IMMIGRANTS' INTEGRATION: THE DYNAMICS AND CONVERGENCE OF COGNITIVE SKILLS

Maryna Tverdostup[1], Tiiu Paas[2]

Abstract

The paper analyses immigrant-native wage gap incorporating cognitive skills to approximate individual human capital profile. Based on the Program of International Assessment of Adult Competencies (PIAAC) data for 15 European countries, we document that on average foreign-born respondents achieve substantially worse scores in literacy and numeracy test domains, but the observed gap in cognitive skill declines over time of host-country stay. The results of analysis show that once we account for these skill use at work in wage regressions, along with actual skill level, no statistically significant gap in earnings across immigrants and natives remain**.** These findings indicate that, despite similar cognitive skill level and background traits, immigrants and natives may apply their skills at work to different extend, yielding a difference in their wage returns. Thus, disparity in skill use at work plays an important role in explaining immigrant-native wage gap addressing us also to conclusions that immigrants are not yet sufficiency well integrated in the European labor markets and the potential for development and utilization of their human capital is still underused.

Keywords: migration; human capital; cognitive skills; PIAAC

JEL: J15, J24,C33

1. Introduction

There is an ample research analyzing disadvantages faced by immigrants on the host market. Majority of studies documents that immigrants tend to earn on average less than natives (Borjas 2015, Dustmann et al. 2013, Borjas 2000). Previous findings also suggest that wage disadvantage is the highest for newly-arrived immigrant, but decreases slowly over years spent in a host country (Sarvimäki 2011, Borjas 1992). However, some part of initial immigrant-native pay gap persists even after long years in a receiving country (Sarvimäki 2011), suggesting that immigrants' earnings do not ultimately converge.

Existing literature addresses various reasons behind an observed wage disadvantage of immigrants. Human capital disparities and particularly poorer skills of immigrants compared to natives were commonly viewed as a factor explaining worse employment outcomes of foreign-born (Chiswick 1978). According to a classical human capital theory (Becker 1975), differences in skills transmit into earnings. Immigrants may lack qualifications and abilities demanded by host country, so called host country-specific human capital, yielding their wage penalty (Zibrowius 2012).

Due to a lack of appropriate data, previous studies mostly approximated human capital with formal education to measure wage gap and occupation-qualification match. In a context of immigrant-native comparison, this approximation yields a number of serious limitations. The major one is potential non-comparability of formal degrees held by natives and immigrants

[1] University of Innsbruck, Austria; University of Tartu, Estonia; maryna.tverdostup@ut.ee
[2] University of Tartu, Estonia; tiiu.paas@ut.ee

(Green and Worswick 2012, Bonikowska et al. 2008), resulting in objective differences in capabilities, as well as simple non-recognition of foreign degree by host-country employers. Hence, when formal education is used as a proxy of qualification, it does not allow to get a pure effect of immigrants' human capital gap on labor market outcomes. The gap in formal education only roughly reflects human capital gap, as formally same degree acquired in host country by natives and in country of origin by immigrants may yield different competencies and skills. Thus, a part of labor market outcome gap attributed to a difference in formal education tells little about actual difference in skills and abilities.

The paper contributes to this debate by incorporating actual literacy and numeracy skills, rather than only formal education, to evaluate actual immigrant-native human capital gap. Namely, we use actual test scores in literacy and numeracy cognitive skill domains, provided by Program of International Assessment of Adult Competencies (PIAAC), conducted within a 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. Additionally to cognitive skill assessment scores, information on the use of skills at home and work is taken into account when analyzing immigrant-native human capital gap.

Thus, the first contribution of the paper concerns a dynamics of immigrants' human capital, approximated with literacy and numeracy skills over immigration tenure. Thus, we test whether immigrants are indeed prone to improve their skill profile, as they acquire skills valued and demanded in a host country. Second contribution relates to incorporation of direct skill use measures in immigrant-native pay gap analysis. We argue that some labor market disadvantages may persist despite immigrants' true skills and abilities. Even when having a relatively strong qualification profile, immigrants still frequently face disadvantages on labor market. The commonly discussed ones are employment-qualification mismatch (Dustmann et al. 2013, Chiswick and Miller 2010), difficulties of labor market entry due to non-acquaintance with institutional settings of a host country labor market, unfair treatment due to employers' statistical or taste discrimination (Quilllian 2006). Extend of skill application at work reflects complexity and reward-level of job (objective factors), as well as individual effort exerted at work (subjective factor). Systematic immigrant-native difference in a degree of skill use at work suggests that this disparity may be one of potential reasons behind a persistent immigrants' pay disadvantage.

Thus, the second contribution of the paper is introducing intensity of skill use at work, as another factor behind immigrant-native pay gap. Intensity of skill use at work has non-trivial association with immigrants' wage improvement. Why should one account for an extent to which immigrant utilizes his skills when analyzing wage disadvantage of immigrants? Previous studies widely documented that immigrants tend to be overqualified, suggesting that even when immigrant is sufficiently qualified, he does not attain position comparable to otherwise similar native. Among other factors, over education can be induced by difficulties of labor market entry, non-familiarity with local labor market, lower level of credibility from employers' perspective, etc. These facts infer that immigrants have lower access to challenging and highly-rewarded jobs. Hence, even when having relatively high human capital, the aforementioned disadvantages may deter immigrants' career progression, leading to persistent wage penalty, which may to a large extent offset positive wage returns to improvement in human capital. Therefore, investments in human capital and own skills development may not immediately translate into positive wage returns, resulting in persistent wage penalty even after long years spent in a host country. This argument can partly explain why increasing language proficiency does not eliminate immigrant-native pay gap (Beyer 2016).

Relying on these rationales, we set two research hypotheses that express our research gap:

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

H2: *Immigrant-native difference in skill use at work, enforced by disparities in job access opportunities, career advancement possibilities, motivational factors etc., largely explain, if not eliminate, immigrant-native pay gap.*

In our approach, we relate intensity of skill use at work with wage returns through two channels. The first one is an 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. Second channel implies the skill use at work is an approximation of (i) complexity, challenge and reward level associated with job; (ii) individual effort and exerted by respondent in dealing with job tasks. The first channel relies on an obvious assumption that skill associates with skill use with no clear direction of causality[3]. While in the second channel we introduce a number of important assumptions. Namely, (a) more complex and challenging work requires more frequent use of certain skills, relative to less complex; (b) extent of skill use at work largely represent individual effort exerted at work; (c) individual skills are generating 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 immigrant-native wage gap debate.

To argue that skill use at work directly enters wage regression as a proxy for job complexity and degree of skill application, one has to verify that this channel exists along with indirect effect through immigrants' skill accumulation. Observationally, both channels are 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 in identical to skill use at work way, but asking how frequently certain activities are performed in non-work related activities. Following our intuition, skill use in everyday life can reflect on wage only indirectly through acceleration of skill. The direct channel is not valid in this case, since intensity of skill use in non-work activities tells nothing neither about complexity of job, nor about individual effort exerted by a respondent. Non-significant wage effect of skill use at work, coupled with significant association for skill use at work, would support our assumption that intensity of skill use at work is one of independent factors affecting wage rate.

Our results suggest that indeed immigrants' literacy and numeracy skills tend to improve over years since migration. However, controlling for cognitive skills does not eliminate statistically significant immigrant-native pay gap. Incorporating skill use at work and skill use in everyday life, as a counterfactual measure, revealed that indeed intensity of skill application at work accounts for a large share of immigrant-native pay gap. As expected, we found that both skill use at work and in everyday life significantly associate with skill level, however, only skill use at work yield positive wage returns when both work and non-work skill use controls are incorporated in wage regression. Thus, not only a mere stock of skills matter in narrowing down immigrant-native pay gap but also access to complex, challenging and highly-rewarding positions, as well as individual effort exerted in solving job tasks account for a large share of

[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.

immigrant-native pay disparity. If immigrants are not well integrated into labor markets, their skills are underused, possibilities for development of human capital are restricted and consequently also immigrants-native wage gap remains.

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

2. Theoretical Background

The issue of immigrants' disadvantageous labor market outcomes is extensively studied in the literature. Here we will focus on the studies most relevant for our analysis. Education-qualification mismatch and immigrant-native pay gap are the most comprehensively studied disadvantages faced by immigrants on the host labor market. The pioneer study by Chiswick (1978), showed that in the U.S. immigrants are earning 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 U.S. 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 U.K., where immigrants tend to be employed in lower level jobs, compared to natives having comparable education level. Reitz et al. (2014) addresses an issue of immigrants' "brain waste", as a result of immigrants' skill underutilization in Canada. Ultimately, limited occupational prospects and inability to fully realize own competencies result in wage penalty for immigrants.

These labor market disadvantages of immigrants have been attributed to various factors. A number of studies stressed that non-recognition of immigrants' credentials and formal education degree accelerates labor market disparities (Green and Worswick 2012). Employers may simply treat host- and foreign-acquired degrees differently. They may statistically discriminate foreign country qualification, due to a lack of knowledge about actual content and quality of received education. It yields lower credibility of foreigners' educational attainments, compared to natives'. Noteworthy, some findings suggest that employment success of immigrants depend heavily on a field of degree. Galarneau and Morissette (2004) found that Canadian immigrants holding a degree in engineering, computer and health sciences benefit relative to their peers with qualification in other fields.

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

Employment related disadvantages faced by immigrants on the host labor market may lead to two types of consequences for individual human capital. One strand of literature suggests that due to reduced employment possibilities immigrants tend to experience further skill downgrading (Akresh 2008). While Duleep (2008) argues that low-skill-transferability immigration is characterized by higher potential to invest in own human capital in order to improve occupational outcomes. Thus, immigrants with low-transferable skills and initially high human capital gap, relative to natives, are motivated to improve individual human capital profile and, thus, to catch up with native-born over time. The argument by Duleep (2008) goes in line with a large body of empirical findings suggesting that immigrants' wages tend to improve over years since immigration. These studies commonly report that immigrant-native pay gap tends to narrow down the longer is the time spent in receiving country (Sarvimäki 2011, Borjas 1992, Chiswick 1978). Observed positive dynamics may be a result of human capital investments, better acquaintance with host labor market and, consequently, getting position which fits actual qualification better (Beyer 2016). A number of studies also underlined the role of state programs in immigrants' economic and social integration. Sarvimäki and Hämäläinen (2016) showed that in Finland Active Labor Market Policy, aiming to design an individual training program for unemployed immigrants, significantly increases compliers' earnings over 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 intension to stay in 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 a higher wage returns to immigrants advanced in written Hebrew, relative to those reporting a language level sufficient for speaking and understanding. Beyer (2016) report that god German writing skills reduce a pay gap between native and foreign born in Germany by one third.

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

3. Data and Method

3.1. Data and sample

Empirical analysis relies on cross-section data from Program of International Assessment of Adult Competencies (PIAAC) survey for 15 countries. The selection of countries is based on availability of data required for the analysis. Namely, we retained only countries fulfilling two criteria: (1) availability of major variables used in analysis, namely, literacy and numeracy skill scores; (2) share of immigrants in total country sample is sufficiently large (more than 4%). 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[5]. National samples are weighted to population in a relevant year. The survey was conducted in two rounds. The first round was performed in 2011 and 2012 and included all analyzed countries except Greece, Lithuania and Slovenia. The latter countries were surveyed in 2014-2015. Along with a rich set of variables on socio-demographic background, employment history and self-assessed employment characteristics, PIAAC provides test scores in three skill domains – literacy, numeracy and problem solving in technology rich environment.

Following the definition used in 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". 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" (OECD 2013, p.3). In this paper the data on individual problem solving skill is not used. Mainly, because problem solving part was completed by respondents who have at least some computer experience and performed a computer-based test, while two other test domains were conducted by all respondents (either in paper- or in computer-based survey). Including problem solving domain would reduce out sample by approximately 30%. Furthermore, France, Italy and Spain did not disclosed problem solving test scores in publicly used data files. Hence, we focus on dynamics and wage effects of literacy and numeracy skills, scaled from 0 to 500 points[6].

The second factor of interest – intensity of skill use at work – encounters three domains. Namely, a degree of skill utilization at work is derived as a frequency of skill use based on a set of background questions related to certain skill domain. PIAAC database provides derived skill use measures. However, to capture all available aspects of skill application, we derive a skill use scale, following Allen et al. (2013). Namely, we define use of literacy skill as an average of eight reading components and four writing components. While a scale for numeracy skill use at work is approximated with six numeracy components. Each component refers to a self-reported frequency of conducting certain activity, requiring reading, writing or numeracy ability and ranges from 1 (never) to 5 (every day)[7]. Frequency of skill use does not reflect employees' productivity and tells nothing about the actual efficiency of skill use. Thus, they reflect solely complexity and skill-intensity of respondents' jobs, as well as a degree of individual effort.

Similarly, to use of literacy and numeracy skills, we define ICT skill use scale. Albeit we do not use a problem-solving skill in our human capital definition, we account for ICT use at work. Primary, because ICT use is defined broader than problem solving and strongly relates to literacy and numeracy skills. Furthermore, substantial share of jobs involves basic computer command or require Internet use, especially among medium and high level positions. Thus, ICT skill use coupled with intensity of literacy and numeracy application at work better reflect complexity of tasks workers are responsible for.

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

[6] 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

[7] 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".

As a counterfactual to use of skills at work, we similarly derive the measures of skill use in everyday life. Namely, we construct variables of literacy, numeracy and ICT skills use in everyday life relying on a set of background question. The latter are identical to skill use at work domain, although ask about activities beyond work. A full list of background questions used to construct 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 certain skill. For the sake of comparability, we estimate skill use scale measure for respondents having all twelve and six components available. A frequency of ICT use is estimated as arithmetic average over eight components for respondents with all ICT use at work components disclosed.

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 nature (complexity and skill-intensity) of job and individual effort exerted at work, we can expect response bias to go both ways. Generally, respondents should have higher propensity to overstate their true effort at work, rather than understate it. However, certain group 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 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, these issues should not bias our estimates.

Appendix B presents summary statistics of immigrants' sample in a pooled PIAAC dataset of 15 countries. We acknowledge several limitations arising from using a cross-section data for analysis of immigrants' human capital dynamics, it's utilization at work and 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 a set of background traits. Thus, the analysis of skills' dynamics controls for a wide set of socio-demographic and employment characteristics in order to ensure that skills' variation over years in a host country is not associated with cross-cohort differences in background characteristics.

3.2. Empirical method

Our methodological approach encounters several empirical tests, addressing two hypotheses posed in the paper. Since PIAAC data reports 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 population mean values, we incorporate final population weight. Skill measurement errors are ruled out by using 80 replication weights under Jackknife replication methodology. Hence, each regression output incorporating skill measures as ten plausible values is a result of 810 replications.

First, we empirically analyze immigrants' cognitive skills dynamics over immigration tenure:

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

where dependent variable CS_i correspond to either literacy or numeracy test score; dummy variable I_i takes value 1 if respondent is foreign-born; variable YSM_i corresponds to number of years immigrant has spent in the host country; ε_i represents independent error term. Since estimation is performed on pooled cross-country sample, we additionally control for a set of country dummies. Main effects of interest are captured by coefficient γ_1, standing for immigrants' skill disadvantage just after arrival, and γ_2, as it reflects average increase in the skill level associated with each additional year of host country stay. To attribute the time effect to immigrants' catching up we need to compare immigrants with different duration of host country stay to similar in background and observable characteristics of natives. Thus, we increase a set of additional controls, denoted by vector X_i', from a demographic and educational characteristics solely in basic model, to a complete specification with language used at home occupation, industry and job training.

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

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

Consequently, based on estimated effects of skill use at work or 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 immigrant-native pay gap. Specifically, we start with a descriptive evidence on (a) skill use frequency across different occupation groups, to illustrate that indeed higher level jobs imply higher frequency of skills use and (b) average wage rate across skill use frequencies, to verify that more intensive application of skills associates with higher earnings. The results will give a crude evidence whether skill use intensity reflect relative complexity and reward level of job.

We proceed with assessment of association between skill use at work, skill use in everyday life and skill level. A complete specification is modeled in the following way:

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

where SUW' and $SUEL'$ are the vectors of measures of skill use at work and in everyday life respectively. Thus, a vector of coefficients ρ' captures an association between skill use at work and skill level, while δ' stands for skill use at home effects on cognitive abilities. 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 extra in terms of skill accumulation from skill use at work and in everyday life, relative to natives. Given observational nature of PIAAC data, we cannot evaluate direction of causality. However, for our analysis it is sufficient to document significant association, as it is quite likely that the causal relation goes both ways.

The final part of our analysis will tackle immigrant-native wage gap. Namely, 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 observable traits. We model the problem in the following way:

$$W_i = \alpha + \gamma I_i + \tau CS_i + \rho' UW' + \delta' SUEL' + \beta' X_i' + \varepsilon_i, \text{(3)}$$

where W_i stands for individual hourly wage. Vectors of coefficients of skill use at work (SUW') and in everyday life ($SUEL'$) capture wage effects of skill application in certain domain. Following our intuition, we can conclude that utilization of skills at work associates with wage rate directly through complexity of tasks and effort exerted only if we find positive and significant association between intensity of skill use at home and wage, while do expect for skill use at work. Coefficient γ stands for a residual immigrant-native pay gap and is a major estimate of interest. Variation of coefficient γ 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 aforementioned controls in explaining immigrant-native pay gap.

Application of Jackknife replication methodology to correctly estimate standard errors with 80 replication eights does not allow to simultaneously cluster standard errors. Although, as we use pooled sample for major analysis, clustering standard errors on country level would be a natural choice as it accounts for interdependencies of observations within country sample. To additionally verify consistency of our conclusions based on models with non-clustered standard errors, we replicate same analysis for each country separately. Thus, we test whether same pattern observed in the pooled sample holds when we disaggregate the dataset into 15 country sub-samples.

4. Empirical Results

In this section, we present empirical results on immigrants' skills dynamics and a role of skill level and intensity of skill use in explaining immigrant-native pay gap. We start with analyzing immigrants' cognitive skills dynamics. Table 1 presents estimation of average increase in literacy (panel a) and numeracy (panel b) skills over time since immigration. In our specification, coefficient of *Immigrant* corresponds to 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 regression coefficient of interaction term *Immigrant # Years since migration.* In a baseline model (M1), with only a set of demographic variables (gender, age, marital status) and education controlled for, initial skill gaps are 76 points in literacy and striking 100 points in numeracy. One additional year in a host country under specification of M1 is associated with 1.4-point increase in literacy score and 1.3 increase in numeracy score, both significant at 1%.

We further extend a list of controls in M2, by adding language control (is a language spoken at home the same as the one used for test). Firstly, this variable to a large extent reflect immigrants' language competence and integration into language environment of a host country, and secondly, capture how easy it was for respondent to understand texts provided as a part of literacy and numeracy tasks. As expected, controlling for language variable drastically reduced an effect of immigration tenure on both literacy and numeracy scores (to 0.9 points and 0.8 points respectively). Estimated skill gap for newly arrived immigrants also declined to 62 and 87 points correspondingly. This results supports earlier evidence on importance of host country language proficiency for immigrants' human capital. Host-country language command captures a significant share of initial gap in literacy and numeracy skills.

Further stepwise inclusion of controls does not chance immigration tenure effect drastically. As expected adding occupational dummies (M3) dramatically decreased initial skill gap estimate (to 51 points in literacy and 73 points in numeracy). Although, when controlling for a full set of demographic and employment characteristic (M5), newly-arrived immigrants are found to have 63 points lower literacy score and 84 points lower numeracy score, relative to stayers with a same set of background traits. Importantly, additional year in a host country is still associated with statistically significant increase in both literacy and numeracy score. Thus, extending a list of controls reduced estimated effect of immigration tenure on skill test attainments, however, the coefficients remained statistically significant at 5%. Noteworthy, we observe a small decline in magnitude and statistical significance of effect of years since migration with adding *Job training* variable in M5, relative to M4. It primary reflects an importance of training and educational programs provided by employers on immigrants' literacy and numeracy skill development.

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	-75.616	-61.939	-50.914	-61.639	-62.721
	19.21***	19.02***	19.13***	20.62***	20.72***
	1.449	0.877	0.741	0.867	0.764
	0.23***	0.23***	0.25***	0.31***	0.31**
	-0.007	-0.002	-0.002	-0.006	-0.004
	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	273.114	252.097	238.144	324.432	262.666
	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)***					
Immigrant	-99.758	-87.17	-72.581	-82.433	-84.031
	23.90***	23.87***	24.15***	24.23***	24.33***
	1.294	0.77	0.604	0.755	0.642
	0.25***	0.23***	0.25**	0.32**	0.32**
	-0.003	0.001	0.002	-0.002	-0.001
	0	0	0	0.01	0.01

	M1 β/se	M2 β/se	M3 β/se	M4 β/se	M5 β/se
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 pulled 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.

Generally, our results based on a pooled sample support part (i) of the first hypothesis, as we found that immigrants' cognitive skills in literacy and numeracy indeed tend to improve over time spent in a host country. A complete model (M5) from Table 1 demonstrates an important role of on-job training on immigrants' skill progression. This result appears as quite intuitive. Training and educational programs facilitated by employers is indeed a powerful tool to help immigrant acquire new skills valued by employer and demanded on a on a host country labor market. Consequently, job training and formal education are two major channels of cognitive skill development.

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

We start with testing the indirect channel by analyzing association between cognitive skills test scores and intensity of skill use at home and in non-work context. Table 2 reports regression results following specification (2). Since an observational nature of our data does not allow 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.

Panel (a) presents regression of literacy score over a set of background controls and different combinations skill use variables and interaction between skill use variables and immigrant dummy. While panel (b) reports identical regression, but with numeracy score as dependent variable. Given a 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 rather narrow way, allowing to assume 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 17.6 and 19.5 points immigrants' average skill gap in literacy and numeracy respectively.

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

	M0 *β/se*	**M1** *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)***							
	-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***
		-0.355	-0.684			-2.099	-2.432
		0.55	0.55			0.58***	0.57***
		5.612	5.606			4.224	4.24
		0.55***	0.56***			0.57***	0.57***
				6.59	6.501	5.619	5.678
				0.63***	0.63***	0.74***	0.71***
				5.846	5.649	4.144	4.178
				0.66***	0.60***	0.68***	0.67***
			3.523				3.525
			2.00*				2.24
			-0.137				-0.335
			1.77				1.8
					0.616		-0.552
					2.23		2.55
					1.533		-0.378
					1.86		2.58
	202.471			174.332	175.007	194.04	194.803
	107.06*		!	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	-19.516	-13.522	-21.169	-18.488	-17.795	-14.132	-11.346
	1.48***	1.57***	5.22***	1.46***	5.51***	1.61***	8.09
Numeracy *use work*		5.494	5.293			1.863	1.791
		0.40***	0.41***			0.55***	0.57***
ICT *use work*		3.357	3.295			3.229	3.497
		0.54***	0.55***			0.68***	0.66***
Numeracy *use non-work*				7.637	7.742	3.873	3.655
				0.43***	0.43***	0.42***	0.45***
ICT *use non-work*				5.934	5.88	5.783	5.976
				0.61***	0.57***	0.47***	0.51***
			2.337				2.317
			1.49				1.52
			0.629				1.007
			1.8				1.84
					-0.968		-1.877

	M0 *β/se*	M1 *β/se*	M3 *β/se*	M4 *β/se*	M5 *β/se*	M6 *β/se*	M7 *β/se*
Immigrant # Numeracy *use non-work*					1.8		1.79
					0.511		-2.754
					2.35		3.11
Constant	170.364			163.619	163.514	178.015	178.461
	120.66			85.79*	86.46*	92.00*	92.77*
N	67439	50092	50092	58795	58795	47337	47337
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 parenthesis. Estimates based on a pulled 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.

Adding use of skill controls (M2) substantially decrease 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 literacy score is positively associated with more intense use of computer and Internet (5.6 points increase in literacy with 1-step increase in frequency of ICT use), but not with literacy use as defined in PIAAC data. Notably, individual numeracy score positively correlates with both numeracy use at work (5.5 points) and ICT skill use (3.4 points). Skill use at home yields stronger degree of association with abilities, than use of skills at work (M4). More intensive use of literacy and ICT competencies at home imply 6.6 points and 5.8 points increase in literacy ability, whereas numeracy and ICT use at home – 7.6 and 5.9 points respectively. When we control for work and non-work skill use simultaneously (M7) effects remain robust.

We additionally explore if immigrants tend to benefit extra from using skills at work and at home, relative to natives. These extra returns to skills are captured by interaction terms between immigrant dummy and degree of skill use. We found only weak positive surplus effect of immigrants' literacy use at work on literacy skill (3.5 points, $p \leq 0.1$). In terms of other skill use dimensions, we did not find that immigrants benefit from intensive skill utilization relatively more than natives. Nevertheless, estimation results supported our expectation that both application of skills at work and in everyday positively reflects on literacy and numeracy scores. Since we do not recognize true causal relationship, we argue that skill use at work can potentially affect earnings through indirect channel, as it facilitates skill improvement[8].

Before we analyze how skill use at work and, as counterfactual in everyday life, associate with wage, we provide a descriptive evidence to verify that skill use at work indeed to some extent reflect complexity of job and reward level associated with position. Table 3A reports association between skill use intensity and complexity of job. The latter is represented by occupation category according to ISCO classification (4 categories based skill requirement). 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 neither for natives, no for

[8] Alternative causal link would be from skill level to skill use. Namely, higher skill level motivates to apply skill at work more often, positively reflecting on wage rate. However, we find it reasonable to assume that higher intensity of skill use to some extent affect skill itself through repeated practicing of certain activity.

immigrants. The result goes in line with our assumption that skill use at work reflects complexity of work, while skill use at home is interrelated to occupation.

Last, we explore variation of average hourly earnings across skill use groups. Here we verify that indeed skill use frequency reflects reward level associated with 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 found clearly increasing wage level with an increase in intensity of skill use for both natives and foreign-born. While we cannot conclude the same with respect to skill use in everyday life, as we observe 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.

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						
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						
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): skill use at work						
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): skill use in everyday life						
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	16.9	19.6	14.5	17.5

Note: Estimates based on a pulled sample of PIAAC public use data files for 15 countries. All estimates are adjusted for population weight.

Finally, we empirically test how skill level, skill use at work and in everyday life affects immigrant-native pay gap. Our rationale here is that increasing a stock of skills is not sufficient to explain immigrant-native pay disparity (part (ii) of the first hypothesis). Skills yield positive wage returns only when utilized at work, meaning that respondent accessed sufficiently complex and rewarding job, as well as that he invests a decent effort into his 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 of specification (3). We separately estimated models with literacy and numeracy skill controls due to their high correlation and technical features of estimation process[9]. 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 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% ($p \leq 0.1$), provided that 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% ($p \leq 0.1$) respectively. This result suggests that cognitive skills in literacy and numeracy account for approximately 30% of pay disadvantage faced by immigrants, compared to natives with similar demographic, educational and employment profile. However, accounting for immigrant-native cognitive skill disparity does not fully explain pay gap of immigrants, as predicted by our hypothesis 1.

The most important findings are reported by models M2 and M6. Namely, M2 which along with literacy score incorporates literacy, numeracy and ICT skill use at work. When controlling for those, wage gap between immigrants and natives turns statistically non-significant and its economic significance declines (2.1% in M2 and 1.8% in M6). This finding support our second hypothesis and shows that indeed immigrant-native pay disparity originates form differences in application of skills at work across immigrants and natives. This difference eventually reflects on earnings profile, since intensity of skill use captures two aspects: (i) nature of performed job; (ii) individual effort invested into work. Both components may drastically differ between immigrant and native population. Firstly, immigrants may more restricted access to positions involving a lot of skill-requiring work, which is more likely to generate higher wage returns, than job 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 into invest effort into job, either due to realized labor market difficulties and low expectancy of further career development, or to low social, cultural, integration, feeling of isolation from society and other psychological factors.

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 utilization of skills at work. Notably, 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 of skill use in everyday life variables further decline and turn statistically

[9] Simultaneous including of literacy and numeracy scores result in 20 possible combinations of plausible values (10 for literacy and 10 for numeracy), which, given 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 with literacy and numeracy included simultaneously in several specifications. The results are comparable to models with only literacy, or only numeracy controlled for.

insignificant. 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 nature of job and effort exerted at work. On its turn skill use in everyday life positively associates with skill level, but not with a wage rate, thus has no power to reflect on immigrant-native pay gap.

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

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*			
	-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
		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***
			0.042		0.043		0.042		0.043
			0.01***		0.01***		0.01***		0.01***
			0.002		0.005		-0.001		0.003
			0		0		0		0
			0.038		0.033		0.039		0.034
			0.01***		0.01***		0.01***		0.01***
				0.016	-0.009			0.017	-0.007
				0.01**	0.01			0.01**	0.01
				-0.001	-0.008			-0.004	-0.011
				0	0.01			0	0.01
				0.012	0.004			0.012	0.004
				0.01*	0.01			0.01*	0.01
	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 pulled 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.

Conclusions

This paper contributes to analysis of immigrant-native wage gap and factors behind it. Earlier literature discus differences in human capital attainments across immigrants and natives as one of the major drivers of observed differential in earnings. However, previous studies 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 domain to approximate individual human capital profile. Furthermore, we argue that several labor market disadvantages may persist despite immigrants' true skills and abilities. Difficulties of labor 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 persistent wage penalty, which may to 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 time 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 observe dynamics suggests gradual catch up of immigrants and narrowing immigrant-native skill gap over time. The rate of catching up in literacy is marginally larger that in numeracy.

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

It motivates a 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 positively associate with reward level. Since we rely on broad occupation categories, controlling for skill use at work allows identifying if immigrants access jobs of similar complexity and associated wage reward as natives. However, frequency of skill use at work also reflects a degree of effort exerted at work. Our data in hand does not allow to disentangle these two effects behind observed intensity of skill use. However, descriptive evidence suggests that skill use variable indeed largely reflect complexity of job (more intensive skill use in higher occupational categories) and reward level associated with job (average earnings increase with an increase in skill use at work).

Once we account for literacy, numeracy and ICT skill use at work in wage regression, along with actual skill level, no statistically significant gap in earnings across immigrants and natives remain. These findings prove that, despite similar cognitive skill level and background traits, immigrants and natives may apply their skills at work to different extend, yielding a difference in their wage returns. It seems reasonable to assume that labor market reward skills when they are actively used to generate positive returns in terms of job tasks. Extent of skill utilization depends on objective nature of job (complexity and skill intensity) and subjective factors (personal motivation effort). We argument that both, job nature and effort components, may systematically differ across immigrants and natives, resulting in wage loss of immigrants.

Our findings, on the one hand, reassure that immigrants are prone to develop and improve their skill profile over time spend in a host country. This finding goes in line with earlier studies suggesting increased human capital investment, mostly though acquiring skills demanded and highly valued on host state labor market, as well as improvement of host-country language command. Consequently, immigrants tend to gradually catch up with natives and rule out 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 turns immigrant-native pay gap statistically insignificant and, thus, suggest that disparity in skill use at work plays an important role in explaining immigrant-native pay disparity.

Thus, disparity in skill use at work plays an important role in explaining immigrant-native pay disparity indicating also that immigrants are not sufficiently well integrated in the European labor markets. Possible difficulties of immigrants in labor market entry and in getting complex and challenging positions to a large extent explain their weak integration. Implementation and development of policy measures should take into account that human capital improvements alone are not sufficient to ensure immigrants' labor integration if several labor market disadvantages may persist and immigrants cannot efficiently use and develop their skills and abilities at work. Further policy measures should consider these indications much more seriously taking also into account that the role of immigrants and their labor supply is remarkably increasing 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 math or statistics	Computer-based or Internet use related tasks include: (1) experience with computer at work; (2) using Internet for mail; (3) using Internet for work related information; (4) using Internet to conduct transactions; (5) using computer for spreadsheets; (6) using computer for Word; (7) using computer for programming language; (8) use computer 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 use related tasks include: (1) experience with computer 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						
			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	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 pulled 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

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

Country	Literacy score		Numeracy score	
	β/se	R^2	*β/se*	R^2
	0.356		0.273	
	0.85		0.97	
	0.21		0.861	
	2.26		2.48	
	1.085		1.283	
	0.50**		0.52**	
	-1.947		-1.882	
	0.71***		0.80**	
	6.112		5.86	
	1.75***		1.89***	
	0.447		0.677	
	0.6		0.67	
	0.883		0.674	
	0.84		0.8	
	-1.232		-1.148	
	2.21		2.32	
	1.095		0.813	
	0.67		0.69	
	1.026		0.903	
	1.27		1.21	
	-0.732		-1.016	
	0.89		0.91	
	2.245		2.975	
	0.78***		0.84***	
	0.377		0.298	
	0.78		0.9	
	-0.558		-0.229	
	0.77		0.85	
	1.966		1.709	
	0.66***		0.75**	
	0.764		0.642	
	0.31**		0.32**	

[A] The effect of immigration tenure is captured by an interaction term between immigrant dummy and 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 D

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
	-0.071		-0.05		-0.051		-0.053		-0.051	
	0.01***		0.02**		0.02**		0.03		0.03	
	-0.108		-0.103		-0.099		-0.095		-0.078	
	0.05**		0.06*		0.06*		0.08		0.07	
	-0.074		-0.054		-0.054		-0.032		-0.033	
	0.01***		0.02**		0.02**		0.03		0.03	
	-0.097		-0.083		-0.085		-0.098		-0.103	
	0.02***		0.03***		0.03***		0.05**		0.05**	
	-0.088		-0.074		-0.072		-0.06		-0.056	
	0.02***		0.03**		0.03**		0.03*		0.03	
	-0.023		-0.009		0		-0.004		0.002	
	0.01**		0.02		0.02		0.03		0.03	
	-0.018		0.008		0.014		-0.006		-0.003	
	0.01*		0.02		0.02		0.02		0.02	
	0.052		0.052		0.052		0.018		0.017	
	0.02***		0.05		0.05		0.09		0.09	
	-0.111		-0.107		-0.109		-0.101		-0.103	
	0.01***		0.04**		0.04***		0.04***		0.04***	
	-0.099		-0.093		-0.091		-0.034		-0.04	
	0.01***		0.04**		0.04**		0.07		0.07	
	-0.048		-0.005		-0.009		-0.015		-0.016	
	0.01***		0.05		0.05		0.05		0.05	
	-0.084		-0.063		-0.059		-0.038		-0.034	
	0.01***		0.03**		0.03**		0.03		0.03	

Appendix D (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
	-0.025		-0.012		-0.003		0.026		0.034	
	0.02		0.03		0.03		0.04		0.04	
	-0.104		-0.084		-0.08		-0.048		-0.045	
	0.02***		0.04**		0.04**		0.06		0.06	
	-0.057		-0.038		-0.034		-0.021		-0.018	
	0.01***		0.01***		0.01***		0.01		0.01	

[A] Immigrant-native wage gap is measured by the coefficient of 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