universität wien

MAGISTERARBEIT

Titel der Magisterarbeit

„Labour Market Outcomes of Immigrants in Austria: With a special Focus on Over-qualification”

Verfasst von

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angestrebter akademischer Grad

Magistra der Sozial- und Wirtschaftswissenschaften
(Mag.rer.soc.oec.)

Wien, im November 2014

Studienkennzahl lt. Studienblatt:	A 066 913
Studienrichtung lt. Studienblatt:	Magisterstudium Volkswirtschaftslehre
Betreuerin / Betreuer	Dr. Karin Mayr, Privatdoz.

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DANKSAGUNGEN

Mein erster Dank geht an meiner Familie, die mein Studium in Wien finanziell ermöglicht hat. Ich möchte sie herzlich für ihre liebevolle Unterstützung in jedem Schritt meines Studiums bedanken. Sie war der Hauptstützpunkt, die mit mir die schwieriegen und glücklichen Momente geteilt hat und mich immer motiviert hat.

Besonders bedanken möchte ich mich bei meiner Betreuerin, Frau Prof. Dr. Karin Mayr, Privatdoz. Trotz der schwierigen Ausgangsdatenlage, hat sie mich dazu motiviert das Thema nicht aufzugeben. Sie hat jeden Schritt meiner Arbeit mit Interesse verfolgt. Dank der Diskussionen mit Ihr habe ich mich in der schwierigen Phasen der Arbeit mit der komplizierten Datensatz mich orientieren können. Schliesslich danke ich Ihr herzlich für die sorgfältige Korrekur und für die kontinuierlich inhaltlichen und stilistischen Verbesserungsvorschläge.

Meinen Dank aussprechen möchte ich auch Herrn ao. Univ.-Prof. Mag. Dr. Peter Rosner für die erste Orientierung bei der Auswahl des Themas, über eine von mir wenig bekannte Problematik des österreichischen Arbeitsmarktes. Ich bedanke mich auch bei Herrn Univ.-Prof. Dr. Wieland Müller und den StudienkollegInnen im Konversatorium für ihre Kommentare und Anmerkungen.

Mein letzter Dank geht an den MitarbeiterInnen der Direktion Bevölkerung von STATISTIK AUSTRIA. Indem sie mir den Zugang zu den Scientific Use Files der PIAAC Erhebung gewährten, haben sie zur einen viel vollständigeren Analyse des Themas beigetragen.

TABLE OF CONTENTS

List of Abbreviations

BQ- Background Questionnaire

CBA- Computer Based Assessment

PBA- Paper Based Assessment

PUF- Pubic Use File

PV- Plausible Value

PIAAC- Program for the International Assessment of Adult Competences

SUF- Scientific Use File

IALS- International Adults Literacy Survey

List of Tables

List of Figures

"After this I go to work at a pizza shop. My wife and I were college professors in Bangladesh. I taught accounting. But one dollar in America becomes eighty dollars when we send it back home."

*People forget, when immigrants come to this country they start from scratch. They could have been lawyers in their home country, but in the US... it means nothing. You think a HS diploma from Bangladesh means anything in this country? My mom was a top student in her home country, went to all the best schools and got the best of everything…but when she got here it meant squat and she was cleaning other people's homes and scrubbing their toilets. This is why I get angry (*word changed) when people talk smack about immigrants. They at least are doing something…..heading for a goal, making sacrifices…what are you doing with your life?* [1]

I.Introduction

The paragraph above, a short statement of a Bangladeshi immigrant working in the U.S. illustrates perfectly various aspects of the economics of migration. Immigrants make an investment in their human capital by moving into another country with the prospect of improving their living conditions (Schulz Th.W., 1963). This decision is often associated with high monetary (transportation costs) and psychic costs - what the Bangladeshi worker refers to as sacrifice (losing the social status, facing stigmatisation and discrimination in the host country, losing friends and connections in the country of origin) (Sjaastad L.J., 1962). Another aspect of international migration is illustrated here, the sending of remittances to the home country. From the statement it also becomes clear that due to discrepancies in economic development between the country of origin and the host country, working in low-skilled jobs may be a rational choice if education acquired abroad is not valued in the host labour market and there is no other alternative possibility of employment.

While studies (both theoretical and empirical) that investigate the investment decision of immigrants to leave their home country and the sending of remittances back home abound, there are only a few empirical studies that deal with the question of over-education of immigrants. This can be partly explained by the lack of data on immigrants but also by the focus that has been placed in over-education studies on paradigm issues: whether too much education is being produced and whether human capital theory is valid. On the other hand, the economics approach to labour market integration of immigrants has concentrated on estimating the rate of assimilation of immigrants measured as the rate of convergence of earnings of natives and

[1] http://ancientrelic.tumblr.com/post/51092560047/humansofnewyork-after-this-i-go-to-work-at-a
original version in :http://www.humansofnewyork.com/post/51086972690/after-this-i-go-to-work-at-a-pizza-shop-my-wife
Wednesday 22 May 2013

foreign born across time (Borjas G.J., 1985, 1987; Chiswick B.R., 1978). The question why highly educated immigrants are relocated in low skilled jobs has been generally neglected.

The interest on the topic and evidence for Austria is even scarcer. With a few exceptions (see Perching B., 2002), studies on over-education and migration from an economic point of view are almost missing. Even in those few studies, which touch on the issue, the evidence is restricted only to estimates of the extent of over-education. Whereas in this paper, we also analyse whether there are any earnings penalties that arise for over-educated immigrants and by incorporating skill measures try to infer the reason for these penalties.

From the immigrants' perspective over-education brings about considerable income losses, as they do not accrue the full benefit from the investment made in their human capital (Piracha M. and Kalfa E., 2013). These losses become particularly serious especially if over-education is a permanent phenomenon. An estimation of the economic costs of over-education of high-skilled immigrants is provided by Weiss Y. et al. (2003). They investigate the immigration of 600.000 high-skilled workers that Israel experienced during 1990-1995. The majority of them (76%) entered the labour market as unskilled workers. The authors estimate a substantial loss of human capital earnings, measured as the difference between the expected actual lifetime earnings and the potential lifetime earnings that the immigrant would have gained if he had been employed in the same jobs as the comparable Israelis, amounting 253.200 US $, which makes 57% of their potential lifetime earnings. A further concern with over-education is that it can lead to skill loss or atrophy if it implies an insufficient use of skills. It also adversely affects skill development, since over-educated workers face lower opportunities to develop their skills (PIAAC, 2011a). In addition, it can have adverse effects on job satisfaction and workers' productivity and labour turnover (Tsang and Levin, 1985; Tsang et al., 1991).

This thesis aims first to quantify the incidence of over-education of immigrants in the Austrian labour market and compare it to the incidence of mismatch of natives, relying on both descriptive statistics and on a logit regression model. By making use of the comprehensive data of the PIAAC survey developed by the OECD, it is possible to estimate the percentage of over-qualified workers by using both a direct measure of over-qualification and a self-assessed measure. In addition, using the direct data on skills proficiency and skill use it is possible to compute also the incidence of skill mismatch and to relate it to qualification mismatch. The use of the skill proficiency and skill use measures as well as skill mismatch indicators allows us to make more profound statements than have been possible so far regarding the nature of over-qualification, whether it is real or simply formal. The second aim is to understand the earnings penalties that arise for over-educated immigrants. To do this an extended version of a Mincerian wage regression with mismatch dummies will be estimated separately for natives and immigrants following the Verdugo R. and Verdugo N. (1989) approach. By using skills proficiency measures as controls we can address to some extent the unobserved heterogeneity issue that arises because of the cross-sectional nature of the data. Further, by extending these models with a measure indicating over-skilling, it is possible to test whether the wage penalties arise due to an under-utilization of skills or due to a deficiency in skills.

The following section will first give a review of the literature dealing with the question of over-education in general. Then a short discussion of the literature on the over-education of immigrants will be given, concluded by a short review of what can be learned from economic theory, and a description of the situation in Austria. Chapter III will describe the survey and sample design. Chapter IV introduces the econometric methods used and chapter V presents the estimates and the regression results. The last chapter concludes and discusses some limitations of the analysis.

II. Literature Review

2.1. Qualification and Skill Mismatch in the labour market

2.1.1. Concepts and Measurement

Qualification mismatch arises when there is a discrepancy between the employees' attained qualification and the qualification required by the employer in a certain job. A range of concepts are used in the literature to describe qualification mismatch. Broadly, a distinction is made between vertical and horizontal mismatch. A vertical mismatch is a discrepancy between the attained level of qualification and the level of qualification required to get or perform the job, whereas a horizontal mismatch refers to a situation in which the field of education is not considered appropriate to perform a job. This thesis will focus on vertical mismatch, particularly on over-qualification, but estimates of under-qualification will also be provided in those cases where they help to better explain the outcomes. A person is considered over-educated, over-qualified or over-schooled if her/his educational attainment exceeds the qualification requirements of the job. Reversely, if the job requires a higher level than that which she/he possesses, the worker will be under-qualified, under-schooled or under-educated for the job. Cedefop (2010) proposes the use of the term over-education in cases where the surplus education is measured in years and the term over-qualification when the surplus education is measured in terms of credentials. Here, we use both terms interchangeably without making this kind of distinction.

In addition to over-education, independently of whether a qualification mismatch occurs or not, Cedefop (2010) defines over-skilling to describe a situation in which a worker does not fully utilize his skills in the current job. In contrast, a skill deficit or under-skilling happens, if the employee does not hold the necessary skills needed for the current job. If over-education is accompanied by skill underutilisation (over-skilling), then there is *real over-education*, as compared to *formal over-education,* where the skills are being fully utilized. Another typology of mismatch has been proposed by Chevalier A. (2003), which links qualification mismatch with job satisfaction. Depending on whether over-education adversely affects job satisfaction or not, he uses the concepts *genuine* or *apparent over-education*, respectively.

A considerable part of the research conducted on over- and under-education from an individual point of view is devoted to the appropriate measurement of mismatch. In order to identify the percentage of mismatched and adequately matched individuals in the workforce in terms of qualifications a way to measure the qualification requirement for the job is needed. Three measures have been used in the literature so far:

1. *The Self-assessment method (SA).* This is a subjective measure, computed by asking individuals directly to state if they consider they hold or not the appropriate level of qualification for the job. Another alternative is to ask them indirectly to state the level of qualification that is required to get or perform the current job, on the basis of which mismatch is being computed by comparing it with the actual level of qualification of the worker. This measure has been criticized by presuming that it biases the incidence of over-education upwards, as individuals are usually prone to overstate the demands of the jobs they hold. (Leuven E. and Ooesterbeek H., 2011; Hartog J., 2000; McGuinness S. 2006; Pellizzari M. and Fichen A., 2013).
2. *Job Analysis Method (JA)* is the second most often used approach. It uses the evaluation of experts (for example the Dictionary of Occupational Titles in the U.S.) about the educational requirements in each occupation. Based on this, the required years of education in each occupation are computed. The method is frequently used due to data availability but its disadvantages lie in the fact that it does not consider variations within occupation levels, and it is not frequently updated, which in the light of rapidly changing job requirements due to technological change can be problematic (Leuven E. and Ooesterbeek H., 2011; Hartog J., 2000; McGuinness S. 2006; Pellizzari M. and Fichen A., 2013).

3. *Realized matches approach (RM) or statistical approach*, is the most objective way to measure job requirements. It uses the actual average or median qualification level at each occupation as a threshold, and categorizes the individual in an occupation as over-qualified if his education level is one standard deviation greater than this threshold value. Similar to the second method, it has also been criticized by arguing that it ignores variations in educational outcomes within occupations, and that the threshold value is arbitrary (Leuven E. and Ooesterbeek H., 2011).

2.1.2. The Incidence of Over- and Under-qualification

Generally, the incidence of over- and under-qualification varies across countries and according to the method that is used to measure the required qualification level. Hartog J. (2000), Sloane P.J. (2003), McGuiness S. (2006) and Dolton P.J. and Silles M. A. (2008) state that the objective measure of Realized Matches generally yields the lowest estimates, while studies using self-reports of the individuals generate the highest estimates. Groot W. and Van den Brink H.M. (2000) in their review of 25 studies of research conducted on qualification mismatch show that there is a considerable variation in the rate of over-qualification, ranging from 10% to over 40% depending on the definition that is used. By controlling for cross-study differences in the measurement approach that is used, in sample composition and years of the sample selection, as well as inter-country variations, the authors estimate that "the true rate of over-education" amounts 26.2%. Chevalier A. (2003) proposes an alternative definition of over-education, to account for the heterogeneity in skills within individuals with similar education levels. He divides the group of the over-qualified in the *apparently over-qualified*- those employees working beyond their level of qualification but who are satisfied with their job- and the *genuinely over-qualified* -those employees which are mismatched and dissatisfied with their job. The implementation of this approach in a sample of UK graduates shows that two out of three of the previously broadly defined over-educated result to be *apparently over-educated.*

Overall, despite cross country differences, the estimation results from regressions that try to explain the incidence of mismatch at the individual level, give a more or less consistent profile of the workers who encounter a higher risk of working in a job for which they are not adequately qualified. There are certain individual and socio-demographic characteristics as well as job characteristics that appear to be significantly linked to the probability of being over-educated. Considering the role played by age, Alba Ramirez A. (1993), Green et al. (2002), Chevalier A. (2003), Rubb S. (2003), Sloane P.J. (2003), Green F. and McIntosh S. (2007), McGuiness S. and Sloane P.J. (2011) and Quintini G. (2011a) all find that younger cohorts are more likely to be over-qualified than older cohorts. The role of labour market experience in the probability and persistence of over-education has been investigated in the context of occupational mobility theory and the human capital trade-off hypothesis, trying to explain the reasons for why individuals accept a job that is not commensurate with their level of qualification. The trade-off hypothesis postulates that younger workers at the beginning of their career are more likely to be over-educated but with increasing job experience will end up at a higher level job.

Sichermann N. (1991) argues that over-education compensates for deficits in other components of human capital (labour market experience, on-the-job training). Using data for the US in the years 1976 and 1978, he finds that over-educated individuals have less work experience and less on-the-job training and higher turnover than adequately qualified workers. The same results have been observed by Alba Ramirez A. (1993) using a sample from the 1985 Living and Working Conditions Survey in Spain.

The second factor that is presumably linked with the risk of mismatch in the labour market is gender. This is on the one hand predicted by the theory of differential qualification mismatch (Frank R.H., 1978), according to which married women are more likely to be over-qualified than men, on the other hand by the fact that women face higher discrimination than men in the labour market. However, the empirical evidence is mixed. Some authors find that women, especially married women with children, suffer higher rates of over-qualification than men (Chevalier A., 2003; Sloane P.J., 2003; Green at al., 2002). Büchel F. and Pollmann-Schult M. (2001) and Quntini G. (2011a) find no gender specific differences, whereas Rubb S. (2003) finds a lower incidence of over-education for women than men. In sum, whether women will be overeducated to a greater extent than men will depend on their preferences to trade off other job characteristics, namely family conditions, labour market conditions, the sectors or occupations they are engaged in, and the extent of discrimination in the labour market.

Another disadvantaged group in the labour market are immigrants or ethnic minorities; they are often disproportionately over-educated compared to natives (Sloane P.J., 2003; Büchel F. and Pollmann-Schult M., 2001; Quintini G., 2011a; OECD, 2013b; Nielsen P. , 2007; Lindely J., 2006; Green et al. 2007).

Possible reasons for this will be discussed in detail in section 2.2., but there are some similarities between both disadvantaged groups that can be gauged from other empirical evidence related to the role played by job characteristics. Green F. and McIntosh S. (2007) show that individuals working part-time, in small workplaces and in the private sector are at a higher risk of being over-qualified. Similar results are found by Green at al. (2002), Dolton P.J. and Silles M.A. (2008) and Bauer T. (2002). Other authors suggest that over-educated individuals may be voluntarily choosing to work in a mismatched occupation, as they seem to prefer certain job characteristics. Green F. and McIntosh S. (2007) for instance, find evidence that the over-qualified are more likely to work in jobs that do not attach a large importance to communication, planning and problem solving skills, which may be more demanding jobs. Similarly, Mc.Guinness S. and Sloane P.J. (2011) show that over-educated workers attach a high importance to job security. More detailed evidence by gender is provided by McGuinness S. and Sloane P.J. (2011). They show that over-educated males choose jobs which they consider the most appropriate for the balance of their family life, and they put a lower weight on earnings. Over-educated women, on the other hand are more likely to be in jobs offering greater security and flexibility. Altogether, this evidence shows that women and immigrants who possibly face more difficulties in entering the labour market (due to family constraints or discrimination in hiring) are more likely to be over-represented in the part-time, less demanding jobs and consequently more likely to be over-educated, since the risk of being over-educated in these kinds of jobs is higher.

Further evidence relates over-education to the situation in the labour market, in particular to the rate of unemployment. Büchel F. and Pollmann-Schult M. (2001) view over-qualification as a form of protection from unemployment. Other authors also find that the likelihood that a person accepts a mismatched occupation increases considerably with the unemployment rate (McGuiness S. and Sloane P.J., 2011; Jochmann M. and Pohlmeier W., 2003; Frennette M., 2004 and Quintinni G., 2011a).

Another robust finding is the role played by the field of study in generating the over-education outcome. Dolton P. and Vignoles A. (2000), Chevalier A.(2003), Frennette M. (2004) and Dolton P.J. and Silles M. A. (2008) find that workers who have studied arts and humanities and social sciences face higher rates of over-qualification as compared to those who have a degree in engineering, technical and science degrees. Nordin et al. (2011) analyze horizontal mismatch and find that students from biology, pharmacology, art and media are more likely to be in a job outside their field of education.

A last issue addressed in the context of the incidence of mismatch is related to the issue of duration of the mismatch outcomes. Sichermann N. (1991) is a proponent of the idea that over-education is a short-run phenomenon, since over-educated have a higher turnover and are more likely to move to a higher-level occupation. However, other authors disagree with the hypothesis of occupational mobility. Korpi T. and Tahlin M. (2003) test it using panel data from the Swedish Level of Living Surveys 1974-2000. Under the occupational mobility theory, the wage gap between over-educated and adequately matched workers should decrease over time, and the over-educated should experience greater than average wage growth, but the results show that the rate of wage growth among over-educated is not significantly higher. They reject the occupational mobility explanation of over-education in Sweden.

The majority of existing empirical evidence suggests that over-education is a persisting phenomenon for individuals. Dolton P. and Vignoles A. (2000), using a graduates survey that follows the UK graduates over a period of six years, shows that 38% of all graduates were over-educated in their first job, and after six years 30% are still over-educated. Frenette M. (2004) also finds evidence of persistence. He estimates that three out of four graduates who are initially over-qualified remain so after five years. The study by Rubb S. (2003) uses longitudinal data from the Current Population Survey in the US and computes inflows into and outflows out of over-education. He concludes that over-education is a long-run phenomenon; three out of four over-educated individuals in year *t* will remain over-educated in the following year *t+1*.

2.1.3. The Consequences of Over-and Under-qualification on Earnings

Apart from the question related to the incidence of mismatch, the more interesting question in the over-education literature is related to the earnings implications arising for the employees working in a job that is not commensurate with their education level. The ideal situation, which would illustrate the real consequences of mismatch on earnings, would be to consider the counterfactual outcome, i.e. what would happen with earnings, if an over-educated individual was relocated from the mismatched position to a job for which he is adequately qualified. Potential answers to the question will be discussed in this section. This causality question is difficult to answer empirically, and no conclusive answer is given. A discussion of the methodological complications that arise will be given below.

In addition to the question of wage differences between over-educated and well-matched individuals, an additional research question in this section addresses the estimation of the returns to over-education. To answer both questions, two standard models are used, the Duncan G. and Hoffman S. D. (1981) Model- also called the ORU (Over-Required-Under-education) model and the Verdugo R. and Verdugo N. (1989) Model. The ORU model is an extended version of the Mincerian wage regression, in which two variables indicating years of over-education and years of under-education are included in addition to years of required education as explanatory variables in a log wage regression. In this specification, the benchmark individual is the actual colleague of the over-educated in their current job within the same firm, who is well-matched but has a lower level of education. The estimates of this version, which are generally robust across studies and measures used (Groot W. and van der Brink H.M., 2000; Chiswick B.R. and Miller P.W., 2010), show that the rate of return to over-education is positive but lower than the rates of return to required education (they earn more than their colleagues but less than workers with their education levels and characteristics who are adequately matched), whereas the returns to under-education are negative (Sichermann N., 1991; Cohn E. and Kahn Sch., 1995; Hartog J., 2000, McGuinness S., 2006).

The second approach is the one proposed by Verdugo R. and Verdugo N. (1989). They include as explanatory variables in the Mincerian wage equation not years of mismatch but dummies indicating mismatch and the level of education. This specification compares mismatched workers with individuals who have the same level of education but work in an adequate job. Estimates of this model show that, independently of the method used to measure mismatch, the over-educated suffer considerable wage penalties relative to similar well-matched individuals, while the under-educated earn a wage premium (Sichermann N., 1991; Cohn E. and Kahn Sch., 1995; Hartog J., 2000, McGuinness S., 2006).

In sum, there is evidence for a pay penalty to over-educated workers and a wage premium to under-educated workers, but this does not mean that the returns to being over-educated are negative; they get partly, if not fully, a reward for their education job match (Cohn E. and Kahn Sch., 1995). The evidence has been interpreted as support for the Assignment Theory, according to which both the characteristics of individuals and characteristics of the job (mismatch status) affect wages (McGuinness S., 2006; Dolton P. and Vignoles A., 2000, Sloane P., 2003).

The main explanation given for the observed pay penalties between over-educated and well-matched workers in OLS estimates is that individuals with the same education level might differ in terms of skills, abilities and other personality traits like motivation and attitudes towards learning. Therefore, the wage gaps resulting from over-education that we observe might arise simply because it is not possible to control for this heterogeneity (Bauer T., 2002; Chevalier A., 2003; Tsai Y., 2010). With this omitted variable problem, the generated estimates of the wage effect of over-education are biased. Several authors address this issue in two different ways: either by using panel data with fixed effects models, or by including direct measures of school quality or skills in the wage regressions; the later approach is a more rarely used approach due to, problems with data availability.

The most convincing evidence for individual differences in ability to be responsible for the earnings differences between over-qualified and well-matched workers comes from fixed effects studies. For example, Bauer T. (2002) uses a German panel data set for the years 1984-1998. He finds that, controlling for individual fixed effects leads to a drop in the wage gap between over-educated and well-matched workers from 10.6% to 1.7% for males, whereas the wage premium for under-educated men almost disappears. Similar but more recent evidence is given by Tsai Y. (2010). He exploits the US Panel Study of Income Dynamics 1979-2005 to test for the hypothesis that over-educated workers have lower ability. Again, the pay penalty drops from 4% to less than 1 % after controlling for individual heterogeneity. A reduction in the estimated penalty to over-education in a fixed effect model is also found in the analysis by Frenette M. (2004) for Canada. Further evidence that supports the hypothesis that over-educated workers are less able is provided also by Jochmann M. and Pohlmeier W. (2003). They reject the fact that over-education implies a pay penalty. The aim of their study is to estimate a causal effect of over-education on earnings. They consider the selection of individuals into a treatment and a non treatment group and estimate the average treatment effect (earnings loss) on the treated (over-qualified). Their Bayesian analysis shows no evidence for over-education to reduce earnings. That means that if the over-educated were relocated in a job for which they are adequately qualified, they would not expect higher earnings than what they actually earn in the mismatched position.

A novel approach for handling unobserved heterogeneity is introduced in a study conducted in Ireland by McGuinness S. and Bennett J. (2007), who test the low ability hypothesis by means of a quintile regression. They assume that the location of the individual in the wage distribution will reflect their relative ability level. Then they look at the effects of over-education across the wage distribution. The results show that a considerable part of the over-educated (50%-60%) is located in the bottom two quintiles of the wage distribution. Incidence in the higher quintiles is lower (14-23%), suggesting that over-education is more prevalent among individuals with lower ability. The pay penalty to over-education falls also quickly from -34.9% in the bottom quintile to -14.1% in the fifth quintile. There is no pay penalty for the over-educated men in the top quintile of the wage distribution, which is evidence for the view that penalties arise due to lower ability only.

Chevalier A. (2003) offers another unconventional approach, testing for the heterogeneous skills hypothesis by looking separately at the pay penalties of apparently and genuinely educated workers. He finds that the pay penalty from a general regression to over-educated workers is 14%. However, the apparently over-educated suffer a much smaller pay penalty of 4.8%, and the genuinely over-educated, who are assumed to be less skilled, incur an estimated pay penalty of 21.6%. Given this higher pay penalty for the genuinely over-educated, he attributes over-education to a lack of skills of workers.

These results, however, cannot be generalized as long as they can be expected to vary depending not only on the econometric methodology used but also on the country context and the processes that lead to the over-education outcome in the labour market. For instance, Korpi T. and Tahlin M. (2003) cannot find support for the low ability hypothesis in Sweden. Based on cross sectional and panel data from the Level of Living Survey, they test whether over-education is a result of lower ability first by estimating an OLS model with health and verbal ability indexes as controls for heterogeneity. In addition, they estimate a fixed effect and IV model. In all the approaches, the differences in returns to over-education remain even after controlling for ability. McGuiness S. and Sloane P.J. (2011) also come to the same conclusion. They adopt a propensity score matching model to correct for unobserved heterogeneity bias, but the results do not differ from the OLS estimates, and the wage penalty remains.

2.1.4. Qualification Mismatch and Skill Mismatch

In recent years, direct measures of skills have become available, which allow for a more explicit way to test for the unobserved heterogeneity hypothesis. Moreover, the skill measures implicitly incorporate differences in the quality of qualifications and allow considering skill gains and skill losses that arise during a working lifetime that cannot be captured by qualification measures (Desjardin R. and Rubenson K., 2011). Levels M. et al. (2014) is the most recent published paper, which exploits PIAAC data to estimate an ORU equation which controls for skills. Their results support the hypothesis that wage penalties are caused by differences in skills. Adding proficiency scores in the cross country regressions reduces the wage effects of over-education by 25%. In a similar vein, more interesting results are presented by Desjardin R. and Rubenson K. (2011). They use a similar survey to control for both skill endowments and skill mismatches and emphasize that a high skill endowment is relevant only to the extent that it is required for the job.

Apart from the unobserved heterogeneity hypothesis, stating that over-educated workers lack the appropriate skills, a second explanation given to the observed wage penalties of over-educated is that working in a job beyond their qualification level imposes a constraint on the productivity of workers, as it does not allow them to fully utilize their skills (Rumberger R.W., 1987; Tsang et.al., 1991; McGuinness S., 2006.; Chiswick B.R. and Miller P.W., 2010, Allen and van der Velden, 2001). This is also called the genuine mismatch hypothesis (Green et al. 2002). To contrast these two explanations, measures of both over-qualification (under-qualification) and over-skilling (under-skilling) are incorporated into the analysis. Green at al. (2002), using the UK International Adult Literacy Survey (IALS) data, conclude that over-skilling has an adverse effect on earnings. They estimate that moving from a job that is fully utilizing the skills to a job that is not implies an annual earnings loss of more than 1700 £. They interpret this as support for the hypothesis that it is the under-utilization of skills among the over-qualified that is causing the pay penalty. McGuinness S. and Sloane P. J. (2011), exploiting REFLEX data of UK graduates, however, find that the pay implications of skill mismatch are much lower than those of educational mismatch. But there is a much larger effect of over-skilling on job satisfaction than of over-qualification on job satisfaction, reflecting partly a voluntary choice of the over-educated workers.

More explicit tests of the genuine mismatch hypothesis are provided by Allen and van der Velden (2001), Green F. and McIntosh S. (2007), Quintini G. (2011a) and Nietro S. (2014). They all find a weak relationship between being over-qualified and over-skilled. Furthermore, the estimates of the coefficients of over-qualification on wages do not change much when over-skilling is included in the ORU equations. The authors conclude that this is evidence that the pay penalty for over-educated workers does not arise because they do not use their skills but due to their lower ability.

2.2. Over- and Under-qualification of Immigrants

As previously mentioned, the empirical evidence from individual mismatch studies shows that highly educated immigrants face a much larger risk of working in low skilled occupations than natives. However, studies that focus explicitly on the over-education of immigrants are scarce. On the other hand, economic theory provides us with no single theory to explain the phenomenon of over-education. Rather, a range of labour market theories are drawn upon (human capital theory, career mobility theory, job competition theory, the assignment theory, signalling and screening) usually to make predictions regarding the duration of over-education.

In the context of immigrants, theories related to migration under asymmetric information (Katz E. and Stark O., 1987) together with labour market theories of screening (Stiglitz J., 1975) and signalling (Spence M., 1973) and theories of discrimination (Becker S., 1957) may provide some important insights. In the case that immigrants have attended schooling in their country of origin, and under the assumption that employers lack information about the quality of the education abroad and therefore cannot form beliefs about the productivity of the workers, immigrants will be located to low-skilled jobs. In this case, education loses its function as a signal of productivity. Faced with this situation, immigrants may improve their labour market outcome by investing in signalling (for instance attend further training courses, have their qualifications recognized or arrive at a higher level of language proficiency). As time passes, the information between the worker and the employer improves, assuming on the job screening, where the employer observes the productivity of the worker and relocates him to a higher level occupation. On the other hand, the immigrant learns more about the labour market functioning in the host country and therefore engages in search and looks for another job appropriate to his level of qualification. This is what the occupational mobility theory predicts. However, this occupational upgrading may occur only in the absence of discrimination. If employers have a taste for discrimination and this taste for discrimination is higher for better-educated workers (Becker, 1957, p.97, 124), then high-skilled immigrants may end up more often in over-educated jobs. This discrimination in hiring, and the time and costs associated with a much longer search for a suitable occupation, explains why highly educated immigrants might accept to work in low-skilled jobs. Often, there are family constraints that also come into play, and the nature of migration (whether for economic or political reasons) and the legal status in the host country also influence the magnitude of over-education of immigrants. Finally, it is important to note that the issues that are mentioned in the discussion above about over-education in general are also relevant for immigrants.

The empirical literature on the mismatch of immigrants focuses mainly on the issue of transferability of human capital skills. There are differences in the quality of schooling and differences in the market structures and technologies that make education not perfectly transferable (Friedberg R.M., 2000). In this context, country of origin plays an important role. Piracha et al. (2012) analyse over-education of immigrants in Australia and find evidence on the role played by the country of origin. Immigrants from Asia have a 13.3% higher probability of being over-educated compared to other groups. Piracha M. and Kalfa E. (2013) also show that immigrants originating from less developed countries have a higher probability of being over-educated. Further evidence is given by Battu H. and Sloane P.J. (2011). Using data from the National Survey of Ethnic Minorities in Britain 1993/1994, they find differences in the incidence of over-education among ethnic groups. According to the estimates, African and Asian with a foreign qualification are less likely to be over-educated as compared to Pakistani and Bangladeshi workers. They also find that working for a non-white boss decreases over-education for non-whites, an indication that they interpret as evidence supporting the hypothesis that over-education is an outcome that results from discrimination.

Country of origin is, however, not the direct reason that increases the risk of over-education. What is crucial is the origin and quality of the qualification, and language ability or familiarity with the host country's language. Nielsen P. (2007) emphasizes the importance of accounting for the source of immigrants' education in order to distinguish between discrimination and imperfect information effects. He uses panel data for 1995-2002 to estimate a random effects model on the likelihood of over-education and finds that immigrants with a foreign education have a higher incidence of over-education (30%) compared to immigrants with a Danish education (20%). Not only education, but also labour market experience in the home country influences the likelihood of over-education. Piracha M. and Kalfa E. (2013) use data from the National Immigrant Survey of Spain for 2007 to estimate a binomial probit model and show that having been over-qualified in the last job held in the home country increases the probability of being over-educated in the Spanish labour market.

Immigrants attending education in the host country have considerable advantages pertaining to language proficiency, and language plays an important role in the successful labour market integration of immigrants (see for instance Chiswick B.R. and Miller P.W., 2014). Green et al. (2007) find that immigrants to Australia with a non-English speaking background are between 50% and 100% more likely to be over-educated compared to immigrants with an English speaking background.

Over-education of immigrants from an earnings perspective has been mainly treated in the work of Chiswick Barry B. R. and Miller P. W. (2008, 2009a, 2009c). They consider over-education and under-education of immigrants as the main reason why the returns to schooling for immigrants are lower than for natives. Their estimates show that 60% of the earnings gap is due to differences in the returns to over-education and under-education faced by both groups. There are lower returns to over-education for immigrants but they face also much smaller negative returns to under-education. This fact is interpreted as supporting evidence for the positive self-selection of immigrants.

Considering now the situation in Austria, there are very few studies that provide some estimates of the percentage of immigrants that are mismatched. They are usually embedded in other studies and do not give a profound analysis of the phenomenon. The most recent estimate is given by Völkerer et al (2014), according to which 32.8% of immigrants works in job not matching their qualifications compared to 21.9% of Austrians. Krause and Liebig (2011) emphasize that Austria has the largest percentage of highly educated foreign-born from low income countries working in low-skilled jobs. They estimate that only half of the high-educated foreign born are employed in high skilled jobs, this estimate is 70% for the natives. Gächter A. (2006, 2010) explains this by the higher demand for low-skilled labour compared to high-skilled, which, combined with the legal status of immigrants, forces them to accept jobs for which they are over-qualified in order to maintain their residence permit.

Knowing the patterns and history of migration and the history of migration policy and regulations might help to interpret those estimates and the country specific problem. The history of migration helps to understand the composition of immigrants in terms of reasons behind migration and to derive hypotheses regarding the over-education of different groups. Immigration to Austria after World War II may be categorized in three main waves: the labour migration of the 1960s (Gastarbeiterabkommen), the refugee waves of the 1980s-1990s and 1994/1999, and the immigration from EU member countries starting with the entrance of Austria in the Union 1995 but increasing rapidly since 2000. (Hahn S., 2010). These immigration waves determined also the composition of immigrants in terms of education level and motivation to stay and work in the country and may also be reflected in the mismatch of workers. There is, however, a lack of data which allows this type of inference, and the data in this thesis do not allow for such a separate analysis either. Another interesting point would be to compare the incidence of mismatch among the first and second generation of immigrants, who have obtained their education in the country. Despite this, a common view shared in all these studies is that the most important factor responsible for the generation of the actual mismatch outcomes is related to institutional issues. The laws and regulations in Austria that regulated the residence permit have been generally bound to the labour market status. Absence of jobs directly implied the loss of the right to live in the country. This has potentially been the main reason why over-education of immigrants is particularly high and presumably permanent (evidence regarding the duration of over-education is missing).

III. Data Description

3.1. PIAAC Survey

3.1.1. Survey and Sample Design

The survey conducted under the Programme for the International Assessment of Adults Competences measures the proficiency of adults in three cognitive skills or key information processing skills: literacy, numeracy and problem solving in technology-rich environments (supply side) as well as the use of the cognitive and non-cognitive skills at work (demand side). The three skill domains are defined as the ability of individuals to understand, evaluate, use and engage with written texts (literacy), mathematical information (numeracy) and use digital technology and communication networks to evaluate information and solve tasks (Problem Solving in Technology Rich Environments) (OECD, 2013c, p.20).

My analysis uses the public use files (PUF) containing micro-level data, released by OECD in June 2013, that comprise data with censored information as well as the Scientific Use Files (SUF) with full data made available by STATISTIK AUSTRIA. The file for Austria includes a set of 1328 variables. Data was gathered between 1. August 2011 – 31. March 2012. The target population consisted of non-institutionalized workers aged 16-65 years which were drawn from the population registry of 2011 using the probability sampling method, according to which each individual in the target population had a non-zero probability of being included in the sample. In Austria, illegal immigrants as well as individuals living in prisons, hospitals or nursing homes were excluded from the target population. Austria implemented a one-stage sample design with no stratification. Sample size amounted to 5130 individuals. In Austria, respondents could answer the background questionnaire in German or Bosnian/Serbian/Croatian and Turkish. But they had to use German to take the cognitive assessment, as this is the language that is relevant for participation in the labour market.

The Survey of Adults Skills uses a complex survey design. It was administered in two stages: the *Background Questionnaire was* run as a computer assisted personal interview (CAPI) and the *Cognitive Assessment* was conducted as a direct assessment of skills based on modules of tasks from the three domains for the respondents to solve. The BQ included 258 questions, but respondents did not answer all the questions of the questionnaire due to routing processes. The direct assessment of skills was taken either as Computer-based assessment (CBA) or as paper-based assessment (PBA), based on the information provided by respondents in the BQ regarding their experience with computers. Those with insufficient computer experience took only the literacy and numeracy tests in the paper based version.

The direct assessment of literacy, numeracy and PSTRE in the computer based mode followed a **multistage adaptive testing design**. This means that respondents did not need to answer all the modules. This was done to increase the accuracy of measurement by reducing the response burden. Respondents were directed to different sets of items according to their educational attainment, whether the native language was the same as the test language, and depending on their social background. In addition, respondents who failed in the core items of the cognitive domains and had thus poor literacy skills took the *reading component* module. This module tests the basic skills needed to understand meaning of a text such as knowledge of vocabulary and fluency in reading. For these individuals, values for the three domains were imputed as incorrect during the computation of plausible values (OECD, 2013a).

The analysis of complex survey data differs from data analysis that is done under simple random sampling, and the complex features of the data have implications for the statistical methods that are required to yield reliable and unbiased estimates (Heeringa et al., 2010). Due to the complex survey design of PIAAC, the Technical Report recommends a number of issues to be considered when analysing PIAAC data. The first issue concerns the use of the sampling weights to insure that inference drawn from the collected data is representative for the total population of the 16-65 year old residents. The PIAAC survey weighting adjusts for the disproportionate sample selection of certain subgroups, for non-response bias, non-coverage in the sample and the use of auxiliary data (imputed values) (OECD, 2013a).

The second concern that arises in the analysis relates to the multistage adaptive testing. Because different groups of respondents answered different sets of items, comparison of scores is inappropriate, as differences may result due to differences in the difficulty of tasks. To overcome this problem, PIAAC uses Item Response Theory (IRT) and combines test responses with information provided in the BQ to implement a multiple imputation of proficiency scores for each individual. This method does not only allow comparison across subgroups who took different paths but it does also capture uncertainty in measuring proficiency at the individual level that results from measuring the competences from only a subset of items. To this aim, 10 plausible values were estimated for each individual. Hence, when competences play a role, the calculation of an estimate has to be performed with each set of plausible values (PV) across all individuals. Then the results are averaged across the plausible values to compute the point estimates (OECD, 2013a).

A last issue to be mentioned is the implication of complex sample design for the calculation of the error variance. The error variance of sample statistics in PIAAC consists of two components: *Sampling variance* that reflects uncertainty due to obtaining a specific sample from the population and *Imputation Variance* reflecting the uncertainty due to the random draw of plausible values. Jackknife Replication Approach was used to calculate replication weights. My analysis uses the tools that have been developed in Stata 13 (PIAACTOOLS developed by Pokropek and Jakubowski) to compute the estimates. They automatically account both for the sample and replicate weights, the plausible values and the replication method for computing variances.

3.1.2. Measurement Issues

3.1.2.1. Measuring Proficiency

Proficiency is measured in terms of a continuous scale of 500 points. The proficiency scale describes the complexity of the information-processing task (OECD, 2013c). At each point on the scale, an individual with a proficiency score of that particular value has a 67% chance of successfully completing test items located at that point (OECD, 2013b, p. 60). At that particular score, he will be able to complete tasks of more difficult complexity with lower probability and easier tasks with a higher probability of success. Proficiency scales have been divided into proficiency levels: six proficiency levels for literacy and numeracy and four for Problem Solving, with level 1 representing low proficiency and level 5 representing high proficiency, according to the following categorization of points:

Table 3.1.1: Proficiency Levels and Equivalent Scores

	Scores	
Proficiency Level	**Lit. and Num**	**PS Tech. Rich Env.**
Below Level 1	<176	<241
Level 1	176-226	241-291
Level 2	226-276	291-341
Level 3	276-326	>342
Level 4	326-376	
Level 5	>376	

Source: PIAAC Technical Report (OECD, 2013a)

A detailed description of the content of the tasks that adults within a particular proficiency level can successfully complete is listed in Table A.1 in the appendix.

3.1.2.2. Measuring Mismatch in PIAAC

One of the major advantages of PIAAC is the wide range of information that it includes, which allows not only to contrast qualification with skill mismatch but also to compare the incidence of qualification and skill mismatch using different measures.

Qualification mismatch

Direct Measurement

The background questionnaire measures the highest level of education obtained using the International Standard of Educational Qualification (ISCED) levels. A list of the equivalent categories in the Austrian education system is given in the Appendix in table A.2. Furthermore, it asks workers about the level of qualification (also measured in terms of ISCED) needed to get the current job. In addition, based on the answers to the highest level of education attained, years of schooling associated with the highest education level was derived and is given (YRSQUAL), and similarly based on the qualification needed to get the job, years of schooling necessary to get current job was derived (YRSGET). We use these two variables in combination to derive of a variable measuring the years of qualification mismatch (YRSQUAL-YRSGET). Based on this, a categorical variable is generated, indicating the over-qualified, under-qualified and well-matched.

Self-Assessed Qualification Mismatch

In addition to the level of required qualification to get the job, individuals are asked to state whether their attained qualification level is necessary for doing the job (well-matched) or whether a lower (over-qualified) or higher level is needed (under-qualified). This question can be used to infer the percentage of respondents who perceive themselves to be over- or under-qualified. The derived distributions will be compared with the direct measure in the previous paragraph, which is expected to differ. This allows us to check for the robustness of the results.

Skill Mismatch

Direct Measurement
Skill Use Measurement- Job Requirement Approach

The Background Questionnaire entails a separate section which asks individuals about the use of the three skill domains and a range of non-cognitive skills. Individuals are asked about the frequency of performing the tasks in work and in everyday situations (ordered in five categories from never performing the tasks to performing the task every day). By using the methodology of Item Response Theory, twelve skill use indices are derived. These indices combine the responses in each of the tasks in a continuous scale (from 0- low frequency of use to 4- high frequency), which represents the level of use of the underlying skill (OECD, 2013c, p.44). The method called the Job Requirement Approach is based on the methodology developed by Feldstead A. et al. (2007) implemented in the British Skill Survey 2006. The method assumes that the skills the workers currently hold and use in the workplace are a reliable proxy for skill requirements of the job. Table A.3 in the Appendix lists the indexes and the tasks that are contained in each of them. These indexes are an important component of the new measure of skill mismatch (OECD Measure) proposed by Pellizzari M. and Fichen A. (2013).

OECD measure of skill mismatch

The computation of skills mismatch estimates follows the proposed steps by Pellizzari M. and Fichen A. (2013). In their paper they develop a theoretical model of skill use in the job to derive a new measure of skill mismatch. Workers are described by a vector of skill endowments η_i and decide to what extent to use their skill endowment (s_i) (to maximize a utility function) in their jobs given the job characteristics (operational costs k_i, returns to deployed skills β_i and the max skill level in job j: max_j). Jobs are identified based on occupations under the assumption that within occupations jobs are homogeneous. Individuals incur a utility cost (c_i), if their use of skills exceeds their skill endowment. The method hence incorporates the endogeneity of skill use to specify job requirements. For each skill domain and each job they propose to define the minimum and maximum requirements as the minimum and maximum proficiency of self-reported well-matched workers. In the next step those individuals whose proficiency score falls between this minimum and maximum requirements are classified as well-matched, those for which the proficiency score is greater than the maximum proficiency score of the self-declared well-matched are considered over-skilled. The under-skilled are those whose proficiency score is lower than the minimum score of the self-reported well-matched workers.

The main advantage of this measure of skill mismatch is that it combines the self-reported skill mismatch with proficiency scores and skill use to compute the incidence of mismatch. In addition, it allows a more detailed picture of skill mismatch, by allowing the estimation of the percentage of mismatched employees separately in each skill domain and in each occupation It also offers also a way to infer the robustness of the results to measurement errors, by providing an alternative measures for skill mismatch (Pellizzari M. and Fichen A., 2013). A detailed description of the steps followed in Stata to derive the measures is given in the Appendix.

Self-Assessed Skill Mismatch

Respondents are asked if they feel they have the skills to cope with more demanding duties (i.e. tasks and responsibilities that would require more knowledge and skills that are required to carry out the tasks and responsibilities that are typical of the respondent's current job) (PIAAC, 2010 p. 84). This allows identifying those respondents who perceive themselves to be over-skilled. A second question, asking them whether they feel they need further training to cope with present duties on the other hand allows to identify those persons who feel they are under-skilled for the job they hold. Persons who negate both questions are classified as well-matched in terms of skills.

3.2. Sample Description

3.2.1. Sample Descriptive Statistics

Table 3.2.1 shows the composition of the sample in terms of country of birth, gender and age groups. 677 individuals in the sample were not born in Austria, the largest share of immigrants is made up by individuals from Germany, Bosnia Herzegovina and Turkey, followed by Romania and Poland, reflecting thus the patterns of migration mentioned in section II.

Table 3.2.1: Sample Composition

	N	%	S.E
Gender			
Male	2530	49.86	0.02
Female	2600	50.14	0.02
Age			
24 or less	898	16	0.18
25-34	958	19.11	0.25
35-44	1117	22.18	0.3
45-54	1188	23.83	0.29
55 plus	968	18.89	0.19
Country of Birth			
Austria	4347	88.65	0.4
Bosnia and Herzegovina	90	2.26	0.24
Germany	122	2.88	0.24
Poland	37	0.95	0.17
Romania	43	1.1	0.16
Serbia	77	2.18	0.23
Turkey	75	1.98	0.21
Country of Birth and Language Status			
Native Born and Native Language	4247	81.65	0.4
Native Born and Foreign Language	100	2.08	0.2
Foreign Born and Native Language	188	4.22	0.28
Foreign Born and Foreign Language	489	12.05	0.43

Nr. of Observations: 5024. Source: Own Calculations using PIAAC Public Use Files (OECD, 2013).
Literacy Related non-Responses are not included in the results (105 observations).
Estimations are done using sample weights and replicate weights.

A more detailed picture of the Immigrants in the sample is shown in table 3.2.2. The majority has been living in Austria for more than 15 years. Individuals who are foreign born and have at least one foreign born parent are defined as first generation of immigrants, whereas individuals who are born in Austria but both parents are foreign born are defined as second generation immigrants (STATISTIK AUSTRIA, 2013).

Table 3.2.2: Description of Immigrants

	Nr of Obs.	%	S.E.
Gender			
Male	329	48.47	1.75
Female	348	51.53	1.75
First and Second Generation			
1st generation Immigrants	666	16.1	0.41
2nd generation Immigrants	160	3.33	0.23
Non 1st or 2nd generation Immigrants	3797	72.75	0.54
Non-Immigrant and one foreign-born parent	384	7.44	0.4
Years in Austria			
0--5	97	2.31	0.24
5--10	129	3.17	0.26
11--15	78	1.84	0.21
more than 15	373	8.65	0.44
Native Born	4347	82.18	0.41
Level of Foreign Qualification			
ISCED 1	33	7.81	1.25
ISCED 2	86	19.95	1.81
ISCED 3C < 2 years	(*)	1.8	0.71
ISCED 3A-B	177	39.54	2.5
ISCED 4A-B	53	9.3	1.2
ISCED 5B	32	5.48	0.94
ISCED 5A Bachelor	21	4	0.83
ISCED 5A Master	70	12.13	1.39

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD, 2013).
Estimations are done using sample weights and replicate weights. Foreign Born: 677 Individuals.
Literacy Related non-Responses are not included (105 observations). (*): nr of observations <20.

Table A.9 and A.10 in the Appendix depict the educational and labour market outcomes of all individuals in the sample. A considerable part has completed an upper secondary education (49.73%) and works in skilled or semi-skilled occupations. With respect to skills, there is a considerable share of individuals who are concentrated in the lower and middle levels of proficiency (over 40% are situated below level 3 in all three skill domains).

To get a general idea about the extent of the mismatched individuals in the whole sample, table 3.2.3 shows the percentage of mismatched individuals both in terms of qualifications and skills using the different measures. 28% of the individuals are over-qualified according to the direct measure. The self-assessed measure yields a lower rate of over-educated workers (17%), contrary to what one may expect. It seems that skill mismatch is a more prevalent problem. More than half of the individuals are under-utilizing their skills, and this is robust to the measure used. Among the occupations with the largest share of over-skilled individuals are Skilled Agriculture and fishery (44% in Literacy and 35% in Numeracy), Elementary Occupations (over 60% in both Literacy and Numeracy) and Plant and Machine Operators (32% in Literacy) (see Table A.7 and Table A.8 in Appendix).

Table: 3.2.3: Incidence of Mismatch –Whole Sample

	Incidence of Qualification Mismatch		
	Over-qualified	**Well-matched**	**Under-qualified**
Self-Assessment	17.12	76.29	6.59
S.E.	0.73	0.84	0.43
Direct Measure	28.08	54.01	17.91
S.E.	0.81	0.81	0.73
	Incidence of Skill Mismatch		
	Over-skilled	**Well-matched**	**Under-skilled**
Self-Assessment	54.61	4.01	41.38
S.E.	0.88	0.4	0.89
New Measure			
Skill Mismatch in Literacy	64.56	20.71	14.73
S.E.	0.87	0.65	0.59
Skill Mismatch in Numeracy	63.84	17.58	18.58
S.E.	0.88	0.66	0.64

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD, 2013).
Sample Size: 3737 (in case of qualification mismatch 3240- self-employed are excluded in this case).
Estimations are done using sample weights and replicate weights. Literacy Related non-Responses are not included (105 observations).

IV. Econometric Models

4.1. Likelihood of over-education

To test whether there is a difference in the likelihood of being over-educated for immigrants compared to natives with similar characteristics a logit regression model will be estimated:

$$\text{logit}(\text{over-educated}_i=1)= \beta_0+ \beta_1 X_i+ \beta_2 Z_i+ \beta_3 \text{Foreign}_i+\varepsilon_i \qquad (4.1.1)$$

where X_i is a vector containing variables of individual characteristics (human capital and family background variables) and Z_i a vector containing variables of job characteristics; Foreign is a dummy variable equal one if the individual was not born in Austria, ε_i is the error term. The model will be estimated with both measures of over-education (direct measure and self-assessed measure) as dependent variables to check for robustness of the results, and a second extended model will be estimated including measures for skills in order to see how the incidence of over-education changes when controlling for skills and test for the unobserved heterogeneity hypothesis

$$\text{logit}(\text{over-educated}_i=1)= \beta_0+ \beta_1 X_i+ \beta_2 Z_i+ \beta_3 \text{Foreign}_i+ \beta_3 \text{Skills}_i +\varepsilon_i \qquad (4.1.2)$$

where Skills_i is a vector containing the skill proficiency scores in literacy and numeracy.

Following the recommendation by Heeringa et al. (2010) on the application of logistic regressions to complex survey data, the model parameters will be estimated using the pseudo-maximum likelihood estimation and the Wald test statistics will be used to test for the significance of parameters. Several specifications were tested and models compared using the pseudo- R^2 goodness of fit measure. A separate regression for immigrants was not possible due to the small number of observations. The model provides therefore a test of the difference in the incidence of over-education between natives and immigrants but does not allow a more detailed analysis regarding the causes of over-qualification among immigrants. The focus of the empirical estimation will therefore lie in the estimation of the gaps in earnings arising from over-education.

4.2. Earnings differences between over-educated and well matched workers.

To estimate differences in earnings between over-educated and well matched workers, the Verdugo R. and Verdugo N. (1989) approach will be used. To compare earnings of over-educated and well-matched individuals with the same education level, the earnings will be regressed on a set of education level dummies and years of work experience (the Mincerian earnings equation), extended by dummies indicating mismatch. The following model is estimated:

$$\log (\text{wage}_i)= \beta_0+ \beta_1 OE_i+ \beta_2 UE_i+ \beta_3 X_i+ \beta_4 Z_i + \varepsilon_i \qquad (4.2.1)$$

where OE_i is a dummy indicating whether the individual is over-educated, UE_i is a dummy equal to one if the individual is under-educated, X_i is a vector containing as arguments individual characteristics (gender, family and social background, highest level of education etc.) and Z_i is a vector containing job characteristics (occupation categories and firm size dummies). From the discussion above, one expects the estimate of β_1 to be negative, indicating the wage penalty that over-educated workers face compared to well-matched workers. The estimate of β_2 is expected to be positive; under-educated workers earn a wage premium. The model will be estimated separately for native born and immigrants to test whether there are differences in the wage penalties and premiums incurred by the two groups.

The second specification that will be estimated extends model 4.2.1 with measures of skills, to compare the wage gap for individuals with the same level of skills. The inclusion of skills as control variables for the heterogeneity of workers is expected to reduce the estimated magnitude of the wage penalty, if over-education reflects lower skills. The second specification is as follows:

$$\log (wage_i) = \beta_0 + \beta_1 OE_i + \beta_2 UE_i + \beta_3 X_i + \beta_4 Z_i + \beta_5 S_i + \varepsilon_i \qquad (4.2.2)$$

with S_i being a vector indicating plausible values in literacy and numeracy for individual i. The PV in problem solving is omitted to avoid multi-collinearity problems. Again the model will be estimated separately for Austrians and foreign born, and the change in the coefficients for both groups will be compared.

Finally, to test whether the wage penalty associated with the over-education status results from the fact that over-educated workers are under-utilizing their skills the third specification includes dummy variables indicating over- and under-skilling:

$$\log (wage_i) = \beta_0 + \beta_1 OE_i + \beta_2 UE_i + \beta_3 X_i + \beta_4 Z_i + \beta_5 OS_i + \beta_6 US_i + \varepsilon_i \qquad (4.2.3)$$

with OS_i indicating that the individual is over-skilled and US_i indicating that he is under-skilled. All specifications are estimated twice, using both the direct and self-assessed measure of mis-qualification.

V. Results

5.1. Descriptive Statistics

5.1.1. Educational and Labour Market Outcomes

Before presenting results regarding the incidence of over-qualification among immigrants and natives, a description of their human capital endowment and labour market performance helps to understand their positioning across occupations. The whole sample statistics are depicted in tables A.9 and A.10 in the Appendix. Results in Table 5.1.1 show that there is no difference in the mean years of schooling between natives and immigrants. There are however differences in the distribution across levels of education. While a higher percentage of the foreign-born individuals have lower levels of education compared to natives, they are also more likely to have attained a tertiary level of education than the natives.

Table 5.1.1: Educational Outcomes

	Natives		Foreign Born		Natives				Foreign Born			
	%	S.E.	%	S.E.	Mean	S.E.	s.d.	S.E.	Mean	S.E.	s.d.	S.E.
Educational Outcomes												
Mean Years of Qualification					11.82	0.02	2.54	0.02	11.74	0.09	3.16	0.07
Lower Secondary	21.49	0.42	29.8	1.58								
Upper Secondary	51.63	0.46	39.88	1.97								
Post-Secondary non-tertiary	11.01	0.21	8.66	0.93								
Tertiary Professional degree	6.62	0.31	5.76	0.76								
Tertiary Bachelor degree	1.19	0.14	3.24	0.66								
Tertiary Master/ Research	8.07	0.29	12.66	1.14								

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013).
Sample Size: 5024. Estimations are done using sample weights and replicate weights. Literacy Related non-Responses are not included (105 observations).

Another component of human capital relevant for the actual performance in the labour market is the skill endowment of workers. Table 5.1.2 shows the distribution of respondents across proficiency levels in Literacy. This gives a different picture from the one in terms of qualifications. There is a large gap in skill proficiency between immigrants and natives across all proficiency levels. The mean proficiency score in literacy for immigrants is 247.8, for natives it is considerably higher at 273.6. The percentage of immigrants who have low proficiency in literacy is clearly much higher than those of natives, and they are also less likely to have high proficiency. It is interesting to look at the differences within immigrant groups. A categorization by country of birth is not possible due to the small number of observations, but a distinction can be made by generation of immigrants and language background. The second section of the table shows that both first and second generation immigrants are more likely to have low skill proficiency in literacy than individuals without an immigration background. There is a slight improvement in the second generation, but they still remain at a disadvantage compared to non-immigrants.

It is interesting, that being born in Austria does not improve skill endowments. The native born but for whom German is not a mothertongue perform similarly to the foreign born, again showing a gap compared to the native born whose mothertongoue is German. It seems therefore clear that there is a language effect. The estimates for numeracy and problem solving in technology rich environments are similar (tables A.11, A.12 in the Appendix).

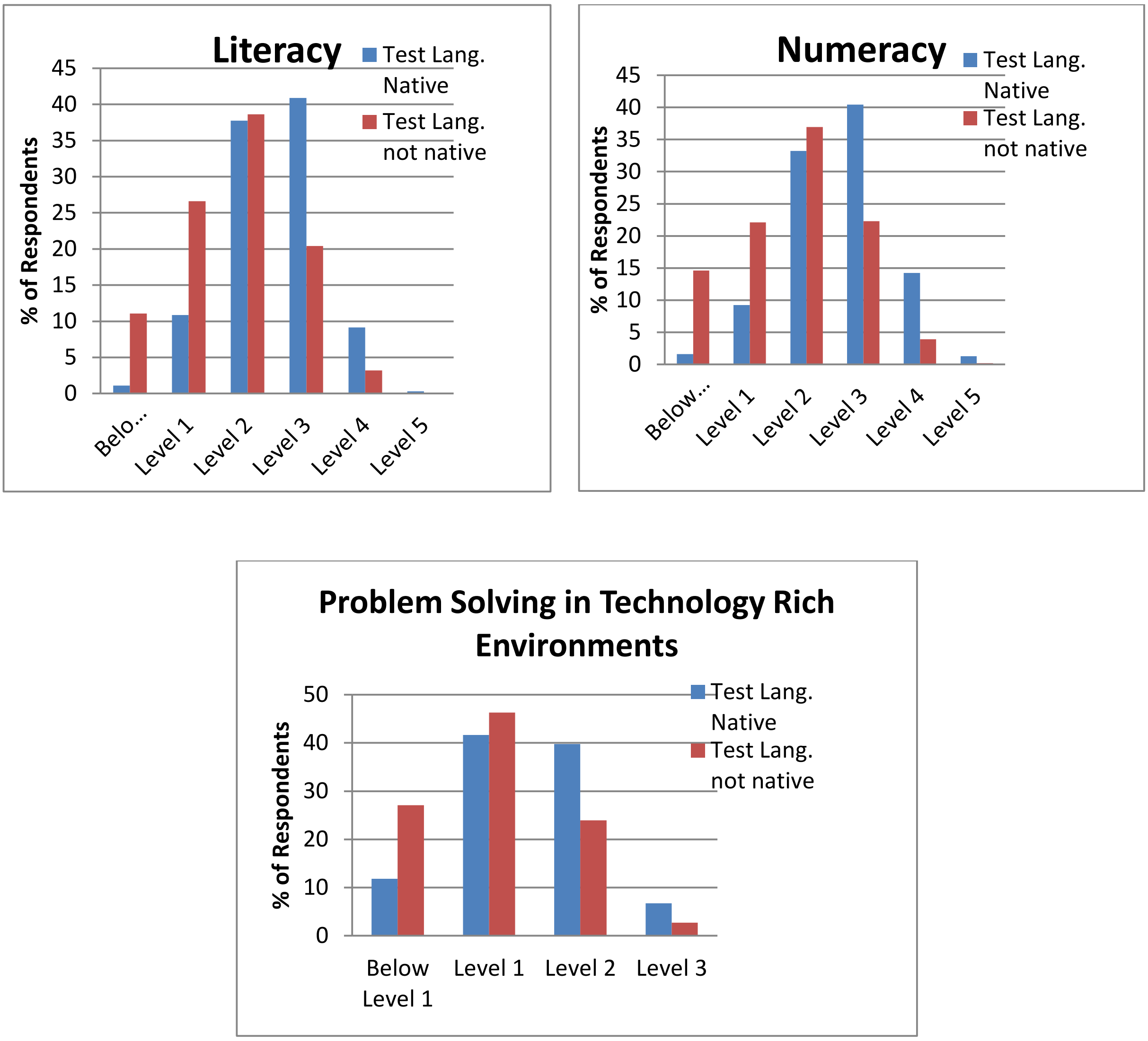
Table 5.1.2 : Proficiency in Literacy- Immigrant versus Natives and within Immigrant Groups

	Below Level 1		Level 1		Level 2		Level 3		Level 4		Level 5	
	%	S.E.	%	S.E.	%	S.E.	%	S.E.	%	S.E.	%	S.E.
Immigrant Status												
Natives	1.07	0.28	11.19	0.69	38.28	1	40.51	0.98	8.67	0.54	0.29	0.1
Foreign Born	9.87	1.27	22.78	1.84	35.69	2.15	25.08	2.16	6.43	1.08	0.16	0.25
Generation of Immigrants												
First Generation Immigrants	9.96	1.27	22.87	1.82	35.74	2.17	24.89	2.21	6.39	1.08	0.16	0.25
Second Generation Immigrants	4.35	1.99	17.5	4.12	44.82	4.91	27.31	5.24	5.97	2.13	0.04	0.2
Non first generation or second generation imm.	0.91	0.28	10.62	0.83	37.88	1.13	41.22	1.01	9.06	0.6	0.32	0.11
Non-Immigrants and one foreign born parent	0.94	0.68	13.37	2.33	38.63	3.52	40.47	3.5	6.5	1.81	0.09	0.19
Interaction Country of Birth and Language Status												
Native Born and Native Language	0.99	0.27	10.85	0.69	38.14	1.03	40.94	0.97	8.79	0.55	0.29	0.1
Native Born and Foreign Language	4.18	2.84	24.46	5.62	43.8	6.16	23.39	5.38	4.16	2.21	0	0
Foreign Born and Native Language	3.12	1.81	10.79	3.2	29.79	4.6	39.85	5.74	16.11	3.28	0.33	0.69
Foreign Born and Foreign Language	3	1.61	26.98	2.29	37.76	2.57	19.91	2.23	3.03	0.96	0.1	0.21

Source: Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013).
Sample Size: 5024. Estimations are done using sample weights and replicate weights. Literacy Related non-Responses are not included (105 observations).

There is one important point to consider when interpreting the estimates on skills for immigrants. The gap in proficiency may reflect mainly a gap in language skills, as for the majority of these respondents the language of direct assessment was not their native language. This implies that they may be highly proficient in literacy, numeracy or problem solving in technology rich environments in their mother tongue but not in German (OECD, 2013c). Therefore, the concentration of immigrants in the lower part of the distribution of skills should not be interpreted as a lack of skills, but possibly as a result of the language of assessment being not their mother tongue. This is confirmed in fig 5.1. In all three skill domains, the skill proficiency of those individuals whose test language is not the native language is worse than that of the respondents with German as a native language. This fact, however, does not affect the interpretation of the regression results when controlling for skills, as those skills, even though tested in German, are relevant and are the ones which are valued in the labour market.

Fig. 5.1: Relationship between Proficiency and Test Language



Source: Own calculations. Dataset: PIAAC Public Use Files (OECD,2013). Nr of individuals for whom the test language is not the native language 589.

Table 5.1.3 shows the labour market outcomes of immigrants and natives. The estimates show that immigrants are disadvantaged. They are less likely to be employed and have fewer years of work experience. They have lower rates of participation in training than natives and admit to be less satisfied with the job. Immigrants are slightly underrepresented in the public sector. Considering occupations, a lower percentage is working in skilled occupations and a much larger share is found in the elementary occupations compared to natives.

Table 5.1.3: Labour Market Outcomes

	Natives		Foreign Born		Natives				Foreign Born			
	%	S.E.	%	S.E.	Mean	S.E.	s.d.	S.E.	Mean	S.E.	s.d.	S.E.
Employment Status												
Employed	74.49	0.59	68.24	1.85								
Unemployed	2.57	0.26	8.04	0.98								
Out of the Labour Force	22.94	0.55	23.72	1.7								
Years of Work Experience					20.64	0.13	12.8	0.07	16.72	0.44	11.2	0.23
Weekly Work Hours					37.91	0.22	12.8	0.2	37.53	0.62	11.9	0.52
Economic Sector												
The private Sector	74.53	0.78	81.72	1.79								
The public Sector	22.55	0.73	15.58	1.68								
A non Profit Organization	2.92	0.28	2.7	0.88								
On the Job Training												
Participated in the last year	22.41	0.59	16.84	1.45								
Did not participate	77.59	0.59	83.16	1.45								
Job Satisfaction												
Satisfied	65.95	0.72	57.21	1.92								
Dissatisfied	34.05	0.72	42.79	1.92								
Occupation												
Skilled	41.54	0.92	31.25	1.86								
Semi-Skilled White Collar	29.23	0.83	24.61	1.91								
Semi-Skilled Blue Collar	22.69	0.68	22.84	1.78								
Elementary	6.54	0.44	21.3	1.82								

Source: Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013).
Nr. of Observations: 5024. For Job related variables only employed respondets are used (3737 observations)
Estimations are done using sample weights and replicate weights. Literacy Related non-Responses are not included (105 observations).

This distribution across occupations is reflected in the renumeration that workers get. The main earnings statistics depicted in table 5.1.4. show that immigrants earn on average a lower hourly wage than workers born in Austria. The wage gap is particulary pronounced in the upper tail of the distribution. We will come back to the earning differences and their relation to the over-education outcome in section 5.2. The next section provides first estimates of the incidence of qualification and skill mismatch among immigrants and natives.

Table 5.1.4. Hourly Earnings of Wage and Salary Earners (Self-employed not included)

	Mean	s.d.	5th perc.	Median	75th perc.
Natives					
Hourly Earnings excluding bonuses	14.03	8.03	5.78	12.57	16.52
S.E	0.16	0.55	0	0.22	0.17
Hourly Earnings including bonuses	16.94	10.3	6.66	14.83	19.87
S.E	0.21	0.54	0.59	0	0.33
Foreign Born					
Hourly Earnings excluding bonuses	12.53	7.63	5.65	10.64	14.42
S.E	0.38	1.02	0.58	0.39	2.28
Hourly Earnings including bonuses	14.83	9.1	6.47	12.45	16.85
S.E	0.45	0.88	0.3	0.5	0.66

Source: Own Calculations,Earnings are measured in €. Data: STATISTIK AUSTRIA, PIAAC 2011/2012 (Scientific Use File). Estimations are done using sample weights and replicates weights.

5.1.2. Incidence of Mismatch

Qualification Mismatch

First we look at the incidence of qualification mismatch. Tables 5.1.2.1 and 5.1.2.2 show the percentage of respondents who are over-qualified, under-qualified and well-matched using the self-assessed and the direct measure of mismatch. The estimates show that according to both measures, immigrants have a higher incidence of over-qualification than natives. This incidence is higher when measured directly using the required and attained level of qualification. The results imply that individuals perceive themself less over-educated than they actually are. This interesting results is much more pronounced for immigrants.

Table 5.1.2.1: Incidence of Qualification Mismatch-Subjective Measure

	Self-assessed Measure					
	Over-qualified		Under-qualified		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Natives	16.17	0.81	6.68	0.48	77.15	0.88
Foreign Born	22.29	2.06	6.11	1.1	71.6	2.3

Source: Own Calculations. Data: PIAAC Public Use Files (OECD,2013). Nr of observations: 3236. Estimations are made using sample weights and replicates weights.

Table 5.1.2.2: Incidence of Qualification Mismatch- Direct Measure

	Direct Measure					
	Over-qualified		Under-qualified		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Natives	25.76	0.85	18.32	0.78	55.93	0.9
Foreign Born	40.81	2.68	15.7	2	43.49	2.37

Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013).Nr of Observations: 3240.
Estimates are made using sample weights and replicates weights.

Likelihood estimates in the following section will provide some more detailed insights about the incidence of mismatch after controlling for skills and other characteristics.

Skill Mismatch

Looking first at the estimates based on the self-assessed measure, there appears to be no significant difference in the incidence of skill under-utilization. Both immigrants and natives perceive themselves as equally over-skilled and there is also only a small difference in the magnitude of self-assessed under-skilling. But differences are evident according to the OECD measure of skill mismatch.

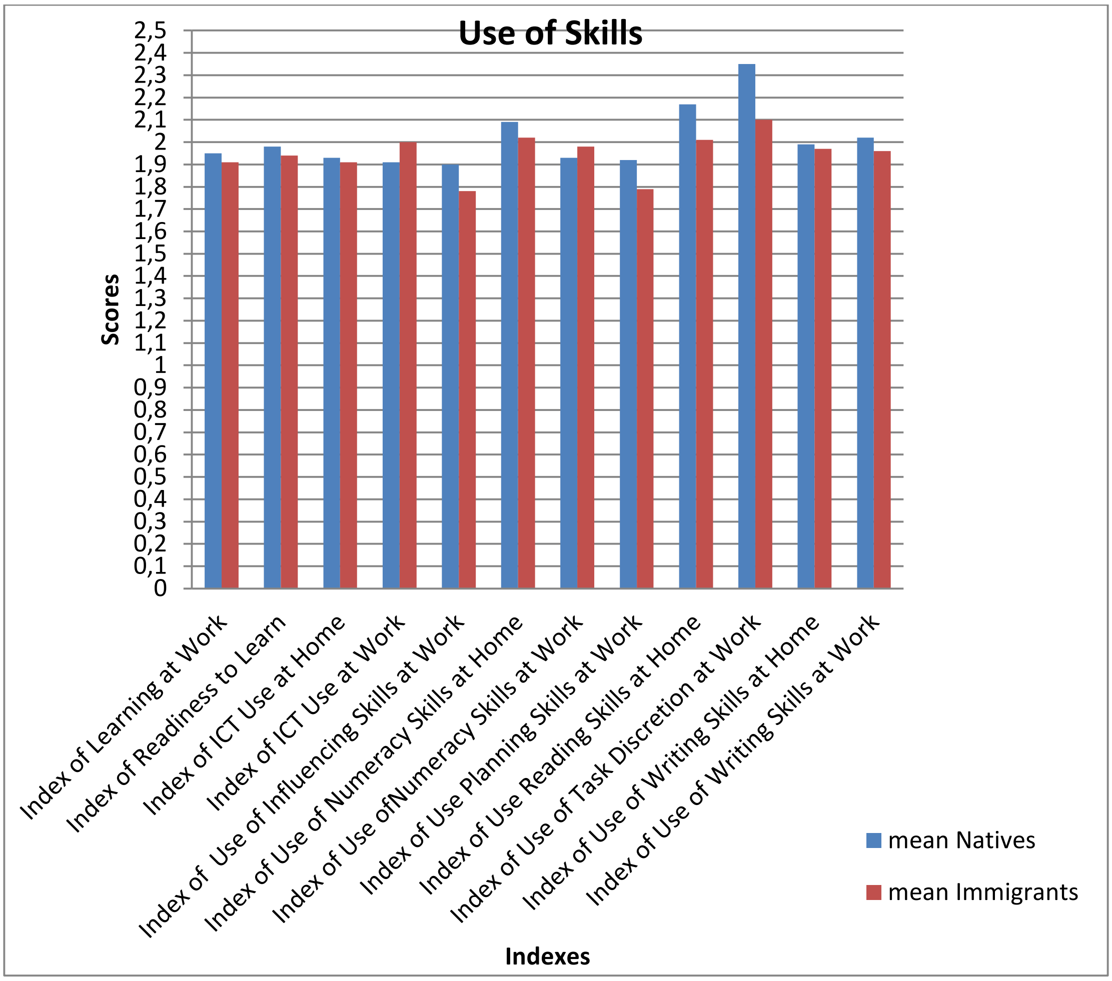
Table 5.1.2.3: Incidence of Skill Mismatch

	Self-assessed Measure					
	Over-skilled		Under-skilled		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Natives	54.21	0.95	42.43	0.98	3.36	0.36
Foreign Born	56.89	2.22	35.46	2.09	7.65	1.31
	Skill Mismatch in Literacy					
	Over-skilled		Under-skilled		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Natives	67.43	0.96	11.78	0.65	20.79	0.74
Foreign Born	48.56	2.42	31.35	1.92	20.09	1.7
	Skill Mismatch in Numeracy					
	Over-skilled		Under-skilled		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Natives	66.72	0.95	15.08	0.67	18.2	0.72
Foreign Born	47.78	2.44	38.06	2.08	14.16	1.5

Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013).Nr of Observations: 3240.
Estimates are made using sample weights and replicates weights.

Immigrants are less likely to be under-utilizing both their literacy and numeracy skills and more likely to be under-skilled than natives according to this measure. The fact that the estimates using the new measure of mismatch reveal different patterns can be explained by the way the measures are computed. Indeed, as fig 5.1.2 shows, immigrants not only have a smaller endowment in literacy and numeracy, but they are also using their skills to a lesser degree than natives.

Fig. 5.1.2: Use of Skill Indices- Native versus Immigrants



Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013). Estimates are made using sample weights and replicates weights.

To understand the degree to which over-qualification is associated with an under-utlisation of skills, table 5.1.2.4 depicts the percentage of over-qualified individuals who are also over-skilled. There is a strong relationship between being over-qualified and being over-skilled. By the self-assessed measure of skill mismatch, more than half of the over-qualified individuals consider themselves to under-utilize their skills. This likelihood is the similar for natives (65%) and immigrants (67%) and invariant to the measure of qualification mismatch. For natives, the pattern is insensitive even to the measure of skill mismatch. Looking at immigrants, the incidence of over-qualified who are over-skilled is lower when the new measures of literacy and numeracy mismatch are used, but still the incidence is high compared with other studies who generally find a weak under-utliziation of skills.

Table 5.1.2.4: Percentage of over-qualified workers who are over-skilled

	Self-Assessed Measure of Over-skilling			
	Natives		Foreign Born	
	%	S.E	%	S.E
Direct Measure of Over-qualification	65.15	1.8	66.91	3.68
Self- assessed Measure of Over-qualification	63.32	2.45	66.12	4.8
	New Over-skilling Measure in Literacy			
Direct Measure of Over-qualification	65.38	2.08	48.25	3.66
Self- assessed Measure of Over-qualification	64.97	2.52	38.87	5.27
	New Over-skilling Measure in Numeracy			
Direct Measure of Over-qualification	64.62	2.15	47.86	3.63
Self- assessed Measure of Over-qualification	63.85	2.59	38.87	5.27

Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013). Estimates are done using sample weights and replicate weights.

5.2. Regression Results

5.2.1. The Likelihood of Over-qualification

The estimates of equations (4.1.1) and (4.1.2) are shown, respectively, in colomns 1 and 2 of table 5.2.1. For ease of interpretation, both coefficients and odd ratios are presented. The dependent variable is the direct measure of over-qualification. The results show that for an additional year of work experience, the odds of being over-qualified decrease by a factor 0.96. Individuals working in semi-skilled and elementary occupations have a significantly higher likelihood to work as over-educated than workers in skilled occupations. The risks of being over-educated rise also with the level of attained qualification. Considering the field of education, individuals with a degree in teacher training and education or health and welfare are significantly less likely to be over-educated than individuals in the reference category: science, mathematics and computing. An advantagous social background proxied by the highest level of education of the father is also associated with a significant lower likelihood of overeducation. These estimates are robust to different specifications used. Finally, looking at our main variable of interest, the estimate for foreign born workers, we see that immigrants are more likely to be over-qualified compared to natives with similar characteristics (The likelihood increases by a factor 1.64. Including controls for skills (specification 2) does not change very much the estimates; compared to natives with similar education and skills, they still face a significantly higher risk of being over-educated. (The odds ratio decreases slightly to 1.56).

Table 5.2.1: Regression Estimates: Likelihood of being Over-educated- direct measure of over-qualification

Overqualifieddirect	(1)					(2)				
	Coeff.	Odds Ratio	Rob. Std. Err.	z	P>|z|	Coeff.	Odds Ratio	Robust Std. Err.	z	P>|z|
constant	-1.63		0.012	2.21	0.027	-0.68		0.895	-0.76	0.445
Individual Characteristics										
age	0.027	1.03**	0.012	2.21	0.027	0.027	1.03**	0.012	2.18	0.029
female	0.174	1.19	0.153	1.14	0.255	0.152	1.16	0.179	0.98	0.325
uncompleted qualification	0.114	1.12	0.148	0.77	0.441	0.136	1.15	0.171	0.92	0.36
training	-0.179	0.84	0.124	-1.43	0.151	-0.165	0.85	0.106	-1.32	0.187
years of work experience	-0.036	0.96***	0.012	-3.01	0.003	-0.037	0.96**	0.012	-3.09	0.002
Like learning new things	-0.061	0.94	0.129	-0.47	0.635	-0.055	0.95	0.122	-0.42	0.672
Get to the bottom of difficult things	-0.022	0.98	0.116	-0.19	0.850	-0.027	0.97	0.113	-0.23	0.815
married	-0.175	0.84	1.152	-1.15	0.250	-0.155	0.86	0.131	-1.02	0.309
children	0.243	1.28	0.152	1.60	0.109	0.238	1.27	0.194	1.57	0.117
foreign born	0.494	1.64**	0.225	2.2	0.028	0.447	1.56*	0.356	1.96	0.05
computer experience	0.231	1.26	0.309	0.75	0.456	0.261	1.30	0.408	0.83	0.407
Highest level of qualification of father (Ref. Cat: Primary or lower secondary)										
Secondary Education	-0.447	0.64***	0.132	-3.39	0.001	-0.438	0.65***	0.851	-3.31	0.001
Tertiary Education	-0.633	0.53***	0.186	-3.41	0.001	-0.616	0.54***	0.101	-3.3	0.001
Non-Austrian Qualification	0.562	1.75	0.387	1.45	0.146	0.441	1.555	0.621	1.11	0.269
Highest Level of Qualification (Ref. Lower Secondary)										
Upper Secondary	-0.592	0.55*	0.327	-1.81	0.07	-0.583	0.56*	0.185	-1.76	0.079
Post Secondary non-tertiary	0.252	1.29	0.359	0.7	0.483	0.350	1.419	0.519	0.96	0.338
Tertiary Professional	1.017	2.77**	0.375	2.71	0.007	1.094	2.99**	1.142	2.86	0.004
Tertiary Bachelor	0.431	1.54	0.641	0.67	0.502	0.515	1.674	1.089	0.79	0.428
Tertiary Master/Research	1.311	3.71***	0.382	3.42	0.001	1.445	4.24***	1.66	3.69	0
Field of Education(Ref. Cat: Science, Mathem. and Computing										
General Programme	-0.053	0.95	0.457	-0.11	0.909	-0.028	0.97	0.447	-0.06	0.95
Teacher Training and Educ Service	-1.162	0.31**	0.457	-2.54	0.011	-1.22	0.29***	0.135	-2.66	0.008
Humanities, lang. And arts	-0.883	0.92	0.469	-0.19	0.851	-0.154	0.86	0.403	-0.33	0.744
Social Sciences, business and law	-0.204	0.82	0.382	-0.53	0.593	-0.245	0.78	0.299	-0.64	0.521
Engeneering, manufact. and constr.	0.029	1.03	0.385	0.08	0.940	-0.004	0.99	0.387	-0.01	0.991
Agriculture and Veterinary	0.373	1.45	0.471	0.79	0.429	0.301	1.35	0.641	0.64	0.524
Health and Welfare	-0.823	0.44*	0.440	-1.87	0.062	-0.896	0.41*	0.18	-2.03	0.043
Services	0.427	1.53	0.409	1.04	0.297	0.365	1.44	0.591	0.89	0.373
Job Characteristics										
Sector (Ref. Cat: public sector)										
private sector dummy	0.079	1.08	0.153	0.52	0.603	0.099	1.10	0.169	0.65	0.518
non-profit organiz. dummy	0.621	1.86*	0.334	1.86	0.063	0.655	1.94*	0.639	1.97	0.048
managing other employees	-0.401	0.67***	0.126	-3.19	0.001	-0.386	0.68***	0.086	-3.06	0.002
job flexibility working hours	-0.178	0.84	0.121	-1.46	0.144	-0.173	0.84	0.102	-1.43	0.154
Occupation (Ref.Cat. Skilled Occupations)										
Semi-skilled white-collar	0.811	2.25***	0.178	4.55	0.000	0.789	2.20***	0.395	4.39	0.000
Semi-skilled blue-collar	1.228	3.41***	0.199	6.17	0.000	1.196	3.31***	0.662	5.98	0.000
Elementary Occupations	2.128	8.40***	0.288	7.39	0.000	2.053	7.79***	2.266	7.06	0.000
Skills										
PV in Litearcy						-0.001	0.99	0.0026	-0.38	0.702
PV in Numeracy						-0.002	0.99	0.0023	-1.06	0.288
Nr of Observations	2058					2058				
Log Pseudolikelihood	-1068					-1066				
Wald Chi2(36)	247.05					249.7				
Prob>chi2	0.000					0.0000				
Pseudo R2	0.133					0.135				

Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013). Estimates are done using sample weights and replicate weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%. Odd ratios have a positive sign.

The estimates of the logit model with the self-assessed measure of over-qualification as a dependent variable are shown in table A.13 in the appendix. Again, the foreign born are more likely to perceive themselves as over-qualified than natives after controlling for individual and job characteristics, but the coefficients in this specification are not significant.

5.2.2. Wage Differences between well matched and over-qualified workers

Tables 5.2.2. and 5.2.3. depict the coefficient estimates of equations 4.2.1-4.2.3 for immigrants and natives using the direct measure of over-qualification as an independent variable. The dependent variables is the log of earnings per hour. The coefficients using the self-assessed measure of over-qualification are shown in the appendix. The first columns in each specification show a short version of the regressions without including job characteristics as control variables. In the second columns job characteristics are added. Looking first at the short specification, coefficient estimates show that over-qualified immigrants earn on average 10.9% per hour less than well-matched immigrants. The under-qualified immigrants gain a 27.4% wage premium. Comparing this with the estimates for natives in table 5.2.3, the magnitude of the estimate for over-education is similar, but the wage premium for being under-qualified is lower for natives (14.1%), almost half of that incurred by immigrants. Adding job characteristics as explanatory variables in the second column improves the fit of the model. The magnitude of the wage penalties and premiums is reduced for both natives and immigrants, but the over-qualified dummy is no longer significant for immigrants in the longer specification.

The second specification introduces the plausible values in literacy and numeracy as additional control variables. Extending the model by these skill measures provides a way to control for unobserved heterogeneinity of individuals with similar education levels. If the OLS estimates are biased upwards due to differences in skills between the over-qualified and well-matched, then we expect the magnitude of the wage penalties to fall in this specification. We see that adding these skill measures in the second specification does not alter much the coefficient estimates, neither for immigrants nor for natives. This may be interpreted as supporting evidence that the wage penalties/ wage premia are not a result of differences in skills.

In the last specification, both skill measures and dummy variables indicating skill mismatch are added in the model. Looking at the estimates for immigrants, the last two columns in table 5.2.2 show that both wage penalties and wage premia fall for immigrants.

Table 5.2.2: Estimates of Earnings Regressions for Immigrants using the Direct Measure of Qualification Mismatch

IMMIGRANTS												
Log w	**1. Specification**				**2. Specification:Skills**				**3. Specification: skill mismatch**			
	Coeff.	Rob.Std. Err.	Coeff.	Rob. Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Rob.Std. Err.	Coeff.	Rob.Std. Err.	C.	Rob. Std. Err.
constant	1.99***	0.093	3.22***	0.35	1.696***	0.114	3.178***	0.375	2.11***	0.1	3.3***	0.378
Indiv. Char.												
female	-0.15***	0.04	-0.175***	0.046	-0.162***	0.039	-0.176***	0.047	-0.15***	0.041	-0.17***	0.048
training	0.024	0.05	0.021	0.056	0.004	0.048	0.0193	0.056	0.0167	0.047	0.009	0.057
experience	0.013	0.01	0.019**	0.008	0.012*	0.007	0.019**	0.008	0.014*	0.0071	0.02**	0.01
(experience)^2	-0.000	0.00	-0.0003*	0.000	-0.000	0.0002	-0.0003*	0.0002	-0.000	0.0002	-0.00*	0.000
children	0.07	0.049	0.039	0.05	0.08*	0.048	0.041	0.051	0.0525	0.0511	0.028	0.054
comp exp	-0.012	0.062	-0.046	0.07	-0.03	0.061	-0.045	0.0696	-0.026	0.0618	-0.06	0.068
Non-Austrian Q.			-0.11**	0.049			-0.101*	0.0515			-0.094*	0.051
Qual. Father (Ref. Cat: Primary or lower 2.nd)												
2.nd Education	0.082*	0.04	0.071	0.046	0.066	0.043	0.069	0.048	0.079*	0.0441	0.0702	0.048
3.tiary Educ.	0.0302	0.065	0.011	0.071	-0.003	0.063	0.007	0.071	0.0243	0.0654	0.0024	0.071
Highest Level of Qualification (Ref. Low 2.nd)												
Upper 2.nd.	0.204***	0.046	0.069	0.055	0.16***	0.04	0.066	0.054	0.19***	0.045	0.058	0.055
Post 2.nd no 3rt	0.434***	0.063	0.228***	0.07	0.37***	0.07	0.223***	0.0737	0.44***	0.0647	0.22***	0.076
3.tiary Profess.	0.38***	0.085	0.222*	0.114	0.31***	0.082	0.217*	0.114	0.37***	0.0869	0.211*	0.116
3.tiary Bach.	0.726***	0.17	0.503**	0.185	0.63***	0.17	0.50*	0.187	0.72***	0.169	0.51**	0.195
3.tiary Master	0.778***	0.09	0.384***	0.101	0.68***	0.087	0.379***	0.103	0.76***	0.089	0.37***	0.101
Job Character.												
Flex work hours			0.117*	0.059			0.113*	0.062			0.105*	0.062
log(w. work hrs)			-0.233***	0.916			-0.234**	0.094			-0.22**	0.095
Occup (Ref.Cat. Skilled)												
Occup Cat 1			-0.208**	0.081			-0.207**	0.081			-0.19**	0.083
Occup Cat 2			-0.173	0.0818			-0.169*	0.082			-0.17*	0.082
Occup Cat 3			-0.315***	0.087			-0.31***	0.086			-0.29***	0.0895
Firm Size (Ref. Cat:>1000 employees)												
01--10			-0.044	0.101			-0.0431	0.101			-0.042	0.101
11--50			-0.13	0.091			-0.128	0.091			-0.132	0.09
51--250			-0.046	0.0934			-0.0469	0.094			-0.033	0.093
251-1000			0.0827	0.0957			0.0802	0.097			0.09	0.095
Qual.Mismatch												
over-qualified	-0.109***	0.0378	-0.061	0.044	-0.101**	0.0375	-0.061	0.044	-0.94**	0.0374	-0.047	0.045
under-qualified	0.274***	0.071	0.171**	0.073	0.263***	0.068	0.171**	0.074	0.26***	0.0715	0.165*	0.073
Skills												
PV in Litearcy					0.0017**	0.0007	0.00012	0.001			0.001	0.001
PV in Numeracy					-0.0003	0.0007	0.00004	0.001			0.0001	0.0007
Skill Mismatch												
over-skilled									-0.006	0.056	-0.044	0.074
under-skilled									-0.064	0.045	-0.064	0.052
Nr of Obs.		369		253		369		253		366		251
R2		0.39		0.54		0.42		0.54		0.40		0.54
F		14.34		9.75		13.73		9.23		13.71		9.1
Prob>F		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000

Source: Own Calculations, Data: STATISTIK AUSTRIA, PIAAC 2011/2012 (Scientific Use File). Estimations are done using sample weights and replicate weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%. Occup. Cat 1 denotes semi-skilled white collar, Occup. Cat 2 denotes semi-skilled blue collar, Occup. Cat 3 denotes Elementary Occupations.

Table 5.2.3. Estimates of Earnings Regression for Natives using the direct measure of Qualification Mismatch

NATIVES												
logw	**1. Specification**				**2. Specification-Skills**				**3. Specification: skill mismatch**			
	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.
constant	1.81***	0.051	2.68***	0.145	1.45***	0.082	2.33***	0.148	1.74***	0.07	2,27***	0.15
Ind. Char.												
female	-0.147***	0.015	-0.172***	0.018	-0.13***	0.015	-0.16***	0.018	-0.15***	0.015	-0.15***	0.02
training	0.038**	0.015	0.017	0.014	0.035**	0.015	0.017	0.014	0.04**	0.015	0.015	0.01
experience	0.034***	0.003	0.033***	0.003	0.034***	0.004	0.03***	0.003	0.034***	0.004	0.03***	0.003
$(experience)^2$	-0.001***	0.001	-0.001***	0.000	-0.001	0.000	-0.001***	0.000	-0.001***	0.00 0	-0.00***	0.001
children	0.006	0.018	-0.02	0.017	0.004	0.017	-0.022	0.017	0.01	0.018	-0.021	0.017
Comp.exp.	0.124	0.036	0.103***	0.035	0.096**	0.036	0.083**	0.035	0.13***	0.036	0.084**	0.035
Non-Aust Qual.			0.36	0.235			0.547*	0.262			0.51**	0.244
Ed. Father (Ref. Cat: Primary or lower 2.nd)												
2.nd Education	0.021	0.017	0.028*	0.016	0.015	0.017	0.024	0.016	0.025	0.017	0.027	0.016
3.tiary Educ	0.047	0.026	0.04*	0. 024	0.033	0.025	0.033	0.024	0.05*	0.027	0.036	0.024
Qual. Lev (Ref. Lower 2.nd)												
Upper 2.nd	0.176***	0.023	0.145***	0.023	0.15***	0.023	0.13***	0.023	0.18***	0.024	0.13***	0.023
Post 2.nd	0.432***	0.029	0.324***	0.032	0.37***	0.031	0.28***	0.033	0.43***	0.029	0.28***	0.033
3.tiary Prof.	0.446***	0.031	0.365***	0.033	0.39***	0.033	0.32***	0.034	0.44***	0.032	0.32***	0.035
3.tiary Bachelor	0.476***	0.069	0.329***	0.076	0.41***	0.072	0.28***	0.077	0.48***	0.070	0.28***	0.077
3.tiary Master	0.711***	0.031	0.564***	0.037	0.63***	0.035	0.49***	0.038	0.71***	0.032	0.49***	0.039
Job Charact												
Flex work hours			0.067***	0.016			0.07***	0.016			0.066***	0.016
log(w work hrs)			-0.168***	0.034			-0.17***	0.034			-0.165***	0.033
Occup (Ref.Cat. Skilled Occup)												
Occup Cat 1			-0.13***	0.021			-0.12***	0.021			-0.12***	0.021
Occup Cat 2			-0.12***	0.025			-0.11***	0.025			-0.106***	0.025
Occup Cat 3			-0.15***	0.036			-0.12***	0.036			-0.12***	0.035
Firm Size (Ref. Cat:>1000 employees)												
01--10			-0.223***	0.029			-0.2***	0.029			-0.22***	0.029
11--50			-0.12***	0.028			-0.11***	0.027			-0.11***	0.027
51--250			-0.08***	0.028			-0.08***	0.028			-0.082***	0.028
251-1000			-0.017	0.031			-0.012	0.031			-0.013***	0.031
Qual. Mismatch												
over-qualified	-0.114***	0.019	-0.097***	0.018	-0.11***	0.019	-0.09***	0.018	-0.11**	0.019	-0.089***	0.017
under-qualified	0.141***	0.021	0.097***	0.02	0.12***	0.021	0.09***	0.020	0.14**	0.021	0.081***	.0.020
Skills												
PV in Literacy					0.0005	0.004	0.0002	0.0003			0.0001***	0.000
PV in Numeracy					0.001***	0.003	0.001***	0.0003			0.001***	0.000
Skill Mismatch												
over-skilled									0.072	0.042	0.07*	0.036
under-skilled									-0.008	0.017	-0.12*	0.016
Nr of Obs.		2415		2356			2415		2356	2409		2350
R^2		0.37		0.447			0.392		0.46	0.38		0.459
F		86.91		71.6			80.5		69.96	81.07		65.34
Prob>F		0.0000		0.0000			0.0000		0.0000	0.0000		0.0000

Source: Own Calculations, Data: STATISTIK AUSTRIA, PIAAC 2011/2012 (Scientific Use File). Estimations are done using sample weights and replicate weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%. Occup. Cat 1 denotes semi-skilled white collar, Occup. Cat 2 denotes semi-skilled blue collar, Occup. Cat 3 denotes Elementary Occupations.

The wage penalties for the over-qualified workers fall from -10.1% in the specification with skill proficiency measures to -9.4% in the specification without job characteristics controls and from -6.1% to -4.7% in the specification including job characteristics. The wage premia fall slightly from 26.3% to 16.5% in the short specification and from 17.1% to 7.3% in the long specification.

The figures for natives in table 5.2.3. show no considerable change in the estimated coefficients for both mismatch variables.

The estimates of the regressions using the self-assessed measure of over-qualification as an independent variable in the appendix show a slightly different picture. Perceiving themselves to be over-qualified is associated with a wage penalty for immigrants (although not significant) which amounts to around -4% in the first two specifications; the wage penalty disappears when skill mismatch controls are included. This wage penalty is much lower than the estimated wage penalty that arises due to being formally over-qualified. However, the estimates using the direct measure of over-qualification approach the same magnitude of wage penalties (-4%) that arise when the full model speicifications are used (both skills and skill mismatch measures). The estimates for wage premia are in this case also much lower than when the direct measure of mismatch is used. Results for natives in table A.15 show a very diffent picture, admitting to be over-qualified for the job does not imply earnings losses for them. The positive coefficient estimate on the over-qualified dummy show that they even face a small earnings premium amounting to around 3 %, although not significant.

In sum, the estimation results show that there is a wage gap between over-qualfied and well-matched workers; the magnitude is similar for natives and immigrants (between 10 and 11%). This estimate is lower when job characteristics are accounted for. Skill differences do not seem to play a big role in the implications of over-qualifications for earnings. Interesting is the fact that for immigrants, the magnitude of the wage penalties and wage premia falls when both skills and skill mismatch variables are controlled for. There is a considerable reduction in the wage gap (-10% from to around -4%) between over-qualified and well-matched immigrants in this case; the lower wage gap is in this case, however, not significant so we may say that the wage gap is reduced to 0% in this specification. One may conclude, therefore, that the wage penalties of immigrants are more resulting from the under-utilization of skills than from a lack of them. This conclusion is further supported by the estimates using the self-assessed measure of mismatch, which yield the same magnitude of wage differences between the over-qualified and well-matched. It is therefore not the fact of being over-qualified in itself, but the fact of not utilizing one's skills, which brings about earnings losses.

VI. Summary and Conclusions

The evidence from economic studies on the labour market outcomes of immigrants emphasizes in particular the lower rates of return to education for immigrants. A majority of these studies neglects the repeatedly observed fact that highly educated immigrants tend to disproportionately work in low-skilled occupations in the host countries, being therefore over-qualified or over-schooled for the job they hold. Over-qualification of immigrants is an outcome of complex processes pertaining to immigration in particular and the labour market in general. Consequently, a complete understanding of the disproportionate representation of immigrants among the over-qualified requires a profound knowledge of migration histories, processes and patterns and labour market conditions as well as respective laws and regulations. In either case, a full understanding is restricted from the data that one has at hand, which also determine the questions one can answer.

This thesis takes a closer look at the phenomenon of over-education among immigrants in the Austrian labour market using data from the PIAAC survey collected during 2011/2012. The nature of the data does not allow us to provide answers to the question of why immigrants are more likely to be over-qualified, although this is a very interesting question in economics. The data also does not allow us to draw causality conclusions regarding the effect of over-qualification on earnings, as it is simply a cross-section data. This also implies that we cannot observe changes of over-qualification over time. The answers to these questions remain open for future research.

Given the available dataset, which despite these drawbacks represents a major improvement in the quality and extent of information that it contains, the first main objective of this thesis was to quantify the extent of over-qualification of immigrants. This is done using both a direct measure of over-qualification, which compares the attained level of qualification with the qualification required in the job and a self-reported measure of over-qualification, which asks individuals to state whether they consider themselves to have the necessary or a higher education than then one which is required for the current holding job. According to both measures, a higher percentage of immigrants than natives are over-qualified. An interesting result is that although a great proportion of immigrants (41%) are over-qualified according to the direct measure, a much lower proportion perceives themselves to be over-qualified (26%). These results are also confirmed in the logit regression estimates when comparing immigrants with natives with similar characteristics.

Another advantage of the dataset is that it incorporates measures of skills proficiency and skill use. The skill proficiency measures allow us to control for part of the unobserved heterogeneity of workers and to obtain more reliable OLS estimates. In addition, by computing also the extent of over-skilling and under-skilling, it is possible to better understand the nature of over-qualification, whether it is merely a formal one, or whether it is asscociated with skill under-utilization. Resuslts show that a large proportion of the over-educated immigrants (67%) are also over-skilled.

Concern on over-education from an economic point of view, arises from the earnings penalties that it implies. Two hypotheses dominate this discussion: the unobserved heterogeneity hypothesis, stating that over-educated workers might have lower skills, abilities, motivation or other personality traits, which are primarily the cause for the lower earnings of the over-educated workers compared to the well-matched. The second hypothesis, the genuine mismatch hypothesis, states that over-qualified jobs put a constraint on the productivity of workers, as they cannot fully utilize their skills, and this under-utilization of skills will be reflected in lower earnings.

The estimation of the wage penalties that over-educated immigrants face is the second main objective of this thesis. The estimates from a simple model a la Verdugo R. and Verdugo N. (1989) show that over-educated immigrants face a 10.9% wage penalty compared to well-matched workers with the same level of education. The magnitude is similar for natives. When skill measures and over-skilling are included in the regressions, there is almost no change in the coefficients in the earnings regressions of natives but interesting results emerge for immigrants. Whereas skills controls do not make a big difference regarding the wage gap, the inclusion of the skill mismatch variables reduces the wage penalty for immigrants from 10.9% to 0% (4.7% but not significant). This is, of course, a considerable reduction, and if one considers that we cannot control for unobserved heterogeniety of individuals, like their innate ability or motivation in the workplace, then one can conclude that the pay penalties of over-educated immigrants are negligible. This is supported also by the estimates based on the self-reported measure of over-qualification, which also show only a marginal wage gap between the over-qualified and adequately qualified workers. The estimates for natives do not change when skill proficiency and skill mismatch variables are added, an indication that the degree of skill-underutilization has more serious consequences on productivity and earnings for immigrants than for natives.

A main drawback of the analysis in this paper is the inability to control for self-selection into employment and over-education. Due to the complicated nature of the data, the statistical software available did not allow me to test for this point. While the self-selection into over-education among immigrants and natives may be of similar magnitude, one expects to have a different selection into employment of the two groups. Given the dataset, it was also impossible to infer the reasons behind mismatch, i.e. whether over-qualification and over-skilling of immigrants is due to preferences or discrimination or arises because of a lack in familiarity with the host labour market. Future research should address these issues.

APPENDIX I

Keywords: over-education, immigrants, wage penalties, Austrian Labour Market

Abstract

This thesis addresses the question of over-education of immigrants in the Austrian labour market. It relies on the recently released PIAAC data of 2011/2012 to give multiple estimates of the extent of over-education of immigrants in the Austrian labour market and compare it to the over-education of natives. Descriptive statistics as well as a logit regression model show that immigrants are much more likely to be over-educated than natives. The incidence of over-education using the direct measure of over-qualification is 40.8% for immigrants, whereas the proportion of natives that is over-qualified is 25.7%. It is interesting that a much lower proportion of immigrants perceive themselves as over-educated. Contrasting over-education with skill mismatch shows that a very high proportion (67%) of the over-qualified immigrants are also over-skilled, indicating that there is a real over-qualification, i.e. that a majority of them are under-utilizing their skills.

The second question of this thesis focuses on the wage differences between over-qualified and adequately qualified workers. Estimations of a simple Verdugo N. and Verdugo R. (1989) model show that over-educated immigrants earn on average 10.9% per hour less than the well-matched colleges with the same level of education. While skill control measures do not play a role for the pay implications, controlling for skill under-utilization yields a much lower estimate of the wage penalty of immigrants, which reduces to 4.7%. This magnitude is, however, insignificant and one can conclude that the wage penalty reduces to 0% when skill proviciency and skill controls are controlled for. This evidence suggests that, for immigrants, the pay penalties are to a large extent the result of their under-utilization of skills.

Kurzfassung

Diese Arbeit untersucht die bildungsinadäquate Beschäftigung bei den ZuwandererInnen am österreichischen Arbeitsmarkt. Beruhend auf Mikrodaten der PIAAC Erhebung aus den Jahren 2011/2012 werden zwei Indikatoren der Überqualifizierung geschätzt und der Anteil der überqualifizierten ZuwandererInnen wird mit dem Anteil der überqualifizierten InländerInnen vergliechen. Sowohl die rein deskriptiven Statistiken als auch die Logit Regressionsergebnisse zeigen, dass ZuwandererInnen viel häufiger überqualifiziert sind als ÖsterreicherInnen. Der Anteil der überqualifizierten Immigranten beträgt 40.8%, während nur 25.7% der Österreicher in einem Job arbeiten, dessen Anforderungen über ihrem Qualifikationsniveau liegt. Interessant ist, dass ein viel kleiner Anteil der tatsächlich überqualifizierten ZuwandererInnen angibt, es zu sein. Wird in der Analyse auch der Ausmaβ der Nutzung von Qualifikationen in Betracht gezogen, so ergibt sich, dass ein relativ hoher Anteil (67%) ihre Qualifikation nicht genügend einsetzt.

Die zweite Frage, der in dieser Arbeit nachgegangen wird, ist die Schätzung der Lohnunterschiede zwischen den überqualifiziert und adäquat Beschäftigten. Schätzungen des Verdugo N. and Verdugo R. (1989) Modells zeigen, dass überqualifizierte ZuwandererInnen im Durchschnitt 10% weniger verdienen als diejenigen, die entsprechend ihrer Qualifikation arbeiten. Fügt man in den Regressionen noch Variablen hinzu, die für Kompetenzen kontrollieren, dann verändern sich die Schätzungen nicht grundlegend. Wenn man aber den ungenügenden Einsatz von Kompetenzen in den Regressionen miteinbezieht, dann sinkt der Lohnunterschied auf 0% (4.7% allerdings nicht signifikant). Dies bedeutet, dass die Lohnunterschiede für ZuwanderInnen, die aus einer Überqualifizierung entstehen, im Grunde mit einem ungenügenden Einsatz von Kompetenzen zusammenhängen.

APPENDIX II

Data Preparation

The descriptive analysis is based mainly on the OECD public use files (PUF). The part of the analysis that discusses earnings uses the Scientific Use files made available by STATISTIK AUSTRIA. The datasets include observations of 1328 variables on 5130 individuals. Following the recommendations of STATISTIK AUSTRIA, estimates with a number of observations smaller than 20 will not be reported. All estimates are derived using sampling weights and are therefore representative of the population; in case of statistics related to competences, the 10 plausible values are included. Furthermore, 80 replicate weights are also incorporated in the calculation of standard errors. The calculated standard errors are then used to check for the reliability of estimates based on the coefficient of variation, a measure calculated as a fraction of the standard error divided by the estimate. All weighted estimates with a coefficient of variation greater than 33.3% are not reported (Statistik Canada, 2002). Before analysing the data, all the variables, that were saved in string format were converted into numerical and checked for consistency. Missing values resulted from the design of the survey. The different categories of missings (valid skips, not stated or inferred and refused, which in either case are negligible and do not affect the quality of the estimates) are recoded into a single missing category. All other variables are retained in the form given, and some new variables were derived from the old ones, mainly those related to mismatch.

The sample includes 5025 complete cases. 105 observations were classified as literacy related non-response (language problem, reading or writing difficulty, learning and mental disability) and therefore were missing values. 1170 individuals took the Paper Based form of the Direct Assessment (435 due to lack of computer experience, 191 failed the ICT Core Stage 1 Test, 543 refused the Computer Based Test) and therefore have no PV in Problem Solving. The majority answered the BQ in German. For 589 individuals the test language was not the same as the native language. Those individuals who failed the core test in literacy and were unable to continue with the more complicated set of tasks were directed to the Reading Component Part of the test (1140 Individuals of which 913 were native born with German as a native language). For these individuals the PV scores are imputed as incorrect in the other part of the tasks. The estimates regarding the mismatch variables are calculated only for the employed individuals, this reduced the number of observations to 3737. In case of the over-qualified, the self-employed are also excluded. The analysis focuses on immigrants, and both male and female workers are included in the analysis. A separate analysis by gender is not possible, due to the smaller number of observations for immigrants. The term immigrant is used to refer to individuals not born in Austria.

Notes on the Implementation of the OECD Measure of Skill Mismatch in Stata

Following Pellizzari M. and Fichen A. (2013), the mismatch in problem solving is excluded from the analysis, due to a lack in observations in this domain. Mismatches are computed for each occupation category using the available ISCO1C one digit occupational codes of current jobs. We include in the computation only the employed respondents from the sample. Pellizari M. and Fichen A. (2013) use bootstrapping methods with sample expanding by replication to compute correct standard errors to account for the variability of the sample across countries. In our case, as our analysis is restricted to Austria, the computation of standard errors will use the replicate weights, similar to what is done in computing other statistics relying on the PIAACTOOLS in Stata. The following steps were undertaken:

*First Ste*p: Identification of the self-assessed well-matched workers.

Computing the skill requirements of jobs requires first identifying the proportion of workers self-assessed as well-matched i. e. those that do not feel they have the skills to cope with more demanding duties and do not feel they need further training in order to cope with their present tasks in the job- based on questions f_q07a and f_q07b (neither over-skilled nor under-skilled). 136 of the employed individuals were self-declared as well-matched in terms of skills. Then I check the number of the well-matched in each sector. (Table A.3.2 in Annex).

The occupation categories ISCO1-1 (armed forces) and ISCO-2 (legislators) have fewer than 10 self-reported well-matched workers and therefore have been dropped. Others with still small number of observations are retained in the analysis, as they are simply an intermediary step and are not the object of analysis.

Second step: The job requirements in each occupation are identified, that is the minimum and maximum level of assessed skills of well-matched workers, identified in step 1, are defined in each occupation. First the mean of the 10 plausible values are computed for each individual, and then the min and max of these mean proficiency scores in each occupation for the well-matched are identified. The computations are repeated for both the domains of literacy and numeracy. Tables A.5 and A.6 report the results of these computations.

The categorization of individuals as under- and over-skilled in each occupation and for each skill domain is based on these minimum and maximum values. Individuals for which the proficiency scores are greater than the maximum proficiency score of well-matched individuals in a given occupation, are considered as over-skilled in that occupation. Those for which the proficiency scores are lower than the minimum are under-skilled. Individuals with proficiency scores within the (min, max) are well-matched. Results for all employed respondents are depicted in tables A.7 and A.8 in the Appendix.

Table A.1 : Description of Proficiency Levels

Level	Literacy	Numeracy	PS in Technology Rich Environment
Below Level 1	Individuals are able to read short texts on familiar topics involving basic vocabulary and easy sentence structures and locate a information identical in form to information in the question.	Individuals can solve simple tasks with explicit mathematical content. They are able to perform basic arithmetic operations with whole numbers or money.	They can perform tasks with explicitly stated goal and solve tasks for which a few number of steps are required. No reasoning, inference or transformation of information is required.
Level 1	Individuals can read short digital or print continuous or non-continuous or mixed texts and locate information identical or synonymous to the information in the question.	Individuals can complete basic tasks, where the mathematical context is explicit with little text and minimal distractions. They can sort basic mathematical operations, understand simple percents and can locate and identify elements of simple graphical representations.	They can perform tasks with explicitly stated goals. They can solve problems in a technology rich environment involving a few number of steps, a restricted range of operators and monitoring and navigation using familiar technology applications such as an email or a web browser.
Level 2	Individuals can integrate information, compare and contrast and reason about information and make easy inferences. They can deal with digital texts to access and identify information.	Individuals can identify explicit mathematical information embedded in common context and are able to compute with decimals and fractions. They can interpret simple data in text, table and graphs.	By using generic and more specific technology applications individuals are able to solve tasks with multiple steps and operators. They can handle unexpected outcomes with a high demand for monitoring and use of complex tools (functions).
Level 3	Can understand long texts, often in discontinuous form in difficult text structures and rhetoric. They are able to identify, interpret and evaluate multiple pieces of information and use them to draw inferences.	Individuals can complete tasks with less explicit mathematical information, embedded in unfamiliar and complicated contexts. They can solve tasks that involve several steps and deal with mathematical relationships, patterns expressed in verbal or numerical form. They can interpret and analyze basic data and statistics in text, table and graphs.	By using generic and more specific technology individuals can complete tasks that involve large number of steps, planning and monitoring to deal with unexpected outcomes. Towards the solution they need to evaluate relevance of information and perform inferential reasoning.
Level 4	Through multistep actions they can integrate, interpret or summarize information from complex, long texts. They can make complex inferences by applying background information and interpret subtle truth claims or arguments.	They can understand complex mathematical information and perform tasks that involve multiple steps and select appropriate problem solving strategies. They can perform complex reasoning about quantities and data. They can understand arguments and formulate well-reasoned explanations.	
Level 5	Individuals are able to search and integrate information from complex, dense texts to summarize similar or contrasting ideas, evaluate evidence and arguments. They can apply and evaluate logical models and the reliability of sources, understand rhetorical cues and are able to make complex inferences using specialized background knowledge.	They can understand mathematical information represented in complex form and statistical ideas embedded in complex texts. They can interpret by integrating several types of mathematical information. They can draw inferences and work and develop mathematical models and evaluate, justify and critically reflect solutions and choices.	

Source: Own Summary from the Readers' Companion (pp. 8)

Table A.2: Highest Level of Education Attained (Question B_Q01a)- Equivalent of ISCED C Categories in the Austrian Education System

International Version	National Version	Years of Schooling
Below ISCED 1	No correspondence	
ISCED 1	Kein Pflichtschulabschluss	7 Years
ISCED 2	Pflichtschulabschluss (8 Jahre)	8 Years
ISCED 3C (<2 years)	Fach-oder Handelsschule: < 2 Jahre	9 Years
ISCED 3C (>=2 years)	No correspondence	
ISCED 3A-B	Lehre mit Berufsschule, Fach oder Handelsschule (>=2 Jahre), AHS	12 Years
ISCED 3	No correspondence	
ISCED 4A-B	Fach-oder Handelsschule: Diplomkrankenpflege, BHS (HAK, HTL, BAKIP)	15 Years
ISCED 4	No correspondence	
ISCED 5B	Meister- und Werkmeisterprüfung, Bauhandwerkerprüfung, Kolleg, Akademie	14 Years
ISCED 5A, bachelor degree	Universität oder Fachhochschule-Bakk/Bach	15 Years
ISCED 5A, master degree	Universität oder Fachhochschule-Mag/Master, Diplomstudium	17 Years
ISCED 6	Doktorat	19 Years

Source: Technical Report (OECD, 2013a).

Table A.3: Skill Use indexes- Tasks Composition

Indicator	Group of Tasks	Variables
INFORMATION PROCESSING SKILLS		
Reading	Reading documents, instructions, letters, memos, e-mails, books, manuals, bills, invoices, diagrams and maps.	G_Q01a-h (at work) H_Q01a-H_Q01h (in everyday life)
Writing	Writing documents (letters, memos, e-mails, articles, reports, forms)	G_Q002a-d (at work) H_Q02a-H_Q02d (in everyday life)
Numeracy	Calculating prices, costs or budgets; use of fractions, decimals or percentages; use of calculators; preparing graphs or tables; algebra or formulas; use of advanced math or statistics (calculus, trigonometry, regression)	G_Q03b-h (at work) H_Q03b-H_Q03h (in everyday life)
ICT Skills	Using e-mail, Internet, Spreadsheets, word processors, programming languages; conducting transactions online; participating in online discussions (conferences, chats)	G_Q05a-h (at work) H_Q04a-H_Q04h (in everyday life)
Problem Solving	Facing Hard Problems (at least 30 min of thinking to find a solution)	F_Q05a-b
OTHER GENERIC SKILLS		
Task Discretion	Choosing or changing sequence of job tasks, the speed of work, working hours, choosing how to do the job	
Learning at work	Learning new things from supervisors or co-workers, learning-by-doing, keeping up to date with new products of services	
Influencing Skills	Instructing, teaching or training people; making speeches or presentations; selling products or services; advising people: planning other's activities; persuading or influencing others; negotiating	F_Q02b-e, F_Q03a-b, F_Q04a-b
Co-operative Skills	Co-operating or collaborating with workers	F_Q01a-b
Self-organizing Skills	Organizing time	F_Q03c
Physical Skills	Working physically for a long period	F_Q06b
Dexterity	Using skill or accuracy with hands or fingers	F_Q06c

Source: BQ & PIAAC Reader's Companion (OECD, 2013) pp. 43.

Table A.4: Nr of self-assessed well matched individuals in terms of skills by occupation

Occupations	Mismatched	Well-Matched
Armed forces	0	20
Legislators	5	234
Professionals	21	657
Technicians	11	775
Clerks	10	363
Service Workers	24	538
Skilled agriculture and Fishery	10	140
Craft and Related Trades	21	401
Plant and Machine Operators	16	185
Elementary Occupations	18	213
Total	**136**	**3667**

Source: Own Calculations using PIAAC Public Use File for Austria (OECD,2013).
Note: Sample and Replicate Weights are used.

Tabel A.5: Minimum and Maximum of Proficiency scores in Literacy of well-matched individuals by occupation category

Professionals

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
285.24	11.72	52.05	10.57	154.09	47.91	357.09	17.02

Technicians and Associate Professionals

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
287.13	16.21	40.54	17.36	193.26	70.21	339.77	21.22

Clerks

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
261.57	13.1	33.14	11.69	212.78	24.19	328.8	41.61

Service workers and shop and market sales workers

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
251.4	9.11	34	7.04	172.33	29.05	314.44	13.52

Skilled agricultural and fishery workers

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
239.93	12.97	32.39	8.79	185.43	23.18	282.45	16.43

Craft and related trades workers

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
237.2	10.09	40.16	7.9	135.16	50.32	311.01	16.58

Plant and machine operators and assemblers

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
229.68	11.68	36.77	8.12	158.2	36.15	294.13	15.27

Elementary Occupations

pvlit

mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
205.14	11.57	34.69	7.83	129.31	33.07	262.26	18.59

Source: Own Calculations Data: PIAAC Public Use File Austria (OECD,2013).
Note: Sample and Replicate Weights are used

Table A.6: Minimum and Maximum of Proficiency Scores in Numeracy of Well-matched Individuals by Occupation

Technicians and Associate Professionals							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
293.69	18.6	49.3	17.6	189.25	61.14	359.87	20.23
Clerks							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
265.93	12.28	29.99	16.53	227.47	15.61	337.99	63.18
Service workers and shop and market sales workers							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
249.2	10.4	38.46	8.36	162.37	37.13	330.09	33.19
Skilled agricultural and fishery workers							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
244.62	13.77	33.31	9.59	188.71	29.4	298.2	26.94
Craft and related trades workers							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
243.84	11.38	51.84	9.83	110.38	46.75	326.72	16.94
Plant and machine operators and assemblers							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
233.42	15.14	51.03	10.36	126.82	55.45	315.65	19.29
Elementary Occupations							
pvnum							
mean	S.E.	sd	S.E.	min	S.E.	max	S.E.
188.46	13.67	43.1	10	110.73	25.75	260.86	28.77

Source: Own Calculations Data: PIAAC Public Use File Austria (OECD,2013).
Note: Sample and Replicate Weights are used

Table A.7 **Mismatch in Literacy- New Measure (OECD) of skill mismatch**

Occupation Categories	Under-skilled		Over-skilled		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Professionals	0.58	0.11	0.76	0.14	98.66	0.17
Technicians and Associate Professionals	2.83	0.25	2.87	0.26	94.3	0.34
Clerks	6.89	0.4	6.26	0.4	86.85	0.57
Service Workers and Shop and market Sellers	1.2	0.17	14.77	0.66	84.03	0.68
Skilled Agricultural and Fishery Workers	2.14	0.23	44.25	0.89	53.61	0.92
Craft and related trades workers	0.31	0.09	17.5	0.68	82.19	0.68
Plant and Machine Operators	0.76	0.13	32.44	0.84	66.81	0.85
Elementary Occupations	0.18	0.07	64.56	0.87	35.26	0.87
Average across sectors	**1.8**		**22.9**		**75.21**	

Source: Own Calculations Data: PIAAC Public Use File for Austria (OECD,2013).
Note: Sample and Replicate Weights are used

Table A.8 **Mismatch in Numeracy: New Measure of Skill Mismatch**

Occupation Category	Under-skilled		Over-skilled		Well-matched	
	%	S.E.	%	S.E.	%	S.E.
Professionals	0.35	0.1	1.65	0.19	98.01	0.22
Technicians and Associate Professionals	2.88	0.29	1.95	0.2	95.16	
Clerks	11.26	0.52	7.6	0.43	81.15	0.56
Service Workers and Shop and market Sellers	1.55	0.18	11.43	0.52	87.02	0.52
Skilled Agricultural and Fishery Workers	2.86	0.28	35.87	0.81	61.27	0.8
Craft and related trades workers	0.14	0.07	13.44	0.6	86.42	0.61
Plant and Machine Operators	0.47	0.11	11.13	0.58	85.92	0.64
Elementary Occupations	0.14	0.07	68.77	0.89	31.09	0.9
Average across sectors	**2.4**		**20.4.**		**70.75**	

Source: Own Calculations using PIAAC Public Use File for Austria (OECD, 2013).
Note: Sample and replicate weights are used. Armed forces and legislators are excluded.

Table A.9: Education Outcomes – Whole Sample

	%	S.E
Highest Level of Qualification		
Lower Secondary (ISCED 1, 2, 3C, short or less)	22.84	0.27
Upper Secondary (ISCED 3A-B, C long)	49.73	0.26
Post Secondary non-tertiary (ISCED 4A-B, C long)	10.62	0.1
Tertiary Professional Degree (ISCED 5B)	6.48	0.25
Tertiary Bachelor Degree (ISCED 5A)	1.53	0.17
Tertiary Master/Hesearch	8.81	0.27
Skill Proficiency Scores		
Mean Proficiency Score in Literacy	269 (s.d: 43.96)	0.74
Mean Proficiency Score in Numeracy	275 (s.d:49.29)	0.88
Mean Proficiency Score in PS	283 (s.d:38.01)	0.73
Distribution across Proficiency Levels in Literacy		
Below Level 1	2.5	0.32
Level 1	13.08	0.68
Level 2	37.87	0.89
Level 3	37.99	0.9
Level 4	8.31	0.46
Level 5	0.27	0.09
Distribution across Proficiency Levels in Numeracy		
Below Level 1	3.46	0.34
Level 1	11.07	0.61
Level 2	33.75	0.88
Level 3	37.85	0.97
Level 4	12.76	0.58
Level 5	1.11	0.17
Distribution across Proficiency Levels in PS		
Below Level 1	13.52	0.74
Level 1	42.14	1.16
Level 2	38.03	1.12
Level 3	6.31	0.57

Nr of Observations: 5024

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013).
Literacy Related non-Responses are not included (105 observations).
Estimations are done using sample weights and replicate weights.

Table A.10: Labour Market Outcomes - Whole Sample

Employment Status		%	S.E
Employed	3737	73.48	0.62
Unemployed	156	3.46	0.27
Out of the Labour Force	1132	23.07	0.59
Economic Sector- Current Work			
The private Sector	2761	75.63	0.72
The public Sector	850	21.49	0.69
Non-Profit Organization	112	2.88	0.28
Occupational Broad Classification			
Skilled Occupations	1888	39.86	0.82
Semi-skilled White collar	1158	28.5	0.76
Semi skilled Blue Collar	930	22.71	0.68
Elementary Occupations	336	8.94	0.46
Distribution across Occupations			
Armed forces	20	0.47	0.1
Legislators, senior officials and managers	239	6.14	0.45
Professionals	678	15.78	0.56
Technicians and associate professionals	786	20.62	0.82
Clerks	378	11.06	0.56
Servic and shop and market sales workers	562	16.35	0.68
Skilled agricultural and fishery workers	150	4.12	0.28
Craft and related trades workers	422	11.91	0.58
Plant and machine operators and assemblers	201	6.11	0.48
Elementary occupations	231	7.44	0.49
Distribution across Industries			
Agriculture, forestry and fishing	156	4.33	0.3
Mining and Quarrying	6	0.2	0.09
Manufacture	600	16.35	0.56
Electricity, gas, steam and air cond.	34	0.95	0.18
Water supply, sewerage, waste management	14	0.35	0.09
Construction	261	7.19	0.46
Wholesale and Retail Trade	524	15.18	0.57
Transportation and Storage	174	5.29	0.39
Accommodation and Food Service Activities	198	5.83	0.41
Information and Communication	100	2.69	0.29
Financial and Insurance Activities	148	4.04	0.36
Real Estate Activities	28	0.81	0.15
Professional, Scientific and Technical	170	4.22	0.34
Administrative support and services activities	106	3.24	0.31
Public Administration and Defence	257	7.05	0.47
Education	404	6.51	0.37
Health and Social Work Activities	66	10.65	0.49
Art, Entertainment and Recreation	104	1.89	0.25
Other Service Activities	10	2.84	0.35
Activities of Househ as Employers/ Extra-terr. Org	3	0.4	0.1

Source: Own Calculations. Dataset: PIAAC Public Use Files (OECD,2013).

Table A.11: Proficiency in Numeracy

	Below Level 1		Level 1		Level 2		Level 3		Level 4		Level 5	
	%	S.E.	%	S.E.	%	S.E.	%	S.E.	%	S.E.	%	S.E.
Immigrant Status												
Natives	1.68	0.27	9.45	0.63	33.74	0.93	40.19	1.12	13.75	0.68	1.19	0.2
Foreign Born	12.65	1.44	19.31	1.84	33.82	2.15	25.82	1.89	7.68	1.15	0.72	0.41
Immigration Generation												
First Generation Immigrants	12.78	1.45	19.37	1.87	33.87	2.18	25.7	1.89	7.57	1.18	0.72	0.41
Second Generation Immigrants	5.5	2.44	15.64	3.95	41.67	4.68	29.23	4.34	7.43	2.31	0.52	0.77
Non first generation or second generation imm.	1.49	0.26	8.99	0.66	33.27	1.01	40.61	1.1	14.34	0.71	1.29	0.22
Non-Immigrants and one foreign born parent	1.16	0.84	10.67	2.03	34.21	3.36	41.97	3.74	11.49	2.04	0.5	0.43
Interaction Country of Birth and Language Status												
Native Born and Native Language	1.55	0.25	9.16	0.64	33.56	0.95	40.53	1.13	13.99	0.69	1.21	0.21
Native Born and Foreign Language	6.59	3.91	20.7	5.46	41.1	6.45	27.18	4.64	4.19	2.32	0.24	0.62
Foreign Born and Native Language	3.07	1.7	10.68	2.88	26.95	4.3	38.35	5.2	18.62	3.31	2.32	1.44
Foreign Born and Foreign Language	16	1.94	22.33	2.31	36.23	2.57	21.43	2.29	3.84	1.27	0.17	0.3

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013). Literacy Related non-Responses are not included (105 observations). Estimations are done using sample weights and replicate weights.

Table A.12: Proficiency in Problem Solving in Technology Rich Environments

	Below Level 1		Level 1		Level 2		Level 3	
	%	S.E.	%	S.E.	%	S.E.	%	S.E.
Immigrant Status								
Natives	12.03	0.75	42.17	1.15	39.27	1.19	6.53	0.61
Foreign Born	23.22	2.66	41.94	3.14	29.98	2.85	4.86	1.5
Immigration Generation								
First Generation Immigrants	23.3	2.69	42.01	3.14	29.77	2.84	4.92	1.53
Second Generation Immigrants	20.03	4.26	46.06	5.96	29.38	4.96	4.54	2.28
Non first generation or second generation imm.	11.33	0.8	41.78	1.28	40.17	1.29	6.72	0.68
Non-Immigrants and one foreign born parent	14.97	2.55	43.63	3.25	35.67	3.25	5.72	1.41
Years in Austria								
Less than 5 years in Austria	19.7	5.86	29.14	7.13	40.63	7.21	10.53	4.81
More than 5 years in Austria	23.86	2.85	44.27	3.38	28.04	3	3.82	1.35
Natives	12.03	0.75	42.17	1.15	39.27	1.19	6.53	0.61
Interaction Country of Birth and Language Status								
Native Born and Native Language	11.75	0.76	42.03	1.17	39.62	1.23	6.6	0.62
Native Born and Foreign Language	22.02	5.48	46.98	6.84	27.16	5.5	3.84	3.06
Foreign Born and Native Language	13.61	3.45	34.41	5.89	42.62	5.29	9.36	3.47
Foreign Born and Foreign Language	28.5	3.42	46.07	3.48	23.04	2.94	2.39	1.62

Source: Own Calculations in Stata. Dataset: PIAAC Public Use Files (OECD,2013).Literacy Related non-Responses are not included (105 observations). Estimations are done using sample weights and replicates weights.

Table A.13: Regression Estimates: Likelihood of being Over-educated- Self-assessed measure of over-qualification

Overqualifiedsubj	(1)					(2)				
	Coeff.	Odds Ratio	Rob. Std. Err.	z	P>|z|	Coeff.	Odds Ratio	Robust Std. Err.	z	P>|z|
constant	-2.41		0.90	-2.68	0.007	-2.36		1.11	-2.12	0.034
Individual Characteristics										
age	-0.004	0.99	0.015	-0.27	0.790	-0.005	0.99	0.015	-0.34	0.736
female	-0.08	0.92	0.176	-0.45	0.651	-0.06	0.94	0.178	-0.34	0.732
uncompleted qualification	-0.23	0.97	0.177	-0.13	0.899	-0.20	0.98	0.177	-0.11	0.909
training	0.02	1.02	0.144	0.14	0.889	0.02	1.02	0.144	0.15	0.880
years of work experience	-0.004	0.99	0.015	-0.30	0.764	-0.004	0.99	0.015	-0.26	0.793
Like learning new things	-0.06	0.94	0.162	-0.37	0.709	-0.06	0.95	0.161	-0.35	0.727
Get to the bottom of difficult things	0.056	1.06	0.143	0.39	0.695	0.052	1.05	0.143	0.37	0.715
married	0.25	1.28	0.201	1.25	0.210	0.24	1.27	0.201	1.19	0.234
children	-0.11	0.9	0.176	-0.60	0.551	-0.105	0.9	0.176	-0.60	0.552
foreign born	0.15	1.16	0.264	0.56	0.576	0.15	1.16	0.264	0.56	0.575
computer experience	-0.01	0.99	0.38	-0.03	0.979	-0.04	0.96	0.382	-0.09	0.927
Highest level of qualification of father (Ref. Cat: Primary or lower secondary)										
Secondary Education	0.084	1.09	0.161	0.52	0.600	0.085	1.09	0.161	0.53	0.595
Tertiary Education	0.01	1.01	0.22	0.05	0.963	0.02	1.02	0.22	0.07	0.944
Non-Austrian Qualification	0.034	1.034	0.455	0.08	0.940	0.058	1.06	0.466	0.13	0.900
Highest Level of Qualification (Ref. Lower Secondary)										
Upper Secondary	-0.31	0.73	0.427	-0.74	0.462	-0.32	0.73	0.427	-0.75	0.452
Post Secondary non-tertiary	-0.19	0.83	0.464	-0.41	0.683	-0.20	0.82	0.466	-0.44	0.663
Tertiary Professional	-0.26	0.77	0.505	-0.51	0.610	-0.26	0.77	0.507	-0.52	0.603
Tertiary Bachelor	-0.49	0.61	0.855	-0.57	0.567	-0.49	0.61	0.858	-0.57	0.565
Tertiary Master/Research	-0.09	0.91	0.487	-0.18	0.854	-0.101	0.90	0.496	-0.20	0.839
Field of Education(Ref. Cat: Science, Mathem. and Computing										
General Programme	0.95*	2.58	0.542	1.75	0.079	0.944***	2.57	0.544	3.45	0.001
Teacher Training and Educ Service	0.33	1.39	0.607	0.54	0.592	0.317***	1.37	0.608	3.21	0.001
Humanities, lang. and arts	-0.33	0.72	0.631	-0.52	0.600	-0.325*	0.72	0.632	1.74	0.082
Social Sciences, business and law	0.311	1.37	0.475	0.66	0.512	0.307	1.36	0.476	0.52	0.602
Engeneering, manufact. and constr.	0.038	1.04	0.477	0.08	0.937	0.022	1.02	0.477	-0.51	0.607
Agriculture and Veterinary	0.201	1.22	0.601	0.34	0.737	0.192	1.21	0.604	0.64	0.519
Health and Welfare	-0.575	0.56	0.610	-0.94	0.346	-0.573	0.56	0.613	0.05	0.963
Services	0.392	1.48	0.502	0.78	0.435	0.395	1.49	0.503	0.32	0.750
Job Characteristics										
Sector (Ref. Cat: public sector)										
private sector dummy	0.72***	2.06	0.206	3.52	0.000	0.715***	2.04	0.207	3.45	0.001
non-profit organiz. dummy	1.16***	3.21	0.357	3.27	0.001	1.15***	3.17	0.359	3.21	0.001
managing other employees	0.25*	1.28	0.144	1.71	0.087	0.245*	1.28	0.144	1.71	0.088
job flexibility working hours	0.01	1.01	0.140	0.06	0.948	0.006	1.01	0.141	0.04	0.967
Occupation (Ref.Cat. Skilled Occupations)										
Semi-skilled white-collar	0.31	1.36	0.186	1.65	0.100	0.307	1.36	0.187	1.64	0.101
Semi-skilled blue-collar	0.05	1.05	0.236	0.20	0.838	0.049	1.05	0.235	0.21	0.836
Elementary Occupations	0.66*	1.93	0.326	2.02	0.043	0.664*	0.904	0.331	2.01	0.045
Skills										
PV in Litearcy						-0.002	0.99	0.003	-0.68	0.499
PV in Numeracy						0.002	1.00	0.003	0.81	0.420
Nr of Observations	2062					2062				
Log Pseudolikelihood	-847.46					-847.15				
Wald Chi2(36)	59.72					60.73				
Prob>chi2	0.0041					0.0061				
Pseudo R2	0.0379					0.0383				

Source: Own Calculations, Data: PIAAC Public Use Files (OECD,2013). Estimates are done using sample weights and replicates weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%.

Table A.14. Estimates of Earnings Regression for Immigrants using the Self-Assessed Measure of Qualification Mismatch

IMMIGRANTS												
logw	**1. Specification**				**2. Specification-Skills**				**3. Specification: skill mismatch**			
	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.	Coeff.	Robust Std. Err.
constant	1.98***	0.086	3.34***	0.367	1.65***	0.115	3.31***	0.399	2.26***	0. 14	3.45***	0.401
Ind.Charact												
female	-0.139***	0.041	-0.177***	0.048	0.16***	0.04	-0.18***	0.048	-0.14***	0.042	-0.17***	0.049
training	0.079	0.049	0.033	0.059	0.052	0.05	0.032	0.058	0.056	0.05	0.013	0.058
experience	0.017**	0.007	0.022**	0.008	0.015**	0.01	0.022**	0.008	0.017**	0.007	0.022**	0.008
$(\text{experience})^2$	-0.0003	0.0002	-0.0004*	0.0002	-0.000	0.00	-0.0004	0.0002	-0.0003	0.0002	-0.001	0.0002
children	0.0631	0.0504	0.029	0.051	0.086*	0.049	0.031	0.053	0.045	0.0522	0.010	0.055
comp exp	-0.14	0.058	-0.067	0.071	-0.035	0.057	-0.066	0.071	0.017	0.0071	-0.076	0.069
Non-Aust. Qual.			-0.116**	0.049			-0.12**	0.051			-0.096*	0.051
Educ Father (Ref. Cat: Primary or lower 2.nd)												
2.nd Educ.	0.096*	0.049	0.081	0.049	0.078*	0.047	0.079	0.051	0.089*	0.048	0.081	0.051
3.tiary Educ.	0.085	0.065	0.041	0.069	0.043	0.063	0.037	0.068	0.061	0.066	0.026	0.068
Qual Lev. (Ref. Lower 2.nd)												
Upper2.nd	0.148***	0.047	0.019	0.053	0.098**	0.046	0.019	0.053	0.14***	0.045	0.018	0.054
Post 2.nd	0.328***	0.065	0.146**	0.065	0.26***	0.069	0.144*	0.07	0.35***	0.068	0.157**	0.073
3.tiary Prof.	0.289***	0.097	0.158	0.117	0.21***	0.091	0.155	0.116	0.29***	0.096	0.165	0.118
3.tiary Bachelor	0.622***	0.126	0.397*	0.187	0.52***	0.133	0.394*	0.189	0.62***	0.131	0.427**	0.197
3.tiary Master	0.618***	0.083	0.227**	0.089	0.52***	0.083	0.226**	0.091	0.61***	0.082	0.232	0.091
Job Charact												
Flex work hours			0.141**	0.062			0.14**	0.065			0.125*	0.064
log(w work. hrs)			-0.238**	0.097			-0.24**	0.099			-0.22**	0.099
Occup.(Ref.Cat. Skilled Occup)												
Occup Cat 1			-0.255***	0.083			-0.25***	0.084			-0.24**	0.084
Occup Cat 2			-0.238***	0.086			-0.24**	0.086			-0.23**	0.085
Occup Cat 3			-0.384***	0.086			-0.38***	-0.085			-0.36***	0.088
Firm Size (Ref. Cat:>1000 employees)												
01--10			-0.06	0.102			-0.056	0.103			-0.051	0.102
11--50			-0.131	0.09			-0.129	0.092			-0.129	0.089
51--250			-0.073	0.093			-0.073	0.094			-0.047	0.092
251-1000			0.058	0.096			0.057	0.097			0.076	0.094
Qual. Mism.												
over-qualified	-0.047	0.06	0.008	0.066	-0.040	0.058	0.008	0.066	0.018	0.069	0.017	0.068
under-qualified	0.025	0.083	-0.08	0.104	0.048	0.082	-0.079	0.0107	-0.107	0.107	-0.105	0.105
Skills												
PV in Literacy					0.003***	0.0008	0.0003	0.001			0.0003	0.001
PV in Numeracy					-0.001	0.0007	-0.000	0.000			-0.000	0.001
Skill Mismatch												
over-skilled									-0.026	0.054	-0.057	0.077
under-skilled									-0.13**	0.048	-0.098	0.052
Nr of Obs.		372		255		372		255		369		253
R2		0.3272		0.5171		0.3554		0.5173		0.3460		0.5286
F		12.35		9.82		12.57		9.25		13.02		8.74
Prob>F		0.0000		0.0000		0.0000		0.000		0.0000		0.0000

Source: Own Calculations, Data: STATISTIK AUSTRIA, PIAAC 2011/2012 (Scientific Use File). Estimations are done using sample weights and replicates weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%. Occup. Cat 1 denotes semi-skilled white collar, Occup. Cat 2 denotes semi-skilled blue collar, Occup. Cat 3 denotes Elementary Occupation.

Table A. 15. Estimates of Earnings Regression for Natives using the Self-Assessed Measure of Qualification Mismatch

NATIVES												
logw	**1. Specification**				**2. Specification-Skills**				**3. Specification: skill mismatch**			
	Coeff.	RobStd. Err.	Coeff.	Robust Std. Err.	Coeff.	Rob Std. Err.	Coeff.	RobStd. Err.	Coeff.	RobStd. Err.	Coeff.	RobStd. Err.
constant	1.76***	0.051	2.65***	0.144	1.32***	0.08	2.26***	0.148	1.74***	0.0 7	2.22***	0.15
Ind.Charact												
female	-0.15***	0.015	-0.171***	0.019	-0.13***	0.015	-0.15***	0.018	-0.2***	0.015	-0.15***	0.018
training	0.06***	0.015	0.028*	0.0142	0.05***	0.015	0.026*	0.014	0.05***	0.016	0.023	0.04
experience	0.035***	0.0035	0.033***	0.003	0.04***	0.0035	0.033***	0.003	0.04***	0.034	0.033***	0.003
(experience)2	-0.001***	0.0008	-0.0004***	0.000	-0.001***	0.000	-0.001***	0.000	-0.01***	0.000	0.004***	0.000
children	0.007	0.018	-0.017	0.073	0.004	0.017	-0.02	0.017	0.008	0.018	-0.02***	0.017
Comp exp	0.17***	0.0355	0.116***	0.035	0.126	0.035	0.093*	0.035	0.163***	0.035	0.092*	0.034
Non-Aus. Qual											0.494*	0.249
Highest level of qualification of father (Ref. Cat: Primary or lower 2.nd)												
2.nd Education	0.035*	0.0174	0.029**	0.020	0.025	0.017	0.030*	0.016	0.039	0.017	0.034**	0.016
Tertiary Education	0,067**	0.027	0.028**	0.0289	0.046*	0.026	0.041*	0.024	0.068	0.027	0.043*	0.024
Qual. Lev. (Ref. Lower 2.nd)												
Upper 2.nd	0.14***	0.024	0.108***	0.023	0.11***	0.023	0.09***	0.022	0.14***	0.024	0.09***	0.022
Post 2.nd	0.38***	0.029	0.26***	0.031	0.31***	0.031	0.21***	0.031	0.38***	0.030	0.21***	0.031
3.tiary Profess	0.37***	0.032	0.287***	0.032	0.31***	0.032	0.25***	0.032	0.36***	0.032	0.24***	0.03
3.tiary Bachelor	0.43***	0.069	0.273***	0.075	0.35***	0.072	0.23***	0.075	0.43***	0.069	0.23***	0.08
3.tiary Master	0.63***	0.03	0.468***	0.035	0.53***	0.033	0.41***	0.0355	0.62***	0.031	0.41***	0.036
Job Character.												
Flex work.hours			0.078***	0.016			0.074***	0.015			0.076***	0.016
log(w work hrs)			-0.157***	0.034			-0.15***	0.034			-0.16***	0.033
Occup (Ref.Cat. Skilled Occup)												
Occup Cat 1			-0.16***	0.021			-0.15***	0.021			-0.14***	0.020
Occup Cat 2			-0.156***	0.025			-0.14***	0.025			-0.13***	0.020
Occup Cat 3			-0.214***	0.035			-0.18***	0.035			-0.17***	0.035
Firm Size (Ref. Cat:>1000 employees)												
01--10			-0.229***	0.029			-0.2***	0.029			-0.22***	0.029
11--50			-0.119***	0.028			-0.11***	0.027			-0.11***	0.028
51--250			-0.083***	0.028			-0.08***	0.027			-0.08***	0.028
251-1000			-0.023***	0.031			-0.02***	0.031			-0.016	0.031
over-qualified	0.026	0.023	0.029	0.020	0.028	0.022	0.03	0.02	0.03	0.022	0.032	0.019
under-qualified	0.027	0.031	0.028	0.028	0.036	0.030	0.039	0.028	0.022	0.030	0.036	0.029
Skills												
PV in Literacy					0.001	0.000	0.0001	0.000			0.0001	0.000
PV in Numeracy					0.001	0.000***	0.001***	0.000			0.0013**	0.000
Skill Mismatch												
over-skilled									0.078*	0.041	0.07**	0.04
under-skilled									-0.04**	0.017	-0.026	0.016
Nr of Observations		2422		2363		2422		2363		2415		2356
R2		0.3487		0.4309		0.3682		0.4446		0.3521		0.4471
F		80.51		67.21		77.25		66.45		75.51		62.57
Prob>F		0.0000		0.0000		0.0000		0.0000		0.000		0.000

Source: Own Calculations, Data: STATISTIK AUSTRIA, PIAAC 2011/2012 (Scientific Use File). Estimations are made using sample weights and replicates weights. Note: * significant at 10% , ** significant at 5% , *** significant at 1%. Occup. Cat 1 denotes semi-skilled white collar, Occup. Cat 2 denotes semi-skilled blue collar, Occup. Cat 3 denotes Elementary Occupations.

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EDUCATION

10/2012 – 11/2014	**University of Vienna**, Master in Economics
10/2009 – 07/2012	**University of Vienna**, Bachelor in Economics
03/2009 – 09/2009	**The Viennese University Preparation Program**
09/2003 – 09/2008	**Business High School Tirana**

INTERNSHIPS

07/2014-09/2014 **UNITED NATIONS INDUSTRIAL DEVELOPMENT ORGANIZATION Vienna**
Internship in the Business, Investment and Technology Services Branch, Clusters and Business Linkages Unit
Research Assistance in the Project “Innovation Clusters”

08/2013 – 09/2013 **GIZ** (German Agency for International Development Cooperation) Tirana
Internship
Economic Development and Employment Promotion Program (**EDEP**)
Analysis of data on Small Medium Enterprises, Entrepreneurship Culture, Informality and Labour Market in Albania

OTHER EXPERIENCES

04/2012 – now **Kultur Kontakt Austria**
Oral and Written Translation in Workshops in Vienna/Tirana (German - Albanian)
Topics: Educations System in Austria, EU-Integration Processes

LANGUAGE SKILLS

Albanian	Native language
English	Cambridge Certificate of Advanced Englisch (C1) - 04/2013
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