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Immigrant-native wage gap, gender, and cognitive skills: Evidence from PIAAC

Master’s Thesis

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I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

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Abstract

The study investigates the effect of cognitive skills and use of these skills in various contexts on the immigrant-native wage gap in 14 European countries by using the data from Programme of International Assessment of Adult Competencies (PIAAC). After revealing the significant disparities in cognitive skills between immigrants and native-born respondents we analyze the effect of skills and their use on the wage gap in a multi-level regression model by controlling for individual demographic and occupational characteristics, as well for a set of host-country characteristics, reflecting economic development and social welfare. Gender differences in immigrant-native wage gap and drivers behind it are paid particular attention. Once the skill-related variables are incorporated, the wage gap considerably decreases for both genders although it still remains significant for females. By analysing immigrants with respect to their tenure in the host country, we observe that in the early years of immigration the foreign-born people are significantly disadvantaged in the host country labour markets regardless of their skills. But in later years the use of skills reveals significant association with hourly earnings of immigrants. The wage decompositions show that Spain, Finland, and Estonia are the countries with the highest immigrant-native wage gaps.

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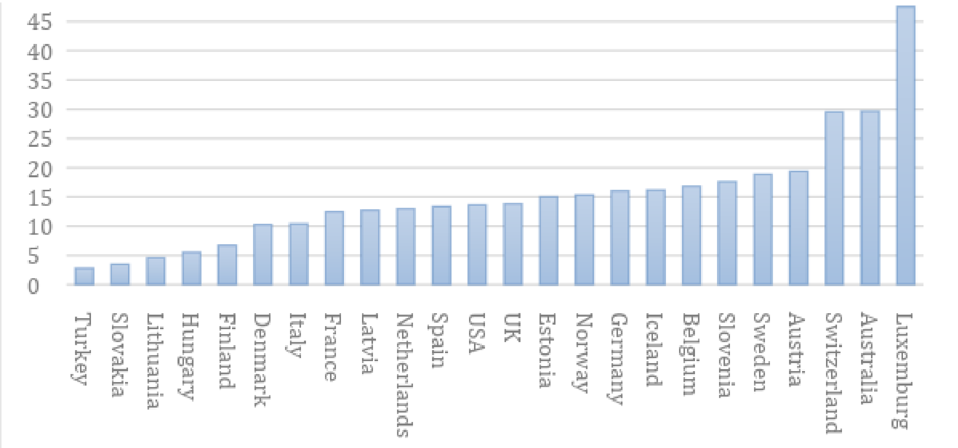
Contents

Introduction

In the age of globalization and eased movement of labour force between countries the number of foreign-born people settling down in different countries is rapidly increasing. This movement especially concerns the economically developed countries since lots of people who are struggling to achieve the desired life standards in their home countries due to various economic and political restrictions see emigration as an the opportunity to build a new life. The increasing percentages of immigrants within the local population in Nordic countries and Denmark have been observed since 2000. As we can see in the Figure 1, as of the end of 2018, more than 10 % of the populations of 19 OECD countries consisted of immigrants. In these circumstances, the authorities of these countries face various issues in their attempt to take benefit of the inflow of these quite heterogeneous sets of people. Being an attractive destination for, particularly, high-skilled foreign labour and proper integration of the newcomers to the society are just some of these issues (Beyer 2019). Thus, studing immigrant-native wage disparities has gained importance for policy makers in recent years, because the wage gap can be considered as a good measure for the level of economic integration of immigrants to the host labour markets (Coulombe et al 2014). By integrating the immigrants well into the society, the governments can take a benefit of the full capacity of human capital and the country-specific skills that they bring from their home countries. Since the current wage gap in earnings of immigrants and natives and the disadvantage of the former group is evident, there is a persistent need for further investigation of the reasons behind the statistics (Adsera and Chiswick 2007; Clark and Drinkwater 2014; Biavaschi and Zimmermann 2014; Grand and Szulkin 2002).

There is a large literature on earnings gap between immigrants and local-born people. Previous studies have focused on language capabilities of immigrants (Chiswick 1991; Chiswick and Miller 1995; Dustman and van Soest 2002, Beyer 2019); cognitive skills (Ferrer et al. 2006; Tverdostup and Pass 2018); quality of human capital (Coulombe 2014); transferability of occupational skills (Imai et al. 2019; Nielsen et al 2001); selection of immigrants into certain industries (Song 2017) and institutional factors (Guzi et al. 2015). However, the literature on actual skill disparities of native-born population and immigrants is rather limited. The only skill domain being relatively well investigated by the existing literature is host-country language command. Among others, Ferrer et al. (2004) conducted an analysis based on IALS (International Adult Literacy Survey) data and documented a significant impact of literacy skills on the earnings of immigrants living in Canada. They conclude that “usability” of cognitive skills is highly dependent on immigrants’ ability to communicate in English or French. Tverdostup and Pass (2019a) find that there is a significant skill gap between the immigrants and natives in OECD countries which in turn affects the wage gap between these groups together with the variables characterizing the use of these skills in different contexts.

Figure 1. Percentage of foreign-born population in selected OECD countries (2018)



Source: OECD data, available from https://data.oecd.org/migration/foreign-born-population.htm?fbclid=IwAR3yqQTXm8-LItVGob2CN_g--G-5jYFH66CKhUmKOuL7YoL2lh2Qdt07654

The main question we pose in this paper relates to key drivers of immigrant-native wage gap in Europe and potential heterogeneities of the latter across men and women. We rely on the Survey of Adult Skills, conducted within the Programme of International Assessment of Adult Competencies (PIAAC).[1] The main advantage of this data is availability of test-based cognitive skill measures, as well as information skill use in different contexts and domains. This allows to empirically test the following hypotheses:

Hypothesis 1: There are significant cognitive skill disparities between the native-born people and immigrants.

[1] For more details, see https://www.oecd.org/skills/piaac/_Technical%20Report_17OCT13.pdf.

Hypothesis 2: There are several factors overwhelmingly driving the wage gap: differences in skill levels and use of these skills between the groups, as well as country-specific factors (macroeconomic and institutional differences).

Hypothesis 3: There is a significant difference in estimates of immigrant-native wage gap and factors behind it across men and women.

The main research gap in the existing literature is that it mainly focuses on the pooled data and ignores the inter-country differences. The contribution of our paper is threefold: (1) incorporation of macro and micro variables together in the analysis of wage differentials of native-born people and immigrants in Europe; (2) the analysis of gender-driven heterogeneities in the immigrant-wage gap; (3) the country-level analysis of the gap which gives us quite interesting results that cannot be observed in the analyses with pooled data.

Our analysis relies on the PIAAC data for 14 European Union countries and incorporates three main parts. First, we identify whether there is a significant difference between the skill levels of the immigrants and native-born people on pooled data by using a simple OLS model. Second, we build a multi-level fixed effect model where the hourly earnings of respondents are regressed over a set of variables such as their skill-levels, usage of these skills in different contexts, occupational, demographic factors, and macro-level characteristics of host countries. In the third part, in order to see the differentials in country level we also employ the Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) which provides us with a reasoning behind the explained and unexplained parts of the gap in each country of analysis.

The results of our analysis indicate that, on average, immigrants attain much lower literacy and numeracy skills, compared to natives. The wage gap in pooled sample appears significant even upon controlling for a full set of micro- and macro-level factors. However, further analysis across men and women shows that the wage gap loses its significance for males when all the mentioned controls and skill-use variables are incorporated, although it remains significant for females. This finding indicates that there is a substantial gender disparity in economic integration of male and female immigrants in Europe, with females facing a stronger wage disadvantage. The latter suggests that policy interventions aiming at reducing wage disproportionalities across foreign- and native-born population should pay particular attention to female immigrants.

The rest of the paper is structured as follows. In the following part of the paper, we briefly discuss the previous literature under different categories according to their explanations of the immigrant-native wage gap. After that we explain the structure of the dataset and variables used in the analysis. Next we present the methodology behind each type of analysis we employ. It is followed by the broad discussion of the results. In the final section, we provide the readers with our general conclusions and recommendations for further research.

Literature Review

In this part we discuss the literature on wage gap in general and immigrant-native wage differentials in specific under two main headlines. The initial section is dedicated to studies focusing on the micro foundations of earnings differentials between immigrant and native-born population. We have also grouped the literature in this category according to the reasoning used to explain the gap, including productivity, self-selection, or pure discrimination. The latter section focuses on the literature dedicated to macro-level factors**.**

Micro-level factors

Productivity

Productivity of an employee in the workplace is the amount of work produced per unit time by an individual. The immigrants who are doing the same job with natives can be less productive due to numerous reasons, including the lack of local labour market experience, mismatch of skills they have gained in their home countries, negative attitude towards work, quality of schooling they have and improper usage of skills at work (Beyer 2019; Coulombe et al. 2014; Imai et al. 2019; Grand et al. 2002; Song 2017). We can say that the first two factors mentioned are generally time-dependent and income differences stemming from them should disappear over the years spent in the host country. Attitude towards work may also change with integrating the immigrants into their new environment. They can also improve their schooling while working in the host country.

Lessem and Sanders (2014) apply the model of human capital accumulation and job search on New Immigrant Survey (US) and report that it takes time for new immigrants to find their optimal occupation in the US job market. An early immigrant-native wage gap reduces by around 7% in case the new-comers can be placed in their long-run occupations. Tverdostup and Pass (2019) show that human capital (measured by cognitive skills) does not explain the gap in wages alone. Immigrants and natives in the same occupational group apply their skills to different extents which leads to differences in their wages.

Local language competency is another significant factor of labour market and social integration. Host country language command allows to transfer previously accumulated occupational skills and knowledge of immigrants to the host country labour market since communication with the native colleagues is crucial for skills application and further accumulation. Beyer (2019) concludes that immigrants from advanced countries with German skills and German degrees experience less discrimination and the wage gap declines by the time spent in Germany. Language command also defines how successfully immigrants integrate into the host-country society. Due to this issue many immigrants experience skills downgrading in their early years in the host countries (Imai et al. 2019).

The attitude towards work can also be different between natives and immigrants, as well as between immigrants of different origin. For example, immigrants may be more inclined to survival rather than career development in comparison to the natives (Bauder 2006; Ley 1999).

Education also plays an important role in early years of immigration. Lower level of education drives the immigrants to concentrate in lower positions in early years. The previous literature reports significantly lower level of education among immigrants (Borjas 1994; Chiswick & Miller 1990). Non-recognition of foreign degrees in the host country can be considered a barrier for the immigrants to find jobs related to their educational backgrounds (Bauder 2003). Even equivalent level of education obtained in home countries may deliver lower returns compared to the human capital obtained in host country (Basilio et al. 2017).

Selection Bias

This section concerns the debate on non-random selection of immigrants into low and high paying employment. There are many factors contributing this selection issue. For example, Aydemir and Skuterud (2008) show that in Canada the immigrants are clustered in low-paying regions (Toronto and Vancouver). In light of this finding, they claim that inter-establishment differentials are more significant than intra-establishment differentials. According to their results establishment fixed effects explain 56 % of variation in log wages. Horrace and Oaxaca (2001) refer to differences in pay scales of various industries to explain the gender wage gap. The same logic can be applied to our case since some industries and occupations may be more open towards immigrants in comparison to others where similar set of skills are required but wages differ considerably. Additionally, due to the lack of knowledge about the local labour market and local language immigrants tend to get jobs in predominantly technical fields rather than the jobs requiring social skills. The growing importance of the latter leads to significant differentials in earnings of the mentioned groups (Song 2017). Tomaskovic-Devey et al.'s (2015) analysis also shows significant wage inequalities among workplaces in Sweden between the non-western immigrants and Swedes. They also show that these differentials are contingent on variation of relative power of groups in organizations – the larger the employment and managerial representation of immigrants, the lower the gap. But these inter and intra-industry differentials are also quite different across the OECD countries. Thus, the immigrants' selection to various countries (Belot & Hatton 2010) may affect the gap in earnings with the locals.

Discrimination

A majority of the literature on immigrant-native wage gap is dedicated to explaining the reason behind it. Thus, most of the time the authors divide the gap into two components – explained and unexplained gap. The explained gap is a component reflecting the differences in skills and attitudes and many other observable characteristics of immigrants and natives. The unobserved gap refers to a component which describes the scale of ignorance of observed skills of immigrants (Coulombe et al. 2014). We may have unexplained gap in our analysis due to many factors including institutional handicaps, market failures and also discrimination (Oreopoulos 2011). Lots of single-country analyses report unequal treatment of natives and immigrants in terms of wage, which signals about underlying discrimination (Kee 1995; Bartolucci 2014; Aldashev et al. 2008).

Several mechanisms have been suggested to explain discrimination in literature. Becker (1957) proposed "taste discrimination" which refers to the unequal treatment of certain racial or ethnic minorities by employers due to their dislike of them. On the other hand, "statistical discrimination" mechanism suggests that discrimination can also be based on imperfect information of employers on individuals' skills and productivity (Altonji and Blank 1999). Since the profit-seeking employers are considering the average productivity of certain category of potential employees by their genders, races and it is also hard to get specific information about individual's background or work attitude, they make their decision according to the approximation mechanism described above (Grand and Szulkin 2002). There are many field experiments conducted in different countries to see whether members of certain minority groups or foreigners are discriminated during recruitment process. By sending randomly manipulated resumes to job postings in Toronto, Oreopoulos (2011) finds that significant discrimination towards people with foreign experience or with Indian, Pakistani, Chinese or Greek names. Several other experimental studies report similar results (Bertrand and Mullaniathan 2004; Andriessen et al. 2012 ; Adida et al. 2010)

In previous sections we made referrals to the studies which were stating that in case of perfect assimilation (newcomer obtains education and work experience in the host country equal to a native counterpart) the unexplained gap should disappear. Still considerable literature reports the opposite (Nielsen et al. 2001; Aldashev et al. 2008). In the analysis conducted on different immigrant groups in Denmark, Nielsen et al. (2001) find that the assimilation component explains the earnings gap for immigrants migrated from Turkey, Africa and India & Sri-Lanka, but discrimination component still remains significant for immigrants from Pakistan. Aldashev et al. (2008) conduct a decomposition analysis for the wage gap between the native Germans and Germans with the migration background and conclude that regardless of similarities in productivity levels, the immigrants are paid significantly less. They also find out that inclusion of educational attainment in Germany significantly reduces the wage gap although it does not eliminate the gap.

Macro-level Factors

A vast amount of literature studies different determinants of native-immigrant wage gap. However, it is very hard to find a paper which analyses how macro-level institutional factor influence this gap. In this aspect, Guzi et al. (2015) bring great contribution to immigrant-native wage gap studies. To study institutional variables effects on immigrant-native wage gap, the paper uses the varieties of capitalism (VoC) framework (Hall and Soskice (2011)). Employment protection indicators related to regular and temporary contracts, union density, and coverage of collective bargaining agreements are the variables from VoC framework, which are likely to have an influence on the wage gap between immigrants and natives. The results indicate that the variables taken from VoC framework have significant effect on both, explained and unexplained wage gaps. For instance, results show that higher protection of regular employment contracts increases unexplained wage gap, while higher protectionism of temporary contacts decreases unexplained wage gap. The reason behind this relationship can be explained easily by unemployment and low-skilled employment. Union density and collective bargaining agreements also show significant effects on native-immigrant wage gap.

Another paper studying immigrant-native labour market gaps is Guzi et al. (2014). The paper studies the relationship between immigrant integration policies and immigrant-native labour market gaps in the EU. Just like other studies on immigrant-native wage gap in the EU, this study also confirms the wage gap existence. The gap is decreasing with the years spent in the host country, however, it still remains and does not fully disappear even after a relatively long time span. The study shows that labour market gaps can be decreased by introducing integration policies. Anti-discrimination, family reunification and labour market access policies help immigrants to find the job which will match their skill-level.

Another paper tackling institutions that affect wage gaps is Schnetzer (2009). The study aims to determine the determinants of native-immigrant wage gap in Austria. The results document that some part of this wage gap is explained by differences in skills, educational backgrounds and occupational segregation. However, the paper also shows that here is part of the gap which cannot be explained. The study suggests antidiscrimination policies are very important for reducing native-immigrant wage gap, however, imperfect information within immigrants about their rights makes such policies less effective towards reducing the wage gap.

Barth, Bratsberg and Raaum (2004) study how macroeconomic variables affect immigrants' assimilation and labour market development. Paper suggests that immigrants are more sensitive to the unemployment rate than natives. During the high unemployment period, immigrant-native wage gap is increasing. However, paper also suggests that non-OECD migrants are more sensitive towards unemployment, than OECD migrants. Moreover, OECD migrants are reacting more or less the same as natives to the unemployment effects. The similar results can also be observed in Guzi et al. (2014), which showed that intra-EU immigrants tend to have higher employment rate and are less sensitive to unemployment comparing to non-EU immigrants.

How economic performance affects immigrants' employment and immigrant-native wage gap is studied by Barret et al. (2016). The study focuses on Ireland and its economic development from 1990s till 2008 Global Economic Crisis. The raw data shows that immigrant-native wage gap grew from 10 per cent to 29 percent in 2006-2009 period. However, using Juhn-Murphy-Pierce methodology (JMP, 1993) decomposition Barret et al. (2016) show that such an increase in immigrant-native wage gap can be explained by compositional changes. More precisely, the solid part of the increase in the raw wage gap can be explained by the decrease in the share of immigrants with degrees and immigrants employed in the relatively high-paid public sector positions.

Dustmann et al. (2009) study the cyclical pattern of employment and native-immigrant wages. The main aim of the paper is to show whether immigrants and native are reacting differently to the cyclical patterns of economy in terms of employment and wages. The study is based on the data of UK and Germany. The results suggest that for both countries unemployment probabilities are more correlated with the economic cycles for the immigrants, than for natives. On the other hand, wages do not show any cyclical patterns neither in UK nor in Germany. The paper also shows that between 1992 and 2005, immigrant-native wage gap has been more or less the same over the years, however, Germany has witnessed a long-term gradual rise of the immigrant-native wage gap.

Data

Our empirical research is based on the Survey of Adult Skills which is collected within the Programme for the International Assessment of Adult Competencies (PIAAC) – a study initiated by Organisation for Economic Co-operation and Development (OECD). The survey has been conducted in more than 40 countries surveying on average 5000 individuals in each country aged between 16 and 65. For our empirical analysis we use data from 14 European countries: Belgium, Czech Republic, Denmark, Estonia, Finland, France, Greece, Ireland, Italy, Netherlands, Norway, Slovenia, Spain and the United Kingdom. These countries were chosen based on two criteria: all the variables we are using for empirical research are available for these countries and immigrant's share in the sample is sufficiently large. We arbitrarily chose 4 % as the threshold for the lowest share of immigrants in the sample country. The first round of survey was held in 2011-2012, which included all the countries mentioned above, except Greece and Slovenia. The latter two countries were surveyed in the second round, held in 2014-2015.

The survey was conducted in 3 modules:

1) Background Questionnaire, which includes the questions about respondents' demographic characteristics, education and training, social and linguistic background, employment status and income.

2) Skills Use Module, in which respondents were asked questions about variety of skills they possessed:

1. Cognitive skills include reading, writing, mathematics and IT competence.
2. Interaction and social skills refer to work-planning, cooperation and negotiation with others, and customer contact.
3. Physical skills reflect motor abilities.
4. Learning skills cover self-development with up-to-date knowledge, continuous learning and instructing others.

3) Direct Assessment Module, which focused on the evaluation of respondents' cognitive skills through tests in 3 categories:

1. Literacy refers to ability to exploit the information from written materials. This is a significant requirement for developing higher-level skills and life-long learning.
2. Numeracy is ability to comprehend and communicate quantitative information and knowledge. It is a necessary skill especially for people of various professions requiring processing larger amounts of mathematical information and those performing different types of computational and analytical work.
3. Problem-Solving in Technology-Rich Environment relates to the set of skills that enables the individuals to cope with complex problems and cognitive tasks. These skills are not the measure of technological literacy but rather of intellectual capabilities that are essential in the information age.

Our analysis focuses on the impact of the numeracy and literacy skills and their use in different domains on the earnings of individuals. There are two main sets of variables that we are using in our analysis. The first set of variables is derived from the test scores of respondents in the Direct Assessment module which shows their capabilities in literacy and numeracy domains. The second set of variables is derived from the questionnaire the respondents answered in the Skills Use Module which indicates the intensity of skills (reading, writing, numeracy and ICT skills) application at work and at home. From now on, these variables will be referred to as 'Skill Use' variables.

The Direct Assessment test results for skill domains vary between 0 and 500 and are reported as a set of ten plausible values. For our analysis, we are using only results of numeracy and literacy skill domains and we have excluded problem solving skill domain, since for certain countries (Italy, Spain and France) the test results are not publicly available. Thus, including problem solving skills in our analysis would decrease the sample size significantly.

The usage of these skills is considered in two sets of variables. First, we look at the skill use in the working environment and then on an everyday basis. We assume that use of skills at the workplace should have a direct effect on wage formation. This set of variables also captures the skill intensity and complexity of the respondent's occupation. The skill use outside the workplace gives additional insight into how intensively and diversely

respondents are using their skills, which could indicate the level of respondents' efforts of self-development.
Since we have excluded problem-solving skills, we decided to include the use of ICT (Information and Communication Technology) skills. It is obvious that in the majority of the workplaces, the ICT skills are highly required, and the use of these skills also indicates the technology intensity of the occupation which is directly linked with the salary that the respondent gets.

Additionally, we have a number of control variables in our analysis that we derived from the background questionnaire. The extended information about these variables is provided in the Appendix I. One has to acknowledge that the skill use variables are self-reported in the questionnaire, thus the possibility of biased replies should not be ignored. However, we do not expect potential questionnaire response biases to inflate our estimates of interest, as long as the problems mentioned above does not lead to correlated deviations.

As mentioned above we are aiming to observe the effect of macro variables on wage gap. For this we have taken several macro-level indicators, which are: union density, employment protection, number of parental weeks given by law, immigrant share in population, unemployment rate, GDP per capita, risk of poverty (for age group 18-64). Data for unemployment rate and GDP per capita was retrieved from the World Bank database and the data for the rest of the variables was taken from the OECD database.

Empirical method

In the first section of our analysis, we identify whether there is a sizable difference between the skill levels of immigrants and natives. We test it separately for both numeracy and literacy skills. Hence for regression analysis, we take literacy and numeracy skill test results as dependent variables. However, PIAAC data includes a set of ten plausible values for each skill domain, derived using the Item Response Theory.[2] To correctly count

[2] For more details see Technical Report of the Survey of Adult Skills (PIAAC), section 17. Available from

standard errors and avoid skill measurement errors, we use Jackknife replication methodology with 80 replication weights to avoid overestimating standard errors. As a result, each regression output is based on 810 replications.[3]

To estimate whether there is difference between natives and immigrants in their literacy and numeracy skill levels, we are using the following model:

$$SCORE_i = \beta_0 + \beta_1 Immig_i + \beta_2 X_i{}' + \varepsilon_i, \qquad (1)$$

where $SCORE_i$ refers to literacy or numeracy score of respondent, $Immig_i$ variable gets value 1 if respondent is immigrant and 0 if respondent is native, ε_i represents error term, vector $X_i{}'$ includes demographic and educational characteristics, occupation, industry and job-related trainings. The detailed information of used control variables is provided in the Appendix I. Consequently, β_1 reflects an unexplained immigrant-native skill gap.

Next, we test if the host country experience affects the skill development of the immigrants. For this, we are adding the variable to the model (1), which captures the number of years an immigrant has spent in the host country. We need to mention that PIAAC is a cross-sectional data, however, the control variables which we have added to the model allow us to certain extent measure the time effect of the change in immigrants' skill level with the increasing years of staying in the host country.[4]

Before moving to the next part of empirical methodology, we need to note that for further analysis, due to computational difficulties, we rely on the first plausible value as an approximation of the actual literacy and numeracy skill levels. Additional robustness checks based on the full set of plausible values show no significant differences with the estimates relying on first plausible value only. This allows us to safely refer to the first

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https://www.oecd.org/skills/piaac/PIAAC%20Tech%20Report_Section%205_update%201SEP14.pdf

[3] For each plausible value 80 replication weights and 1 population weight applies. This results in $10\times80+10\times1=810$ replications.

[4] One has to acknowledge the cohort effects when interpreting the coefficients of host-country tenure. For instance, immigrants, who arrived twenty years ago could be systematically different from those, who arrived within the last five years. We largely capture these heterogeneities by controlling for a large set of demographic and employment controls. Nonetheless, one has to keep in mind potential unobserved heterogeneities.

plausible value in literacy and numeracy skill domains as a valid approximation of actual skills.

Once we have shown that there is a significant difference in the skill levels between immigrants and natives, we move on to analyzing the wage gap between the two groups. For this purpose, we build a multi-level model, which can be expressed by following formula:

$$LogEarnHR_{ij} = \beta_{0j} + \beta_{1j}\, Immig_{ij} + \beta_2\, ScoreLIT_{ij} + \\ + \beta_3\, ScoreNUM_{ij} + \beta_4\, Skill\_USE'_{ij} + \beta_5\, X'_{ij} + \beta_6\, M'_j + \varepsilon_{ij}, \tag{2}$$

where subscript i refers to an individual, subscript j refers to the country of where an individual resides. $LogEarnHR_{ij}$ refers to logarithm of individual hourly earning, $Immig_{ij}$ again gets value 1 if individual is immigrant and 0 if individual is native, $ScoreLIT_{ij}$ and $ScoreNUM_{ij}$ are literacy and numeracy skills respectively, vector $Skill\_USE'_{ij}$ include variables for use of Reading, Writing, Numeracy and ICT skills at work and non-work environment, X'_{ij} is the same vector as described in model (1) and vector M'_j include macro-level factors, which are: Union Density, Number of Parental Leave, Population, Share of Immigrants, Unemployment, GDP per Capita, Poverty at Risk by Country (age 18-64). In this model, we are mostly interested in the β_{1j} coefficient, as this coefficient is going to show us the residual native-immigrant wage gap, once all micro- and macro-level factors are accounted for.

Introducing the macro-level factors to the analysis adds the problem of estimating group-level predictors to our analysis. The type of model where depended variable is observed on individual level, however, it is affected by both individual and group-level factors is often referred as micro-macro data situation (Snijders & Bosker, 2012). According to Foster-Johnson and Kromrey (2018), in education and social sciences, hierarchical linear and random-effect models are most commonly used for micro-macro data situations. As long as our model also exhibits the same structure as described above, we decided to apply multi-level regression analysis to our model.
One of the most important, if not the most important, part of multi-level modeling is the model selection. For our model selection, we follow the steps provided by Zuur et al.

(2009). Once the model is fully fitted, keeping the fixed effects unchanged, we compare different random effects models to each other using Akaike information criterion (AIC). Then, keeping random effects unchanged, we compare different fixed effects model restricted (or “residual”) (REML) maximum likelihood F-statistic. In addition, we compare fixed effects model with random effects model using Hausman test. Based on the statistical test results, the correct model is chosen and presented using REML estimation. The REML estimates are chosen over ML estimates, as REML provides unbiased estimates of variance components if the model is correct.[5]

After analyzing the overall wage gap, we additionally estimate immigrant-native wage differentials for men and women separately due to two major reasons. Firstly, our analysis for numeracy and literacy skill gap showed that gender variable has a highly significant effect on the skill level. Secondly, there is vast literature in economics, which shows that there is a significant gender wage gap around the world, including the countries we are analysing (Christofides et al. 2013; Gannon et al. 2017; Tverdostup & Pass 2019b). Hence, female immigrants may face even stronger disadvantages than their male counterparts solely due to their gender. Thus, to isolate the gender effect on the native-immigrant wage gap, we are analyzing native-immigrant wage gap separately for males and females.

To validate results given by multi-level fixed effects model and to get deeper insights on the wage gap, we use Oaxaca-Blinder (Blinder 1973; Oaxaca 1973) decomposition methodology, which is one of the most used technique for wage gap studies (Tverdostup, M., & Paas, T. 2017, Gogoladze 2019). Similarly to the multi-level analysis,we decompose the wage gap firstly for the whole pooled sample and then we separate the sample by genders. For this decomposition, we have used the same model as we used for multi-level regression model, provided in specification (2). In addition, to get country-fixed effects and again to validate results given from the pooled data models, the same decomposition method is used separately for each country, controlling for micro-level factors solely. Using this method allows us to explain the difference in the means of

[5] Estimation results obtained while selecting the model are not provided in the paper due to the paper length consideration, however, they are available upon request.

dependent variable (hourly wages) between natives and immigrants by decomposing the gap into the differences in the means of independent variables within immigrants and natives.

Empirical Results

Descriptive Profile

The analysis was performed in 14 European countries, where the immigrant share of population was more than 4%. The immigrant share in the pooled sample is equal to 11.3%. The descriptive statistics (presented in Appendix II) show that average hourly earnings for natives, both for male and female, are higher than immigrants' hourly earnings in all analysed countries. The only exception is Czechia, where immigrant males are averagely earning more than native males. Descriptive statistics also show the gap in numeracy and literacy skill levels in favour of natives in all countries. The only exception in this case is Ireland, where male immigrants have higher numeracy skills on average than native males. No pattern can be observed for the skill usage variables. Natives and immigrants seem to have reported similar level of skill usage intensity across their occupation levels and industries. No significant difference between males and females can be observed from descriptive profile, except their occupation sectors, where distribution of occupation sectors for males and females is notably different.

Cognitive Skills Gaps

Table 1 and Table 2 present the results for skill differences between natives and immigrants. In our specification, variable immigrant presents the native-immigrant skill gap. As results show, the numeracy skill gap between immigrants and natives is 21.35 points (std=2.1, $p<0.01$) and literacy skill the gap is 19.41 points (std=2.34, $p<0.01$). These results suggest that the numeracy and literacy skill gap between immigrants and natives definitely exists in the countries of interest, hence, trying to explain immigrant-native wage gap with the skill gap undoubtedly gives immigrant-native wage gap literature valuable contribution.

In addition, it is worth to pay attention that for both, literacy and numeracy skill, the gender variable has significant effect. The results indicate that females attain on average 11.28 points lower numeracy skill (std=0.99, p<0.01) and 3.61 points lower literacy skill (std=0.91, p<0.01). The gender gap in skill level might arise from different factors, like educational background, type of work experience gained, innate abilities, etc. (Tverdostup and Pass 2017; Christofides et al. 2010; Triventi 2013). Since our point of interest is not the gender skill gap and since we do not want the gender skill gap to influence the immigrant-native wage gap, for further analysis, we decided to divide the whole sample into 2 groups by their gender and perform wage-gap analysis separately. In addition, the literature suggests that significant gender pay gap exists in the countries of our interest (Tverdostup and Pass 2019b, Gannon et al. 2017, Gogoladze 2019). Hence, this fact supports our decision to proceed with native-immigrant wage gap analysis separately for males and females.

Table 1. OLS model for Literacy Skill

	Estimate	**Std. Error**	**T-value**
Intercept	269.00***	6.08	44.27
Immigrant	-19.41***	2.34	-8.31
Age	-0.55***	0.04	-12.45
Female	-3.61***	0.92	-3.93
Trainings	-0.10	0.14	-0.72
Observations: 52,180			

Note: Dependent variable is Literacy skill score. The model controls for age, gender, immigrant status, formal education attained, occupation sector and industry. Additional information about control variables is given in Appendix I. OLS regressions with standard errors were estimated using Jackknife replication methodology. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Table 2. OLS model for Numeracy Skill

	Estimate	**Std. Error**	**T-value**
Intercept	259.50***	6.46	40.17

Immigrant	-21.35***	2.10	-10.16
Age	-0.31***	0.04	-7.35
Female	-11.28***	0.99	-11.39
Trainings	0.01	0.13	0.05
Observations: 52,180			

Note: Dependent variable is Numeracy skill score. The model controls for age, gender, immigrant status, formal education attained, occupation sector and industry. Additional information about control variables is given in Appendix I. OLS regressions with standard errors were estimated using Jackknife replication methodology. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Immigrant-Native Wage Gap: Multi-Level Analysis

Next, we analyze the immigrant-native wage gap in relation to (i) micro-level factors, including cognitive skills and their use at work and non-work environment; (ii) macro-level factors reflecting the level of economic development and social welfare of the host country. Tables 3, 4 and 5 present the hourly wage regression separately for pooled sample, female and male individuals respectively. The first column of the tables presents the raw wage gap, controlled only by educational, social-demographic and work sector and industry variables. In the second column only macro-level factors are added as controls, similarly, only micro-level factors are added for the results given in the third column. Finally, we include both micro and macro-level factors for the results presented in the fourth column.

Table 3: Multi-level Fixed Effect model for pooled sample.

	(1)	(2)	(3)	(4)
Micro-level factors:				
Immigrant	-0.073***	-0.073***	-0.062***	-0.062***
	-0.015	-0.015	-0.018	-0.018
Literacy skill (1st plausible value)			0.023	0.023
			-0.017	-0.017
Numeracy skill (1st plausible value)			0.098***	0.098***
			-0.016	-0.016
Numeracy use work			-0.002	-0.002
			-0.005	-0.005
ICT use work			0.028***	0.028***
			-0.005	-0.005

Reading work			0.028***	0.028***
			-0.007	-0.007
Writing work			0.012**	0.012**
			-0.005	-0.005
Numeracy use non-work			-0.005	-0.005
			-0.006	-0.006
ICT use non-work			-0.006	-0.006
			-0.006	-0.006
Reading non-work			-0.008	-0.008
			-0.008	-0.008
Writing non-work			0.011*	0.011*
			-0.006	-0.006
Female	-0.122***	-0.122***	-0.092***	-0.092***
	-0.008	-0.008	-0.009	-0.009
Macro-level factors:				
Employment protection		0.011		-0.026
		-0.168		-0.163
Union density		0.002		0.0002
		-0.004		-0.004
Parental leave		0.0005		0.001
		-0.005		-0.005
Population		0.002		0.002
		-0.002		-0.002
Immigrant share		1.17		0.838
		-2.222		-2.161
Unemployment		0.005		0.004
		-0.01		-0.01
GDP per capita		0.00002***		0.00002***
		-0.00001		-0.00001
Poverty risk		0.001		0.002
		-0.008		-0.008
Constant	2.289***	1.071*	1.759***	0.644
	-0.109	-0.605	-0.115	-0.591
Observations	17,277	17,277	12,709	12,709

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Table 4. Multi-level Fixed Effect model for female

	(1)	(2)	(3)	(4)
Micro-level factors:				
Immigrant	-0.080***	-0.080***	-0.075***	-0.075***
	-0.02	-0.02	-0.023	-0.023
Literacy skill (1st plausible value)			0.046**	0.046**
			-0.023	-0.023
Numeracy skill (1st plausible value)			0.071***	0.070***
			-0.021	-0.021

Numeracy use work			-0.005	-0.004
			-0.006	-0.006
ICT use work			0.034***	0.034***
			-0.007	-0.007
Reading work			0.035***	0.035***
			-0.009	-0.009
Writing work			0.005	0.005
			-0.007	-0.007
Numeracy use non-work			-0.0001	0.0001
			-0.007	-0.007
ICT use non-work			-0.023***	-0.024***
			-0.009	-0.009
Reading non-work			-0.016	-0.016
			-0.011	-0.011
Writing non-work			0.023***	0.023***
			-0.008	-0.008
Macro-level factors:				
Employment protection		0.095		0.056
		-0.146		-0.153
Union density		0.003		0.001
		-0.004		-0.004
Parental leave		0.002		0.003
		-0.004		-0.004
Population		0.002		0.002
		-0.002		-0.002
Immigrant share		2.09		1.741
		-1.923		-2.023
Unemployment		0.008		0.006
		-0.009		-0.009
GDP per capita		0.00002***		0.00002***
		-0.00001		-0.00001
Poverty risk		-0.001		0.002
		-0.007		-0.007
Constant	2.376***	0.788	1.951***	0.44
	-0.141	-0.532	-0.152	-0.564
Observations	9,461	9,461	6,879	6,879

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Table 5: Multi-level Fixed effects model for Male

	(1)	(2)	(3)	(4)
Micro-level factors:				
Immigrant	-0.056**	-0.056**	-0.045	-0.045
	-0.024	-0.024	-0.027	-0.027

Literacy skill (1st plausible value)			0.001	0.001
			-0.024	-0.024
Numeracy skill (1st plausible value)			0.123***	0.123***
			-0.023	-0.023
Numeracy use work			0.008	0.008
			-0.007	-0.007
ICT use work			0.022***	0.022***
			-0.008	-0.008
Reading work			0.021**	0.021**
			-0.01	-0.01
Writing work			0.017**	0.017**
			-0.008	-0.008
Numeracy use non-work			-0.011	-0.011
			-0.009	-0.009
ICT use non-work			0.01	0.011
			-0.009	-0.009
Reading non-work			-0.00002	-0.0003
			-0.011	-0.011
Writing non-work			-0.005	-0.005
			-0.009	-0.009
Macro-level factors:				
Employment protection		-0.129		-0.159
		-0.201		-0.179
Union density		-0.0005		-0.002
		-0.005		-0.005
Parental leave		-0.002		-0.001
		-0.006		-0.005
Population		0.002		0.001
		-0.002		-0.002
Immigrant share		-0.111		-0.398
		-2.661		-2.364
Unemployment		0.0002		-0.0002
		-0.012		-0.011
GDP per capita		0.00002***		0.00002***
		-0.00001		-0.00001
Poverty risk		0.004		0.004
		-0.01		-0.009
Constant	2.108***	1.472**	1.499***	0.977
	-0.111	-0.726	-0.127	-0.652
Observations	7,816	7,816	5,830	5,830

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

As we can see from the Table 3, the raw wage gap between immigrants and natives in the pooled sample is 7.3% (SE=-0.015 and p<0.01). Including macro-level factors didn't change neither numeric nor statistical significance of the wage gap. However, once we include micro-level factors, more specifically skill level and skill usage variables to the model, we observe that numeric value of the wage gap decreases from 7.3% to 6.2% (SE=-0.018 and p<0.01%), however, the wage gap remains statistically highly significant. These results suggest that literacy and numeracy skills along with skill usage at work and non-work environment constitute around 15 percentage points of the wage disparity against the immigrants.

In table 3, we are also showing the estimates for the gender variable. As the results show, gender is highly significant in formation of wage gap. This result justifies our decision to separate the sample by genders and observe how the wage gap separately for males and females.

As shown on table 4, the raw immigrant-native wage gap for females is 8% (SE=-0.02 and p<0.01) and once all skill level and skill usage variables are added, the wage gap decreases to 7.5% (SE=-0.023 and p<0.01). As we can see, the wage gap still stays economically and statistically significant and skill level and usage variables only contribute 6 percentage points of wage gap disadvantage faced by immigrant females against native females.

However, from table 5, we observe that native-immigrant wage gap for males is 5.6% (SE=0.024 and p<0.01), which itself is 2.4 percentage points lower than the raw wage gap for females. Once we add skill level and usage factor to the model, the wage gap decreases to 4.5% (SE=-0.027 and p>0.1) and it loses its statistical significance. Such result indicates that the wage gap for the pooled sample was mainly driven by wage disparity between immigrant and native females[6].

For robustness, the total group of immigrants are divided into four categories according to the number of years they have stayed in the host country (1-5 years, 5-10 years, 10-15 years, 15+ years). The same model following specification (2) is applied to the different

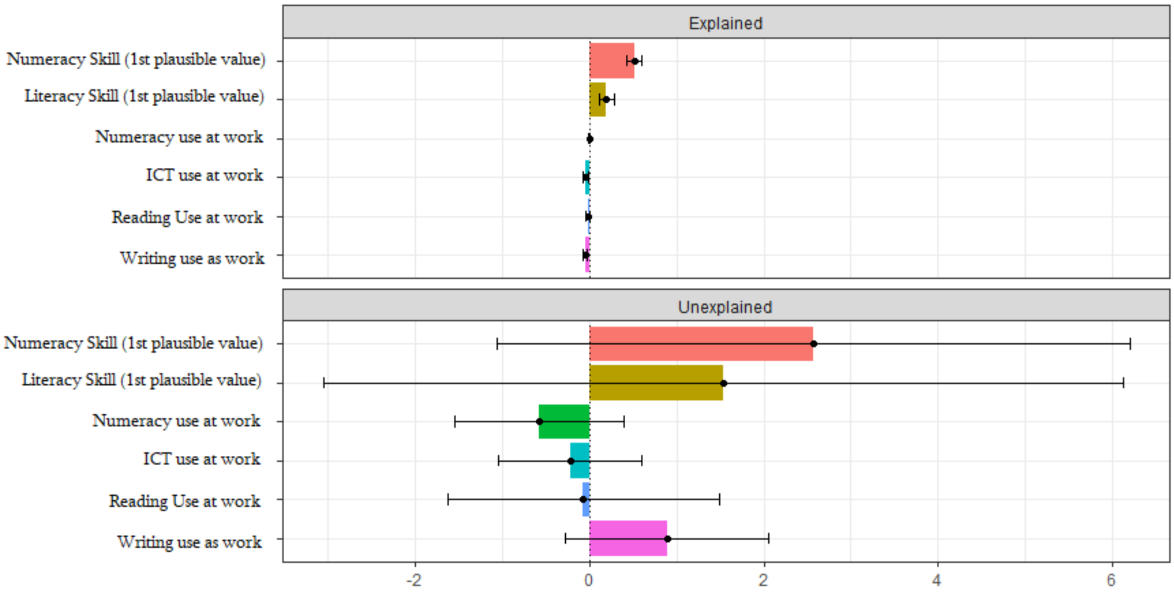
[6] To make sure that results are statistically significantly different across two gender groups, we use the Chow test. According to the test results, we can reject null hypothesis that there is no significant improvement in fit by dividing the sample in two sub-samples (in our case, by genders)

groups (see Appendix IV). Integration of immigrants to the local market is a long-term process and intuitively it highly depends on immigrant characteristics. Hence, it is understandable that strong institutional factors in the host country should be helping immigrants to integrate the local labour market. The results also are in accordance with this basic intuition. We can observe that for those immigrants, who have lived in the country for 5-10 years, macro factors are playing a large role in the formation of their wages. However, for immigrants who have already lived for more than 10 years in the host country skill usage variables become more important. This result is logical as after 10 years of living in the host country the immigrants should already be relatively integrated in local society and their wage should be largely based on their skills. In addition, the skill gap may also shrink over years spent in the host country (Tverdostup and Pass 2019a). However, we acknowledge that these results might not be accurate and there is a high chance of type 2 error, which is caused by the small size of the sample.

Immigrant-Native Wage Gap: Oaxaca-Blinder Decomposition

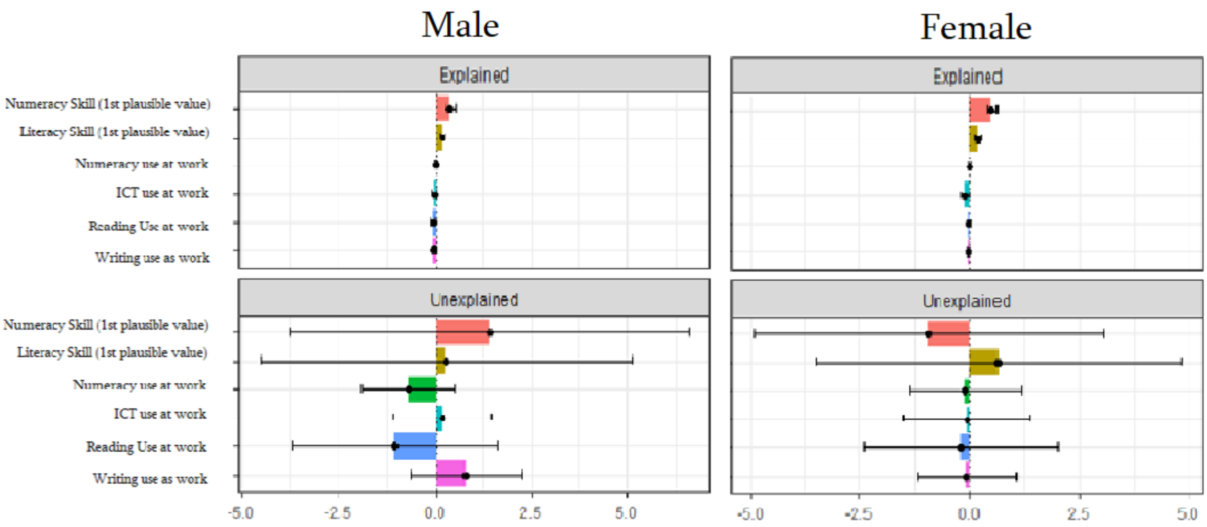
Next, we perform an Oaxaca-Blinder decomposition of immigrant-native wage gaps to elicit explained and unexplained gaps. Figure 2 shows the Oaxaca-Blinder decomposition results for the pooled cross-country sample and Figure 3 shows results for males and females respectively.

Figure 2. Oaxaca-Blinder decomposition, pooled sample



Note: The model controls for age, gender, immigrant status, formal education attained, occupation sector, industry and macro-level factors. Additional information about control variables is given in Appendix I.

Figure 3. Oaxaca-Blinder decomposition, males (left), females (right)



Note: The model controls for age, gender, immigrant status, formal education attained, occupation sector, industry and macro-level factors. Additional information about control variables is given in Appendix I.

According to the Oaxaca-Blinder decomposition, in the pooled cross-country sample the explained part of the wage gap is mainly driven by lower numeracy and literacy skills among immigrants and both skill effects achieve non-marginal statistical significance. Numeracy skills have a bigger effect on wage-gap formation than literacy skills. On the other hand, the skill usage at work doesn't seem to have any significant contribution in forming the explained part of the wage gap. On the other hand, the skill and skill usage variables do not show any significant effect on the unexplained part of the wage gap (standard errors are too high and error bars cross 0). The effects observed separately for males and females are similar to the pooled cross-country sample as seen on Figure 3.

To validate previously derived results from the pooled data and see cross-country heterogeneities, we have decomposed the wage gap for each country separately using the Oaxaca-Blinder method. Table 6 presents wage gaps given by Oaxaca-Blinder decomposition for females, males and total country samples for each country used in our analysis. The relative wage gap is calculated by dividing the total wage gap of the country by average hourly income in the same country.

Table 6. Wage Gaps given by Oaxaca-Blinder Decomposition

Country	Female	Male	Total	Average Hourly Income	Relative Wage Gap	Observations for Country Sample
Belgium	0.38	-1.09	-0.55	19.54	-0.03	1514
Czechia	0.55	-2.66	-1.82	8.98	-0.2	1371
Denmark	1.69	2.39	2.05	23.75	0.09	3048
Estonia	0.69	1.26	1.01	9.56	0.11	2035
Finland	3.15	0.9	2.45	18.79	0.13	2438
France	-0.75	-0.23	-0.56	15.45	-0.04	1920
Greece	-1.49	-0.22	-0.82	10.2	-0.08	490
Ireland	2.53	2.08	2.28	22.14	0.1	1457
Italy	0.18	0.54	0.37	15.53	0.02	672
Netherlands	0.47	1.1	0.91	20.06	0.05	2551
Norway	-0.46	2.5	1.06	24.29	0.04	2551

Slovenia	-0.44	2.69	0.96	9.17	0.1	965
Spain	3.83	2.18	2.9	13.92	0.21	1196
United Kingdom	0.02	0.5	0.1	17.54	0.01	2850

Note: The table reports the total wage gap (sum of explained and unexplained part of the wage gap) for male, female and total country samples. Regression model (2) was used for Oaxaca-Blinder decomposition.

The results show that the gender wage gap estimates vary considerably across analysed countries. Four out fourteen countries (Belgium, Czechia, France and Greece) show wage gap in favour of migrants and the rest of the countries (Denmark, Estonia, Finland, Ireland, Italy, Netherlands, Norway, Spain, Slovenia and United Kingdom) display wage gap in favour of natives.

Figures for wage gap Oaxaca-Blinder decomposition for each country and the effects of skill usage on wage gap are presented in the Appendix VI.
For Belgium, Czechia, France and Greece the wage gap given by Oaxaca-Blinder, being in favour of immigrants can be explained by different types of compositions of natives and immigrants. For example, in the case of Belgium, there is a higher share of lawyers, legislators, senior officials and managers (CEO, CFO, etc.) among male immigrants compared to male natives, which is the main driver of wage gap being in favour of immigrants. The same compositional factors can be observed in Czechia, Greece and France.

The biggest wage gap relative to the average hourly wage is observed in Spain, while the smallest absolute gap is noticed in the United Kingdom. In addition, some countries reveal different wage gap signs if we observe population separately by gender. In Belgium and Czechia, male immigrants have advantage over native males in terms of hourly earnings, however, female natives have advantage over female immigrant. Opposite effect can be seen in Norway and Slovenia, where male natives and female immigrants have advantage over male immigrants and female immigrants in terms of hourly earnings.

As expected, the numeracy skill level is the main driver of explained part of wage gap in most of the counties. In seven out of fourteen countries the Numeracy skill variable reaches non-marginal statistical significance. On the other hand, Literacy skill variable does not display any statistically significant effect on the explained part of the wage gap. Skill usage variables again do not seem to display any effects on the explained part of the wage gap.

For the unexplained part of the wage gap, all of the skill usage variables are again highly statistically insignificant, and their insignificance is higher comparing to the pooled data results. The statistical insignificance of the variables might be caused by the small sample of data.

Being able to speak local language also does not seem to be the main driver of the wage gap in most of the countries. However, in some countries being able to speak the local language has small but significant effect on the wage gap. In Denmark, Ireland and Norway, some part of explained wage gap can be accounted for the lack of native language knowledge among immigrants.

Conclusion

The paper provides an empirical analysis of key factors driving the wage disparities between natives and immigrants in 14 European countries. Additionally, it explores the potential heterogeneities of the wage gap across men and women. The analysis was based on the PIAAC dataset.

The paper proposes and tests 3 hypotheses. Firstly, we test whether there is significant cognitive skill disparities between native-born people and immigrants, particularly, we analyse numeracy and literacy skill differences between the mentioned groups. Results suggest that indeed there are differences between native-born population and immigrants in their cognitive skill levels. Immigrants attain, on average, substantially worse literacy and numeracy abilities. Moreover, we document substantial skill disparity associate with gender, suggesting that men have stronger skill profile in both domains.

Next, we test whether there is a significant immigrant-native wage gap and analyse the factors driving this disproportionality. The analysis indicates that there is wage disparity against the immigrants. The skill-level differences turn out to be a significant factor that explains most of the explained part of immigrant-native wage gap in the pooled data and for both genders. There is no significant effect of macro variables in forming the gap, however, the wage differentials are quite heterogeneous for the countries that were used in analysis. For instance, in countries with larger populations (excluding Spain) the wage gap is either very small or in favour of immigrants.

Additionally, empirical tests show that skill use variables are playing a less important role in wage formation for immigrants in early years of immigration, but they have a significant effect on wages in later years. Therefore, we may state that the host country experience is quite an important factor for immigrant integration. Although, literacy and numeracy skill levels have significant effect on forming the explained part of immigrant-native wage gap, they turned out to be insignificant for the unexplained part of the wage-gap. In addition, the unexplained part of the wage gap given by Oaxaca-Blinder decomposition turned out to be bigger than the explained part of wage gap. Our model (numeracy and literacy skills and skill usage at work) fails to justify how unexplained part of the wage gap is formed.

Finally, we examine the potential differences in wage gap and factors behind it across two genders. Inclusion of skill-level difference together with disparities in usage of these skills in the regression model fully explains the gap for males (the coefficient of gap variable becomes insignificant), although the gap remains significant for females. Thus, we conclude that there are significant gender-specific factors that are unobserved in our model that may explain the immigrant-native wage gap for females.

All in all, despite the limitations of cross-sectional data and plausible sampling problems, PIAAC data gives us a lot of insights on wage differentials among groups with various demographic backgrounds. We have tried to explain wage disparities between immigrants and natives by analysing their skill usage and incorporating macro-level factors to the analysis. However, we can conclude that there is a need for combined studies on wage disparities, which will include different factors affecting native-immigrant gaps directly or indirectly, as there is still part of the gap left, which cannot be explained by the factors studied so far.

Observed skill differences between the immigrants and native-born people, which are one of the main drivers of the earning gap between the two groups, suggest that policymakers should support newcomers with various skill-related trainings in order to let them gain the necessary skills required by the local labour market. Moreover, since women are facing a larger immigrant-native wage gap than men (in some countries), we suggest that immigrant women in these countries might need some particular support.

References:

Adida, C. L., Laitin, D. D., & Valfort, M. A. (2010). Identifying barriers to Muslim integration in France. *Proceedings of the National Academy of Sciences*, *107*(52), 22384-22390.

Adsera, A., & Chiswick, B. R. (2007). Are there gender and country of origin differences in immigrant labour market outcomes across European destinations?. *Journal of Population Economics*, *20*(3), 495.

Aldashev, A., Gernandt, J., & Thomsen, S. L. (2008). The immigrant wage gap in Germany. *ZEW-Centre for European Economic Research Discussion Paper*, (08-089).

Altonji, J. G., & Blank, R. M. (1999). Race and gender in the labour market. *Handbook of labour economics*, *3*, 3143-3259.

Andriessen, I., Nievers, E., Dagevos, J., & Faulk, L. (2012). Ethnic discrimination in the Dutch labour market: Its relationship with job characteristics and multiple group membership. *Work and Occupations*, *39*(3), 237-269.

Aydemir, A., & Skuterud, M. (2008). The immigrant wage differential within and across establishments. *ILR Review*, *61*(3), 334-352.

Barret, A., Bergin, A., Kelly, E., & McGuinness, S. (2016). Ireland's Recession and The Immigrant Native Earnings Gap'in Kahanec. *M., and KF Aimmermann (Eds.) Labour Migration EU Enlargement and the Great Recession*.

Bartolucci, C. (2014). Understanding the native–immigrant wage gap using matched employer-employee data: evidence from germany. *ILR Review*, *67*(4), 1166-1202.

Basilio, L., Bauer, T. K., & Kramer, A. (2017). Transferability of human capital and immigrant assimilation: An analysis for Germany. *Labour*, *31*(3), 245-264.

Bauder, H. (2003). "Brain abuse", or the devaluation of immigrant labour in Canada. *Antipode*, *35*(4), 699-717.

Bauder, H. (2006). Origin, employment status and attitudes towards work: immigrants in Vancouver, Canada. *Work, employment and society*, *20*(4), 709-729.

Belot, M. V., & Hatton, T. J. (2012). Immigrant Selection in the OECD. *The Scandinavian Journal of Economics*, *114*(4), 1105-1128. Dustmann, C., & Van Soest, A. (2002). Language and the earnings of immigrants. *ILR Review*, *55*(3), 473-492.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labour market discrimination. *American economic review*, *94*(4), 991-1013.

Beyer, R. C. (2019). Wage Performance of Immigrants in Germany. German Economic Review, 20(4), e141-e169.

Biavaschi, C., & Zimmermann, K. F. (2014). Eastern partnership migrants in Germany: outcomes, potentials and challenges. *IZA Journal of European Labour Studies*, *3*(1), 7.

Blinder, A. S. 1973. Wage discimination: Reduced form and structural estimates. Journal of Human Resources 8: 436–455.

Borjas, G. J. (1994). The economics of immigration. *Journal of economic literature*, *32*(4), 1667-1717.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society*, 1287-1294.

Chiswick, B. R. (1991). Speaking, reading, and earnings among low-skilled immigrants. *Journal of labour economics*, *9*(2), 149-170.

Chiswick, B. R., & Miller, P. W. (1990). Language in the Labour Market: The Immigrant Experience in Canada and the United States.

Chiswick, B. R., & Miller, P. W. (1995). The endogeneity between language and earnings: International analyses. *Journal of labour economics*, *13*(2), 246-288.

Christofides, L. N., Polycarpou, A., & Vrachimis, K. (2010). The gender wage gaps,'sticky floors' and'glass ceilings' of the European Union.

Christofides, L. N., Polycarpou, A., & Vrachimis, K. (2013). Gender wage gaps,‘sticky floors’ and ‘glass ceilings’ in Europe. *Labour Economics*, *21*, 86-102.

Clark, K., & Drinkwater, S. (2014). Labour migration to the UK from Eastern partnership countries. *IZA Journal of European Labour Studies*, *3*(1), 15.

Coulombe, S., Grenier, G., & Nadeau, S. (2014). Human capital quality and the immigrant wage gap. *IZA Journal of Migration*, *3*(1), 14.

Dustmann, C., & Van Soest, A. (2002). Language and the earnings of immigrants. *ILR Review*, *55*(3), 473-492.

Dustmann, C., Glitz, A., & Vogel, T. (2010). Employment, wages, and the economic cycle: Differences between immigrants and natives. European Economic Review, 54(1), 1-17.

Ferrer, A., Green, D. A., & Riddell, W. C. (2006). The effect of literacy on immigrant earnings. *Journal of Human Resources*, *41*(2), 380-410.

Foster-Johnson, L., & Kromrey, J. D. (2018). Predicting group-level outcome variables: An empirical comparison of analysis strategies. Behavior research methods, 50(6), 2461-2479.

Gannon, B., Plasman, R., Ryex, F., & Tojerow, I. (2007). Inter-industry wage differentials and the gender wage gap: evidence from European countries. *Economic and Social Review*, *38*(1), 135.

Gogoladze, P. (2019). Gender Income Gap Over Life-Cycle: Cross-Country Analysis. *Available at SSRN 3420836*.

Grand, C. L., & Szulkin, R. (2002). Permanent disadvantage or gradual integration: explaining the immigrant–native earnings gap in Sweden. *Labour*, *16*(1), 37-64.

Guzi, M., Kahanec, M., & Mytna Kurekova, L. (2015). What explains immigrant-native gaps in European labour markets: The role of institutions.

Guzi, M., Kahanec, M., Kureková, L. M., & Levandovska, L. (2014). The impact of migration and integration policies on native-migrant labour market gaps.

Hlavac, Marek (2018). oaxaca: Blinder-Oaxaca Decomposition in R.

Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.2. https://CRAN.R-project.org/package=stargazer

Horrace, W. C., & Oaxaca, R. L. (2001). Inter-industry wage differentials and the gender wage gap: An identification problem. *ILR Review*, *54*(3), 611-618.

Imai, S., Stacey, D., & Warman, C. (2019). From engineer to taxi driver? Language proficiency and the occupational skills of immigrants. *Canadian Journal of Economics/Revue canadienne d'économique*, *52*(3), 914-953.

Kee, P. (1995). Native-immigrant wage differentials in the Netherlands: discrimination?. *Oxford Economic Papers*, 302-317.

Lessem, R., & Sanders, C. (2014). *Immigrant Wage Assimilation in the United States: The Role of Occupational Upgrading*. Mimeo, Carnegie Mellon University

Ley, D. (1999). MYTHS AND MEANINGS OF IMMIGRATION AND THE METROPOLIS: Wiley Lecture delivered to a joint meeting of the Canadian Association of Geographers and the Royal Canadian Geographical Society, Ottawa, June 3, 1998. *Canadian Geographer/Le Géographe canadien*, *43*(1), 2-19.

Nielsen, H. S., Rosholm, M., Smith, N., & Husted, L. (2004). Qualifications, discrimination, or assimilation? An extended framework for analysing immigrant wage gaps. *Empirical Economics*, *29*(4), 855-883.

Oaxaca, R. (1973). Male-female wage differentials in urban labour markets. *International economic review*, 693-709.

Oreopoulos, P. (2011). Why do skilled immigrants struggle in the labour market? A field experiment with thirteen thousand resumes. *American Economic Journal: Economic Policy*, *3*(4), 148-71.

Paas, T., & Tverdostup, M. (2018, July). Skills heterogeneity and immigrants-native wage gap in European countries. In *Proceedings of International Academic Conferences* (No. 7809585). International Institute of Social and Economic Sciences.

R package version 0.1.4. https://CRAN.R-project.org/package=oaxaca

Schnetzer, M. (2009). *The immigrant wage gap in Austria* (Doctoral dissertation, uniwien).

Snijders, T. A., & Bosker, R. J. (2011). Multi-level analysis: An introduction to basic and advanced multi-level modeling. Sage.

Song, T. (2017). Honey, Routinization Shrunk My Wage! Native-Immigrant Wage Gaps and the Growing Importance of Social Skills.

Tomaskovic-Devey, D., Hällsten, M., & Avent-Holt, D. (2015). Where do immigrants fare worse? Modeling workplace wage gap variation with longitudinal employer-employee data. *American Journal of Sociology*, *120*(4), 1095-1143.

Triventi, M. (2013). The gender wage gap and its institutional context: a comparative analysis of European graduates. Work, employment and society, 27(4), 563-580.

Tverdostup, M., & Paas, T. (2017). Gender-specific human capital: identification and quantifying its wage effects. *International Journal of Manpower*.

Tverdostup, M., & Paas, T. (2019a). Immigrant-native wage gap in Europe: the role of cognitive skills and their use at work. *International Journal of Manpower*.

Tverdostup, M., & Paas, T. (2019b). Valuation of human capital and the gender wage gap in Europe. *Available at SSRN 3460494*.

Zuur, A., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). Mixed effects models and extensions in ecology with R. Springer Science & Business Media.

Appendix

Appendix I

Major Variables Used in Analysis

Variable	Definition
Immigrant	Shows if the respondent was born in the country of residence or not (value ‘0’ corresponds to being native and ‘1’ -to being immigrant)
Literacy Skill	Test Score Variable measuring literacy ability as part of PIAAC Survey. The variable is reported as a set of 10 plausible values, each scaled from 0 to 500 points.
Numeracy Skill	Test Score Variable measuring numeracy ability as part of PIAAC Survey. The variable is reported as a set of 10 plausible values, each scaled from 0 to 500 points.
Numeracy Use at Work	Shows the intensity of numeracy skill usage at work environment. Measured based on background questionnaire. All questions used to derive skill use measure had ordinal responses as follows: 1 – “never use”; 2 – “use less than once a month”; 3 – “use less than once a week, but at least once a month”; 4 – “use at least once a week, but not every day”; 5 – “use every day”
Reading Use at Work	Shows the intensity of reading skill usage at work environment. Measured identically as Numeracy Use at Work.
Writing Use at Work	Shows the intensity of writing skill usage at work environment. Measured identically as Numeracy Use at Work.
ICT Use at Work	Shows the intensity of ICT skill usage at work environment. Measured identically as Numeracy Use at Work.
Numeracy Use Non-Work	Shows the intensity of numeracy skill usage beyond work (at home, in leisure activities). Measured identically as Numeracy Use at Work.
Reading Use at Non-Work	Shows the intensity of reading skill usage beyond work (at home, in leisure activities). Measured identically as Numeracy Use at Work.
Writing Use at Non-Work	Shows the intensity of writing skill usage beyond work (at home, in leisure activities). Measured identically as Numeracy Use at Work.
ICT Use at Non-Work	Shows the intensity of ICT skill usage beyond work (at home, in leisure activities). Measured identically as Numeracy Use at Work.
Born Language	Ability to speak a host-country language.
Education	Highest level of formal education obtained, based on ISCED 2011 levels of education : Primary or less, Lower secondary, Upper secondary, Post-secondary, professional degree, bachelor degree, master degree, research degree.
Occupation	Occupational classification of respondent's job based on The International Standard Classification of Occupations (ISCO-08).
Age	Respondent’s age.

Gender	Respondent’s gender.
Industry	Industry classification of respondent's job at 1-digit level based on International Standard Industrial Classification (ISIC rev 4).
Trainings	Number of job-related trainings during the previous year.
Macro-level factors	Union density, employment protection, number of parental weeks given by law, immigrant share in population, risk of poverty (for age group 18-64) – taken from OECD data for respective year when PIAAC survey was conducted in each country. Unemployment rate, GDP per capita – taken from World Bank data for respective year when PIAAC survey was conducted in each country.

Appendix II

Descriptive Statistics

Descriptive Profile

	Male		Female	
	Native	Immigrant	Native	Immigrant
Distribution	42%	5%	46%	6%
Average Age	41.1	40.8	41.3	40.9
Average Literacy Score	274	245	273	245
Average Numeracy Score	276	246	265	238
Education				
Primary or less (ISCED 1 or less)	7%	9%	7%	10%
Lower secondary (ISCED 2, ISCED 3C short)	19%	21%	19%	19%
Upper secondary (ISCED 3A-B, C long)	41%	33%	36%	30%
Post-secondary, non-tertiary (ISCED 4A-B-C)	4%	5%	4%	5%
Professional degree (ISCED 5B)	9%	8%	12%	10%
Bachelor degree (ISCED 5A)	9%	9%	11%	12%
Master degree (ISCED 5A)	8%	10%	7%	9%
Research degree (ISCED 6)	1%	2%	1%	1%
Occupation				
Armed forces	1%	0%	0%	0%
Legislators, senior officials and managers	10%	7%	6%	4%
Professionals	19%	16%	25%	21%
Technicians and associate professionals	15%	12%	16%	11%
Clerks	6%	5%	14%	9%
Service workers and shop and market sales workers	11%	13%	24%	29%
Skilled agricultural and fishery workers	4%	2%	1%	1%
Craft and related trades workers	18%	19%	2%	2%
Plant and machine operators and assemblers	11%	12%	3%	4%

Elementary occupations	6%	13%	8%	19%

Descriptive statistics for hourly earnings

	Native		Immigrant	
	Male	Female	Male	Female
Belgium	19.93	18.72	17.25	15.45
Czechia	9.79	8.30	10.87	7.22
Denmark	24.23	22.56	21.12	19.66
Estonia	11.79	8.42	9.93	7.21
Finland	20.08	17.25	16.96	14.57
France	16.05	14.40	15.93	12.87
Greece	10.80	9.65	8.89	9.44
Ireland	22.06	20.80	19.10	18.14
Italy	15.56	15.24	12.56	10.55
Netherlands	20.71	18.34	18.69	17.47
Norway	25.21	21.95	21.57	20.56
Slovenia	9.68	9.11	7.26	7.89
Spain	14.74	13.31	12.09	9.49
United Kingdom	18.18	15.93	17.51	16.12

Note: Table shows average hourly earnings across 14 European countries based on PIAAC survey data.

Skill-level differences across gender and native-immigrant groups

	Numeracy				Literacy			
	Male		Female		Male		Female	
	Native	Immigrant	Native	Immigrant	Native	Immigrant	Native	Immigrant
Belgium	290.82	251.05	274.56	242.68	281.26	241.35	277.19	238.48
Czechia	282.35	268.02	271.57	254.44	279.18	270.75	275.89	263.70
Denmark	289.57	248.94	278.80	240.17	275.71	236.92	275.09	236.12
Estonia	276.94	263.33	271.49	256.27	276.88	255.42	280.01	255.25
Finland	292.55	246.71	281.31	246.38	290.40	248.60	293.21	259.70
France	267.29	224.91	256.53	205.63	267.58	231.69	268.47	226.79
Greece	254.57	244.27	248.15	247.80	250.87	241.53	255.77	255.89
Ireland	263.42	264.86	251.43	258.51	270.41	265.73	267.70	268.20
Italy	258.76	242.70	246.88	232.85	256.43	233.25	257.15	232.27
Netherlands	293.29	250.10	277.95	236.97	291.50	250.39	286.01	249.27
Norway	295.12	248.68	280.66	235.07	288.00	252.24	284.44	248.07
Slovenia	264.29	228.65	261.30	222.91	258.38	231.55	261.36	233.48
Spain	252.93	221.03	241.10	213.97	255.59	225.81	251.35	223.39
United Kingdom	268.88	251.94	257.03	239.03	274.49	261.91	271.91	259.71

Note: The table presents averages of numeracy and literacy skills (1st plausible value) across gender groups of immigrants and natives

Skill Usage differences across the occupational groups within natives and immigrants

	Native										Immigrant									
	0	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	8	9
NUMWORK	1.71	2.57	2.15	2.23	2.11	1.73	1.68	1.79	1.59	1.37	2.19	2.56	2.19	2.16	2.17	1.66	1.77	1.81	1.54	1.24
ICTWORK	1.86	2.59	2.20	2.17	2.12	1.45	1.39	1.46	1.21	1.25	2.56	2.67	2.30	2.23	2.30	1.43	1.38	1.61	1.10	1.20
READWORK	2.34	2.65	2.63	2.32	2.05	1.78	1.86	1.66	1.44	1.12	2.70	2.59	2.66	2.28	2.07	1.68	1.76	1.48	1.40	0.98
WRITWORK	2.34	2.43	2.31	2.25	2.02	1.75	1.23	1.60	1.53	1.24	2.56	2.43	2.35	2.21	2.10	1.76	1.34	1.58	1.57	1.14
NUMHOME	2.00	2.12	2.14	2.02	1.83	1.86	1.81	1.85	1.78	1.70	2.64	2.10	2.14	2.01	1.91	1.85	1.77	1.70	1.66	1.61
ICTHOME	2.26	2.33	2.34	2.17	2.07	1.94	1.53	1.72	1.67	1.76	2.69	2.34	2.45	2.21	2.21	2.00	1.83	1.72	1.67	1.76
READHOME	2.16	2.35	2.47	2.23	2.06	2.03	1.75	1.89	1.82	1.72	2.51	2.38	2.53	2.30	2.16	2.05	1.76	1.70	1.73	1.68
WRITHOME	2.05	2.25	2.30	2.07	2.02	1.94	1.60	1.71	1.66	1.74	2.44	2.23	2.31	2.07	2.07	1.95	1.73	1.65	1.73	1.70

Note: The table presents average of skill use variable across 9 different occupation categories for natives and immigrants

0 - Armed forces
1 - Legislators, senior officials and managers
2 - Professionals
3 - Technicians and associate professionals
4 - Clerks
5 - Service workers and shop and market sales workers
6 - Skilled agricultural and fishery workers
7 - Craft and related trades workers
8 - Plant and machine operators and assemblers
9 - Elementary occupations

Skill Usage differences across the educational groups within natives and immigrants

	Native								Immigrant							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
NUMWORK	1.55	1.64	1.91	1.98	2.13	2.17	2.38	2.58	1.37	1.52	1.78	1.80	1.95	2.07	2.26	2.75
ICTWORK	1.39	1.55	1.79	1.90	2.07	2.18	2.38	2.47	1.34	1.38	1.73	1.78	2.06	2.23	2.38	2.53
READWORK	1.26	1.54	1.87	2.11	2.33	2.49	2.67	2.96	1.15	1.32	1.66	1.83	2.12	2.23	2.56	2.98
WRITWORK	1.30	1.60	1.86	1.98	2.23	2.30	2.38	2.54	1.28	1.47	1.76	1.88	2.10	2.12	2.29	2.50
NUMHOME	1.38	1.95	1.97	1.95	2.03	2.15	2.31	2.49	1.31	1.79	1.86	1.93	1.95	2.14	2.31	2.50
ICTHOME	1.40	1.90	2.02	1.95	2.17	2.34	2.45	2.60	1.23	1.79	1.98	2.10	2.23	2.42	2.55	2.68
READHOME	1.29	1.83	2.05	2.19	2.34	2.48	2.54	2.66	1.25	1.69	2.00	2.24	2.36	2.45	2.59	2.71
WRITHOME	1.44	1.91	1.98	2.01	2.16	2.31	2.36	2.47	1.40	1.77	1.93	2.09	2.13	2.28	2.36	2.52

Note: The table presents average of skill use variable across 8 different education categories for natives and immigrants

Column Name Description

1 - Primary or less (ISCED 1 or less)
2 - Lower secondary (ISCED 2, ISCED 3C short)
3 - Upper secondary (ISCED 3A-B, C long)
4 - Post-secondary, non-tertiary (ISCED 4A-B-C)
5 - Professional degree (ISCED 5B)
6 - Bachelor degree (ISCED 5A)
7 - Master degree (ISCED 5A)
8 - Research degree (ISCED 6)

Appendix III

OLS models for each country
Belgium

	Male	Female	Total
Immigrant	0.032	0.023	0.025
	-0.052	-0.069	-0.042
Literacy	0.009	-0.006	-0.002
	-0.051	-0.061	-0.039
Numeracy	0.077*	0.113**	0.094***
	-0.046	-0.055	-0.035
Numeracy skills usage at work	0.005	-0.007	-0.0002
	-0.013	-0.016	-0.01
ICT Skills usage at work	0.018	0.004	0.005
	-0.018	-0.021	-0.014
Reading skills usage at work	-0.014	-0.007	-0.009
	-0.02	-0.026	-0.016
Writing skills usage at work	0.016	0.047**	0.032***
	-0.015	-0.021	-0.012
Numeracy skills usage (non-work)	-0.005	0.011	0.006
	-0.015	-0.018	-0.011
ICT skills usage non-work)	-0.006	-0.028	-0.018
	-0.019	-0.022	-0.014
Reading skills usage (non-work)	-0.001	0.025	0.008
	-0.022	-0.029	-0.018
Writing skills usage at work	0.01	-0.013	-0.005
	-0.018	-0.023	-0.014
Age	0.016***	0.016***	0.016***
	-0.001	-0.001	-0.001
Gender_Female			-0.042**
			-0.019
Ability to speak local language	0.0002	-0.063	-0.028
	-0.057	-0.055	-0.039
Constant	2.094***	2.131***	2.123***
	-0.176	-0.286	-0.142
Observations	777	737	1,514

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Czechia

	Male	Female	Total
Immigrant	0.048	-0.135	0.009
	-0.141	-0.261	-0.132
Literacy	0.201***	0.098	0.142**
	-0.077	-0.104	-0.064
Numeracy	-0.052	0.085	0.018
	-0.077	-0.104	-0.064
Numeracy skills usage at work	-0.035	-0.011	-0.032*
	-0.024	-0.029	-0.019
ICT Skills usage at work	0.016	0.097***	0.064***
	-0.03	-0.037	-0.023
Reading skills usage at work	0.078**	0.017	0.050*
	-0.035	-0.049	-0.029
Writing skills usage at work	-0.002	-0.027	-0.005
	-0.022	-0.03	-0.019
Numeracy skills usage (non-work)	0.042	-0.100**	-0.022
	-0.037	-0.044	-0.029
ICT skills usage non-work)	-0.038	0.027	-0.014
	-0.029	-0.04	-0.024
Reading skills usage (non-work)	-0.004	-0.054	-0.018
	-0.036	-0.052	-0.031
Writing skills usage at work	-0.025	0.031	-0.0002
	-0.028	-0.034	-0.022
Age	0.006***	0.002	0.004**
	-0.002	-0.002	-0.001
Gender_Female			-0.134***
			-0.035
Ability to speak local language	0.201	-0.186	0.106
	-0.191	-0.337	-0.176
Constant	0.944**	3.557***	1.674***
	-0.389	-0.667	-0.352
Observations	687	686	1,373

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Denmark

	Male	Female	Total
Immigrant	-0.064	-0.067	-0.066
	-0.069	-0.057	-0.045
Literacy	-0.041	0.003	-0.022
	-0.049	-0.039	-0.031
Numeracy	0.125***	0.065*	0.100***
	-0.044	-0.036	-0.028
Numeracy skills usage at work	0.01	0.020*	0.014*
	-0.013	-0.01	-0.008
ICT Skills usage at work	0.046***	0.011	0.032***
	-0.014	-0.012	-0.009
Reading skills usage at work	0.018	0.013	0.017
	-0.02	-0.016	-0.013
Writing skills usage at work	0.011	-0.006	0.004
	-0.015	-0.012	-0.009
Numeracy skills usage (non-work)	0.004	0.0003	0.003
	-0.017	-0.012	-0.01
ICT skills usage non-work)	-0.009	0.001	-0.006
	-0.018	-0.014	-0.011
Reading skills usage (non-work)	-0.011	0.018	0.002
	-0.023	-0.018	-0.014
Writing skills usage at work	-0.042***	-0.016	-0.030***
	-0.015	-0.013	-0.01
Age	0.010***	0.009***	0.009***
	-0.001	-0.001	-0.001
Gender_Female			-0.026*
			-0.015
Ability to speak local language	-0.021	-0.022	-0.029
	-0.071	-0.058	-0.046
Constant	2.227***	2.126***	2.229***
	-0.185	-0.216	-0.129
Observations	1,513	1,535	3,048

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Estonia

	Male	Female	Total
Immigrant	-0.172**	-0.105**	-0.123***
	-0.079	-0.051	-0.043
Literacy	-0.044	0.054	0.024
	-0.078	-0.055	-0.045
Numeracy	0.218***	0.157***	0.173***
	-0.078	-0.055	-0.045
Numeracy skills usage at work	0.004	0.002	0.001
	-0.025	-0.017	-0.014
ICT Skills usage at work	0.037	0.056***	0.047***
	-0.025	-0.017	-0.014
Reading skills usage at work	0.04	0.116***	0.080***
	-0.031	-0.026	-0.019
Writing skills usage at work	-0.007	0.019	0.004
	-0.029	-0.021	-0.017
Numeracy skills usage (non-work)	-0.033	-0.038*	-0.039**
	-0.032	-0.02	-0.017
ICT skills usage non-work)	0.027	0.002	0.013
	-0.033	-0.025	-0.02
Reading skills usage (non-work)	-0.036	-0.075**	-0.051**
	-0.037	-0.029	-0.023
Writing skills usage at work	-0.015	0.035**	0.017
	-0.025	-0.017	-0.014
Age	0.004**	0.001	0.002*
	-0.002	-0.001	-0.001
Gender_Female			-0.266***
			-0.025
Ability to speak local language	0.027	-0.097	-0.045
	-0.122	-0.078	-0.065
Constant	1.709***	0.878***	1.345***
	-0.308	-0.286	-0.193
Observations	759	1,276	2,035

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Finland

	Male	Female	Total
Immigrant	0.007	-0.084*	-0.053
	-0.069	-0.049	-0.04
Literacy	0.009	0.002	0.008
	-0.035	-0.032	-0.023
Numeracy	0.059*	0.076**	0.067***
	-0.034	-0.031	-0.023
Numeracy skills usage at work	-0.01	-0.015	-0.014*
	-0.012	-0.011	-0.008
ICT Skills usage at work	0.018	0.030**	0.023**
	-0.014	-0.012	-0.009
Reading skills usage at work	0.008	0.031*	0.022*
	-0.018	-0.016	-0.012
Writing skills usage at work	0.048***	0.036***	0.043***
	-0.013	-0.011	-0.008
Numeracy skills usage (non-work)	-0.004	0.01	0.004
	-0.017	-0.014	-0.011
ICT skills usage non-work)	-0.016	-0.007	-0.012
	-0.016	-0.014	-0.011
Reading skills usage (non-work)	0.012	0.001	0.005
	-0.02	-0.017	-0.013
Writing skills usage at work	-0.008	-0.023*	-0.014
	-0.013	-0.012	-0.009
Age	0.011***	0.005***	0.008***
	-0.001	-0.001	-0.001
Gender_Female			-0.092***
			-0.013
Ability to speak local language	-0.039	-0.025	-0.026
	-0.063	-0.047	-0.038
Constant	2.343***	2.116***	2.440***
	-0.156	-0.169	-0.116
Observations	1,149	1,289	2,438

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

France

	Male	Female	Total
Immigrant	-0.026	-0.01	-0.015
	-0.06	-0.056	-0.041
Literacy	-0.055	0.038	-0.018
	-0.056	-0.049	-0.037
Numeracy	0.159***	0.008	0.092***
	-0.052	-0.046	-0.035
Numeracy skills usage at work	0.014	-0.013	-0.002
	-0.015	-0.013	-0.01
ICT Skills usage at work	0.037*	0.023	0.029**
	-0.02	-0.016	-0.012
Reading skills usage at work	-0.048**	-0.009	-0.030**
	-0.021	-0.021	-0.015
Writing skills usage at work	0.033*	0.024	0.035***
	-0.017	-0.015	-0.011
Numeracy skills usage (non-work)	-0.0004	0.004	0.002
	-0.019	-0.016	-0.012
ICT skills usage non-work)	-0.005	0.007	0.001
	-0.019	-0.018	-0.013
Reading skills usage (non-work)	-0.008	-0.004	-0.011
	-0.023	-0.023	-0.016
Writing skills usage at work	0.016	-0.02	-0.005
	-0.018	-0.016	-0.012
Age	0.020***	0.016***	0.018***
	-0.001	-0.001	-0.001
Gender_Female			-0.068***
			-0.019
Ability to speak local language	-0.026	0.111*	0.056
	-0.071	-0.066	-0.048
Constant	1.337***	1.824***	1.644***
	-0.238	-0.262	-0.167
Observations	928	992	1,920

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Ireland

	Male	Female	Total
Immigrant	-0.053	-0.112*	-0.079
	-0.09	-0.064	-0.053
Literacy	-0.192	0.105	-0.05
	-0.141	-0.104	-0.083
Numeracy	0.342***	0.014	0.188**
	-0.131	-0.095	-0.077
Numeracy skills usage at work	-0.045	-0.002	-0.017
	-0.039	-0.025	-0.021
ICT Skills usage at work	-0.003	0.023	-0.001
	-0.039	-0.028	-0.022
Reading skills usage at work	0.067	0.111***	0.102***
	-0.051	-0.038	-0.03
Writing skills usage at work	0.046	0.025	0.029
	-0.041	-0.028	-0.024
Numeracy skills usage (non-work)	0.066	0.009	0.041*
	-0.041	-0.03	-0.024
ICT skills usage non-work)	0.04	0.009	0.023
	-0.047	-0.036	-0.028
Reading skills usage (non-work)	-0.111*	-0.07	-0.103***
	-0.057	-0.042	-0.034
Writing skills usage at work	0.065	0.024	0.048
	-0.05	-0.04	-0.031
Age	0.017***	0.012***	0.015***
	-0.004	-0.002	-0.002
Gender_Female			0.011
			-0.041
Ability to speak local language	0.192	0.085	0.161**
	-0.13	-0.106	-0.081
Constant	1.326**	2.144***	1.488***
	-0.607	-0.813	-0.431
Observations	631	826	1,457

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Italy

	Male	Female	Total
Immigrant	-0.067	-0.121	-0.029
	-0.147	-0.28	-0.124
Literacy	0.191*	-0.15	0.027
	-0.104	-0.129	-0.08
Numeracy	0.031	0.216*	0.127*
	-0.097	-0.12	-0.075
Numeracy skills usage at work	0.064**	-0.037	0.018
	-0.027	-0.035	-0.021
ICT Skills usage at work	-0.03	0.069	0.001
	-0.032	-0.042	-0.025
Reading skills usage at work	0.037	0.016	0.022
	-0.038	-0.048	-0.029
Writing skills usage at work	0.011	0.019	0.02
	-0.032	-0.041	-0.025
Numeracy skills usage (non-work)	-0.056*	-0.0002	-0.023
	-0.032	-0.037	-0.024
ICT skills usage non-work)	0.025	0.029	0.02
	-0.031	-0.041	-0.024
Reading skills usage (non-work)	-0.023	-0.023	-0.021
	-0.041	-0.048	-0.031
Writing skills usage at work	0.038	-0.0002	0.022
	-0.031	-0.038	-0.024
Age	0.021***	0.013***	0.018***
	-0.003	-0.004	-0.002
Gender_Female			0.008
			-0.041
Ability to speak local language	0.12	-0.158	0.023
	-0.132	-0.298	-0.121
Constant	1.709***	1.734**	1.440***
	-0.592	-0.741	-0.393
Observations	349	323	672

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Netherlands

	Male	Female	Total
Immigrant	0.045	0.078	0.035
	-0.063	-0.053	-0.042
Literacy	0.018	0.003	0.016
	-0.05	-0.038	-0.032
Numeracy	0.080*	0.063*	0.079***
	-0.043	-0.034	-0.028
Numeracy skills usage at work	0.009	-0.005	0.002
	-0.013	-0.011	-0.009
ICT Skills usage at work	0.040***	0.021	0.028***
	-0.015	-0.013	-0.01
Reading skills usage at work	0.016	-0.005	0.01
	-0.02	-0.016	-0.013
Writing skills usage at work	0.018	0.040***	0.030***
	-0.015	-0.011	-0.009
Numeracy skills usage (non-work)	-0.02	-0.002	-0.007
	-0.015	-0.012	-0.01
ICT skills usage non-work)	-0.041**	-0.012	-0.027**
	-0.017	-0.015	-0.012
Reading skills usage (non-work)	-0.008	-0.021	-0.013
	-0.021	-0.018	-0.014
Writing skills usage at work	0.01	0.022*	0.015
	-0.015	-0.012	-0.01
Age	0.009***	0.008***	0.009***
	-0.001	-0.001	-0.001
Gender_Female			-0.105***
			-0.014
Ability to speak local language	0.132**	0.068	0.085**
	-0.066	-0.054	-0.043
Constant	2.410***	2.445***	2.429***
	-0.139	-0.115	-0.093
Observations	1,348	1,203	2,551

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Norway

	Male	Female	Total
Immigrant	0.045	0.078	0.035
	-0.063	-0.053	-0.042
Literacy	0.018	0.003	0.016
	-0.05	-0.038	-0.032
Numeracy	0.080*	0.063*	0.079***
	-0.043	-0.034	-0.028
Numeracy skills usage at work	0.009	-0.005	0.002
	-0.013	-0.011	-0.009
ICT Skills usage at work	0.040***	0.021	0.028***
	-0.015	-0.013	-0.01
Reading skills usage at work	0.016	-0.005	0.01
	-0.02	-0.016	-0.013
Writing skills usage at work	0.018	0.040***	0.030***
	-0.015	-0.011	-0.009
Numeracy skills usage (non-work)	-0.02	-0.002	-0.007
	-0.015	-0.012	-0.01
ICT skills usage non-work)	-0.041**	-0.012	-0.027**
	-0.017	-0.015	-0.012
Reading skills usage (non-work)	-0.008	-0.021	-0.013
	-0.021	-0.018	-0.014
Writing skills usage at work	0.01	0.022*	0.015
	-0.015	-0.012	-0.01
Age	0.009***	0.008***	0.009***
	-0.001	-0.001	-0.001
Gender_Female			-0.105***
			-0.014
Ability to speak local language	0.132**	0.068	0.085**
	-0.066	-0.054	-0.043
Constant	2.410***	2.445***	2.429***
	-0.139	-0.115	-0.093
Observations	1,348	1,203	2,551

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Spain

	Male	Female	Total
Immigrant	-0.126	-0.135*	-0.119*
	-0.09	-0.071	-0.066
Literacy	-0.075	-0.165**	-0.09
	-0.1	-0.079	-0.073
Numeracy	0.292***	0.204***	0.220***
	-0.101	-0.078	-0.073
Numeracy skills usage at work	-0.022	0.003	-0.005
	-0.023	-0.019	-0.017
ICT Skills usage at work	0.037	-0.021	0.006
	-0.032	-0.025	-0.023
Reading skills usage at work	0.019	0.017	0.02
	-0.031	-0.025	-0.023
Writing skills usage at work	0.082***	-0.01	0.053***
	-0.028	-0.022	-0.02
Numeracy skills usage (non-work)	-0.028	-0.011	-0.017
	-0.028	-0.021	-0.02
ICT skills usage non-work)	0.004	-0.046*	-0.002
	-0.031	-0.028	-0.024
Reading skills usage (non-work)	-0.027	0.018	-0.036
	-0.033	-0.03	-0.025
Writing skills usage at work	0.03	0.059**	0.037
	-0.032	-0.025	-0.023
Age	0.018***	0.012***	0.015***
	-0.002	-0.002	-0.002
Gender_Female			-0.096***
			-0.037
Ability to speak local language	-0.197*	-0.018	-0.098
	-0.108	-0.075	-0.074
Constant	1.348***	1.496***	2.012***
	-0.358	-0.423	-0.281
Observations	510	455	965

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

United Kingdom

	Male	Female	Total
Immigrant	-0.06	-0.002	-0.025
	-0.063	-0.041	-0.035
Literacy	0.082	0.008	0.039
	-0.069	-0.046	-0.039
Numeracy	0.067	0.101**	0.092***
	-0.063	-0.042	-0.035
Numeracy skills usage at work	0.039**	-0.007	0.011
	-0.018	-0.012	-0.01
ICT Skills usage at work	0.054***	0.053***	0.052***
	-0.021	-0.014	-0.012
Reading skills usage at work	0.001	0.016	0.014
	-0.023	-0.017	-0.014
Writing skills usage at work	0.059***	0.029**	0.042***
	-0.021	-0.013	-0.011
Numeracy skills usage (non-work)	-0.026	0.012	-0.002
	-0.023	-0.014	-0.012
ICT skills usage non-work)	-0.001	-0.019	-0.008
	-0.023	-0.017	-0.013
Reading skills usage (non-work)	0.011	-0.016	-0.01
	-0.027	-0.02	-0.016
Writing skills usage at work	-0.007	0.005	0.004
	-0.025	-0.018	-0.015
Age	0.014***	0.007***	0.010***
	-0.001	-0.001	-0.001
Gender_Female			-0.091***
			-0.02
Ability to speak local language	-0.03	0.001	-0.015
	-0.076	-0.056	-0.045
Constant	1.500***	2.174***	1.893***
	-0.215	-0.155	-0.129
Observations	1,150	1,700	2,850

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Slovenia

	Male	Female	Total
Immigrant	0.02	0.157**	0.077
	-0.088	-0.076	-0.057
Literacy	0.047	0.004	0.037
	-0.062	-0.061	-0.043
Numeracy	0.135**	0.104*	0.114***
	-0.058	-0.056	-0.04
Numeracy skills usage at work	0.060***	-0.002	0.022*
	-0.022	-0.017	-0.013
ICT Skills usage at work	-0.018	0.029	0.011
	-0.024	-0.021	-0.016
Reading skills usage at work	0.059**	0.008	0.034**
	-0.027	-0.022	-0.017
Writing skills usage at work	0.033*	-0.012	0.008
	-0.02	-0.018	-0.013
Numeracy skills usage (non-work)	-0.008	-0.014	-0.006
	-0.024	-0.021	-0.016
ICT skills usage non-work)	0.004	-0.016	-0.005
	-0.025	-0.023	-0.017
Reading skills usage (non-work)	-0.022	0.006	-0.009
	-0.03	-0.024	-0.019
Writing skills usage at work	-0.005	0.011	0.00003
	-0.021	-0.021	-0.015
Age	0.010***	0.011***	0.011***
	-0.002	-0.002	-0.001
Gender_Female			-0.100***
			-0.023
Ability to speak local language	0.134*	0.059	0.093*
	-0.078	-0.081	-0.055
Constant	1.089***	1.343***	1.297***
	-0.228	-0.261	-0.169
Observations	542	654	1,196

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Greece

	Male	Female	Total
Immigrant	0.155	0.102	0.133
	-0.174	-0.114	-0.092
Literacy	0.004	0.096	0.05
	-0.103	-0.098	-0.068
Numeracy	0.01	0.001	0.001
	-0.099	-0.099	-0.068
Numeracy skills usage at work	-0.034	-0.037	-0.03
	-0.031	-0.028	-0.02
ICT Skills usage at work	0.081*	-0.005	0.032
	-0.048	-0.043	-0.03
Reading skills usage at work	0.031	0.042	0.046*
	-0.042	-0.037	-0.028
Writing skills usage at work	-0.037	-0.035	-0.052**
	-0.039	-0.035	-0.025
Numeracy skills usage (non-work)	-0.038	-0.029	-0.031
	-0.047	-0.034	-0.027
ICT skills usage non-work)	-0.01	0.093**	0.042
	-0.04	-0.037	-0.026
Reading skills usage (non-work)	0.043	0.009	0.016
	-0.051	-0.045	-0.032
Writing skills usage at work	0.009	-0.007	-0.001
	-0.038	-0.033	-0.024
Age	0.029***	0.028***	0.028***
	-0.004	-0.003	-0.002
Gender_Female			-0.055
			-0.043
Ability to speak local language	0.054	0.378	0.179
	-0.243	-0.229	-0.162
Constant	1.119***	0.714	1.005***
	-0.426	-0.467	-0.292
Observations	233	257	490

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

Appendix IV

OLS model for four different groups of male immigrants devided by the number of years spent in the host country

	0-5 Years	5-10 Years	10-15 Years	15+ Years
Literacy	0.475	0.28	-0.408	-0.09
	-0.329	-0.325	-0.755	-0.148
Numeracy	-0.479	-0.325	1.125	0.285*
	-0.308	-0.284	-0.657	-0.151
Numeracy skills usage at work	0.195**	-0.263**	0.034	0.022
	-0.083	-0.105	-0.205	-0.043
Literacy skills usage at work	0.061	-0.098	-0.107	0.045
	-0.083	-0.124	-0.171	-0.045
Reading skills usage at work	0.089	0.088	-0.039	-0.009
	-0.108	-0.092	-0.217	-0.067
Writing skills usage at work	-0.09	0.057	0.865*	0.04
	-0.102	-0.074	-0.357	-0.047

Numeracy skills usage (non-work)	-0.185	0.218**	0.305	0.02
	-0.131	-0.092	-0.38	-0.054
ICT skills usage non-work)	-0.035	-0.007	0.211	-0.008
	-0.096	-0.089	-0.286	-0.061
Reading skills usage (non-work)	0.137	-0.26	-0.717	0.038
	-0.144	-0.159	-0.422	-0.069
Writing skills usage (non-work)	-0.067	0.412*	0.346	-0.122**
	-0.113	-0.212	-0.235	-0.058
AGE	0.021*	0.031***	0.02	0.002
	-0.012	-0.008	-0.021	-0.004
Able to speak local language	0.279	0.084	1.779*	-0.064
	-0.184	-0.196	-0.886	-0.08
Number of Job-related Trainings	-0.002	-0.064	-0.076	-0.018
	-0.074	-0.061	-0.122	-0.038
Employment Protections	1.089	3.831***	-1.145	-0.096
	-1.487	-1.207	-2.183	-0.213
Union Density	0.009	0.072**	0.014	-0.003

	-0.031	-0.024	-0.048	-0.004
# of Parental weeks	0.035	0.096**	0.019	-0.002
	-0.04	-0.038	-0.041	-0.007
Immigrant Share in Population	10.96	34.972**	-60.628**	-0.214
	-9.401	-13.624	-19.288	-2.746
Unemployment Rate	-0.052	0.178***	0.122	0.022
	-0.067	-0.05	-0.148	-0.016
GDP per Capita	-0.00001	-0.00003	0.00004	0.00002***
	-0.0001	-0.00003	-0.0001	-0.00001
Poverty at risk by country age 18-64	0.012	-0.059	-0.058	-0.005
	-0.063	-0.036	-0.133	-0.011
Constant	-3.33	-15.451**	9.069	1.493
	-3.035	-5.421	-6.802	-1.197
Observations	83	61	54	232

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

OLS model for four different groups of male immigrants devided by the number of years spent in the host country

	0-5 Years	5-10 Years	10-15 Years	15+ Years
Literacy	-0.081	0.118	-0.219	-0.068
	-0.313	-0.193	-0.263	-0.103
Numeracy	0.013	0.135	0.296	0.220**
	-0.273	-0.2	-0.307	-0.094
Numeracy skills usage at work	-0.016	0.089	-0.027	-0.057**
	-0.063	-0.057	-0.08	-0.027
Literacy skills usage at work	-0.15	-0.05	-0.131	0.061**
	-0.114	-0.048	-0.096	-0.031
Reading skills usage at work	0.006	-0.132	-0.275**	0.089**
	-0.127	-0.097	-0.105	-0.044
Writing skills usage at work	0.034	0.072	0.014	0.019
	-0.107	-0.06	-0.086	-0.029
Numeracy skills usage (non-work)	-0.004	-0.143	0.054	0.008
	-0.091	-0.088	-0.07	-0.03

ICT skills usage (non-work)	-0.049	0.034	0.023	0.01
	-0.157	-0.103	-0.119	-0.034
Reading skills usage (non-work)	-0.095	-0.064	-0.161	0.038
	-0.153	-0.087	-0.14	-0.041
Writing skills usage (non-work)	-0.066	0.152	0.579***	-0.004
	-0.106	-0.101	-0.161	-0.034
AGE	0.013	0.014**	0.025***	0.009***
	-0.009	-0.007	-0.007	-0.002
Able to speak local language	-0.237	-0.04	-0.441**	0.008
	-0.185	-0.114	-0.166	-0.059
Number of Job-related Trainings	0.106	0.052	0.372***	0.005
	-0.067	-0.044	-0.116	-0.021
Employment Protections	-1.574	-0.648	3.864***	0.424***
	-1.794	-0.516	-0.898	-0.146
Union Density	-0.023	-0.007	0.054***	0.003
	-0.031	-0.012	-0.015	-0.003
# of Parental weeks	-0.012	-0.013	0.122***	0.010**

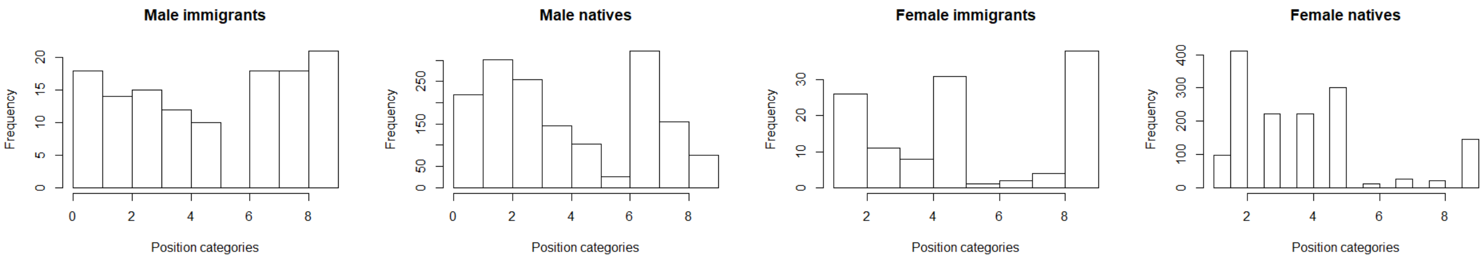
	-0.045	-0.017	-0.025	-0.005
Immigrant Share in Population	-9.224	3.876	23.681**	5.072***
	-6.159	-5.927	-8.361	-1.851
Unemployment Rate	-0.057	-0.073**	0.024	0.013
	-0.095	-0.029	-0.04	-0.011
GDP per Capita	0.0001	0.00001	-0.0001***	0.00002***
	-0.00004	-0.00002	-0.00003	-0.00001
Poverty at risk by country age 18-64	0.067	0.043	-0.120**	-0.009
	-0.07	-0.029	-0.046	-0.01
Constant	2.326	1.309	-9.393***	-0.943
	-3.82	-1.793	-2.971	-0.623
Observations	69	93	63	303

Note: Dependent variable is log hourly wage. The model additionally controls for occupational (occupational sector and industry) and education. Additional information about control variables is given in Appendix I. *,**,*** represent significance at 10, 5, 1 percent levels, respectively.

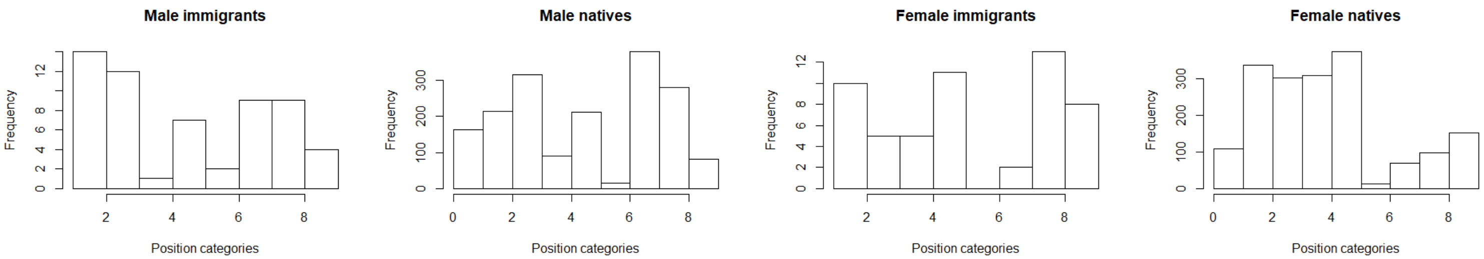
Appendix V

Distribution of Occupation across gender and immigrant-native groups

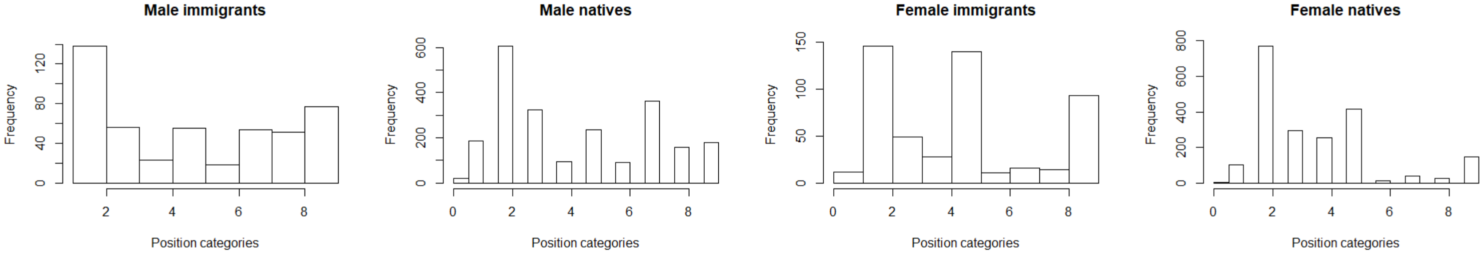
Belgium



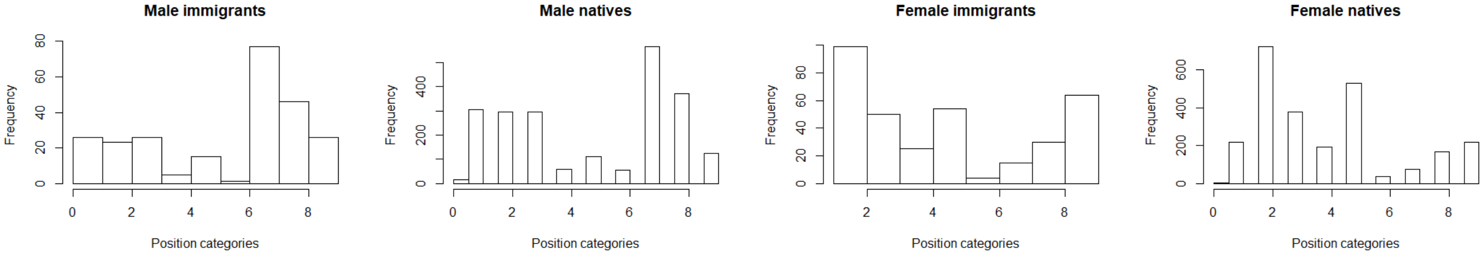
Czechia



Denmark



Estonia



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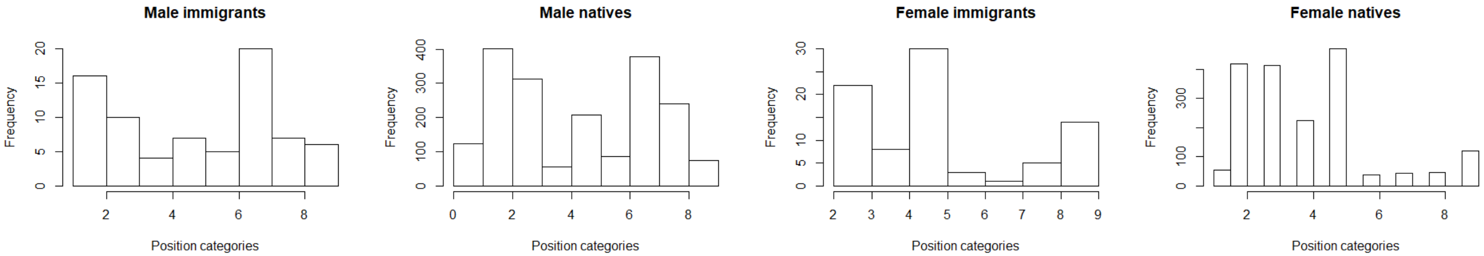

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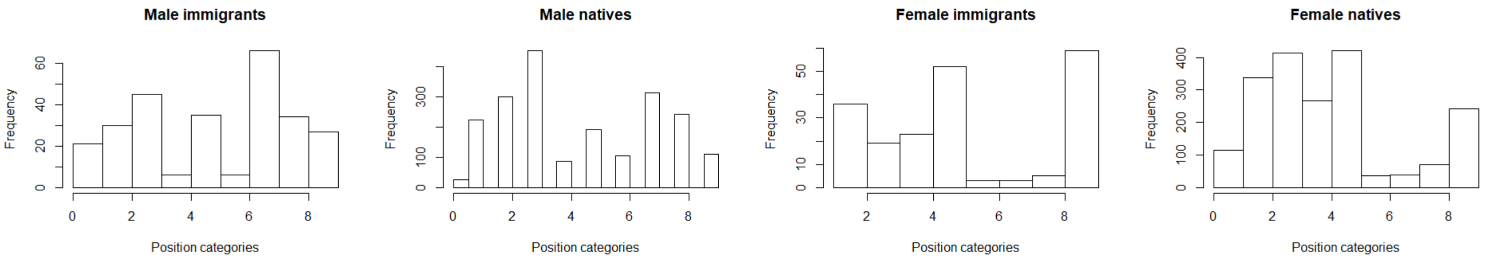

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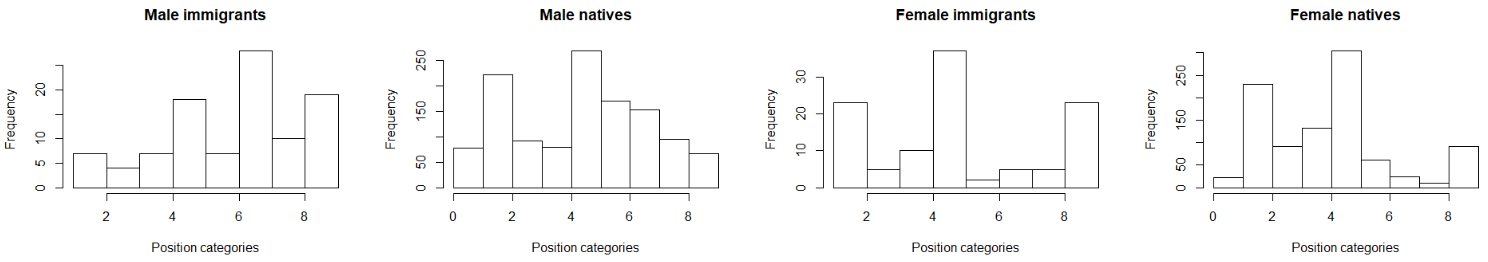

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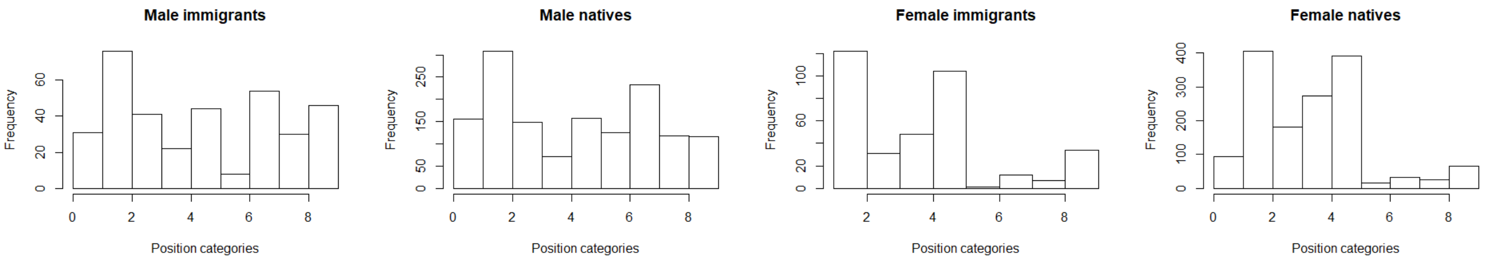

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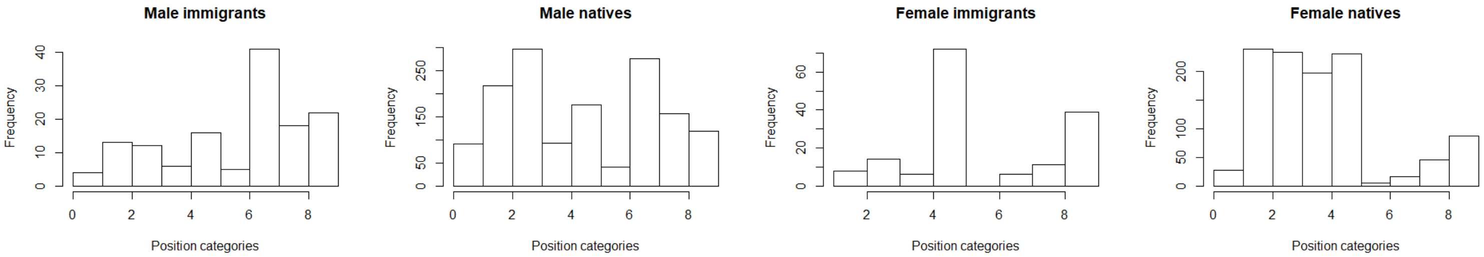

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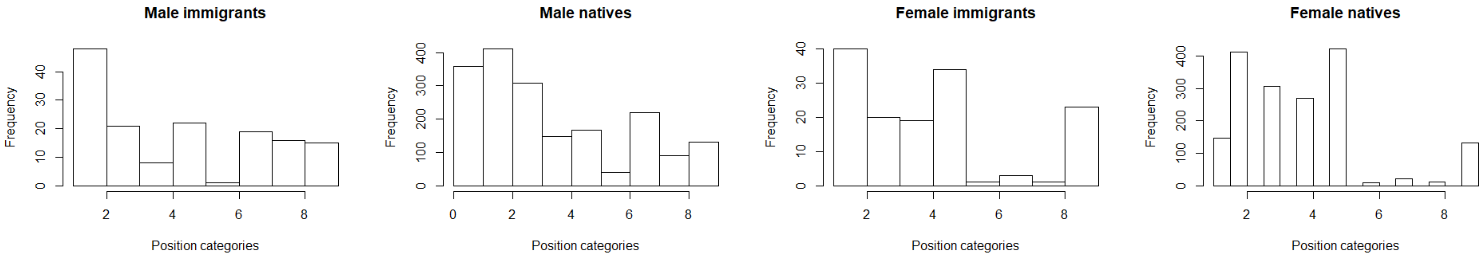

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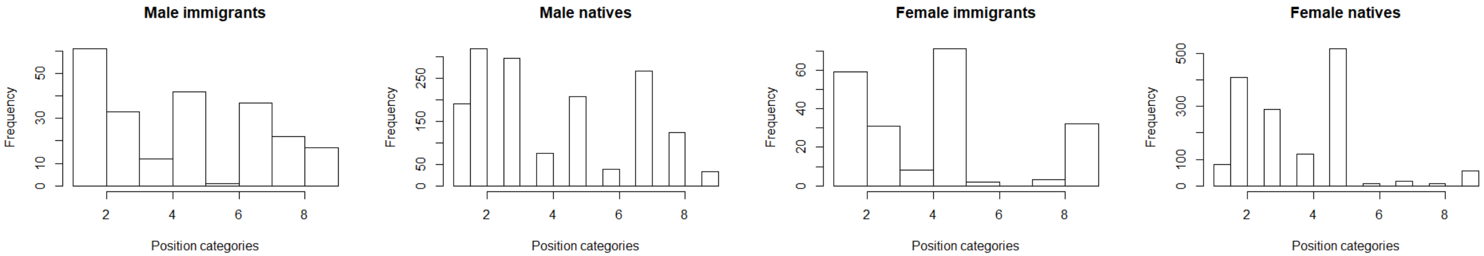

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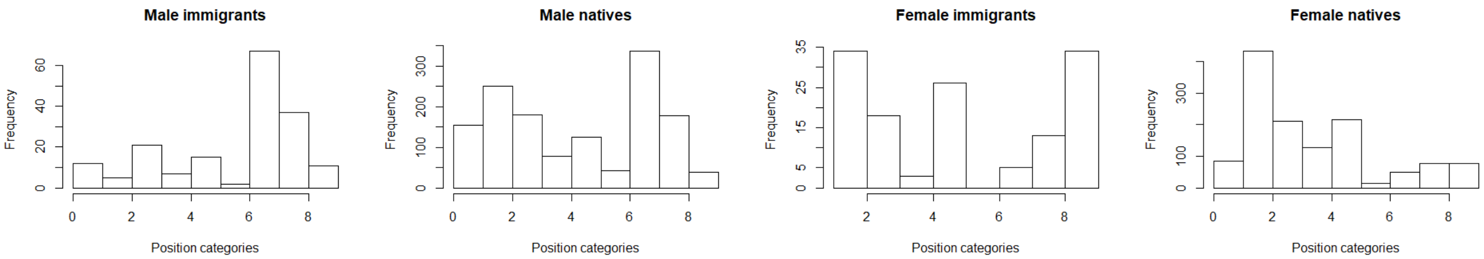

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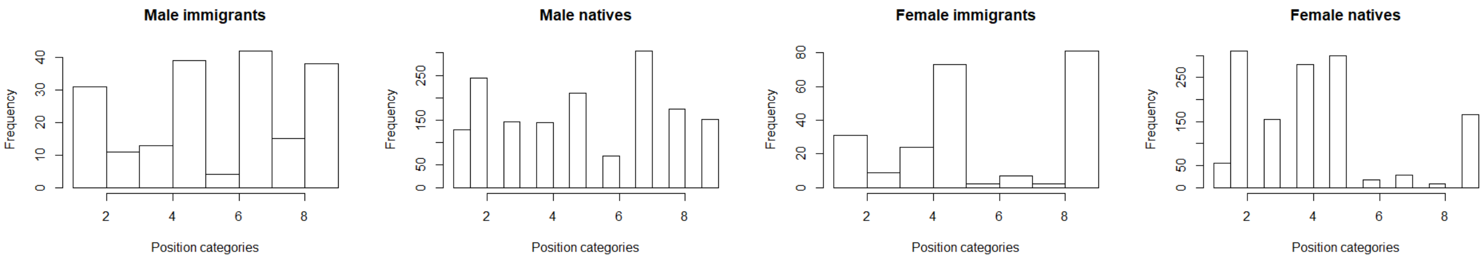

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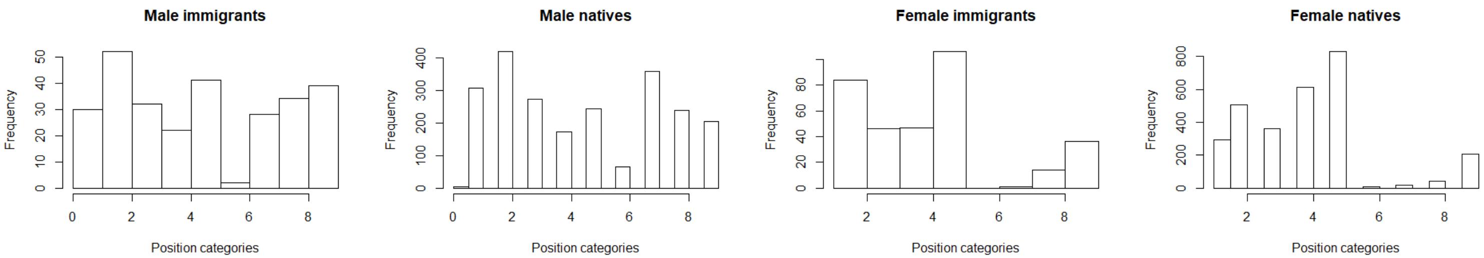
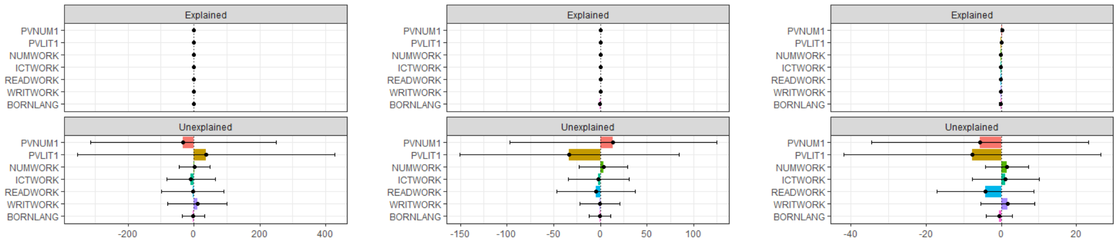


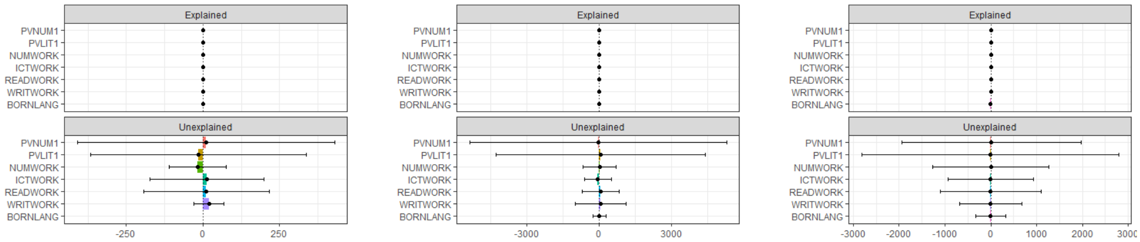
Appendix VI

Wage decompositions for Countries (Female, Male, Total in given order)

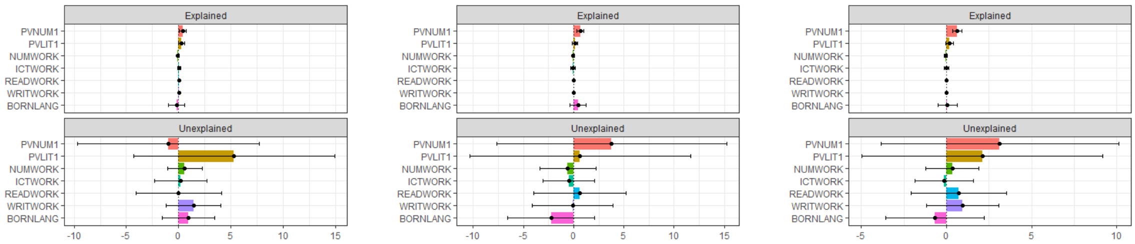
Belgium



Czechia



Denmark



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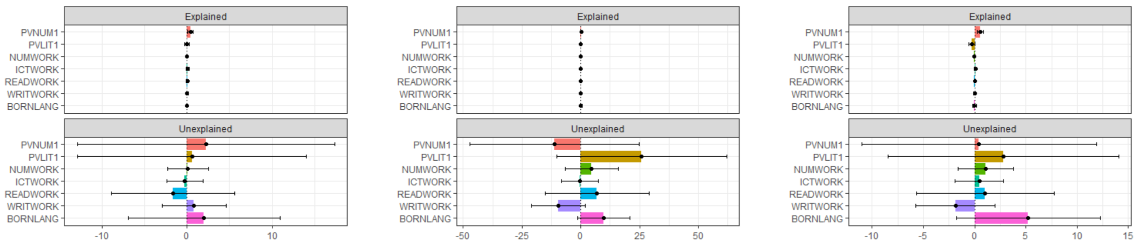

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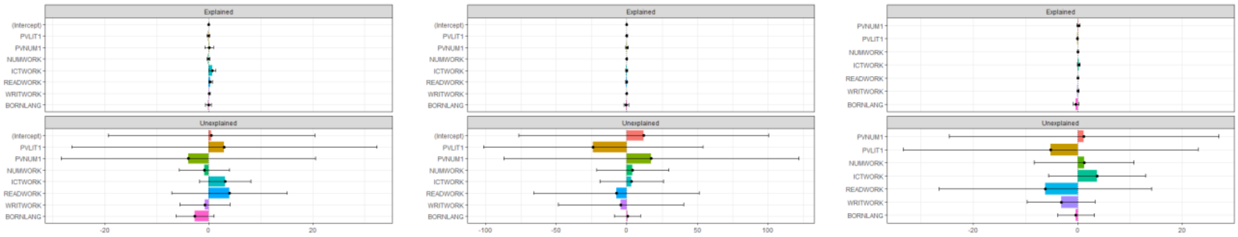

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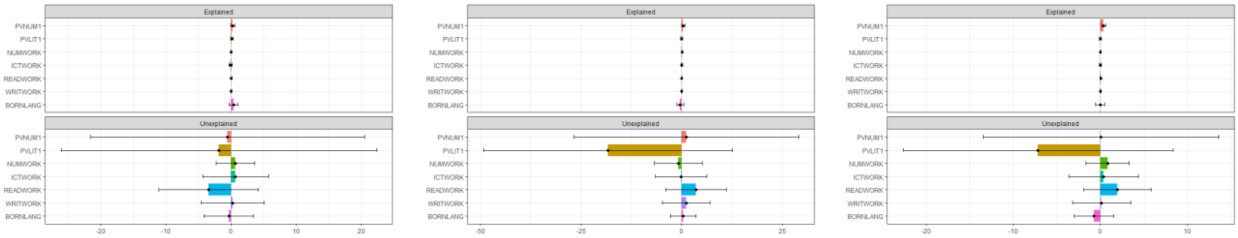

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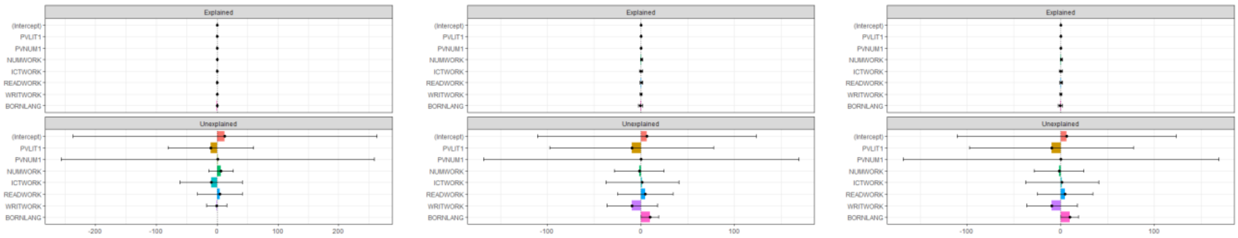

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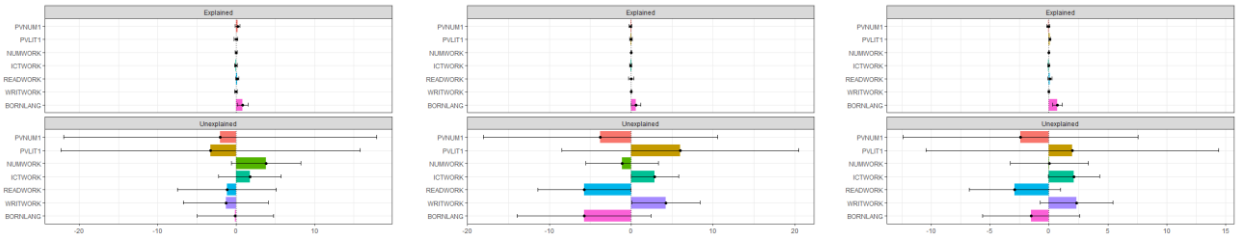
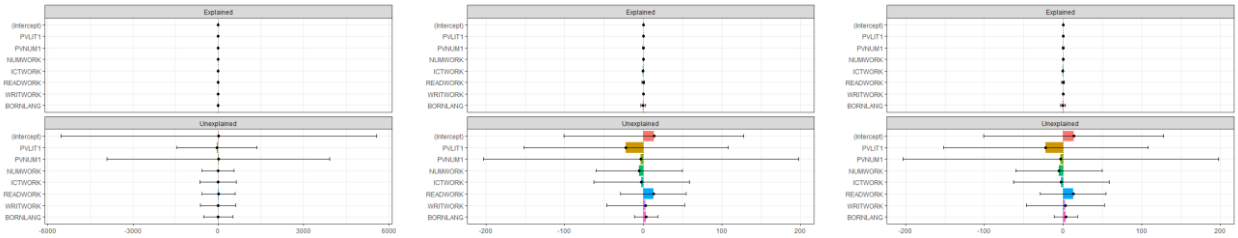
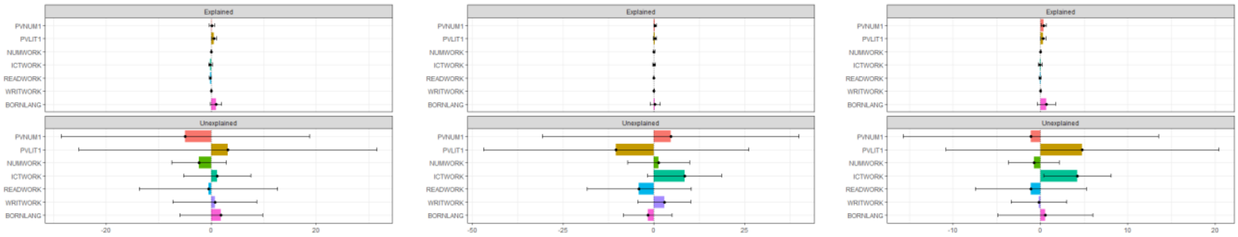


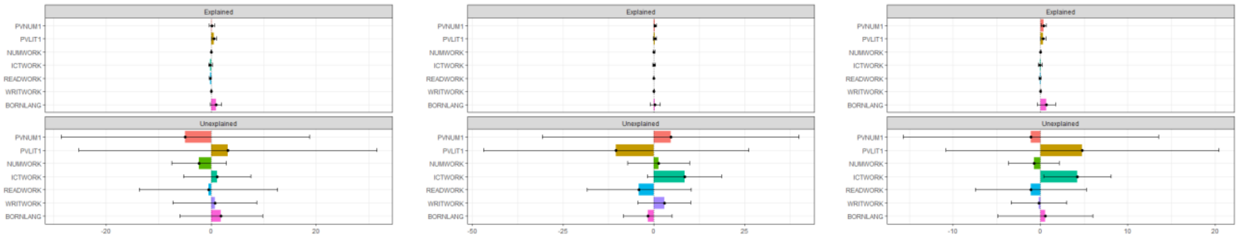
Italy



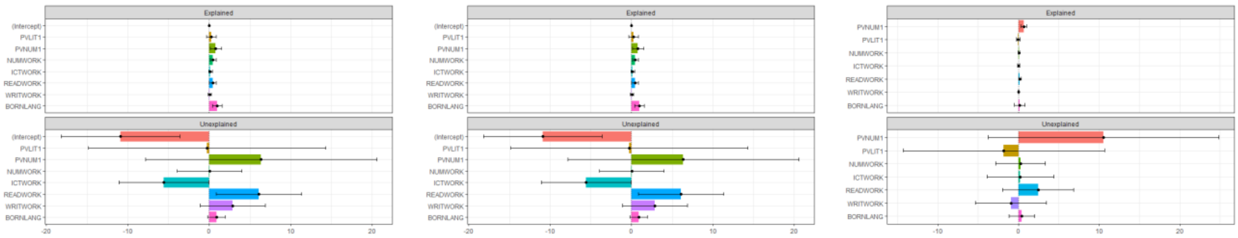
Netherlands



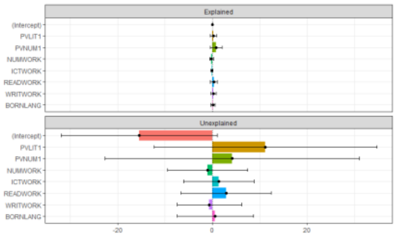
Norway

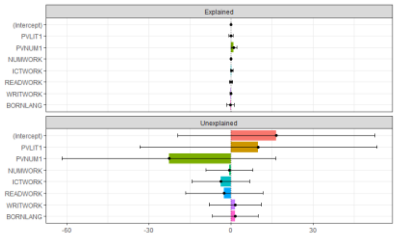


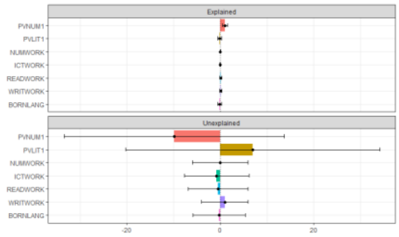
Slovenia



Spain







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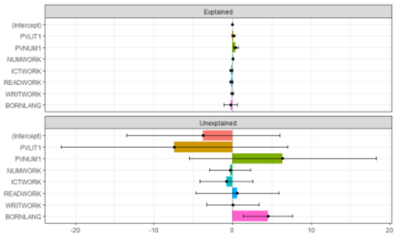

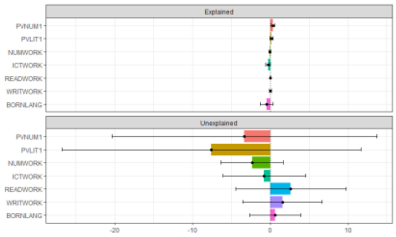

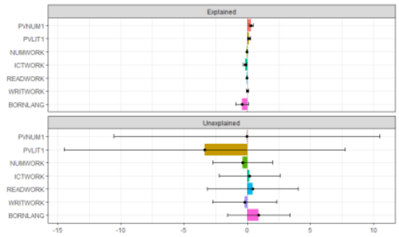

Appendix VII

Spearman correlations between macro-level factors and wage gap relative to average hourly income

Macro-level Factor	Correlation Coefficient
Employment Protection	-0.2703297
Union Density	0.1428571
Number of Parental Leave	-0.2651974
Population	-0.4593407*
Share of Immigrants	0.1736264
Unemployment	0.1780220
GDP per Capita	0.1340659
Poverty at Risk by Country(age 18-64)	0.3846154
Attitude Toward Immigrants	0.54442181*

Note: to calculate Spearman Correlation coefficients, we used relative wage gaps derived by Oaxaca-Blinder decomposition and given in Table 6.

The correlation coefficients for all of the macro-level factors are quite low. The population has the highest correlation coefficient. In addition, test for Spearman rank correlation coefficients show that the only correlation of population with wage gap has statistically significant correlation coefficient (at 5% significance level). Although the correlations are quite weak and evidence does not suggest there is correlation with most of the macro-level factors, the signs of estimated correlation coefficients are as expected. However, we cannot also deny the high chance of type 2 error, as the data used to derive Spearman rank correlation coefficient was quite limited. The same reason also might be behind the insignificance of other results.

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