947)	
27	.4736847 ***	.0307388 ***	.1781299 ***	-.0030321 ***	-2.692575 ***	.2236914 ***	.1998119	.1625778	.2585644 *	4.150363 ***	0.3190
	(.0482715)	(.0097764)	(.0320384)	(.0006154)	(.2431894)	(.0519392)	(.2496916)	(.2005551)	(.1388008)	(.7187059)	
28	.6397826 ***	.0391617 ***	.017252	-.001284	-1.174686 ***	.1020095 *	.1893475	.4653162 **	-.3797628 ***	7.749969 ***	0.1258
	(.0896375)	(.0124647)	(.0375476)	(.0008962)	(.1758899)	(.0554448)	(.3522213)	(.2003606)	(.1393649)	(.6290419)	
29	1.205911 ***	.0051869	.1622038 ***	-.0032523 ***	-.9998263 ***	.0025717	.5525726	-.192688	-.0039445	1.367669 *	0.1714
	(.1169959)	(.0146104)	(.0336594)	(.0008373)	(.2631285)	(.0594345)	(.3369884)	(.2400869)	(.174646)	(.8254243)	
30	1.061425 ***	.0338016 **	.0013277	.0002276	-1.133379 ***	.3258681 ***	-.0726977	-.3252052	-.0737027	1.571659 *	0.2233
	(.0580746)	(.0166422)	(.0356455)	(.0010078)	(.254717)	(.0863562)	(.4050918)	(.2936689)	(.1832869)	(.8458354)	
31	.6496917 ***	-.002794	.1121525 ***	-.0020266 ***	-.7551444 **	.3252517 ***	-.5519023 **	-.2597129	.0159663	1.67176 **	0.1502
	(.0688195)	(.0227685)	(.0271272)	(.0005448)	(.2927651)	(.0690246)	(.2659483)	(.2376284)	(.2636544)	(.6481851)	

A.5[◊]: Quantile regression at the (0.9) with mis1 (undereducation) and mis3 (overeducation)

q90											
Country	edu	tenure	exper	exper2	gender	companysize	mis1	mis3	companysec~r	_cons	R-squared
1	0	0	0	0	0	0	0	0	0	10 ***	-0.0000
	(.1095718)	(.0081797)	(.0472693)	(.0009662)	(.2441885)	(.0309082)	(.1390147)	(.1840006)	(.1312981)	(.5219095)	
2	0	0	0	0	0	0	0	0	0	10 ***	-0.0000
	(.0280968)	(.0032868)	(.0278067)	(.0005163)	(.101325)	(.006398)	(.0377429)	(.0285362)	(.0196749)	(.4082826)	
3	.7837636 ***	.0874198 ***	.0856104	-.0017801 *	-1.45793 ***	.133815	-.0490372	.5422529	.1377518	4.403769 ***	0.2406
	(.111164)	(.0188657)	(.0538425)	(.0009709)	(.3087611)	(.1532624)	(.3878942)	(.3551733)	(.1817249)	(.983164)	
4	.619555 ***	.088201 ***	.1373697	-.0041775 **	-2.354549 ***	-.0293826	.3598091	-.1468814	-.168694	7.563635 ***	0.1928
	(.1786808)	(.0302772)	(.0865102)	(.0019491)	(.5690394)	(.1167414)	(.6329144)	(.5995895)	(.2411264)	(.1438908)	
5	.1461297 ***	.018192	.1091882 ***	-.0018058 **	-1.128729 ***	-.0210987	.6652256 ***	-.1188216	.1478176	8.319724 ***	0.0882
	(.0301406)	(.0129332)	(.0372421)	(.0007667)	(.2344723)	(.0568711)	(.2462984)	(.1963452)	(.1925004)	(.5330849)	
6	.2616379 ***	.010134	.1166164 ***	-.0022884 ***	-1.493936 ***	.060687	-.3484489	-.3429894	-.3905458 *	8.808987 ***	0.2017
	(.0696207)	(.0114235)	(.0208884)	(.0002981)	(.2521711)	(.0541044)	(.2883838)	(.2112523)	(.233306)	(.7406567)	
7	.0832246	-.0013537	.0334424	-.0013281	-2.094448 ***	.3769821 **	-.3205394	-.3920796	.0485522	9.287256 ***	0.1683
	(.0978899)	(.0226412)	(.0627125)	(.0013259)	(.3239096)	(.1460198)	(.4419768)	(.4636552)	(.2107256)	(1.12972)	
8	.416651 ***	.0163962	.1113064 ***	-.0015072 **	-.6499083 **	-.059549	.8698252 **	.015803	.0267559	6.173888 ***	0.1179
	(.0716686)	(.0135631)	(.0282854)	(.0005983)	(.2982338)	(.0607359)	(.3968415)	(.1877079)	(.2023409)	(.5737917)	
9	-8.52e-17	2.88e-18	-3.02e-17	7.43e-19	-1 ***	2.73e-17	-5.59e-16	-2.18e-16	-7.69e-17	11 ***	0.0619
	(.066358)	(.0044861)	(.0198623)	(.0003616)	(.0671382)	(.0361964)	(.3109627)	(.1184036)	(.0461516)	(.6528726)	
10	.476925 ***	.0206192	.0497266	-.0005409	-.9789228 ***	.0309026	-.4953411	-.1183041	-.3892471 **	6.998825 ***	0.1331
	(.0784288)	(.0156385)	(.044086)	(.0010042)	(.2069289)	(.0605275)	(.3301999)	(.2575827)	(.1642394)	(.7675997)	

[◊] * signals significant at 10% level, ** signals significant at 5% level and *** signals significant at 1% level. Values between parentheses are standard errors.

11	.1869082 ***	.0176751 *	.1147333 ***	-.0025866 ***	-.671979 ***	-.0296386	-.1737119	.1121606	-.0400137	8.443029 ***	0.0874
	(.0435842)	(.0091387)	(.0247049)	(.0004762)	(.1707935)	(.0440175)	(.2246391)	(.183046)	(.1159436)	(.563685)	
12	.6867279 ***	.010256	.0193599	-.0001248	-1.437938 ***	-.0001011	.1559802	.2558939	-.3723598 **	4.434314 ***	0.1805
	(.0858404)	(.0182458)	(.0412638)	(.000932)	(.3261924)	(.0794941)	(.5231558)	(.3569978)	(.1585818)	(.7584285)	
13	.5187763 ***	.0163541	.1620034 ***	-.0029028 ***	-.9734843 **	.1009265 **	-.2708621	.2531233	-.2794892 *	6.281784 ***	0.0599
	(.1408253)	(.0128418)	(.0326497)	(.000695)	(.4167187)	(.0453425)	(.2823667)	(.2201704)	(.1488633)	(.8054575)	
14	.2421406 ***	.0049358	.1650229 ***	-.0021708 ***	-.8550864 ***	.0409028	.4958057	.0845159	-.4575834 *	7.293254 ***	0.1233
	(.0851209)	(.0104046)	(.0333111)	(.0006128)	(.3005627)	(.0523366)	(.4982641)	(.2197973)	(.2453106)	(.7237572)	
15	.9873459 ***	.0129169	.0175074	-.0011191	-1.900691 ***	.0744844	.9602389 ***	1.066218 ***	-.202484	5.777895 ***	0.1880
	(.1461243)	(.0208838)	(.0453742)	(.0009263)	(.3923004)	(.1101808)	(.3553165)	(.3488547)	(.1689999)	(1.186225)	
16	.1711088 ***	.0339622 **	.0706347	-.0013149	-.9291276 ***	.0549336	.0369464	-.1234846	.3745129 *	7.221964 ***	0.0727
	(.0322192)	(.0166112)	(.0587812)	(.001308)	(.2696083)	(.050241)	(.2721239)	(.2119781)	(.2055225)	(.9127916)	
17	.8788991 ***	.0407532 **	.0134752	-.0015152	-2.20196 ***	.0023212	-.733648 **	-.3612508	-.7920878 ***	8.687654 ***	0.1905
	(.1285756)	(.0162775)	(.0443725)	(.0009523)	(.3066221)	(.1196397)	(.3687173)	(.3999667)	(.192192)	(1.047906)	
18	.3407805 ***	.058051 ***	.0347984	-.000864	-1.919432 ***	.1134891	-.4755071	-.0691705	-.426523 ***	8.358824 ***	0.1756
	(.0673208)	(.0159873)	(.051217)	(.0011494)	(.3272483)	(.075844)	(.7505185)	(.28396159	(.1367808)	(1.006234)	
19	.4932996 ***	.0173229	.2384576 ***	-.0045713 ***	-1.362875 ***	.1527939	-.5090311	-.3114311	-.3481421	3.073339 **	0.2512
	(.1276829)	(.028946)	(.058861)	(.0013556)	(.4433741)	(.1363297)	(.5979959)	(.4197211)	(.2961511)	(1.356878)	
20	1.19366 ***	.001071	.0643341	-.0003919	-2.601672 ***	.0124852	.2197068	-.070777	-.5283388 **	4.675277 ***	0.1964
	(.1538918)	(.0250165)	(.077578)	(.0019101)	(.4376105)	(.092597)	(.5685035)	(.4598657)	(.265459)	(1.249192)	
21	.793355 ***	.0397431 **	.1449388 ***	-.0027709 ***	-1.46786 ***	.1137501 *	.9478714	.3710581	-.139427	5.274751 ***	0.2487
	(.0842381)	(.0172561)	(.031038)	(.0006018)	(.2787942)	(.0632465)	(.5874707)	(.3429276)	(.2441228)	(.7365843)	
22	.5888451 ***	-.0178359	.1039499 ***	-.0011333	-1.159557 ***	.1483725 ***	-.1051576	.078701	-.353857 **	6.0408 ***	0.1093
	(.1015394)	(.011513)	(.0286987)	(.0007211)	(.1651482)	(.044444)	(.3821512)	(.1594825)	(.1593061)	(.6391626)	

23	.6906326 ***	-.0289857	.0896171 **	-.0010645	-.542281 **	-.043747	.1825486	.4117598	.2864335	5.034936 ***	0.1207
	(.1049141)	(.0225113)	(.0440387)	(.0011818)	(.2506713)	(.088905)	(.4494707)	(.3077365)	(.2506647)	(1.040573)	
24	.5504551 ***	-.0064868	.211842 ***	-.0046213 ***	-2.568786 ***	.1216339	.3482718	-.5472934	-.375945	7.684085 ***	0.1441
	(.1110417)	(.0217288)	(.0785517)	(.0016729)	(.34496)	(.0917513)	(.3896936)	(.4289403)	(.2382388)	(1.118042)	
25	.7026827 ***	.0273881	.1477827 ***	-.0027246 ***	-1.615083 ***	.0124502	-.6674082	.1135273	-.1491504	4.962514 ***	0.1377
	(.1749647)	(.023672)	(.0508851)	(.0009749)	(.3586207)	(.0902647)	(.9276567)	(.3282502)	(.1768403)	(1.45189)	
26	.7797014 ***	.0068242	.2089187 ***	-.0033293 ***	-2.170993 ***	.2072858 **	.4067838	.2208465	-1.129324 ***	5.520867 ***	0.2288
	(.0887696)	(.0161898)	(.045875)	(.0009536)	(.3126041)	(.0944833)	(.4048144)	(.3519942)	(.3136686)	(.6926696)	
27	.3993315 ***	.0328279 **	.1979482 ***	-.0036454 ***	-2.192845 ***	.2188899 ***	.1130502	.1781506	.0276788	5.266905 ***	0.2006
	(.0864338)	(.0153815)	(.0583913)	(.0010586)	(.3835059)	(.0713172)	(.3169343)	(.3326116)	(.2171596)	(1.029135)	
28	.5 ***	-9.64e-17	5.88e-16	-1.30e-17	-1 ***	-1.78e-16	-2.32e-15	-3.50e-15	-6.72e-16	9 ***	0.0230
	(.1247146)	(.007748)	(.0156352)	(.0005364)	(.2570364)	(.0242364)	(.2411468)	(.0998084)	(.1286163)	(.2929829)	
29	1.113851 ***	.0028483	.1968533 ***	-.004204 ***	-1.376021 ***	-.0948572	.2298308	-.3075979	-.2298308	4.483009 ***	0.1857
	(.1735104)	(.0211042)	(.0603566)	(.0014917)	(.2525069)	(.0697529)	(.3526148)	(.2936309)	(.2875966)	(.8879878)	
30	.7443803 ***	.0221028	.021266	-.0001073	-1.061346 ***	.1121256	-.1249881	-.2518587	-.0477792	5.354246 ***	0.1222
	(.092253)	(.0166417)	(.0400159)	(.0012279)	(.3248261)	(.0901059)	(.3783542)	(.3350357)	(.1929183)	(.850577)	
31	.6389999 ***	-.0224313	.0934358 *	-.0013975 *	-.5842538	.1941712 **	-.1803053	.2273731	-.2383189	3.838998 ***	0.1025
	(.105075)	(.0249504)	(.0489379)	(.000797)	(.4434841)	(.0844706)	(.3940191)	(.3890349)	(.2513101)	(1.162508)	