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Decomposing the impacts of overeducation and overskilling on earnings and job satisfaction: an analysis using REFLEX data

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This article assesses the extent to which the impact of overeducation and overskilling on labour market outcomes such as earnings and job satisfaction relate to mismatches in particular competency areas. The analysis uses REFLEX data, which collects information about 19 key competence areas related to job performance. We find that the penalties to both forms of mismatch are insensitive to the inclusion of controls for overskilling in a wide range of job-specific competencies. The research suggests that the problem of mismatch relates to an inability to fully utilise general or innate ability as opposed to specific areas of acquired learning. We conclude that the problem of mismatch can only be effectively addressed by raising general levels of job quality within developed labour markets.

Keywords: overeducation; overskilling; job satisfaction; earnings

JEL Classifications: J24; J31

1. Introduction

There now exists a substantial international literature examining the link between overeducation and labour market outcomes such as earnings, career mobility and job satisfaction (see McGuinness 2006, for a review). However, overeducation represents a very broad measure of mismatch and will be prone to inaccuracy in circumstances where (a) job entry requirements represent a poor proxy for job skill content and (b) educational attainment represents a poor proxy for accumulated human capital. Thus, the overeducation measure will tend to be affected on the demand side by credentialism and grade inflation and on the supply side by on-the-job training and unmeasured innate ability (McGuinness and Wooden 2009). A more recent strand of the literature has focused on overskilling as a measure of mismatch, as it asks respondents to compare actual job content directly with their work-related skills (Allen, Badillo-Amador, and van der Velden 2006; Green and Zhu 2010; Mavromaras, McGuinness, and Fok 2009; McGuinness and Sloane 2011). It is argued that overskilling overcomes many of the perceived measurement problems associated with overeducation as respondents directly compare all skills and abilities, whether they relate to formal/informal schooling or innate ability, with the actual skill requirements of their job. A further conceptual advantage of the overskilling measure is that it is conceivable that we can separate AQ2

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overskilling into its various work-related components, in order to identify the degree to which any observed wage or job satisfaction penalty relates to a specific area of skill accumulation. However, to date, presumably mainly as a consequence of data constraints, no study has examined the correlation between aggregate measures of mismatch and their individual components, and it is this gap in the literature that we attempt to address in this paper.

The underlying rationale for our attempt to decompose the elements of mismatch stems from the large body of evidence that has demonstrated lower earnings and job satisfaction among mismatched workers (see Mavromaras et al. 2010; McGuinness and Sloane 2011). Research has also demonstrated that mismatch tends to be non-transitory in nature (Mavromaras and McGuinness 2012; McGuinness and Wooden 2009) and has negative implications for firm-level productivity (Tsung 1987). Thus, the evidence suggests that mismatch will have negative consequences for macroeconomics growth by constraining the performance levels of both individuals and firms. Consequently, it is important to identify the areas where the costs of skill under-utilisation are greatest in order to facilitate the formulation of an appropriate policy response aimed at improving the quality of employment matches for workers and limiting the costs to individuals, firms and the economy from mismatch. However, if it transpires that the mismatch penalty is relatively poorly correlated with specific observable skill attributes, then the obvious conclusion is that constraints relate primarily to unused general or innate ability. Such a finding would support the view that overskilled workers feel generally unchallenged within their work environments, suggesting that the mismatch problem relates more heavily to a general poor quality of employment as opposed to a poor match on specific acquired skills. The central aim of this paper is to shed light on these issues and consider the implications for policy.

In terms of the evidence linking mismatch with lower job satisfaction and earnings, the bulk of the literature has focused on the impacts of both overeducation and overskilling on lowering pay (Mavromaras, McGuinness, and Wooden 2007; McGuinness 2006; McGuinness and Wooden 2009); however, the impacts on job satisfaction have received much less attention. While a number of studies have shown overeducated workers have lower levels of job satisfaction (Battu, Belfield, and Sloane 1999; Fleming and Kler 2007), the situation becomes more complex when overskilling is brought into consideration. For Britain, Green and Zhu (2010) find that overqualification is not a problem for job satisfaction in itself if it is not accompanied by skill mismatch. Similarly, for Spain, Badillo-Amador, Lopez Nicolas, and Vila Lladosa (2008) also find that skill mismatches are a better predictor of job satisfaction than educational mismatches. McGuinness and Sloane (2011), in their study of the UK Graduate labour market, found that overskilling was associated with a lower pay penalty but a higher job satisfaction when compared with overeducation. McGuinness and Sloane (2011) conclude that overeducated workers may, at least to some extent, trade-off other job attributes, such as an improved work–life balance, for lower wages thus explaining the reduced impact on job satisfaction. The object of this paper is to examine the relationship between labour market mismatches, wages and job satisfaction across a range of countries. Clearly, if overskilling can be attributed to mismatch in a specific competency areas, then potential policies that encourage employers to develop and expand particular aspects of job requirements can help alleviate some of the negative aspects of skills mismatch. Conversely, if we find that overskilling relates to a general feeling of under-utilisation, then the policy remedy becomes more complex as the result will imply that mismatch is primarily driven by a general perception of an unchallenging work environment.

2. Data

In this paper, we use the Flexible Professional in the Knowledge Society (REFLEX) project financed as a Specific Targeted Research Project of the European Union's Sixth Framework Programme covering 15 countries.[1] It is limited to graduates in the 1999/2000 academic year, who were interviewed five years later in 2005. The REFLEX data contain information on 15 countries (we only consider the 13 European countries within the data).[2] It is limited to graduates in the 1999/2000 academic year, who were interviewed five years later in 2005. The use of graduate cohort data is relatively common within the mismatch literature (see e.g. Chevalier 2003; Dolton and Vignoles 2000; McGuinness and Bennett 2007). Indeed, some authors argue that such data are less prone to unobserved heterogeneity bias due to the fact that respondents have uniform levels of education and labour market experience (e.g. Kelly, O'Connell, and Smith 2010; McGuinness and Bennett 2007). For the purposes of our study, we restrict our sample to those individuals currently employed (ignoring self-employment, and unemployment) and who studied for their third-level qualification on a full-time basis.

With respect to our key mismatch variables, in keeping with the approach adopted by McGuinness and Sloane (2011), we include measures of both educational (overeducation and undereducation) and skill mismatch (overskilling and underskilling), both of which are measured subjectively within the data. As a result of our exclusions, the effective sample falls from 34,347 to 16,810. Individual country samples range from 291 for Portugal to 3033 in the Czech Republic. Overeducation and undereducation are defined strictly in terms of vertical mismatch, that is, having a level of education above or below that required for their current job. Respondents were defined as overeducated if they indicated that a below tertiary level of education was most appropriate for the job. Conversely, they were deemed to be undereducated if the most appropriate level of education was above that actually acquired. Overskilling was based on the response to a question asking individuals to rate on a 1−5 scale[3] the extent to which their skills and knowledge were utilised in their work with a response of 1 or 2 deemed consistent with overskilling. Using the same scale, workers were deemed to be underskilled if they responded 4 or 5 to a question indicating that their job demanded more knowledge and skills than they could actually offer. Summary statistics for our sample of countries are provided in Table 1. Overeducation rates ranged from 2% in Belgium to 16% in Spain, while overskilling, at 14%, was found to be highest in Spain, the UK and France and lowest in Portugal at 3% of the sample. It is important to note that mismatch rates are based on a graduate's only sample and, therefore, will tend not to align exactly with other published studies based on population data. Nevertheless, the overall pattern of overeducation is consistent with previous estimates with overeducation rates highest in countries such as Spain and Italy and lowest in Finland and Belgium (Cedefop 2012).

A unique feature of the REFLEX is that, in addition to collecting information of overall skill utilisation, it is also asked specific questions with respect to skill acquisition and usage in 19 key competency areas related to job performance.

The competency fields are (1) knowledge (knowledge of own discipline), (2) otherknowledge (knowledge of other disciplines), (3) thinking (analytical thinking), (4) learning (ability to acquire new knowledge), (5) negotiate (ability to negotiate), (6) pressure (ability to perform under pressure), (7) openmind (alertness to new opportunities), (8) coordination (ability to coordinate activities), (9) effective (ability to use

Table 1. Descriptive by countries.

	No. observ.	Mean		No. observ.	Mean
Italy			*Finland*		
Overeducated	1175	.129	Overeducated	1350	.057
Undereducated	1175	.122	Undereducated	1350	.109
Overskill	1175	.108	Overskill	1350	.062
Underskill	1175	.225	Underskill	1350	.263
Spain			*Norway*		
Overeducated	2269	.160	Overeducated	1522	.028
Undereducated	2269	.071	Undereducated	1522	.116
Overskill	2269	.143	Overskill	1522	.043
Underskill	2269	.238	Underskill	1522	.291
France			*Chez Republic*		
Overeducated	949	.044	Overeducated	3033	.030
Undereducated	949	.144	Undereducated	3033	.111
Overskill	949	.139	Overskill	3033	.093
Underskill	949	.154	Underskill	3033	.178
Austria			*Portugal*		
Overeducated	773	.106	Overeducated	291	.065
Undereducated	773	.084	Undereducated	291	.226
Overskill	773	.084	Overskill	291	.034
Underskill	773	.306	Underskill	291	.508
Germany			*Belgium*		
Overeducated	998	.047	Overeducated	908	.020
Undereducated	998	.063	Undereducated	908	.064
Overskill	998	.088	Overskill	908	.083
Underskill	998	.259	Underskill	908	.255
The Netherlands			*Estonia*		
Overeducated	2129	.070	Overeducated	401	.022
Undereducated	2129	.053	Undereducated	401	.184
Overskill	2129	.089	Overskill	401	.084
Underskill	2129	.252	Underskill	401	.331
UK					
Overeducated	1078	.137			
Undereducated	1078	.055			
Overskill	1078	.140			
Underskill	1078	.261			

time effectively), (10) workgroup (ability to work productively with others), (11) influence (ability to mobilise the capabilities of others), (12) communication (ability to make your meaning clear to others), (13) authority (ability to assert your authority), (14) computers (ability to use computers and the internet), (15) creative (ability to come up with new ideas and solutions), (16) flexible (willingness to question your own ideas and others), (17) presentation (ability to present products and ideas), (18) write (ability to write reports, etc.), and (19) foreignlanguage (ability to write and speak in a foreign language). To derive a measure of overskilling in each area, we compared acquired skills and their level of utilisation in the workplace. The survey asks respondents to rate, on a five-point scale, both their level of expertise in a given competency and the extent to which this competency is required for their current job. If the acquired competency level is two points higher than the required job level, then individuals were defined as overskilled[4] in that specific field.

Proof only

It is somewhat difficult to distinguish clear patterns from 19 competencies distributed across 13 countries; however, it is probably fair to say that the individual competency overskilling rates appear relatively tightly distributed within countries. In terms of cross-country comparisons, the evidence suggests that overskilling is generally higher in terms of individual's alertness to new opportunities and language skills with individual's time management skills relatively well utilised. Given the central question posed within the analysis, a key point of interest relates to the extent to which overskilling in individual competency areas relates to our more general measures of overskilling and overeducation. Furthermore, it is clear that many of the individual competency areas will be highly correlated with each other and to explore these issues further we present a skill correlation matrix in Table 2. The first thing to note is that, consistent with the findings of previous research, the two central measures of mismatch are moderately correlated with each other with a correlation coefficient of .38. What is much more striking is that both overeducation and overskilling are relatively poorly correlated with overskilling in specific skill areas. This suggests that either (a) the key competency driving general mismatch has been omitted from our data or (b) the perception of general under-utilisation relates more heavily to unused innate or general ability as opposed to specific acquired skills. Given the comprehensive nature of the job competency information collected within the REFLEX data, we would argue that the latter explanation is likely to be most reliable. In terms of the skill-specific overskilling variables, these all appear strongly related to each other with correlation coefficients generally in the order of .7. The possible exception to the rule is the variable 'language skills' (the ability to write or read in a foreign language) with a lower correlation coefficient (.5) with respect to the other competency areas.

3. Econometric analysis

The approach adopted here centres around an attempt to quantify the proportion of the overall earnings/job satisfaction overskilling/overeducation penalties that can be attributed to mismatch in individual skill competencies. In our models, we begin by estimating an ordinary least-square/ordered probit model in a basic specification including only controls for mismatch in first and current employment before adding the skill mismatch variables for current employment to allow an assessment of the sensitivity of the general penalty to these effects. Our models are based on a pooled sample containing controls for sector and country-level fixed effects.[5] We did separate our data into groups of countries[6] to assess the extent to which differential pattern occurred; however, the results were largely indistinguishable from those of the pooled sample.[7]

With respect to concerns related to both sample selection and unobserved heterogeneity bias, specifically with regard to the possibility that mismatched workers have lower ability levels which accounts for lower wages, we assume these to be trivial given the evidence from recent studies that demonstrate that the estimated impact of overskilling on both wages and job satisfaction is unaffected by such factors (Mavromaras, McGuinness, and Fok 2009; McGuinness 2008). In fact, a recent study by McGuinness and Sloane (2011) uses propensity score matching and a sensitivity test for unobserved influences to demonstrate the robustness of the overskilling and overeducation measures used in this data set. Furthermore, McGuinness and Bennet (2007), who use quantile regression models applied to a similar graduate cohort data as a control for unobserved factors, find little evidence of significant variations across the wage\human capital distribution pointing again to an absence of bias.

Table 2. Correlation matrix.

	Overeduc	Undereduc	Overskill	Underskill	Ownf	Othf	Anal	Ackn	Negot	Press	Alert	Coord	Time	Woth	Mob	Cmean	Auth	Compu	Solut	Quest	Pres	Write	Lang
Overeducated	1																						
Undereducated	−0.086	1																					
Overskill	0.380	−0.054	1																				
Underskill	−0.081	0.091	−0.030	1																			
Overownf	0.072	−0.071	0.074	−0.141	1																		
Overothf	0.041	−0.066	0.038	−0.129	0.709	1																	
Overanal	0.062	−0.072	0.048	−0.138	0.741	0.71	1																
Overackn	0.047	−0.066	0.036	−0.137	0.728	0.70	0.742	1															
Overnegot	−0.001	−0.054	−0.007	−0.123	0.690	0.67	0.692	0.694	1														
Overpress	−0.003	−0.060	−0.011	−0.126	0.738	0.70	0.731	0.737	0.747	1													
Overalert	0.025	−0.060	0.020	−0.124	0.681	0.66	0.689	0.690	0.708	0.729	1												
Overcoord	0.024	−0.062	0.012	−0.129	0.722	0.69	0.724	0.716	0.719	0.766	0.723	1											
Overtime	0.003	−0.062	−0.002	−0.127	0.745	0.70	0.741	0.732	0.731	0.794	0.720	0.786	1										
Overwoth	0.007	−0.060	−0.002	−0.119	0.707	0.67	0.701	0.703	0.702	0.748	0.685	0.752	0.775	1									
Overmob	0.019	−0.057	0.003	−0.127	0.708	0.67	0.700	0.701	0.717	0.737	0.705	0.755	0.766	0.759	1								
Overcmean	0.008	−0.063	−0.004	−0.125	0.734	0.69	0.724	0.719	0.729	0.760	0.706	0.761	0.786	0.755	0.770	1							
Overauth	0.019	−0.065	0.010	−0.124	0.699	0.67	0.691	0.688	0.715	0.734	0.692	0.740	0.747	0.718	0.747	0.768	1						
Overcompu	0.031	−0.063	0.010	−0.122	0.686	0.65	0.685	0.681	0.657	0.706	0.652	0.689	0.713	0.679	0.672	0.705	0.669	1					
Oversolut	0.038	−0.069	0.031	−0.135	0.714	0.68	0.713	0.712	0.698	0.731	0.717	0.730	0.744	0.713	0.725	0.748	0.723	0.711	1				
Overquest	0.063	−0.068	0.049	−0.125	0.680	0.66	0.688	0.679	0.666	0.695	0.683	0.702	0.706	0.682	0.695	0.718	0.697	0.663	0.75	1			
Overpres	0.058	−0.077	0.035	−0.127	0.678	0.65	0.674	0.673	0.678	0.693	0.676	0.694	0.700	0.672	0.696	0.707	0.690	0.663	0.70	0.687	1		
Overwrite	0.084	−0.079	0.059	−0.133	0.700	0.66	0.701	0.680	0.672	0.702	0.659	0.703	0.712	0.678	0.686	0.712	0.684	0.684	0.70	0.678	0.731	1	
Overlang	0.019	−0.079	0.017	−0.113	0.562	0.55	0.561	0.558	0.544	0.583	0.546	0.563	0.583	0.555	0.562	0.578	0.557	0.568	0.57	0.554	0.574	0.5	1

Proof Only

However, this is not to say that the evidence on the impacts of unobserved heterogeneity is completely consistent. A number of studies have used panel data to show that the estimated wage impacts of overeducation fell dramatically when estimated within a fixed-effects panel framework (Bauer 2002; Mavromaras et al. 2010) with some commentators citing the reduction as evidence of the importance of unobserved variables that are not taken into account in most cross-section analysis, but can be included as a fixed effect in panel data (Bauer 2002; Leuven and Ooosterbeek 2012). However, more recent work has shown that where there is low variation in the dependent variable, as is the case with overeducation, a good deal of the wage impact is absorbed into the model fixed effect, implying that the impacts of unobserved ability bias may have been overstated within the panel framework (Mavromaras et al. 2010). A more interesting aspect of unobserved heterogeneity is related to unobserved personality traits. Blazquez and Budría (2012) report that entry rates into overeducation are associated with extraversion, conscientiousness and an external locus of control. If such traits also impact earnings and job satisfaction then it is possible that our results may be confounded to an extent; however, while this is certainly an area for future research, accounting for such impacts are beyond the scope of this paper.

Table 3 presents the results from the ordered probit model for job satisfaction. The original survey information on satisfaction was collected on an ordered scale ranging from 0 (absolutely dissatisfied) to 5 (absolutely satisfied). The results in Table 3 are expressed in terms of coefficients and marginal effects. In line with McGuinness and Sloane (2011), we find that overskilling has the most significant impact on job satisfaction with overskilled workers 18.2% less likely to be satisfied (JS = 5) in the current employment. Overeducation was found to lower the probability of job satisfaction by 12.4%. Underskilled workers were found to have a slightly higher probability of job satisfaction at 5.0%, while no effects were detected for undereducation.

Table 3. JS equation: marginal effects and ordered probit estimates.

	Full sample	Women	Men
Male	−.063*** (.018)		
Labexp	.001** (.000)	.001 (.000)	.001 (.001)
Overeducated	−.476*** (.036)	−.502*** (.046)	−.432*** (.061)
Undereducated	.030 (.029)	.054 (.039)	.007 (.044)
Overskill	−.768*** (.031)	−.731*** (.041)	−.822*** (.048)
Underskill	.158*** (.019)	.144*** (.026)	.174*** (.030)

Marginal effects full sample	JS = 1	JS = 2	JS = 3	JS = 4	JS = 5
Overeducated	.027	.070	.083	−.056	−.124
Undereducated	−.001	−.003	−.006	.001	.009
Overskill	.055	.121	.118	−.113	−.182
Underskill	−.005	−.018	−.031	.004	.050

Notes: No. of observations: 16,810. Between brackets stand error. All equations also include controls for country-level fixed effects and other variables such as age, hours worked per week, number of employers since graduation and dummy variables. Dummy variables are the field of study, if possessed a master's degree, if job matched to field of study or related to field of study, if have been unemployed since graduation, if course was prestigious, if course was vocational, if employed in a research-intensive firm, if employed in a public sector and dummy firm size. We also estimate robust variance by country and the coefficients which measure skill mismatches continue being significant.
**Significant at the 5% level.
***Significant at the 10% level.

Proof Only

Table 4. Wage equation.

	Full sample	Women	Men
Male	.086*** (.007)		
Labexp	.003*** (.000)	.002*** (.000)	.004*** (.000)
Overeducated	−.290*** (.015)	−.293*** (.019)	−.270*** (.024)
Undereducated	−.003 (.012)	.016 (.016)	−.026 (.017)
Overskill	−.056*** (.012)	−.063*** (.017)	−.045*** (.019)
Underskill	.012 (.008)	.009 (.010)	.017 (.012)

Notes: No. of observations: 16,810. Between brackets stand error. All equations also include the same controls as in Table 3. We also estimate robust variance by country and the coefficients which measure skill mismatches continue being significant.

The results from the wage equation are presented in Table 4. Again, these are consistent with previous research (Green and McIntosh 2007; Mavromaras, McGuinness, and Fok 2009) showing that the overeducation pay penalty is much more substantial than that for overskilling. Overeducated workers were found to earn 29% less than their well-matched counterparts, while overskilled workers earned 5.6% below than that of workers reporting full skill utilisation. No wage impacts were found with respect to undereducation or underskilling.

When we add the specific domains of overskilling to our model (Table 5), we detect a variety of influences not all of which lower job satisfaction. While overskilling in the areas of non-specialist knowledge, analytical ability (thinking), knowledge acquisition (learning), alertness to opportunities (openmind), idea creation (creative) and language skills all reduced job satisfaction, we found that surplus skills in time management and the ability to work under pressure actually raised satisfaction levels. The result suggests that surplus competencies in the ability to manage work requirements are viewed positively by workers. Crucially, the general overeducation and overskilling penalties remained more or less unchanged when the additional controls were added, suggesting that the general effects of overeducation and overskilling on job satisfaction cannot be adequately attributed to under-utilised skills in any specific area. Furthermore, the marginal effects of the individual competencies are much lower than those of the general mismatch variables.[8] The results suggest that the widely observed penalties associated with overeducation and overskilling relate more to a sense of unused general potential as opposed to under-utilised specific skills, despite the fact that many of the competency areas, such as analytical ability and idea creation, refer to under-utilised aspects of intellectual capacity.

On the basis that observed patterns might vary by gender, we estimated our job satisfaction separately for males and females. With respect to job satisfaction, our overriding conclusion that the previously observed effects of overeducation and overskilling on job satisfaction were unrelated to under-utilisation in any specific skill area held. Nevertheless, some impacts were significant with consistent patterns emerging in that both males and females experienced lower levels of job satisfaction as a consequence of overskilling in analytical thinking, the ability to acquire new knowledge, the ability to question ideas, and creative and foreign language skills. Female job satisfaction was reduced as a consequence of overskilling with respect to assert authority, while surplus skills with regard to present products or ideas raised satisfaction. Male levels of satisfaction were reduced (raised) as a consequence of overskilling in a non-core field of study.

Proof only

Table 5. JS equation considering skill acquisition (probit coefficients).

	Full sample	Women	Men
Male	−.055*** (.018)		
Labexp	.000 (.000)	.000 (.000)	.000 (.001)
Overeducated	−.423*** (.036)	−.45*** (.046)	−.365*** (.062)
Undereducated	.023 (.029)	.051 (.039)	−.003 (.045)
Overskill	−.716*** (.031)	−.684*** (.041)	−.763*** (.049)
Underskill	.143*** (.019)	.133*** (.026)	.151*** (.030)
Knowledge	−.107*** (.038)	−.125** (.050)	−.063 (.061)
Otherknowledge	−.049 (.033)	.006 (.045)	−.107*** (.050)
Thinking	−.103*** (.037)	−.096** (.048)	−.109** (.058)
Learning	−.191*** (.035)	−.154** (.046)	−.244*** (.056)
Negotiate	.018 (.035)	.007 (.047)	.025 (.054)
Pressure	.274*** (.042)	.354*** (.056)	.159*** (.066)
Openmind	−.074*** (.033)	−.024 (.044)	−.145*** (.052)
Coordination	−.103*** (.039)	−.144*** (.052)	−.060 (.060)
Effective	.147*** (.045)	.144** (.058)	.192*** (.071)
Workgroup	.013 (.038)	.008 (.050)	.017 (.059)
Influence	.007 (.038)	.017 (.051)	−.012 (.059)
Communication	.086*** (.042)	.085 (.056)	.093 (.066)
Authority	−.001 (.037)	−.088 (.049)	.107** (.056)
Computers	.125*** (.033)	.177*** (.044)	.050 (.050)
Creative	−.151*** (.038)	−.200*** (.050)	−.070 (.059)
Flexible	−.196*** (.033)	−.180*** (.043)	−.235*** (.051)
Presentation	.013 (.033)	.042 (.043)	−.009 (.052)
Write	−.038 (.034)	−.049 (.043)	−.026 (.056)
Foreignlanguage	−.079*** (.023)	−.072*** (.030)	−.098*** (.039)

Notes: No. of observations: 16,810. Between brackets stand error. All equations also include the same controls as in Table 3. We also estimate robust variance by country and the coefficients which measure skill mismatches continue being significant.
***Significant at the 10% level.

When the controls for specific overskilling were introduced in the wage equation, the general mismatch pay penalties again remained largely unchanged, confirming the view that lower earnings among mismatched workers related more heavily to an inability to use their general or innate ability as opposed to a lack of opportunities in specific skill areas. The analysis suggests that overeducation and overskilling wage penalties are primarily driven by low job quality that leads, in turn, to a general under-utilisation of worker abilities. Table 6 also revealed that overskilling in the areas of non-specialist knowledge and presentation skills resulted in modest wage premiums, while an inability to fully utilise writing skills lowered earnings by 3%.

With regard to earnings, overskilling in particular competency areas has little impact associated with any observed impacts specific to the female earnings distribution (Table 6). Females overskilled in the areas of analytical thinking and report writing incurred pay penalties of between 4% and 5%; nevertheless, the overall overskilling wage impact fell by less than one percentage point when the field-specific variables were included in the model.

Generally, our results align well with recent research highlighting the impact of mismatch on job satisfaction and earnings. Mavromaras et al. (2010), using panel data for Australia, find that overeducation and overskilling are distinct phenomena and have separate impacts on earnings and job satisfaction. Mavromaras et al. (2010) report

Table 6. Wage equation considering skill acquisition.

	Full sample	Women	Male
Male	.087*** (.007)		
Labexp	.003*** (.000)	.000 (.000)	.004*** (.000)
Overeducated	−.283*** (.015)	−.173*** (.022)	−.268*** (.025)
Undereducated	−.004 (.012)	.022 (.017)	−.027 (.017)
Overskill	−.051*** (.013)	−.252*** (.019)	−.045*** (.019)
Underskill	.011 (.008)	.056*** (.011)	.016 (.012)
Knowledge	−.001 (.016)	−.043** (.023)	−.013 (.024)
Otherknowledge	.025** (.013)	−.019 (.020)	.026 (.020)
Thinking	−.021 (.015)	−.039** (.022)	.015 (.023)
Learning	.003 (.014)	−.040** (.021)	.008 (.022)
Negotiate	−.010 (.014)	.003 (.021)	−.025 (.022)
Pressure	.038*** (.017)	.076*** (.022)	.049* (.027)
Openmind	.004 (.013)	−.010 (.019)	−.015 (.020)
Coordination	.007 (.016)	−.029 (.023)	.0210 (.024)
Effective	.015 (.018)	.036 (.024)	.024 (.028)
Workgroup	−.002 (.015)	.005 (.022)	.001 (.024)
Influence	−.006 (.016)	.026 (.022)	−.038 (.024)
Communication	−.002 (.017)	.030 (.024)	−.013 (.271)
Authority	−.027 (.015)	−.025 (.022)	−.021 (.022)
Computers	−.016 (.013)	.065*** (.018)	−.012 (.020)
Creative	.005 (.015)	−.055*** (.023)	.011 (.024)
Flexible	−.019 (.013)	−.075*** (.020)	−.021 (.020)
Presentation	.004 (.013)	.006 (.019)	−.009 (.021)
Write	−.030*** (.014)	−.014 (.019)	.004 (.023)
Foreignlanguage	−.014 (.009)	−.037*** (.013)	−.019 (.015)

AQ15

Notes: No. observations: 16,810. Between brackets stand error. All equations also include the same controls as in Table 3. We also estimate robust variance by country and the coefficients which measure skill mismatches continue being significant.
**Significant at the 5% level.
***Significant at the 10% level.

that, compared with overskilling, overeducation had a much larger relative impact on pay but a lower influence on job satisfaction. Similar results were reported by McGuinness and Sloane (2011) for the UK. Thus, the research is generally indicating that workers are more adversely affected by overskilling, despite the fact that it is associated with lower pay penalties relative to overeducation. These findings reinforce the conclusions that (a) overskilling represents a more accurate measure of skill mismatch and (b) overeducated workers are likely, at least to some extent, to be compensated for lower wages by other positive job attributes, thus leading to less pronounced impacts on job satisfaction.

Finally, in an attempt to get a clearer picture of the key skill areas where workers' under-utilisation is most pronounced, we next attempt to reduce the competency data to a more meaningful level using principal components analysis (PCA). This method is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences, since patterns in data of high dimensions, such as ours, can be hard to find. It is potentially informative to present the data in a lower dimension without any notable information loss.

Perhaps not surprisingly, given the high correlations between the individual skill components, the Kaiser–Meyer–Olkin (KMO) test has a value of just over .9,[9]

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indicating that the data are highly suited to such an approach. Within PCA, the vector with the largest eigenvalue is called the first principal component and explains most of the differences in our data, and the vector with the next largest eigenvalue is called the second principal component, and so on. We retain the number of factors which explain 78% of the variance in the data, that is to say 4 factors. The determination of the number of factors to extract should be guided by theory (Kaiser criterion), but also informed by running the analysis to determine the number of factors that yield the most interpretable results.[10] Our selection of factors was, in this instance, determined on the basis of interpretability, as opposed to their statistical properties, that allow for an assessment of the impact of easily understandable competency areas on both job satisfaction and earnings.

We perform a Varimax rotation[11] in order to make the interpretation of the retained factors easier.[12] The first component gathers together under-utilisation in the areas of pressure working, opportunity alertness, coordination, time management, productive co-operation, mobilisation, expression and authority and can collectively be referred to as elements of 'work productivity'. The second component consists of overskilling in the areas of computer use, problem-solving, questioning ideas, presentation and writing and these can be collectively viewed as relating to 'problem-solving and communication'. The third component relates to under-utilisation in the areas of one's own specialist discipline, other disciplines, analytical thinking, knowledge acquisition and negotiation which we term 'acquired learning'. Finally, the fourth component relates to 'language skills'. Within the subsequent empirical analysis, we test the impact of these collective components, alongside the individual competencies, on both job satisfaction and earnings.

When the principal components are introduced into the regression, for job satisfaction, we find that while overskilling in the areas of 'problem-solving and communication', 'knowledge acquisition', 'innovation' and 'language skills' all reduce job satisfaction, overskilling in areas related to job 'productivity' actually raises it (see Table A1 in Appendix). This would suggest that job satisfaction is higher in circumstances where workers have surplus skills in areas considered core to their performance, implying that workers prefer to have a skill buffer zone that allows them to comfortably perform key tasks within their given job. With respect to wages (Table A2) we obtained, a 1% pay penalty was observed for overskilling in the areas of 'innovation'. Again we observe that the introduction of the principal component measures of overskilling do not result in any marked reduction in the overall penalties to either overeducation or overskilling, reinforcing our view that disadvantage is not been driven by surplus skills in any specific area included within our data.

4. Summary and conclusions

This paper utilised cross-country graduate cohort data from REFLEX to test the hypothesis that the widely observed effects of both overeducation and overskilling on job satisfaction and wages can be attributed to an under-utilisation in employment of specific key work-related skills. We found that even after the inclusion of controls for skill under-utilisation in 19 areas key to job performance, the observed effects of both overeducation and overskilling remain unchanged. These differences held when the analysis was conducted separately by gender and were largely insensitive to re-organisation of the data by country groupings. The work points to the conclusion that the observed impacts of both forms of mismatch relate to a general perception of under-utilised innate or general ability rather than a constrained ability to make full use of specific areas of acquired learning or skills. The implication of such a finding is that the problem of mismatch cannot easily be addressed by focusing policy on improving the job match of individuals possessing certain skill sets. The research suggests that graduate mismatch can only be alleviated by increasing general levels of job quality within economies. Finally, an interesting finding emanating from the analysis is that surplus skills in areas related to job productivity performance actually raise levels of job satisfaction by, presumably, providing workers with an operational comfort zone within their given job.

An obvious question arising from our central conclusion relates to the extent to which levels of mismatch are likely to persist or fall into the future. According to theories of skill-biased technological change, future labour demand will continue to be skewed towards more educated labour suggesting that the relative share of graduate-level jobs will continue to rise into the future. However, levels of educational attainment across developed economies are also expanding; thus, we might expect the incidence of mismatch to fall only if the relative demand for skilled labour rises at a faster rate than the supply of skilled workers. Cedefop estimate that the number of jobs employing highly qualified people in Europe is due to increase by 16 million between 2012 and 2010 (Scarpetta and Sonnet 2012), suggesting that we might expect the incidence of overskilling to fall. Nevertheless, the situation remains uncertain and the uneven distribution of high-level employment growth coupled with rising educational supply is likely to ensure that the incidence of overskilling remains high in many regions for some time to come.

Notes

1. The countries included in the analysis are Italy, Spain, France, Austria, Germany, the Netherlands, UK, Finland, Norway, Chez Republic, Portugal, Belgium and Estonia.
2. There are also data for Japan which we exclude in order to focus on European countries.
3. Where 1 was not at all and 5 to a very high extent.
4. We tested the sensitivity of our analysis to variations of this definition and found that our results remained largely unchanged.
5. The controls are not reported in the paper; however, detailed results are available from the authors on request.
6. We check four country groupings: Central Europe countries: Austria, Germany, France, the Netherlands and Belgium; East Europe countries: Check Republic and Estonia; Nordic countries: Finland, Norway and UK; and finally Mediterranean countries: Portugal, Spain and Italy.
7. Results available from the authors.
8. Results available on request.
9. A KMO of above 0.5 is generally considered desirable for PCA.
10. According to Kaiser's rule only factors with eigenvalues greater than 1 is retained, but in our case, this criterion is not useful because only 1 factor achieves this value. So, we try retaining 3, 4, 5, and 6 factors and conclude that 4 factors are the most appropriate for our analysis considering both the explained variance and the interpretable results.
11. Varimax rotation is the most popular rotation method. Formally Varimax searches for a rotation of the original factors such that maximises the sum of the variances of the squared loadings, all the coefficients will be either large or near zero, with few intermediate values. This simplifies the interpretation because after a varimax rotation, each original variable tends to be associated with one or a small number of factors.
12. Scoring coefficients could be available on request.

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Appendix

Table A1. JS equation considering skill acquisition using PCA (probit coefficients).

	Full sample	Women	Men
Male	−.005*** (.018)		
Labexp	.000 (.000)	.000 (.000)	.000 (.000)
Overeducated	−.427*** (.036)	−.466*** (.046)	−.355*** (.062)
Undereducated	.023 (.029)	.047 (.039)	−.000 (.044)
Overskill	−.725*** (.031)	−.700*** (.041)	−.762*** (.049)
Underskill	.148*** (.019)	.138*** (.026)	.159*** (.030)
Productivity	.027*** (.008)	.019 (.011)	.033*** (.013)
Innovation	−.067*** (.010)	−.063*** (.013)	−.071*** (.016)
Knowledge	−.049*** (.011)	−.027** (.014)	−.079*** (.017)
Languages	−.015 (.010)	−.009 (.013)	−.024 (.017)

Notes: No. observations: 16,810. Between brackets stand error. All equations also include the same controls as in Table 3.
**Significant at the 5% level.
***Significant at the 10% level.

Table A2. Wage equation considering skill acquisition using PCA.

	Full sample	Female	Male
Male	.087*** (.007)		
Labexp	.003*** (.000)	.002*** (.000)	.004*** (.000)
Overeducated	−.284*** (.015)	−.285*** (.019)	−.268*** (.025)
Undereducated	−.004 (.012)	.014 (.016)	−.027 (.017)
Overskill	−.052*** (.012)	−.056*** (.017)	−.045*** (.019)
Underskill	.011 (.008)	.008 (.010)	.017 (.012)
Productivity	.000 (.003)	.006 (.004)	−.005 (.005)
Innovation	−.012*** (.004)	−.015*** (.005)	−.009 (.006)
Knowledge	.004 (.004)	−.003 (.006)	.015*** (.006)
Languages	−.006 (.004)	−.005 (.005)	−.007 (.006)

Notes: No observations: 16,810. Between brackets stand error. All equations also include the same controls as in Table 3.
***Significant at the 10% level.

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