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Article

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ORIGINAL ARTICLE

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Born abroad and educated here: examining the impacts of education and skill mismatch among immigrant graduates in Europe

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Abstract

This paper examines the wage and job satisfaction effects of over-education and overskilling among migrants graduating from EU-15 based universities in 2005. Female migrants with shorter durations of domicile were found to have a higher likelihood of overskilling. Newly arrived migrants incurred wage penalties which were exacerbated by additional penalties resulting from overskilling in the male labour market and overeducation in the female labour market. Established migrants were found to enjoy wage premia, with no evidence of disproportionate wage impacts arising as a consequence of mismatch. Female migrants were found to have a lower probability of being job satisfied.

JEL Classification: J21; J31; J61

Keywords: Overeducation; Overskilling; Mismatch; Migrants; Gender; Pay; Job satisfaction

Introduction

This paper contributes to the existing literature that examines the relationship between migrant status and labour market mismatch (Piracha et al. 2012; Lindley 2009; Messinis 2008a, 2008b; Battu and Sloane 2004). This paper adds to the debate on a number of levels. To begin with, it considers and compares the labour market position of migrants and natives within a group of 11 European countries using high quality graduate cohort data. By considering the outcomes of graduates from European universities who have stayed to work in the country of graduation post-study, it is arguably free of many of the biases associated with many previous studies of migrants in relation to (a) quality differences in the education of migrants, (b) location specific human capital effects and (c) unobserved language differences. That is, it considers the outcomes of graduates from European universities, controlling for time since arrival, who have stayed to work in the country of graduation post-study. Although there now exists a vast body of research on overeducation, relatively little research has been conducted on mismatch processes and their effects in the European graduate labour market (see Alpin et al. 1998; Dolton and Vignoles 2000; Dolton and Silles 2008; Green and Zhu 2010 in the UK; Kler 2006; Mavromaras et al. 2010 in Australia;

Nordin et al. 2010 in Sweden; Barone and Ortiz 2011 in eight European countries). Furthermore, less research has considered the outcomes of migrant males and females respectively with regard to mismatch processes.

To date, the position of migrants in the labour market has attracted considerable attention within the literature (Lindley 2009; Kucel and Byrne 2008; Dex and Lindley 2007; Battu and Sloane 2004; Alpin et al., 1998; Blackaby et al. 1998, 1999, 2002, 2005; Bell 1997; Duncan and Hoffman 1981; Chiswick 1980). These studies have produced conflicting findings regarding the labour market outcomes of migrant groups. On the one hand, a body of work has empirically demonstrated that migrants and specific ethnic minority groups occupy an unequal and disadvantaged position in the labour market in terms of higher unemployment rates, lower earnings and higher rates of overeducation (Blackaby et al. 1998, 1999, 2002, 2005; Duncan and Hoffman 1981; Alpin et al. 1998; Battu and Sloane 2004; Kucel and Byrne 2008; Messinis 2008a, 2008b; Lindley 2009, Nielsen 2011, Joonas et al. 2014). However, a number of studies have also found that, on average, migrants perform better than natives in the labour market in terms of both higher employment and earnings (Bell 1997; Clark and Lindley 2005). Nevertheless, within those studies reporting that migrants perform better, clear ethnic differences exist, with non-white migrants tending to perform poorly relative to both white natives and white migrants (Clark and Lindley 2005). Within this literature, women and ethnic minority groups have been particularly identified as groups that are more likely to experience mismatch. Studies have identified that women and immigrants (particularly non-English speaking immigrants) and ethnic minority groups are more likely to be overeducated or overskilled than males and whites (Sicherman 1991 in the US; Groot 1996; Lindley 2009; McGuinness and Sloane 2011 in the UK; Green et al. 2007 in Australia; McGuinness and Bennett 2007 in Northern Ireland).

Explanations for higher rates of educational mismatch among migrants tend to centre on labour market discrimination. If migrant groups find it more difficult to acquire a suitable job, they may well be more likely to take a job that is not commensurate with their qualifications, resulting in higher proportions being overeducated. With the level of educational attainment rising amongst migrant groups as a whole, discrimination, if reflected in greater levels of mismatch and thus lower earnings and job satisfaction, may place doubts on the importance of human capital attainment as an avenue for escaping disadvantage (Leslie and Drinkwater, 1999).

These effects may be more pronounced for migrant females. Gender differences on the labour market are found along a large number of dimensions (see Wolbers 2003). In general, women have less favourable prospects on the labour market than men (Blossfeld and Hakim 1997). It is likely that gender processes play an additional role with regard to job mismatches among female migrant graduates. Because of the higher stakes associated with female employment, women may be more likely to accept jobs outside their own occupational domain or field of study. Also, because opportunities for career mobility are smaller for females than males, they experience a lower probability of moving from a non-matching job to a better fitting job. Furthermore, females are also more likely to experience constrained choices around job search and job acceptance (Robst 2007).

Measurement considerations

It has been argued that differentials in levels of mismatch may be observed without necessarily attributing this to labour market discrimination (Lindley 2009). There may be differences in the 'quality' of education received in terms of subjects, grades and institutions attended (Bhattacharyya et al. 2003; Jones and Elias 2005); furthermore, in many studies, differences in language skills are not observed. Finally, migrant education and experience may be location specific with respect to their home labour market, which will also impact on levels of labour market progression within the host labour market. To date, only a small number of studies have emphasised the differential returns to location-specific human capital, with human capital that is acquired in the host country demonstrating higher returns (Bell 1997; Shields and Wheatley Price 1998). With respect to mismatch, Piracha et al. (2012) report that a history of mismatch in the country of origin is strongly correlated with subsequent mismatch in the country of destination.

While previous studies may have restricted exploration of the labour market position of migrant minority groups to those who have attained native qualifications (see for example Lindley 2009), this study provides a more ready comparison of a homogenous population, comparing like with like, by focusing on similarly aged/experienced entrants to the graduate labour market. Furthermore, as the graduates in this study have successfully completed third-level qualifications in the host country, we can confidently assume that language difficulties are much less of a factor. The paper also extends the literature on the labour market position of migrants with respect to gender, education and skill mismatch. Finally, this research provides more rigorous econometric testing of labour market outcomes in relation to the incidence of mismatch, wages and job satisfaction. Few studies have accounted for selectivity bias or unobserved heterogeneity, and while arguably, such factors are less of an issue within such a relatively homogenous sample, it is still important that they are considered.

In terms of labour market outcomes, our primary goal is to determine the degree to which migrants experience higher rates of job mismatch relative to natives. We are also interested in the extent to which such exposures exacerbate existing (gender) differentials with respect to both earnings and job satisfaction.

Data and methods

The Flexible Professional in the Knowledge Society (REFLEX) project was financed as a Specific Targeted Research Project (STREP) of the European Union's Sixth Framework Programme covering 15 countries. It is limited to graduates in the 1999/2000 academic year, who were interviewed five years later in 2005. We focus on graduates from the EU member states of Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, Norway, Portugal, Spain and the UK, thus excluding observations from the Czech Republic, Estonia and Japan.

To date, all studies of mismatch and immigration,/ethnicity have focused exclusively on overeducation; however, there is an emerging strand of literature which argues that overskilling is a much more dependable measure of mismatch (Mavromaras et al. 2010, 2012, Mavromaras and McGuinness 2013; McGuinness and Wooden 2009). Overeducation has been criticised on the grounds that it represents a relatively imprecise measure of

human capital mismatch, whereby education proxies individual human capital and job entry requirements proxy the skill requirements of the job. Clearly individual human capital can be accumulated through both formal and informal means, thus overeducation ignores skills acquired while on-the-job. Similarly, in a world of rising educational attainment and credentialism, job entry requirements represent an increasingly imprecise measure of job complexity. It has also been argued that overeducated workers may be of lower ability and that the observed pay penalty merely reflects this, suggesting that studies of overeducation are heavily affected by unobserved individual heterogeneity bias. It has been asserted that overskilling, which directly compares actual human capital, whether that be acquired formally or informally or related to innate ability, with actual job requirements overcomes all of the measurement problems associated with overeducation and is, therefore, potentially a much more robust measure of mismatch (McGuinness and Wooden 2009; Mavromaras et al. 2010, 2012; Mavromaras and McGuinness 2013). Within the context of studies of immigration, the use of skill mismatch is particularly advantageous as language abilities should be encompassed within individual responses, thus lessening the impacts of unobserved bias within the measure. In the data, migrant status is identified on the basis of a question on the respondent's country of birth.

In terms of the individuals selected for this study, we restrict our sample to employees domiciled within EU 15 countries who were in full-time study prior to graduation. This leaves us with an effective sample of 15,005, with individual country samples varying from 2,296 for the Netherlands to 360 in Portugal. Migrants account for 3.31% of the sample, which equates to just under 500 effective observations (Table 12). There exists a substantial variation in the migrant share across countries, ranging from under 1% in Italy, Portugal and Belgium to over 9% in the UK, with the remaining country migrant shares ranging from 1.7 to 4.6% (Table 11). It is important to reiterate that the sample is representative of the population of host educated migrant graduates active in the native labour market, as opposed to the population of all migrants per se. Within the data individuals were defined as overeducated if they indicated that a below tertiary level of education was most appropriate for the job. Overskilling was based on the response to a question asking individuals to rate on a 1 to 5 scale the extent to which their skills and knowledge were utilised in their work, with a response of 1 or 2 deemed consistent with overskilling (Table 13).

Some previous studies have used the reflex data to examine the issue of labour market mismatch (Sánchez-Sánchez and McGuinness 2015; Allen et al. 2006; Verhaest and Van der Velden 2012; McGuinness and Sloane 2011); however, none of these provided any evidence with regards to the relationship between migration and mismatch. An obvious advantage of our dataset is that it enables us to study the relative impacts of both overeducation and overskilling among migrant and native male and female graduates, controlling for the effects of educational quality, location specific human capital and language difficulties. The main drawback of the data is that it does not allow us to disaggregate our data in terms of ethnic background. Nevertheless, we believe that the study makes an important contribution on the grounds of the uniqueness of the sample and the robustness of the estimates presented. In terms of the methods adopted, we add to the traditional analysis of this topic by including a range of checks and controls for the influences of sample selection and unobserved heterogeneity bias.

Given the view that relationships may vary according to gender, our models are estimated firstly on a pooled sample, then separately for males and females.

Results

Table 1 reports the incidence of graduate overeducation and overskilling five years beyond graduation within our sample of countries. At between 2 and 3%, overeducation rates were lowest in Belgium and Norway and highest in Spain, the UK and Italy, where rates ranged from 13 to 17%. The country level distribution of overskilling was somewhat different, with Spain and France exhibiting the highest rates and Portugal and Norway the lowest. Nevertheless, with the exception of France and Belgium, where the rates of overskilling substantially exceeded those for overeducation, there appears a relatively strong relationship between the incidences of overeducation and overskilling within countries. However, this is not to say that the same individuals are simultaneously identified as mismatched under each measure; in fact, we found that just 49% of overeducated graduates were also overskilled, while 43% of overskilled graduates were also overeducated. This reinforces the view that both measures of mismatch are likely to be very different in nature (see Mavromaras et al. 2010; McGuinness and Sloane 2011), thus justifying their separate analysis with respect to their relationship with immigration status.

With respect to our multivariate analysis, we begin by assessing the extent to which migrant graduates educated within the host country are prone to educational and skills mismatch. The data enables us to refine our definition of migrants in some important ways: firstly, we can control for “time since arrival” as the questionnaire asks whether the individual lived in the host country at age 16. Accordingly, 65% of our migrant sample was designated as “established migrants”, with the balance subsequently referred to as “new migrants”. Secondly, the data contains information on country of origin; however, as is evident from Appendix: Table 11, the distribution is highly dispersed and requires some aggregation to be of any use within an econometric framework. We subsequently group the country of origin variable into the following categories: (a) EU 15, (b) EU accession states, (c) high income countries and (d) the rest of the world. We begin by estimating three specifications to test for the sensitivity of the estimates

Table 1 Graduate Mismatch levels in current employment by country

	<i>Overeducation</i>	<i>Overskilling</i>
Italy	0.13	0.11
Spain	0.17	0.15
France	0.04	0.14
Austria	0.10	0.08
Germany	0.05	0.09
Netherlands	0.07	0.09
UK	0.14	0.14
Finland	0.06	0.07
Norway	0.03	0.04
Portugal	0.06	0.03
Belgium	0.02	0.08

to the migrant definition applied. Our models contain a range of controls related to faculty of study, years spent in higher education, field mismatch, employment history, employer characteristics and country level fixed effects. The models relate to employment status five years after graduation, and the results for the overeducation equation are presented in Table 2.

The model reveals that an individual's single most important determinant of overeducation in current employment is overeducation in their first job, thus confirming earlier research that supports the notion of overeducation as a non-transitory phenomenon (see Mavromaras and McGuinness 2012; Rubb 2003). There was no gender effect, which is contrary to studies in other institutional contexts (Carroll and Tani 2013 in Australia). That is, females are no more likely to be over-educated than males as in the Australian graduate labour market. Interestingly, current overeducation was negatively associated with initial overskilling although the marginal effects are very low. With respect to the other variables in the model, overeducation was found to be positively correlated with previous unemployment and job mobility and inversely related to years of HE study, field mismatch, participation in a degree programme perceived as prestigious, supervisory responsibilities, hours worked, employment in an R&D intensive firm and employment in a small firm. After accounting for such effects, relative to the base case of Germany, overeducation was higher in Italy and Austria and lower in France, the Netherlands, the UK, Norway and Belgium. Regarding the mismatch variables, crucially, there was no evidence to suggest that graduates from a migrant background were more likely to be overeducated, with the result holding when time since arrival and country of origin were controlled for.

On the grounds that relationships may vary according to gender, we re-estimated the overeducation models for males and females separately (Table 3). The overall migrant variable and those controlling for time since arrival and country of origin were again insignificant. The results from Tables 2 and 3 suggest that, contrary to the findings of previous research, migrant graduates are not prone to higher risks of overeducation in models that fully control for the impacts of location specific human capital and language differences, suggesting that previous studies may have been prone, at least to some degree, to individual unobserved heterogeneity bias.

The results of the overall overskilling model are reported in Table 4. The model results are similar to those for overeducation, with overskilling in first employment again proving to be the most important determinant of current overskilling. The incidence of overskilling was found to be higher among males, older workers and those with a history of unemployment, while it was inversely related to labour market experience, field mismatch, course prestige, perceived course reputation among employers, R&D intensity, public sector employment and having a supervisory role. With respect to country level effects, after controlling for individual level differences, only Finland was found to have a lower rate of overskilling relative to the base case of Germany. In contrast to overeducation, we found that migrants were 3% more likely to be overskilled relative to native graduates, with specification 2 indicating that the disadvantage relates exclusively to migrants who had been domiciled in the host country at the age of 16. This is certainly a somewhat surprising result on the grounds that this grouping is likely to have been the most assimilated and are also likely to have undertaken second level schooling in the host country. Finally, specification 3 shows a higher overskilling

Table 2 Probability of overeducation (probit, marginal effects)

VARIABLES	(1) Spec1	(2) Spec1	(3) Spec1
Overedjob1	0.07*** (0.004)	0.07*** (0.004)	0.07*** (0.004)
Overskilljob1	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)
Male	0.00 (0.003)	0.00 (0.003)	0.00 (0.003)
Labour exp	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)
Age	0.00** (0.000)	0.00** (0.000)	0.00** (0.000)
Years HE	-0.01*** (0.002)	-0.01*** (0.002)	-0.01*** (0.002)
Humanities	-0.00 (0.004)	-0.00 (0.004)	-0.00 (0.004)
Social	-0.00 (0.004)	-0.00 (0.004)	-0.00 (0.004)
Science	-0.00 (0.005)	-0.00 (0.005)	-0.00 (0.005)
Engineering	-0.00 (0.005)	-0.00 (0.005)	-0.00 (0.005)
Unemploy hist	0.01*** (0.003)	0.01*** (0.003)	0.01*** (0.003)
Migrant	-0.00 (0.007)		
Estab migrant		0.00 (0.008)	
New migrant		-0.01 (0.012)	
EU 15			-0.00 (0.010)
EU other			0.03 (0.023)
High income			-0.05 (0.030)
Rest of world			0.00 (0.010)
Course employer	0.00 (0.003)	0.00 (0.003)	0.00 (0.003)
Course prestige	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)
Vocational course	0.00 (0.003)	0.00 (0.003)	0.00 (0.003)

Table 2 Probability of overeducation (probit, marginal effects) (*Continued*)

Fieldmatchnow	-0.09*** (0.005)	-0.09*** (0.005)	-0.09*** (0.005)
Fieldrelatednow	-0.08*** (0.004)	-0.08*** (0.004)	-0.08*** (0.004)
Hours	-0.00** (0.000)	-0.00** (0.000)	-0.00** (0.000)
R&D Firm	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)
Size 50–99	-0.01*** (0.005)	-0.01*** (0.005)	-0.01*** (0.005)
Size 100–249	-0.01** (0.005)	-0.01** (0.005)	-0.01** (0.005)
Size 250–999	-0.00 (0.004)	-0.00 (0.004)	-0.00 (0.004)
Size 1000+	-0.01* (0.003)	-0.01* (0.003)	-0.01* (0.003)
Public sector	-0.01*** (0.003)	-0.01*** (0.003)	-0.01*** (0.003)
N of employers	0.00* (0.000)	0.00* (0.000)	0.00* (0.000)
Supervisor	-0.02*** (0.003)	-0.02*** (0.003)	-0.02*** (0.003)
Italy	0.03*** (0.006)	0.03*** (0.006)	0.03*** (0.006)
Spain	0.01 (0.006)	0.01 (0.006)	0.01 (0.006)
France	-0.04*** (0.008)	-0.04*** (0.008)	-0.04*** (0.008)
Austria	0.02** (0.007)	0.02** (0.007)	0.02*** (0.007)
Netherlands	-0.02** (0.007)	-0.02** (0.007)	-0.02** (0.007)
UK	-0.02** (0.007)	-0.02** (0.007)	-0.01** (0.007)
Finland	-0.01 (0.007)	-0.01 (0.007)	-0.01 (0.007)
Norway	-0.01* (0.008)	-0.01* (0.008)	-0.01* (0.008)
Portugal	0.02* (0.010)	0.02* (0.010)	0.02* (0.010)
Belgium	-0.04*** (0.010)	-0.04*** (0.010)	-0.04*** (0.010)
Constant	0.01 (0.016)	0.01 (0.016)	0.01 (0.016)

Table 2 Probability of overeducation (probit, marginal effects) (*Continued*)

Pseudo R ²	0.394	0.394	0.395
Observations	13,342	13,342	13,342

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

risk among migrants from EU 15 member states. The gender specific equations (Table 5) indicate that the observed effects of migration relate specifically to female migrants, with those domiciled within the host country at the age of 16 experiencing a 4% increased probability of being overskilled in employment five years following graduation (relative to native female graduates). Given that we have, arguably, largely eliminated many of the usual concerns related to both the nature of acquired human capital and language competencies from our estimates, these findings raise some significant concerns with respect to labour market access among established female migrants. As a next step, it would be useful to assess the extent to which the findings are related to ethnic minority status; however, as stated, this was not possible using this data.

Propensity score and quantile regression based estimates

We sought to check that our estimates of the incidence of overeducation and overskilling were not affected by selection bias, i.e. the possibility that the observable characteristics of

Table 3 Probit model for overeducation estimated by gender (marginal effects for selected variables)

VARIABLES	(1) Male 1	(2) Male 2	(3) Male 3	(4) Female 1	(5) Female 2	(6) Female 3
Overedjob1	0.06*** (0.006)	0.06*** (0.006)	0.06*** (0.006)	0.07*** (0.005)	0.07*** (0.005)	0.07*** (0.005)
Overskilljob1	-0.01 (0.004)	-0.01 (0.004)	-0.01 (0.004)	-0.01** (0.004)	-0.01** (0.004)	-0.01** (0.004)
Migrant	-0.00 (0.010)			-0.00 (0.008)		
Estab migrant		0.00 (0.012)			0.00 (0.010)	
New migrant		-0.01 (0.018)			-0.01 (0.016)	
EU 15			-0.03 (0.023)			0.01 (0.012)
EU other			0.03 (0.034)			0.03 (0.030)
High income			-0.04 (0.037)			-0.06 (0.046)
Rest of world			0.01 (0.013)			-0.01 (0.013)
Pseudo R ²	0.393	0.393	0.395	0.40	0.40	0.40
Observations	5251	5251	5251	8091	8091	8091

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 Probability of overskilling (probit, marginal effects)

VARIABLES	(1) Spec1	(2) Spec1	(3) Spec1
Overedjob1	-0.01 (0.005)	-0.01 (0.005)	-0.01 (0.005)
Overskilljob1	0.10*** (0.005)	0.10*** (0.005)	0.10*** (0.005)
Male	0.01** (0.004)	0.01** (0.004)	0.01** (0.004)
Labour exp	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)
Age	0.00** (0.001)	0.00** (0.001)	0.00** (0.001)
Years HE	0.00 (0.003)	0.00 (0.003)	0.00 (0.003)
Humanities	-0.01 (0.007)	-0.01 (0.007)	-0.01 (0.007)
Social	-0.00 (0.006)	-0.00 (0.006)	-0.00 (0.006)
Science	0.01 (0.007)	0.01 (0.007)	0.01 (0.007)
Engineering	0.00 (0.007)	0.00 (0.007)	0.00 (0.007)
Unemploy hist	0.01*** (0.004)	0.01*** (0.004)	0.01*** (0.004)
Migrant	0.03*** (0.009)		
Estab migrant		0.03*** (0.011)	
New migrant		0.02 (0.017)	
EU 15			0.03** (0.014)
EU other			0.01 (0.042)
High income			0.03 (0.029)
Rest of world			0.02* (0.014)
Course employer	-0.01** (0.004)	-0.01** (0.004)	-0.01** (0.004)
Course prestige	-0.02*** (0.004)	-0.02*** (0.004)	-0.02*** (0.004)

Table 4 Probability of overskilling (probit, marginal effects) (*Continued*)

Vocational course	-0.00 (0.004)	-0.00 (0.004)	-0.00 (0.004)
Fieldmatchnow	-0.14*** (0.006)	-0.14*** (0.006)	-0.14*** (0.006)
Fieldrelatednow	-0.10*** (0.005)	-0.10*** (0.005)	-0.10*** (0.005)
Hours	-0.00* (0.000)	-0.00* (0.000)	-0.00* (0.000)
R&D Firm	-0.01*** (0.004)	-0.01*** (0.004)	-0.01*** (0.004)
Size 50 – 99	-0.02** (0.008)	-0.02** (0.008)	-0.02** (0.008)
Size 100–249	0.01 (0.007)	0.01 (0.007)	0.01 (0.007)
Size 250–999	0.01 (0.006)	0.01 (0.006)	0.01 (0.006)
Size 1000+	0.00 (0.005)	0.00 (0.005)	0.00 (0.005)
Public sector	-0.02*** (0.004)	-0.02*** (0.004)	-0.02*** (0.004)
N of employers	0.00* (0.001)	0.00* (0.001)	0.00* (0.001)
Supervisor	-0.03*** (0.004)	-0.03*** (0.004)	-0.03*** (0.004)
Italy	0.00 (0.009)	0.00 (0.009)	0.00 (0.009)
Spain	0.00 (0.009)	0.00 (0.009)	0.00 (0.009)
France	-0.00 (0.010)	-0.00 (0.010)	-0.00 (0.010)
Austria	-0.01 (0.011)	-0.01 (0.011)	-0.01 (0.011)
Netherlands	-0.01 (0.009)	-0.01 (0.009)	-0.01 (0.009)
UK	-0.01 (0.011)	-0.01 (0.011)	-0.01 (0.011)
Finland	-0.02 (0.010)	-0.02 (0.010)	-0.02 (0.010)
Norway	-0.01 (0.010)	-0.01 (0.010)	-0.01 (0.010)
Portugal	-0.02 (0.019)	-0.02 (0.019)	-0.02 (0.019)
Belgium	-0.01 (0.011)	-0.01 (0.011)	-0.01 (0.011)

Table 4 Probability of overskilling (probit, marginal effects) (*Continued*)

Constant	-0.06** (0.025)	-0.06** (0.025)	-0.06** (0.025)
Pseudo R ²	0.27	0.27	0.27
Observations	13,342	13,342	13,342

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

migrants were not distributed in a non-random fashion with respect to mismatch. Failure to account for such influences can result in naive probit models, such as those presented in Tables 2–5, generating biased estimates. Within the existing literature linking mismatch with migrant status, the issue of selection has been largely ignored. We consequently estimate the likelihood of mismatch among migrants relative to natives with similar observable characteristics, and thus similar probabilities of mismatch, using propensity score matching (PSM). Due to sample size problems, it was only possible to assess the robustness of the overall migrant coefficients for males and females as any further disaggregation, according to either date of arrival or country of origin, was not feasible.

We estimate our PSM models using the Nearest Neighbour with replacement algorithm. In terms of the stage one model that describes the characteristics of migrants, we include controls for age, years spent in higher education, field of study,

Table 5 Probit model for overskilling estimated by gender (marginal effects for selected variables)

VARIABLES	(1) Male 1	(2) Male 2	(3) Male 3	(4) Female 1	(5) Female 2	(6) Female 3
Overedjob1	-0.00 (0.009)	-0.00 (0.009)	-0.00 (0.009)	-0.01 (0.006)	-0.01 (0.006)	-0.01 (0.006)
Overskilljob1	0.11*** (0.008)	0.11*** (0.008)	0.11*** (0.008)	0.09*** (0.006)	0.09*** (0.006)	0.09*** (0.006)
Migrant	0.00 (0.018)			0.04*** (0.011)		
Estab migrant		0.02 (0.021)			0.04*** (0.013)	
New migrant		-0.03 (0.031)			0.04** (0.019)	
EU 15			0.02 (0.026)			0.03** (0.016)
High income			0.01 (0.048)			0.05 (0.035)
Rest of world			-0.01 (0.027)			0.04** (0.016)
EU other						0.04 (0.044)
Pseudo R ²	0.259	0.259	0.259	0.282	0.283	0.283
Observations	5251	5251	5240	8091	8091	8091

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

degree course characteristics, exposure to overeducation and overskilling in their first jobs, unemployment history and whether the individuals current job is related to their field of study. Unfortunately, the Reflex data does not contain any standardised measure of degree grade, identify individual universities or information on the graduates socio-economic background. The first stage of the PSM revealed that migrants tended to be older, have fewer years of labour market experience, spent fewer years in higher education and were more likely to complete a degree programme that was perceived to be prestigious. However, perhaps crucially, they were not more likely to be overeducated or overskilled in their initial employment, suggesting that they did not have a higher exposure to the key determinant of mismatch in current employment. The results generated under the Nearest Neighbour algorithm indicate that migrants are around 4% more likely to be overskilled with the impact more pronounced within the female labour market. The PSM estimate corresponds closely to the key estimates from the probit models, suggesting that, at least in relation to the incidence of mismatch, selection bias is not an issue (Table 6).

The reliability of any propensity score matching estimate is dependent upon the Conditional Independence Assumption (CIA) being met, i.e. that selection to the treatment is based solely on observables within the dataset and that all variables that simultaneously impact both the treatment and outcome variable are also observed. Given the richness of our models, we are confident that the variables at hand sufficiently describe migrant characteristics. Nevertheless, despite the richness of our data, it is not possible to completely rule out the possibility that our estimates are unaffected by one or more unobserved effects that simultaneously influence both the treatment and outcome variables. As a final check we ran the MHBOUNDS procedure in STATA on the overskilling estimate for all migrants to assess its robustness to potential unobserved confounding factors that simultaneously impact the probability of both overskilling and migrant status. We begin with the assumption of zero bias, i.e. $\Gamma = 1$. The intuition here is that the results are robust to unobservables that positively impact both the likelihood of immigration status and an overskilling and subsequent increase in the odds ratio of immigration (termed positive selection bias) up to a factor of 1.15 ($\Gamma = 1.15$). Thus, while our analysis suggests that our key overskilling estimates are not prone to selection bias, it is also clear that they will relatively quickly become unreliable in the presence of any substantial unobserved confounding influence.

Having established that migrants do not have higher probabilities of overeducation but are somewhat prone to a higher risk of overskilling, we next test the hypothesis that

Table 6 Results of propensity score models (earnings)

	Overeducated current job	Overskilled current job
All migrant workers	-0.02 (0.02)	0.044** (0.021)
Migrant males	0.000 (0.029)	0.042 (0.032)
Migrant females	-0.007 (0.025)	0.045* (0.027)

T-Statistics in parentheses
Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

graduates from migrant backgrounds incur larger pay and job satisfaction penalties when overeducated and overskilled. Within the general mismatch literature, a general pattern has emerged of higher pay penalties associated with overeducation relative to overskilling, with overskilling associated with a much larger negative impact on job satisfaction (Mavromaras et al. 2010). This has led some authors to conclude that an aspect of the overeducation pay differential may relate to a compensating wage differential with workers trading lower wages for other aspects of the job that enhance individual lifestyles (McGuinness and Sloane 2011). The large impact of overskilling on job satisfaction has led to suggestions that this represents a more genuine form of mismatch (Mavromaras et al. 2013). It is clearly necessary to examine the relative impacts of mismatch on both job satisfaction and wages in order to achieve a concise picture of the extent to which workers are being constrained by the phenomenon.

The issue of selection bias is again considered, and given that we have observed that migrants tend to be older, have lower levels of labour market experience and are less likely to have completed a prestigiously perceived degree programme, it seems that sample selection bias represents a more substantial risk in the context of the wage equation. To date, propensity score matching has been used to test the robustness of estimates of overeducation and overskilling on earnings (Mavromaras et al. 2008; McGuinness 2007; McGuinness and Sloane 2011). However, given that we are interested in variations of any wage/job satisfaction penalty in terms mismatch status for migrants relative to native, propensity score matching is no longer appropriate due to the problem of small sample size among the various treatment groups.

In addition to the problem of sample selection, the issue of unobserved heterogeneity bias has been widely discussed within the literature both within the context of education/skill mismatch and immigration. While we are confident that by restricting our analyses to graduates of native universities and using of skills mismatch as a key variable we overcomes many of the usual omitted variable problems, additional checks are still undertaken. It has been argued that, within the context of graduate cohort data, where respondents tend to be very similar in terms of both their education and labour market experience profiles, that quantile regression may provide a solution to any outstanding missing variables problem (McGuinness and Bennett 2007). Following the rationale of McGuinness and Bennet (2007), we argue that unobserved differences in the human capital levels of (a) mismatched workers due to, for example, lower ability or (b) migrants due, for example, to poor language skills, will be reflected in their position within the wage distribution, which will reflect differences in graduates, levels of human capital. By comparing the impacts of immigration and mismatch within quantiles of the graduate cohort wage (human capital) distribution, we are limiting the impacts of unobserved heterogeneity. The quantile regression model can be formally written as follows (see Buchinsky 1994):

$$\ln w_i = x_i \beta_\phi + u_{\phi i} \quad \text{with} \quad \text{Quant}_\phi(\ln w_i | x_i) = x_i \beta_\phi, \quad (1)$$

where x_i is a vector of exogenous variables. $\text{Quant}_\phi(\ln w_i | x_i)$ denotes the ϕ_{th} conditional quantile of w given x . The ϕ_{th} regression quantile, $0 < \phi < 1$, is defined as the solution to the problem:

$$\min \beta \varepsilon R^k \left(\sum_{i: y_i \geq x_i \beta} \phi \left| \ln w_i - x_i \beta_\phi \right| + \sum_{i: y_i < x_i \beta} (1-\phi) \left| \ln w_i - x_i \beta_\phi \right| \right) \quad (2)$$

The above equation is usually written as:

$$\min \beta \varepsilon R^k \sum_i \rho_\phi \left(\ln w_i - x_i \beta_\phi \right), \quad (3)$$

where $\rho_{\phi(\varepsilon)}$ is the check function defined as $\rho_{\phi(\varepsilon)} = \phi \varepsilon$ if $\varepsilon \geq 0$ or $\rho_{\phi(\varepsilon)} = (\phi - 1)\varepsilon$ if $\varepsilon < 0$.

It should be noted that the median estimator of $\phi = 0.5$ is a special case of the quantile regression method. The method is most usefully thought of as providing a parsimonious way of describing the wage distribution, and as such it has the potential to add significantly to any empirical analysis should the relationship between the regressors and the exogenous variables evolve across the conditional wage distribution. We also again control for sample selection within this framework; we follow Buchinsky (2001) by implementing a two stage approach, whereby step one involves estimating selection models for both established and new migrants using a semi-nonparametric estimator, and in step 2, we augment the quantile regressions with level and squared terms of the inverse mills ratios derived from step 1.

From a practical perspective, to ensure that models of this nature are correctly identified, equation 1 (the selection equation) must contain at least one variable that is absent from equation 2 (the quantile regressions), and the selected instruments should have some theoretical foundation (Himler 2001). In the selection model we include controls for time spent abroad and cohabitation status while studying, as clearly these will tend to vary more for migrants and will be unrelated to earnings. Generally, our selected identification instruments perform well.

Table 7 presents the results from our wage equations for various quantiles of the wage distribution. The hypothesis that the costs of mismatch are lower for native graduates is tested using interactions between the two key migrant dummies and the mismatch terms, which can then be compared to the mismatch level terms in the model. Given our earlier results, we favour the specification that distinguishes migrants in terms of their length of stay within the host country. The wage models are well specified and generally conform to expectations. Ignoring distributional aspects of the results for now, we found that males have higher earnings than females, and earnings increase with labour market experience and years in higher education. Earnings were found to increase with hours worked and were higher for those graduating from prestigious courses, engineering degrees and individuals employed in larger firms. Earnings declined with a previous history of unemployment and public sector employment. With respect to the mismatch variables, the results are in line with those reported by McGuinness and Sloane (2009), with an overeducation pay penalty in current employment of over 20%, while overskilling is associated with a lower wage cost of approximately 4 to 5%. Crucially, we found that newly arrived migrant graduates incur a pay penalty, while male graduates domiciled in the host country at age 16 earned a premium relative to native male graduates (no such effect was evident among females). With regard to the interaction terms, we found that more newly arrived male migrants who were overskilled incurred a wage disadvantage within the low and median ranges of the wage/human capital distribution; however, no

Table 7 Quantile wage equations: all employees

VARIABLES	(1) Q .2	(2) Q .4	(3) Q .5	(4) Q .7	(5) Q .9
Overedjob1	-0.02* (0.013)	-0.05*** (0.010)	-0.06*** (0.010)	-0.07*** (0.011)	-0.08*** (0.014)
Overskilljob1	-0.00 (0.012)	0.01 (0.010)	0.00 (0.009)	-0.01 (0.010)	-0.00 (0.013)
Overed now	-0.26*** (0.018)	-0.27*** (0.014)	-0.26*** (0.014)	-0.22*** (0.015)	-0.20*** (0.019)
Overskilled now	-0.05*** (0.016)	-0.05*** (0.013)	-0.04*** (0.012)	-0.05*** (0.014)	-0.04** (0.017)
Overed*estab mig	0.11 (0.096)	0.06 (0.076)	0.13* (0.074)	0.12 (0.082)	-0.02 (0.104)
Oversk*estab mig	0.01 (0.080)	0.01 (0.064)	-0.06 (0.062)	-0.06 (0.069)	-0.08 (0.088)
Overed*new mig	0.18 (0.165)	0.08 (0.132)	-0.03 (0.127)	-0.24* (0.142)	-0.05 (0.181)
Oversk*new mig	-0.38*** (0.132)	-0.44*** (0.105)	-0.38*** (0.101)	-0.16 (0.113)	-0.12 (0.144)
Male	0.09*** (0.009)	0.10*** (0.007)	0.10*** (0.007)	0.10*** (0.008)	0.13*** (0.010)
Labour exp	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)	0.00*** (0.000)
Age	0.00 (0.002)	-0.00 (0.001)	-0.00 (0.001)	-0.00 (0.001)	-0.00** (0.002)
Years HE	0.05*** (0.006)	0.06*** (0.004)	0.06*** (0.004)	0.07*** (0.005)	0.09*** (0.006)
Humanities	0.01 (0.013)	0.02 (0.010)	0.02 (0.010)	0.01 (0.011)	0.01 (0.014)
Social	0.06*** (0.012)	0.07*** (0.010)	0.08*** (0.009)	0.08*** (0.010)	0.10*** (0.013)
Science	0.06*** (0.016)	0.07*** (0.012)	0.07*** (0.012)	0.06*** (0.013)	0.03* (0.017)
Engineering	0.13*** (0.015)	0.12*** (0.012)	0.13*** (0.012)	0.11*** (0.013)	0.12*** (0.017)
Unemploy hist	-0.04*** (0.009)	-0.07*** (0.007)	-0.07*** (0.007)	-0.07*** (0.008)	-0.09*** (0.010)
Estab migrant	0.39 (0.268)	0.44** (0.214)	0.65*** (0.207)	0.95*** (0.231)	1.32*** (0.293)
New migrant	-0.30 (0.465)	-1.11*** (0.371)	-1.33*** (0.358)	-1.86*** (0.400)	-2.01*** (0.508)
Course employer	0.03*** (0.009)	0.02*** (0.007)	0.02*** (0.007)	0.02*** (0.008)	0.03*** (0.010)

Table 7 Quantile wage equations: all employees (*Continued*)

Course prestige	0.03*** (0.010)	0.03*** (0.008)	0.03*** (0.007)	0.03*** (0.008)	0.03** (0.010)
Vocational course	0.03*** (0.009)	0.02** (0.007)	0.02** (0.007)	0.01 (0.008)	0.01 (0.010)
Fieldmatchnow	-0.01 (0.015)	0.01 (0.012)	0.02 (0.011)	0.02 (0.012)	0.00 (0.016)
Fieldrelatednow	0.02 (0.013)	0.03*** (0.010)	0.03*** (0.010)	0.02* (0.011)	-0.00 (0.014)
Hours	0.02*** (0.001)	0.02*** (0.000)	0.02*** (0.000)	0.01*** (0.000)	0.01*** (0.001)
R&D Firm	0.01 (0.008)	0.01** (0.007)	0.01** (0.006)	0.02** (0.007)	0.02*** (0.009)
Size 50-99	0.09*** (0.016)	0.06*** (0.013)	0.05*** (0.012)	0.04*** (0.014)	0.02 (0.017)
Size 100-249	0.08*** (0.014)	0.06*** (0.011)	0.05*** (0.011)	0.04*** (0.012)	0.04*** (0.016)
Size 250-999	0.08*** (0.013)	0.07*** (0.010)	0.07*** (0.010)	0.06*** (0.011)	0.08*** (0.014)
Size 1000+	0.14*** (0.010)	0.13*** (0.008)	0.12*** (0.008)	0.11*** (0.009)	0.12*** (0.011)
Public sector	-0.06*** (0.009)	-0.05*** (0.007)	-0.04*** (0.007)	-0.04*** (0.008)	-0.04*** (0.010)
N of employers	-0.01*** (0.002)	-0.00** (0.002)	-0.00*** (0.002)	-0.00 (0.002)	-0.00 (0.002)
Supervisor	0.06*** (0.009)	0.06*** (0.007)	0.06*** (0.007)	0.07*** (0.008)	0.08*** (0.010)
Italy	-0.70*** (0.021)	-0.65*** (0.017)	-0.63*** (0.016)	-0.59*** (0.018)	-0.51*** (0.023)
Spain	-0.76*** (0.019)	-0.71*** (0.015)	-0.68*** (0.015)	-0.62*** (0.016)	-0.54*** (0.021)
France	-0.31*** (0.022)	-0.30*** (0.018)	-0.29*** (0.017)	-0.28*** (0.019)	-0.30*** (0.024)
Austria	-0.26*** (0.022)	-0.26*** (0.018)	-0.26*** (0.017)	-0.25*** (0.019)	-0.20*** (0.024)
Netherlands	-0.13*** (0.019)	-0.14*** (0.015)	-0.16*** (0.015)	-0.17*** (0.017)	-0.21*** (0.021)
UK	-0.17*** (0.023)	-0.12*** (0.019)	-0.09*** (0.018)	-0.02 (0.020)	0.07*** (0.026)
Finland	-0.15*** (0.020)	-0.19*** (0.016)	-0.19*** (0.015)	-0.20*** (0.017)	-0.23*** (0.022)
Norway	0.14*** (0.020)	0.10*** (0.016)	0.09*** (0.015)	0.07*** (0.017)	0.08*** (0.021)

Table 7 Quantile wage equations: all employees (*Continued*)

Portugal	-0.93*** (0.031)	-0.91*** (0.025)	-0.87*** (0.024)	-0.83*** (0.027)	-0.77*** (0.034)
Belgium	-0.16*** (0.023)	-0.16*** (0.018)	-0.17*** (0.018)	-0.19*** (0.020)	-0.21*** (0.025)
Oldmills	-0.11 (0.220)	0.01 (0.175)	-0.13 (0.169)	-0.35* (0.189)	-0.21 (0.240)
Oldmills2	0.24* (0.135)	0.43*** (0.108)	0.42*** (0.104)	0.41*** (0.116)	0.88*** (0.148)
Newmills	-0.70* (0.400)	0.12 (0.319)	0.33 (0.308)	0.77** (0.344)	0.48 (0.436)
Newmills2	-0.95*** (0.316)	-0.80*** (0.252)	-0.79*** (0.243)	-0.80*** (0.272)	-1.32*** (0.345)
Constant	6.30*** (0.435)	7.25*** (0.347)	7.45*** (0.335)	8.01*** (0.374)	8.19*** (0.475)
Pseudo R ²	0.407	0.394	0.381	0.340	0.278
Observations	12,622	12,622	12,622	12,622	12,622

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

differential aspects were observed with regard to either migrants with longer domicile or overeducation. The selection terms indicate that newly arrived (established) migrants, a priori, have lower (higher) than expected average earnings by virtue of their observable human capital characteristics.

Regarding the distributional aspects of the results, and assuming that an individual's position in the wage distribution reflects their productivity potential, the model suggests that the disproportional wage penalty associated with overskilling incurred by newly arrived migrants is restricted to those with low to median levels of human capital. Newly arrived migrants with above average levels of human capital incur no additional penalty as a consequence of becoming mismatched. With respect to the distributional spread of the remaining covariates in the model, while most impacts are relatively stable throughout the distribution, some notable patterns are evident. For instance, the return to vocational programmes and field related employment is only significant within the lower to median portions of the wage distribution.

Disaggregating our models by gender, some substantial differences become apparent. We find that within the male distribution (Table 8), the premium to established migrants is positive and rising throughout the wage/human capital distribution, while for newly arrived migrants it is negative only in the upper regions of the wage/human capital distributions. Within the female model, the wage penalty for newly arrived migrants is relatively persistent throughout, while a pay premium is only evident for long-term migrants at the very top of the wage/human capital distribution. Regarding the migrant/mismatch interactions, the results indicate that newly arrived male migrants incur a higher pay penalty from overskilling relative to natives. Within the female distribution (Table 9), relative to mismatched natives, newly arrived migrants who are overeducated

Table 8 Quantile wage equations (selected coefficients): males

VARIABLES	(1) Q .2	(2) Q .4	(3) Q .5	(4) Q .7	(5) Q .0
Overedjob1	-0.06*** (0.020)	-0.08*** (0.018)	-0.05*** (0.016)	-0.08*** (0.019)	-0.09*** (0.024)
Overskilljob1	-0.00 (0.017)	0.00 (0.015)	-0.00 (0.014)	-0.02 (0.016)	-0.02 (0.021)
Overed now	-0.26*** (0.028)	-0.24*** (0.024)	-0.23*** (0.022)	-0.18*** (0.026)	-0.20*** (0.033)
Overskilled now	-0.02 (0.023)	-0.05** (0.020)	-0.02 (0.018)	-0.03 (0.021)	-0.02 (0.027)
Overed*estab mig	0.04 (0.164)	-0.11 (0.142)	-0.10 (0.128)	0.03 (0.154)	0.28 (0.196)
Oversk*estab mig	0.03 (0.134)	-0.09 (0.116)	-0.13 (0.104)	-0.11 (0.126)	-0.43*** (0.160)
Overed*new mig	0.04 (0.218)	-0.00 (0.189)	-0.17 (0.170)	0.08 (0.205)	-0.08 (0.260)
Oversk*new mig	-0.74*** (0.218)	-0.45** (0.189)	-0.53*** (0.169)	-0.84*** (0.205)	-0.31 (0.260)
Estab migrant	0.66* (0.359)	0.96*** (0.311)	0.82*** (0.279)	1.00*** (0.337)	1.31*** (0.427)
New migrant	-0.08 (0.679)	-0.62 (0.589)	-1.13** (0.528)	-0.66 (0.638)	-1.93** (0.809)
Oldmills	-4.84 (6.260)	-10.87** (5.090)	-9.09** (4.501)	-7.44 (5.415)	-8.94 (7.528)
Oldmills2	0.22 (0.170)	0.28* (0.147)	0.31** (0.132)	0.38** (0.160)	0.69*** (0.203)
Newmills	-1.10* (0.610)	-0.50 (0.529)	0.26 (0.474)	-0.65 (0.573)	0.94 (0.727)
Newmills2	-1.19** (0.463)	-1.02** (0.401)	-0.65* (0.360)	-1.34*** (0.435)	-0.75 (0.552)
Pseudo R ²	0.399	0.381	0.368	0.334	0.267
Observations	5018	5018	5018	5018	5018

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(overskilled) and located at the bottom (top) of the wage/human capital distribution incur larger pay penalties.

Job Satisfaction

With respect to job satisfaction, respondents were asked to rate their level of satisfaction with their current work on a scale from 1 to 5, where 1 was very dissatisfied and 5 very satisfied; we classify individuals responding 4 or 5 to this question as being job satisfied. The model specification approach is similar to that adopted for the wage equations; however, as the dependant variable is binary in nature, this rules out the use of quantile regression as a control for unobserved heterogeneity (Table 10).

Table 9 Quantile wage equations (selected coefficients): females

VARIABLES	(1) Q .2	(2) Q .4	(3) Q .5	(4) Q .7	(5) Q .0
Overedjob1	-0.02 (0.017)	-0.05*** (0.013)	-0.05*** (0.013)	-0.08*** (0.014)	-0.08*** (0.017)
Overskilljob1	0.01 (0.016)	0.01 (0.013)	0.01 (0.013)	-0.00 (0.013)	0.01 (0.017)
Overed now	-0.25*** (0.023)	-0.27*** (0.018)	-0.25*** (0.018)	-0.23*** (0.018)	-0.19*** (0.024)
Overskilled now	-0.07*** (0.022)	-0.05*** (0.017)	-0.07*** (0.017)	-0.06*** (0.017)	-0.07*** (0.022)
Overed*estab mig	0.13 (0.118)	0.07 (0.093)	0.11 (0.093)	0.11 (0.096)	-0.04 (0.122)
Oversk*estab mig	0.05 (0.101)	0.05 (0.079)	-0.01 (0.079)	-0.01 (0.081)	-0.07 (0.103)
Overed*new mig	0.21 (0.245)	-0.26 (0.191)	-0.26 (0.193)	-0.47** (0.197)	-0.55** (0.251)
Oversk*new mig	-0.44** (0.172)	0.01 (0.135)	-0.15 (0.135)	-0.01 (0.139)	-0.10 (0.176)
Estab migrant	0.18 (0.431)	-0.11 (0.337)	-0.02 (0.340)	0.48 (0.348)	1.30*** (0.443)
New migrant	-0.61 (0.642)	-1.29** (0.502)	-1.28** (0.505)	-2.03*** (0.518)	-2.57*** (0.658)
Oldmills	-0.05 (0.337)	0.43 (0.264)	0.37 (0.266)	0.01 (0.272)	-0.07 (0.346)
Oldmills2	0.15 (0.235)	0.45** (0.184)	0.44** (0.185)	0.44** (0.190)	1.03*** (0.241)
Newmills	-0.07 (0.523)	0.48 (0.409)	0.52 (0.412)	0.98** (0.422)	0.33 (0.536)
Newmills2	-0.57 (0.435)	-0.60* (0.340)	-0.57* (0.343)	-0.70** (0.351)	-1.99*** (0.446)
Pseudo R ²	0.402	0.372	0.353	0.306	0.253
Observations	7604	7604	7604	7604	7604

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Furthermore, the estimation of a treatment model cannot be easily accommodated, with sample size restrictions again ruling out the possibility of using PSM in terms of both immigration and mismatch status. In order to account, at least to some extent, for the influences of selection, we estimate an augmented regression, within which the individual predicted probability of each migrant status is included in the model as an additional covariate (see Card and De La Rica 2006). In our initial specification we find job satisfaction to be positively related to studying in the area of education/humanities, undertaking a course perceived to have a good reputation among employers, that is prestigious and vocational in nature, being employed in a job related to ones field of study, employed in an R&D intensive firm and working

Table 10 Probability of job satisfaction (probit, marginal effects)

VARIABLES	(1) Spec1	(2) Spec2	(3) Spec3	(4) Male	(5) Female
Overedjob1	-0.00 (0.014)	-0.00 (0.014)	-0.00 (0.014)	-0.01 (0.023)	-0.00 (0.017)
Overskilljob1	-0.02* (0.013)	-0.02* (0.013)	-0.02 (0.013)	-0.02 (0.020)	-0.02 (0.017)
Overed now	-0.17*** (0.018)	-0.17*** (0.018)	-0.18*** (0.018)	-0.18*** (0.032)	-0.18*** (0.023)
Overskilled now	-0.28*** (0.016)	-0.28*** (0.016)	-0.28*** (0.017)	-0.28*** (0.026)	-0.27*** (0.022)
overed*Estab migrant			0.12 (0.098)	0.31 (0.193)	0.06 (0.117)
overskill*Estab migrant			-0.01 (0.085)	-0.11 (0.157)	0.03 (0.101)
Overed*new migrant			0.01 (0.205)	-0.06 (0.291)	0.02 (0.284)
Oversk*new migrant			-0.15 (0.157)		-0.04 (0.182)
Male	-0.02* (0.009)	-0.02* (0.009)	-0.01 (0.010)		
Labour exp	0.00 (0.000)	0.00 (0.000)	0.00* (0.000)	0.00** (0.001)	0.00 (0.001)
Age	-0.00*** (0.001)	-0.00*** (0.001)	-0.01*** (0.002)	-0.01*** (0.003)	-0.00* (0.002)
Years HE	-0.01** (0.005)	-0.01** (0.005)	-0.01** (0.005)	0.00 (0.009)	-0.02*** (0.007)
Humanities	0.05*** (0.014)	0.05*** (0.014)	0.05*** (0.015)	0.05* (0.030)	0.05*** (0.017)
Social	0.00 (0.013)	0.00 (0.013)	0.01 (0.013)	0.01 (0.024)	0.01 (0.016)
Science	0.02 (0.017)	0.02 (0.017)	0.02 (0.017)	0.03 (0.027)	0.02 (0.022)
Engineering	-0.00 (0.016)	-0.00 (0.016)	-0.00 (0.016)	0.01 (0.024)	-0.02 (0.024)
Unemploy hist	-0.03*** (0.010)	-0.03*** (0.010)	-0.03*** (0.010)	-0.03* (0.016)	-0.03** (0.013)
Migrant	-0.07*** (0.023)				
Estab migrant		-0.04 (0.028)	-0.05* (0.031)	0.03 (0.054)	-0.10** (0.039)
New migrant		-0.13*** (0.039)	-0.12*** (0.041)	-0.09 (0.068)	-0.14*** (0.051)

Table 10 Probability of job satisfaction (probit, marginal effects) *(Continued)*

Course employer	0.04*** (0.009)	0.04*** (0.009)	0.04*** (0.009)	0.05*** (0.015)	0.03*** (0.012)
Course prestige	0.04*** (0.010)	0.03*** (0.010)	0.03*** (0.010)	0.04*** (0.016)	0.02 (0.014)
Vocational course	0.03*** (0.010)	0.03*** (0.010)	0.03*** (0.010)	0.03** (0.015)	0.03** (0.013)
Fieldmatchnow	0.06*** (0.015)	0.06*** (0.015)	0.05*** (0.015)	0.04* (0.025)	0.06*** (0.020)
Fieldrelatednow	0.01 (0.014)	0.01 (0.014)	0.01 (0.014)	0.00 (0.022)	0.01 (0.017)
Hours	0.00 (0.001)	0.00 (0.001)	0.00 (0.001)	0.00 (0.001)	0.00 (0.001)
R&D Firm	0.11*** (0.009)	0.11*** (0.009)	0.11*** (0.009)	0.13*** (0.014)	0.11*** (0.012)
Size 50-99	-0.01 (0.017)	-0.01 (0.017)	-0.01 (0.017)	0.01 (0.029)	-0.03 (0.022)
Size 100-249	-0.02 (0.015)	-0.02 (0.015)	-0.02 (0.016)	-0.01 (0.027)	-0.03 (0.020)
Size 250-999	-0.02* (0.014)	-0.02* (0.014)	-0.02* (0.014)	-0.02 (0.023)	-0.03 (0.017)
Size 1000+	0.00 (0.011)	0.00 (0.011)	-0.00 (0.011)	0.00 (0.018)	-0.01 (0.015)
Public sector	0.09*** (0.010)	0.09*** (0.010)	0.09*** (0.010)	0.09*** (0.018)	0.10*** (0.013)
N of employers	0.00 (0.002)	0.00 (0.002)	-0.00 (0.002)	0.00 (0.004)	-0.00 (0.003)
Supervisor	0.02*** (0.009)	0.02*** (0.009)	0.02** (0.009)	0.04*** (0.015)	0.01 (0.012)
Italy	-0.13*** (0.021)	-0.13*** (0.021)	-0.11*** (0.029)	-0.09** (0.043)	-0.11*** (0.040)
Spain	-0.05*** (0.020)	-0.05*** (0.020)	-0.04 (0.024)	-0.03 (0.036)	-0.04 (0.033)
France	-0.03 (0.024)	-0.03 (0.024)	-0.02 (0.025)	-0.01 (0.040)	-0.02 (0.034)
Austria	0.03 (0.024)	0.04 (0.024)	0.04 (0.024)	0.05 (0.035)	0.02 (0.035)
Netherlands	-0.07*** (0.021)	-0.07*** (0.021)	-0.07*** (0.021)	-0.08** (0.031)	-0.07** (0.029)
UK	-0.09*** (0.025)	-0.09*** (0.025)	-0.11*** (0.037)	-0.14** (0.059)	-0.12** (0.048)
Finland	-0.11*** (0.021)	-0.11*** (0.021)	-0.09*** (0.024)	-0.07* (0.037)	-0.10*** (0.034)

Table 10 Probability of job satisfaction (probit, marginal effects) *(Continued)*

Norway	-0.06*** (0.021)	-0.06*** (0.021)	-0.06*** (0.021)	-0.03 (0.031)	-0.08*** (0.030)
Portugal	-0.16*** (0.033)	-0.16*** (0.033)	-0.15*** (0.036)	-0.14** (0.059)	-0.14*** (0.047)
Belgium	-0.04 (0.024)	-0.04 (0.024)	-0.02 (0.028)	-0.03 (0.041)	-0.01 (0.039)
Scores			0.50 (0.486)	1.44* (0.824)	0.35 (0.621)
Constant	0.26*** (0.057)	0.25*** (0.057)	0.26*** (0.057)	0.20** (0.101)	0.28*** (0.070)
Pseudo R ²	0.092	0.092	0.092	0.095	0.093
Observations	13,342	13,342	13,342	5246	8091

Standard errors in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in the public sector. Job satisfaction was inversely related to age, years spent in higher education and having experienced a previous spell of unemployment. We found that being overeducated in current employment reduced the likelihood of job satisfaction by almost 20%, with the effect considerably larger for overskilling at approximately 30%. Crucially, we found that migrants were 7% less likely to be job satisfied, with this effect almost exclusively driven by a 14% lower probability of job satisfaction among more recent migrants (Specification 2). When we introduce our interaction terms, we do not find that mismatch status among migrant workers exacerbates the already substantial effects of either overeducation or overskilling (Specification 3).

When we estimate the models separately by gender (specifications 4 and 5), we found no evidence of lower job satisfaction among male migrants, and, in fact, established overeducated migrants exhibited a positive interaction effect, which more or less eliminated the level effect for overeducation, suggesting that such migrants do not have lower job satisfaction levels relative to matched workers. It may well be that such workers are being compensating for lower earnings associated with overeducation by other positive job attributes, such as increased security and/or a greater work-life balance. The situation is very different for females, with those domiciled (not domiciled) in the host country at aged 16 found to have a ten (fifteen) per cent lower likelihood of being job satisfied relative to native graduates. While these effects were found not to be exacerbated by the presence of either form of mismatch, they represent important findings in their own right and certainly provide grounds for further research.

Summary and conclusions

This paper examines the extent to which migrant graduates have a higher exposure to educational and skill mismatch and the degree to which the previously well documented negative impacts of mismatch on earnings and job satisfaction were heightened as a consequence of migrant status. Contrary to previous research, we found little evidence to suggest that migrants had a higher exposure to overeducation. However, female migrants domiciled in the host country at age

16 were found to have a higher exposure to overskilling relative to their native counterparts. With respect to earnings, the research showed that more newly arrived migrants incurred wage penalties which were exacerbated by higher levels of penalisation resulting from overskilling in the male labour market and overeducation in the female labour market. Established migrants were found to enjoy wage premia, particularly within the male labour market, with no evidence of disproportionate wage impacts arising as a consequence of mismatch. In terms of job satisfaction, while there was no evidence to suggest that the negative effects of mismatch were made worse by migrant status, we found that female migrants, particularly newly arrived, had a much lower likelihood of being satisfied in their jobs relative to their native counterparts.

The research presented here is unique in terms of its robustness given that it is free from many of the biases usually associated with studies of migrant workers within the labour market. In addition, the integrity of the results was also ensured with additional checks for the effects of both sample selection bias and unobserved heterogeneity.

Endnotes

¹Gender effects have not been found in other studies of mismatch (Battu et al. 2000; McGoldrick and Robst 1996 in the US), and Wolbers (2003), in his identification of job mismatch among European school leavers, found that male school leavers more often have a job mismatch than their female counterparts.

²for exceptions see Blackaby et al., 2002

³Where 1 was 'not at all' and 5 to 'a very high extent'

⁴A question on ethnicity was asked for the UK portion of the sample alone.

⁵In this instance host country refers to the country within which the survey is conducted.

⁶Australia, Canada, US, Switzerland and New Zealand.

⁷As measured by the number of previous employers. This finding supports the view that increased mobility levels among mismatched workers often result in the individual moving from one state of mismatch to another (McGuinness 2003, McGuinness & Wooden 2009).

⁸Who report that females are more likely to be over-educated than males in the Australian graduate labour market.

⁹For the purposes of brevity, we report only the key coefficients. Full results are available from the authors on request.

¹⁰For the purposes of brevity, we report only the key coefficients. Full results are available from the authors on request.

¹¹Results available from the authors.

¹²Results available from the authors.

¹³The models are fitting through the semi-nonparametric estimators of Gallant & Nychka (1987) using the *snp* procedure in Stata.

¹⁴For the purposes of brevity, we report only the key coefficients. Full results are available from the authors on request.

¹⁵For the purposes of brevity, we report only the key coefficients. Full results are available from the authors on request.

Data appendix

Table 11 Distribution of migrant population by country

<i>Country of birth of respondent</i>	<i>Freq.</i>	<i>Percent</i>
Germany	49	9.88
France	24	4.84
Greece	21	4.23
Suriname	21	4.23
Sweden	21	4.23
Italy	19	3.83
United States	19	3.83
Ireland	18	3.63
Switzerland	18	3.63
Morocco	14	2.82
United Kingdom	13	2.62
Belgium	12	2.42
India	11	2.22
Poland	11	2.22
Venezuela	11	2.22
Turkey	10	2.02
Iran	9	1.81
Korea, south	9	1.81
Denmark	8	1.61
Netherlands	8	1.61
Russia	8	1.61
Vietnam	8	1.61
Netherlands antilles	7	1.41
Romania	7	1.41
South Africa	6	1.21
Canada	5	1.01
Israel	5	1.01
Australia	4	0.81
China	4	0.81
Hong Kong	4	0.81
Iceland	4	0.81
Spain	4	0.81
Bosnia and Herzegovina	3	0.6
Finland	3	0.6
Gibraltar	3	0.6
Hungary	3	0.6
Japan	3	0.6
Kenya	3	0.6
Luxembourg	3	0.6
Mauritius	3	0.6
Tunisia	3	0.6
Andorra	2	0.4
Argentina	2	0.4

Table 11 Distribution of migrant population by country (*Continued*)

Bangladesh	2	0.4
Brazil	2	0.4
Cote d ivoire	2	0.4
Croatia	2	0.4
Cyprus	2	0.4
Estonia	2	0.4
Ghana	2	0.4
Latvia	2	0.4
Monaco	2	0.4
Nepal	2	0.4
New Zealand	2	0.4
Nigeria	2	0.4
Philippines	2	0.4
Portugal	2	0.4
Singapore	2	0.4
Slovakia	2	0.4
Ukraine	2	0.4
united Arab emirates	2	0.4
Zambia	2	0.4
Afghanistan	1	0.2
Aruba	1	0.2
Austria	1	0.2
Belize	1	0.2
Bermuda	1	0.2
Bolivia	1	0.2
Bulgaria	1	0.2
Cambodia	1	0.2
cape Verde	1	0.2
Colombia	1	0.2
Congo, democratic republic of the	1	0.2
Czech republic	1	0.2
Eritrea	1	0.2
French Guiana	1	0.2
Georgia	1	0.2
Honduras	1	0.2
Indonesia	1	0.2
Iraq	1	0.2
Jersey	1	0.2
Kazakhstan	1	0.2
Kuwait	1	0.2
Lebanon	1	0.2
Madagascar	1	0.2
Malaysia	1	0.2
Mauritania	1	0.2
Mexico	1	0.2

Table 11 Distribution of migrant population by country (*Continued*)

Norway	1	0.2
Oman	1	0.2
Pakistan	1	0.2
Peru	1	0.2
Slovenia	1	0.2
Sudan	1	0.2
Thailand	1	0.2
Uganda	1	0.2
Western Sahara	1	0.2
	496	99.83

Table 12 Summary statistics

<i>Variable</i>	<i>Obs</i>	<i>Mean</i>	<i>Std. Dev.</i>
Overedjob1	15,005	0.17	0.38
Overskillj ~ 1	15,005	0.19	0.39
Male	15,005	0.38	0.49
Labour exp	13,991	52.75	13.87
Age	14,543	30.08	3.85
Humanities	15,005	0.20	0.40
Social	15,005	0.30	0.46
Science	15,005	0.12	0.32
Engineering	15,005	0.16	0.37
Unemploy hist	15,005	0.36	0.48
Migrant	15,005	0.03	0.18
Course employer	15,005	0.40	0.49
Course prestige	15,005	0.35	0.48
Vocational course	15,005	0.40	0.49
Fieldmatch ~ w	15,005	0.30	0.46
Fieldrelat ~ w	15,005	0.54	0.50
Hours	14,888	36.39	8.01
R&D Firm	15,005	0.40	0.49
Size 50–99	15,005	0.08	0.27
Size 100–249	15,005	0.10	0.30
Size 250–999	15,005	0.15	0.35
Size 1000+	15,005	0.37	0.48
Public sector	15,005	0.43	0.50
N of employers	14,439	2.34	2.22
Supervisor	15,005	0.32	0.47
Italy	15,005	0.10	0.30
Spain	15,005	0.17	0.37

Table 12 Summary statistics (*Continued*)

France	15,005	0.07	0.26
Austria	15,005	0.06	0.23
Netherlands	15,005	0.15	0.36
UK	15,005	0.08	0.26
Finland	15,005	0.10	0.30
Norway	15,005	0.11	0.31
Portugal	15,005	0.02	0.15
Belgium	15,005	0.07	0.25
Germany	15,005	0.07	0.26

Table 13 Variable definitions

Lwage:	Gross monthly earnings in main employment logged.
Overednow:	Dummy variable takes value 1 if overeducated in current job and zero otherwise
Overedjob1:	Dummy variable takes value 1 if overeducated in first job and zero otherwise
Overskillnow:	Dummy variable takes value 1 if overskilled in current job and zero otherwise
Overskilljob1:	Dummy variable takes value 1 if overskilled in first job and zero otherwise
Male:	Dummy variable takes value 1 if Male and zero otherwise
Labour exp	Number of months employed since graduation
Age:	Age in years
Years HE:	Years spent in Higher Education
Humanities:	Dummy variable takes value 1 if main field of study was Humanities and zero otherwise
Social:	Dummy variable takes value 1 if main field of study was Social Science and zero otherwise
Science:	Dummy variable takes value 1 if main field of study was Science and zero otherwise
Engineering:	Dummy variable takes value 1 if main field of study was Engineering and zero otherwise
Supervisor:	Dummy variable takes value 1 if supervised staff members and zero otherwise
Fieldmatchnow:	Dummy variable takes value 1 if current job matched exclusively to field of study and zero otherwise
Fieldrelatednow:	Dummy variable takes value 1 if current job matched on own or a related field of study and zero otherwise
Course employer:	Dummy variable takes value 1 if employers were familiar with course and zero otherwise
Course prestige:	Dummy variable takes value 1 if course was academically prestigious and zero otherwise
Vocational course:	Dummy variable takes value 1 if course was vocationally and zero otherwise
Hours:	Regular contract hours per week
R&Dfirm:	Dummy variable takes value 1 if employed in a research intensive firm and zero otherwise
Size 50–99:	Dummy variable takes value 1 if employed in a firm with 50 to 99 workers and zero otherwise
Size 100–249:	Dummy variable takes value 1 if employed in a firm with 100 to 249 workers and zero otherwise
Size 250–999:	Dummy variable takes value 1 if employed in a firm with 250 to 999 workers and zero otherwise
Size 1000+:	Dummy variable takes value 1 if employed in a firm with over 1000 workers and zero otherwise
Public sector:	Dummy variable takes value 1 if employed in a public sector organisation and zero otherwise
N of employers:	Number of employers since graduation

Competing interests

The IZA Journal of Migration is committed to the IZA Guiding Principles of Research Integrity. The authors declare that they have observed these principles.

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