

Skill mismatch in Europe: Educational attainment, educational expansion and skill utilization

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## Description of deliverable (100 words)

Strong beliefs in increasing skill requirements have in recent decades contributed to an expansion of education at almost all levels. However, whether this raise in educational attainment actually has been put to use in the labor market remains unclear. Relatively little is known regarding how the utilization of skills has changed in response to the inflow of graduates, as most studies have tried to make inferences regarding the relationship between education and skill requirements based on the evolution of wage inequality. Using representative data for 24 European countries, Deliverable 3.4 instead studies how the relationship between individual educational attainment, societal educational expansion, and direct measures of skill utilization at the individual level has changed among young workers between 2005 and 2015. We find clear indications that rapid expansion of the educational system, particularly the system of tertiary education, lowers the risk of over-skilling. This suggests that while the labor market may have difficulties adapting to the change in labor supply, this will at least to some extent eventually occur allowing many new graduates to make use of their skills.



### 1. Introduction

Recent decades have seen a widespread expansion of the educational system. After the rapid increase in educational attainment that in many countries took place in the 1960s and 1970s, a similar surge in attainment occurred around the turn of the millennium. As with the earlier wave, the more recent one involved an increase in enrolment at both the upper secondary and the tertiary level of education.

While the reasons for this dramatic rise in human capital investments vary across countries, one common theme relates to the perception of increasing skill requirement in the labor market. International organizations such as the OECD, the ILO, and the EU as well as various domestic actors propagated a narrative in which countries needed to invest more in education in order for their citizens to be employable on the labor markets of the future – and legislators responded. The Europe 2020 program agreed upon by the European Union in 2010 for instance stated that at least 40 % of the 30- to 34-year-olds should have obtained a tertiary degree by 2020. This ambitious target was reached in 2019, which meant that the share of university-educated Europeans had almost doubled in less than 20 years (Eurostat 2020).

The background to this narrative was the belief that technological changes had generated a need for additional communication skills, problem-solving skills, team-working skills and skills related to information and communications technology, rising skill requirements that primarily should be met through increased education and training. The image was that of the arrival of the knowledge economy, a term coined in the 1960s describing an economy in which physical resources would have been superseded by information and knowledge as the primary source of value.

However, while it is undoubtedly the case that information and communications technology (ICT) has revolutionized the way production is carried out, it is less certain that the recent graduates are able to put their acquired skills to productive uses. This would seem to crucially depend on the relative rate of change in production methods and the skills of the labor force, and any differences could have dramatic implications for workers. If, for instance, the rapid changes in European education outpaced that of production, the university trained may have had to accept less qualified jobs. This may in turn have made it more difficult for workers



Evidence on the labor market effects of this enormous investment in humans has mainly come in the form of analyses of the development of the education wage premium, the difference in the wages received by college- and non-college labor. Yet this can at best only be seen as indirect evidence, as wages may be affected by factors such as changes in unionization and collective bargaining as well as demographic changes (Lemieux 2006, 2008)

An alternative approach to the question of mismatch is to examine direct evidence on skill utilization by workers, evidence stemming from interview responses regarding whether or not employees have the opportunity to use their skills in their daily work. This would provide more immediate evidence on the relationship between educational expansion and skill utilization. This is the approach taken here, using data from the European Working Conditions Survey covering 24 countries and the years 2005 to 2015. The subsequent section, Section 2, briefly reviews the scholarly debate on the evolution of skill requirements in the labor market, focusing specifically on the issue of skill mismatch. Section 3 then turns to the data and the methods used in this analysis, with the results being presented in Section 4. Section 5 concludes, followed by two appendixes with supplementary analyses.

#### 2. Education and skill requirements

The relationship between education and technology has attracted substantial attention in recent years, as the rapid growth in wage inequality during the 1980s and 1990s was said to be the driven by the ICT revolution. The standard interpretation became that of skill-biased technological change (SBTC), a technology-driven transformation of labor demand favoring highly skilled labor and leading to increasing wage inequality (e.g. Autor et al. 1998, Bound and Johnson 1992, Katz and Murphy 1992).

This was thus another version of a technology-based transformation of production impacting on the skill requirements of employers and of the workforce. The conclusions regarding widespread upskilling fundamental to SBTC was the latest version of earlier accounts regarding the transformation of production, akin to the hypotheses regarding the arrival of post-industrial society (Bell 1973, Blauner 1964, Clark 1948). In contrast, other, partly technology-driven, scenarios foretold pervasive de-skilling, with machines depleting work of

its' most interesting components (Braverman 1974). Finally, some observers distinguished both trends simultaneously, leading to a bifurcation of working conditions and polarization in the labor market (Doeringer and Piore 1971, Edwards 1979). This idea of polarization was resurrected in the notion of task-biased technological change (TBTC) (Autor et al. 2003), the modified version of SBTC that centered on the varied impact technologies may have on different types of jobs (see Goos and Manning 2007 for an initial analysis).

Little attention was initially paid to education, as the search for explanations for the rapid rise in inequality focused almost entirely on the role of structural change. This changed with theories focusing explicitly on the role of skill supply for production choices, a process labeled directed technical change (e.g. Acemoglu 1998). The relationship between technology and education was further highlighted by Goldin and Katz (2008) who posited that development of inequality was determined precisely by the interplay between these two factors. The "race between technology and education" thus implied that inequality tended to grow during periods in which the rate of technological change outpaced that of educational expansion, and shrank when education expanded quicker (see Autor et al. 2020 for a recent statement).

Despite the theoretical focus on production technologies and job requirements, much of the empirical literature used wages as indirect evidence on the evolution of labor demand. This was almost exclusively the case in the early literature on SBTC and the education wage premium, and although the TBTC literature brought specific tasks into the discussion the relationship between job requirements and worker skills was still primarily examined through the development of employment and wages (for a recent review of these two strands of literature, see e.g. Sebastian and Biagi 2018).

This indirect approach to the analysis of the relationship between education, jobs and workers, contrasts starkly with that of the large literature on educational and skill mismatch (see McGuinness 2006, McGuinness et al. 2018b for reviews). This literature starts from the presumption that there might be a discrepancy between the qualifications and skills required to carry out a job and the qualifications and skills actually held by an incumbent worker. The wages obtained by the worker may consequently be an imperfect indicator of the skill requirements of the worker's job.

Such a discrepancy, or mismatch, may be of many different kinds; a worker can thus have either more or less qualifications and skills than required, or different qualifications and skills than those required. The former is sometimes discussed under the heading vertical mismatch, in contrast to the later which is then labelled horizontal mismatch. Most of the mismatch literature has focused on educational mismatch, that is differences in the level of education required to carry out a job and the level of education attained by the worker. However, a substantial literature on skills mismatch also exists, referring to either over- or under-skilling. Mismatch is here normally subjectively defined, that is the workers themselves stating whether or not they find that they possess more or less skills than required by their current job.

Mismatch studies of both kinds have largely focused on the consequences of mismatch, primarily in terms of wages but also in the form of e.g. job satisfaction. These studies show that mismatched workers are rewarded for their surplus skills and qualifications, but not quite to the same extent as matched workers. Likewise, workers with skill deficits are rewarded less than matched workers. Another large strand of the mismatch literature deals with determinants of mismatch, primarily individual characteristics and to some extent labor market characteristics. Typical results are for instance that women and immigrants tend to be mismatched relatively often, that mismatch is countercyclical in nature and that it may be related to strong employment protection legislation.

A striking feature of the literature examining the determinants of both educational and skills mismatch is the relative lack of attention given the development of the educational system. Despite the strong rhetoric around the need for additional education at both the individual and societal level and the massive additional investment that has taken place, little is known about the extent to which these newly acquired skills are put to productive usage.

One of the few studies in this field is Di Pietro (2002) who in a cross-sectional analysis of 11 European countries found that recent increases in the educational attainment of the population in 1995 were associated with greater over-education rates. Another is McGuinness et al (2018a) who in an analyses of 28 European countries reported mixed effects of the share of the young labor force (20- to 24-years) with tertiary degrees on overeducation rates across the period 1998 to 2012 as a whole. Finally, there is Delaney et al. (2020) who more directly tried to examine the link between educational expansion and mismatch. Focusing on the period 2000 to 2016, they looked at how over-education rates among young (15- to 29-year-olds) workers in 30 European countries was related to upper

secondary and tertiary education attainment rates in the same age group. Their conclusion was that the expansion of education that took place during this period actually lead to lower rates of over-education, suggesting that employers had successfully adapted to the expanding supply of highly educated labor and created jobs that matched the qualifications of the young labor force entrants.

These studies, in particular the one by Delaney et al. (2020), provide interesting information on the adaptability of the labor market to rapid changes in labor supply. A general conclusion would seem to be that there is little evidence that the expansion of education that in recent decades has taken place has created a rising level of under-utilization of skills. However, from the perspective of skill utilization is it notable that all existing studies examine overeducation, that is the match between the workers' formal qualifications and some indicator of the formal requirements of the job they are in. There is in other words no evidence on the (mis-)match between workers' actual skills and the actual requirements of their jobs. The distinction between actual skill and formal qualifications may be important, as employers for instance may raise the formal requirements in response to the deluge of increasingly qualified applicants with changing the tasks actually carried out as part of the job. Such discrepancies may be exacerbated when, as in McGuinness et al (2018a) and Delaney et al. (2020), formal requirements are measured using the so-called realized matches approach. Rather than referring to the requirements of the job the worker actually holds, this defines requirements as the most frequent level of education within a relatively broad occupational group leaving a fair amount of uncertainty as to whether this corresponds to the requirements of the workers' jobs. There is in other words a need for additional analyses of the link between educational expansion and mismatch, focusing explicitly on skill utilization at work.

#### 3. Data and methods

The data comes from the European Working Conditions Survey (EWCS), a survey of a random sample of Europeans that has been conducted since 1991. It consists of multi-stage, stratified, random samples of the working population in each country, specifically all residents aged 15 or older and in employment at the time of the survey. The target sample size has in most countries and years been around 1 000.



The survey itself has also expanded, from one page of questions in 1991 to 51 pages in 2015. Questions on skill utilization have been posed since 1995, but due to a change in the wording of the question between the third and the fourth wave we will here primarily make use of the data from the surveys in 2005, 2010 and 2015.<sup>1</sup> In these three waves, the question was phrased as: "Which of the following alternatives would best describe your skills in your own work?" The response alternatives were: "I need further training to cope well with my duties," "My duties correspond well with my present skills," and "I have the skills to cope with more demanding duties."

This question on skill utilization is similar in construction to questions on skill match posed in other surveys. As with many questions focusing on skill use it is subjective, indicating how the respondent views the match between acquired and required skills. Subjective measures are also found in relation to questions in other surveys on educational mismatch, although when it comes to education many non-subjective measures exist as well. Compared to some of these objective educational mismatch measures, the skill utilization measure in the EWCS lacks an indication of the extent of skill mismatch. It is thus not possible to distinguish workers who are only slightly over-skilled from those who think they possess a large number of vital skills that go largely unused. All in all, however, the skill mismatch measure available in the EWCS can be considered standard.

As the overarching question here relates to the relationship between educational expansion and skill utilization, it seems natural to focus on the extent of over-skilling. The three ordinal response categories have therefore been recoded into a dichotomous mismatch indicator, with the first two response categories defined as not over-skilled (coded 0) and the third as over-skilled (1).

<sup>&</sup>lt;sup>1</sup> Analyses of the two earlier waves can be found in the Appendix. In addition to the changing in wording of the mismatch question, earlier waves of the EWCS also lack information on attained education.



In addition to the dependent variable, the EWCS also includes information pertaining to a number of key individual level independent variables. This in particular includes attained level of education, which is coded according to the International Standard Classification of Education (ISCED) 1997 schema.<sup>2</sup> ISCED97 distinguishes between seven levels of education; Pre-primary education, Primary education, Lower secondary education, Upper secondary education, Post-secondary non-tertiary education, First stage of tertiary education, and Second stage of tertiary education. Due to the structure of the data on the level of education in the labor force (see below), this has here been grouped into three levels; (1) Less than upper secondary education, (2) Upper secondary education and post-secondary non-tertiary education. Finally, the EWCS also provides information on the sex and the age of the respondent.

We measure educational expansion using data on educational attainment among those between 25 and 34 years-of-age, the youngest age group for which the OECD provides separate information on attainment in their publication Education at a Glance. The data for the core analyses comes from OECD (2017) which provides information on the share of 25- to 34-year-olds with below upper secondary education, with upper secondary or postsecondary non-tertiary education, or with tertiary education for the years 2000, 2005, 2010 and 2015. For the supplementary analyses of the earlier waves, the data comes from earlier editions of the same publication (OECD 1993, 1996, and 1998). This data has been used to capture differences in both the level of qualifications in the young labor force as well as short-term changes in the level. In the analyses we have thus included both the share of 25to 34-year-olds with upper secondary or tertiary education and changes in the shares between two successive waves (i.e. 5-year differences).

<sup>&</sup>lt;sup>2</sup> Prior to the 2015 survey, ISCED97 was updated to ISCED11. This did however not implicate the educational classification employed here, as the principal changes affected the classification of different levels and types of tertiary education which here are grouped together.



Technequality

Finally, as noted clear business cycle effects on over-skilling has been found in previous research and for this reason the annual unemployment rate for each country (% of labor force) has been included among the independent variables with the data coming from the World Bank.

The data from the EWCS consists of repeated cross sections of residents in a number of European countries, implying a three-level structure with individuals nested in years nested in countries. In addition to simple descriptive analyses, 3-level random effects logistic regression will therefore be used in exploring the link between educational expansion and skill utilization. The likelihood of an individual being over-skilled, i.e. y<sub>ipc</sub>= 1, can here be written as

$$\log(\pi_{ipc}/(1 - \pi_{ipc})) = \beta_0 + X_{ipc}\beta_1 + Z_{pc}\beta_2 + e_{ipc} + u_{pc} + u_{c},$$
(1)

where  $\pi_{ipc} = \Pr(y_{ipc} = 1)$  is the outcome variable,  $\beta_0$  an intercept,  $X_{ipc}$  a vector of level-1 variables,  $\beta_1$  a corresponding vector of parameters,  $Z_{pc}$  a vector of level-2 variables,  $\beta_2$  a corresponding vector of parameters and sub-indexes i, p and c denote observations at level-1 (here individuals), level-2 (periods) and level-3 (countries) respectively.  $e_{ipc}$  is the level-1 residual with  $e_{ipc} \sim N(0,\sigma^2_e)$ ,  $u_{pc}$  is the level-2 residual with  $u_{pc} \sim N(0,\sigma^2_u)$ , and  $u_c$  is the level-3 residual with  $u_c \sim N(0,\sigma^2_u)$ . In this setting, there are no level-3 variables.

However, when there are time-varying variables involved, specification (1) runs the risk of conflating the effects of these variables with the effects any trends in y unrelated to Z. In an alternate specification, we therefore include a time variable, W, transforming (1) into

$$\log(\pi_{ipc}/(1 - \pi_{ipc})) = \beta_0 + X_{ipc}\beta_1 + Z_{pc}\beta_2 + W_{pc}\beta_3 + e_{ipc} + u_{pc} + u_{c},$$
(2)

In order to make the results representative for the European workforce, all analyses have been carried out using post-stratification weights.

#### 4. Results

To provide a baseline for the subsequent analyses of the link between educational expansion and skill-mismatch, the evolution of educational attainment among young Europeans is illustrated in Figure 1. The figure shows the share of the 25- to 35-year-old population with tertiary degrees from 1995 to 2015, and it is clear that there has been a dramatic increase in attainment. The share of university graduates rose from 17 % in 1995 to 40 % twenty years later, and although not shown in the figure there was a concomitant drop in the share with



The figure also shows the evolution of attainment in Poland and the UK, illustrating the variation in both levels and rates of change within Europe. While the UK started out as one of the European countries with the highest level of attainment, Poland belonged to the opposite end of the spectrum. These two "extreme" countries evince the remarkable convergence in attainment across Europe, with most young Europeans obtaining either an upper secondary or a tertiary degree.



#### Figure 1. Educational attainment in Europe

Source: OECD Education at a Glance, various years.

A first glance at the over-skilling data is provided by Table 1 showing the development of over-skilling over time as well as by educational level. An immediate observation from Panel A is that while there has been relatively little change in the extent of over-skilling in Europe, there is nonetheless a slight tendency for over-skilling to fall over time. As for skill match and attained education, Panel B somewhat surprisingly indicates that over-skilling becomes more frequent with increasing attainment. While the differences are rather limited there is nevertheless a clear gradient across the groups.



Table 1.	Over-skilling in Europe, by year and by level of education. Perc	ent.
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Panel A	2005	2010	2015
Under- or matched skills	66	69	71
Over-skilled	34	31	29
			Tautians
Panel B	Below upper sec. education	Upper sec. education	education
Panel B Under- or matched skills	Selow upper sec. education	education 69	education 67
Panel B Under- or matched skills Over-skilled	Below upper sec. education 72 29	Upper sec.         education         69         31	education 67 33

The analysis of the relationship between over-skilling and educational expansion has proceeded from here using a basic model including individual educational attainment, age and sex as well as the national unemployment rate. This model has then in a series of steps been augmented with country level indicators of the share of the young population with upper secondary and tertiary degrees as well changes in these shares between the surveys. In a final step, year dummies have been added to the model to take account for any time trends.

Table 2 displays the results from these analyses, where for the sake of parsimony only the estimates for the variables of main interest are shown. In Model 1 it is clear that in comparison to employees with upper secondary degrees or less, workers with credential from tertiary education are more likely to state that they are over-skilled.

These results remain stable when the share of workers with high school and university degrees are included in Model 2. The two latter variables only appear weakly related to the likelihood of over-skilling, were solely the share of upper secondary education graduates show any indication of being associated with over-skilling. However, even though there are only very limited tendencies for the stock of graduates to be related to over-skilling, changes in the stock are another matter. As shown in Model 3, changes in both the share of the young labor force with upper secondary and with tertiary degrees are negatively related to over-skilling, something which in particular applies to university graduates.



## Table 2. Over-skilling in Europe. 3-level random effects logistic regression. Robust

standard errors in parenthesis.

	Model 1	Model 2	Model 3	Model 4	
Fixed effect coefficients					
Lower secondary education or less	-0.030 (0.069)	-0.028 (0.069)	-0.033 (0.075)	-0.031 (0.075)	
Tertiary education	0.463*** (0.077)	0.463*** (0.077)	0.460*** (0.080)	0.461*** (0.080)	
Share w/ upper secondary ed.		0.008* (0.005)	0.007 (0.005)	0.006 (0.004)	
Share w/ tertiary ed.		0.003 (0.006)	0.002 (0.006)	-0.013** (0.006)	
$\Delta$ Share w/ upper secondary ed.			-0.023* (0.012)	-0.018* (0.010)	
Δ Share w/ tertiary ed.			-0.032*** (0.010)	-0.021*** (0.008)	
Year 2010				0.113 (0.082)	
Year 2015				0.292*** (0.111)	
Constant	-0.826*** (0.257)	-1.133*** (0.0430	-1.114*** (0.012)	-0.650* (0.358)	
Random effect variances					
Country-year	0 .049 (0 .012)	0 .052 (0 .013)	0 .048 (0 .011)	0 .040 (0 .010)	
Country	0.123 (0.048)	0.099 (0.045)	0.083 (0.035)	0.075 (0.034)	
Log pseudo- likelihood	-17067.4	-17066.7	-16540.0	-16536.4	
No. of units of analysis	Respondents = 37 568, country-years = 71, countries = 24		Respondents = 36 634, country-years = 69, countries = 24		
Note: *** = $p < 0.01$ , ** = $p < 0.05$ , * = $p < 0.10$ . Maximum likelihood estimation, standard					

errors clustered on country. All models also contain the level-1 variables sex and age as well as the level-2 variable unemployment rate. Source EWCS, own calculations.

Despite the fact that university graduates remain more likely to state that they are overskilled, increases in the share of university educated in the young labor force thus lowers the likelihood. This somewhat contradictory results could be the consequence of a trend over time towards less over-skilling, independent of the changes in educational policy. To control for this possibility, Model 4 includes time (wave) dummies, and it is clear that such a trend is indeed present. However, this does not change the qualitative conclusion from Model 3, increases in the share of the labor force with upper secondary and tertiary educational degrees reduces the likelihood of over-skilling.

It is conceivable that the relationship between skill match and educational expansion varies depending on e.g. economic structure or the level of economic development. As a rough approximation for such differences, the analyses presented in Table 2 have also been conducted separately for Western and Eastern Europe. Western Europe has here encompassed Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom, while Eastern Europe has included the Czech Republic, Estonia, Latvia, Hungary, Poland, Slovenia, and Slovakia.

These results are presented in Appendix 1, Table A1 and A2, and provide little support for this conjecture. The results for the Western and Eastern parts of the continent are largely similar, in particular if account is take of the smaller sample size in Eastern Europe. There are thus no indications that the results presented in Table 2 is dependent on industrial structure or level of development.

While the period covered by these analyses does span 15 years of continuous and dramatic educational expansion, it would nevertheless be of obvious interest to see if the above results also applies to earlier periods. However, changes to the survey prevents us from carrying out more than rudimentary analyses for the preceding decade, the period 1991 to 2000. The results are presented in Table A2, Appendix 2. Although the differences between the surveys limits the comparison that can be made between the 1990s and the 2000s, the final model presented in the table, Model 3, would nonetheless seem to suggest that there may have been a negative association between the rate of university expansion and the occurrence of over-skilling also during the earlier period.



#### 5. Conclusions

Many countries have in recent years invested heavily in the skills and qualifications of the labor force, radically expanding the educational system. Europe is here a case in point, and the educational attainment of the European labor force has risen dramatically. While there have been many arguments put forth for a renewed expansion of education, one central argument has been the purportedly increasing skill requirements in the labor market. Both national and international actors have thus claimed that new production methods linked to widespread adaption of information and communications technology would require a labor force with substantially longer education than previous generations.

Relatively little is however known regarding the returns of this massive social investment. Do for instance the new university graduates find jobs commensurate to their educational qualifications, jobs in which they can make use of the skills they have acquired? Or do they run the risk of have set aside a number of years for additional schooling only to find that the jobs that are available have not evolved at the same pace?

This paper offers evidence on these issues, examining the relationship between over-skilling in the European labor market and educational attainment at the individual and population level. The period examined is 2005 to 2015, a relatively short period but precisely the period during which educational attainment in the youngest age groups almost doubled.

The results suggest that the risk of over-schooling may have been exaggerated. While it is the case that university graduates tend to state that they have more skills than they make use of in their job, the expansion of tertiary education is generally associated with a lowered risk of over-skilling. These are results very much in line with those found by Delaney et al. (2020) using different data, different methods and a different mismatch indicator.

While the results for university graduates and share of university educated may appear contradictory, the paradox may be resolved by considering the difference between the average likelihood that workers consider themselves over-skilled and changes over time in this likelihood. Note that the result that tertiary graduates are more likely to regard themselves as over-skilled applies the period as a whole, while the result for the share of university graduates refers to changes over time. It is thus perfectly possible that university educated are more likely to believe they are over-qualified, yet that the extent to which they

find this has diminished over time. This in turn suggests that the labor market if not completely so at least to some extent has adapted to the increasingly high levels of qualifications acquired by the young cohorts.

Unfortunately, the period analyzed here is too short to allow a more detailed analysis of the adjustment process. Questions regarding the overall rate of adjustment, and whether it the pace varies across sectors or countries, will have to be examined elsewhere. Nonetheless, the overall results would appear to be positive for both individual workers and for policy makers. While it undoubtedly will be difficult to optimize the rate of educational expansion, and there therefore is a clear risk that both societal and individual resources will be falsely allocated, there is hope that the extra skills that individuals have acquired through additional years of education will come to productive usage.



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#### Appendix 1. Skill mismatch in Western and Eastern Europe

Table A1a.Over-skilling in Western Europe. 3-level random effects logisticregression. Robust standard errors in parenthesis.

	Model 1	Model 2	Model 3	Model 4	
Fixed effects coefficients					
Lower secondary education or less	-0.017 (0.078)	-0.014 (0.011)	-0.022 (0.086)	-0.020 (0.086)	
Tertiary education	0.384*** (0.079)	0.383** (0.079)	0.376*** (0.084)	0.376*** (0.085)	
Share w/ upper secondary ed.		0.014 (0.011)	0.010 (0.010)	0.010 (0.010)	
Share w/ tertiary ed.		0.002 (0.006)	0.002 (0.009)	0.002 (0.009)	
$\Delta$ Share w/ upper secondary ed.			-0.016 (0.020)	-0.016 (0.020)	
$\Delta$ Share w/ tertiary ed.			0.046*** (0.014)	0.046*** (0.014)	
Year 2010				0.087 (0.116)	
Year 2015				0.406*** (0.148)	
Constant	-0.618** (0.319)	-1.273** (0.519)	-0.849 (0.538)	-0.375 (0.325)	
Random effects val	riances	-			
Country-year	0.056 (0.018)	0.065 (0.019)	0.046 (0.018)	0.034 (0.016)	
Country	0.013 (0.065)	0.081 (0.050)	0.082 (0.047)	0.046 (0.025)	
Log pseudo- likelihood	-12434.2	-12433.4	-11904.8	-11897.7	
No. of units of analysis	Respondents = 28 164, country-years = 50, countries = 17		Responden country-y countri	ts = 27 230, ears = 48, es = 17	
Note: *** = $p < 0.01$ , ** = $p < 0.05$ , * = $p < 0.10$ . Maximum likelihood estimation, standard					

errors clustered on country. All models also contain the level-1 variables sex and age as well as the level-2 variable unemployment rate. Source EWCS, own calculations.

## Table A1b. Over-skilling in Eastern Europe. 3-level random effects logistic

#### regression. Robust standard errors in parenthesis.

Fixed effects coefficients				
Lower secondary education or less	-0.156 (0.110)	-0.158 (0.107)	-0.146 (0.104)	-0.140 (0.108)
Tertiary education	0.682** (0.158)	0.681*** (0.156)	0.685*** (0.154)	0.686*** (0.153)
Share w/ upper secondary ed.		-0.011 (0.025)	-0.022 (0.031)	-0.041 (0.055)
Share w/ tertiary ed.		-0.012 (0.024)	-0.029 (0.024)	-0.072 (0.089)
$\Delta$ Share w/ upper secondary ed.			-0.015 (0.022)	-0.011 (0.018)
Δ Share w/ tertiary ed.			0.031 (0.024)	0.044* (0.024)
Year 2010				0.237 (0.356)
Year 2015				0.381 (0.709)
Constant	-1.450*** (0.223)	-0.420 (2.300)	0.620 (2.736)	0.620 (2.736)
Random effects val	riances			
Country-year	0.035 (0.014)	0.033 (0.016)	0.018 (0.009)	0.018 (0.009)
Country	0.068 (0.056)	0.074 (0.064)	0.113 (0.078)	0.113 (0.078)
Log pseudo- likelihood	-4606.1	-4606.0	-4604.7	-4604.2
No. of units of analysis	Respondents = 9 404, country- years = 21, countries = 7			

Note: \*\*\* = p < 0.01, \*\* = p < 0.05, \* = p < 0.10. Maximum likelihood estimation, standard errors clustered on country. All models also contain the level-1 variables sex and age as well as the level-2 variable unemployment rate. Source EWCS, own calculations.

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fechnequality

![](_page_21_Picture_1.jpeg)

The EWCS has evolved substantially over time, the number of countries as well as the questionnaire has expanded and some of the questions have been reformulated. With regard to the countries, the smaller set initially covered by the survey means that we here will be analyzing data from the EU-15; viz. Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

With regard to the questionnaire, the most relevant changes include the reformulation of the question of skill match and the inclusion of information on the respondent's attained education. As noted above, the question posed in 2005 to 2015 was phrased as: "Which of the following alternatives would best describe your skills in your own work?" The response alternatives were: "I need further training to cope well with my duties," "My duties correspond well with my present skills," and "I have the skills to cope with more demanding duties." These data have been used as an ordinal measure of the degree of over-skilling; with the three alternatives counted as (1) under-skilled, (2) matching skills, and (3) over-skilled, respectively.

The question posed in 1995 and 2000 was similar: "How well do you think your skills match the demands imposed on you by your job?" The response alternatives were here: "The demands are too high", "They match", and "The demands are too low." This data can also be used in analyses of over-skilling, with the last response alternative coded as 1 and the two previous ones as 0. However, despite the seeming similarities, the questions would nonetheless appear to differ regarding for instance the extent to which they capture vertical vs. horizontal mismatch. In addition, the distribution of the answers in the individual countries differs between the adjacent 2000 and 2005 surveys in ways that suggest that the questions have been interpreted differently by respondents. These two earlier waves have therefore been analyzed separately and the results are presented in Table A2.

Although the analyses for the earlier years also differ in that the earlier waves do not contain any information on the respondents' level of education, the basic analyses in which overskilling is related to the level of education in the workforce and the changes in the levels remain possible. Needless to say, given the differences in the question comparisons between the two sets of analyses should only be made with care. However, a very tentative

![](_page_22_Picture_1.jpeg)

conclusion, based primarily on the results from Model 3 and taking into account the relatively limited information available, seem to suggest that there may have been a negative relationship between the share of tertiary graduates and over-skilling in this earlier period as well.

## Table A2.Over-skilling in Western Europe 1995 to 2000. 3-level

random effects logistic regression. Robust standard errors in parenthesis.

	Model 1	Model 2	Model 3			
Fixed effects coeffients						
Share w/ upper secondary ed.	-0.010* (0.005)	-0.001 (0.006)	-0.003 (0.006)			
Share w/ tertiary ed.	-0.016 (0.011)	0.006 (0.015)	0.015 (0.017)			
$\Delta$ Share w/ upper secondary ed.		0.003 (0.010)	0.003 (0.010)			
$\Delta$ Share w/ tertiary ed.		-0.022 (0.015)	-0.028* (0.016)			
Year 2000			-0.162 (0.172)			
Constant	-1.515 (0.526)	-2.454*** (0.573)	-2.384*** (0.531)			
Random effects variances						
Country-year	0.059 (0.028)	0.046 (0.019)	0.040 (0.019)			
Country	0.125 (0.053)	0.122 (0.057)	0.132 (0.053)			
Log pseudo-likelihood	-5254.0	-4754.1	-4753.8			
No. of units of analysis	Respondents = 21 049, country-years = 30, countries = 15	Respondents = 19 695, country-years = 27, countries = 15				
Note: *** = $p < 0.01$ , ** = $p < 0.05$ , * = $p < 0.10$ . Maximum likelihood estimation, standard errors						

Note: \*\*\* = p < 0.01, \*\* = p < 0.05, \* = p < 0.10. Maximum likelihood estimation, standard errors clustered on country. All models also contain the level-1 variables sex and age as well as the level-2 variable unemployment rate. Source EWCS, own calculations.