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THE ROLE OF COGNITIVE SKILLS AND THEIR USE AT WORK IN EXPLAINING THE IMMIGRANT-NATIVE WAGE GAP

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The role of cognitive skills and their use at work in explaining the immigrant-native wage gap

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Abstract

This paper analyses the immigrant-native wage gap and incorporates cognitive skills to approximate an individual human capital profile. Based on data from the Programme for the International Assessment of Adult Competencies (PIAAC) for 15 European countries, we document that on average foreign-born respondents achieve substantially worse scores in literacy and numeracy test domain, and the observed gap in cognitive skill declines over the period of the host-country stay. The results of the analysis show that once we account additionally skill use at work in wage regressions, along with actual skill level, no statistically significant gap in earnings across immigrants and natives remains**.** These findings indicate that, despite similar cognitive skill levels and background traits, immigrants and natives may apply their skills at work to different extents, yielding a difference in their wage returns. Therefore, disparity in skill use at work plays an important role in explaining the immigrant-native wage gap. This leads us to conclude that immigrants are not yet sufficiently well integrated in European labour markets, and the potential for the development and application of their human capital is still underutilised. Further policy measures should profoundly consider these indications, taking into account that the role of immigrants and their labour supply is increasing remarkably in European societies.

Keywords: migration, human capital, cognitive skills, PIAAC.

JEL codes: J15, J24, J31, J61

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1. INTRODUCTION

There is ample research analysing the disadvantages faced by immigrants on the host market. The majority of studies document that immigrants tend to earn on average less than natives (Borjas 2015, Dustmann et al. 2013, Borjas 2000). Previous findings also suggest that the wage disadvantage is the highest for newly-arrived immigrants, but decreases slowly over the years spent in the host country (Sarvimäki 2011). However, some part of the initial immigrant-native pay gap persists even after many years of living in a receiving country (Sarvimäki 2011), suggesting that the immigrant wage penalty does not ultimately disappear.

Existing literature addresses the various reasons behind an observed wage disadvantage for immigrants. According to classical human capital theory (Becker 1975), differences in skills transmit into earnings. However, immigrants may lack the qualifications and abilities demanded by the host country, often referred to as the host country-specific human capital, thereby yielding their wage penalty (Zibrowius 2012). Due to a lack of appropriate data, previous studies mostly approximated human capital using formal education to measure the wage gap and occupation-qualification match. In the context of an immigrant-native comparison, this approximation yields several serious limitations. The major one being the potential non-comparability of formal degrees held by natives and immigrants (Green and Worswick 2012, Bonikowska et al. 2008). This results in objective differences in capabilities, as well as simple non-recognition of foreign degrees by host-country employers. Hence, using formal education as a proxy of qualification does not make it possible to obtain a pure effect of the immigrant human capital gap on labour market outcomes. The gap in formal education only roughly reflects the human capital gap, as the same degree formally acquired in the host country by natives and in the country of origin by immigrants may yield different competencies and skills. Therefore, the part of the labour market outcome gap attributed to a difference in formal education tells us little about any actual difference in skills and abilities.

This paper contributes to this debate by incorporating actual literacy and numeracy skills, rather than only formal education, to evaluate the actual immigrant-native human capital gap. We use actual test scores in literacy and numeracy cognitive skill domains provided by the Programme for the International Assessment of Adult Competencies (PIAAC), conducted within the Survey of Adult Skills. Relying on PIAAC-based measures of individual cognitive skills, we evaluate systematic skill differences across immigrants and natives in 15 European countries. Therefore, the first contribution of the paper concerns the dynamics of immigrant human capital, approximated using literacy and numeracy skills over immigration tenure. The paper tests whether immigrants are indeed prone to improve their skill profile, as they acquire skills valued and in demand in their host country.

The second contribution relates to the incorporation of skill use measures in an immigrant-native pay gap analysis. The intensity of skill use at work has a non-trivial association with immigrant wage improvement. Why should we account for the extent to which an immigrant utilizes his skills when analysing the wage disadvantage of immigrants? We argue that some labour market disadvantages may persist despite the immigrants' true skills and abilities. Even with a relatively strong qualification profile, immigrants still frequently face disadvantages on the labour market.

Previous studies widely documented that immigrants tend to be overqualified (Dustmann et al. 2013, Chiswick and Miller 2010), suggesting that even when an immigrant has sufficiently good abilities, he does not attain a position comparable to an otherwise similar native. Among other factors, over education can be induced by the difficulties of labour market entry, nonfamiliarity with the local labour market, lower level of credibility from the employers' perspective (Quilllian 2006), and other factors. These considerations infer that immigrants have lower access to challenging and highly-rewarding jobs. Hence, even with relatively profound competencies, the aforementioned disadvantages may deter immigrant career progression leading to a persistent wage penalty, which may to a large extent offset positive wage returns on human capital improvement. Therefore, an immigrant's investments in his or her human capital and skills development may not immediately translate into positive wage returns, resulting in a persistent wage penalty even after many years spent in a host country.

Relying on these rationales, we set two research hypotheses, which outline the scope of our research:

H1: *(i) Immigrants acquire and develop their cognitive skills over years spent in a host country; however, (ii) the improvement of their skill profile is not sufficient in itself to fully eliminate immigrant-native pay disparity.*

H2: *Immigrant-native difference in skill use at work, largely explain, if not eliminate the immigrant-native pay gap.*

In our approach, we relate intensity of skill use at work to wage returns through two channels. The first is the indirect effect of skill use at work on wages through skill accumulation, as there is a strong association between skill application at work and cognitive skill level. The second channel implies that skill use at work is an approximation of (i) the complexity, challenge and reward level associated with the job; and (ii) individual effort exerted by the respondent when dealing with job tasks. The first channel relies on an obvious assumption that skill is associated with skill use with no clear direction of causality[3], while in the second channel we introduce several important assumptions. Specifically, (a) more complex and challenging work requires more frequent use of certain skills, relative to less complex; (b) the extent of skill use at work largely represents individual effort exerted at work; (c) individual skills generate positive wage returns only when utilized at work. We find empirical evidence for all four assumptions, allowing us to safely argue that skill use at work is an important factor in the immigrant-native wage gap debate.

To argue that skill use at work directly enters the wage regression as a proxy for job complexity and degree of skill application, one must verify that this channel exists along with an indirect effect through immigrant skill accumulation. Both channels are observationally equivalent, since a coefficient of skill use at work captures both direct effect and indirect association through acquired competence[4]. To address this issue, we refer to skill use in everyday life control, which is defined as identical to skill use at work, but ask how frequently certain activities are performed in non-work-related activities. Following our intuition, skill use in everyday life can reflect upon wage, but only indirectly through the acceleration of the skill. The direct channel is not valid in this case, since intensity of skill use in non-work activities tells us nothing neither about the complexity of the job, nor about the individual effort exerted by a respondent. The non-significant wage effect of skill uses at work, coupled with the

[3] Allen et al. (2013) reports that there is a positive correlation between skill level and intensity of skill use in PIAAC dataset. The direction of causality is not clear with observational data in hand. However, in our research causality direction of skill and skill use is not of a prime interest and does not directly affect our results.

[4] Even when controlling for literacy or numeracy score in wage regression, skill channel may be still present. Cognitive test scores measure just one dimension of cognitive skills in a stylized way, leaving particular dimension of given skill, as well as other cognitive competencies unobserved.

significant association of skill use at work, would support our assumption that intensity of skill use at work is an independent factor affecting the wage rate.

Our results suggest that immigrant literacy and numeracy skills indeed tend to improve over the years since migration. However, controlling for cognitive skills does not eliminate the statistically significant immigrant-native pay gap. Incorporating skill use at work and skill use in everyday life as a placebo variable revealed that intensity of skill application at work indeed accounts for a large share of the immigrant-native pay gap. As expected, we found that both skill use at work and in everyday life are significantly associated with skill level; however, only skill use at work yields positive wage returns when both work and non-work skill use controls are incorporated in the wage regression. The empirical results of the paper proved that, not only a mere stock of skills matter in narrowing down the immigrant-native pay gap but access to complex, challenging and highly-rewarding positions, as well as individual effort exerted in solving job tasks also account for a large share of the immigrant-native pay disparity. If immigrants are not well assimilated into labour markets, their skills are underused, opportunities for the development of their human capital are restricted and consequently the immigrant-native wage gap remains.

The rest of the paper is organized as follows. The next section presents an overview of related literature followed by an explanation of the data and research methodology and discussions of the main empirical results. The final part presents conclusions and some policy implications.

2. THEORETICAL BACKGROUND

The issue of disadvantageous labour market outcomes for immigrants is extensively studied in the literature. Here we will focus on the studies most relevant for our analysis. The education-qualification mismatch and immigrant-native pay gap are the most comprehensively studied disadvantages faced by immigrants on the host labour market. The pioneer study by Chiswick (1978) showed that immigrants in the US earn significantly less that than native-born. Similarly, significant immigrant-native pay disproportionalities were documented in influential papers by Borjas (2000 and 1985). In the study of immigrants in Ireland, Barrett et al. (2006) documented a significant occupational gap between immigrants and natives, controlling for a range of background characteristics. Chiswick and Miller (2009) reported that foreign-born in the US are more prone to be overeducated, with the highest likelihood for newly-arrived immigrants. Dustmann et al. (2013) documented a similar pattern in the context of the UK, where immigrants tend to be employed in lower level jobs compared to natives with a comparable education level. Reitz et al. (2014) addresses the issue of immigrant “brain waste” as a result of immigrant skill underutilisation in Canada. Ultimately, limited occupational prospects and inability to fully realize their own competencies result in a wage penalty for immigrants.

These labour market disadvantages for immigrants have been attributed to various factors. Several studies stressed that the non-recognition of immigrants’ credentials and formal education accelerates labour market disparities (Green and Worswick 2012). Employers may simply treat degrees acquired in the host country and abroad differently. They may statistically discriminate against the foreign country qualification due to a lack of knowledge about the actual content and quality of the received education. This results in lower credibility of educational attainments for immigrants compared to natives. It is worth noting that some findings suggest that employment success among immigrants depends heavily on the field of their degree. Galarneau and Morissette (2004) found that Canadian immigrants with a degree in engineering, computer and health sciences benefit more relative to their peers with qualifications in other fields. Similarly, Lehmer and Ludsteck (2011) reported that the size of the wage penalty varies across wage distribution, with the largest penalty being in the lower quantiles.

However, labour market gaps may stem not from non-recognition solely; immigrant and native populations may differ in actual qualifications and competencies due to differences in the content and quality of educational programmes in the sending and receiving countries. Differences in educational standards, study curriculum and formal requirements yield objective disparities in the acquired competencies. Hence, the extent of human capital acquired while studying may differ drastically across natives with a host-country diploma and immigrants with formally similar foreign-acquired education. To address this issue, Chiswick (1978) developed the concept of skill transferability as a generalized approach to assessing the degree to which immigrants' skills can be successfully utilized in the host country. Immigrants' knowledge and skills may not be entirely equivalent to the host-country degree (Reitz et al. 2014, Sweetman 2004). Furthermore, the individual skill profile of immigrants may not entirely match the host-country needs (Bonikowska et al. 2008). All in all, this induces low transferability of immigrants' skills, and lowers employer trust in the true competence of foreign-born employees, potentially resulting in statistical discrimination towards immigrants.

Employment related disadvantages faced by immigrants on a host labour market may lead to two types of consequences for individual human capital. One strand of the literature suggests that due to reduced employment possibilities, immigrants tend to experience further skill downgrading (Akresh 2008), while Duleep (2007) argues that low-skill-transferability immigration is characterized by greater potential to invest in human capital to improve an immigrant's occupational outcomes. Therefore, immigrants with low-transferable skills and an initially high human capital gap relative to natives, are motivated to improve their individual human capital profile, and in so doing, catch up with the native-born over time. The argument by Duleep (2007) goes in line with a large body of empirical findings suggesting that immigrant wages tend to improve over the years since immigration. These studies commonly report that the immigrant-native pay gap tends to narrow the more time the immigrant spends in the receiving country (Sarvimäki 2011, Chiswick 1978). The observed positive dynamics may be a result of human capital investments, better acquaintance with the host labour market and, consequently, acquiring a position that better matches the immigrant's actual qualifications (Beyer 2016). Several studies have also underlined the role of state programmes in immigrant economic and social integration. Sarvimäki and Hämäläinen (2016) showed that the Active Labour Market Policy in Finland, aiming to design an individual training programme for unemployed immigrants, significantly increases complier earnings in subsequent years.

Host-country language proficiency, as an important factor of wage improvement and career development, is also widely discussed in the literature. In a recent study, Geurts and Lubbers (2017) documented that immigrants changing their intention to stay in the Netherlands from temporary to permanent have a larger increase in Dutch language proficiency. Earlier studies reported a positive association between host-county language command and employment outcomes (Van Tubergen and Kalmijn 2009). Chiswick and Repetto (2001) report higher wage returns for Israeli immigrants who became advanced in written Hebrew, relative to those reporting a language level sufficient for speaking and understanding. Beyer (2016) reports that good German writing skill reduces the pay gap between native and foreign-born in Germany by one third.

Therefore, we can summarize that earlier literature heavily discussed the difference in human capital attainments across immigrants and natives as one of the major drivers of the observed differential in earnings. However, the highlighted factors mostly left a substantial part of the immigrant-native pay gap unexplained (Beyer 2016, Dustmann 1993). We anticipate this to potentially arise from (i) the limited explanatory power of education and language skills, as they only partly reflect human capital; and (ii) ignoring the actual utilization of individual competencies at work as a possibility to generate positive wage returns on abilities. These arguments are extensively addressed in this paper.

3. DATA AND METHOD

3.1. Data and Sample

The empirical analysis relies on cross-sectional data from the Programme for the International Assessment of Adult Competencies (PIAAC) survey for 15 countries. The selection of countries is based on the availability of the data required for the analysis. We retained only countries that met two criteria: (1) the availability of the major variables used in the analysis – literacy and numeracy skill scores; (2) the share of immigrants in the total country sample was sufficiently large (more than 4%[5]). Hence, the final set of countries includes: Belgium, Czech Republic, Denmark, Estonia, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Slovenia, Spain and Sweden[6]. National samples are weighted to the population in a relevant year. The survey was conducted in two rounds. The first round was performed in 2011 and 2012 and included all the analysed countries except Greece and Slovenia. The latter countries were surveyed in 2014–2015. Along with a rich set of variables dealing with socio-demographic background, employment history and self-assessed employment characteristics, PIAAC provides test scores in three skill domains – literacy, numeracy and problem solving in a technology rich environment.

Following the definition used in the PIAAC dataset, literacy skill is defined as "understanding, evaluating, using, and engaging with written text to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (OECD 2013, p.3). Numeracy ability is viewed as "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (Ibid.). In this paper, the data on individual problem-solving skills are not used mainly because the problem-solving section was completed by respondents who have at least some computer experience and performed a computer-based test, while the other two test domains were conducted by all respondents (either on paper or online). Including the problem-solving domain would reduce our sample by approximately 30%. Furthermore, France, Italy and Spain did not disclose their problem-solving test scores in the publicly used data files. Hence, we focus on the dynamics and wage effects of literacy and numeracy skills, scaled from 0 to 500 points.[7]

The second factor of interest – intensity of skill uses at work – encounters three domains. The degree of skill utilization at work is derived as the frequency of skill use based on a set of background questions related to a certain skill domain. The PIAAC database provides skill use measures. However, to capture all available aspects of skill application, we create a skill use

[5] Threshold was chosen arbitrary, as there is a considerable variation of share of immigrants across countries and the lowest shares are under 4%.

[6] Swedish public use data file does not disclose earnings related variables. Hence, Sweden is excluded from pay gap analysis.

[7] For detailed technical description of PIAAC dataset see: OECD (2013). "Technical Report on the Survey of Adult Skills (PIAAC)", *OECD Publishing*. http://www.oecd.org/site/piaac/_Technical%20Report_17OCT13.pdf

scale following Allen et al. (2013). We define the use of literacy as an average of eight reading components and four writing components. The scale for numeracy use at work is approximated using six numeracy components. Each component refers to a self-reported frequency of conducting a certain activity, requiring reading, writing or numeracy ability and ranges from 1 (never) to 5 (every day)[8]. Frequency of skill use does not need to reflect employee productivity and does not tell us the actual efficiency of the skill use. Consequently, they solely reflect the complexity and skill-intensity of the respondents' jobs, as well as the degree of individual effort.

Similarly, we define an ICT skill use scale. Although we do not use the problem-solving skill in our human capital definition, we account for ICT use at work primarily because ICT use is defined more broadly than problem solving and strongly relates to literacy and numeracy skills. Furthermore, many jobs involve basic computer abilities or requires the use of the internet, especially among medium and high-level positions. Therefore, ICT skill use coupled with the intensity of literacy and numeracy application at work better reflects the complexity of the tasks workers are responsible for.

As a counterfactual to the use of skills at work, we similarly derive the measures of skill use in everyday life. We construct variables for literacy, numeracy and ICT skills use in everyday life relying on a set of background questions. The latter are identical to those asking about skill use at work, although they ask about activities beyond work. A full list of background questions used to construct the three domains of skill use at work and in everyday life is enclosed in Appendix A. Estimating literacy and numeracy skill use as a simple arithmetic average of respectively twelve and six components captures different variations of tasks requiring a certain skill. For the sake of comparability, we apply a skill use scale for respondents that have all skill components (twelve and six) available. A frequency of ICT use is estimated as an arithmetic average from eight components for respondents that have disclosed all ICT use at work components.

As we rely on quite broadly defined self-reported questions to derive skill use levels, we recognize several limitations. Firstly, respondents may misreport their true skill use. Since each question appeals to both the nature (complexity and skill-intensity) of the job and individual effort exerted at work, we can expect a response bias to go both ways. Generally, respondents should have a higher propensity to overstate their true effort at work, rather than understate it. However, certain groups of workers may tend to report lower skill use frequencies, especially if they are employing different types of skills simultaneously, and hence may put less emphasis on a certain domain. Furthermore, since background questions and ordinal answers are quite broad, respondents may reply with less precision, resulting in higher standard errors. Since both highlighted issues do not imply correlated deviations, they should not bias our estimates.

Appendix B presents summary statistics of the immigrant sample in a pooled PIAAC dataset of 15 countries. We acknowledge several limitations arising from using cross-sectional data for the analysis of human capital dynamics among immigrants, its utilization at work and the related wage effects. Firstly, the data may encounter a sizeable cohort effect (Borjas 1985 and 2015). Immigrants arriving now may be substantially different from earlier cohorts in a set of characteristics. In order to ensure that post-migration skills dynamics is not related to heterogeneous characteristics across cohorts, we check whether cohorts are balanced in terms

[8] All background questions used to derive skill use measures provide 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".

of a set of background traits. Therefore, the analysis of skills dynamics controls for a wide set of socio-demographic and employment characteristics in order to ensure that skill variation over years in a host country is not associated with cross-cohort differences in background characteristics.

3.2. Empirical Method

Our methodological approach includes several empirical tests, addressing the hypotheses posed in the paper. Since PIAAC data report cognitive skill scores in each domain as a set of ten plausible values, we rely on a full set of plausible values for both literacy and numeracy skills when referring to proficiency in our analysis. To account for sampling error and correctly estimate mean population values, we incorporate a final population weight. Skill measurement errors are ruled out using 80 replication weights under the Jackknife replication methodology. Hence, each regression output incorporating skill measures as ten plausible values is a result of 810 replications.

First, we empirically analyse immigrant cognitive skill dynamics over immigration tenure:

$$CS_i = \alpha + \gamma_1 I_i + \gamma_2(I_i * YSM_i) + \gamma_3(I_i * YSM_i^2) + \beta' X_i' + \varepsilon_i \, , \tag{1}$$

where dependent variable CS_i corresponds to either the literacy or numeracy test score; dummy variable I_i takes value 1 if the respondent is foreign-born; variable YSM_i corresponds to the number of years the immigrant has spent in the host country; and ε_i represents an error term. Since the estimation is performed on a pooled cross-country sample, we additionally control for a set of country dummies. The main effects of interest are captured by coefficient γ_1, standing for immigrant skill disadvantage immediately after arrival, and γ_2, as it reflects the average increase in skill level associated with each additional year of the host-country stay. To attribute the time effect to immigrants catching up, we need to compare immigrants with host-country stays of different durations to natives with similar backgrounds and observable characteristics. Therefore, we increase a set of additional controls, denoted by vector X_i', from demographic and educational characteristics solely in the basic model, to a complete specification with language used at home, occupation, industry and job training. As a robustness check, we extend model (1) by adding skill use at work and in everyday life variables. This accounts for potential correlation between years since migration and extent of skill use, thereby allowing us to reduce the omitted variable bias.

Next, we introduce a measure for skill use intensity at work and then analyse whether it contributes to explaining the immigrant-native pay gap. However, before we introduce skill use at work into the wage regression, we verify that it indeed associates with the wage differently than only through the skill-accumulating mechanism. Otherwise, it would not have any value added for wage analysis once cognitive skills are controlled for. Our fundamental assumptions here are that skill use at work associates with wage level not only indirectly (through skill accumulation), but also directly in the sense that, (i) frequency of skill use largely reflects complexity, challenge and reward level associated with job; and (ii) it also approximates individual effort exerted by the respondent in dealing with job tasks.

The challenging task here is to verify that skill use at work is associated with wages through both direct and indirect channels, as they are observationally equivalent in the usual regression model. Hence, we introduce a counterfactual variable of skill use in everyday life, estimated in the same way as the skill use at work factors, but targeting non-work-related activities (home, leisure time activities, etc.). The rationale for this is straightforward. Naturally, the utilization of a certain skill by performing particular actions either at work, or in everyday life develops the skill itself. For instance, writing reports by definition positively reflects literacy skills, regardless of whether it was written in a work or non-work context. However, only when written at work the report can in some way relate to wage outcomes. Following this simple logic, we argue that the use of skills in everyday life can affect the wage rate only through indirect channels, as it facilitates skills improvement, which in turn positively affects earnings. At the same time, skill use at work may enforce the wage rate variation through both indirect and direct channels by approximating the nature of the job and the individual effort exerted.

Consequently, based on the estimated effect of skill use at work and in everyday life on skill level and wage rate, we conclude whether skill use at work is indeed a valid proxy for job complexity (job assess, career progression) and individual effort (motivational component) as factors behind the immigrant-native pay gap. Specifically, we start with descriptive evidence on (a) skill use frequency across different occupation groups, to illustrate that indeed higher-level jobs imply higher frequency of skill use, and (b) average wage rate across skill use frequencies, to verify that a more intensive application of skills is associated with higher earnings. The results will give crude evidence of whether skill use intensity reflects relative complexity and reward level of the job.

We proceed by assessing the association between skill use at work, skill use in everyday life and skill level. A complete specification is modelled in the following way:

$$CS_i = \eta + \gamma I_i + \rho' SUW' + \delta' SUEL' + \theta'(SUW' \cdot I_i) + \mu'(SUEL' \cdot I_i) + \vartheta' X_i' + \varepsilon_i, \quad (2)$$

where SUW' and $SUEL'$ are the vectors of measures of skill use at work and in everyday life respectively. Therefore, a vector of coefficient ρ' captures an association between skill use at work and cognitive skill level, while δ' stands for skill use in everyday life effects on cognitive skills . These are the estimates of major interest, as they show whether both skill use at home and in everyday life yield positive association with skill level. Vectors θ' and μ'convey interesting evidence, as they measure if immigrants benefit more in terms of skill accumulation from skill use at work and in everyday life, relative to natives. Given the observational nature of the PIAAC data, we cannot evaluate the direction of causality. However, for our analysis the significance of association is of prime interest.

The final part of our analysis will tackle the immigrant-native wage gap. We will model individual hourly wage, controlling for literacy or numeracy skill, literacy, numeracy and ICT skill use at work and in everyday life, as well as a broad set of background and employment controls to ensure maximal comparability of immigrants and natives in terms of observable traits. We model the problem in the following way[9,10]:

$$W_i = \zeta + \lambda I_i + \tau CS_i + \nu' SUW' + \varphi' SUEL' + \omega' X_i' + \varepsilon_i, \quad (3)$$

where W_i stands for individual hourly wage. The vectors of the coefficients of skill use at work (SUW') and in everyday life ($SUEL'$) capture the wage effects of skill application in a certain

[9] We acknowledge potential multicollinearity issue, as cognitive skills, their use at work and/or in everyday life may correlate. However, empirical estimations of model (3) performed later in the paper will verify that multicollinearity concern is of minor importance.

[10] We performed additional estimations of model (3), extended by a set of interaction terms between immigrant and cognitive skill levels, immigrant and skill use at work, immigrant and skill use in everyday life. The estimates revealed that immigrants do not earn additional wage premium to their cognitive skills or their use at work and everyday life, compared to natives. Results are available upon request.

domain. Following our rationale, we can conclude that the utilization of skills at work is associated with the wage rate directly through the complexity of tasks and the effort exerted only if we find a positive and significant association between intensity of skill use at work and wages, and no significant association between skill use in everyday life and wages. Coefficient λ stands for a residual immigrant-native pay gap and is an estimate of major interest. Variation of coefficient λ across model specifications with only background controls, and with skill level and skill use measures included step-by-step, will indicate a relative importance of the aforementioned controls in explaining the immigrant-native pay gap.

The application of the Jackknife replication methodology to correctly estimate standard errors with 80 replication eights, does not allow us to simultaneously cluster standard errors. Although, as we use a pooled sample for the main analysis, clustering standard errors at the country level would be a natural choice, as it accounts for the interdependencies of observations within the country sample. To additionally verify the stability of our conclusions based on the models with non-clustered standard errors, we replicate the same analysis for each country separately. Therefore, we test whether the same pattern observed in the pooled sample holds when we disaggregate the dataset into fifteen country sub-samples.

4. EMPIRICAL RESULTS

In this section, we present the empirical results on immigrant skill dynamics and a role of skill level and intensity of skill use in explaining the immigrant-native wage gap. We start by analysing immigrant cognitive skill dynamics. Table 1 presents estimations of the average increase in literacy (panel a) and numeracy (panel b) skills over time since immigration. In our specification, the coefficient of *Immigrant* corresponds to the skill gap between newly-arrived immigrants (0 years in a host country) and natives. An increase in skill level associated with every additional year of immigration is captured by the regression coefficient of interaction term *Immigrant # Years since migration.* In a baseline model (M1), only controlling for a set of demographic variables (gender, age, marital status) and education, the initial skill gaps are 76.61 points in literacy and a striking 99.76 points in numeracy. One additional year in the host country under specification M1 is associated with a 1.45-point increase in the literacy score and 1.29 increase in the numeracy score, both significant with $p < 0.01$.

We further extend a list of controls in M2, by adding a language control. This variable, to a large extent, first reflects immigrant language competence and assimilation into the language environment of the host country, and second, captures how easy it was for the respondent to understand texts provided as a part of literacy and numeracy tasks. As expected, controlling for the language variable drastically reduces the effect of immigration tenure on both literacy and numeracy scores (to 0.87 points and 0.77 points respectively). The estimated skill gap for newly-arrived immigrants also declines to 61.94 and 87.17 points respectively. This result supports earlier evidence on the importance of host-country language proficiency for immigrant human capital. Host-country language command captures a significant share of the initial gap in literacy and numeracy skills.

The further stepwise inclusion of controls does not change the immigration tenure effect drastically. As expected, adding occupational dummies (M3) dramatically decreases the initial skill gap estimate (to 50.91 points for literacy and 72.58 points for numeracy). Although, when controlling for a full set of demographic and employment characteristics (M5), newly-arrived immigrants are found to have a literacy score 62.72 points lower and numeracy score 84.03 points lower relative to stayers with the same set of background traits. Importantly, an additional year in the host country is still associated with a statistically significant increase in both literacy and numeracy scores. Therefore, extending a list of controls reduces the estimated effect of immigration tenure on skill test results; however, the coefficients remain statistically significant with $p < 0.05$. It is worth noting that we observe a small decline in magnitude and statistical significance of years since migration after adding the *Job training* variable in M5, relative to M4. This primarily reflects the importance of training and educational programmes provided by employers on immigrant literacy and numeracy skill development.

In addition to the main estimations, Appendix C presents robustness check results. We extend a full specification (M5) using a set of skill use at work and in everyday life variables. A potential estimation problem addressed by the robustness check is the correlation between duration of host-country stay and skill use at work (in everyday life). Immigrants may improve their skill application over the time spent in a host country, having a beneficial effect on their skill level. In order to verify that cognitive skills dynamics are not affected by such a correlation, we estimate additional models for literacy and numeracy skills. The results revealed that even when controlling for skill use, the immigrant catch-up process remains positive and statistically significant.

Generally, our results, based on a pooled sample, support part (i) of the first hypothesis, as we found that immigrant cognitive skills in literacy and numeracy indeed tend to improve over time spent in the host country. A complete model (M5) from Table 1 demonstrates the important role of on-job training for immigrant skill progression. This result appears as quite intuitive. Training and educational programmes facilitated by employers are indeed powerful tools for helping acquiring new skills valued by the employer and in demand on the host-country labour market.

Table 1. Cognitive skills dynamics over immigration tenure – pooled sample

	M1 *β/se*	**M2** *β/se*	**M3** *β/se*	**M4** *β/se*	**M5** *β/se*
Panel (a): dependent variable ***– Literacy score (0-500 points)***					
Immigrant	-75.62	-61.94	-50.91	-61.64	-62.72
	19.21***	19.02***	19.13***	20.62***	20.72***
Immigrant # Years since migration	1.45	0.88	0.74	0.87	0.76
	0.23***	0.23***	0.25***	0.31***	0.31**
Immigrant # Years since migration^2	-0.01	0	0	-0.01	0
	0	0	0	0.01	0.01
Demographic characteristics and education	Yes	Yes	Yes	Yes	Yes
Language used at home		Yes	Yes	Yes	Yes
Occupation			Yes	Yes	Yes
Industry				Yes	Yes
Job training					Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	273.11	252.10	238.14	324.43	262.67
	26.22***	210.71	300.77	509.1	262.98
N	12309	12161	9971	7510	7428
R^2	0.266	0.3	0.321	0.343	0.345
Panel (b): dependent variable ***– Numeracy score (0-500 points)***					

	M1 *β/se*	M2 *β/se*	M3 *β/se*	M4 *β/se*	M5 *β/se*
Immigrant	-99.76	-87.17	-72.58	-82.43	-84.03
	23.90***	23.87***	24.15***	24.23***	24.33***
Immigrant # Years since migration	1.29	0.77	0.60	0.76	0.64
	0.25***	0.23***	0.25**	0.32**	0.32**
Immigrant # Years since migration^2	0	0	0	0	0
	0	0	0	0.01	0.01
Demographic characteristics and education	Yes	Yes	Yes	Yes	Yes
Language used at home		Yes	Yes	Yes	Yes
Occupation			Yes	Yes	Yes
Industry				Yes	Yes
Job training					Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	280.7	261.7	242.7	315.3	257.7
	45.99***	178.27	313.09	438.46	246.86
N	12309	12161	9971	7510	7428
R^2	0.278	0.303	0.324	0.348	0.35

Note: Estimates based on a pooled sample of PIAAC public use data files for 15 countries. Measures of literacy and numeracy skills are estimated using 10 plausible values for each skill domain. Sample is weighted using final population weight. Standard errors estimated using 80 replication weights and applying the Jackknife replication methodology.
***, **, * Indicate parameters significant at 1%, 5% and 10% levels respectively.

Next, we focus on the second major aspect of our research: skill use at work. We refer to skill use at work as a factor that correlated with labour market returns independently from skill level. Hence, the following analysis will test part (ii) of the first hypothesis and the second hypothesis, referring to the role of skill level and skill utilization at work in explaining the immigrant-native pay gap. Including intensity of skill use at work in the wage gap analysis requires several assumptions. Most importantly, we need to prove that skill use at work independently affects the wage rate, but not via the skill accumulation associated with frequency of skill application. To that end, we introduce skill use in everyday life, which is expected to have a similar effect on skill accumulation as work-related skill use (indirect channel), however, is not directly associated with wage.

We start by testing the indirect channel by analysing the association between the test scores for cognitive skills and the intensity of skill use at work and in the non-work context. Table 2 reports the regression results following this specification (2). Since the observational nature of our data does not allow us to identify the direction of causality between skill use and skill level, we carefully interpret point estimates as associations between skill use intensity and level of skill.

Table 2. Association between skill level and intensity of skill use at work – pooled sample

	M1 *β/se*	M2 *β/se*	M3 *β/se*	M4 *β/se*	M5 *β/se*	M6 *β/se*	M7 *β/se*
Panel (a): dependent variable – ***Literacy score (0-500 points)***							
Immigrant	-17.61	-12.20	-22.37	-16.64	-22.25	-13.08	-20.22
	1.28***	1.49***	5.38***	1.29***	5.48***	1.49***	7.71***

	M1 β/se	M2 β/se	M3 β/se	M4 β/se	M5 β/se	M6 β/se	M7 β/se
Literacy *use at work*		-0.36	-0.68			-2.10	-2.43
		0.55	0.55			0.58***	0.57***
ICT *use at work*		5.612	5.606			4.224	4.24
		0.55***	0.56***			0.57***	0.57***
Literacy *use non-work*				6.59	6.50	5.62	5.68
				0.63***	0.63***	0.74***	0.71***
ICT *use non-work*				5.85	5.65	4.14	4.18
				0.66***	0.60***	0.68***	0.67***
Immigrant # Literacy *use at work*			3.52				3.53
			2.00*				2.24
Immigrant # ICT *use at work*			-0.137				-0.335
			1.77				1.8
Immigrant # Literacy *use non-work*					0.62		-0.55
					2.23		2.55
Immigrant # ICT *use non-work*					1.53		-0.38
					1.86		2.58
Constant	202.47	201.58	202.70	174.33	175.01	194.04	194.80
	107.06*	129.59	131.11	97.68*	97.53*	91.52**	92.18**
N	67439	50067	50067	58788	58788	47315	47315
R^2	0.333	0.252	0.252	0.314	0.314	0.254	0.255
Panel (b): dependent variable – ***Numeracy score (0–500 points)***							
Immigrant	-19.52	-13.52	-21.17	-18.49	-17.80	-14.13	-11.35
	1.48***	1.57***	5.22***	1.46***	5.51***	1.61***	8.09
Numeracy *use at work*		5.49	5.29			1.86	1.79
		0.40***	0.41***			0.55***	0.57***
ICT *use at work*		3.36	3.30			3.23	3.50
		0.54***	0.55***			0.68***	0.66***
Numeracy *use non-work*				7.64	7.74	3.87	3.66
				0.43***	0.43***	0.42***	0.45***
ICT *use non-work*				5.93	5.88	5.78	5.98
				0.61***	0.57***	0.47***	0.51***
Immigrant # Numeracy *use at work*			2.34				2.32
			1.49				1.52
Immigrant # ICT *use at work*			0.63				1.01
			1.8				1.84
Immigrant # Numeracy *use non-work*					-0.97		-1.88
					1.8		1.79
Immigrant # ICT *use non-work*					0.51		-2.75
					2.35		3.11
Constant	170.36	197.00	198.31	163.62	163.51	178.06	178.46
	120.66	134.44	132.60	85.79*	86.46*	92.00*	92.77*
N	67439	50092	50092	58795	58795	47337	47337

	M1	M2	M3	M4	M5	M6	M7
	β/se	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*	*β/se*
R^2	0.34	0.266	0.267	0.311	0.311	0.263	0.263

Note: All models additionally control for gender, age, age squared, education level, language used at home, occupation, industry, job training and country of residence. Standard errors are reported in parentheses. Estimates based on a pooled sample of PIAAC public use data files for 15 countries. Measures of literacy and numeracy skills are estimated using 10 plausible values for each skill domain. Sample is weighted using final population weight. Standard errors estimated using 80 replication weights and applying Jackknife replication methodology.
***, **, * Indicate parameters significant at 1%, 5% and 10% levels respectively.

Panel (a) presents the regression of the literacy score over a set of background controls, different combinations skill use variables and the interaction between skill use variables and the immigrant dummy. Panel (b) reports the identical regression but using the numeracy score as the dependent variable. Given the broad definition of ICT skill use, we expect it to relate to both literacy and numeracy abilities, while literacy and numeracy use are defined in a rather narrow manner, allowing us to assume an association only with literacy and numeracy competencies respectively. A background model (M0), controlling for a rich set of demographic and employment variables but not skill use, reports 17.61 and 19.52 points for the average immigrant skill gap in literacy and numeracy respectively.

Adding use of skill controls (M2) substantially decreases the gap in both literacy (by 5.4 points) and numeracy (by 6 points). Furthermore, point estimates for literacy and ICT use at work suggest that the literacy score is positively associated with more intense use of computers and the internet (5.6 point increase in literacy with 1-step increase in frequency of ICT use), but not with literacy use as defined in PIAAC data. Notably, the individual numeracy score positively correlates with both numeracy use at work (5.49 points) and ICT skill use (3.36 points). Skill use in everyday life yields a stronger degree of association with abilities than use of skills at work (M4). The more intensive use of literacy and ICT competencies in the non-work context implies a 6.59 point and 5.85 point increase in literacy ability, whereas numeracy and ICT use in everyday life a 7.64 and 5.93 point increase in the numeracy score respectively. When we control for work and non-work skill use simultaneously (M7), the effects remain robust.

We additionally explore whether immigrants tend to obtain extra benefits from using skills at work and in everyday life, relative to natives. These extra returns to skills are captured by the interaction terms between the immigrant dummy and degree of skill use. We find only a weak positive surplus effect of literacy use at work on literacy skill among immigrants (3.52 points, $p \leq 0.1$). In terms of other skill use dimensions, we do not find that immigrants benefit from intensive skill utilization relatively more than natives. Nevertheless, the estimation results support our expectation that the application of skills both at work and in everyday positively reflect on literacy and numeracy scores. Since we do not recognize a true causal relationship, we argue that skill use at work can potentially affect earnings through indirect channels, as it facilitates skill improvement.[11]

Before we analyse how skill use at work, and counterfactually in everyday life, is associated with wage levels, we provide descriptive evidence to verify that skill use at work indeed to some extent reflects complexity of the job and the reward level associated with the position. Table 3A reports an association between skill use intensity and complexity of job. The latter is

[11] The alternative causal link would be from skill level to skill use. Namely, higher skill level motivates individuals to apply their skill more often at work, and this is positively reflected in the wage rate. However, we find it reasonable to assume that the higher intensity of skill use to some extent affects the skill itself through repeated practice of a certain activity.

represented by occupation category according to ISCO classification (4 category-based skill requirements). We find that skill use at work is the highest among skilled employees, while there is no clear pattern of association between skill use at home and occupation for natives or for immigrants. This result goes in line with our assumption that skill use at work reflects complexity of work, while skill use at home is unrelated to occupation.

Table 3A. Average intensity of skill use across occupation categories – pooled sample

	Immigrants			**Natives**		
Occupations	**Literacy**	**Numeracy**	**ICT**	**Literacy**	**Numeracy**	**ICT**
Panel (a): skill use at work (scaled from 1 to 5)						
Skilled	3.1	2.7	3.0	3.1	2.8	2.9
Semi-skilled white-collar	2.2	2.0	2.4	2.4	2.2	2.4
Semi-skilled blue-collar	1.8	1.7	1.9	2.1	1.9	2.1
Elementary	1.4	1.3	1.6	1.6	1.4	1.8
Panel (b): skill use in everyday life (scaled from 1 to 5)						
Skilled	2.9	2.2	2.8	2.8	2.1	2.7
Semi-skilled white-collar	2.6	2.0	2.6	2.6	2.0	2.5
Semi-skilled blue-collar	2.1	1.8	2.3	2.3	1.9	2.3
Elementary	2.2	1.9	2.4	2.3	1.9	2.4

Table 3B. Average hourly earnings (PPP-adjusted) across skill use groups – pooled sample

	Immigrants			**Natives**		
Skill use frequency	**Literacy**	**Numeracy**	**ICT**	**Literacy**	**Numeracy**	**ICT**
Panel (a): wage over skill use at work groups						
Never	16.6	16.5	13.3	12.2	14.5	13.3
Less than once a month	12.7	14.8	15.2	13.9	17.2	16.3
Less than once a week but at least once a month	18.4	16.5	20.7	19.5	18.5	21.3
At least once a week but not every day	22.1	21.3	23.0	21.6	20.4	22.7
Every day	31.9	31.7	22.4	27.0	22.7	22.0
Panel (b): wage over skill use in everyday life groups						
Never	28.0	19.5	12.7	12.7	15.6	14.9
Less than once a month	12.3	15.0	14.0	15.4	17.7	17.5
Less than once a week but at least once a month	17.3	16.7	17.4	18.4	18.3	18.6
At least once a week but not every day	19.1	18.0	17.5	21.6	18.5	18.9
Every day	17.8	34.2[A]	16.9	19.6	14.5	17.5

[A] High average wage in this group of respondents is generated by several outliers (median earnings are 13.5 $US, wages in 90th and 99th quantiles are respectively 32.2 $US and 83.1 $US).
Note: Estimates based on a pooled sample of PIAAC public use data files for 15 countries. All estimates are adjusted for population weight.

Lastly, we explore the variation of average hourly earnings across skill use groups. Here we verify that indeed skill use frequency reflects reward level associated with the job. Table 3B reports average hourly earnings across various frequencies of literacy, numeracy and ICT skill use at work for immigrants and natives. As expected, we find clearly increasing wage levels with an increase in intensity of skill use for both natives and foreign-born. However, we cannot conclude the same with respect to skill use in everyday life, as we observe the variation of average earnings across different frequencies of skill application in non-work activities. Coupled, these two findings support our assumptions on skill use at work as a valid proxy for complexity of tasks, challenge and reward associated with employment.

Finally, we empirically test how skill level and skill use at work and in everyday life affects the immigrant-native pay gap. Our rationale here is that increasing a stock of skills is not sufficient to explain the immigrant-native pay disparity (part (ii) of the first hypothesis). Skills yield positive wage returns only when utilized at work, meaning that the respondent accessed a sufficiently complex and rewarding job, as well as that he or she invests a decent effort into his or her work. Both are to a large extent captured by a frequency of skill use at work in our model and may differ across immigrant and natives, translating into their wage disparity (second hypothesis).

Table 4 discloses estimates of wage regression for specification (3). We separately estimated models with literacy and numeracy skill controls due to their high correlation and the technical features of the estimation process.[12] Panel (a) reports four different specifications of wage regression with literacy score controlled for, while panel (b) presents identical models, although with numeracy ability included. The point estimate of the immigrant dummy in M0 stands for a raw pay gap, when neither skill itself, nor use of skill is accounted for. The estimated immigrant pay disadvantage in a pooled cross-country sample is 5.7% ($p \leq 0.01$), if immigrants and natives have comparable socio-demographic, educational and employment characteristics. Including literacy score (M1) and numeracy score (M5) declines pay disparity to 3.8% and 3.4% ($p \leq 0.01$) respectively, compared to model M0. This result suggests that cognitive skills in literacy and numeracy account for approximately 30% of the pay disadvantage faced by immigrants, compared to natives with similar demographic, educational and employment profiles. However, accounting for immigrant-native cognitive skill disparity does not fully explain the pay gap for immigrants, as predicted by hypothesis 1.

The most important findings are reported in models M2 and M6, which along with literacy scores incorporate literacy, numeracy and ICT skill use at work. When controlling for those, the wage gap between immigrants and natives becomes statistically non-significant and its economic significance declines (2.1% in M2 and 1.8% in M6). This finding supports our second hypothesis and shows that indeed immigrant-native pay disparity originates from differences in the application of skills at work across immigrants and natives. This difference eventually reflects in the earnings profile, since intensity of skill use captures two aspects: (i) nature of performed job; (ii) individual effort invested in work. Both components may drastically differ between immigrant and native population. Firstly, immigrants may have more restricted access to positions with skill-requiring tasks, which is more likely to generate higher wage returns than jobs with low skill involvement. Secondly, immigrants may more often face difficulties when opting for career progression, compared to otherwise similar natives. Thirdly, immigrants may simply have lower motivation to put effort into a job, either due to realized labour market difficulties and low expectancy of further career development, or due to low social and cultural assimilation, feelings of isolation in society and other psychological factors.

[12] Simultaneous including literacy and numeracy scores results in 20 possible combinations of plausible values (10 for literacy and 10 for numeracy), which, given the population and replication weights, yields 810^2 replications required to correctly calculate point estimates and standard errors. However, we conducted a number of robustness checks for literacy and numeracy simultaneously in several specifications. The results are comparable to models that control only for literacy, or only numeracy.

Table 4. Skill level, skills use and wage – pooled sample

Control variables	M0 *β/se*	M1 *β/se*	M2 *β/se*	M3 *β/se*	M4 *β/se*	M5 *β/se*	M6 *β/se*	M7 *β/se*	M8 *β/se*
		Panel (a): models controlling for literacy skill				*Panel (b): models controlling for numeracy skill*			
Immigrant	-0.057	-0.038	-0.021	-0.036	-0.016	-0.034	-0.018	-0.033	-0.013
	0.01***	0.01***	0.01	0.01**	0.02	0.01***	0.01	0.01**	0.02
Skill score (0-500)		0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Literacy use work			0.042		0.043		0.042		0.043
			0.01***		0.01***		0.01***		0.01***
Numeracy use work			0.002		0.005		-0.001		0.003
			0		0		0		0
ICT skills use work			0.038		0.033		0.039		0.034
			0.01***		0.01***		0.01***		0.01***
Literacy use non-work				0.016	-0.009			0.017	-0.007
				0.01**	0.01			0.01**	0.01
Numeracy use non-work				-0.001	-0.008			-0.004	-0.011
				0	0.01			0	0.01
ICT skills use non-work				0.012	0.004			0.012	0.004
				0.01*	0.01			0.01*	0.01
Constant	0.814	0.601	0.569	0.435	0.666	0.608	0.601	0.441	0.688
	0.02***	1.2	1.68	2.12	2.11	1.32	1.81	2.21	2.18
N	51480	51480	38082	45307	36121	51480	38082	45307	36121
R^2	0.421	0.425	0.413	0.418	0.41	0.427	0.414	0.419	0.412

Note: Dependent variable is log of individual hourly wage. All models additionally control for gender, age, age squared, education level, language used at home, occupation, industry, job training and country of residence. Estimates based on a pooled sample of PIAAC public use data files for 14 countries. Measures of literacy and numeracy skills are estimated using 10 plausible values for each skill domain. Sample is weighted using final population weight. Standard errors estimated using 80 replication weights and applying Jackknife replication methodology. ***, **, * Indicate parameters significant at 1%, 5% and 10% levels respectively

As a placebo test, we estimated same models as M2 and M6, but with skill use in everyday life domains (M3 and M7). As expected, skill use in non-work-related activities yield economically and statistically much lower wage returns compared to utilization of skills at work. Notably, the immigrant-native pay gap, when controlling for non-work skill use, remains statistically significant and of the same magnitude as without any skill use measures. Furthermore, when we simultaneously include skill use at work and skill use in everyday life measures (M4, M8), positive wage returns to literacy and ICT skill application at work remains significant, while point estimates for skill use in everyday life variables further decline and become statistically insignificant[13]. This result clearly supports our assumption that skill use at work acts as an important driver of immigrant-native pay disparity, as it directly associates with wage level through the nature of the job and the effort exerted at work. In turn, skill use in everyday life positively associates with skill level, but not with wage rate, and therefore has no power to reflect on immigrant-native pay gap.

To further support the robustness of our conclusions, we present the effects of immigration tenure on skill level within-country (see Appendix D) and replicate M0, M1, M2, M5 and M6 on country-specific samples. Estimates of immigrant-native pay gap under several specifications across the analysed countries are enclosed in Appendix E. The same pattern as in the pooled sample was detected in Belgium, Czech Republic, Denmark, Finland, Italy, Norway and Spain. While in the PIAAC samples for France, Great Britain, Greece (notable positive pay gap) and the Netherlands, the statistically significant pay disparity disappears once skill itself is controlled for.

[13] This result covers the issue of the multicollinearity of skill use at work and in everyday life. The stability of the skill use at work coefficients proves that the regression results enclosed in Table 4 are not affected by multicollinearity.

5. Conclusions

This paper contributes to analysis of the immigrant-native wage gap and factors behind it. Earlier literature discusses the differences in human capital attainments across immigrants and natives as a major driver of the observed differential in earnings. However, previous studies mainly relied on formal education or, at best, host-country language proficiency as measures of individual human capital. In our paper, we develop this argument further and incorporate cognitive skills in literacy and numeracy domains to approximate individual human capital profiles. Furthermore, we argue that several labour market disadvantages may persist despite the true skills and abilities of immigrants. Difficulties of labour market entry and access to complex, challenging and rewarding positions result in occupation-qualification mismatch and slower career progression compared to natives. This will lead to a persistent wage penalty, which may to a large extent offset positive wage returns to improvement in human capital. This issue constitutes a focal point of our research.

The paper suggests and empirically tests two hypotheses. Firstly, we ask whether immigrants tend to increase their human capital over time spent in a host country, and if this investment is enough to explain pay disparity relative to natives. We specifically focus on cognitive components of human capital, namely literacy and numeracy abilities, as measured by PIAAC data. We find that, on average, immigrants have higher test scores the longer they spend in a host country. As we control for a comprehensive set of background and employment characteristics when measuring skill convergence, we admit that the observed dynamics suggest a gradual catch-up for immigrants and a narrowing of the immigrant-native skill gap over time. The rate of catching up in literacy is marginally larger that in numeracy.

A further analysis of the immigrant-native pay gap revealed that even when literacy or numeracy cognitive skills are controlled for, the wage penalty remains. This evidence reaffirms that even with similar skill levels along with a comparable demographic, educational and employment profile, immigrants tend to earn less than natives. This surprising result holds both in the pooled cross-country sample and in country-specific sub-samples, suggesting that human capital improvements alone are indeed not sufficient to fully explain the immigrant pay disadvantage.

This provides the motivation for the second part of our analysis, focused on the extent to which immigrants utilize their skills at work. Our rationale is that frequency of literacy, numeracy and ICT skill use at work reflects complexity and challenge of position, which is positively associated with reward level. Since we rely on broad occupation categories, controlling for skill use at work allows us to identify whether immigrants access jobs as complex and wages at similar levels as natives. However, frequency of skill use at work also reflects the degree of effort exerted at work. Our data does not allow us to disentangle these two effects from the observed intensity of skill use. However, descriptive evidence suggests that the skill use variable indeed largely reflects the complexity of jobs (more intensive skill use in higher occupational categories) and reward levels associated with jobs (average earnings increase with an increase in skill use at work).

Once we account for literacy, numeracy and ICT skill use at work in our wage regression, along with actual skill level, no statistically significant gap in earnings across immigrants and natives remains. These findings prove that, despite similar cognitive skill levels and background traits, immigrants and natives may apply their skills at work to different extents, yielding a difference in their wage returns. It seems reasonable to assume that the labour market rewards skills when they are actively used at the workplace. The extent of skill utilization depends on the objective nature of the job (complexity and skill intensity) and subjective factors (personal motivation effort). We argue that both job nature and effort components may systematically differ across immigrants and natives, resulting in a wage loss for immigrants.

Our findings, on the one hand, reaffirm that immigrants are prone to develop and improve their skill profile over time in the host country. This finding goes in line with earlier studies suggesting increased human capital investment, mostly through acquiring skills demanded and highly valued on the host country's labour market, as well as an improvement in their command of the host-country language. Consequently, immigrants tend to gradually catch up with natives and rule out the wage disadvantage associated with their relatively weaker human capital profile. But, on the other hand, we documented that immigrants, even when attaining skills comparable to natives, less frequently use them at work. Acknowledging this difference in wage analysis makes the immigrant-native pay gap statistically insignificant, and therefore suggests that the disparity in skill use at work plays an important role in explaining the immigrant-native pay disparity. That also indicates that immigrants are not sufficiently well assimilated in the European labour markets. Possible difficulties in labour market entry and in obtaining complex and challenging positions to a large extent explains the poor assimilation of immigrants. The implementation and development of policy measures should consider that human capital improvements alone are not sufficient to ensure immigrant labour integration if several labour market disadvantages persist. These may deter efficient skill use and development at the workplace among immigrants. Further policy measures should profoundly consider these indications, taking into account that the role of immigrants and their labour supply is increasing remarkably in European societies.

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Appendix A

Components (PIAAC background questions) used to construct literacy, numeracy, ICT use at work variables

	Literacy use	Numeracy use	ICT skills use
At work	A. Reading components: reading (1) directions or instructions; (2) letters, memos or mails; (3) newspapers or magazines; (4) professional journals or publications; (5) books; (6) manuals or reference materials; (7) financial statements; (8) diagrams, maps or schemes. B. Writing components: writing (1) letters, memos or mails; (2) articles; (3) reports; (4) filling in forms.	Tasks demanding numeracy skill include: (1) calculating costs or budgets; (2) using or calculating fractions or percentages; (3) using a calculator; (4) preparing charts, graphs or tables; (5) using simple algebra or formulas; (6) using advanced maths or statistics	Computer-based or internet related tasks include: (1) experience with computers at work; (2) using the internet for mail; (3) using the internet for work-related information; (4) using the internet to conduct transactions; (5) using computers for spreadsheets; (6) using computers for Word; (7) using computers for programming language; (8) using computers for real-time discussions.
In everyday life	Components identical to literacy use at work, but related to non-work activities.	Components identical to numeracy use at work, but related to non-work activities.	Computer-based or internet related tasks include: (1) experience with computers in everyday life; remaining 7 components are identical to ICT use at work, but related to non-work activities.

Appendix B

Descriptive profile – pooled sample of immigrants

	Natives	Immigrants						
		All	Duration of host-country stay, years					
			0-5	5-10	11-15	16-20	21-25	25+
Panel (a): socio-demographic characteristics								
Male, %	50.0	48.2	44.1	45.9	51.7	47.7	52.8	49.8
Age	41 (0.029)	39 (0.202)	31.6	34.8	36.1	38.1	42.3	49.9
Native speaker, %	97.4	29.2	18.7	21.2	27.1	22.0	30.9	46.1
Cohabiting, %	68.7	71.9	62.5	71.9	67.4	65.9	72.8	83.2
Education, %								
Basic	29.3	69.3	60.2	70.0	73.6	73.2	67.1	72.0
Medium	43.7	8.7	8.2	10.3	6.4	8.7	9.5	8.9
Higher	27.0	22.0	31.6	19.7	20.0	18.1	23.4	19.1
Panel (b): employment characteristics								
Employed, %	64.4	62.3	58.2	64.1	60.1	60.8	66.9	64.2
Occupation, %								
Skilled occupations	37.7	27.2	26.2	19.1	22.9	24.1	30.3	37.0
Semi-skilled white-collar occupations	30.1	30.3	32.7	31.1	27.6	33.3	30.5	28.5
Semi-skilled blue-collar occupations	22.0	23.2	19.4	24.3	26.2	26.1	25.1	21.6
Elementary occupations	10.2	19.3	21.7	25.6	23.4	16.5	14.1	12.8
Training at work, %	26.4	19.5	18.5	20.2	16.5	19.6	23.0	20.0
Use of skills at work (0-5 points)								
Literacy	2.6	2.2	2.1	2.0	2.1	2.2	2.5	2.5
Numeracy	2.3	2.0	1.9	1.8	1.9	1.9	2.1	2.2
ICT skill	2.6	2.6	2.7	2.5	2.6	2.6	2.6	2.6

Appendix B (continued)

	Natives	Immigrants						
		All	Duration of host-country stay, years					
			0-5	5-10	11-15	16-20	21-25	25+
Use of skills in everyday life (0-5 points)								
Literacy	2.6	2.5	2.7	2.5	2.4	2.4	2.4	2.5
Numeracy	2.0	2.0	2.2	2.0	2.1	2.0	2.0	1.9
ICT skill	2.6	2.6	2.7	2.5	2.5	2.6	2.5	2.4
Average hourly wage, $US PPP adjusted*	17.21 (0.327)	14.92 (0.239)	13.66 (0.644)	13.50 (0.401)	14.35 (0.578)	16.07 (1.183)	15.85 (0.813)	16.89 (0.418)
Panel (c): cognitive skills								
Literacy	267.12 (0.304)	239.75 (1.121)	234.37 (2.815)	235.63 (2.125)	237.47 (2.501)	237.838 (3.581)	245.16 (3.232)	247.56 (1.708)
Numeracy	262.73 (0 .318)	232.56 (1.222)	226.44 (2.890)	229.67 (2.145)	230.85 (2.788)	230.42 (3.671)	236.45 (3.295)	240.07 (2.038)
Number of observations	94328	12325	2381	2091	1689	1254	1066	3827

* Average hourly wage estimates exclude Sweden, due to restricted earnings data.

Note: Standard errors are reported in parenthesis. Estimates based on a pooled sample of PIAAC public use data files for 15 countries. All estimates are adjusted for population weight. Measures of average literacy and numeracy skills across sub-samples are estimated using 10 plausible values for each skill domain, with standard errors estimated using Jackknife replication methodology.

Appendix C

Dependent variable (0-500 points):	Literacy score		Numeracy score	
	β/se	*β/se*	*β/se*	*β/se*
Immigrant	-49.18	-53.49	-70.83	-74.99
	20.40**	20.39***	25.51***	25.51***
Immigrant # Years since migration	0.72	0.90	0.66	0.71
	0.35**	0.34***	0.35*	0.34**
Immigrant # Years since migration^2	-0.01	-0.01	0	0
	0.01	0.01	0.01	0.01
Literacy use work	0.84	-0.93		
	2.24	2.37		
Numeracy use work			6.90	5.59
			1.47***	1.48***
ICT use work	5.13	3.43	3.00	1.90
	1.75***	1.79*	2.06	2.13
Literacy use everyday life		5.21		
		2.65**		
Numeracy use everyday life				3.53
				1.78**
ICT use everyday life		3.70		0.90
		2.70		2.88
Constant	248.87	275.56	253.03	291.66
	207.45	334.63	160.10	344.68
N	4585	4364	4585	4364
R^2	0.254	0.265	0.284	0.281

Note: Estimates based on a pooled sample of PIAAC public use data files for 15 countries. Measures of literacy and numeracy skills are estimated using 10 plausible values for each skill domain. Sample is weighted using final population weight. Standard errors estimated using 80 replication weights and applying Jackknife replication methodology. All models additionally control for demographic characteristics, education level, occupation, industry of employment, job training and country of residence. ***, **, * Indicate parameters significant at 1%, 5% and 10% levels respectively.

Appendix D

Effect of immigration tenure[A] on skill level – within-country estimates

Country	Literacy score		Numeracy score	
	β/se	R^2	*β/se*	R^2
Belgium	0.356 0.85	0.477	0.273 0.97	0.451
Czech Republic	0.21 2.26	0.653	0.861 2.48	0.749
Denmark	1.085 0.50**	0.314	1.283 0.52**	0.289
Estonia	-1.947 0.71***	0.162	-1.882 0.80**	0.218
Finland	6.112 1.75***	0.381	5.86 1.89***	0.357
France	0.447 0.6	0.475	0.677 0.67	0.51
Great Britain	0.883 0.84	0.321	0.674 0.8	0.353
Greece	-1.232 2.21	0.478	-1.148 2.32	0.433
Ireland	1.095 0.67	0.283	0.813 0.69	0.275
Italy	1.026 1.27	0.319	0.903 1.21	0.283
Netherlands	-0.732 0.89	0.437	-1.016 0.91	0.447
Norway	2.245 0.78***	0.401	2.975 0.84***	0.403
Slovenia	0.377 0.78	0.315	0.298 0.9	0.389
Spain	-0.558 0.77	0.277	-0.229 0.85	0.28
Sweden	1.966 0.66***	0.375	1.709 0.75**	0.357
Pooled sample	0.764 0.31**	0.345	0.642 0.32**	0.35

[A] The effect of immigration tenure is captured by an interaction term between the immigrant dummy and the continuous variable of years since migration.
Note: Estimates based on PIAAC public use country data files. Measures of literacy and numeracy skills are estimated using 10 plausible values for each skill domain. Sample is weighted using final population weight. Standard errors estimated using 80 replication weights and applying Jackknife replication methodology.
***, **, * Indicate parameters significant at 1%, 5% and 10% levels respectively.

Appendix E

Immigrant-native pay gap[A] w.r.t skill level and intensity of skill use – within-country estimates

Country	**M1[a]**		**M2[b]**		**M3[c]**		**M4[d]**		**M5[e]**	
	β/se	R^2	*β/se*	R^2	*β/se*	R^2	*β/se*	R^2	*β/se*	R^2
Belgium	-0.071 0.01***	0.351	-0.05 0.02**	0.358	-0.051 0.02**	0.359	-0.053 0.03	0.303	-0.051 0.03	0.305
Czech Republic	-0.108 0.05**	0.218	-0.103 0.06*	0.223	-0.099 0.06*	0.221	-0.095 0.08	0.194	-0.078 0.07	0.191
Denmark	-0.074 0.01***	0.296	-0.054 0.02**	0.302	-0.054 0.02**	0.304	-0.032 0.03	0.323	-0.033 0.03	0.325
Estonia	-0.097 0.02***	0.315	-0.083 0.03***	0.318	-0.085 0.03***	0.322	-0.098 0.05**	0.298	-0.103 0.05**	0.3
Finland	-0.088 0.02***	0.455	-0.074 0.03**	0.459	-0.072 0.03**	0.462	-0.06 0.03*	0.45	-0.056 0.03	0.453
France	-0.023 0.01**	0.315	-0.009 0.02	0.32	0 0.02	0.325	-0.004 0.03	0.334	0.002 0.03	0.338
Great Britain	-0.018 0.01*	0.421	0.008 0.02	0.434	0.014 0.02	0.435	-0.006 0.02	0.43	-0.003 0.02	0.431
Greece	0.052 0.02***	0.362	0.052 0.05	0.362	0.052 0.05	0.363	0.018 0.09	0.403	0.017 0.09	0.405
Ireland	-0.111 0.01***	0.2	-0.107 0.04**	0.202	-0.109 0.04***	0.205	-0.101 0.04***	0.201	-0.103 0.04***	0.203
Italy	-0.099 0.01***	0.296	-0.093 0.04**	0.297	-0.091 0.04**	0.298	-0.034 0.07	0.335	-0.04 0.07	0.334
Netherlands	-0.048 0.01***	0.235	-0.005 0.05	0.242	-0.009 0.05	0.242	-0.015 0.05	0.293	-0.016 0.05	0.293
Norway	-0.084 0.01***	0.287	-0.063 0.03**	0.293	-0.059 0.03**	0.296	-0.038 0.03	0.332	-0.034 0.03	0.335

Appendix E (continued)

Country	M1[a]		M2[b]		M3[c]		M4[d]		M5[e]	
	β/se	R^2	*β/se*	R^2	*β/se*	R^2	*β/se*	R^2	*β/se*	R^2
Slovenia	-0.025 0.02	0.377	-0.012 0.03	0.395	-0.003 0.03	0.403	0.026 0.04	0.376	0.034 0.04	0.383
Spain	-0.104 0.02***	0.311	-0.084 0.04**	0.317	-0.08 0.04**	0.319	-0.048 0.06	0.285	-0.045 0.06	0.286
Pooled sample	-0.057 0.01***	0.421	-0.038 0.01***	0.425	-0.034 0.01***	0.427	-0.021 0.01	0.413	-0.018 0.01	0.414

[A] Immigrant-native wage gap is measured by the coefficient of the immigrant dummy variable
[a] M1 controls for immigrant status, gender, age, age squared, education level, language used at home, occupation, industry, job training.
[b] M2 controls for literacy score additionally to M1
[c] M3 controls for numeracy score additionally to M1
[d] M4 controls for literacy, numeracy and ICT skill use at work additionally to M2
[e] M5 controls for literacy, numeracy and ICT skill use at work additionally to M3

KOKKUVÕTE

Töötajate kognitiivsed oskused ja nende kasutamine immigrantide ja põliselanikest töötajate palgalõhe selgitamisel

Artiklis otsitakse vastust uurimisküsimusele, mis on need tegurid, mis selgitavad immigrantide ja põliselanikest töötajate võimalikku palgalõhet Euroopa Liidu riikide tööturgudel. Täiendusena varasematele selles valdkonnas tehtud uurimistöödele saab käesoleva uurimistöö puhul välja tuua kaks uudset momenti, millele senistes inimkapitali teooriale tuginevates empiirilistes uuringutes on suhteliselt vähe tähelepanu pööratud. Esiteks, lisaks haridusele ja töökogemusele on selles uurimistöös arvesse võetud ka töötajate kognitiivseid oskusi (funktsionaalne lugemisoskus, matemaatiline kirjaoskus) ning teiseks, analüüsitud on ka oskuste kasutamist nii tööl kui igapäevaelus.

Empiirilise analüüsi läbiviimisel oleme kasutatud Majanduskoostöö ja Arengu Organisatsiooni (OECD) poolt käivitatud täiskasvanute oskuste uuringu PIAAC (*Programme for the International Assessment of Adult Competencies*) andmeid. Oskusi on hinnatud skaalal 0 – 500 punkti. Lisaks on olemas ka inimeste endi poolt skaalal 1 (väga harva) kuni 5 (kasutan iga päev) antud hinnangud oma oskuste kasutamisele tööl ja igapäevaelus. Riikide valimi komplekteerimisel lähtusime lisaks vajaliku info olemasolule (sh info küsitletavate sotsiaal-demograafiliste taustatunnuste jm kohta) ka immigrantide valimite suurusest riikides (vähemalt 4%). Nendest kriteeriumidest lähtuvalt kujunes meie valimi suuruseks 94 328 vastanut viieteistkümnest riigist, nendest 12 325 on esimese põlvkonna immigrandid. Sellise valimi põhjal hindasime erinevaid palgavõrrandeid ning oskuste dünaamikat selgitavaid võrrandeid.

Uurimistulemused näitavad, et immigrantidest töötajate oskused erinevad põliselanikest töötajate omadest seda vähem, mida kauem on nad selles riigis elanud. Sihtriigis elamise aasta lisandudes väheneb immigranttöötaja funktsionaalse lugemisoskuse erinevus võrreldes kohalikega keskmiselt 0.8 ning matemaatilise kirjaoskuse puhul 0.6 hinnangupunkti võrra. Erinevused oskustes keskmiselt siiski säilivad ning säilib ka palgalõhe. Immigrantidest töötajate palk on keskmiselt 5.7% madalam, kui oleme palgavõrrandite hindamisel arvesse võtnud taustatunnustena töötaja hariduse, vanuse, soo, keeleoskuse, koolitustel osalemise, ameti ja tegevusala ning ka riigi spetsiifikat iseloomustava fiktiivse muutuja. Kui lisaks võtta arvesse ka töötajate kognitiivseid oskusi iseloomustavad tunnused, siis keskmine palgalõhe on ligilähedaselt kolmandiku võrra väiksem (see on 3.8% funktsionaalse lugemisoskuse ning 3.4% matemaatilise kirjaoskuse arvestamise korral). Kui palgavõrrandite hindamisel arvestada lisaks eeltoodule veel ka oskuste kasutamist iseloomustavate tunnustega, siis tulemused ei kinnita statistiliselt olulise palgalõhe olemasolu.

Uurimistulemuste robustsuse testimiseks hindasime palgavõrrandid ka iga viieteistkümne riigi kohta eraldi ning saime kinnitust tulemuste stabiilsusele. Eristusid vaid Eesti ja Iirimaa, kus statistiliselt oluline palgalõhe põhirahvusest ja immigrantidest töötajate vahel säilib ka siis, kui lisaks sotsiaaldemograafilistele ja muudele taustatunnustele võtta arvesse ka info töötajate kognitiivsete oskuste ja nende kasutamise kohta. Siit tulenevad uued uurimisküsimused. Näiteks, milles ikkagi seisnevad Eesti ja Iirimaa tööturgude erinevused ning mis on nende erinevuste võimalikud põhjused, mis selgitavad immigranttöötajate ja kohalike palgalõhet?

Kokkuvõtteks: uurimistöö tulemused näitasid, et immigranttööjõu puhul on sageli tegemist nende potentsiaali alarakendamisega ning nende oskuste mittepiisava kasutamisega tööturgudel. Immigrantidest töötajatel on tööturule sisenemisel ning oma oskuste rakendamisel

veel olulised barjäärid, sageli ka vähene motivatsioon oma oskusi paremini rakendada, kui nad ei tunne end töökollektiivis piisavalt hästi integreerituna. Ka ei toeta tööturu institutsioonid veel piisavalt määral immigranttöötajate integreerimist ja nende potentsiaali paremat ärakasutamist.