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

(Draft version)

Abstract

Participation in the labor market is an important aspect of immigrants' successful integration. Previous research on this topic particularly focuses on education mismatch (e.g., Dustmann & Glitz, 2011; Piracha & Vadean, 2012) and on the selection into certain occupations (Peri & Sparber, 2009, 2011). Reasons for mismatch among immigrants can be imperfect transferability and signaling of skills (Chiswick & Miller, 2007, 2009a). However, over-qualification does not necessarily imply that someone is over-skilled when it comes to actual skills and vice versa (Allen & van der Velden, 2001). Reasons for the selection into certain occupations are comparative advantages in certain skills compared to natives (Peri & Sparber, 2009, 2011).

In this paper I bring these two research branches together and investigate the occurrence of immigrants' and natives' education mismatch in different occupations. I also add the dimension of skill mismatch when examining the employment fit of immigrants and natives (Allen, Levels, & van der Velden, 2013; Perry, Wiederhold, & Ackermann-Piek, 2014).

The Programme for the International Assessment of Adult Competencies (PIAAC 2012) provides most recent data on basic skills of the working-age population (24 to 54 years). With this data I compare education and literacy mismatch of first generation immigrants and natives in manual and quantitative jobs in 13 OECD countries.

My results suggest that over-skilling is a minor problem for immigrant workers, as their over-qualification does not always translate into over-skilling. This suggests that mechanisms are in place that correct for inappropriate signaling of skills (reflected in over-qualification) through foreign educational degrees.

Keywords: education mismatch, skill mismatch, integration, labor migration, PIAAC

JEL: J15, J24, J61

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

Integration into the labor market is more difficult for immigrants than for natives. Immigrants have disadvantages when they do not have sufficient skills in the host country's dominant language (Dustmann & van Soest, 2002), often select into risky jobs (Orrenius & Zavodny, 2009), and need to rely on ties to non-migrant friends (Lancee & Hartung, 2012). A major problem for immigrant workers is over-qualification. Immigrants face it more often than natives (e.g., Dustmann & Glitz, 2011; Piracha & Vadean, 2012). The main reasons for over-qualification among immigrants are imperfect transferability and signaling of skills (Chiswick & Miller, 2007, 2009a) However, over-qualification does not necessarily imply that someone is over-skilled when it comes to actual skills and vice versa (Allen & van der Velden, 2001).

There is further evidence that immigrants and natives select into different types of occupations in which each group has comparative advantages. For example, Peri and Sparber (2009, 2011) examined the labor market integration process of immigrants in the U.S. and could show that immigrants specialize in manual and quantitative jobs while natives select into communicative jobs.

While previous literature focused on immigrants' selection into certain types of jobs (Peri & Sparber, 2009, 2011) and immigrants' over-qualification (Chiswick & Miller, 2009b; Dustmann & Frattini, 2013; Nowotny, 2016; Piracha & Vadean, 2013) separately, this paper brings these two research branches together. First, I look at immigrants' over-qualification at the workplace in different types of occupations (manual, quantitative, communicative). Second, I add the aspect of (mis-)match regarding actual possessed skills (rather than formal qualification). Due to insufficient skill measures, this aspect has been neglected in the previous literature. Recent data provided by the Programme for the International Assessment of Adult Competencies (PIAAC) allows us to investigate natives' and immigrants' qualification and skill mismatch in 13 countries while simultaneously looking at the task intensity at their workplace (Allen et al., 2013; Perry et al., 2014). As I investigate immigrants' labor market integration in 13 different countries, I distinguish four different country groups based on their history of immigration and migration policies (Bauer, Lofstrom, & Zimmermann, 2001; Freeman, 1995).

After reviewing previous findings on immigrants, their qualification mismatch and selection into occupation, I derive hypotheses on the occurrence of qualification and skill mismatch among immigrants compared to natives in different types of occupations. In section 3 I describe the empirical approach to test my hypotheses. I describe my results in section 4 and discuss them in section 5.

Theoretical Background

Developed countries attract immigrants as they hope to find better living conditions in their new host country. Therefore most OECD countries have seen an increase in immigration in recent years. Immigrants thereby differ regarding their educational attainments. Highly educated immigrants often come into the country in the prospect of better job opportunities than they have in their home country. Low educated immigrants enter the country often through family-reunification, as refugees, or even as illegal immigrants (OECD, 2014).

Those 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). However, despite high motivation to work and favorable self-selection, labor market integration can be difficult for immigrants. Typically, factors, such as gender, language skills, and country of origin impact the chances of finding employment in the host country and the immigrants' wages (Dustmann & van Soest, 2002; Fleischmann & Dronkers, 2010; OECD, 2012).

Furthermore, there is evidence that migrants and natives select into different type of jobs. Orrenius and Zavodny (2009) found that immigrants often select into risky professions with higher risks of injury and higher fatality rates. This could be due to lower chances to find adequate jobs and/or to receive a risk premium to compensate for lower wages compared to natives. Peri and Sparber (2009, 2011) can show that migrants tend to select into professions in that they have comparative advantages, such as manual and quantitative jobs and are less likely to select in communicative jobs due to weaker language skills compared to their native counterparts. Research by Forlani, Lodigiani, and Mendolicchio (2015) supports these findings as they find that especially low-skilled immigrants choose jobs in the household service sector. This in turn allows increased labor supply of high-skilled native women.

Throughout the next sections I combine the research findings on migrants' occupational choice with findings on migrants' over-qualification and derive hypotheses on migrants' mismatch on the labor market. Doing so, I not only focus on mismatch regarding formal qualifications but add an important additional dimension: the (mis)match of actual skills of immigrant workers.

Migration history, migration policy, and their impact on labor market integration

Visintin, Tijdens, and van Klaveren (2015) can show that the likelihood of migrant workers being over-qualified is related to differences in host countries as well as home countries. In order to account for differences in migrants' occupational choice and mismatch on the labor market I draw on research by Bauer et al. (2001) and Freeman (1995) to distinguish between four different country groups. The distinction is based on their migration policies nowadays and in the past which shapes the composition of migrant populations in these countries. In Table 1 I present the countries examined in this paper and the country groups each country is assigned to.

Table 1: Countries examined and assigned country groups

Country group	Country
English speaking settler countries	Australia
	Canada
	USA
Post-colonial and guest worker migration countries	Austria
	France
	Netherlands
	Germany
	United Kingdom
New immigration countries	Ireland
	Spain
Nordic countries	Denmark
	Norway
	Sweden

Immigrant workers and over-qualification

Migrants often have difficulties finding employment in their host country (OECD, 2016). Problems applying ones skills in the new labor market after immigrating into the host country can have different reasons. They may arise due to limited language skills (Green, 1999), cultural differences (Bevelander, 2001; Rosholm, Scott, & Husted, 2006), not knowing how the labor market operates, or different skill sets required in the same profession in another country, caused by different measures and conventions used. The technology level may also be different in the host country as a result of different endowments of resources and, thus, different relative factor prices (Chiswick & Miller, 2009a).

If migrants do find employment they are more often over-qualified immigrants than native workers (see Piracha & Vadean, 2012 for a literature review). 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). 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, 2009a, p. 8) might downgrade immigrants' credentials (Piracha & Vadean, 2012). 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. Also, very often foreign education certificates are not accepted abroad because of occupational licensing. Thus, migrants, just 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. Some may take a job below his or her qualification level while working on acquiring the license required in the host country. Hence, the length of residence allows one to acquire the necessary degrees or accumulate job references that provide additional information regarding the immigrant's skill suggesting that the observed effects are temporary (Chiswick & Miller, 2009a).

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

H1: In line with previous research ***immigrant workers are more often over-qualified*** *than native workers.*

Migrants' selection of jobs and qualification mismatch

Ottaviano and Peri (2012) suggest that migrants cannot perfectly substitute natives within the same education and experience groups in production. Rather, Peri and Sparber (2009, 2011) argue that migrants specialize in occupations that they have comparative advantages in. Migrants typically have weaker language skills than natives but they possess physical and/or quantitative skills similar to natives. Migrants 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 higher compensation of language/communication skills, it is this selection into different types of professions which let negative wage effects caused by immigration turn out to be lower than commonly anticipated (Ottaviano & Peri, 2012; Peri & Sparber, 2009, 2011).

Migrants' qualification mismatch in manual jobs. Very often, manual jobs do not require advanced cognitive skills (OECD, 2013) and therefore low educational degrees or no degrees at all. As low educational requirements naturally leave a wider spectrum of workers with higher degrees than required, workers in these professions are in general more likely to be over-educated compared to professions that require higher educational degrees. Low-educated migrants typically select into these professions (Peri & Sparber, 2009). I can therefore assume that immigrant workers are more affected by over-qualification in general. I propose, however, that, even by only considering manual workers, the rate of over-qualification is higher for migrants than for natives. Due to limited acceptance of foreign credentials (and therefore limited abilities to signal their skills owning foreign degrees, Chiswick & Miller, 2009a), migrants are encouraged to take manual jobs with requirements below the (already low) educational degree that they possess. Such jobs can be temporary jobs in the manual sector involving elementary tasks. This is especially true for migrants who have recently migrated to the host country. While working in these low-skilled temporary jobs; migrants can better signal their actual skills to their employer and may move on to better matched positions later on. Thus,

H2: Immigrant workers in manual occupations are ***more often over-qualified*** *than native workers.*

Migrants' qualification mismatch in quantitative jobs. Highly educated migrants tend to select into high-skilled quantitative jobs. Peri and Sparber (2011) use the O*NET database and combine it with U.S. Census data and further individual level survey data to show that highly educated migrants who possess graduate degrees select into jobs with a high intensity of quantitative skills and low intensity of interactive skills. These jobs are, for example, analysts, economists, physicists, and mathematicians. On the contrary, highly educated natives have a higher share in occupations such as teaching and law. Typically, immigrants PhD graduates remain in their field of occupation while natives more often change to other fields. Levin, Black, Winkler, and Stephan (2004) find evidence that a higher share (7.6 %) of native PhD graduates in science and engineering take jobs outside this field than immigrant PhD graduates in the same field (4.2 %). One reason can be that “science involves internationally transferable skills in contrast to the tendency for the humanities to be much more country specific” (Chiswick, 1999, p. 216).

There are factors that suggest that over-education is a lesser problem for highly educated migrants in the high-skilled quantitative sector. First, higher job requirements leave a smaller spectrum of workers with higher degrees than required compared to jobs with lower educational requirements. This suggests that workers in these professions are in general less likely to be over-educated compared to professions that require lower educational degrees. Second, one can argue that higher degrees are easier to compare across educational systems than lower degrees which are often country or region specific, such as vocational education in the German speaking countries in mid-Europe. Especially doctorate degrees are highly specialized “requiring the investment of a great deal of time and effort, and the training is very specific” (Borjas, 2006, p. 4). To support this view, Borjas (2006) as well as Bound and Turner (2006) find no wage differences between U.S. born and foreign PhD graduates. Third, Peri and Sparber (2011) argue, following research by Bhagwati and Rao (1999) and Chiswick (1999), that substitutability, meaning the replacement of native workers with immigrant workers, is restricted to quantitative jobs and may be due to selection. Immigrants coming to the new host country may focus on quantitative sciences because it involves internationally transferable skills in contrast to more country specific humanity sciences.

Despite these arguments, various other reasons for immigrants' over-qualification remain. They may still have difficulties to signal their skills with educational degrees below the PhD level (Chiswick & Miller, 2009a), lack sufficient knowledge of the host country's labor market or they may be discriminated based on foreign sounding names (Carlsson & Rooth, 2008; Oreopoulos, 2009) or their nationality (Bratsberg, Ragan, & Nasir, 2002). Therefore over-qualification in quantitative occupations may still exist to a greater extent for immigrant than for native workers, even though this increase might be smaller compared to manual occupations. Thus,

H3: Immigrant workers in quantitative occupations are more often over-qualified than native workers.

Migrants' skill mismatch

The previous findings and the proposed hypotheses on immigrants' over-qualification raise the question of whether this qualification mismatch translates into actual skill mismatch. The terms qualification mismatch and skill mismatch are often used interchangeably as education was and is still often used as a proxy for skills. Since large-scale assessments of skills, such as PIAAC, are now available, I should carefully distinguish between the two constructs. Skill mismatch occurs when the skills possessed by workers are lower or higher than the level of skills required at the workplace. If possessed skills are lower, workers are under-skilled. If possessed skills are higher, workers are over-skilled. Allen and van der Velden (2001) argue that 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. Therefore the authors show that only a small proportion of wage effects of education mismatch are accounted for by actual skill mismatch.

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 literacy mismatch, meaning the respondent's match regarding the "understanding, evaluation, usage and engagement with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (Jones et al., 2009, p. 6). Literacy is an integral skill for daily life and is needed for achieving one's goals at work and in daily life. It also serves as an indicator for the extent to which immigrants have achieved important prerequisites for social participation in the host country (Maehler, Massing, & Rammstedt, 2014). However, immigrants' language skills are a necessary prerequisite of literacy skills tested in the language of the host country.[1]

So far there has been no research on actual skill mismatch among immigrants. There are, thus, no theoretical arguments that can clearly suggest whether skill mismatch is a problem for immigrant workers and, if so, whether there are more often over-skilled or more often under-skilled. Figure 1 presents the shares of over- and under-skilled native and immigrant workers by country group. These first descriptive results suggest that immigrants are less likely to be over-skilled in their job compared to natives. However, in each country group there is a much higher share of under-skilled immigrant workers compared to native workers. Compared to over-qualification, the shares of skill mismatch appear rather small. While the shares of over-qualification range between 20 % and 47 % (and between 20 % and 35 % if I only consider natives) across all country groups[2], the share of skill mismatch can range between 3 % and 40 % (and between 5 % and 14 % if only native workers are considered). Thus, skill mismatch appears to be a smaller problem compared to qualification mismatch.

[1] Measuring numeracy mismatch would not solve the language problem as all tasks, also the numeracy tasks, were presented in the countries' official languages.

[2] Shares of under-qualification are typically lower. For operationalization of qualification mismatch see Section "Empirical Approach". Results available upon request.

However, while there is heterogeneity in educational degrees and an individual who is over-qualified may be employed appropriately according to his or her skills, the problem of actual skill mismatch is more severe. If actual possessed skills are not used at work, the mismatched individual may lose these skills (Krahn & Lowe, 1998; Schooler, 1984). At the same time, under-skilling can lead to insufficient skill endowments for facilitating technological development. Furthermore, the comparatively large shares of skill mismatch among immigrants suggest that this is a research question worth pursuing.

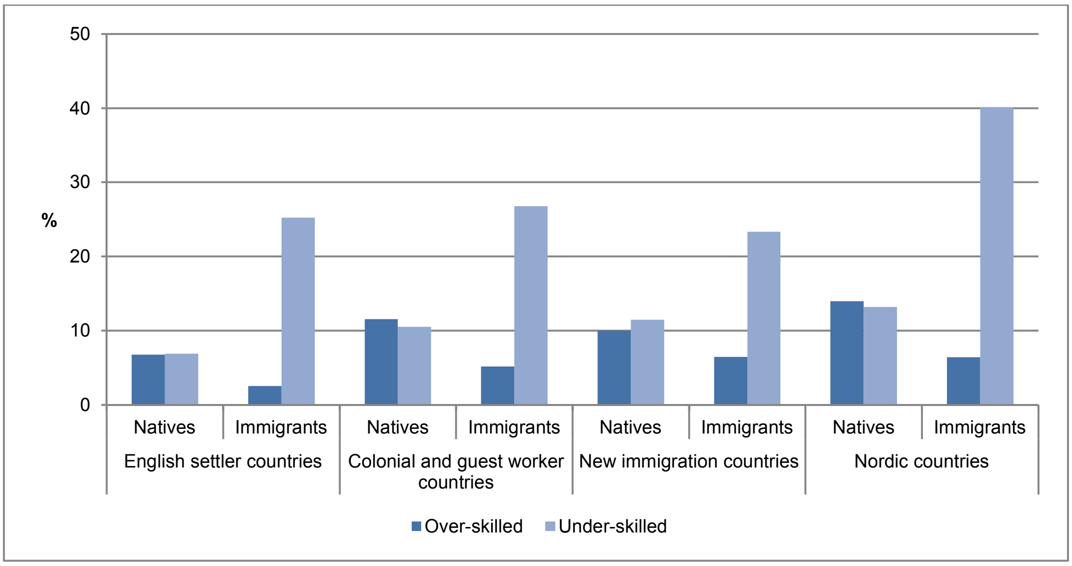

Figure 1: Shares of over- and under-skilled native and immigrant workers by country group

Notes. First generation immigrants compared to natives. For operationalization of skill mismatch see Section “Empirical Approach”. Shares weighted by sampling weights.

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, 2007, 2009a). Furthermore, immigrants may not be able to apply their skills in the host country due to the same problems that typically lead to over-qualification, namely language problems, differences in technology used, or entrance barriers, such as licensing and citizenship (Bratsberg et al., 2002; Chiswick & Miller, 2009a). In this case they are over-skilled regarding these particular skills.

They may at the same time be under-skilled regarding basic skills required in the labor market as they generally possess lower basic skills than natives (Green, 1999; Maehler et al., 2013; Maehler et al., 2014; OECD, 2013). Nowotny (2016) takes a look at self-selection and over-qualification of migrants and draws conclusions for the skill level of over-qualified immigrants. He empirically shows that, if migrants are positively selected, those who are willing to accept jobs for which they are over-qualified are "the worst of the best", meaning negatively selected from the pool of positively selected individuals. Hence, employees are not employed according to their educational degrees but rather according to their skills. These migrants, while being over-qualified, may therefore be well-matched regarding their skills or even under-skilled. This reasoning, however, only applies under the circumstance that the foreign educational degree overstates the individual's actual skills. As soon as the problems associated with over-qualification, such as insufficient signaling of possessed skills (Chiswick & Miller, 2009a), licensing and other entry barriers (Chiswick & Miller, 2009a), and discrimination (Carlsson & Rooth, 2008; Oreopoulos, 2009), exist and immigrants fail to appropriately employ their skills on the labor market, there is a higher chance for immigrants to be over-skilled.

As it is unclear which theoretical arguments have larger impacts on the skill mismatch of immigrants I suggest two hypotheses,

*H4a: Due to an increased likelihood of being over-qualified in their job immigrants are **more often over-skilled** regarding their literacy skills than natives.*

*H4b: Due to lower language skills immigrants are **more often under-skilled** regarding their literacy skills than natives.*

Empirical Approach

Data

I use PIAAC data for my analyses 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 (2015). In addition to this, I use additional national data for Australia (Australian Bureau of Statistics, 2012), Austria (Statistics Austria, 2011/12), Canada (Statistics Canada, 2012) and Germany (Rammstedt et al., 2015).

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.

The countries in focus differ regarding their immigration policies in the past and, as a result, in their immigration population. These differences in immigration policies are likely to affect the integration of immigrants into the labor market. I therefore split the countries into four groups of historic immigration policy regimes (see Table 2).

Sample

A sample of at least 5,000[3] adults was surveyed for PIAAC in each (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 (Mohadjer, Krenzke, & Van de Kerchove, 2014b).

In my analyses I include persons who were between 25 and 54 years old and employed full-time 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 the self-employed.

[3] 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 (Mohadjer, Krenzke, & Van de Kerchove, 2014a). Canada surveyed a large oversample. These differing numbers of cases are corrected in the descriptive analyses and in the regression models by using adjusted weights.

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 an ambiguous theoretical assignment to the other two comparison groups they are excluded from the analyses. Table 2 provides a descriptive overview of the immigrant subsample in the selected countries and the classification regarding the countries' historic regimes of immigration policies.

Table 2: Sample description of first-generation immigrants compared to natives

Country group	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
English speaking settler countries	Australia	33.3	47.7	-9.7	21.0
	Canada	27.8	30.1	-2.3	17.2
	United States	16.1	21.2	17.6	-1.7
Post-colonial and guest worker migration countries	Austria	17.2	25.4	11.9	5.6
	France	11.0	34.6	26.1	-7.5
	Netherlands	10.2	20.4	13.2	-7.0
	Germany	13.7	19.9	20.0	-8.2
	Utd. Kingdom	14.7	33.9	-6.1	18.4
New immigration countries	Ireland	22.2	44.1	-13.4	12.1
	Spain	11.9	59.5	4.6	-15.1
Nordic countries	Denmark	9.9	6.3	9.3	3.1
	Norway	13.0	2.9	4.4	0.4
	Sweden	14.8	6.4	16.2	-0.1

Particularly in the Scandinavian countries (Denmark, Norway, and Sweden) few immigrants are native speakers in their host country's language. This is contrary to Spain, where more than half of the immigrants speak the language of the host country as their mother tongue. Moreover, immigrants in traditional immigration countries such as Australia, Canada, Ireland, and the United Kingdom have often a higher educational attainment than the natives. A deeper look into the data reveals that the host countries differ regarding the immigrants' origin countries. While some PIAAC countries are characterized by a high proportion of immigrants from former colonies, such as France (e.g. from Algeria, Morocco), Spain (e.g. from Peru, Morocco) or United Kingdom (e.g. from Indian, Pakistan), other countries show strong immigration from neighboring countries and territories such as Austria (e.g., from Germany, Bosnia and Herzegovina, see Maehler et al., 2014).[4]

Job tasks

PIAAC also offers information on the skills used at work. Using the information from the job-requirement module in PIAAC (Felstead, Gallie, Green, & Zhou, 2007), I focus on high vs. low use of physical skills at work (equivalent to manual and physical task jobs investigated by Peri and Sparber (2009)) and high vs. low use of numeracy skills at work (equivalent to quantitative task jobs, Peri & Sparber, 2011). In order to get a more fine-grained picture, I distinguish also between basic quantitative and advanced quantitative tasks. Doing so, I may find support for the findings by Peri and Sparber (2011) that highly educated immigrants choose quantitative occupations. For completion, I add the dimension of high vs. low use of influential skills at work (equivalent to communicative jobs, Peri & Sparber, 2009; Peri & Sparber, 2011). I classify a worker as using the respective skills to a small extent when he or she indicated using it less than once a month and as using the respective skills to a large extent when he or she indicated using it at least once a week. Table 3 presents the shares of immigrant and native workers in each occupation type by country group.

[4] No data on countries of origin available in PIAAC for Australia, Ireland, Norway, Sweden and United States.

Table 3: Shares of native and immigrant workers in different occupation types by country group, in percent

		Manual occupations	Quantitative occupations	Basic quantitative occupations	Advanced quantitative occupations	Communi-cative occupations
English speaking settler countries	Natives	45.34	33.71	53.27	15.83	53.58
	Immigrants	43.46	39.21	54.25	25.39	47.75
Post-colonial and guest worker migration countries	Natives	40.00	33.07	47.04	17.77	47.68
	Immigrants	53.80	24.68	36.33	15.20	35.64
New immigration countries	Natives	45.15	28.68	47.10	15.93	44.87
	Immigrants	62.17	22.47	38.20	14.61	37.08
Nordic countries	Natives	39.05	27.88	43.14	13.51	56.05
	Immigrants	53.36	25.72	37.46	18.57	42.90

Operationalization of qualification mismatch

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

Operationalization of skill mismatch

Contrary to qualification mismatch, actual 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.

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) 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.[5] Students and apprentices were also excluded from the sample when deriving these benchmarks.

To derive the skill mismatch measure I followed four steps:

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

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

The regression equations read as follows:

$$\begin{aligned} &Logit\left(Overqualification_{1/0} | X_i = x_i\right) \\ &\qquad = \beta_0 + \beta_1 L_i + \beta_2 S_i + \beta_3 G_i + \beta_4 E_i + \beta_5 O_i + \beta_6 I_i + \beta_7 C_i \end{aligned} \tag{2}$$

$$\begin{aligned} &Logit\left(Overskilling_{1/0} | X_i = x_i\right) \\ &\qquad = \beta_0 + \beta_1 L_i + \beta_2 S_i + \beta_3 G_i + \beta_4 E_i + \beta_5 O_i + \beta_6 I_i + \beta_7 C_i \end{aligned} \tag{3}$$

$$\begin{aligned} &Logit\left(Underskilling_{1/0} | X_i = x_i\right) \\ &\qquad = \beta_0 + \beta_1 L_i + \beta_2 S_i + \beta_3 G_i + \beta_4 E_i + \beta_5 O_i + \beta_6 I_i + \beta_7 C_i \end{aligned} \tag{4}$$

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

where *Overqualification* is a dummy variable taking the value 1 for being over-qualified and 0 otherwise. *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. L is the individual's literacy skills, S is the number of years of schooling (average or most usual time that it takes to complete a qualification), G is a dummy variable taking the value 1 for male and 0 for female, E is the work experience. O is a dummy variable for occupations on the 1 digit level (International Labour Organization, 2012), I is a dummy variable for the individual's migration status, C is a country dummy. [6]

To test my hypotheses (H1 through H4) I define six logistic regression models, estimating the likelihood of being over-qualified (equation 2), being over-skilled (equation 3) and being under-skilled (equation 4). Model 1 is run for all occupations combined. The remaining models are run for workers in manual jobs (model 2), in quantitative jobs (model 3) in basic quantitative (model 4), advanced quantitative (model 5) and in communicative jobs (model 6). I run these models separately for all countries combined and for each country group defined by their historic regimes of immigration policies (see above). The dummy for occupation is dropped in models 2 through 6.

Results

In a first step I want to look at the likelihood of over-qualification among immigrants and natives. Table 4 gives an overview of the estimated increased likelihood of immigrants being over-qualified in their job in the different occupations for all countries and each of the four country groups. While I do not find an increased likelihood of immigrant workers to be over-qualified across all countries and occupations, these results differ for different country groups.

[6] Literacy skills as well as the resulting skill mismatch measures are represented as 10 plausible values (Perry et al., 2014). For this draft, only plausible value 1 is used, the computation with the full set of plausible values will be included in a later, full version of the paper. I expect the results to change only slightly. Literacy skills are divided by 100, to facilitate exposition.

In *English speaking settler countries* being immigrant is not related with a higher likelihood of being over-qualified. This is true in general and in the different occupation types.

Being immigrant is related to a higher likelihood of being over-qualified in *post-colonial and guest worker migration countries* in general (confirming hypothesis 1) and in manual jobs (confirming hypothesis 2) as well as in communicative jobs (at the level of 0.1). The latter is an occupation type into which immigrants are less likely to select.

Similarly, being immigrant is related to a higher likelihood of being over-qualified in *new immigration countries* (at the level of 0.1). I find a higher likelihood for immigrants being over-qualified in manual jobs (confirming hypothesis 2) and basic quantitative jobs.

In *Nordic countries* being immigrant is related to a higher likelihood of being over-qualified in general (confirming hypothesis 1) and also in manual (confirming hypothesis 2), basic quantitative jobs, and influential jobs.

Throughout all country groups I find no evidence that immigrants are more likely to be over-qualified in quantitative and in advanced quantitative jobs (rejecting hypothesis 3). In basic quantitative occupations immigrants in new immigration countries and in the Nordic countries have a higher likelihood to be over-qualified.

The full regression tables can be found in the appendix (A.1).

Table 4: Increased likelihood of immigrant workers being over-qualified by occupation type and country group

	Model 1 (Total)	**Model 2** (Manual Occ.)	**Model 3** (Quantitative Occ.)	**Model 4** (Basic Quantitative Occ.)	**Model 5** (Adv. Quantitative Occ.)	**Model 6** (Communi-cative Occ.)
All Countries	no	no	no	no	no	no
English Speaking Settler Countries	no	no	no	no	no	no
Post-Colonial and Guest-Worker Migration Countries	**yes***	**yes****	no	no	no	**yes^{+}**
New Immigration Countries	**yes^{+}**	**yes****	no	**yes****	no	no
Nordic Countries	**yes*****	**yes*****	no	**yes***	no	**yes****

Notes. Logistic Regression model: DV: over-qualification (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. ** $p < .01$. * $p < .05$. $^{+}$ $p < 0.1$.

The two concepts (education and skill mismatch) define different phenomena (Allen & van der Velden, 2001). As most previous research on labor market integration focuses on immigrants' education mismatch I want to point out differences in the occurrence of both types of mismatches. Thus, in a second step I examine the likelihood of immigrant and native workers to be under-skilled. The likelihood that under-skilling occurs more often for immigrants varies across occupations and country groups.

Correspondingly to the lacking evidence that immigrant workers are over-qualified in *English speaking settler countries* I do not find evidence for an increased likelihood for immigrants to be over-skilled (rejecting hypothesis 4a for this country group). In the remaining country groups I find only partial evidence that immigrants in occupations in which they are more likely to be over-qualified are also over-skilled. Especially, I cannot confirm this to be true in the general worker population in these countries and manual occupations in *post-colonial and guest worker migration countries*. Correspondingly to the increased likelihood of over-qualification among immigrants in manual occupations in *new immigration countries* and *Nordic countries* and in basic quantitative occupations in *new immigration countries* I find a higher likelihood for immigrants to be over-skilled (Table 5). Hence, hypothesis 4a can only partially be confirmed.

The full regression tables can be found in the appendix (A.2).

Table 5: Increased likelihood of immigrant workers being over-skilled by occupation type and country group

	Model 1 (Total)	**Model 2** (Manual Occ.)	**Model 3** (Quantitative Occ.)	**Model 4** (Basic Quantitative Occ.)	**Model 5** (Adv. Quantitative Occ.)	**Model 6** (Communi-cative Occ.)
All Countries	no	no	no	no	no	no
English Speaking Settler Countries	no	no	no	no	no	no
Post-Colonial and Guest-Worker Migration Countries	no	no	no	no	no	**yes***
New Immigration Countries	no	**yes**$^{+}$	no	**yes**$^{+}$	**yes***	**yes**$^{+}$
Nordic Countries	no	**yes**$^{+}$	no	no	no	**yes**$^{+}$

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. ** $p < .01$. * $p < .05$. $^{+}$ $p < 0.1$.

Due to high shares of under-skilling among immigrants (see Figure 1) I also take a look at the likelihood of being under-skilled. However, contrary to these descriptive findings I partially find decreased likelihoods of being under-skilled for immigrants after controlling the aspects literacy skills, gender, education, work experience and occupation. Table 6 summarizes the regression results for a decreased likelihood of being under-skilled as an immigrant. I find evidence for a decreased likelihood for immigrants of being under-skilled in *English speaking settler counties* in general and in manual, advanced quantitative and in communicative occupations. Further, I find a decreased likelihood for immigrants of being under-skilled in the three types of quantitative occupations in *post-colonial and guest worker* *migration countries*, in which I do not find a higher likelihood for them to be over-qualified. This correspondence cannot be found in *new immigration countries* and *Nordic countries.* I do not find evidence for an increased likelihood of under-skilling for immigrant workers. Hypothesis 4b is therefore rejected.

The full regression tables can be found in the appendix (A.3).

Table 6: Decreased likelihood of immigrant workers being under-skilled by occupation type and country group

	Model 1 (Total)	**Model 2** (Manual Occ.)	**Model 3** (Quantitative Occ.)	**Model 4** (Basic Quantitative Occ.)	**Model 5** (Adv. Quantitative Occ.)	**Model 6** (Communi-cative Occ.)
All Countries	**yes***	**yes***	no	**yes***	**yes***	**yes***
English Speaking Settler Countries	**yes***	**yes***	no	no	**yes***	**yes***
Post-Colonial and Guest-Worker Migration Countries	no	no	**yes****	**yes****	**yes***	no
New Immigration Countries	no	**yes***	no	no	no	no
Nordic Countries	no	no	**yes**$^{+}$	**yes**$^{+}$	no	**yes***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. ** $p < .01$. * $p < .05$. $^{+}$ $p < 0.1$.

Discussion

Differences in immigrants' qualification and skill mismatch across country groups

As expected, the likelihood for immigrant workers of being over-qualified varies widely in the four country groups I examine here. I cannot confirm that migrant workers are generally over-qualified as the likelihood for migrant workers to be over-qualified differs across occupations. The *English speaking settler countries* stand out in that I do not find evidence for an increased likelihood for immigrants of being over-qualified or for being over-skilled. Immigrants in these countries are also less likely to be under-skilled compared to natives in manual, advanced quantitative, and in communicative occupations. Hence, one can say that, once immigrants find employment, they are better integrated into the labor markets in these countries regarding their qualification and their skill levels. Various aspects can contribute to this result. First, these countries are typical immigration countries and have, with the exception of the U.S., mechanisms in place to strongly select immigrants regarding their fit into the domestic labor market (Bauer et al., 2001). Often, a job offer for which the immigrant is a better fit than other natives is a requirement for moving to the country. This assures a high level of match between achieved qualification / possessed skills and the requirements of the job. Second, all three countries have rather liberal labor markets (Hall & Soskice, 2001), allowing fast corrections of mismatched hires and therefore faster adjustments compared to more coordinated labor markets, such as Germany, Sweden, and Denmark. Hiring strategies in liberal labor markets are less focused on formal qualifications, represented by certificates, but more so on signaled skills through personal networks. Third, the English language is spoken throughout the world which motivates immigrants to learn the language (if they do not already speak the language) and makes easier for them to integrate and find appropriate employment. And fourth cultural aspects may play a role. All three countries have high shares of Asian immigrants who typically have a strong work ethic and willingness to adapt to the new environment. It may, thus, be easier for them to find appropriate employment in the host country.

In *post-colonial and guest worker migration countries* immigrants are in general more likely to be over-qualified, however, when distinguishing between different occupation types, I find this result only for manual and for communicative occupations. Immigrants in these countries are either not specifically selected for the countries' labor market needs (in post-colonial countries where immigrants from former colonies are allowed to settle in the former colonial power) or were selected to fill gaps in the labor supply in the industry, typically fulfilling low-skilled tasks (so-called guest workers). Both groups of immigrants are typically low-educated. The results suggest that they tend to work in manual occupations for which they are, although having low educational degrees already, over-qualified, because yet a lower or even no degree is needed for the job. In post-colonial migration countries, immigrants speaking the host country's language might also select into communicative occupations even though these are occupations which immigrants are less likely to choose (Peri & Sparber, 2009, 2011). This may explain the increased likelihood of immigrants being over-qualified in these occupations. I find no evidence that immigrant workers in quantitative jobs (basic and advanced) are more often over-qualified than natives. A reason could be that I also do not find evidence for a strong selection of immigrants into quantitative occupations. In this country group a higher share of immigrants can only be found in manual occupations (see Table 3).

These results are similar in the *new immigration countries* and in the *Nordic countries* with the exception that immigrants in basic quantitative occupations in these countries are more likely to be over-qualified. On explanation for the *Nordic countries* could be that migrants (very often refugees) who do not speak the host country's language and have lower educational attainments than the natives also select into basic quantitative occupations as their low qualification prevents them to enter advanced quantitative occupations.

The lacking evidence that immigrant workers are over-qualified in *English speaking settler countries* corresponds to the lacking evidence for an increased likelihood for immigrants to be over-skilled. Results for the remaining country groups are mixed but in most cases equal to the findings for *English speaking settler countries*. This suggests that the immigrant workers' over-qualification is not necessarily reflected in a surplus of skill. Further, immigrants in occupations in which they are not more often over-qualified, they are often less likely to be under-skilled. This is the case for *English speaking settler counties* (all professions) and *post-colonial and guest worker migration countries* (with exception of communicative jobs). Hence, in many cases they are employed appropriately according to their educational level and according to their literacy skills.

Further, in manual occupations in *post-colonial and guest worker migration countries* immigrants are more often over-qualified and at the same time neither more likely to be over-skilled nor less likely to be under-skilled; hence, employed appropriately according to their literacy skills. Further research should investigate which mechanisms correct for inappropriate signaling of skills through formal qualification (reflected in over-qualification) leading to a matching of actual skills.

In manual occupations in new immigration countries and the *Nordic countries* as well as in basic quantitative occupations in *new immigration countries*, and communicative occupations in *post-colonial and guest worker migration countries* and in the *Nordic countries* over-qualification of immigrants appears to be reflected in higher likelihoods of over-skilling among migrant workers. Here, the labor market seems to lack mechanisms to establish matching between of immigrants' formal qualification and literacy skills to job requirements.

Generally, mismatch of actual skills appears not to be a severe problem for immigrant workers in the examined OECD countries, despite their higher likelihood to be over-qualified. Only in some cases immigrants' over-qualification goes along with over-skilling (f.ex., in manual occupations in *new immigration countries* and in the *Nordic countries*). My findings suggest that very often labor market integration yields appropriate employment regarding actual skills, despite over-qualification, thus, correcting for inappropriate signaling of skills through formal qualification.

Limitations

Several limitations 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 currently available data. 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; Maehler, Teltemann, Rauch, & Hachfeld, 2015) and language spoken at work. Information on whether immigrants moved from less developed origin countries to industrialized destination countries and their motivation to come to the host country (e.g., hoping for better economic perspectives or coming as an ex-patriate) 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, the skill mismatch measures in PIAAC can cover only literacy and numeracy skills and are very broad. Further research should look into more *job-specific skills and skill mismatch measures*. Such measures could also better capture the skills in which immigrants are well-matched and shed light on which skills are primarily used by immigrants compared to natives.

Conclusion

In this paper I analyze the incidence of qualification and literacy mismatch among native and immigrant workers. I find that in line with previous research (Chiswick & Miller, 2009a; Dustmann & Glitz, 2011; Piracha & Vadean, 2012) immigrant workers in most countries are more often over-qualified. English speaking settler countries stand out in that I do not find evidence for an increased likelihood for being over-qualified for immigrants. In the remaining country groups (*post-colonial and guest worker migration countries*, *new immigration countries*, and *Nordic countries*) I find mixed results depending on the type of occupation into which immigrants are either more likely or less likely to select.

With new data on skills from PIAAC I can also shed light on immigrants' literacy mismatch. This appears to be a minor problem for immigrant workers, as their over-qualification does not always translates into over-skilling, suggesting mechanisms that correct for inappropriate signaling of skills through educational degrees.

My research is an important contribution to the literature on immigrant workers and their mismatch that has only focused on formal qualification mismatch so far, due to the lack of appropriate skill measures. In addition, the fact that immigrants and natives select into different types of occupations (Peri & Sparber, 2009, 2011) has so far been neglected by research on immigrants' over-qualification. By adding this aspect, the problems of over-qualification and over-skilling of immigrants can be targeted more precisely.

Further research can focus on mechanisms that yield to skill match despite prevailing over-qualification and on the consequences of immigrants' qualification and skill mismatch. An important question to answer is whether immigrants who remain mismatched after some time will return to their country of origin, hoping to fit better into the labor markets there. Another strategy of immigrants to find employment in the host country is to create their own business for which they often do not need sufficient language skills. However, this can cause immigrants to become more encapsulated in their own ethnic group in terms of both labor activity and social life. These mechanisms deserve further research regarding immigrants' mismatch, earnings, and other factors such as job satisfaction and learning on the job and job-related continuing education.

In several European countries it is discussed how informal learning can be better identified and certified. This seems to be particularly important regarding the current migration flows and attempts to integrate refugees into the labor market. As I show, mismatch regarding formal qualification does not necessarily mean that the individual does not have other vocationally relevant qualifications or competencies. For instance in a recent study, Gaylor, Schöpf, and Severing (2015) emphasize that competences can be acquired informally in work or leisure time or in further education without receiving a formal qualification. Denmark, France, the Netherlands, and Norway, for instance, have started programs that acknowledge job experience and informal knowledge, while in Germany and the United Kingdom no such structures were built or put in place so far.

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A.1 Regression tables – Over-qualification

All countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	-0.1708+	-0.2374+	-0.5849**	-0.4068**	-0.4129	-0.2254
Gender	-0.2079*	-0.0376	-0.4047**	-0.3058**	-0.3032+	-0.1492
Years of schooling	0.3435***	0.2156***	0.2128***	0.2208***	0.1708***	0.1829***
Migration status	0.1021	0.0705	0.0705	-0.0194	-.0193564	-0.0104
Work experience	-0.0013	-0.0080	0.0035	-0.0029	-0.0029+	-0.0104
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	31.402	13.619	10.059	15.212	5.313	15.714
Pseudo-R^2	0.0969	0.0655	0.0528	0.0547	0.0422	0.0414
Wald-χ^2	760.5***	383.33***	159.67***	268.96***	81.31***	242.16***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. + p <0.1.

English speaking settler countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	-0.3030+	-0.3331	-0.7969**	-0.5115*	-.5880892	-0.2512
Gender	-0.3143*	-0.0674	-0.3995*	-0.3137+	-.3460336	-0.1945
Years of schooling	0.3926***	0.2638***	0.2275***	0.2568***	0.1706**	0.2060***
Migration status	-0.0722	-0.2458	-0.3915	-0.2125	.001146	-0.1631
Work experience	0.0076	-0.0067	0.0139	0.0060	.0321**	0.0038
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	13.088	5.846	4.546	6.986	2.326	6.856
Pseudo-R^2	0.0964	0.0652	0.0513	0.0593	0.0457	0.0421
Wald-χ^2	135.86***	60.83***	30.55***	50.75***	15.86***	38.66***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. + p <0.1.

Post-colonial and guest worker migration countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	-0.1424562	-0.2295	-0.3980*	-0.3770**	-0.2795	-0.3704*
Gender	0.0143	0.1068	-0.4786***	-0.2423**	-0.2532	-0.1000
Years of schooling	0.2510***	0.1288***	0.2079***	0.1540***	0.1512**	0.1243***
Migration status	0.2486*	0.3799**	0.2930	0.2624	0.2624	0.2797
Work experience	-0.0195***	-0.0147**	-0.0170*	-0.0252***	-0.0252^{+}	0.2797**
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9.325	3.833	3.032	4.315	1.65	4.359
Pseudo-R^2	0.1126	0.0784	0.0610	0.0457	0.0373	0.0317
Wald-χ^2	715.97***	263.05***	117.47***	145.54***	41.37***	103.63***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. $^{+}$ p <0.1.

New immigration countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	0.0800	-0.2512	1.1346***	0.2368	1.1829**	0.0180
Gender	-0.2254^{+}	-0.2198	-0.4154^{+}	-0.5592**	-0.3725	0.1510
Years of schooling	0.3627***	0.2178***	0.0540	-0.0191***	0.1460*	0.1248**
Migration status	0.3127^{+}	0.6271**	0.6271	0.1196**	-0.0290	0.3521
Work experience	-0.0096	-0.0086	-0.0259^{+}	-0.0191^{+}	-0.0280	-0.0246*
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	3.356	1.605	930	1.534	528	1.465
Pseudo-R^2	0.1600	0.0864	0.0583	0.0560	0.0859	0.0310
Wald-χ^2	309.67***	110.66***	29.84***	52.37***	24.4***	23.73***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. $^{+}$ p <0.1.

Nordic countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	0.1456	0.0775	-.04389	-0.0861	-0.1133	-0.1093
Gender	0.0987	0.2360+	-0.0218	-0.1286	0.5152*	0.1120
Years of schooling	0.4136***	0.1963	0.180***	0.1878***	0.1846**	0.1787***
Migration status	0.5166***	0.7180***	0.7180	0.5091*	0.5091	0.6018**
Work experience	-0.0219***	-0.0136+	-0.0247**	-0.0258***	-0.0258	0.6018**
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	5.633	2.335	1.551	2.377	809	3.034
Pseudo-R²	0.1341	0.0504	0.0482	0.0579	0.0436	0.0471
	441.54***	90.57***	66.00***	112.45***	28.53***	97.96***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. * p < .05. + p <0.1.

A.2 Regression tables – Over-skilling

All countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	15.8334***	9.7432***	11.293***	10.3058***	12.4370***	11.9034***
Gender	-0.3108+	0.305	0.269	0.2869	0.2727	0.2949
Years of schooling	-0.0562	-0.3421***	-0.3667***	-0.3744***	-0.3909**	-0.3683
Migration status	-0.0121	0.1187	0.361	0.2896	0.813	0.5705
Work experience	-0.0030	-0.0078	0.0074	-0.0024	0.0375	-0.0214+
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	31402	13619	10059	15212	5313	15714
Pseudo-R^2	0.7035	0.5568	0.5786	0.5529	0.6103	0.6009
Wald-χ^2	688.04***	163.77***	156.09***	228.81***	100.46***	275.9***

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. * p < .05. + p <0.1.

English speaking settler countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	17.2949***	8.9952***	10.3523***	9.3479***	12.6445***	12.1453***
Gender	-0.4237	0.1203	0.2416	0.394	-0.2732	0.6842+
Years of schooling	-0.1176	-0.3730**	-0.4732**	-0.4432***	-0.6031**	-0.4733***
Migration status	-0.1765	0.1947	0.5648	0.3065	1.5043	0.2436
Work experience	-0.0030	0.0054	0.0038	-0.0073	0.0646	-0.0301
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	13088	5846	4546	6986	2326	6856
Pseudo-R^2	0.7338	0.5379	0.5613	0.531	0.6235	0.6043
Wald-χ^2	172.2***	62.27***	58.52***	91.34***	25.94***	79.68***

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. + p <0.1.

Post-colonial and guest worker migration countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	15.7600***	10.7149***	13.1280***	11.9514***	13.5075***	11.9754***
Gender	-0.0213	0.9204***	0.5742*	0.4715*	0.8786**	0.0276
Years of schooling	-0.0310226	-0.3540***	-0.2946***	-0.3482***	-0.2557***	-0.2609***
Migration status	0.3094	-0.1586	-0.0455	0.0667	-0.0703	0.8283*
Work experience	0.0039	-0.0211+	0.0262+	0.0156	0.0267	-0.0017
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9325	3833	3032	4315	1650	4359
Pseudo-R^2	0.6912	0.5801	0.6165	0.5841	0.6238	0.5993
Wald-χ^2	653.06***	340.29***	252.93***	338.99***	118.69***	380.69***

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. ** $p < .01$. * $p < .05$. + $p < 0.1$.

New immigration countries

	Model 1 (Total)	Model 2 (Manual Occ.)	Model 3 (Quantitative Occ.)	Model 4 (Basic Quantitative Occ.)	Model 5 (Adv. Quantitative Occ.)	Model 6 (Communi-cative Occ.)
Literacy	15.0399***	10.6004***	11.2347***	10.8597***	14.0489***	13.2821***
Gender	-0.8614**	-0.8126*	0.2097	-0.1655	0.5879	0.1338
Years of schooling	-0.0807	-0.2982***	-0.1635	-0.2679**	-0.3389*	-0.3136**
Migration status	0.569	0.8921+	1.1204	1.3409+	2.9348*	1.8038+
Work experience	-0.0227	-0.0369+	-0.0081	-0.0245	-0.0625*	-0.0320
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	3356	1605	930	1534	528	1465
Pseudo-R^2	0.674	0.5388	0.5624	0.5647	0.6268	0.6052
Wald-χ^2	277.57***	98.99***	71.47***	122.33***	44.1***	75.73***

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. ** $p < .01$. * $p < .05$. + $p < 0.1$.

Nordic countries

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	17.0803***	15.4168***	11.5621***	11.1483***	11.9657***	11.4640***
Gender	-0.7594***	0.1022	-0.6370*	-0.5639**	-0.2837	-0.6938**
Years of schooling	0.0009	-0.5155***	-0.2839***	-0.3074***	-0.1855^{+}	-0.2859***
Migration status	0.1235	0.6962^{+}	0.2525	0.3573	0.6058	0.7335^{+}
Work experience	-0.0245**	-0.0266^{+}	-0.0152	-0.0178	-0.0024	-0.02526^{+}
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	5633	2335	1551	2377	809	3034
Pseudo-R^2	0.7014	0.6713	0.5368	0.543	0.582	0.5525
Wald-χ^2	511.85***	200.52***	230.69***	317.78***	138.11***	388.06***

Notes. Logistic Regression model: DV: over-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. $^{+}$ p <0.1.

A.3 Regression tables – Under-skilling

All countries

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	-13.8651***	-8.4636***	-10.1470***	-9.3980***	-12.2305***	-8.9127***
Gender	0.6010**	-0.0789	0.3535	0.1176	-0.2137	0.1433
Years of schooling	0.1149**	0.2715***	0.5230***	0.4402***	0.7494***	0.4220***
Migration status	-0.5366*	-0.6414*	-0.4873	-0.6671*	-0.9457*	-0.9390*
Work experience	0.0105	0.0246*	0.0078	0.0268*	-0.0216	0.0131
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	31.402	13.619	10.059	15.212	5.313	15.714
Pseudo-R²	0.7341	0.5808	0.6003	0.5884	0.6386	0.5747
Wald-χ²	398.06***	371.86***	151.20***	294.43***	139.35***	320.53***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. $^{+}$ p <0.1.

English speaking settler countries

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	-13.9881***	-8.0844***	-10.2507***	-9.1866***	-14.9581***	-8.9310***
Gender	0.9840*	0.0091	0.4912	0.1509	-0.5670	0.1901
Years of schooling	0.1859*	0.2965**	0.5958***	0.4649***	1.0180***	0.4721***
Migration status	-0.9337*	-0.8079*	-0.4391	-0.6139	-1.3578*	-1.2070*
Work experience	0.0236	0.0330*	-0.0056	0.0324^{+}	-0.0471	0.0100
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	13.088	5.846	4.546	6.986	2.326	6.856
Pseudo-R²	0.7452	0.5597	0.6020	0.5822	0.6685	0.5709
Wald-χ²	142.43***	147.69***	53.65***	116.92***	49.16***	132.36***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** p < .001. ** p < .01. * p < .05. $^{+}$ p <0.1.

Post-colonial and guest worker migration countries

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	-15.8037***	-8.9678***	-10.2906***	-9.7400***	-10.6302***	-9.0278***
Gender	0.1932	-0.3867$^+$	-0.0109	-0.1744	0.0249	0.0756
Years of schooling	0.1000**	0.2790***	0.4199***	0.4174***	0.4905***	0.3696***
Migration status	-0.1514	-0.1401	-1.4987**	-1.1960**	-1.7073*	-0.2524
Work experience	-0.0171$^+$	0.0064	0.0163	0.0156	0.0065	0.0130
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9.325	3.833	3.032	4.315	1.650	4.359
Pseudo-R^2	0.7609	0.6083	0.6149	0.6047	0.6327	0.5813
Wald-χ^2	591.18***	453.76***	245.29***	366.40***	97.89***	390.19***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. ** $p < .01$. * $p < .05$. $^+$ $p < 0.1$.

New immigration countries

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	-18.5732***	-11.6295***	-10.2706***	-10.1284***	-11.8455**	-9.3934***
Gender	1.3633***	0.6080$^+$	1.2607*	0.6103	0.2524	-0.0263
Years of schooling	-0.0073	0.2236**	0.2142	0.2739**	0.3551$^+$	0.3577***
Migration status	-0.4849	-0.8376*	0.6371	0.2015	12,020	-0.8751
Work experience	0.0310*	0.0423*	0.0101	0.0141	0.0543	0.0134
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	3.356	1.605	930	1.534	528	1.465
Pseudo-R^2	0.7862	0.6583	0.6347	0.6077	0.6545	0.5826
Wald-χ^2	195.27***	143.03***	53.36***	76.71***	21.77***	70.42***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. ** $p < .01$. * $p < .05$. $^+$ $p < 0.1$.

Nordic countries

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	(Total)	(Manual Occ.)	(Quantitative Occ.)	(Basic Quantitative Occ.)	(Adv. Quantitative Occ.)	(Communi-cative Occ.)
Literacy	-15.6726***	-10.1660***	-12.3252***	-10.6185***	-13.4559***	-10.6773***
Gender	0.8592***	0.0783	0.7387*	0.5371*	0.5239	0.7332***
Years of schooling	-0.0205	0.3308***	0.3354***	0.3158***	0.2509*	0.3187***
Migration status	-0.1550	-0.3776	-0.9028^{+}	-0.6345^{+}	0.2821	-0.7491*
Work experience	-0.0134	-0.0182	-0.0062	0.0006	-0.0151	0.0083
Occupation	incl.	-	-	-	-	-
Country	incl.	incl.	incl.	incl.	incl.	incl.
Observations	5.633	2.335	1.551	2.377	809	3.034
Pseudo-R^2	0.7444	0.6301	0.6522	0.6056	0.7355	0.6293
Wald-χ^2	638.29***	431.88***	125.05***	276.77***	93.24***	435.09***

Notes. Logistic Regression model: DV: under-skilling (y/n), IV: literacy, gender, years of schooling, migration status, work experience, country dummies, occupation dummies (ISCO 1-digit-level) in Model 1. Sampling weights used in the regression. *** $p < .001$. * $p < .05$. $^{+}$ $p < 0.1$.