Are over-qualified immigrants mismatched according to their actual skills? An international comparison of labor market placement in OECD countries

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Table of Contents

Abstract

Previous research finds that immigrants are more often over-qualified than natives. Reasons can be imperfect transferability and signaling of skills. However, over-qualification does not necessarily imply that someone is over-skilled when it comes to actual skills and vice versa. The Programme for the International Assessment of Adult Competencies (PIAAC 2012) provides most recent data on basic skills of the working-age population. With this data I examine numeracy mismatch of first generation immigrants and natives in 13 OECD countries. My results suggest that especially non-native speaking immigrant workers have difficulties finding employment that aligns with their skill level. This results in genuine mismatch of immigrants, meaning that they are more often over-qualified than native workers and at the same time (comparing individuals at the same skill level) more often over-skilled. Hence, their skills are not put into effective use. These findings differ across occupations.

Keywords: educational economics, human capital, labor migration, skills, skill mismatch, occupational choice

JEL: J15, J24, J61

1 Introduction

Integration into the labor market is more difficult for immigrants than for natives. A major problem for immigrant workers identified in previous literature is over-qualification. The general consensus is that immigrants are more often over-qualified than natives (see Chiswick & Miller, 2009, 2011; Piracha & Vadean, 2013 for a literature review). The main reasons for over-qualification among immigrants are stated to be imperfect transferability and signaling of skills (Chiswick & Miller, 2009, 2011). Further barriers are occupational licensing, citizenship (Piracha & Vadean, 2013), lower language proficiencies (e.g., Dustmann & van Soest, 2002), lacking knowledge about how the labor market works as well as missing networks in the host country (Lancee & Hartung, 2012). But also discrimination can play a role (Carlsson & Rooth, 2008; Oreopoulos, 2009).

The question arises whether over-qualified immigrants also possess a surplus of actual skills. I therefore distinguish between qualification mismatch and skill mismatch as over-qualification does not necessarily imply that someone is over-skilled vice versa (Allen & van der Velden, 2001). In this paper I examine natives' and immigrants' workers and their actual mismatch regarding numeracy skills (Perry, Wiederhold, & Ackermann-Piek, 2014). Recent data provided by the Programme for the International Assessment of Adult Competencies (PIAAC) allows investigating natives' and immigrants' numeracy mismatch in 13 countries. Doing so, I make an important addition to previous research on immigrant's over-qualification by focusing on actual skills when examining immigrants' labor market integration.

After reviewing previous findings on immigrants' qualification mismatch, I derive hypotheses on the likelihood of numeracy mismatch among native-speaking and non-native speaking immigrants compared to natives. Furthermore, I investigate skill mismatch among over-qualified immigrant and native workers and the occurrence of skill mismatch in different occupations. Section 3 provides the empirical approach to test my hypotheses. I describe my results in Section 4 and discuss them in Section 5.

2 Theoretical Background

Developed countries attract immigrants as they hope to find better living conditions in another country. Therefore most OECD countries have seen an increase in immigration in recent years (OECD, 2015a). The individuals who decide to migrate tend to be positively self-selected in that they are more ambitious, more aggressive, more entrepreneurial, and more able than those staying at home (Chiswick, 2008; Dustmann & Glitz, 2011). However, despite high motivation to work and favorable self-selection, adequate labor market integration can be difficult for immigrants. And even when immigrants do find employment, these factors have an impact on the choice of jobs and on wages (cf. Dustmann & Glitz, 2011). A number of factors could be identified as potential reasons. These factors are country of origin (Fleischmann & Dronkers, 2010; Sanromá, Ramos, & Simon, 2015), limited language skills (e.g. Chiswick, 1991; Dustmann & van Soest, 2002; Rivera-Batiz, 1990), cultural differences (Bevelander, 2001; Rosholm, Scott, & Husted, 2006), limited knowledge of how the labor market operates and missing local network (Lancee & Hartung, 2012), or different skill sets required in the same profession in another country caused by different measures and conventions used (Chiswick & Miller, 2011). Regarding earnings, Chiswick (1978) argues that immigrants start with lower wages shortly after their migration but outperform natives after 10-15 years of residence due to positive selection. However, Borjas (1985) could show that immigrants' assimilation patterns are flatter than suggested by Chiswick (1978) and mainly cohort specific, indicating that the initial problems of labor market integration may remain.

2.1 Previous findings on immigrants' over-qualification

A substantial number of papers look at the immigrants' formal educational attainment and their placement in the labor market. The general consensus is that immigrants are more often over-qualified than natives (see Piracha & Vadean, 2013 for a literature review), which also affects immigrants' wages (e.g., Chiswick & Miller, 2009, 2011). Qualification mismatch is defined as a divergence between the required level of education for a particular job and the worker's attained level of education. Thereby a worker with a higher level of educational attainment than required for the current work is over-qualified and a worker with a lower level than required is under-qualified (cf. Hartog, 2000).

A main reason for immigrants' over-qualification is that foreign credentials are not accepted. Education credentials can be used as a signal to the firm, indicating a certain level of ability that the individual may possess and thereby narrowing the informational gap (Spence, 1973). "Understandably risk averse employers and consumers not knowing how to evaluate foreign credentials compared to the credentials of workers trained in the destination country" (Chiswick & Miller, 2011, p. 8) might downgrade immigrants' credentials (Piracha & Vadean, 2013). Nielsen (2007), for example, showed that the probability of being mismatched in the labor market decreases if immigrants have attained their education in the host country. Thus, migrants, also like natives newly entering the labor market, often start in jobs that do not correspond to their educational attainment and search for a better match. Also further barriers, such as licensing or citizenship can lead to over-qualification (Chiswick & Miller, 2011; McDonald, Warmon, & Worswick, 2009).

But also weak language skills often prevent immigrants to apply their skills in their host country. Language skills are a crucial prerequisite for the transfer of immigrants' skills from their home to the host country. An immigrant who does not speak the host country's language is often less likely to apply his or her skills in that country.[1] And it is evident that lower language proficiency results in lower wages (Chiswick & Miller, 2002, 2003, 2011; Dustmann & van Soest, 2002). Also, immigrants from Latin America in Spain or from English speaking countries in Australia and New Zealand are found to be less likely to be over-qualified compared to immigrants from other countries (Green, Kler, & Leeves, 2007; Sanromá, et al., 2015).

Also, not all skills are transferable to the host country. There are occupation specific skills that are dependent on the type of technology used (Chiswick & Miller, 2011). Not being able to apply one's skills in the original profession can lead to over-qualification when the immigrant is, thus, forced to choose an occupation below his or her educational attainment. Sanromá, et al. (2015) could show that over-qualification was less severe among immigrants from developed countries (that use similar technologies) in Spain compared to immigrants from lower developed countries.

Besides these, other factors, such as discrimination (Carlsson & Rooth, 2008; Oreopoulos, 2009) and a missing local network (Lancee & Hartung, 2012) can play a role.

Immigrant's over-qualification can be temporary as immigrants can use their experience in lower-skilled jobs to better signal their actual skills (Chiswick & Miller, 2008, 2011; Green, et al., 2007; Nielsen, 2007). They may work in lower-skilled jobs while working on attaining a license to be able to work in their original profession in the host country. Once the license is earned it is easier to switch back to their previous job and work according to their educational degree and their possessed skills. Also, once sufficient language skills are acquired, immigrants may be better able to find jobs that match their actual skills (Chiswick & Miller, 2002, 2003).

2.2 Skill mismatch

Skill mismatch occurs when the skills possessed by workers are lower or higher than the level of skills required at the workplace. Allen and van der Velden (2001) argue that the two constructs, qualification and skill mismatch should be carefully distinguished. A person can be over-qualified, but at the same time be appropriately matched regarding their skills or even under-skilled. Differences between both constructs are due to the heterogeneity of educational programs both on the individual level as well as on the program/school/country level. Also, skills can be acquired outside the schooling system, f.ex., through on the job training (Desjardins, 2003) and therefore not be signaled through formal qualification. Allen and van der Velden (2001) show that only a small proportion of wage effects of education mismatch are accounted for by actual skill mismatch.

The questions arises whether formal education and over-qualification is the correct variable of interest when examining labor market placements of immigrants. As Chiswick and Miller (2011) and Sanromá, et al. (2015) argue, differing skill requirements in the home country might lead to qualification mismatch in the host country. In this case, skill mismatch is not a necessary consequence of qualification mismatch. Hanushek and Woessmann (2015) make a similar point. While formal qualification levels cannot fully explain nations' growth, differing skill levels do. The authors emphasize this point by comparing immigrants from the same origin countries with schooling received in their home country versus in their host country, the US, regarding their wages in the US. They conclude that production is different from signaling of schooling. If schooling in the home country is of lower quality than in the host country, qualification mismatch in the host country may not translate into actual skill mismatch. The immigrants may then be employed according to their skill level that their education equipped them with.

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[1] Unless, he or she works in an, for example, English speaking environment where the host country's language plays a minor role.

Also, qualification mismatch itself may not be problematic as long as it does not translate into skill mismatch. The problem of actual skill mismatch is more severe. In today's knowledge society it can be problematic when unused skills depreciate. Over-skilled workers lose their skills when they cannot use them at work (Krahn & Lowe, 1998; Schooler, 1984). Individuals whose skills have depreciated may have difficulties apting to technological changes once their job becomes obsolete (e.g., Acemoglu & Autor, 2011). At the same time, under-skilling can lead to insufficient skill endowments for facilitating technological development. Further, skill mismatch affects individuals' wages, job satisfaction, and employee turnover (Allen, Levels, & van der Velden, 2013; Allen & van der Velden, 2001; Perry, et al., 2014).

Numeracy mismatch. For these reasons, instead of focusing on immigrants' over-qualification I examine actual skill mismatch among immigrant workers compared to their native counterparts. Most recent large-scale assessment data from PIAAC from various countries allow to measure actual skill mismatch regarding key cognitive skills (OECD, 2013). The skill mismatch measures that can be used with the PIAAC data focus on numeracy and literacy, the two basic skill domains measured in PIAAC across all countries. In this paper I focus on numeracy mismatch.[2] Numeracy mismatch is the respondent's mismatch regarding the "ability to access, use, interpret, and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (Gal, Alatorre, Close, Evans, Johansen, Maguire, et al., 2009, p. 21). Numeracy is an integral skill and is needed for achieving one's goals at work and in daily life. It also serves as indicator for the extent to which immigrants have achieved important prerequisites for social participation in the host country (OECD, 2013).

Constraints when examining immigrants' skill mismatch. Language skills are a necessary prerequisite of numeracy skills tested in PIAAC. Skills were tested in the language of the host country and the tasks were presented in the countries' official languages and are text-intensive (OECD, 2013).[3] Hence, skill levels of immigrants are, unsurprisingly, generally lower than those of natives (OECD, 2013). While one can argue that immigrants need to have sufficient skills in the host country's language, suggesting that the OECD's approach of testing in the respective host countries' languages is justified, it is also true that in a globalized world many immigrant workers are not required to speak the host countries' language as many global enterprises introduced English as their working language. Unfortunately, we cannot distinguish whether the immigrants in the PIAAC sample are required to speak the host country's language at work or not.

Also, beyond the numeracy skills and in contrast to educational achievement, skills have multiple dimensions. Immigrants may possess skills in addition to what is required in the host country's labor market, such as a certain technology only applied in the country of origin (Chiswick & Miller, 2009, 2011). Furthermore, immigrants may not be able to apply their sets of skills in the host country due to the same problems that typically lead to over-qualification, namely failed signaling, language problems, or other entrance barriers (Bratsberg, Ragan, & Nasir, 2002; Chiswick & Miller, 2011). For example, an immigrant may have a strong sales talent and worked as a sales person before he or she emigrated. However, due to language difficulties he or she cannot work in his or her old job and finds employment in a different profession with lower demands on language proficiency (Peri & Sparber, 2009, 2011). In this case he or she is over-skilled (possesses skills that are not required in the job) regarding this particular skill, sales, but might be well-matched or even under-skilled regarding another skill that his or her (new) profession demands.

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[2] I analyzed also literacy mismatch and the results are similar to those on numeracy presented in this paper. Results are available upon request.

[3] See http://www.oecd.org/skills/piaac/samplequestionsandquestionnaire.htm for sample test items of PIAAC.

Despite these constraints, it is nevertheless important to examine numeracy mismatch of immigrants as it is a basic skill and builds the foundation of further, more specific skills. A lack of this skill will hinder immigrants' labor market integration to certain extents. Identifying such a lack can help to train it in order to enhance immigrants' integration into the labor market (OECD, 2013).

Immigrants' numeracy skills. In general, immigrants' cognitive skills are lower than that of natives (Maehler, Massing, & Rammstedt, 2014; OECD, 2013). This may be because of a different quality of schooling (Hanushek & Woessmann, 2015) or due to lower language proficiency (see above). The fact that immigrants possess lower numeracy skills naturally leads to an increased incidence of under-skilling and decreased incidence of over-skilling compared to natives (see descriptive results below and Cim, Kind, & Kleibrink, 2017).

However, the aim of this paper is to test whether immigrant workers, who are more likely to be over-qualified than native workers (Piracha & Vadean, 2013) also have difficulties finding jobs that align with their skill endowment. Hence, it is important to compare individuals on the same skill level. Doing so, it is even plausible that immigrants, even though immigrants generally have lower numeracy skills, are more likely to be over-skilled when compared to natives at the same skill level.

2.3 Immigrants' numeracy (mis-)match

It is important to distinguish in which cases over-qualification translates into actual skill mismatch and in which not. If different technologies are applied in the host country, immigrants' skills cannot be applied in the same profession (Chiswick & Miller, 2011). This could be the case if the technology used in the home country is mainly manual labor based while the same profession is technology instensive in the host country. It is then likely, that the formal qualification earned in the home country could not teach the skills necessary to work in an environment using different technologyies (Hanushek & Woessmann, 2015). In this case, the immigrants' over-qualification does not necessarily translate into actual skill mismatch. They may work in jobs that require lower degrees than their educational attainment. But because manual labor intensive work requires lower educational degrees in the host country they may be well-matched even though they are over-qualified. Nowotny (2016) can show, based on the potential immigrants' earnings, that among potential and positively self-selected immigrants (Chiswick, 2008), immigrants that are willing to accept jobs in which they are over-qualified are negatively self-selected (earning less than those unwilling to accept over-qualification). This implies, that this group of immigrants possess lower skills compared to immigrants unwilling to accept over-qualification and is therefore less likely to be over-skilled.

If, however, language difficulties prevent skills from being transferred to the host country's labor market, the immigrants' may be over-qualified and also possess the skills to work in jobs with higher skills required (Sanromá, et al., 2015). In this case, they are, at the same time, over-skilled. Also if foreign educational degrees fail to signal actual possessed skills that actually fit the host country's labor market (Chiswick & Miller, 2011), over-qualification will translate into actual over-skilling, in other words, genuine mismatch (Quintini, 2011). This is also true for occupational licensing and labor markets with high entry barriers in certain professions, such as coordinated market economies (Hall & Soskice, 2001).

Previous research could provide on hint on actual skill mismatch of immigrants. Chiswick and Miller (2008) find that this return on over-education is lower for immigrants than for natives. However, assuming that only those skills are reimbursed that are put in effective use at the workplace, this could, again, mean two things: First, immigrants indeed possess fewer skills leading to lower payoffs, or, secondly, immigrants possess the skills necessary for a higher-skilled job but they are not put in effective use at their workplace. The heterogeneity in occupational choice and skill requirements in different jobs make it necessary to take a look at the actual skills of immigrants.

Generally, lower cognitive requirements in these jobs naturally leave a wider spectrum of workers with higher numeracy skills than required. Therefore, workers in these professions are in general more likely to be over-skilled compared to workers in professions corresponding to their educational degree and requiring matching cognitive skills.

Further, taking into account that immigrants are positively selected (Chiswick, 2008) and that the decision to migrate impacts the investment in human capital prior to migration (Dustmann & Glitz, 2011), I argue that immigrants possess the skills needed in the host country's labor market. However, they are not able to apply these skills because of failed signalling of educational degrees, licensing, or other entry barriers. As a consequence, they work in jobs below their educational level (Chiswick & Miller, 2009, 2011; Piracha & Vadean, 2013) and cannot appropriately apply their skills at work. They are, thus, genuinely mismatched (Quintini, 2011), meaning over-qualified and at the same time over-skilled. Possessing insufficient or inadequate skills may be true for a small group of immigrants for whom the decision to migrate came suddenly, for example for refugees from communist countries in the past or from less developed countries of war. Thus,

H1a: Immigrant workers are **more likely to be over-skilled** regarding numeracy skills than native workers.

H1b: Immigrant workers are **less likely to be under-skilled** regarding numeracy skills than native workers.

Ottaviano and Peri (2012) suggest that immigrants cannot perfectly substitute natives within the same education and experience groups in production Rather, there is evidence that migrants and natives, when an influx of immigration occurs, select into different type of occupations. In two papers, Peri and Sparber (2009, 2011) argue that immigrants specialize in occupations that they have comparative advantages in. Immigrants typically have weaker language skills than natives but they possess physical and/or quantitative skills similar to natives. They have, thus, comparative advantages in occupations that require physical skills, such as construction work or household services, or quantitative skills, such as STEM occupations. Native workers, in contrast, have comparative advantages in jobs requiring communicative skills instead, such as teaching and sales (Peri & Sparber, 2009, 2011; Ricardo, 1821). Due to varying compensation of skills, the selection into different types of professions lets negative wage effects caused by immigration turn out to be lower than commonly anticipated (Ottaviano & Peri, 2012; Peri & Sparber, 2009, 2011). The occupational choice of immigrants affects the occurrence of immigrant's qualification, too. Chiswick and Miller (2011) can show that immigrants's qualification mismatch and its pay-off in different occupations differ. As compensations in different professions are closely tied to the skills applied at work, it is very likely that the occurrence of immigrants' skill mismatch differs, depending on which occupations they select into.

Also differences in over-qualification, as examined by Chiswick and Miller (2011), suggest that there are differences in occupations either in selection or in the appreciation of foreign educational degrees. For example, engineers from less developed countries may sort into different occupations because they are do not have the skills to use the technologies applied in engineering jobs in more developed countries. Thus, in their new, more basic jobs they may be over-qualified and over-skilled. However, in engineering jobs over-qualification and over-skilling may be a lesser problem as immigrants from more developed countries are able to select into thes job with the appropriate skills. Thus,

H2: Immigrant workers in different occupations **differ** regarding their likelihood of being mismatched regarding numeracy skills compared to native workers.

3 Empirical Approach

3.1 Data

I use PIAAC data which provides most recent data about skills of the adult population that is internationally comparable. It was designed to provide representative measures of the cognitive skills possessed by adults aged 16 to 65 years. For my analyses I use the public use file provided by the OECD (2015b). In addition to this, I use additional national data for Australia (Australian Bureau of Statistics, 2012), Austria (Statistics Austria, 2011/12), Canada (Statistics Canada, 2016) and Germany (Rammstedt, Zabal, Martin, Perry, Helmschrott, Massing, et al., 2015).

3.2 Country selection

Of the 33 countries surveyed in PIAAC, I focus on those countries with a sample of at least 10 % first-generation immigrants. These are Australia, Austria, Canada, Denmark, France, Germany, Ireland, the Netherlands, Norway, Spain, Sweden, United Kingdom, and the United States. Estonia could not be included in my analyses due to data restrictions in the public use file.

Different migration policies in the past have shaped the migrant population in the countries included in the analyses (Bauer, Lofstrom, & Zimmermann, 2001; Freeman, 1995) and are likely to affect labor market integration. To control for such differences I include country fixed effects in each regression model (see below).

3.3 Sample

A sample of at least 5,000[4] adults was surveyed for PIAAC in each country (OECD, 2013). Sampling weights are used to reduce potential bias due to nonresponse, deficiencies in the sampling frame and further difficulties that may have occurred during the selection process (Leyla Mohadjer, Tom Krenzke, & Wendy van de Kerckhove, 2013b).

In my analyses I include persons who were between 25 and 54 years old and full-time employed at the time of the survey. Like Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) and Perry, et al. (2014), I define full-time employees as those who work 30 hours or more per week. I exclude students, apprentices, and self-employed. This results in a total of 31,396 respondents.

3.4 Migration status

For the purpose of this investigation, i.e. labor market integration across countries, only individuals who have immigrated themselves to the receiving countries (first generation) are classified as immigrants. Individuals without immigrant background (natives) include all those who have at least one native-born parent. Second-generation immigrants, i.e. persons living in the host country and having two foreign-born parents, constitute a very small percentage in most of the PIAAC countries. Due to

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4 In countries that did not implement the skill domain problem solving in technology-rich environments, f.ex., France and Spain, at least 4,500 adults were assessed (Leyla Mohadjer, Tom Krenzke, & Wendy van de Kerckhove, 2013a) . Canada surveyed a large oversample. These differing sample sizes are corrected in the descriptive analyses and in the regression models by using adjusted weights.

an ambiguous theoretical assignment to the other two comparison groups they are excluded from the analyses.

As language plays an important part for labor market integration (Dustmann & van Soest, 2002; Green, et al., 2007) and affects the test performance in the PIAAC assessment (see above), I distinguish between immigrants whose native language is different from the language spoken in the host country and those whose native language is the same as spoken in the host country. Table 1 provides a descriptive overview of the immigrant subsample in the selected countries regarding their native language and their educational attainment compared to natives in each country.[5]

Table 1: Sample description of first-generation immigrants compared to natives

Country	Share of 1st generation immigrants in population	Share of native speakers among 1st generation immigrants	Percentage difference between immigrants and natives	
			Low educational attainment	High educational attainment
Australia	33.3	47.7	-9.7	21.0
Austria	17.2	25.4	11.9	5.6
Canada	27.8	30.1	-2.3	17.2
Denmark	9.9	6.3	9.3	3.1
France	11.0	34.6	26.1	-7.5
Germany	13.7	19.9	20.0	-8.2
Ireland	22.2	44.1	-13.4	12.1
Netherlands	10.2	20.4	13.2	-7.0
Norway	13.0	2.9	4.4	0.4
Spain	11.9	59.5	4.6	-15.1
Sweden	14.8	6.4	16.2	-0.1
Utd. Kingdom	14.7	33.9	-6.1	18.4
United States	16.1	21.2	17.6	-1.7

3.5 Operationalization of qualification mismatch

I define qualification mismatch as deviation of the achieved qualification (measured in years of schooling) from the required qualification (measured in years of required schooling) by at least two years. A respondent is over-qualified when his or her years of schooling exceeds the number of required years of schooling by at least two years and under-qualified when his or her years of schooling is below the number of required years of schooling by at least two years (Levels, van der Velden, & Allen, 2013).

3.6 Operationalization of numeracy mismatch

Skill mismatch is defined as the deviation of the actual possessed skills which are measured in a large-scale assessment, from the required skills in the individual's job. This measure is irrespective of the attained qualification level. In this paper I focus on numeracy mismatch.

[5] Examining the immigrant population using a survey that is not specifically designed to target immigrants, such as large scale assessments (Maehler, Martin, & Rammstedt, 2017) always imposes the risk of not capturing the actual immigrant population in a country. Nevertheless, the sample quality of PIAAC is considered to be very high (Leyla Mohadjer, Tom Krenzke, & Wendy van de Kerckhove, 2013).

Various skill mismatch measures have been suggested in previous research (Flisi, Goglio, Meroni, Rodrigues, & Vera-Toscano, 2014; Perry, et al., 2014). I find the Realized Matches (RM) measure suggested in Perry, et al. (2014) the most promising measure.

To diminish the disadvantages of the measure I improve the existing RM measure (Perry, et al., 2014) by defining the benchmarks as the median skill level in each profession and country +/- 1.5 deviations (analogous to the standard deviation)[6] around the median:

$$D = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \tilde{X}\right)^2} \tag{1}$$

where D stands for deviation, n for sample size, X_i for the characteristics of element i of the sample, and $\tilde{X}$ for the sample median. To account for differences in hiring procedures during and shortly after the global financial crisis, the median skill level is determined by full-time workers between 25 and 54 years old that where hired before 2007.[7]

To derive the skill mismatch measure I followed four steps:

1) Calculate the median numeracy proficiency level for each profession in each country.
2) Calculate the deviation around the numeracy median (according to equation (1)).
3) Define benchmarks by adding and subtracting 1.5 times the deviation from the numeracy median.
4) Compare the possessed numeracy profession to the benchmarks and define a worker as mismatched if he or she falls above or below the benchmark.

3.7 Predicting the likelihood of being over-skilled or under-skilled: Empirical model

To test my hypotheses I define two logistic regression models, estimating the likelihood of being over-skilled (equation 2) and being under-skilled (equation 3) regarding numeracy skills. The regression equations read as follows:

$$\begin{aligned} &Logit\left(Overskilling_{1/0} \mid X_i = x_i\right) \\ &\qquad = \beta_0 + \beta_1 I_i + \beta_2 N_i + \beta_3 S_i + \beta_4 E_i + \beta_5 G_i + \beta_6 C_i \end{aligned} \tag{2}$$

$$\begin{aligned} &Logit\left(Underskilling_{1/0} \mid X_i = x_i\right) \\ &\qquad = \beta_0 + \beta_1 I_i + \beta_2 N_i + \beta_3 S_i + \beta_4 E_i + \beta_5 G_i + \beta_6 C_i \end{aligned} \tag{3}$$

where *Overskilling* is a dummy variable taking the value 1 for being over-skilled and 0 otherwise. *Underskilling* is a dummy variable taking the value 1 for being under-skilled and 0 otherwise. *I* is a dummy variable for the individual's migration status, *N* is the individual's numeracy skills, *S* is the number of years of schooling (average or most usual time that it takes to complete a qualification), *E* is the work experience, *G* is a dummy variable taking the value 1 for male and 0 for female, and *C* is a country dummy. Rubin's rule (Perry, et al., 2014; Rubin, 1987) is used to account for multiple imputation of

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[6] Choosing 1.5 standard deviations from the median ensures a conservative measure of mismatch (Allen, et al., 2013).

[7] The hiring date is not available for the U.S. data and this condition was therefore excluded for the U.S.

competency scores in PIAAC (Yamamoto, Khorramdel, & Davier, 20013). This affects also the numeracy mismatch variable as it is derived based on the competency scores (Perry, et al., 2014).

I run different regression models. In model 1 I regress immigration status on over- and under-skilling, respectively. In a next step I add numeracy skills and years of schooling to the model first separately (model 2 and 3) and then jointly (model 4). In model 5 I control for work experience and gender, analyzing the main specifications as presented above (equations 2 and 3). I control for occupations on the ISCO 1-digit level (International Labour Organization, 2012) in model 6. In Model 7 and 8 I restrict my sample to respondents that are over-qualified, while controlling for occupations in Model 8. In Models 9 through 16 I run the main specification separately for each occupation category.[8] However, due to small sample size within each occupation, Rubin's rule cannot be applied. The results of these analyses have to be interpreted with care as not using all plausible overestimates the statistical significance of the results (von Davier, Gonzalez, & Mislevy, 2009). Country dummies are included in all models.

3.8 Robustness checks

To check the robustness of my results, I run regressions that include only immigrants that have lived in the host country for at least 5 and 10 years (Table A.1 in Appendix).[9] I also control for child/children in the household and for participation in further education during the last 12 months (Table A.2 in Appendix).

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8 ISCO category 6 (Skilled Agricultural, Forestry and Fishery Workers) is excluded as in this sample no native-speaking immigrants are working in this occupation.

9 Due to data restrictions, length of stay in the host country is not available for Australia. Australia is therefore not included in these analyses.

4 Results

4.1 Descriptive results

Figure 1 presents the shares of overqualified workers by immigrant status and length of residence in the host country. In line with previous research, the shares of over-qualified immigrant workers are slightly higher than that of native workers, with the largest shares among immigrants with a foreign mother tongue. These shares of over-qualification among immigrants are reduced and aligned with that of natives over the course of five and 10 years of residence in the host country.[10]

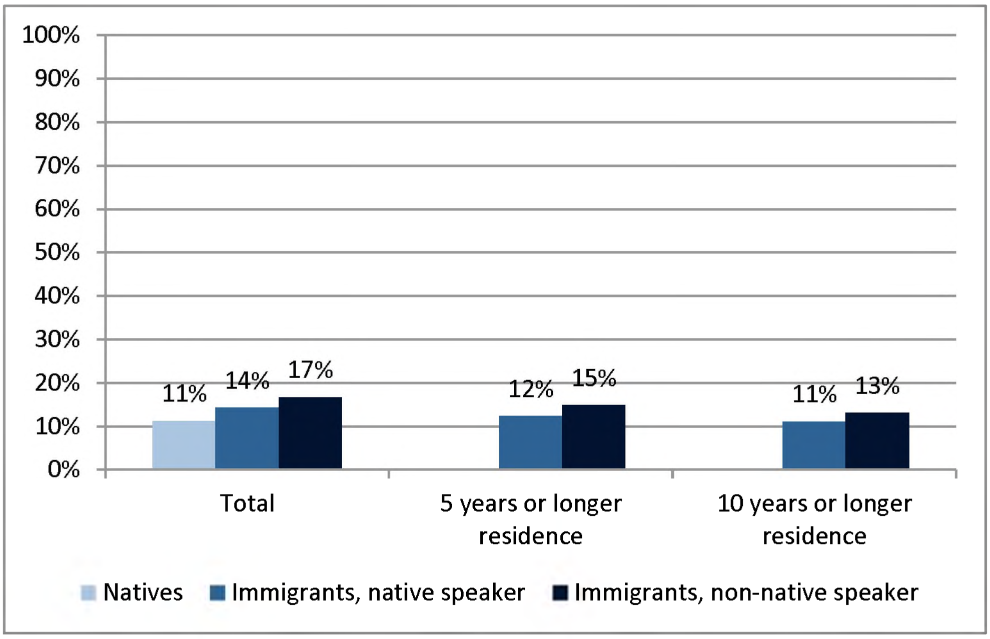
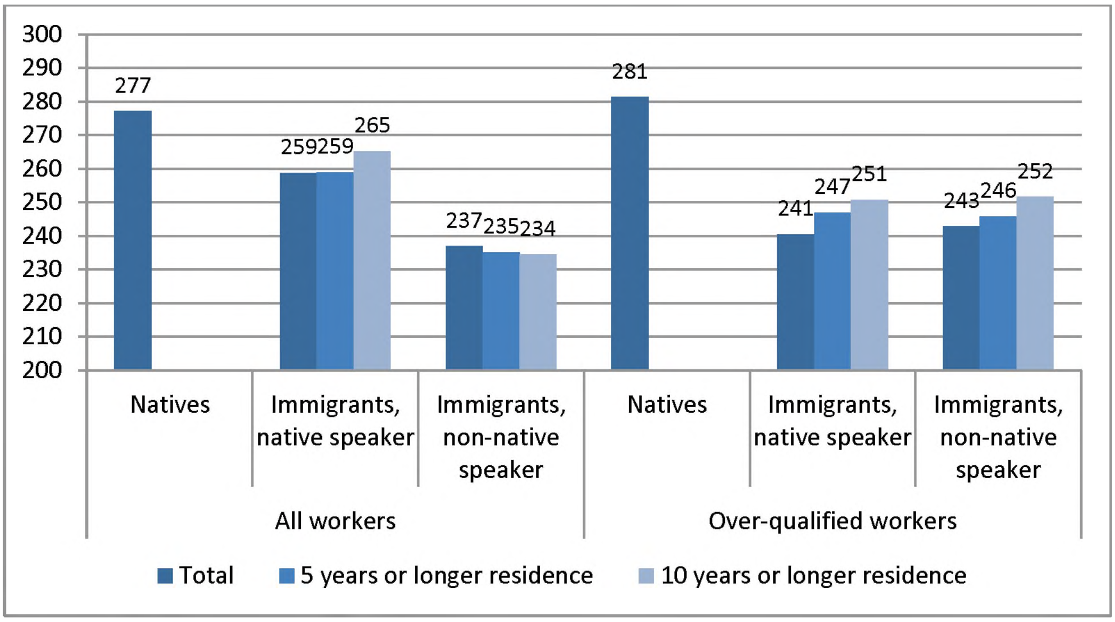


Figure 1: Shares of over-qualified workers by immigrant status and length of residence in host country

Figure 2 presents the skill levels of immigrants (native and non-native speakers) and natives in general and with focus on over-qualified workers. It becomes apparent that immigrant workers have lower numeracy skills than natives. The difference is especially low for non-native-speaking immigrants. Their average numeracy score is 40 points lower than that of natives.[11] Interestingly, the numeracy skills of over-qualified non-native speaking immigrants are slightly higher compared to the whole group while this relation is reversed for native-speaking immigrants.

[10] The shares of under-qualification yield no significant differences between immigration status and also no changes regarding length of residence in the country. Results available upon request.

[11] The OECD numeracy average 269 with a standard deviation of 51 points.



Note. Scores range from 0 to 500.

Figure 2: Numeracy scores in general and for over-qualified workers, by immigrant status and length of residence in host country

Immigrants' lower numeracy skills are also reflected when looking at shares of over- and under-skilling (Figure 3 and Figure 4) The shares of over-skilling among immigrant workers are generally lower than those among native workers with the lowest among non-native speaking immigrants. The reverse is true for under-skilling. Immigrants have higher shares of under-skilled workers with the highest shares found among non-native speaking immigrants. These shares do not differ significantly regarding length of residence in the host country.

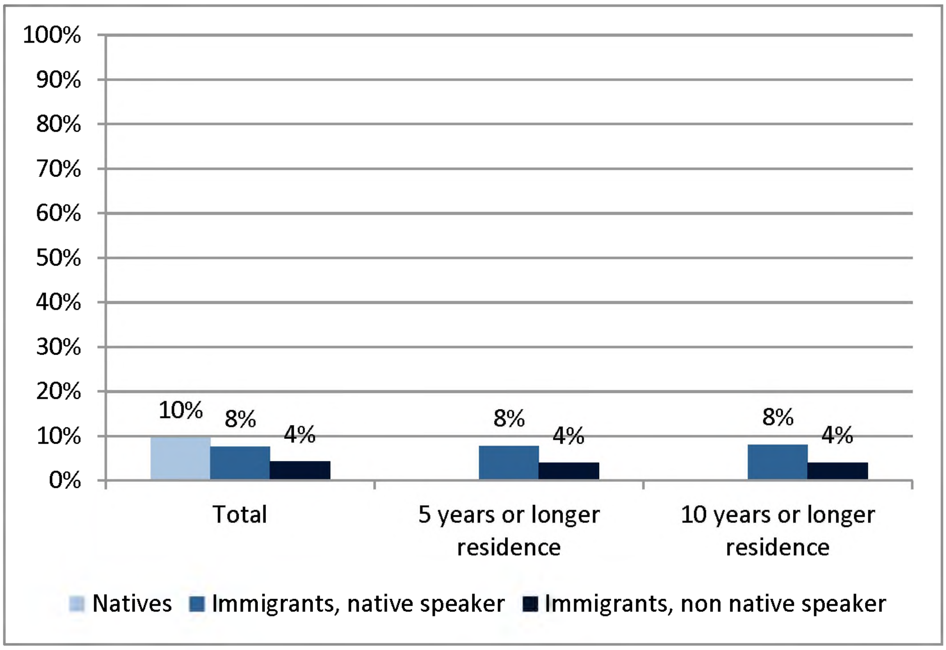


Figure 3: Shares of over-skilled workers by immigrant status and length of residence in host country

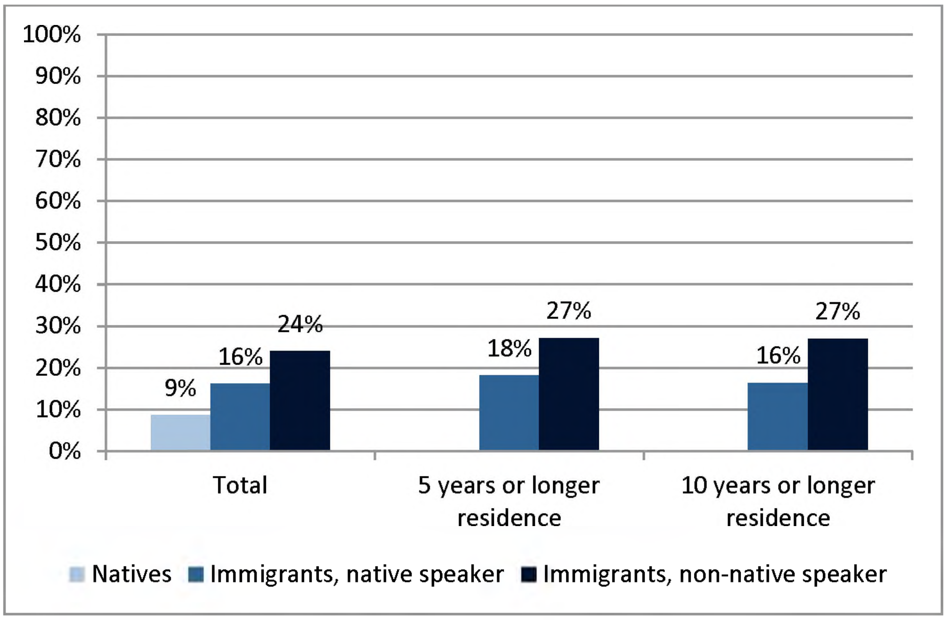


Figure 4: Shares of under-skilled workers by immigrant status and length of residence in host country

Lower shares of over-skilling and higher shares of under-skilling among immigrants may suggest that immigrants' over-qualification does not translate into over-skilling, or rather and even worse, reflects in greater under-skilling among immigrants (see Cim, et al., 2017). This contradicts the suggested hypotheses above. In the following paragraphs I present the results of regression analyses taking various additional factors into account in order to test my hypotheses.

4.2 Regression results

Table 2 presents the regression results for over-skilling.[12] When regressing only migration status on over-skilling (Model 1), both coefficients are below 1 and that of non-native speaking immigrants is statistically highly significant. However, pseudo-R^2 is very low. This result reflects the lower shares of over-skilled workers in this group as well as the results presented by (Cim, et al., 2017). The coefficients increase to larger than 1 after controlling for numeracy skills and years of schooling, yielding a higher pseudo R^2 (Model 4). After controlling for the factors mentioned in equation 2, non-native speaking immigrant workers have a 37.8 % higher chance of being over-skilled than native workers. The coefficient for native speaking immigrants is smaller and not statistically significant (Model 5). Immigrant workers do not, however, have an increased chance of being over-skilled compared to native workers when controlling for professions (Model 6). Over-qualified non-native speaking immigrant workers have even a 90.1 % higher chance of being over-skilled than over-qualified native workers (Model 7). Again, this coefficient is statistically insignificant when controlling for occupations (Model 8). When restricting the analysis to immigrants that lived in the country for more than 5 and 10 years, respectively, immigrant workers do not have a higher chance of being over-skilled than native workers. Interestingly, an increased likelihood for being over-skilled remains for over-qualified non-native speaking immigrant workers at the 10 % level after 5 of residence in the host country (see Table A.1 in Appendix).

[12] I also predicted the likelihood for being over-qualified by immigrant status and my results are in line with previous findings. Results are available upon request.

Table 2: Likelihood of being over-skilled, odds ratios

	Over-skilling							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Immigrant, non-native speaker	0.578***	0.956	0.500***	1.437*	1.378*	1.057	1.901*	1.289
	(0.049)	(0.122)	(0.042)	(0.195)	(0.188)	(0.174)	(0.488)	(0.409)
Immigrant, native speaker	0.928	0.898	0.810+	1.125	1.137	1.076	1.298	1.328
	(0.110)	(0.165)	(0.098)	(0.210)	(0.210)	(0.239)	(0.488)	(0.646)
Numeracy		1.074***		1.087***	1.088***	1.137***	1.087***	1.126***
		(0.002)		(0.002)	(0.002)	(0.003)	(0.005)	(0.009)
Years of schooling			1.181***	0.731***	0.717***	0.955+	0.716***	0.936
			(0.011)	(0.012)	(0.012)	(0.023)	(0.037)	(0.062)
Work experience					0.985**	0.993	0.989	0.998
					(0.004)	(0.005)	(0.009)	(0.012)
Gender					0.828**	0.580***	0.781+	0.563*
					(0.059)	(0.057)	(0.115)	(0.127)
Occupation						incl.		incl.
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.198***	0.000***	0.015***	0.0000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	31,907	31,770	31,556	31,420	31,396	31,396	4,030	4,030
Pseudo-R^2	0.011	0.500	0.034	0.529	0.530	0.700	0.527	0.659
F	7.69***	110.40***	23.99***	96.93***	79.67***	37.04***	18.85***	9.41***

Notes. Logistic Regression model: DV: over-skilling (y/n). Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.

Regression results on under-skilling are presented in Table 3. Vice versa, when regressing only migration status on under-skilling (Model 1), both coefficients are larger than 1 and statistically highly significant. This reflects the higher shares of under-skilled workers in this group as well as the results presented by (Cim, et al., 2017). The coefficients decrease and become smaller than 1 after controlling for numeracy and years of schooling, again yielding a higher pseudo-R^2 (Model 4). After controlling for the factors mentioned in equation 3, non-native speaking immigrant workers are, compared to native workers, 0.65 times as likely to be under-skilled. The coefficient for native speaking immigrants is closer to 1 and not statistically significant (Model 5). Similarly to over-skilling, the coefficient for non-native speaking immigrant workers becomes insignificant when controlling for occupations (Model 6). Over-qualified non-native speaking immigrant workers are, compared to over-qualified native workers, 0.43 times as likely to be under-skilled, without a statistically significantly decreased chance when controlled for occupations (Model 7 and 8).

A statistically significant decreased chance of being under-skilled remains for non-native immigrants that lived in the host country for at least 5 years at the 1 % level and for non-native immigrants that lived in the host country for at least 10 years at the 10 % level. The same is true for over-qualified non-native immigrants when accounting for length of residence (see Table A.1 in Appendix). The results do not differ when controlling whether there is a child in the household or whether the workers participated in further education during the last 12 months (see Table A.2 in Appendix).

Table 3: Likelihood of being under-skilled, odds ratios

	Under-skilling							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Immigrant, non-native speaker	2.712***	0.877	3.069***	0.612***	0.651***	0.891	0.428**	0.673
	(0.140)	(0.084)	(0.169)	(0.061)	(0.066)	(0.125)	(0.106)	(0.209)
Immigrant, native speaker	1.597***	1.198	1.814***	0.868	0.900	0.956	0.652	0.912
	(0.139)	(0.173)	(0.162)	(0.137)	(0.144)	(0.176)	(0.204)	(0.361)
Numeracy		0.938***		0.927***	0.927***	0.882***	0.924***	0.877***
		(0.001)		(0.002)	(0.002)	(0.003)	(0.005)	(0.009)
Years of schooling			0.821***	1.357***	1.365***	1.063**	1.385***	1.085
			(0.007)	(0.023)	(0.022)	(0.019)	(0.079)	(0.079)
Work experience					1.010*	0.998	1.007	0.991
					(0.004)	(0.005)	(0.012)	(0.013)
Gender					1.005	1.918***	1.038	2.142**
					(0.070)	(0.200)	(0.204)	(0.622)
Occupation						incl.		incl.
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.168***	2.607E+06***	3.19***	6.497E+05***	4.782E+05***	2.28E+13***	4.252E+05***	5.01E+13***
	(0.000)	(9.92E+05)	(2.55E+05)	(2.55E+05)	(1.93E+05)	(2.18E+13)	(5.59E+05)	(1.52E+14)
Observations	31,907	31,770	31,556	31,420	31,396	31,396	4,030	4,030
Pseudo-R^2	0.027	0.545	0.066	0.576	0.577	0.722	0.600	0.743
F	30.31***	156.70***	57.86***	130.49***	119.64***	42.00***	19.16***	7.02***

Notes. Logistic Regression model: DV: under-skilling (y/n). Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.

Interestingly, when analyzing the immigrants' likelihood of numeracy mismatch by occupation (Table 4 and Table 5) the odds ratios switch in some cases from higher to lower chances and vices versa. However, only few findings are statistically significant and using only one plausible value overestimates statistical significance (von Davier, et al., 2009). I therefore will only mention the two statistically significant results on the 1%-level: Non-native speaking immigrants working as professionals (ISCO group 2) are more likely to be under-skilled than native workers of the same profession and non-native speaking immigrants in ISCO group 5 (services and sales workers) are less likely to be under-skilled.

Table 4: Likelihood of being over-skilled by occupation, odds ratios

	Model 9 ISCO 1 (Managers)	Model 10 ISCO 2 (Professionals)	Model 11 ISCO 3 (Technicians and Associate Pro-fessionals)	Model 12 ISCO 4 (Clerical Support Workers)	Model 13 ISCO 5 (Services and Sales Workers)	Model 14 ISCO 7 (Craft and Re-lated Trades Workers)	Model 15 ISCO 8 (Plant and Ma-chine Operators and Assemblers)	Model 16 ISCO 9 (Elementary Occupations)
Non-native speaking immgrant	0.613	0.669^{+}	0.754	0.759	0.906	0.712	1.356	1.846
	(0.292)	(0.163)	(0.233)	(0.329)	(0.280)	(0.410)	(0.686)	(0.791)
Native speaking immgrant	0.252*	0.912	0.777	0.804	1.862^{+}	1.194	0.501	1.364
	(0.158)	(0.264)	(0.320)	(0.594)	(0.655)	(0.537)	(0.353)	(0.991)
Numeracy	1.192***	1.157***	1.173***	1.247***	1.126***	1.120***	1.172***	1.136***
	(0.014)	(0.005)	(0.009)	(0.018)	(0.006)	(0.006)	(0.017)	(0.015)
Years of schooling	.753***	1.065	1.017	1.039	0.917^{+}	0.848**	0.926	1.133
	(0.047)	(0.035)	(0.041)	(0.071)	(0.041)	(0.053)	(0.062)	(0.091)
Work experience	.949***	0.991	0.991	1.008	0.986	0.980^{+}	1.024	0.989
	(0.013)	(0.008)	(0.009)	(0.015)	(0.009)	(0.011)	(0.016)	(0.016)
Gender	1.299	0.417***	0.548***	0.925	0.387***	0.369*	1.718	0.369**
	(0.327)	(0.053)	(0.087)	(0.238)	(0.069)	(0.167)	(0.780)	(0.134)
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,273	8,435	6,114	2,997	4,102	2,838	2,128	1,408
Pseudo-R^2	0.741	0.690	0.727	0.800	0.652	0.651	0.755	0.716
Wald-χ^2	265.74***	1070.05***	591.21***	287.61***	578.19***	445.34***	152.26***	115.34***

Notes. Logistic Regression model: DV: over-skilling (y/n). ISCO 0 (Armed Forces) and ISCO 6 (Skilled Agricultural, Forestry and Fishery Workers) excluded. Only one plausible value used, statistical significance of results may be overestimated. Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.

Table 5: Likelihood of being under-skilled by occupation, odds ratios

	Model 9 ISCO 1 (Managers)	**Model 10** ISCO 2 (Professionals)	**Model 11** ISCO 3 (Technicians and Associate Professionals)	**Model 12** ISCO 4 (Clerical Support Workers)	**Model 13** ISCO 5 (Services and Sales Workers)	**Model 14** ISCO 7 (Craft and Related Trades Workers)	**Model 15** ISCO 8 (Plant and Machine Operators and Assemblers)	**Model 16** ISCO 9 (Elementary Occupations)
Non-native speaking immgrant	0.891	1.721**	1.152	1.261	0.514**	0.910	0.834	1.237
	(0.418)	(0.331)	(0.315)	(0.681)	(0.106)	(0.230)	(0.401)	(0.556)
Native speaking immgrant	0.495	1.415	1.614	3.491+	1.034	0.616	1.093	1.054
	(0.292)	(0.354)	(0.552)	(2.544)	(0.366)	(0.252)	(0.716)	(0.779)
Numeracy	0.860***	0.860***	0.835***	0.806***	0.885***	0.897***	0.828***	0.836***
	(0.007)	(0.004)	(0.007)	(0.013)	(0.005)	(0.006)	(0.016)	(0.016)
Years of schooling	1.274***	0.963	0.952	1.041	1.040	1.086+	1.015	0.916
	(0.064)	(0.033)	(0.041)	(0.071)	(0.034)	(0.049)	(0.055)	(0.082)
Work experience	1.045***	0.977**	1.024*	0.991	0.991	0.993	1.022	0.997
	(0.013)	(0.007)	(0.010)	(0.014)	(0.008)	(0.010)	(0.017)	(0.017)
Gender	1.106	3.626***	0.694*	1.149	1.793**	2.767**	1.859	1.042
	(0.246)	(0.536)	(0.125)	(0.349)	(0.338)	(1.065)	(0.739)	(0.457)
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	1.090E+14	3.140E+17	2.380E+18	3.250E+19	5.720E+11	6.930E+10	6.510E+17	2.690E+18
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,273	8,435	6,114	2,997	4,102	2,838	2,128	1,408
Pseudo-R^2	0.761	0.745	0.792	0.823	0.708	0.705	0.826	0.84
Wald-χ^2	351.50***	1113.96***	507.19***	219.01***	609.55***	351.99***	116.25***	132.94***

Notes. Logistic Regression model: DV: under-skilling (y/n). ISCO 0 (Armed Forces) and ISCO 6 (Skilled Agricultural, Forestry and Fishery Workers) excluded. Only one plausible value used, statistical significance of results may be overestimated. Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.

5 Discussion

While the descriptive analyses show that there are more under-skilled and less over-skilled immigrant workers than native workers (see also Cim, et al., 2017) it is necessary to draw a more nuanced picture. My results show that, by comparing individuals on the same skill and qualification level, non-native speaking immigrant workers are more likely to be over-skilled regarding numeracy skills than native workers. At the same time, they are less likely to be under-skilled. Thus, hypotheses H1a and H1b are only confirmed for non-native speaking immigrants. This is an important finding as it indicates, as suggested in previous research (Dustmann & van Soest, 2002; Green, et al., 2007; Sanromá, et al., 2015) that languages skills help to transfer skills from the home to the host country.

Their likelihood of being over-skilled is increased when they are also over-qualified. This implies a chance to be genuinely mismatched that is almost twice as high for over-qualified non-native speaking immigrant compared to over-qualified native workers. This reflects the barriers to qualification adequate employment for immigrants. While native workers may be over-qualified due to heterogeneity of skills within on qualification level (Allen & van der Velden, 2001), and thus employed adequately regarding their actual skills, this might not be the case for over-qualified immigrants. Here over-qualification is likely to also translate into actual over-skilling.

Occupational choice plays a major role for immigrants' labor market placement (Peri & Sparber, 2009, 2011). Hence, my results vary for different occupations on the ISCO 1-digit level with the likelihoods of over- and under-skilling for immigrants even switching in some occupation groups. However, due to small sample sizes, these analyses are only performed with one plausible value and may vary with additional plausible values and need to be interpreted with care. I focus only on statistically significant results in the 1%-level. Very interestingly, non-native speaking immigrants working as professionals (f.ex., researchers, engineers, IT specialists, and doctors) are more likely to be under-skilled compared to their native colleagues. Typically, workers in these occupations are high-skilled. Their under-skilling may reflect their lower language proficiency which may not necessarily affect their work performance. Very often they do not necessarily need to be proficient in the host country's language as English is often the main language spoken in these work environments. Hence, these highly skilled immigrants may actually match their job well as the results tend towards a lower likelihood of over-skilling.

Peri and Sparber (2009, 2011) show that native workers tend to select into communicative jobs once an influx of migrants occur while immigrants select into manual and quantitative jobs. However, non-native speaking immigrant working in services and sales (ISCO group 5) (typically considered as communicative jobs) are less likely to be under-skilled. This finding could be explained by a phenomenon of immigrants not finding employment in the host country opening shops that sell goods from their home country and which are also mainly frequented by other immigrants of the same origin. The immigrants analyzed in this sample may work in the family shop or for employers of the same descent and do not even need to speak the host country's language while working in sales. Hence, hypothesis H2 is partly confirmed.

Non-native immigrants who stayed in the country for at least 5 (and 10) years generally do not have increased chances of over-skilling compared to native workers (Table A.1). However, they do still after 5 years of residence, if they are also over-qualified. This suggests that, just like over-qualification, the likelihood of over-skilling decreases with length of stay, for example because language proficiency increases or because immigrant workers are able to better signal their actual skills through work experience in the host country. However, it seems that immigrants in positions in which they are over-qualified may have more difficulties signaling their actual skills as they cannot fully employ their skills when they are genuinely mismatched. The lower likelihood for non-native speaking immigrants to be under-skilled remains after 5 and 10 years.

Thus, for non-native speaking immigrant workers mismatch of qualification and actual skills appears to be a severe problem in the examined OECD countries. This is an important finding, as it suggests that non-native speaking immigrant bring skills from their home countries that are not put into effective use in the home country. Consequences of not applying one's skills can be severe as they may depreciate over time (Krahn & Lowe, 1998; Schooler, 1984). They will be missing the necessary skills to find skill and qualification adequate employment later on and this can lead immigrants to remain in their over-qualified jobs in which they underutilize their skills.

Several limitations, beyond those mentioned above, make the analyses on skill mismatch among immigrant workers difficult and constrain the interpretation of my results:

First, the *number of immigrants in the country samples* is rather low. In order to allow further research on skills and skill mismatch I suggest an oversample of immigrants in further PIAAC cycles. This is especially important as questions regarding labor market integration are closely related to circumstances leading up to migration which can be reflected in different waves of migration. A distinction between different waves of migration is not possible with the data currently available. Questions of labor market integration will, however, become even more urgent within the next years when a large number of refugees from the Middle East will endeavor to integrate into European labor markets.

Second, further *background information* is needed when analyzing skills and skill mismatch among immigrants, such as the country of origin (see Levels, Dronkers, & Kraaykamp, 2008) and language spoken at work. Information on whether immigrants moved from less developed origin countries to industrialized destination countries[13] and their motivation to come to the host country (e.g., hoping for better economic perspectives, coming as an ex-patriate, or coming as refugees) can shed further light on immigrants' skill mismatch. Also the information on whether or not the educational degree was obtained abroad is not very exact in PIAAC and needs improvement in further cycles.

Furthermore regarding the importance of the native language, I believe it could be feasible to *test immigrants in their native language* as various translations of the assessment into other languages exist for the different participating countries. In a globalized world, language use and the use of related skills in the work place will be more and more internationalized. Therefore competencies tested in the language of the host country do not supply enough evidence of adequate job placement. This is especially true for high-skilled jobs such as research and development, where the working language is often English, or for small businesses of immigrant workers for which only limited knowledge of the host countries' languages is necessary.

And fourth, my results are based on *cross-sectional analyses*. A panel on immigrant's and native skills could shed more light on unobserved heterogeneity, i.e. cohort effects, and on causal links between immigrant status, language proficiency and over-skilling and its changes over time and length of residence.

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[13] This information is, unfortunately, not available for each country that participated in PIAAC due to data restrictions.

6 Conclusion

In this paper I analyze the incidence of numeracy mismatch among native and immigrant workers. I find that, comparing workers on the same qualification and skill level, non-native speaking immigrants are more likely to be over-skilled. This is especially true for non-native speaking immigrant workers who are already over-qualified, suggesting that this group of workers is more likely to genuinely mismatch than natives. I do not find increased over-skilling among native-speaking immigrants. This is in line with previous research on over-qualification that showed that language proficiency also reduces the risk of over-qualification (Green, et al., 2007; Sanromá, et al., 2015).

This is an important contribution to the literature on immigrants' over-qualification that has so far, due to the lack of appropriate skill measures, only focused on formal qualification mismatch (see Piracha & Vadean, 2013). Recent large scale assessment data from PIAAC allows to jointly analyzing immigrants' over-qualification and their match regarding actual skills and revealing actual skill mismatch.

As Peri and Sparber (2009, 2011) have shown, immigrants and natives select into different type of occupations. This likely has an impact on over-qualification (Chiswick & Miller, 2011) as well as on over-skilling. I can show that occupations do impact my findings and that my results vary across occupations. Further research on this aspect should shed more light on the problems of over-qualification and over-skilling of immigrants in different professions so that both can be targeted more precisely.

Also, barriers preventing immigrants from adequately integrating into the labor market should be examined based on these new findings. Intensive language classes can help to improve immigrants' chances to apply their skills at work in the long run. However, immigrants are only motivated to learn the host country's language when their migration is permanent (Dustmann & Glitz, 2011). They may, however, be demotivated to permanently stay in the host country if they are mismatched regarding their qualification and their skills. Also, better ways for immigrants to signal and prove their actual skills to potential employers should be discussed as they may help them to find a better match despite language deficits and reduced signaling functions of foreign degrees.

My findings can also help to better understand the compensation of additional years of schooling, which is found to be lower compared to natives (Chiswick & Miller, 2008). Further research should, thus, investigate the interplay of qualification and skill mismatch of immigrants regarding earnings. This can also shed light on the motivation of immigrants to remain in mismatched position. If compensation of required and additional years of schooling and surplus skills is lower for immigrants than for natives but still higher than in the home country they may stay for the higher earnings and willingly accept mismatch.

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A.1 Regression table: Numeracy mismatch by length of stay

	Over-skilling				Under-skilling			
	Immigrants that stayed at least 5 years		Immigrants that stayed at least 10 years		Immigrants that stayed at least 5 years		Immigrants that stayed at least 10 years	
	All	Over-qualified workers	All	Over-qualified workers	All	Over-qualified workers	All	Over-qualified workers
Immigrant, non-native speaker	1.194	1.748^{+}	1.138	1.513	0.713**	0.466*	0.782^{+}	0.497^{+}
	(0.195)	(0.560)	(0.231)	(0.672)	(0.079)	(0.135)	(0.103)	(0.187)
Immigrant, native speaker	1.027	1.285	0.941	1.311	0.887	0.720	0.981	0.926
	(0.268)	(0.691)	(0.292)	(1.052)	(0.190)	(0.270)	(0.247)	(0.486)
Numeracy	1.089***	1.087***	1.090***	1.087***	0.927***	0.925***	0.926***	0.925***
	(0.002)	(0.005)	(0.003)	(0.005)	(0.002)	(0.005)	(0.002)	(0.006)
Years of schooling	0.717***	0.712***	0.715***	0.717***	1.372***	1.431***	1.380***	1.450***
	(0.013)	(0.041)	(0.013)	(0.044)	(0.024)	(0.094)	(0.024)	(0.121)
Work experience	0.985**	0.991	0.984**	0.989	1.010*	1.007	1.009*	1.004
	(0.005)	(0.010)	(0.005)	(0.010)	(0.004)	(0.013)	(0.004)	(0.014)
Gender	0.818*	0.765	0.824*	0.784	0.975	1.019	0.958	0.932
	(0.064)	(0.125)	(0.065)	(0.138)	(0.075)	(0.210)	(0.072)	(0.231)
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.000***	0.000***	0.000***	0.000***	5.42E+05***	3.33E+05***	5.66E+05***	3.31E+05***
	(0.000)	(0.000)	(0.000)	(0.000)	(2.78E+05)	(5.51E+05)	(2.88E+05)	(5.98E+05)
Observations	28,114	3,387	26,906	3,046	28,114	3,387	26,906	3,046
Pseudo-R^2	0.531	0.523	0.531	0.516	0.568	0.579	0.565	0.571
F	80.18***	21.49***	77.93***	19.69***	115.29***	15.97***	110.74***	13.80***

Notes. Logistic Regression model: DV: over-skilling/under-skilling (y/n). Australia excluded from analyses due to data restrictions. Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.

A.2 Regression tables: Further controls

	Over-skilling				Under-skilling			
	Controlled for child in household		Controlled for participation in further education		Controlled for child in household		Controlled for participation in further education	
	All	Over-qualified workers	All	Over-qualified workers	All	Over-qualified workers	All	Over-qualified workers
Immigrant, non-native speaker	1.384*	1.905*	1.332*	1.830*	0.653***	0.428**	0.674***	0.453**
	(0.191)	(0.501)	(0.185)	(0.474)	(0.067)	(0.105)	(0.068)	(0.113)
Immigrant, native speaker	1.138	1.300	1.126	1.273	0.902	0.651	0.921	0.694
	(0.213)	(0.507)	(0.210)	(0.499)	(0.145)	(0.204)	(0.147)	(0.217)
Numeracy	1.088***	1.087***	1.089***	1.088***	0.927***	0.924***	0.926***	0.922***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.005)
Years of schooling	0.717***	0.7156***	0.724***	0.723***	1.364***	1.385***	1.347***	1.357***
	(0.012)	(0.038)	(0.012)	(0.039)	(0.022)	(0.080)	(0.022)	(0.078)
Work experience	0.986**	0.989	0.985**	0.990	1.011**	1.007	1.009*	1.005
	(0.004)	(0.010)	(0.004)	(0.009)	(0.004)	(0.012)	(0.004)	(0.012)
Gender	0.828*	0.781	0.820**	0.782	1.004	1.037	1.032	1.077
	(0.059)	(0.117)	(0.059)	(0.117)	(0.071)	(0.207)	(0.072)	(0.213)
Have a child	1.066	1.015			1.029	1.017		
	(0.078)	(0.177)			(0.091)	(0.258)		
Participated in further education			0.682***	0.695*			1.511***	1.708*
			(0.048)	(0.122)			(0.106)	(0.350)
Country	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.000***	0.000***	0.000***	0.000***	4.59E+05***	4.19E+05***	5.58E+05***	5.27E+05***
	(0.000)	(0.000)	(0.000)	(0.000)	(2.07E+05)	(5.57E+05)	(2.26E+05)	(7.71E+05)
Observations	31,395	4,030	31,390	4,030	31,395	4,030	31,390	4,030
Pseudo-R^2	0.531	0.528	0.533	0.53	0.577	0.600	0.579	0.603
F	85.69***	22.47***	85.86***	22.20***	113.96***	17.88***	114.14***	17.83

Notes. Logistic Regression model: DV: over-skilling/under-skilling (y/n). Robust standard errors in parentheses. Sampling weights used in the regression. *** p < .001. ** p < .01* p < .05. + p < .1.