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Jan Kleibrink

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Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

RWI Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

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Merve Cim, Michael Kind, and Jan Kleibrink[1]

Occupational Mismatch of Immigrants in Europe: The Role of Education and Cognitive Skills

Abstract

Occupational mismatch is a wide-spread phenomenon among immigrants in many European countries. Mismatch, predominantly measured in terms of education, is often regarded as a waste of human capital. Such discussions, however, ignore the imperfect comparability of international educational degrees when comparing immigrants to natives. An accurate analysis of occupational mismatch requires looking beyond internationally incomparable educational degrees and considering more comparable skill measures. Using PIAAC data, it is possible to exploit internationally comparable cognitive skill measures to analyze the presence of mismatch disparities between immigrants and natives. This allows us to examine whether overeducation implies only an apparent phenomenon or rather a genuine overqualification observed also in the form of cognitive overskilling. In this study, we analyze differences in the incidence of being overeducated and being cognitively overskilled between immigrants and natives in 11 European countries. Results show that immigrants are more likely to be overeducated than natives, while the opposite is true for being cognitively overskilled. Furthermore, significant heterogeneity among immigrants in the incidence of overeducation and cognitive overskilling can be detected.

JEL Classification: I21, J15, J24, J71

Keywords: Occupational mismatch; migration; education; cognitive skills

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1 Merve Cim, RGS Econ and RWI; Michael Kind, RWI; Jan Kleibrink, UDE. - All correspondence to: Merve Cim, RWI , Hohenzollernstr. 1/3, 45128 Essen, Germany, e-mail: merve.cim@rwi-essen.de

1 Introduction

Migration is often stated to be a promising remedy to counteract demographic change in industrialized countries. Technological change and rapid aging have led many European countries to implement more liberal policies to attract high-qualified immigrants not only at national but also at EU level, such as the blue card.[1] The economic success of such migration-oriented strategies depends –among other factors– on the quality of occupational matches of immigrants in the receiving labor markets.

Up to now, the mismatch literature mainly focused on *overeducation* of immigrants, describing a state of holding more education than necessary to perform their jobs. Specifically, previous research has found that immigrants are more frequently overeducated than natives in many developed countries – for example Green, Kler, and Leeves (2007) in Australia, Joona, Gupta, and Wadensjö (2014) in Sweden, and Sanroma, Ramos, and Simón (2008) in Spain. Overeducation is widely considered as not fully utilizing the available human capital. Thus, governments are asked for policy interventions, such as regulating the recognition of educational degrees from abroad or implementing skill-based entry criteria to improve job match quality of immigrants for a more efficient utilization of human capital. However, these discussions generally disregard the international incomparability of educational systems. Educational degrees of immigrants obtained in their home countries are only imperfectly comparable to the degrees of natives obtained in the host countries. Thus, the sole focus of the mismatch discussions on educational degrees, i.e., years of education, might be shortsighted.

Compared to formal skills, cognitive skills are less prone to incomparability between countries. Cognitive skills, such as numeracy and literacy skills, can be measured on country-independent scales and thus allow for more suitable comparisons between natives and immigrants. Following Hanushek and Woessmann (2012), cognitive and formal skills are seen as components of overall qualification. Thus, considering only one dimension cannot answer the question whether someone is genuinely overqualified. In this paper, we distinguish between three definitions of occupational mismatch: formal overeducation, cognitive

[1] For a detailed review of migration policies in Europe, see Kahanec and Zimmermann (2011) and 2015 Annual Report of the Expert Council of German Foundations on Integration and Migration (SVR, 2015).

overskilling and genuine overqualification. We first study the prevalence of *formal overeducation*, i.e., holding more formal education than required for the job, among immigrants. Additionally, we analyze whether immigrants are more likely than natives to be *cognitively overskilled*, i.e., whether immigrants have on average more cognitive skills than needed to perform their jobs. Lastly, we examine whether immigrants are more likely to be *genuinely overqualified*, i.e., whether among those who are formally overeducated, immigrants are also more likely to be cognitively overskilled than natives. [2]

The main contribution of this paper is its new approach to analyze occupational mismatch by taking both perspectives – cognitive skills and formal education – into consideration. In contrast to the dominant view in the empirical literature, we claim that overeducation does not per se imply overqualification, unless an individual is cognitively overskilled at the same time. The OECD data of the Programme for the International Assessment of Adult Competencies (PIAAC), a dataset mainly designed to assess labor market related skills, allow us to use comprehensive cognitive skill measures on a representative, international level to analyze differences between immigrants and natives. Furthermore, using a rich set of information on individual characteristics, our paper offers a detailed subgroup analysis of immigrants based on their ethnic background and the length of residency in the host country.

Our results show that immigrants are more likely than natives to be formally overeducated but not cognitively overskilled. Therefore, the interpretation of excess education as a waste of human capital, so-called brain waste, is shortsighted. The international incomparability of educational degrees requires considering more comparable measures, such as cognitive skills to assess the occupational mismatch of immigrants. Focusing on genuine overqualification (the state of being overeducated and cognitively overskilled at the same time) shows that in numerous European labor markets, immigrants do not suffer from unused human capital compared to their native counterparts. Our analysis further shows that countries of origin and the length of stay are important determinants of occupational mismatch among immigrants.

[2] Throughout this paper, we sometimes use shortly overeducation instead of formal overeducation and overskilling instead of cognitive overskilling. It should, however, be kept in mind that in our definition overeducation only refers to excess formal education and overskilling refers to excess cognitive skills. The terms overqualification and genuine overqualification are also used interchangeably.

The remainder of the paper is structured as follows: Section 2 provides an overview of the literature on educational as well as skill mismatch and discusses differences and empirical findings. Section 3 introduces the data source of our empirical analysis. The empirical strategy as well as results are presented in section 4. Section 5 presents concluding remarks.

2 Overeducation and Overskilling

The vast majority of the occupational mismatch literature has considered overeducation – defined as having more formal education than required for a job – as an indicator for a waste of human capital. Empirical evidence shows that immigrants are more likely to be subject to overeducation than natives (Nieto, Matano, and Ramos, 2013). Various explanations for the higher incidence of overeducation among immigrants exist. Some studies claim that immigrants compensate the lack of country-specific human capital with excess education (Kler, 2005; Green, Kler, and Leeves, 2007). Others argue that at arrival, immigrants have a lack of knowledge in local labor markets, which results in inadequate job-matches (Piracha, Tani, and Vadean, 2012). However, these short-term frictions are expected to disappear over time as immigrants gain more experience in the host country labor market. Finally, not all educational degrees obtained abroad are officially recognized by the host countries, e.g., the *Meister* degree/licence in Germany, or by employers due to quality differences in education in different countries.

While overeducation has received considerable attention in empirical labor economics, there is no consensus on how to measure it. Three common methods are applied in the literature. The first one is the subjective method using the difference between the formal education of a worker and the educational requirement of her job (Sicherman, 1991; Sloane, Battu, and Seaman, 1999; Frei and Sousa-Poza, 2012; Pecoraro, 2014). This method has been argued to be a suitable measure of educational matches because the evaluation of jobs comes directly from those individuals performing the jobs. However, the main strength of this method has also been shown to be its biggest weakness. Subjective evaluations can be subject to different sources of problems. For instance, the benchmark of the answers is unclear (Bauer, 2002). While some respondents might consider the education necessary to get a job as a benchmark, others might rather evaluate their experience concerning day-to-day tasks. Furthermore, individual educational attainment will most likely serve as orientation and therefore influence answers.

The second method is based on experts' job analyses. In this method, job analysts define educational requirements for each occupation. Commonly used classifications are the Dictionary of Occupational Titles (DOT) in the US (Rumberger, 1987; McGoldrick and Robst, 1996) or the Standard Occupation Classification of Statistics Netherlands (Baert, Cockx, and Verhaest, 2013). Individuals with more years of schooling than required are defined as overeducated. One major shortcoming of this approach is that such classifications do not exist for many countries. On the other hand, although an evaluation by labor market experts can provide precise information on the necessary education for most jobs, it has to be updated regularly. Otherwise it can lead to an increasing prevalence of measurement errors over time (Kiker, Santos, and de Oliveira, 1997).

The third method uses realized job matches (RM) as a measure of educational mismatch (Verdugo and Verdugo, 1989; Kiker, Santos, and de Oliveira, 1997; Bauer, 2002; Voon and Miller, 2005; Nielsen, 2011)). In the RM approach, the individual educational attainment is compared to the mean education within an occupation. Some studies use the average years of education in each occupation and add one standard deviation to determine the threshold of being overeducated (e.g., Verdugo and Verdugo, 1989; Bauer, 2002), while others use the mode years of schooling as the educational requirement (e.g., Kiker, Santos, and de Oliveira, 1997; Bauer, 2002; Mendes de Oliveira, Santos, and Kiker, 2000; Ng, 2001; Bauer, 2002; Chiswick and Miller, 2009; Kleibrink, 2013). The RM method can be automatically updated with every wave of a panel dataset and relying on realized matches is not prone to subjective misspecifications.

Following Verdugo and Verdugo (1989); Kiker, Santos, and de Oliveira (1997); Bauer (2002); Voon and Miller (2005); Nielsen (2011), the RM method is applied in this study by using average years of education within an occupation as a benchmark. While educational mismatch can appear in the form of over- as well as undereducation, the focus of the literature – and the following empirical analysis – lies on overeducation as this is far more prevalent. Furthermore, in contrast to overeducation, undereducation is not regarded as a problem per se.

While a comparison of the formal education attained in different countries is relatively simple – either by comparing the years spent in education or educational titles – the set of abilities that is connected to an educational title can vary considerably between educational systems (e.g., Kahn, 2004; Pellizzari and Fichen, 2013). International studies, like the Programme for International Student Assessment (PISA) by the OECD, compare cognitive skills of students in the same age groups around the world. Results show that the test scores of 15-year-old students in several subjects, e.g., science, reading, mathematics, vary substantially across countries . As a result, overeducation of immigrants can be a result of imperfect international comparability of educational degrees rather than simply implying a waste of human capital. Moreover, immigrants might engage in overeducation as a strategy to compensate for a lack of country-specific knowledge or abilities. Previous analyses (e.g., Green, McIntosh, and Vignoles, 1999; Bauer, 2002; Korpi and Tåhlin, 2009; Poot and Stillman, 2010) argue that human capital compensation is a driving force behind overeducation. Here, individuals compensate for their lack of innate abilities with extra years of schooling. Therefore, individuals appear to be overqualified in terms of education but this does not necessarily imply overqualification in terms of ability. Hence, overeducation does not per se correspond to genuine overqualification and cannot always be regarded as brain waste.

In order to overcome the shortcoming of imperfect comparability of educational degrees between immigrants and natives, this study explores differences in cognitive skills. Here, the question arises on how to measure cognitive skills. Some studies use proxy variables for skills. Sohn (2010), for example, uses school grades in mathematics as a proxy for cognitive skills. However, comparing the success within educational systems still suffers from quality differences between educational systems. Alternatively, the subjective method of self-assessment can be used to determine the skill-occupation match. Individuals respond to survey questions on the utilization of their skills at work (Allen and Van der Velden, 2001). This approach, however, suffers from the same problems as the subjective approach for measuring overeducation mentioned above. One of the most commonly applied methods is to use scores from ability tests (Allen, Levels, and van der Velden, 2013), such as the IALS (Kahn, 2004) or the PIAAC (Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015). These tests are specifically designed to assess the cognitive skills of individuals and are preferred by many authors on the grounds of objectivity. Against the background of this discussion, we utilize individual-level cognitive skill tests from the PIAAC as a proxy for the unobserved abilities of individuals.

3 Data

We employ cross-sectional survey data from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD in 24 countries[3] between 2011 and 2012. Approximately 166,000 individuals aged 16 to 65 answered the survey. Each participating country is represented by around 5,000 individuals.[4]

The strength of the PIAAC data is the information provided on internationally comparable measures of cognitive skills. Individuals engage in tests aiming at assessing their cognitive abilities in three domains – literacy, numeracy and problem-solving in technology-rich environments. The tests are computer-based and conducted in the official language of the participating countries.[5] The test on problem-solving in technology-rich environments is only answered by those who declare previous computer experience. The core test lasts approximately 60 minutes where individuals answer 20 questions in each skill domain from a large pool of sample questions. The scores of the tests are reported on a scale of 0-500 for each skill domain.[6]

We restrict our sample to a smaller subset of countries due to two reasons. First, the immigrants are significantly underrepresented in some countries and the immigrant sample size is not sufficient to conduct a meaningful analysis.[7] Second, the information on some key variables essential for our analysis is not available or coarsened in some countries. [8]

[3] Australia, Austria, Belgium (Flanders), Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), and the United States.

[4] An exception in terms of sample size is Canada with around 26,000 observations.

[5] Individuals without computer skills take a paper-and-pencil test. Some countries apply the test in multiple languages which are widely spoken within the country.

[6] For a detailed description of obtaining the skill measures, see OECD (2013). The data provide ten plausible values for the cognitive skill scores. We use the first plausible value reported as suggested by Allen, Levels, and van der Velden (2013) and Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).Reapplying the analyses using other plausible values/the mean of ten plausible values does not change our results.

[7] Japan, Korea, Poland, Slovak Republic.

[8] Austria, Canada, Estonia and Finland due to occupational information and the US due to region of

This leaves us with a final sample of 11 European countries (Belgium, Denmark, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Sweden, UK).[9] We further restrict our sample to employed individuals, i.e., part-time or full-time employed, excluding the unemployed, students, interns and compulsory military servants. Finally, our sample of immigrants consists of first-generation immigrants only, who migrated after finishing their education in the home country. As second-generation immigrants attend school fully in the host country, they are not subject to imperfect international transferability of education. Therefore, they are excluded from our sample in the main analyses and are examined separately. Our final sample consists of 38,594 individuals.

In a first step, we reproduce the results from the existing literature by examining the likelihood of formal overeducation. Applying the realized match (RM) method, the binary overeducation variable takes the value one if a person is formally overeducated and zero otherwise. We calculate mean years of education within each occupation using the two-digit ISCO classification [10] in each country. [11] [12] We add one standard deviation to the average years of education in order to determine the threshold for being overeducated. Those who are above the threshold are defined as overeducated.

Among the three skill domains in the dataset, we use numeracy and literacy skills separately as measures of cognitive ability.[13] We assume that numeracy scores measure the skill dimension which is least dependent on language proficiency. The validity of the results is examined using also literacy scores. A pretest of the survey allows us to identify and sort out those individuals who do not possess any host country language skills. Thus, our final sample includes only individuals with at least a minimum level of language proficiency.

birth information.

[9]We further excluded Cyprus and Czech Republic as they differ from the other countries in our sample with respect to their migration history. We additionally exclude Russian Federation as the data are claimed to be preliminary. Due to coarsened information on many variables in the public-use-file of Germany, we use the scientific-use-file obtained from GESIS and merge it to public-use-files of the other countries.

[10]A three-digit ISCO classification is available for a subset of countries and it leads to very small cell sizes when estimating the mean education separately in each country. Estimation results using the three-digit ISCO classification in the pooled sample are in line with the results using the two-digit ISCO classification in each country. Results are available on request.

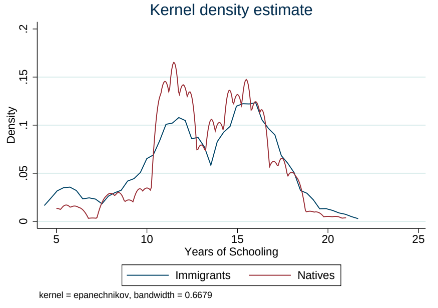
[11]Occupation cells with less than 20 observations are excluded.

[12]Applying median or mode instead of mean results in similar incidence of overeducation. However, we stick to the mean in order to have a comparable overeducation measure with the overskilling measure which is calculated from a continuous cognitive skill measure on a scale of 0 to 500. The large range of cognitive skill measure hinders using the alternative methods for overskilling.

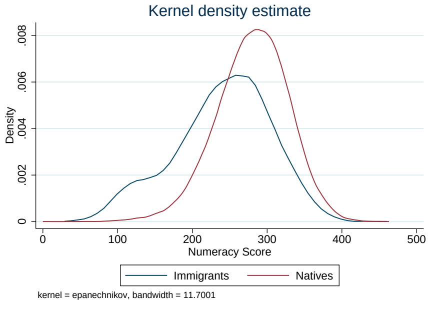
[13]Problem-solving in technology-rich environment domains is not applied in all countries. Therefore, we exclude this test from our analysis.

In order to compare the likelihoods of cognitive overskilling and formal overeducation, we construct the skill mismatch variable in the same way as the overeducation variable, i.e., adding one standard deviation to the mean value of cognitive skill scores calculated in each occupation based on the two-digit ISCO classification in each country. Following the same reasoning, our overskilling variable takes the value one if an individual is cognitively overskilled and zero if not.

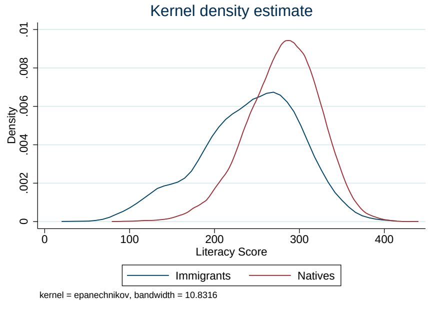
Figure 1: Kernel Density Estimate of Education and Skill Measures



(a) Years of Schooling



(b) Numeracy Score



(c) Literacy Score

Note: Authors' calculations based on the PIAAC.

Figure 1 displays the kernel density estimates of years of education and the two skill measures for natives and immigrants. The first panel shows that natives and immigrants are very similar in their educational attainment. The average years of schooling of natives (13.4) and immigrants (13.1) are almost identical. However, such a pattern is not observed in the skill measures. Immigrants have a more left-skewed distribution compared to natives in both numeracy and literacy skills. The average of the skill scores of immigrants (240) is approximately 40 points lower than it is for natives (280) in both skill domains, which is a statistically significant difference.

In line with previous findings, the incidence of overeducation is much higher for immigrants, i.e., compared to 25% of the immigrants only 13% of the natives are formally overeducated. On the contrary, the share of cognitively overskilled immigrants (7-9%) is lower than the share of overskilled natives (15%) in both literacy and numeracy domains. While shares of formally overeducated and cognitively overskilled natives are very close, the difference is substantial for immigrants, suggesting that education and cognitive skills are not equivalent indicators of overall qualification.[14]

In the following regression analysis, we control for commonly used covariates in the overeducation literature (age, sex, marital status, having children, health status, full/part-time employment, public/private sector). [15] Our main variable of interest is the migration status. We define immigrants as those individuals, who obtained their whole education in the home country, excluding those who attained their education partly in their host country. Immigrants who arrived before the age of five and immigrants born in the host country are grouped as 'second-generation immigrants' and are analyzed separately. Migration status is defined as a dummy variable, taking the value one for immigrants and zero for natives.

4 Empirical Strategy and Results

Our main analysis is based on separate logit estimations on being overeducated, overskilled and overqualified at the individual level using the pooled sample of 11 countries. Each estimation accounts for the individual control variables mentioned in the previous section as well as country fixed effects.

We start with a binomial logit model on being overeducated in order to examine whether immigrants are more likely to be overeducated than natives. We proceed with an analysis

[14]The shares of overeducated and overskilled individuals in each country are presented in Table A11 in the appendix.

[15]See A1 in the appendix for the definition of control variables and Table A2 for the descriptive statistics.

of the probability of being cognitively overskilled in a second step. If formal education and cognitive skills measured the same dimension of mismatch, similar coefficients on migration status in both models would be expected. Positive coefficients in both models, i.e., being more likely to be overeducated and overskilled, would suggest that immigrants are more likely to suffer from brain waste than natives, while opposite signs of the coefficients would suggest that heterogeneity between educational systems is an important factor of occupational mismatch of immigrants.

The logit estimations allow us to conclude whether immigrants are more likely to be formally overeducated or cognitively overskilled compared to natives. However, they do not answer the question whether immigrants are more likely to suffer from genuine overqualification – being overeducated and cognitively overskilled at the same time. As previously discussed, it has been argued that immigrants who suffer from overeducation are subject to a waste of human capital. Economies could benefit from the unused human resources by ensuring appropriate occupational matches of immigrants. We question this conclusion and extend the previous literature by examining whether among those who are classified as overeducated, immigrants are also more likely to be cognitively overskilled. Thus, we estimate a logit model on being cognitively overskilled conditional of being overeducated and examine whether overeducation of immigrants is a reliable indicator of genuine overqualification.

In a final step, we split our binary measure of cognitive skill mismatch into three categories, i.e., overskilled, matched and underskilled, to estimate multinomial logit models among the group of formally overeducated individuals. The binary measure of cognitive skill mismatch classifies the groups of underskilled and correctly matched individuals in one group. The separation into three categories allows us to examine the genuine overqualification in more depth. More specifically, we can examine whether overeducation is a result of human capital compensation. This means that overeducated individuals possess excess schooling as a compensation for the lack of cognitive skills, which can be observed as underskilling in our classification. Those who are overeducated and correctly matched in cognitive skills are worse off than the former group and this might be considered as a form of mismatch, however, they are not subject to overqualification by our definition.

4.1 Occupational Mismatch of Immigrants

The first column of Table 1 shows the results from logit estimations on overeducation. Our results confirm previous findings by showing that immigrants are about 7% more likely to be overeducated than natives.

Table 1: Logit on Overeducation and Overskilling by Migration Status

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Immigrant	0.074***	-0.085***	-0.154***	-0.119***	-0.191***
	(0.008)	(0.014)	(0.031)	(0.014)	(0.034)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

Columns (2) and (4) of Table 1 reveal that immigrants are about 9-12% less likely to be cognitively overskilled than natives. Thus, occupational mismatch appears to be a less severe problem for immigrants than natives when cognitive skills are considered. A potential explanation for this finding is the screening process of employers. The assessment of educational degrees from abroad is difficult for employers as it requires elaborate knowledge on educational systems of other countries. Therefore, employers may screen the skills of immigrant employees to a larger extent in order to observe their true level of productivity. As cognitive skills of immigrants are monitored more carefully, they become less likely to be placed in jobs for which they are cognitively overskilled.

So far the results show the likelihood of occupational mismatches in terms of education and cognitive skills, separately. However, they do not yet indicate whether immigrants are more likely to suffer from genuine overqualification than natives. Therefore, we examine the likelihood of genuine overqualification (columns (3) and (5) of Table 1), which indicates the likelihood of being overskilled among the group of overeducated. Overeducated immigrants are 15-19% less likely to be cognitively overskilled than their native counterparts. This finding stresses that immigrants are significantly less likely to suffer from genuine overqualification than natives. Similar to cognitive overskilling, lower likelihood of genuine overqualification among immigrants might be a result of the screening of employers. Even though the higher incidence of overeducation among immigrants represents an apparent problem, it cannot necessarily be interpreted as a genuine overqualification, i.e., a waste of unused human capital.

In order to examine whether there are differences across countries, we also apply the same analyses on formal overeducation, cognitive overskilling and genuine overqualification separately in each country (see Table A12 in the appendix). Overall, country-specific regressions give qualitatively similar results in most countries to those obtained from the pooled sample. With the exception of Spain, immigrants in all countries covered in our sample are more likely to be overeducated than natives. Italy, which has experienced a recent and rapid increase in its immigrant population, displays the highest probability of formal overeducation among immigrants (17%). While immigrants are not significantly different than natives in Spain in their probability of being formally overeducated, they are less likely to be cognitively overskilled. However, this does not correspond to a genuine overqualification at the same time. Spain and Ireland appear to be the only countries where immigrants do not significantly differ from their native counterparts in terms of genuine overqualification, whereas in Ireland, they have a higher probability of being formally overeducated.

Table 2: Multinomial Logit on Skill Match Conditional on Being Overeducated

	Numeracy Skills			Literacy Skills		
	Underskilled	Matched	Overskilled	Underskilled	Matched	Overskilled
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	0.085^{***}	0.057^{*}	-0.142^{***}	0.121^{***}	0.051	-0.172^{***}
	(0.013)	(0.032)	(0.031)	(0.013)	(0.034)	(0.033)
N	5,127	5,127	5,127	5,127	5,127	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

The main focus of our analyses has been on formal overeducation and cognitive overskilling. In a further step, we consider also cognitive underskilling as a separate outcome in a multinomial logit model, which allows us to examine the human capital compensation hypothesis by showing whether a formally overeducated individual possesses lower cognitive skills than required by his job. Table 2 shows the results on the cognitive skill match (in numeracy as well as literacy skills) conditional on being overeducated. Among the overeducated, immigrants have a higher probability of being cognitively underskilled and correctly matched compared to natives. This finding provides evidence supporting the human capital compensation hypothesis by showing that overeducated immigrants are more likely to be underskilled, meaning that immigrants compensate for a lack of skills caused by differences in educational systems by more years of schooling. Thus, their overeducation can neither be regarded as genuine overqualification nor as brain waste. Furthermore, the previously identified lower likelihood of immigrants to suffer from genuine overqualification can also be found applying a multinomial logit model – irrespective of the skill domain applied.

Empirical evidence shows that overeducation is more widespread among younger workers and its prevalence decreases by experience (Alba-Ramirez, 1993). Altonji and Pierret (2001) argue that employers discriminate against young workers as they put more emphasis on easily observed characteristics, such as formal education, as a measure of productivity. In order to examine whether the differences between immigrants and natives shown by our earlier results can be attributed to age differentials, we divide our sample into four age groups and estimate the occupational mismatch of immigrants in each group (see Table A7 in the appendix). Formal overeducation seems to be a problem for the elderly immigrants while the younger group of immigrants between the ages of 16 and 25 do not differ from their native counterparts. On the contrary, the elderly group of those over 55 years appear to be similar to natives in terms of cognitive overskilling and genuine overqualification while a significant difference to natives in formal overeducation prevalence remains.

We further examine formal overeducation and cognitive overskilling of immigrants in two different education groups, i.e., holding a university degree or more vs. a lower degree (see Table A8 in the appendix). When we restrict the sample only to highly educated individuals, the likelihood of being overeducated reaches up to 20% while the overskilling and overqualification profiles remain similar to the results from the overall sample. The results indicate that overeducation is a more relevant problem for highly educated individuals.

Finally, we divide the sample into occupational skill groups (see Table A10 in the appendix).[16] Formal overeducation seems to be less common in the skilled occupations while it is remarkably high in the semi-skilled white collar and elementary occupations. Another interesting finding is that only for those immigrants holding skilled occupations, cognitive overskilling and overqualification in numeracy and literacy domains appear to be similar. This is contrary to the common finding that the difference between natives and immigrants in cognitive overskilling is higher in literacy than in numeracy. Skilled occupations are characterized by strong communication as well as high-level numeracy and literacy skill requirements. In line with the skill requirements, immigrants in this skill level category have higher cognitive skill scores and the difference with natives is lower than in other skill categories. This explains why the difference in the probability of being cognitively overskilled in literacy is low between immigrants and natives in skilled occupations.

4.2 Years since Migration

Immigrants acquire local labor market knowledge and obtain host country-specific labor market skills by the length of stay. Thus, an assimilation in the likelihood of occupational mismatches appears to be likely. Therefore, we split the immigrant sample into three categories based on their lengths of stay. Table 3 reports heterogeneous effects for different lengths of residence in the host country. The longer a migrant lived in the host country, the less pronounced are the differences to natives in terms of occupational matches.

Immigrants who arrived within the last five years are 14% more likely than natives to be subject to overeducation. This effect appears to become smaller with the length of stay. Those immigrants who have been living in the host country for more than ten years are only 5% more likely to be overeducated than natives. While there is no clear and notable pattern of decrease in the probability of being cognitively overskilled, we observe a remarkable decrease in the probability of genuine overqualification for those who have been residing in the host country for longer than ten years.

The assimilation pattern of immigrants might reflect two features. First, the focus of

[16] We use four ISCO skill level categories mapped to 1-digit ISCO occupational classification (See Table A9 for the definition of skill categories).

Table 3: Logit on Overeducation and Overskilling by Years Since Migration

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Years Since Migration:					
0-5	0.139***	-0.074***	-0.172***	-0.097***	-0.197***
	(0.026)	(0.015)	(0.034)	(0.012)	(0.031)
6-10	0.090***	-0.089***	-0.179***	-0.096***	-0.190***
	(0.021)	(0.012)	(0.034)	(0.012)	(0.034)
>10	0.052***	-0.054***	-0.064*	-0.075***	-0.075**
	(0.014)	(0.014)	(0.039)	(0.011)	(0.038)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regression weighted by sampling weights. Reference category is natives. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

the screening of employers might be on education for more recent immigrants making them remarkably more likely to be formally overeducated. For immigrants residing in the host country for a longer time other characteristics, such as the labor market experience obtained in the host country, might play a more important role. Besides, immigrants might increase their skill level in the host country and acquire country-specific skills, which make them more similar to their native counterparts in their occupational match. Finally, the results might also reflect cohort differences. However, we cannot test this hypothesis due to the cross-section nature of our data.

4.3 Ethnic Origin

Previous studies (e.g., Piracha, Tani, and Vadean, 2012; Nieto, Matano, and Ramos, 2013) found that immigrants coming from culturally similar countries are less likely to be overeducated. Against this background, we split the immigrant sample into subgroups based on their ethnic background (see Table 4). According to the first column, all immigrant subgroups are 9-13% more likely to be overeducated than natives except the immigrants from North America & Western Europe. Employers do not fully recognize the educational degrees of immigrants who come from culturally distinct countries while those from North America & Western Europe, which are more similar to the host countries in our sample, are not significantly different from their native counterparts in terms of formal overeducation. However, a different pattern emerges when we examine cognitive skills. All immigrant subgroups regardless of their ethnic background are less likely to be cognitively overskilled than natives.

Table 4: Logit on Overeducation and Overskilling by Immigrant Ethnic Origin

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Born in:					
Arab States	0.096***	-0.084***	-0.091*	-0.111***	-0.171***
& Sub-Saharan Africa	(0.025)	(0.014)	(0.048)	(0.011)	(0.039)
Asia	0.107***	-0.081***	-0.200***	-0.120***	-0.229***
& the Pacific	(0.031)	(0.022)	(0.041)	(0.015)	(0.044)
Latin America	0.087***	-0.063***	-0.136**	-0.049**	-0.096
& the Caribbean	(0.031)	(0.022)	(0.064)	(0.023)	(0.067)
Central	0.126***	-0.061***	-0.141***	-0.097***	-0.181***
& Eastern Europe	(0.022)	(0.018)	(0.038)	(0.013)	(0.034)
North America	-0.001	-0.060***	-0.073	-0.045**	-0.020
& Western Europe	(0.017)	(0.018)	(0.056)	(0.019)	(0.059)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Reference category is natives. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Reference category is natives. Full table including the control variables is presented in the Appendix.

When we condition on being formally overeducated, all immigrants seem to be less likely to be cognitively overskilled (columns (3) and (5) in Table 4), except the group of North American & Western European immigrants.[17] For those immigrants, genuine overqualification is just as likely as it is for natives. This finding may arise from a lower effort invested by employers in the screening of North American & Western European immigrants due to their cultural proximity. As a result, culturally dissimilar immigrants experience more appropriate job placements with a lower likelihood of a waste of human capital.

Language skills are a substantial determinant of occupational success of immigrants. Therefore, we divide the immigrants into two groups based on the language they speak.

[17] Immigrants from Latin America & the Caribbean are not significantly different from natives only in literacy overqualification.

Table 5: Logit on Overeducation and Overskilling by Native Language

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Non-native Speaker	0.096***	-0.078***	-0.159***	-0.103***	-0.189***
	(0.013)	(0.010)	(0.024)	(0.007)	(0.021)
Native Speaker	0.063**	-0.037*	-0.010	-0.031	-0.015
	(0.026)	(0.021)	(0.067)	(0.021)	(0.073)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Reference category is natives.

Table 5 shows the differences between the immigrants whose native language is the same as the language spoken in the host country (native speakers) and those immigrants speaking a different language (non-native speakers). While native speakers still have a higher probability than natives to be formally overeducated, this probability is smaller compared to non-native speaking immigrants. While this result might be attributed to the differences in the language skills, this could also reflect the similarities in the educational systems of the host and home countries –where the same native language is spoken– due to colonial relations. Contrary to formal overeducation, native speaking immigrants appear not to be different from natives in the prevalence of overskilling and overqualification. However, non-native speaking immigrants are about 8-10% less likely than natives to be cognitively overskilled and 16-19% less likely to be genuinely overqualified.

4.4 Second Generation Immigrants

In our previous analysis, we excluded second generation immigrants. As second generation immigrants attend school fully in the host country, they are not subject to imperfect international transferability of human capital. Previous empirical findings show that education obtained in the host country is significantly more valued than the human capital acquired abroad (Friedberg, 2000; Nielsen, 2011). This makes second generation immigrants less prone to overeducation compared to their parents. They are additionally expected to possess better language skills than their parents and to be similar to their native counterparts. However, the ethnic discrimination hypotheses at the heart of overeducation discussions suggest that second generation immigrants would experience worse occupational matches than natives. Therefore, studying the second generation immigrants is important especially to examine the discrimination hypothesis.

Table 6: Logit on Overeducation and Overskilling of Second Generation Immigrants

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Second Generation Imm.	-0.005	-0.073***	-0.031	-0.085***	-0.050
	(0.011)	(0.014)	(0.042)	(0.014)	(0.041)
N	38594	38594	5039	38594	5039

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column represents results from separate logit regression weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table 6 shows the results for the second generation immigrants. Natives and second generation immigrants do not show a statistically significant difference in their prevalence of being formally overeducated. While second generation immigrants are less likely to be cognitively overskilled than natives in both numeracy and literacy, they show no difference in their overqualification probability compared to natives. These results suggest that the observed formal overeducation among first generation immigrants does not imply an ethnic discrimination and may arise from the screening process of employers. Similarities between the second generation and the natives provide evidence against the ethnic discrimination and supports the previous findings that employers value the education obtained in the host country more highly.

5 Conclusion

Using PIAAC data for 11 European countries, this paper analyzes differences in the prevalence of occupational mismatch between immigrants and natives. Previous literature has stressed that overeducation appears to be a severe problem among immigrants. As a result, overeducation of immigrants is argued to imply foregone human capital for an economy. However, due to the international incomparability of educational degrees, this conclusion might be misleading.

By using test scores of computerized numeracy and literacy tests, we introduce cognitive skills as a measure of occupational mismatch which is not subject to the imperfect international comparability as formal education. We extend previous research by examining the occurrence of genuine overqualification among immigrants and analyze the likelihood of being cognitively overskilled conditional on being overeducated.

Concerning overeducation, our results are in line with previous studies. Formal overeducation appears to be much more common among immigrants than among natives. Estimates show that immigrants are about 7% more likely to suffer from overeducation than natives. However, results are remarkably different when analyzing cognitive skills. It is shown that immigrants are about 9% less likely to be cognitively overskilled and about 15% less likely to be genuinely overqualified than natives. Thus, the overeducation of immigrants does not imply an inefficient use of human capital as the higher incidence of overeducation does not correspond to a similar degree of genuine overqualification compared to natives.

Furthermore, our results highlight the importance of taking the heterogeneity among immigrants into account when assessing their occupational attainments. We show that the likelihood of overeducation, cognitive overskilling and genuine overqualification vary by the length of stay in the host country. An assimilation in the likelihood of being genuinely overqualified suggests that a potential waste of human capital seems to be mainly a problem of recent immigrants. By the length of residence in the host country, immigrants become more similar to natives in their probability of being genuinely overqualified. In addition, ethnic origin of immigrants appears to be of high importance. Immigrants from culturally similar regions, i.e., North America & Western Europe, do not significantly differ from their native counterparts in terms of overeducation and genuine overqualification, whereas other immigrants groups appear to be more likely to be overeducated but less likely to be overqualified. Therefore, considering the origin of immigrants is important when talking about human capital.

Our results suggest that labor markets work more appropriately than considered when it comes to the screening of immigrants. Employers seem to be aware of the international incomparability of educational degrees – as seen by the higher overeducation probability of immigrants – and invest more effort into the screening of immigrants. This is observed by a lower probability of immigrants in terms of overskilling and overqualification. As a higher incidence of formal overeducation does not correspond to an equivalent level of cognitive overskilling and as it is also shown by the overqualification analysis, we cannot talk about a prevalent waste of human capital among immigrants.

The results of this study are of descriptive nature. We neither show labor market outcomes of realized matches in the labor markets, nor can we make any statements concerning migration policies. However, we can show that the focus on educational degrees when examining occupational mismatches of immigrants appears to be shortsighted. Quality differences between educational systems have been extensively studied in economic and education research and have long been subject to political and societal debates. Not considering these factors when analyzing differences between natives and migrants in matching processes in the labor market is shortsighted and misleading. Our results for 11 European countries suggest that unused human capital – commonly referred to as brain waste – is a considerable issue in many countries. However, this cannot solely be seen as a problem of migration policies and must be treated as a general labor market problem concerning not only immigrants but also natives. Using cognitive skills as a proxy for the set of skills of individuals shows that the matching process in the labor market appears to be more adequate than suggested by studies with a pure focus on formal education.

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References

Alba-Ramirez, A. (1993): "Mismatch in the Spanish Labor Market: Overeducation?," *Journal of Human Resources*, pp. 259–278.

Allen, J., M. Levels, and R. van der Velden (2013): "Skill Mismatch and Skill Use in Developed Countries: Evidence from the PIAAC Study," Discussion paper, Maastricht University, Research Centre for Education and the Labour Market (ROA).

Allen, J., and R. Van der Velden (2001): "Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction, and on-the-Job Search," *Oxford Economic Papers*, 53(3), 434–452.

Altonji, J. G., and C. R. Pierret (2001): "Employer Learning and Statistical Discrimination," *The Quarterly Journal of Economics*, 116(1), 313–350.

Baert, S., B. Cockx, and D. Verhaest (2013): "Overeducation at the Start of the Career: Stepping Stone or Trap?," *Labour Economics*, 25, 123–140.

Bauer, T. K. (2002): "Educational Mismatch and Wages: A Panel Analysis," *Economics of Education Review*, 21(3), 221 – 229.

Chiswick, B. R., and P. W. Miller (2009): "The international transferability of immigrants human capital," *Economics of Education Review*, 28(2), 162–169.

Frei, C., and A. Sousa-Poza (2012): "Overqualification: permanent or transitory?," *Applied Economics*, 44(14), 1837–1847.

Friedberg, R. M. (2000): "You Can't Take It with You? Immigrant Assimilation and the Portability of Human Capital," *Journal of Labor Economics*, 18(2), 221–251.

Green, C., P. Kler, and G. Leeves (2007): "Immigrant Overeducation: Evidence from Recent Arrivals to Australia," *Economics of Education Review*, 26(4), 420–432.

Green, F., S. McIntosh, and A. Vignoles (1999): "Overeducation and Skills – Clarifying the Concepts," Discussion paper, Centre for Economic Performance, LSE.

Hanushek, E. A., G. Schwerdt, S. Wiederhold, and L. Woessmann (2015): "Returns to skills around the world: Evidence from {PIAAC}," *European Economic Review*, 73, 103 – 130.

Hanushek, E. A., and L. Woessmann (2012): "Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation," *Journal of Economic Growth*, 17(4), 267–321.

Joona, P. A., N. D. Gupta, and E. Wadensjö (2014): "Overeducation among Immigrants in Sweden: Incidence, Wage Effects and State Dependence," *IZA Journal of Migration*, 3(1), 9.

Kahanec, M., and K. F. Zimmermann (2011): "High-Skilled Immigration Policy in Europe," Discussion paper, DIW Berlin Discussion Paper No. 1096.

Kahn, L. M. (2004): "Immigration, Skills and the Labor Market: International Evidence," *Journal of Population Economics*, 17(3), 501–534.

Kiker, B., M. C. Santos, and M. de Oliveira (1997): "Overeducation and Undereducation: Evidence for Portugal," *Economics of Education Review*, 16(2), 111 – 125.

Kleibrink, J. (2013): "Causal Effects of Educational Mismatch in the Labor Market," Discussion paper, SOEPpapers on Multidisciplinary Panel Data Research.

Kler, P. (2005): "Graduate Overeducation in Australia: A Comparison of the Mean and Objective Methods," *Education Economics*, 13(1), 47–72.

Korpi, T., and M. Tåhlin (2009): "Educational Mismatch, Wages, and Wage Growth: Overeducation in Sweden, 1974 - 2000," *Labour Economics*, 16(2), 183 – 193.

McGoldrick, K., and J. Robst (1996): "Gender Differences in Overeducation: A Test of the Theory of Differential Overqualification," *The American Economic Review*, 86(2), pp. 280–284.

Mendes de Oliveira, M., M. C. Santos, and B. F. Kiker (2000): "The Role of Human Capital and Technological Change in Overeducation," *Economics of Education Review*, 19(2), 199–206.

Ng, Y. C. (2001): "Overeducation and undereducation and their effect on earnings: evidence from Hong Kong, 1986–1996," *Pacific Economic Review*, 6(3), 401–418.

Nielsen, C. P. (2011): "Immigrant over-education: evidence from Denmark," *Journal of Population Economics*, 24(2), 499–520.

Nieto, S., A. Matano, and R. Ramos (2013): "Skill mismatches in the EU: Immigrants vs. natives," Discussion paper, IZA Discussion Paper.

OECD (2013): "Technical Report of the Survey of Adult Skills (PIAAC)," .

Pecoraro, M. (2014): "Is there still a wage penalty for being overeducated but well-matched in skills? A panel data analysis of a swiss graduate cohort," *Labour*, 10.1111/labr.12031.

Pellizzari, M., and A. Fichen (2013): "A New Measure of Skills Mismatch: Theory and Evidence from the Survey of Adult Skills (PIAAC)," Discussion paper, OECD Publishing.

Piracha, M., M. Tani, and F. Vadean (2012): "Immigrant Over-and Under-Education: The Role of Home Country Labour Market Experience," *IZA Journal of Migration*, 1(1), 1–21.

Poot, J., and S. Stillman (2010): "The Importance of Heterogeneity When Examining Immigrant Education-Occupation Mismatch: Evidence from New Zealand," Discussion paper, Discussion paper series//Forschungsinstitut zur Zukunft der Arbeit.

Rumberger, R. W. (1987): "The Impact of Surplus Schooling on Productivity and Earnings.," *Journal of Human Resources*, 22(1), 24 – 50.

Sanroma, E., R. Ramos, and H. Simón (2008): "The Portability of Human Capital and Immigrant Assimilation: Evidence for Spain," *IZA Discussion Paper*.

Sicherman, N. (1991): "Overeducation in the Labor Market," *Journal of Labor Economics*, 9(2), pp. 101–122.

Sloane, P. J., H. Battu, and P. T. Seaman (1999): "Overeducation, undereducation and the British labour market," *Applied Economics*, 31(11), 1437–1453.

Sohn, K. (2010): "The Role of Cognitive and Noncognitive Skills in Overeducation," *Journal of Labor Research*, 31(2), 124–145.

SVR (2015): "Immigration Countries: Germany in an International Comparison. 2015 Annual Report," Discussion paper, SVR, Berlin.

Verdugo, R. R., and N. T. Verdugo (1989): "The Impact of Surplus Schooling on Earnings," *The Journal of Human Resources*, 24(4), 629–643.

Voon, D., and P. W. Miller (2005): "Undereducation and Overeducation in the Australian Labour Market*," *Economic Record*, 81(s1), S22–S33.

A Appendix

Table A1: Definition of Control Variables

Variable	
Gender:	Dummy; 1 if the person is female
Age:	Continuous age; 16-65
Married:	Dummy; 1 if the person is married
Have Child:	Dummy; 1 if the person has at least one child
Health:	Self-assessed health status; 1(Excellent)-5(Poor)
Part time:	Dummy; 1 the person has a part-time job
Public sector:	Dummy; 1 if the person works in public sector
Self-employed:	Dummy; 1 if the person is self-employed

Table A2: Control Variables

	Natives		*Immigrants*	
	(Mean)	(Standard Dev.)	(Mean)	(Standard Dev.)
Gender	0.49	0.50	0.50	0.50
Age	42.63	11.58	41.61	10.03
Married	0.81	0.39	0.82	0.38
Have Child	0.69	0.46	0.75	0.43
Health	2.34	0.96	2.44	0.96
Part time	0.23	0.42	0.25	0.43
Public Sector	0.29	0.45	0.21	0.41
Self-employed	0.13	0.33	0.12	0.32
N	33,990	33,990	3,269	3,269

Note: Authors' calculations based on the PIAAC. A ttest applied on the mean differences between the native and immigrant samples shows no statistically significant difference in the means.

Table A3: Logit on Overeducation and Overskilling by Migration Status

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	0.000	-0.060***	-0.096***	-0.023***	-0.073***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.010***	0.010***	0.010	0.013***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.007)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.007	0.026***	0.047*	0.016**	0.035
	(0.007)	(0.008)	(0.027)	(0.008)	(0.027)
Have Child	-0.046***	-0.017**	-0.020	-0.026***	-0.057**
	(0.007)	(0.008)	(0.025)	(0.007)	(0.024)
Health	-0.008***	-0.009***	-0.009	-0.009***	-0.019**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.015**	0.006	0.013	0.017**	0.027
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.008*	0.012**	-0.003	0.011**	0.032*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.028***	0.006	-0.013	-0.000	-0.006
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Immigrant	0.074***	-0.085***	-0.154***	-0.119***	-0.191***
	(0.008)	(0.014)	(0.031)	(0.014)	(0.034)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country.

Table A4: Multinomial Logit on Skill Match Conditional on Being Overeducated

	Numeracy Skills			Literacy Skills		
	Underskilled	Matched	Overskilled	Underskilled	Matched	Overskilled
Female	0.022**	0.074***	-0.096***	-0.017	0.091***	-0.074***
	(0.011)	(0.021)	(0.019)	(0.013)	(0.021)	(0.019)
Age	0.002	-0.012	0.010	-0.003	-0.015**	0.017***
	(0.004)	(0.008)	(0.007)	(0.004)	(0.007)	(0.007)
Age Squared	-0.000	0.000**	-0.000**	0.000	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.015	-0.061**	0.046*	0.009	-0.045	0.036
	(0.013)	(0.029)	(0.027)	(0.016)	(0.029)	(0.027)
Have Child	-0.006	0.027	-0.020	0.002	0.056**	-0.058**
	(0.015)	(0.026)	(0.025)	(0.015)	(0.026)	(0.024)
Health	0.003	0.005	-0.009	-0.002	0.021**	-0.019**
	(0.006)	(0.011)	(0.010)	(0.007)	(0.011)	(0.009)
Part-time	-0.003	-0.011	0.014	0.020	-0.047	0.027
	(0.015)	(0.028)	(0.026)	(0.018)	(0.029)	(0.026)
Private Sector	0.008	-0.005	-0.003	0.006	-0.037*	0.032*
	(0.014)	(0.022)	(0.019)	(0.013)	(0.021)	(0.018)
Self-employed	-0.010	0.023	-0.013	0.005	0.002	-0.006
	(0.014)	(0.029)	(0.027)	(0.016)	(0.029)	(0.026)
Immigrant	0.085***	0.057*	-0.142***	0.121***	0.051	-0.172***
	(0.013)	(0.032)	(0.031)	(0.013)	(0.034)	(0.033)
N	5,127	5,127	5,127	5,127	5,127	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.5; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country.

Table A5: Logit on Overeducation and Overskilling by Years Since Migration

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	-0.001	-0.060***	-0.097***	-0.023***	-0.073***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.011***	0.010***	0.011	0.012***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.007)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.006	0.026***	0.052*	0.016**	0.038
	(0.007)	(0.008)	(0.027)	(0.008)	(0.027)
Have Child	-0.045***	-0.017**	-0.021	-0.026***	-0.059**
	(0.007)	(0.008)	(0.025)	(0.007)	(0.024)
Health	-0.008***	-0.009***	-0.010	-0.009***	-0.020**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.015**	0.006	0.022	0.017**	0.033
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.008*	0.012**	-0.004	0.011**	0.030*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.028***	0.006	-0.012	-0.000	-0.005
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Years since migration:					
0-5	0.139***	-0.074***	-0.172***	-0.097***	-0.197***
	(0.026)	(0.015)	(0.034)	(0.012)	(0.031)
6-10	0.090***	-0.089***	-0.179***	-0.096***	-0.190***
	(0.021)	(0.012)	(0.034)	(0.012)	(0.034)
>10	0.052***	-0.054***	-0.064*	-0.075***	-0.075**
	(0.014)	(0.014)	(0.039)	(0.011)	(0.038)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regression weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A6: Logit on Overeducation and Overskilling by Immigrant Ethnic Origin

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	0.000	-0.060***	-0.098***	-0.023***	-0.076***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.010***	0.010***	0.011	0.013***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.006)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.007	0.025***	0.048*	0.016**	0.035
	(0.007)	(0.008)	(0.027)	(0.008)	(0.026)
Have Child	-0.048***	-0.017**	-0.019	-0.025***	-0.056**
	(0.007)	(0.008)	(0.024)	(0.007)	(0.024)
Health	-0.009***	-0.008***	-0.010	-0.009***	-0.019**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.014**	0.006	0.017	0.017**	0.030
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.009*	0.012**	-0.004	0.011**	0.031*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.029***	0.006	-0.015	-0.001	-0.008
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Born in:					
Arab States	0.096***	-0.084***	-0.091*	-0.111***	-0.171***
&Sub-Saharan Africa	(0.025)	(0.014)	(0.048)	(0.011)	(0.039)
Asia	0.107***	-0.081***	-0.200***	-0.120***	-0.229***
&the Pacific	(0.031)	(0.022)	(0.041)	(0.015)	(0.044)
Latin America	0.087***	-0.063***	-0.136**	-0.049**	-0.096
&the Caribbean	(0.031)	(0.022)	(0.064)	(0.023)	(0.067)
Central	0.126***	-0.061***	-0.141***	-0.097***	-0.181***
&Eastern Europe	(0.022)	(0.018)	(0.038)	(0.013)	(0.034)
North America	-0.001	-0.060***	-0.073	-0.045**	-0.020
&Western Europe	(0.017)	(0.018)	(0.056)	(0.019)	(0.059)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country. Reference category is natives.

Table A7: Logit on Overeducation and Overskilling by Age Groups

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Age 16-25:					
Immigrant	-0.019	-0.120*	-0.283	-0.219***	-0.719***
	(0.041)	(0.066)	(0.256)	(0.079)	(0.184)
N	4,222	4,222	410	4,222	410
Age 26-40:					
Immigrant	0.065***	-0.131***	-0.195***	-0.189***	-0.274***
	(0.015)	(0.023)	(0.047)	(0.024)	(0.056)
N	12,797	12,797	2,270	12,797	2,270
Age 41-55:					
Immigrant	0.082***	-0.053***	-0.126***	-0.058***	-0.129***
	(0.011)	(0.020)	(0.044)	(0.018)	(0.044)
N	14,505	14,505	1,850	14,505	1,850
Age >55:					
Immigrant	0.056***	-0.013	-0.007	-0.032	0.016
	(0.021)	(0.027)	(0.076)	(0.026)	(0.064)
N	5,735	5,735	597	5,735	597

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each panel presents separate logit regressions for different age groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A8: Logit on Overeducation and Overskilling by Educational Level

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Low & Medium Educated:					
Immigrant	0.017***	-0.067***	-0.155**	-0.106***	-0.228***
	(0.005)	(0.017)	(0.078)	(0.017)	(0.088)
N	22,236	22,236	765	22,236	765
High Educated:					
Immigrant	0.207***	-0.111***	-0.163***	-0.139***	-0.191***
	(0.020)	(0.023)	(0.035)	(0.025)	(0.037)
N	15,023	15,023	4,357	15,023	4,357

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each panel presents separate logit regressions for different education groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A9: Mapping of Occupations to Skill Groups

Skill Level	*Occupation*
Skilled Occupations	Legislators, senior officials and managers
	Professionals
	Technicians and associate professionals
Semi-skilled white-collar occupations	Clerks
	Service workers and shop and market sales workers
Semi-skilled blue-collar occupations	Skilled agricultural and fishery workers
	Craft and related trades workers
	Plant and machine operators and assemblers
Elementary occupations	Elementary occupations

Table A10: Logit on Overeducation and Overskilling by Skill Groups

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Skilled occ.:					
Immigrant	0.032^{**}	-0.092^{***}	-0.114^{*}	-0.110^{***}	-0.118^{*}
	(0.013)	(0.024)	(0.064)	(0.025)	(0.067)
N	17,066	17,066	1,799	17,066	1,799
Semi-skilled white-collar occ.:					
Immigrant	0.106^{***}	-0.047^{*}	-0.185^{***}	-0.103^{***}	-0.228^{***}
	(0.015)	(0.025)	(0.052)	(0.025)	(0.058)
N	10,758	10,758	1,929	10,758	1,929
Semi-skilled blue-collar occ.:					
Immigrant	0.049^{***}	-0.143^{***}	-0.164^{**}	-0.174^{***}	-0.235^{***}
	(0.019)	(0.032)	(0.069)	(0.033)	(0.075)
N	6,536	6,536	1,000	6,536	1,000
Elementary occ.:					
Immigrant	0.092^{***}	-0.109^{***}	-0.213^{***}	-0.125^{***}	-0.173^{**}
	(0.021)	(0.029)	(0.071)	(0.030)	(0.076)
N	2,899	2,899	399	2,899	399

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each panel presents separate logit regressions for different skill groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A11: Shares of Overeducated and Overskilled Individuals in Each Country

	Belgium		Denmark		France		Germany		Ireland		Italy	
	N	I	N	I	N	I	N	I	N	I	N	I
Overeducated	11	17	14	30	11	18	11	21	16	25	20	42
Numeracy Overskilled	16	7	15	7	16	6	17	7	16	18	16	16
Literacy Overskilled	16	6	14	7	16	7	16	6	15	13	17	8
N	2,994		4,711		3,640		2,941		3,105		2,593	

	Netherlands		Norway		Spain		Sweden		UK	
	N	I	N	I	N	I	N	I	N	I
Overeducated	9	18	11	29	13	16	14	26	12	23
Numeracy Overskilled	15	3	15	7	15	10	17	5	14	9
Literacy Overskilled	15	3	15	8	16	10	16	3	14	9
N	3,475		3,077		3,114		2,699		4,910	

Note: Percentage shares of the overeducated and overskilled people among natives (N) and immigrants (I).

Table A12: Logit on Overeducation and Overskilling in Each Country

	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	Norway	Spain	Sweden	UK
Overeducated	0.055**	0.113***	0.081***	0.068***	0.073***	0.170***	0.072***	0.126***	0.023	0.092***	0.082***
	(0.022)	(0.013)	(0.017)	(0.018)	(0.018)	(0.025)	(0.018)	(0.016)	(0.019)	(0.018)	(0.015)
Num. Overskilled	-0.123***	-0.108***	-0.121***	-0.129***	0.009	-0.001	-0.177***	-0.124***	-0.058**	-0.159***	-0.062***
	(0.042)	(0.019)	(0.033)	(0.037)	(0.019)	(0.028)	(0.054)	(0.030)	(0.024)	(0.033)	(0.021)
Num. Overqualified	-0.365***	-0.194***	-0.158*	-0.238***	-0.061	-0.043	-0.291**	-0.212***	-0.068	-0.262***	-0.104*
	(0.127)	(0.041)	(0.084)	(0.087)	(0.056)	(0.059)	(0.128)	(0.069)	(0.069)	(0.069)	(0.056)
Lit Overskilled	-0.131***	-0.110***	-0.100***	-0.123***	-0.027	-0.117***	-0.173***	-0.100***	-0.072***	-0.243***	-0.068***
	(0.044)	(0.018)	(0.032)	(0.037)	(0.020)	(0.037)	(0.054)	(0.027)	(0.025)	(0.044)	(0.022)
Lit. Overqualified	-0.198*	-0.214***	-0.080	-0.158*	-0.082	-0.164**	-0.340**	-0.201***	-0.103	-0.405***	-0.222***
	(0.110)	(0.041)	(0.081)	(0.081)	(0.054)	(0.068)	(0.146)	(0.066)	(0.075)	(0.083)	(0.065)
N	2,994	4,711	3,640	2,941	3,105	2,593	3,475	3,077	3,114	2,699	4,910

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each line presents results from separate logit regressions weighted by sampling weights in each country. Regressions include individual controls.