Working Paper 271

FEBRUARY 2026

Beyond occupational sorting:

How skills shape task allocation and immigrant disadvantage

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Research for this paper was financed by the Anniversary Fund of the Oesterreichische Nationalbank (Project No. 18934). Support provided by the Oesterreichische Nationalbank for this research is gratefully acknowledged.

Abstract

Immigrants across Europe earn less and work in lower-quality jobs than natives, but the mechanisms underlying these disparities remain poorly understood. This paper asks whether immigrant disadvantage reflects barriers to accessing good jobs or skill deficits that persist even within similar positions. Using PIAAC Cycle 2 data (2018-2023) for eight European countries, we compare immigrants and natives working in the same occupation-industry cells and performing the same types of tasks. We find that immigrants score 35 to 40 points lower in literacy and numeracy than natives overall, with 70 to 75 percent of this gap persisting within jobs. Immigrants also perform fewer cognitively demanding tasks than natives in similar jobs. However, these task differences disappear entirely once we account for within-job skill gaps, while manual task use shows no immigrant-native differences at all. The evidence points to a skill-mediated mechanism: immigrants perform fewer complex tasks because they have lower cognitive proficiency, not because employers restrict their access to such work. This finding redirects policy attention from workplace discrimination toward skill development and credential recognition as the key margins for improving immigrant labour market integration.

Keywords: Immigration; cognitive skills; job tasks; skill mismatch; labour market integration; PIAAC

JEL classification: J15, J24, J23, C81

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1 Introduction

Immigrants earn less, work in lower-quality jobs, and face limited mobility relative to observationally similar natives across OECD countries. A large body of research attributes these disparities to imperfect transferability of foreign qualifications, language barriers, and institutional constraints that limit integration into host-country labour markets (Aleksynska & Tritah, 2013; Bratsberg, Raaum, & Røed, 2017; Brenzel & Reichelt, 2018; Han & Hermansen, 2024; Hermansen et al., 2025; Huang & Kathryn, 2019; Ingwersen & Thomsen, 2021; OECD, 2025; Pivovarova & Powers, 2022). Despite extensive evidence on wage penalties and occupational sorting, a fundamental dimension of immigrant disadvantage remains poorly understood: do immigrants perform different tasks than natives within the same jobs, and if so, do these differences reflect genuine skill deficits or unequal treatment in task assignment? This question is essential for understanding whether disadvantage originates primarily in pre-market human capital differences or persists through post-market constraints within workplaces.

Distinguishing between skill-driven and discrimination-driven task allocation is critical for integration policy. If immigrants and natives in similar jobs are systematically assigned to different bundles of tasks, with immigrants performing fewer cognitively demanding activities even after accounting for measured proficiency, this would suggest that disadvantage persists through workplace practices. Such within-job task segregation could reflect discriminatory assignment, imperfect recognition of foreign skills, language barriers that restrict access to interactive work, or organisational routines that limit immigrant mobility within firms. In this case, policy would need to target workplace regulation and anti-discrimination enforcement. Alternatively, if task differences disappear once workers' cognitive proficiency is accounted for, this would indicate that apparent task downgrading is skill-mediated rather than structurally imposed. This interpretation would redirect policy emphasis toward skill development, credential recognition, and language training. Empirical evidence distinguishing these channels has been limited by the absence of data combining direct skill assessments with detailed information on work content.

This paper overcomes these data challenges by exploiting unique features of the Programme for the International Assessment of Adult Competencies (PIAAC) Cycle 2 (2018-2023), the most recent wave that has seen limited application to migration research. PIAAC provides both direct assessments of literacy and numeracy proficiency and self-reported measures of task use at work across a large set of countries. This combination enables us to examine how measured skills translate into task performance and whether task allocation differs between immigrants and natives within narrowly defined jobs. We focus specifically on within-job comparisons, holding occupational content approximately constant, to isolate whether task assignment varies systematically with migrant status conditional on cognitive proficiency.

We implement a three-layer empirical decomposition that progressively isolates the sources of immigrant disadvantage. First, we document overall immigrant-native differences in literacy and numeracy, capturing the combined effects of educational background, skill transferability, and language acquisition. Second, we examine within-job skill gaps by comparing immigrants and natives employed in identical occupation-industry cells, revealing whether immigrants bring lower cognitive proficiency even into observationally similar positions. Third, we analyse within-job task allocation to assess whether immigrants perform systematically different bundles of abstract, routine, and manual tasks than natives in the same jobs, and crucially, whether these differences persist after conditioning on measured skills. This sequential approach is essential because it distinguishes between three conceptually distinct mechanisms: pre-market skill deficits, occupational sorting on the basis of those deficits, and residual task assignment conditional on both job placement and proficiency. Only the third mechanism, operating conditional on skills, would constitute evidence of unequal treatment within jobs.

Our empirical strategy exploits within-job variation by constructing narrowly defined occupation-industry cells using ISCO 2-digit occupations crossed with ISIC 1-digit industries. We compare workers within these cells to hold job content approximately constant. While occupations mask substantial heterogeneity in average task levels (Bittarello, Kramarz, & Maître, 2024), our design isolates whether task allocation within jobs varies systematically with migrant status. We construct harmonised indices of abstract, routine, and manual task use from PIAAC's Skill Use at Work module. Our task classification builds on and extends the approach of De La Rica, Gortazar, and Lewandowski (2020), incorporating a broader range of cognitive, interpersonal, and numerical indicators aligned with Cycle 2's enhanced measurement framework. Crucially, we control for both absolute cognitive proficiency (literacy and numeracy scores) and relative skill position within the job (deviations from job-cell means), allowing us to separate skill-driven task allocation from potential discrimination. If task assignment responds efficiently to cognitive proficiency, controlling for within-job skill positioning should eliminate observed task gaps. If instead gaps persist conditional on skills, this would indicate discriminatory assignment or organisational barriers.

We make three contributions to the literature on immigrant integration and task-based inequality. First, we provide the first systematic evidence that immigrant-native task gaps within jobs are largely explained by skill deficits rather than discriminatory assignment, redirecting policy attention from workplace assignment practices toward skill development and credential recognition. Second, we introduce a unified decomposition framework that jointly examines skill differences, within-job skill gaps, and within-job task allocation using harmonised cross-national data, enabling us to trace immigrant disadvantage across interconnected labour market stages and quantify the relative importance of occupational sorting versus within-job positioning. Third, we extend existing PIAAC-based task classifications to Cycle 2, incorporating enhanced coverage of cognitive and interpersonal work activities and providing the first analysis of immigrant task allocation using the improved measurement framework implemented after 2018.

Our main results reveal a coherent pattern across all three analytical layers. Immigrants display substantial disadvantages in literacy and numeracy of approximately 35 to 40 points (0.6 to 0.8 standard deviations) that persist across age groups and education levels. Occupational sorting accounts for part of these differences, but even among workers performing similar jobs, immigrants retain meaningful skill deficits of 24 to 30 points (approximately 0.5 to 0.6 standard deviations). These within-job skill gaps translate directly into reduced performance of cognitively demanding tasks. Immigrants in the same occupation-industry cells perform approximately 0.2 to 0.3 standard deviations fewer abstract and routine tasks than natives. However, once we condition on within-job literacy and numeracy deviations, these task gaps become small and statistically insignificant. In contrast, manual task use shows no systematic immigrant-native differences, either unconditionally or after controlling for skills.

Three findings are particularly novel. First, approximately 70 to 75 percent of overall immigrant-native skill gaps persist within narrowly defined jobs, indicating that occupational sorting accounts for at most 25 to 30 percent of total disadvantage. This quantitative decomposition reveals the limited scope of policies targeting job access alone. Second, the complete disappearance of task gaps once we condition on within-job skills provides the first direct evidence that task assignment responds to cognitive proficiency rather than to immigrant status per se. This rules out systematic discrimination in access to cognitively demanding work conditional on skill levels. Third, the null result for manual tasks, which are insensitive to cognitive proficiency, serves as a validation check: if unobserved discrimination or organisational barriers were driving task allocation, we would expect similar patterns across all task types. The fact that disparities emerge only for cognitive tasks and are fully explained by cognitive proficiency differences indicates that labour markets allocate tasks largely on the basis of workers' relevant capabilities. Taken together, the evidence highlights skill acquisition and recognition, not workplace task assignment, as the key margins for improving labour market integration.

Our findings contribute to two interconnected literatures. First, we advance research on task-based approaches to labour market inequality. Recent evidence by Bittarello et al. (2024) demonstrates that task assignment within occupations is endogenous, responding to local labour market conditions and skill supply. Our study extends this perspective to immigrant-native comparisons, showing that within-job task differentiation primarily reflects skill heterogeneity rather than organisational or discriminatory constraints. This complements broader evidence that technological and organisational change has increased the value of abstract and interactive tasks in modern labour markets (Acemoglu & Restrepo, 2018; Autor, 2019; Lewandowski, Park, Hardy, Du, & Wu, 2022). We show that immigrants' lower participation in these high-value activities reflects skill composition rather than exclusionary assignment, though restricted access to complex tasks may still limit on-the-job learning and reinforce disadvantage over time.

Second, we contribute to the immigrant labour market integration literature by providing the first systematic analysis of within-job task allocation using internationally comparable data. While Storm (2022) finds that immigrants are more likely to perform manual and routine tasks and less likely to engage in interactive work even after controlling for education and language proficiency, and Haas, Lucht, and Schanne (2013) show that migrants and natives are imperfect substitutes within firms, neither study directly measures cognitive skills or implements within-job comparisons that hold occupational content constant. Our within-job design, combined with PIAAC's direct assessments of literacy and numeracy, enables sharper identification of whether observed task differences reflect genuine productivity gaps or unequal treatment. By showing that task gaps are primarily skill-mediated, we reconcile the persistence of wage and job-quality disparities with limited evidence of direct discrimination in task assignment.

Our approach integrates two foundational paradigms in labour economics. The human capital framework (Becker, 1964; Mincer, 1974) views wages and employment outcomes as determined by workers' productive skills, shaped by education, training, and experience. From this perspective, immigrant-native gaps arise mainly from differences in skill endowments and imperfect cross-border transferability of human capital. In contrast, task-based models (Acemoglu & Autor, 2011; Autor & Handel, 2013; Autor, Levy, & Murnane, 2003; D'Amuri & Peri, 2014; Deming, 2017; Gathmann & Schönberg, 2010; Peri & Sparber, 2009) emphasize how workers' skills are mapped into productive activities within firms. The structure of work, specifically what tasks are done and by whom, adjusts endogenously to technology and available skill supplies. Combining these perspectives implies that immigrant disadvantage may reflect both differences in cognitive proficiency and the way organisations allocate tasks conditional on these differences. Crucially, the two frameworks generate distinct empirical predictions.

If task differentiation reflects discriminatory assignment or structural barriers, gaps should persist even after conditioning on measured proficiency. If instead task allocation responds efficiently to genuine skill differences, controlling for literacy and numeracy should eliminate observed gaps. Our findings support the latter interpretation, indicating that labour markets allocate tasks largely on the basis of cognitive capacity rather than migrant status per se.

The remainder of the paper proceeds as follows. Section 2 describes the data, measurement of skills and tasks, and empirical strategy. Section 3 presents results on overall skill gaps, within-job skill differences, and within-job task allocation. Section 4 discusses implications and concludes.

2 Data and Methodology

2.1 Data and Sample Selection

We draw on data from the Programme for the International Assessment of Adult Competencies (PIAAC), a large-scale international survey coordinated by the OECD to assess adults' cognitive skills and their use in everyday life and work. PIAAC provides direct assessments of literacy, numeracy, and problem-solving in technology-rich environments, alongside rich background information on education, employment, and demographic characteristics (*Survey of Adult Skills 2023 Technical Report*, 2025). Of particular relevance to our analysis is the Skill Use at Work module, which records the frequency with which respondents engage in a range of cognitive, interactive, and manual activities in their current jobs. This combination of direct skill assessments and detailed task-use measures enables us to examine how cognitive proficiency translates into work content and whether task allocation differs between immigrants and natives within comparable jobs.

Our empirical analysis relies on Cycle 2 of PIAAC, conducted between 2018 and 2023, which includes both newly participating countries and substantial updates to the conceptual and psychometric framework. Cycle 2 improvements are particularly valuable for our research question. Enhanced measurement of information-processing and technology-related tasks better captures the cognitive dimensions where immigrant-native gaps may be most pronounced. Expanded coverage of social and communication tasks enables finer distinctions between abstract and routine work. Improved scaling for low-performing adults reduces measurement error at the lower end of the proficiency distribution, where immigrants are disproportionately represented. These refinements strengthen the reliability of indicators used to analyze task composition and potential disparities between immigrant and native workers.

We analyze eight European countries from PIAAC Cycle 2: Austria, Czechia, France, Germany, Italy, Latvia, Poland, and Spain. These countries provide complete information on migration background, detailed occupational codes (ISCO 2-digit), and unrestricted age and education variables necessary for our analysis. We access Scientific Use Files (SUFs) for Austria and Germany, which provide finer granularity on age, education, and occupational codes than the corresponding Public Use Files, and Public Use Files (PUFs) for the remaining six countries. Other Cycle 2 countries suppress or coarsen key variables in the PUFs for confidentiality reasons, preventing construction of harmonized job cells and consistent identification of immigrant status.[1] We restrict the sample to adults aged 16 to 64

[1] PIAAC Public Use Files are available at `https://www.oecd.org/skills/piaac/data/`. Scientific Use Files for Austria and Germany require application through Statistics Austria and the German Federal Statistical Office's Research Data Centre (FDZ).

years who report being employed at the time of the interview, ensuring a consistent focus on the core working-age population across countries. This results in an analytical sample of 20,323 respondents, of whom 2,614 (12.86%) are foreign-born. Appendix Table A1 reports descriptive statistics.

Our analysis compares workers within narrowly defined jobs, which we define as occupation-industry cells constructed by crossing ISCO 2-digit occupations with ISIC 1-digit industries. Henceforth, we refer to these cells as job cells. This definition balances the need to capture systematic variation in task content across industries while retaining sufficiently large and stable cell sizes across countries in the PIAAC data. Each respondent is assigned to a single job cell, and all job-level task and skill measures are computed within that cell. This within-job comparison strategy follows the logic emphasized by Bittarello et al. (2024) and De La Rica et al. (2020), who show that workers classified into the same occupation may perform meaningfully different tasks depending on the job context. By holding both occupation and industry constant, we isolate variation in task allocation and skill utilization that occurs within observationally similar employment positions. We identify 665 distinct job cells across the eight countries, with an average cell size of 270 workers. Approximately 56.5 percent of job cells contain both immigrants and natives, enabling direct within-cell comparisons.[2] As robustness checks, we re-estimate core specifications using alternative definitions, including ISCO 2-digit $\times$ ISIC 2-digit cells.

2.2 Measurement of Skills and Tasks

To capture within-job task heterogeneity, we construct three indices reflecting abstract, routine, and manual task use based on harmonized Skill Use at Work items. Abstract tasks capture cognitively intensive and non-routine activities such as problem solving, advanced reading and writing, analytical reasoning, influencing others, and complex numerical work. Routine tasks include structured information-processing activities such as organizing and planning work, standard reading and writing, basic numerical operations, teaching, and regular information exchange with colleagues. Manual tasks capture physical, sensory, and fine-motor activities such as working physically for long periods and using hands or fingers. Each index is derived from the first principal component of the corresponding item set to enhance comparability and mitigate measurement error. For abstract tasks, the first principal component explains 41.7 percent of total variance across items; for routine tasks, 31.9 percent; and for manual tasks, 72.7 percent. All indices are standardized within countries (mean 0, standard deviation 1) to preserve cross-national comparability in job-cell averages while allowing within-country interpretation of individual deviations. Table 1 presents the complete mapping of PIAAC Cycle 2 items to task domains.

[2] Poland contributes a large number of native observations but very few immigrants (less than 1% of the Polish sample). We retain Poland because it improves precision of baseline estimates and job-cell means without biasing the immigrant coefficient, which is identified through country fixed effects primarily from countries with substantial immigrant populations. All main results are quantitatively unchanged when Poland is excluded.

Table 1 **Allocation of PIAAC Skill Use at Work Items to Task Domains**

Task domain	**PIAAC Cycle 2 items**
Abstract	Solving complex problems Influencing people Negotiating with people Reading professional journals, publications, newspapers or magazines Reading financial statements Reading books Writing reports Writing articles Undertaking calculations Preparing charts, graphs or tables Using advanced mathematics or statistics
Routine	Planning own activities Organising own time Teaching people Giving presentations Reading directions or instructions Reading letters, memos or e-mails Writing letters, memos or e-mails Filling in forms Using maps, plans or GPS Undertaking measurements Solving simple problems Cooperating with co-workers Sharing work-related information Reading manuals or reference materials
Manual	Working physically for long periods Using hands or fingers

Note: The table reports the PIAAC "Skill Use at Work" items used to construct the abstract, routine, and manual task indices.

Our classification of PIAAC Skill Use at Work items into abstract, routine, and manual domains builds directly on the now-standard tripartite distinction used in the task-based literature and, in particular, on the PIAAC-based strategy of De La Rica et al. (2020). Their contribution demonstrates that task indices constructed from PIAAC at the worker level are well validated relative to earlier measures, closely aligned with the conceptual framework of non-routine abstract, routine, and manual work originating in Autor and Handel (2013) and the job-polarization literature (e.g. Goos, Manning, & Salomons, 2014). Using cross-country PIAAC data, De La Rica et al. (2020) show that their abstract, routine, and manual indices display the expected gradients across occupations and are strongly and systematically associated with wages, thus providing external validation of the underlying task constructs. A strand of empirical work has adopted similar groupings of PIAAC items to measure task content within occupations and across countries, confirming that these dimensions capture meaningful cross-sectional and cross-country variation in the organization of work (Kawaguchi & Toriyabe, 2022).

Our approach is explicitly anchored in this framework but extends it systematically. We construct our indices using a richer set of PIAAC items from the Skill Use at Work module than De La Rica et al. (2020), incorporating additional reading, writing, calculation, problem-solving, and interpersonal items that are conceptually aligned with the abstract and routine dimensions. Specifically, we add 6 items to the abstract domain, including reading professional journals and publications, reading financial statements, writing reports and articles, undertaking calculations, preparing charts and graphs, and using advanced mathematics or statistics. For routine tasks, we incorporate 9 additional items, such as planning and organizing own activities, teaching people, giving presentations, reading manuals and reference materials, and using maps, plans, or GPS. This yields task measures covering 11 items for abstract tasks (compared to 5 in De La Rica et al.), 14 items for routine tasks (compared to 5), and 2 items for manual tasks (unchanged at 2). This richer task measurement strategy provides more elaborate and inclusive coverage of both information-processing and interaction-intensive aspects of abstract and routine work, rather than relying on a narrower subset of indicators. In combination with the within-job perspective and rigorous weighting procedures described below, this enhanced classification enables more detailed assessment of within-job variation in task composition across countries and industries.

2.3 Estimation Strategy

Our empirical strategy proceeds in three steps, corresponding to the three-layer decomposition outlined in the introduction. First, we estimate overall immigrant-native skill gaps in literacy and numeracy and test for life-cycle heterogeneity. Second, we examine within-job skill gaps to assess whether immigrants are underskilled relative to the average proficiency level in their job cells. Third, we analyze within-job task gaps to determine whether task assignment differs between immigrants and natives conditional on measured skills. This sequential approach isolates where immigrant disadvantage originates: in pre-market skill formation, in occupational sorting, or in within-job allocation of work activities.

We begin by estimating overall immigrant-native gaps in cognitive proficiency. Our research question is whether immigrants have lower literacy and numeracy proficiency than natives, and if so, whether this gap varies across the life cycle or by observable characteristics. We estimate:

$$\text{Skill}_{id} = \alpha_k + \beta \cdot \text{Immigrant}_i + X_i'\gamma + \delta_c + \varepsilon_i, \tag{1}$$

where $d \in \{\text{literacy}, \text{numeracy}\}$ and Skill_{id} denotes the test-based skill level of individual i in domain d. The indicator Immigrant_i equals one for foreign-born individuals. The vector X_i includes demographic controls (gender, age-group dummies, household composition, and education), which isolate the immigrant coefficient β from compositional differences in observed characteristics, enabling interpretation as the gap among observationally similar workers. The term δ_c represents job-related controls: ISCO 2-digit occupation indicators, ISIC 1-digit industry indicators, contract type (permanent vs. temporary), and weekly work hours. These controls account for level differences in skill requirements and work arrangements across jobs. Country fixed effects α_k absorb mean differences across national labor markets. The coefficient β is identified from cross-sectional variation, comparing immigrants and natives with similar observed characteristics and employment attributes. The specification is estimated separately for each plausible value $m = 1, \ldots, 10$, and coefficients are combined using Rubin's rules to account for measurement uncertainty in latent proficiency.

To assess whether immigrant-native skill differences vary systematically over the life cycle, we augment the baseline model with interactions between immigrant status and age-group indicators. We distinguish between three potential mechanisms. Assimilation predicts narrowing gaps with age through on-the-job learning and language acquisition. Negative selection into migration at older ages predicts widening gaps. Cohort effects, such as improvements in educational systems in origin countries, predict that younger immigrant cohorts have smaller gaps. We test these predictions by estimating:

$$\text{Skill}_{id} = \alpha_k + \omega\,\text{Immigrant}_i + \sum_a \omega_a\,(\text{Immigrant}_i \times \text{AgeGroup}_{ia}) + X_i'\chi + \varepsilon_i, \tag{2}$$

where the coefficients ω_a trace the evolution of the immigrant-native skill gap across age groups.

We next compare workers performing similar jobs to assess whether immigrants are systematically underskilled relative to natives in the same job cells. To quantify how a worker's proficiency compares with the skill levels typically observed in their job, we compute job-cell literacy and numeracy means using all ten plausible values (PVs). For each plausible value $m = 1, \ldots, 10$, we compute the weighted mean proficiency within each job cell c using PIAAC sampling weights. These ten PV-specific means are then averaged to obtain multiple-imputation-consistent estimates of job-level skill requirements, following the standard OECD methodology for combining plausible values (see *Survey of Adult Skills 2023 Technical Report*, 2025). Let S_{im} denote worker i's plausible value for literacy or numeracy skill, and let $\overline{S}_{c(i)}$ denote the corresponding mean for worker i's job cell $c(i)$. We define the within-job skill gap at the PV level as:

$$\text{SkillGap}_{im} = S_{im} - \overline{S}_{c(i)}. \tag{3}$$

Positive values indicate that the worker's latent skill exceeds the level typical in their job, while negative values indicate relative underskilling. Because PIAAC's plausible-value methodology already incorporates measurement uncertainty through Bayesian imputation, we do not apply additional shrinkage to proficiency variables. Unlike task measures, which are subject to reporting heterogeneity, proficiency scores are based on extensive direct assessments. This approach is consistent with established practice in the PIAAC literature (e.g., Han & Hermansen, 2024; Kawaguchi & Toriyabe, 2022).

Because the dependent variable SkillGap_{id} is constructed as the deviation from the job-cell mean (Equation 3), job-cell fixed effects are mechanically absorbed. The specification becomes:

$$\text{SkillGap}_{id} = \alpha_k + \lambda \cdot \text{Immigrant}_i + X_i'\pi + u_i. \tag{4}$$

The coefficient λ captures the average within-job immigrant-native skill differential, identified from the fact that immigrant status varies within job cells. A negative coefficient indicates that immigrants, on average, have lower proficiency than natives performing the same jobs.

We then turn to task allocation within jobs to test whether immigrants systematically perform different sets of tasks than observationally similar natives, and whether these differences persist after conditioning on measured skills. We construct job-level task indices based on respondents' self-reported frequency of performing cognitive and manual activities at work. Unlike proficiency scores, which are assessed through extensive testing, these task-use indicators are prone to idiosyncratic noise due to reporting heterogeneity and small sample sizes within certain job cells. We therefore apply empirical Bayes shrinkage to stabilize cell-level task estimates. The intuition is straightforward: we partially pool each job cell's raw task mean toward its occupation's mean, with the degree of pooling inversely proportional to the cell's effective sample size. Large, precisely measured cells are shrunk minimally; small, noisy cells are pulled substantially toward the occupation benchmark. This approach enhances cross-country comparability and reduces the influence of sampling variation and outliers (see Autor & Handel, 2013; Goos et al., 2014). Formally, stable job-level task intensities are estimated as

$$\hat{T}_{ck}^{\text{shrunk}} = \lambda_c \, \bar{T}_{ck}^{\text{raw}} + (1 - \lambda_c) \, \bar{T}_{ok}, \tag{5}$$

where $k \in \{\text{abstract}, \text{routine}, \text{manual}\}$, $\bar{T}_{ck}^{\text{raw}}$ is the weighted mean task-use measure in job cell c, $\bar{T}_{ok}$ is the ISCO 2-digit occupation mean, and $\lambda_c = n_c^*/(n_c^* + \kappa)$ is a shrinkage factor based on the effective sample size n_c^* adjusted for design effects using Kish weights. The constant κ governs the degree of pooling; we set $\kappa = 10$ in our baseline specification and verify robustness to alternative values. In our data, λ_c ranges from approximately 0.3 for small cells (heavily shrunk toward occupation mean) to 0.9 for large cells (minimal shrinkage). Similar shrinkage methods have been widely adopted in applied microeconomics to improve precision of cell-level statistics derived from survey or administrative data while maintaining unbiased population averages (see Chetty, Friedman, & Rockoff, 2014; Chetty, Hendren, Kline, & Saez, 2014).

For worker i, the within-job task deviation is defined as

$$\text{TaskGap}_{ik} = T_{ik} - \hat{T}_{c(i)k}^{\text{shrunk}}, \tag{6}$$

with positive (negative) values indicating that the worker performs more (less) of a given task than is typical in their job cell. After computing these deviations, we standardize them by the job-cell-specific standard deviation of task use for comparability across jobs and task domains. This standardization accounts for heterogeneity in task variance across jobs: some occupations have wide task dispersion (e.g., managers performing diverse activities), others narrow (e.g., assembly workers with standardized routines). Standardization ensures coefficients are interpretable as within-job effect sizes, enabling meaningful comparisons across structurally different employment positions.

By aligning both skill gaps and task gaps within the same occupation-industry framework and weighting scheme, this two-step procedure ensures that proficiency and task deviations are directly comparable across countries and analytical samples. This design allows us to separate disparities arising from differences in skill endowments from those stemming from variation in task allocation within otherwise similar jobs. We estimate:

$$\text{TaskGap}_{i\tau} = \alpha_k + \rho^{(\tau)} \cdot \text{Immigrant}_i + X_i'\kappa^{(\tau)} + \Omega_i'\phi^{(\tau)} + e_i, \tag{7}$$

where $\tau \in \{\text{abstract}, \text{routine}, \text{manual}\}$ indexes task domains. The vector Ω_i contains skill controls, specified in three ways across models to progressively condition on proficiency: (i) empty (baseline specification), (ii) absolute literacy and numeracy proficiency, or (iii) within-job skill gaps (deviations from job-cell means as defined in Equation 3). This progressive conditioning isolates whether task differences reflect absolute skill levels, relative position within jobs, or residual factors unrelated to measured cognitive proficiency. The coefficient $\rho^{(\tau)}$ therefore distinguishes whether disparities in task assignment reflect differences in productivity-relevant skills or unequal treatment conditional on those skills. Because task deviations are standardized by the job-cell-specific standard deviation (as described above), coefficients are interpreted in within-job standard deviation units, enabling comparability across task domains and occupations.

We further examine life-cycle variation in within-job outcomes by applying the age-interaction specification from Equation (2) to both SkillGap_{id} and each of the task-gap measures $\text{TaskGap}_{i\tau}$. This allows us to assess whether age-related patterns in immigrant-native disparities arise from differences in absolute proficiency, sorting across jobs, or task allocation within jobs.

All analyses apply design-based sampling weights supplied by the OECD to correct for differential probabilities of selection and nonresponse. Point estimates are computed using final population weights to ensure national representativeness, while standard errors are obtained with the 80 Fay-balanced replicate weights provided in PIAAC. This replication approach accounts for PIAAC's complex multi-stage design, including stratification and clustering, and yields unbiased variance estimates under the survey design. For cognitive skill outcomes (Equations 1, 2, and 4), we implement the multiple-imputation framework recommended by the OECD. PIAAC reports cognitive proficiency as ten plausible values (PVs) per respondent, which are multiple imputations drawn from the posterior distribution of proficiency conditional on item responses, rather than single point estimates. We estimate each model separately for all ten plausible values and combine coefficients and standard errors using Rubin's rules, which properly accounts for both sampling variance and measurement error in proficiency. This approach is standard in the PIAAC literature (e.g., Han & Hermansen, 2024; Kawaguchi & Toriyabe, 2022) and ensures that our inferences are not biased by measurement uncertainty in the latent skill constructs. Job-cell means for skills are computed by first calculating weighted means within each cell for each plausible value separately, then averaging across the ten PV-specific means. This ensures that job-level benchmarks incorporate the full measurement uncertainty inherent in latent cognitive proficiency. For task outcomes (Equation 7), we apply final population weights and replication weights but do not use multiple imputation, as task-use variables are directly observed rather than latent.

3 Empirical Results

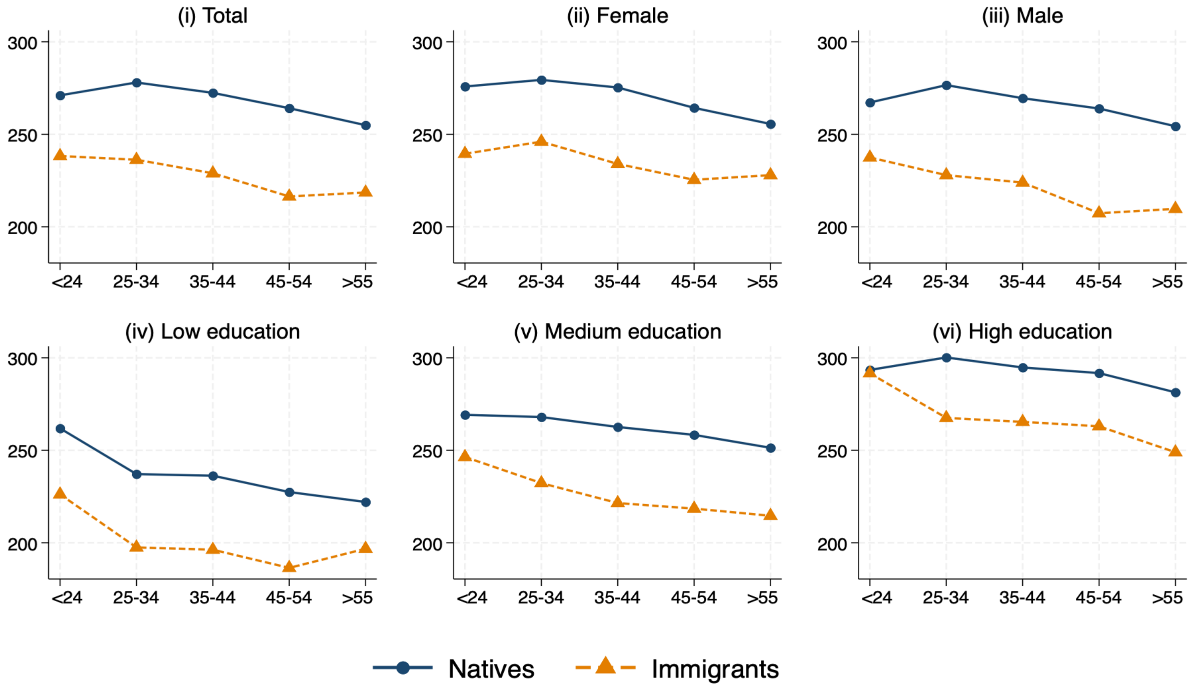
We begin by documenting overall immigrant-native skill gaps, then examine whether these gaps persist when comparing workers within the same occupation-industry cells (Section 3.2), and finally analyze whether within-job skill differences translate into differential task allocation (Section 3.3).

3.1 Overall Immigrant-Native Skill Gaps

Immigrants face substantial cognitive skill disadvantages of 35 to 40 points on PIAAC's literacy and numeracy assessments, equivalent to 0.7 to 0.8 standard deviations (Figures 1 and 2, panels i). To contextualize: a 35-point gap approximates the difference between completing upper secondary education (ISCED 3) and obtaining a bachelor's degree (ISCED 6) among natives. The average immigrant with tertiary qualifications scores at levels comparable to natives with only secondary credentials. The OECD estimates that a one-standard-deviation increase in literacy proficiency is associated with 10 to 15 percent higher wages (OECD, 2013), suggesting that immigrant skill gaps of this magnitude could explain a substantial portion of observed immigrant-native wage disparities in European labor markets (Hermansen et al., 2025).

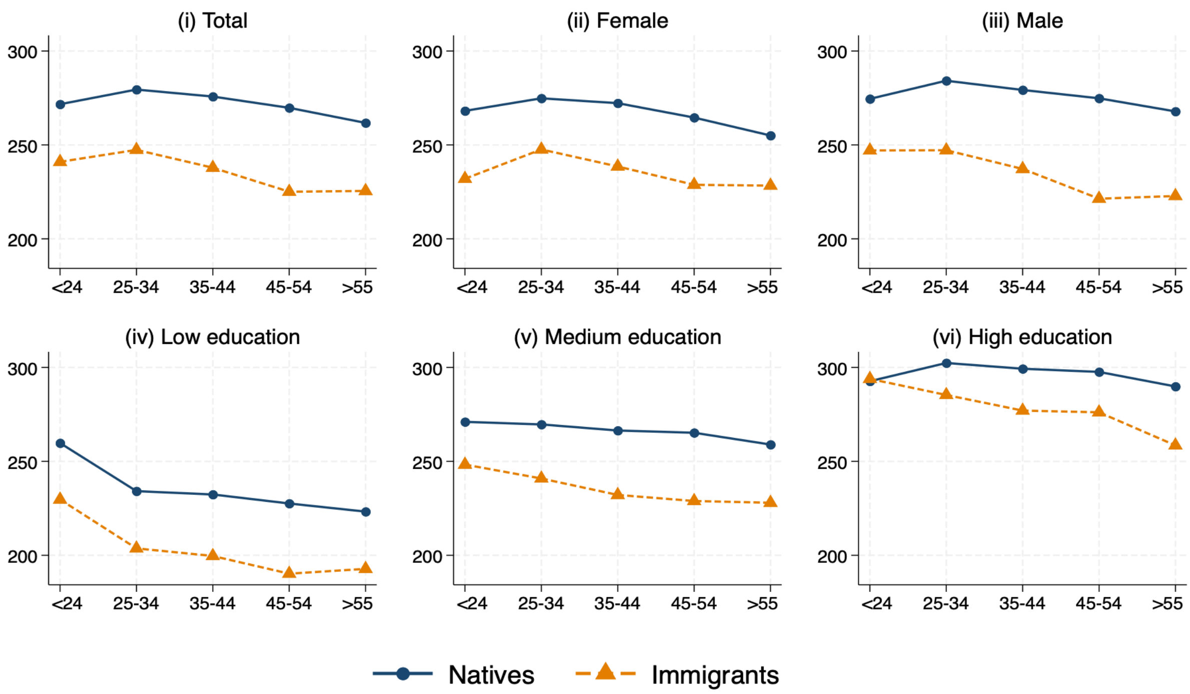
Figures 1 and 2 present average proficiency by age and migrant status. In the pooled sample (panel i), immigrants score approximately 40 to 50 points below natives in literacy and 30 to 40 points below in numeracy across all age groups. Both groups exhibit the standard inverted-U age-skill profile, with broadly parallel trajectories suggesting that immigrant-native differentials reflect persistent proficiency differences established before labor market entry rather than diverging accumulation patterns over the life cycle.

Figure 1 **Average literacy skills by origin, age group, gender and education – Weighted average estimates**



Notes: Final population weights are used in all estimations.
Source: PIAAC Cycle 2 data. Own calculations.

Figure 2 **Average numeracy skills by origin, age group, gender and education – Weighted average estimates**



Notes: Final population weights are used in all estimations.
Source: PIAAC Cycle 2 data. Own calculations.

Subgroup analysis reveals important heterogeneity that is confirmed econometrically in Appendix Tables A2 and A3. Among men, the fully specified model yields gaps of 32.0 points in literacy (s.e. =

4.2, $p < 0.001$) and 31.5 points in numeracy (s.e. = 4.1, $p < 0.001$). Among women, gaps are smaller and statistically insignificant: 3.6 points in literacy (s.e. = 5.1, $p = 0.48$) and 8.0 points in numeracy (s.e. = 4.9, $p = 0.10$). This gender difference, visible in Figure panels ii and iii where immigrant and native female profiles are nearly parallel with constant gaps while male immigrant proficiency declines more steeply with age, suggests that female migrants are positively selected on cognitive skills, consistent with concentration in healthcare and service sectors where cognitive abilities are directly screened (Schieckoff & Sprengholz, 2021).

Educational stratification (Figure panels iv-vi) uncovers the most striking pattern. Among the highly educated (panel vi), young immigrants (under 24) score only marginally below natives with gaps of 5 to 10 points, but this near-parity disappears rapidly with age. By ages 25 to 44, gaps widen to 35 to 45 points. Among the low and medium educated (panels iv-v), gaps are substantial at all ages (20 to 40 points) and remain relatively stable across the life cycle. The regression estimates with age interactions corroborate these descriptive patterns: among the highly educated, young immigrants under 24 exhibit minimal gaps of 8 to 11 points ($p > 0.05$), but gaps widen dramatically to 40 to 43 points among those aged 25 to 44 ($p < 0.001$). Across education groups, gaps are smallest among the low-educated (14 points literacy, 18 points numeracy, $p > 0.10$), largest among the medium-educated (31 points both domains, $p < 0.01$), and intermediate among the highly educated (30 points literacy, 28 points numeracy, $p < 0.01$). The small gaps among the low-educated likely reflect floor effects in both cognitive proficiency and job skill requirements.

The widening gaps among highly educated immigrants over the life cycle suggest three possible mechanisms, each with distinct policy implications. First, skill mismatch and atrophy: highly educated immigrants may face greater difficulties securing skill-appropriate employment, leading to cognitive skill depreciation from underutilization (Chiswick & Miller, 2009). Second, selective return migration: highly skilled immigrants who successfully integrate may be more likely to remain while those experiencing difficulties return to origin countries, generating an increasingly negatively selected population at older ages (Borjas & Bratsberg, 1996; Dustmann & Weiss, 2007). Third, cohort effects: younger immigrant cohorts may be drawn from improved educational systems or represent more positively selected migrants (Bratsberg, Raaum, & Røed, 2012). The absence of convergence among low- and medium-educated immigrants provides clear evidence against strong assimilation effects in these groups, underscoring the importance of formal credential recognition and structured retraining programs.

Appendix Figures A1 and A1 illustrate substantial cross-country variation, though the direction is uniformly negative. Germany and Austria exhibit the largest disparities (45 to 50 points), while Spain and Ireland show more modest gaps (25 to 30 points), likely reflecting differences in immigrant composition: Germany and Austria draw substantially from Turkey and the former Yugoslavia, while Spain and Ireland receive larger shares from Latin America and Anglophone countries respectively, where linguistic proximity facilitates skill transferability.[3] The universally negative direction across all countries strengthens the inference that cognitive disadvantage is a general feature of immigration to Europe rather than specific to particular contexts.

Table 2 complements the descriptive evidence with regression-based estimates implementing the full

[3] Poland contributes 3,876 native observations but only less than 1 percent of the sample is foreign-born. We retain Poland because it improves precision without biasing the immigrant coefficient, which is identified through country fixed effects.

Table 2 **Cognitive skill gaps – Weighted OLS regression results**

	Literacy			Numeracy		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-44.597***	-38.381***	-35.699***	-39.513***	-32.146***	-29.812***
	(3.791)	(3.776)	(3.924)	(3.729)	(3.775)	(3.969)
Female		0.153	-0.573		-12.187***	-11.175***
		(2.107)	(2.815)		(2.348)	(3.033)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.		-7.342*	-6.108		-8.852**	-7.182
		(3.984)	(4.481)		(4.278)	(4.415)
35 - 44 y.o.		-11.415**	-9.800*		-12.444**	-10.272**
		(4.827)	(5.214)		(4.971)	(5.168)
45 - 54 y.o.		-16.810***	-15.722***		-15.725***	-14.071***
		(4.687)	(5.377)		(4.759)	(5.154)
55 y.o. and above		-25.952***	-25.341***		-24.371***	-23.106***
		(5.401)	(5.801)		(5.282)	(5.442)
Cohabiting		4.403	3.341		6.361**	5.155*
		(2.951)	(3.126)		(3.009)	(3.120)
Number of children *(base - no children)*:						
One child		-3.014	-2.155		-2.358	-1.625
		(3.290)	(3.507)		(3.335)	(3.627)
Two children		-0.686	-0.487		1.304	1.600
		(3.461)	(3.673)		(3.693)	(3.925)
Three children		-4.019	-2.958		-1.943	-0.716
		(4.970)	(5.208)		(4.573)	(4.859)
Four and more children		-6.932	-4.417		-6.993	-4.219
		(6.221)	(6.724)		(6.075)	(6.679)
Education *(base - ISCED 1 and below)*:						
ISCED 2		24.681***	21.998***		28.584***	26.475***
		(8.266)	(8.257)		(9.010)	(9.008)
ISCED 3		43.083***	34.559***		51.600***	43.552***
		(7.691)	(7.627)		(8.780)	(8.822)
ISCED 4		61.385***	49.981***		67.495***	57.591***
		(8.306)	(8.369)		(9.059)	(9.459)
ISCED 5		58.363***	45.050***		69.900***	57.122***
		(7.860)	(7.847)		(8.943)	(9.154)
ISCED 6		70.532***	53.460***		81.038***	64.649***
		(8.106)	(8.416)		(9.207)	(9.553)
ISCED 7		83.702***	63.088***		93.137***	72.917***
		(7.157)	(7.504)		(8.194)	(8.595)
Permanent contract			0.871			2.552
			(4.106)			(3.931)
Weekly work hours			-0.087			-0.061
			(0.137)			(0.149)
Occupation			Yes			Yes
Industry			Yes			Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	264.993***	222.148***	249.005***	264.541***	210.738***	257.675***
	(5.189)	(10.047)	(36.741)	(4.304)	(11.372)	(35.865)
N	20323	20323	20323	20323	20323	20323
R-squared	0.136	0.311	0.312	0.123	0.310	0.311

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

set of plausible values and PIAAC's replication weights, following Equation (1) from Section 2.3. Column 1 reports unconditional gaps of 44.6 points in literacy (s.e. = 3.79, p < 0.001) and 39.5 points in numeracy (s.e. = 3.73, p < 0.001), approximately 0.9 and 0.8 standard deviations respectively, representing one of the largest documented immigrant-native skill differentials in the international literature (OECD, 2025).

Adding demographic controls in Column 2 reduces the literacy gap to 38.4 points and the numeracy gap to 32.1 points, indicating that age, gender, education, and household composition explain only 14 percent of the literacy disparity and 19 percent of the numeracy disparity. For context, the difference between primary schooling (ISCED 1) and a master's degree (ISCED 7) among natives is approximately 60 to 70 points. The residual immigrant gap of 35 to 38 points conditional on education, more than half the entire native education range, suggests that formal qualifications substantially overstate skill similarity between immigrants and natives with equivalent credentials.

Controlling for occupation and industry in Column 3 produces minimal additional attenuation. The literacy gap declines from 38.4 to 35.7 points (7 percent), and the numeracy gap from 32.1 to 29.8 points (7 percent), indicating that occupational sorting accounts for at most 20 percent of overall skill disparities. Put differently: eliminating all occupational segregation would leave approximately 80 percent of the skill gap intact.

The conditional immigrant gap, 30 to 36 points after controlling for demographics, education, and occupation, represents proficiency differences not captured by observable characteristics. This residual likely reflects multiple mechanisms: educational quality differences between origin and destination countries (Hanushek & Woessmann, 2008), language barriers beyond reading comprehension (Chiswick & Miller, 2015), negative selection into migration from origin-country skill distributions (Chiquiar & Hanson, 2005), and imperfect measurement equivalence of ISCED classifications across countries. The persistence of gaps even among tertiary-educated immigrants suggests that credential equivalence is a poor proxy for true skill similarity. Traditional approaches that grant equivalence based solely on degree titles may systematically overestimate immigrant human capital. More rigorous assessment mechanisms that directly evaluate competencies may be necessary to accurately match immigrants to appropriate positions.

Three findings motivate our within-job analysis. First, immigrants face large cognitive skill deficits (35 to 40 points, or 0.7 to 0.8 standard deviations) that persist across gender, age-education combinations, and countries. Second, controlling for occupation and industry reduces gaps by approximately 20 percent, suggesting that sorting into lower-skill jobs explains at most one-fifth of the disparity. Third, occupation and industry are coarse categories (ISCO 2-digit, ISIC 1-digit) that mask substantial within-job heterogeneity. Two workers in the same occupation-industry cell may nonetheless differ in cognitive proficiency and perform different roles within their organizations. Section 3.2 examines whether the remaining four-fifths of the skill gap persists when comparing workers performing the same job.

3.2 Within-job skill gaps

Section 3.1 established that occupational sorting accounts for at most 20 percent of immigrant-native skill disparities. We now examine the remaining 80 percent by comparing workers within narrowly defined occupation-industry cells. This within-job comparison holds job content approximately constant, isolating whether skill gaps persist at the point of task performance or primarily reflect sorting into different types of employment. Figures 3 and 4 present within-job skill disparities by measuring individual proficiency relative to the average skill level of workers in the same occupation-industry cell.[4] This distinction between job access and within-job positioning is crucial for policy design: if gaps disappear within jobs, interventions should focus on occupational mobility; if gaps persist within jobs, skill development and credential recognition become primary policy levers.

[4]By construction, deviations from the job-cell mean sum to zero within each cell. However, subgroup averages (immigrants, natives, or specific age groups) need not sum to zero as groups differ in their distribution across job cells and cell means are estimated using the full population.

The central empirical finding is that immigrants score 20 to 30 points below natives within the same jobs in literacy and 15 to 25 points below in numeracy across all age groups (Figure panel i). These within-job gaps represent approximately 65 to 75 percent of the overall skill disparities documented in Section 3.1, indicating that occupational sorting accounts for at most 25 to 35 percent of total inequality. Put differently: even if all occupational segregation were eliminated and immigrants redistributed across jobs to match the native distribution, roughly two-thirds of the aggregate skill gap would remain. This decomposition is central to policy design, as it identifies the relative importance of barriers to job access versus deficits in human capital that persist after job placement.

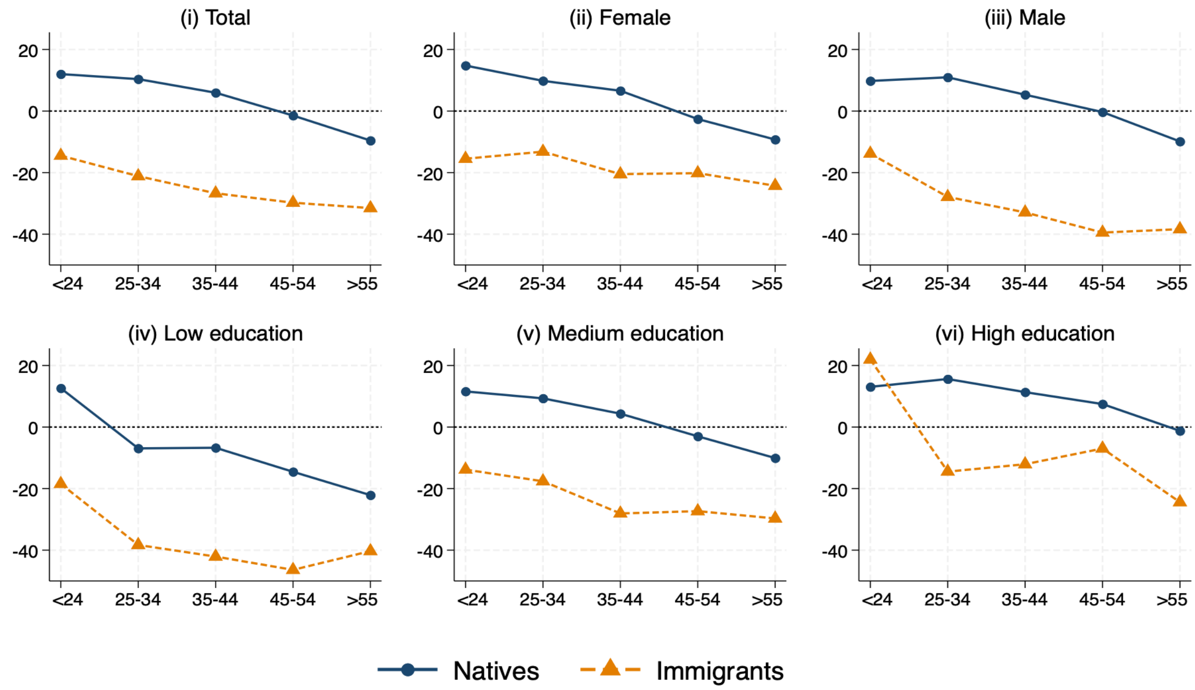
Across gender and education subgroups (Figure panels ii-vi), the patterns observed in Section 3.1 largely carry through to the within-job comparison, though with some notable differences in magnitude. Among men, within-job gaps remain substantial and statistically significant, while among women the disparities are smaller, consistent with positive selection of female migrants. Educational stratification shows that even highly educated immigrants score below natives within the same job cells, indicating that formal credential equivalence does not ensure comparable cognitive proficiency in practice. The exception remains young highly educated immigrants, who achieve near-parity with natives in their jobs, but this advantage dissipates with age.

The persistence of within-job gaps across the life cycle is particularly informative. If immigrants systematically acquired cognitive proficiency through workplace experience at rates comparable to natives, within-job skill positioning should converge over time. Instead, gaps remain relatively stable or widen with age among certain groups, providing no evidence of catch-up through on-the-job learning. This pattern is consistent with evidence that cognitive skills are primarily formed during schooling and early career stages, with limited scope for remediation through unstructured workplace experience alone (Cunha & Heckman, 2007; Heckman, 2006). The implication is that interventions targeting skill development must occur early in the integration process rather than relying on workplace exposure to close proficiency gaps.

Appendix Tables A4 and A5 provide econometric confirmation of these visual patterns using the full PIAAC estimation framework with age interactions. The regression estimates support that within-job gaps are pervasive across all demographic subgroups and validate the magnitudes observed in the figures. Appendix Figures A3 and A4 document cross-country patterns, showing that immigrants score below natives within jobs across all European contexts except Latvia, with magnitudes ranging from 15 and 20 points in Spain and Czechia to 35 and 45 points in Germany and Austria. This cross-national consistency indicates that within-job skill gaps constitute a general feature of immigrant integration rather than reflecting country-specific institutional arrangements, strengthening the case for coordinated policy responses at the European level.

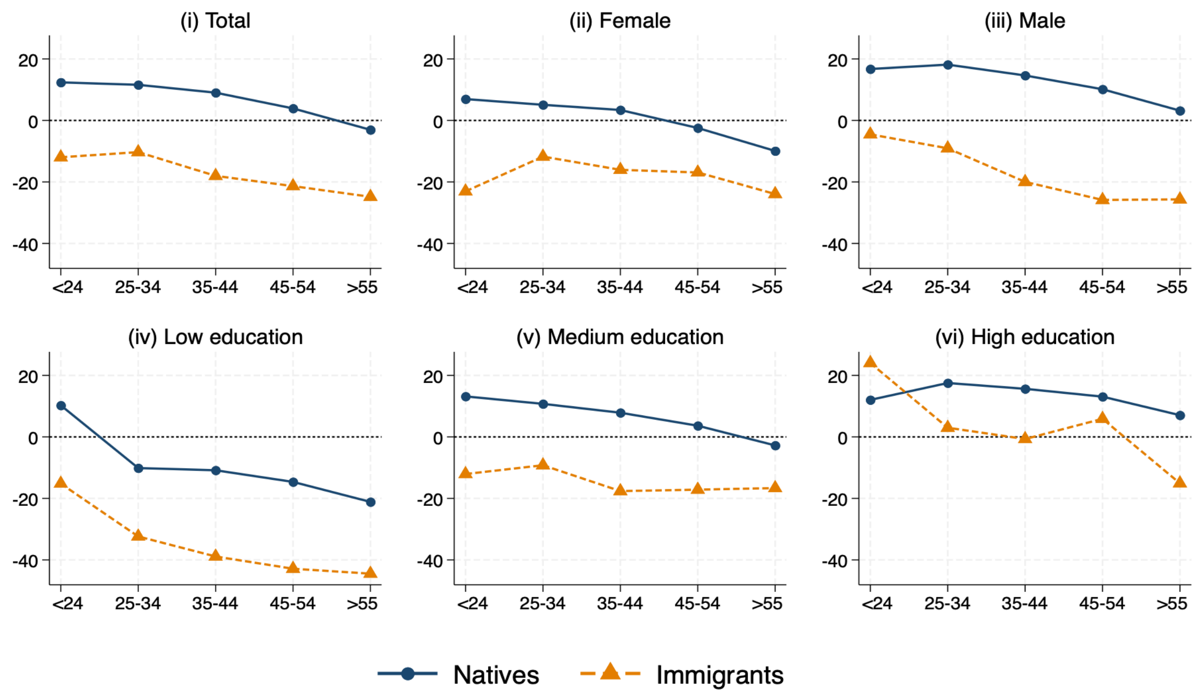
Table 3 presents pooled regression results examining whether immigrants are systematically under-skilled relative to natives performing the same job. The dependent variables are deviations of individual proficiency from job-cell means, constructed as described in Equation (3). Because the dependent variable is defined as a deviation from the job-level mean, occupation and industry fixed effects are mechanically absorbed by construction, ensuring that all identification comes from within-job variation.

Figure 3 **Within-job literacy skill gaps by origin, age group, gender and education – Weighted average estimates**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual skill level and job-average skill level in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

Figure 4 **Within-job numeracy skill gaps by origin, age group, gender and education – Weighted average estimates**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual skill level and job-average skill level in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

In the baseline models (columns 1 and 4), which include only country fixed effects, immigrants score on average 32.4 points lower in literacy (s.e. = 3.7, $p < 0.001$) and 27.6 points lower in numeracy (s.e.

Table 3 **Within-job cognitive skill gaps – Weighted OLS regression results**

	Literacy			Numeracy		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	-32.405***	-29.977***	-30.029***	-27.573***	-24.035***	-23.931***
	(3.743)	(3.829)	(3.807)	(3.560)	(3.739)	(3.726)
Female		0.637	-0.424		-12.011***	-12.627***
		(2.028)	(2.090)		(2.124)	(2.310)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.		-5.727	-4.786		-5.998	-6.044
		(4.219)	(4.406)		(4.359)	(4.359)
35 - 44 y.o.		-9.431*	-8.431*		-9.146*	-9.293*
		(5.004)	(5.116)		(5.149)	(5.109)
45 - 54 y.o.		-15.578***	-14.468***		-12.944**	-13.084***
		(5.088)	(5.237)		(5.041)	(4.979)
55 y.o. and above		-24.893***	-23.909***		-21.887***	-22.110***
		(5.783)	(5.865)		(5.656)	(5.542)
Cohabiting		2.184	2.449		4.420	4.433
		(3.043)	(3.072)		(3.001)	(3.070)
Number of children *(base - no children)*:						
One child		-1.605	-1.639		-0.806	-0.903
		(3.496)	(3.527)		(3.565)	(3.569)
Two children		-0.555	-0.679		1.565	1.422
		(3.699)	(3.717)		(3.975)	(3.991)
Three children		-1.831	-2.075		0.286	0.092
		(5.045)	(5.061)		(4.807)	(4.826)
Four children and more		-2.100	-2.250		-2.386	-2.414
		(6.767)	(6.766)		(6.731)	(6.743)
Education *(base - ISCED 1 and below)*:						
ISCED 2		17.058**	17.305**		21.663***	21.770***
		(7.393)	(7.331)		(7.859)	(7.830)
ISCED 3		23.789***	24.243***		33.191***	33.261***
		(6.964)	(6.854)		(7.751)	(7.671)
ISCED 4		31.802***	32.237***		39.144***	39.105***
		(7.729)	(7.637)		(8.154)	(8.086)
ISCED 5		28.243***	28.867***		41.206***	41.316***
		(7.022)	(6.928)		(8.089)	(7.970)
ISCED 6		29.986***	30.638***		41.586***	41.756***
		(7.048)	(6.950)		(7.921)	(7.851)
ISCED 7		34.141***	34.970***		44.496***	44.815***
		(6.596)	(6.463)		(7.203)	(7.138)
Permanent contract			-0.385			1.946
			(3.821)			(3.576)
Weekly work hours			-0.164			-0.101
			(0.124)			(0.134)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	18.957***	8.419	7.578	18.455***	-2.644	-2.976
	(5.179)	(9.951)	(9.806)	(4.285)	(10.180)	(10.148)
N	20323	20323	20323	20323	20323	20323
R-squared	0.091	0.142	0.143	0.085	0.149	0.150

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

= 3.6, p < 0.001) than natives performing the same job. These coefficients are precisely estimated and highly significant, reflecting both the large sample size and the consistency of within-job gaps across job cells and countries. Comparing these within-job estimates to the overall gaps reported in Table 2 (44.6 points in literacy, 39.5 points in numeracy) reveals that approximately 73 percent of the overall literacy gap and 70 percent of the overall numeracy gap persist within jobs. This quantification is central to interpreting the relative importance of job access versus within-job skill positioning in generating immigrant disadvantage.

Adding demographic controls in columns 2 and 5 attenuates the within-job gaps modestly to 30.0

points in literacy and 24.0 points in numeracy. The fact that controlling for age, gender, education, and household composition reduces within-job gaps by only 7 to 13 percent indicates that compositional differences across immigrants and natives within the same jobs play a limited role. This contrasts with the overall skill gaps in Section 3.1, where demographic controls explained 15 to 20 percent of the disparity. The implication is that, conditional on being employed in a particular job cell, immigrants and natives are more similar in observable characteristics than they are in the overall labor market, yet substantial skill differences remain.

Columns 3 and 6 add job-level characteristics, contract type (permanent vs. temporary) and weekly working hours, which have virtually no effect on the estimated immigrant coefficient. The within-job immigrant disadvantage in the fully specified models is approximately 30 points in literacy and 24 points in numeracy. The stability of the coefficient across specifications provides reassurance that the estimated within-job skill gap is not confounded by differences in employment arrangements or work intensity within job cells. It also suggests that immigrants and natives within the same jobs work under similar contractual conditions, ruling out differential treatment in contract type as an explanation for skill positioning.

Relative to the PIAAC proficiency scale (mean 250, standard deviation 50), these differences correspond to approximately 0.6 standard deviations in literacy and 0.5 standard deviations in numeracy. To contextualize these magnitudes, recall from Section 3.1 that a 35-point gap approximates the difference between completing upper secondary education and obtaining a bachelor's degree among natives. The within-job gaps documented here are slightly smaller but still economically meaningful, suggesting that immigrants and natives performing the same job possess cognitive proficiencies that differ by roughly one educational qualification level. This has direct implications for productivity, task assignment, and wage determination within occupational categories.

The pattern of results closely mirrors the overall immigrant-native skill gaps documented in Section 3.1, both in magnitude (approximately 70-75 percent of overall gaps persist) and in the limited role of demographic controls. This consistency reinforces the interpretation that immigrant cognitive disadvantage is deeply rooted and not primarily an artifact of occupational sorting or compositional differences. Even among workers performing observationally identical jobs, immigrants bring systematically lower cognitive proficiency, pointing to fundamental differences in human capital accumulation, skill transferability, or skill maintenance post-migration.

Most relevant for the next stage of our analysis is the documented existence of substantial within-job skill gaps, which raises a critical question: do these differences translate into systematic variation in task assignment? If immigrants and natives performing the same jobs differ by 0.5 to 0.6 standard deviations in cognitive proficiency, it is plausible that they are assigned different bundles of tasks within those jobs, with immigrants performing less cognitively demanding activities. Alternatively, task allocation within jobs may be relatively rigid, such that immigrants and natives in the same position perform similar tasks despite differences in underlying proficiency. Distinguishing between these possibilities is essential for understanding whether immigrant disadvantage operates primarily through differences in human capital endowments, through differential treatment in task allocation, or through both channels simultaneously. We turn to this question in Section 3.3.

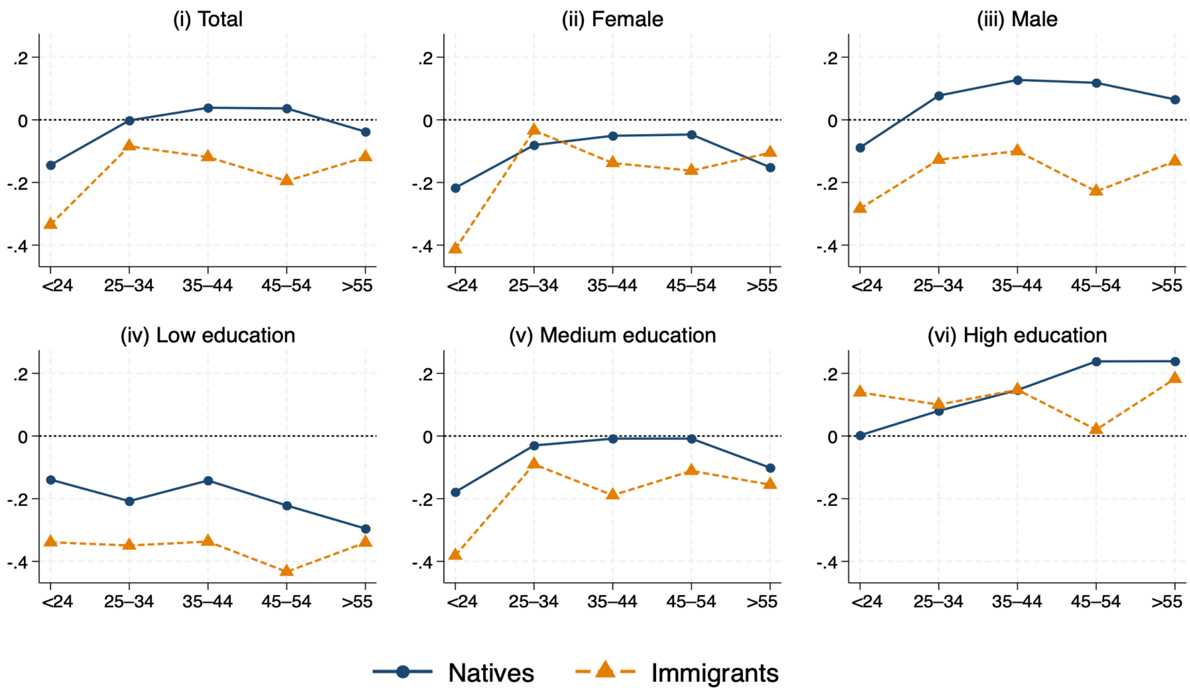
3.3 Within-job task composition

Having documented substantial within-job skill gaps (24 to 30 points, or approximately 0.5 to 0.6 standard deviations), we now examine whether these cognitive proficiency differences translate into systematic variation in task allocation. Do immigrants and natives in the same occupation-industry cells perform different bundles of tasks, or does task assignment adjust efficiently to reflect skill differences? This distinction is central to understanding the nature of immigrant disadvantage. If task gaps persist even after conditioning on cognitive proficiency, this would indicate discriminatory assignment or organizational barriers to accessing complex work. If task gaps disappear once skills are accounted for, this would suggest that labor markets allocate tasks primarily on the basis of cognitive capacity rather than immigrant status per se.

3.3.1 Abstract tasks

We begin with abstract tasks, which capture cognitively intensive and non-routine activities such as problem solving, advanced reading and writing, analytical reasoning, influencing others, and complex numerical work, with the complete mapping of items to task categories reported in Table 1. Task-gap measures are defined as deviations of individual task intensity from the job-cell average, standardized by the job-cell standard deviation to ensure comparability across occupations with different task variances.

Figure 5 **Within-job gaps in abstract tasks by origin, age group, gender and education**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual task frequency and job-average task frequency.
Source: PIAAC Cycle 2 data. Own calculations.

Figure 5 presents within-job gaps in abstract task use across demographic subgroups. In the pooled sample (panel i), immigrants perform fewer abstract tasks than natives within the same jobs across all age groups, with gaps averaging approximately 0.2 standard deviations. The pattern is more pronounced among men (panel iii) than women (panel ii), consistent with the gender differences in cognitive skill gaps documented in Sections 3.1 and 3.2. Educational stratification (panels iv-vi) reveals that gaps narrow with education but remain present even among highly educated workers, though

Table 4 **Abstract job tasks – Weighted OLS regression results**

	(1)	(2)	(3)	(4)
Immigrant	-0.227***	-0.169**	-0.163*	-0.124
	(0.077)	(0.080)	(0.086)	(0.082)
Female		-0.167***	-0.150***	-0.142***
		(0.051)	(0.051)	(0.051)
Age *(base - under 24 y.o.)*:				
25 - 34 y.o.		-0.009	-0.005	0.001
		(0.093)	(0.092)	(0.092)
35 - 44 y.o.		0.012	0.017	0.028
		(0.112)	(0.110)	(0.109)
45 - 54 y.o.		0.021	0.024	0.044
		(0.111)	(0.111)	(0.110)
55 y.o. and above		-0.064	-0.058	-0.024
		(0.119)	(0.118)	(0.118)
Cohabiting		0.079	0.075	0.070
		(0.068)	(0.068)	(0.068)
Number of children *(base - no children)*:				
One child		0.019	0.019	0.021
		(0.088)	(0.088)	(0.088)
Two children		0.037	0.035	0.034
		(0.081)	(0.081)	(0.082)
Three children		0.022	0.021	0.022
		(0.105)	(0.105)	(0.103)
Four and more children		0.004	0.007	0.008
		(0.130)	(0.131)	(0.130)
Education *(base - ISCED 1 and below)*:				
ISCED 2		0.163	0.148	0.121
		(0.138)	(0.137)	(0.134)
ISCED 3		0.331***	0.304**	0.267**
		(0.120)	(0.122)	(0.119)
ISCED 4		0.487***	0.456***	0.412**
		(0.174)	(0.177)	(0.172)
ISCED 5		0.471***	0.433***	0.391***
		(0.125)	(0.128)	(0.123)
ISCED 6		0.565***	0.525***	0.485***
		(0.128)	(0.135)	(0.128)
ISCED 7		0.632***	0.589***	0.546***
		(0.127)	(0.133)	(0.126)
Permanent contract		0.041	0.037	0.037
		(0.064)	(0.063)	(0.063)
Weekly work hours		0.014***	0.014***	0.014***
		(0.003)	(0.003)	(0.003)
Literacy skill			Yes	
Numeracy skill			Yes	
Within-job literacy gap				Yes
Within-job numeracy gap				Yes
Country controls	Yes	Yes	Yes	Yes
Constant	-0.013	-0.991***	-1.069***	-0.982***
	(0.078)	(0.171)	(0.212)	(0.170)
N	20323	20323	20323	20323
R-squared	0.022	0.086	0.088	0.094

Notes: Standard errors in parentheses. Final population weights are applied in all models. Additionally, a full set of eighty replication weights and Jackknife replication methodology are used in used in models (3) and (4). Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: PIAAC cycle 2 data. Own calculations.

young tertiary-educated immigrants occasionally reach parity with natives. Appendix Table A6, which reports regression estimates separately by gender and education using the full PIAAC estimation framework with replication weights, confirms that within-job abstract task gaps are negative and statistically significant across all major demographic subgroups.

Table 4 reports pooled regression estimates that progressively condition on different sets of controls to identify the mechanism underlying task differences. In the baseline specification (column 1), which includes only country fixed effects, immigrants perform 0.23 standard deviations fewer abstract tasks than natives in the same jobs (s.e. $= 0.08$, $p < 0.001$). This substantial gap indicates that immigrants are systematically less engaged in cognitively demanding activities even when job content is held constant. Adding demographic controls, education, and job characteristics in column 2 reduces the coefficient to 0.17 standard deviations (s.e. $= 0.08$, $p < 0.05$), suggesting that compositional differences in observable characteristics account for roughly one-quarter of the raw gap.

The critical specifications are columns 3 and 4, which introduce cognitive skill controls. Column 3 adds absolute literacy and numeracy proficiency, reducing the immigrant coefficient to 0.16 standard deviations (s.e. $= 0.09$, $p < 0.10$). While this further attenuation indicates that overall cognitive proficiency explains part of the task gap, a marginally significant difference remains. Column 4 replaces absolute proficiency with within-job skill deviations, which measure each worker's literacy and numeracy relative to the average in their specific job cell. Once we condition on within-job skill positioning, the immigrant coefficient becomes small (0.12 standard deviations) and statistically insignificant (s.e. $= 0.08$, $p = 0.13$). The progressive attenuation from 0.23 to 0.12 standard deviations, with the final coefficient indistinguishable from zero, provides strong evidence that abstract task allocation responds to relative cognitive proficiency rather than to immigrant status per se.

This finding has a clear interpretation: immigrants perform fewer abstract tasks than natives in the same jobs primarily because they possess lower cognitive proficiency relative to their coworkers, not because they face exclusion from cognitively demanding activities conditional on their skill levels. Task assignment appears to be meritocratic in the sense that it reflects workers' cognitive capacity rather than demographic characteristics. This skill-mediated mechanism is consistent with efficiency wage models and internal labor market theories, which predict that firms allocate complex tasks to workers with higher cognitive skills to maximize productivity (Gibbons & Waldman, 2006; Lazear & Shaw, 2007).

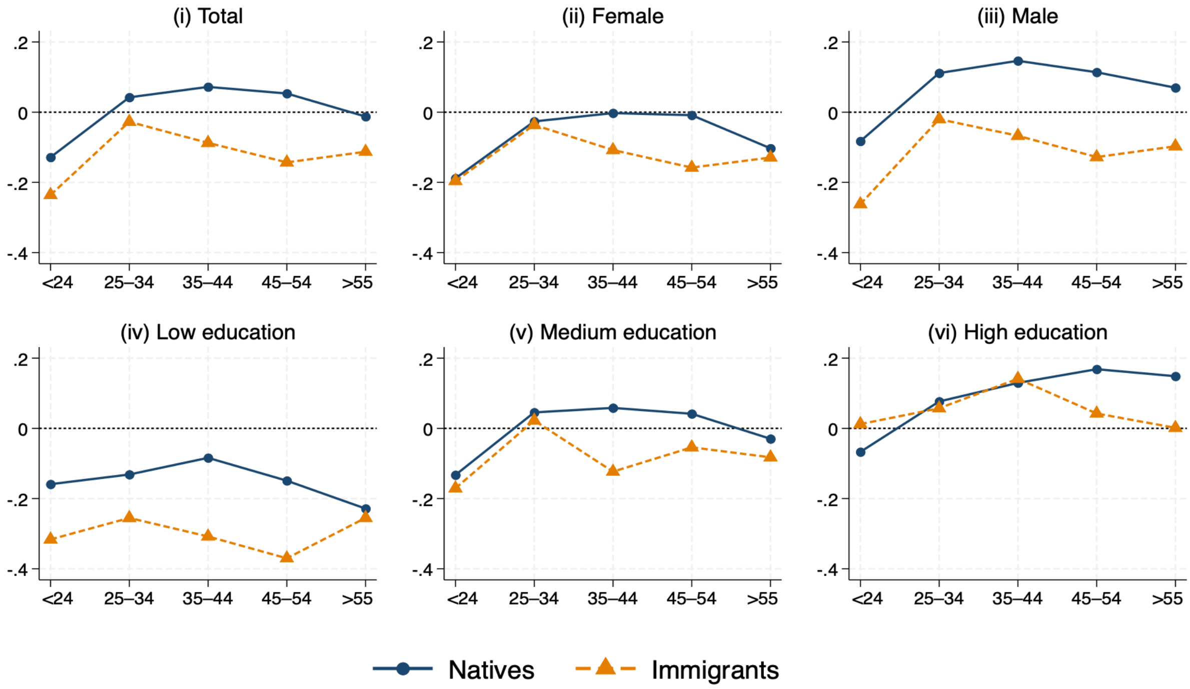
3.3.2 Routine tasks

Routine tasks encompass structured information-processing activities such as organizing and planning work, standard reading and writing, basic numerical operations, teaching, giving presentations, and regular information exchange with colleagues (Table 1). While less cognitively intensive than abstract tasks, routine activities still require literacy, numeracy, and organizational skills, and their performance may be sensitive to workers' cognitive proficiency levels (Autor & Handel, 2013).

Figure 6 reveals patterns strikingly similar to those observed for abstract tasks. Immigrants perform routine tasks less frequently than natives within the same jobs across all age groups (panel i), with larger gaps among men (panel iii) than women (panel ii), and some convergence at higher education levels (panels iv-vi). The consistency of this pattern across both abstract and routine task dimensions suggests a general mechanism whereby cognitive proficiency shapes task allocation across multiple domains of work. Appendix Table A7 provides econometric confirmation, showing uniformly negative within-job routine task gaps across all gender and education subsamples.

Table 5 presents regression estimates following the same specification structure as Table 4. The baseline immigrant coefficient is 0.25 standard deviations (column 1, s.e. $= 0.08$, $p < 0.001$), slightly larger

Figure 6 **Within-job gaps in routine tasks by origin, age group, gender and education**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual task frequency and job-average task frequency.
Source: PIAAC Cycle 2 data. Own calculations.

than the corresponding estimate for abstract tasks. Adding demographic and job controls reduces the coefficient to 0.19 standard deviations (column 2, s.e. $= 0.09$, $p < 0.05$), while including absolute proficiency measures produces a further decline to 0.16 standard deviations (column 3, s.e. $= 0.09$, $p < 0.10$). Crucially, once within-job skill deviations are introduced in column 4, the coefficient falls to 0.13 standard deviations and becomes statistically insignificant (s.e. $= 0.09$, $p = 0.14$).

The progressive attenuation pattern for routine tasks precisely parallels that for abstract tasks, reinforcing the interpretation that task allocation responds to relative cognitive proficiency rather than to immigrant status. The fact that this mechanism operates consistently across two distinct task dimensions, both cognitively demanding but differing in complexity and structure, strengthens confidence in the underlying skill-based allocation process. These results are inconsistent with models of discriminatory task assignment or organizational barriers that would restrict immigrants' access to cognitively demanding work conditional on their proficiency levels.

3.3.3 Manual tasks

Manual tasks capture physically intensive activities and the use of hands or fingers, reflecting job content that is only weakly related to cognitive proficiency. Unlike abstract and routine tasks, manual activities depend primarily on physical capacity, dexterity, and stamina rather than literacy or numeracy skills. This distinction provides a natural comparison group for assessing whether the null results observed for cognitive tasks conditional on skills reflect genuine skill-based allocation or alternative mechanisms.

Figure 7 reveals a fundamentally different pattern from that observed for cognitive tasks. Immigrants and natives report very similar levels of manual task intensity when employed in the same job cells

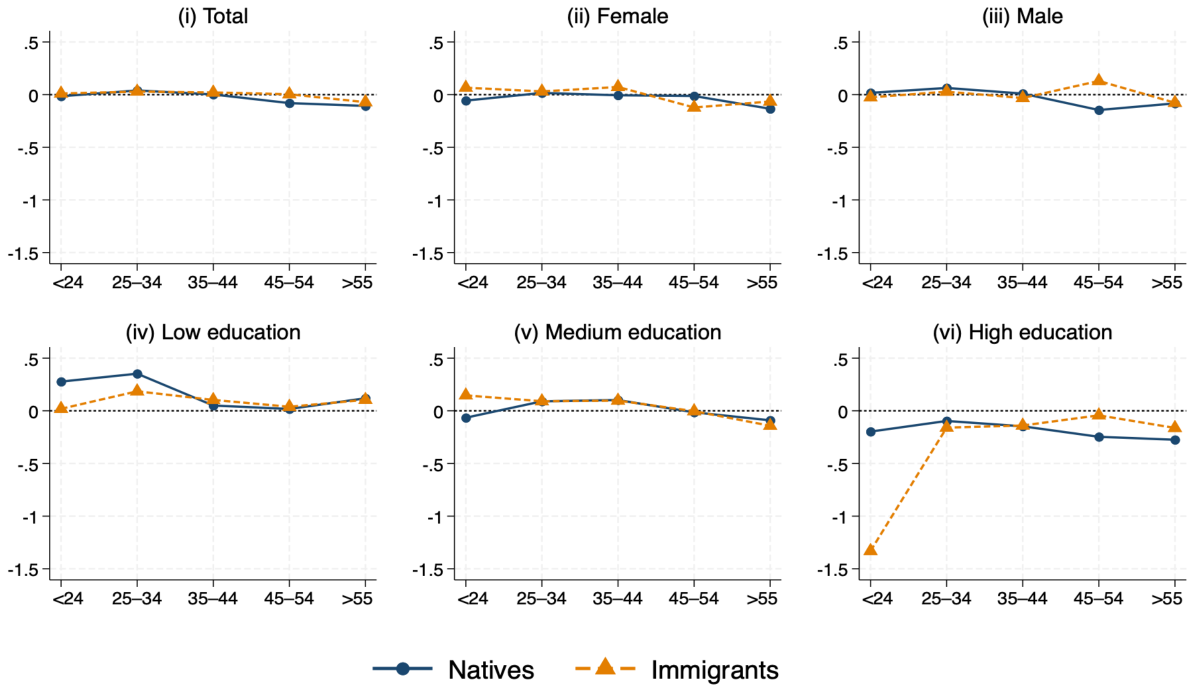
Table 5 **Routine job tasks – Weighted OLS regression results**

	(1)	(2)	(3)	(4)
Immigrant	-0.249***	-0.190**	-0.160*	-0.127
	(0.082)	(0.086)	(0.086)	(0.085)
Female		-0.137***	-0.131**	-0.123**
		(0.052)	(0.054)	(0.054)
Age *(base - under 24 y.o.)*:				
25 - 34 y.o.		0.042	0.047	0.053
		(0.097)	(0.096)	(0.094)
35 - 44 y.o.		0.039	0.048	0.058
		(0.106)	(0.105)	(0.103)
45 - 54 y.o.		0.018	0.030	0.049
		(0.109)	(0.107)	(0.105)
55 y.o. and above		-0.082	-0.062	-0.030
		(0.125)	(0.123)	(0.121)
Cohabiting		0.120	0.116	0.112
		(0.073)	(0.074)	(0.074)
Number of children *(base - no children)*:				
One child		0.042	0.044	0.045
		(0.085)	(0.085)	(0.085)
Two children		0.060	0.059	0.059
		(0.075)	(0.075)	(0.076)
Three children		0.021	0.023	0.023
		(0.097)	(0.097)	(0.097)
Four and more children		0.028	0.034	0.033
		(0.135)	(0.135)	(0.135)
Education *(base - ISCED 1 and below)*:				
ISCED 2		0.204	0.182	0.158
		(0.137)	(0.132)	(0.130)
ISCED 3		0.398***	0.358***	0.330***
		(0.130)	(0.128)	(0.124)
ISCED 4		0.562***	0.507***	0.478***
		(0.169)	(0.170)	(0.167)
ISCED 5		0.541***	0.487***	0.459***
		(0.134)	(0.135)	(0.129)
ISCED 6		0.583***	0.519***	0.498***
		(0.134)	(0.138)	(0.132)
ISCED 7		0.541***	0.466***	0.447***
		(0.145)	(0.150)	(0.142)
Permanent contract		0.093	0.091	0.092
		(0.068)	(0.068)	(0.068)
Weekly work hours		0.016***	0.016***	0.016***
		(0.003)	(0.003)	(0.003)
Literacy skill			Yes	
Numeracy skill			Yes	
Within-job literacy gap				Yes
Within-job numeracy gap				Yes
Country controls	Yes	Yes	Yes	Yes
Constant	0.015	-1.211***	-1.400***	-1.202***
	(0.085)	(0.173)	(0.229)	(0.170)
N	20323	20323	20323	20323
R-squared	0.030	0.099	0.100	0.109

Notes: Standard errors in parentheses. Final population weights are applied in all models. Additionally, a full set of eighty replication weights and Jackknife replication methodology are used in used in models (3) and (4). Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

across most age groups (panel i), education levels (panels iv-vi), and for both genders (panels ii-iii). The near-zero differences contrast sharply with the substantial gaps observed for abstract and routine tasks, suggesting that task allocation mechanisms differ qualitatively depending on whether tasks are cognitively or physically demanding. One notable exception appears among highly educated immigrants in the youngest age group, who report lower manual task use than comparable natives,

Figure 7 **Within-job gaps in manual tasks by origin, age group, gender and education**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual task frequency and job-average task frequency.
Source: PIAAC Cycle 2 data. Own calculations.

potentially reflecting their concentration in professional occupations where physical work is minimal.

Table 6 provides statistical confirmation of this null result. Across all specifications, the estimated immigrant coefficient is close to zero and statistically insignificant. In the baseline specification (column 1), the coefficient is 0.06 standard deviations (s.e. = 0.11, p = 0.50). Adding demographic and job controls produces a coefficient of 0.04 (column 2, s.e. = 0.10, p = 0.69), while including absolute proficiency yields a small negative coefficient of -0.04 (column 3, s.e. = 0.10, p = 0.68). Conditioning on within-job skill deviations (column 4) similarly produces a coefficient of -0.04 (s.e. = 0.10, p = 0.61). The stability of the coefficient across specifications and its consistent insignificance indicate that manual task allocation is genuinely insensitive to both immigrant status and cognitive proficiency. Appendix Table A8 confirms that this null result holds across all gender and education subsamples.

The sharp contrast between manual tasks and cognitive tasks is theoretically informative. If observed task gaps for abstract and routine activities reflected discriminatory assignment or organizational barriers unrelated to skills, we would expect similar patterns for manual tasks. The fact that manual task allocation shows no immigrant-native differences suggests instead that task assignment mechanisms differ by task type: cognitively demanding activities are allocated based on cognitive proficiency, while physical activities are allocated based on other factors (physical capacity, job requirements) that do not vary systematically with immigrant status. This pattern strengthens the interpretation that cognitive task gaps are skill-mediated rather than reflecting differential treatment.

Appendix Figures A5, A6 and A7 document cross-country patterns, providing external validity evidence. Across almost all countries in the sample, natives perform abstract and routine tasks more frequently than immigrants within the same jobs, while manual task patterns show no consistent differences. The magnitudes vary across countries, with larger cognitive task gaps in Germany and Austria

Table 6 **Manual job tasks – Weighted OLS regression results**

	(1)	(2)	(3)	(4)
Immigrant	0.063	0.028	-0.036	-0.044
	(0.092)	(0.089)	(0.087)	(0.086)
Female		0.044	0.033	0.027
		(0.049)	(0.052)	(0.052)
Age *(base - under 24 y.o.)*:				
25 - 34 y.o.		0.060	0.048	0.047
		(0.100)	(0.100)	(0.100)
35 - 44 y.o.		0.003	-0.015	-0.019
		(0.110)	(0.110)	(0.110)
45 - 54 y.o.		-0.065	-0.091	-0.100
		(0.104)	(0.106)	(0.107)
55 y.o. and above		-0.088	-0.130	-0.148
		(0.119)	(0.120)	(0.122)
Cohabiting		-0.008	0.001	0.001
		(0.080)	(0.079)	(0.078)
Number of children *(base - no children)*:				
One child		0.064	0.060	0.061
		(0.090)	(0.090)	(0.090)
Two children		0.065	0.066	0.067
		(0.076)	(0.078)	(0.078)
Three children		0.042	0.037	0.040
		(0.113)	(0.112)	(0.112)
Four and more children		0.026	0.014	0.021
		(0.160)	(0.160)	(0.156)
Education *(base - ISCED 1 and below)*:				
ISCED 2		0.012	0.059	0.065
		(0.167)	(0.174)	(0.170)
ISCED 3		-0.066	0.016	0.011
		(0.129)	(0.141)	(0.135)
ISCED 4		-0.087	0.028	0.009
		(0.147)	(0.163)	(0.153)
ISCED 5		-0.128	-0.017	-0.035
		(0.151)	(0.171)	(0.159)
ISCED 6		-0.192	-0.060	-0.095
		(0.136)	(0.152)	(0.140)
ISCED 7		-0.292**	-0.137	-0.185
		(0.140)	(0.168)	(0.149)
Permanent contract		-0.098	-0.093	-0.096
		(0.069)	(0.070)	(0.070)
Weekly work hours		0.004	0.005	0.004
		(0.003)	(0.003)	(0.003)
Literacy skill			Yes	
Numeracy skill			Yes	
Within-job literacy gap				Yes
Within-job numeracy gap				Yes
Country controls	Yes	Yes	Yes	Yes
Constant	0.079	0.054	0.451**	0.045
	(0.087)	(0.175)	(0.228)	(0.173)
N	20317	20317	20317	20317
R-squared	0.025	0.039	0.044	0.051

Notes: Standard errors in parentheses. Final population weights are applied in all models. Additionally, a full set of eighty replication weights and Jackknife replication methodology are used in used in models (3) and (4). Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

(0.3 to 0.4 standard deviations in baseline specifications) and smaller gaps in Spain and Czechia (0.1 to 0.2 standard deviations), but the direction and the pattern of attenuation when conditioning on skills are remarkably consistent. This cross-national replication strengthens confidence that the skill-mediated mechanism operates generally across diverse European labor markets rather than reflecting country-specific institutions or data peculiarities.

3.3.4 Robustness

We assess the sensitivity of our findings to alternative job-cell definitions and statistical procedures. Appendix Table A9 reports results under three variations. First, we re-estimate all specifications using finer job-cell definitions constructed from ISCO 2-digit × ISIC 2-digit rather than ISCO 2-digit × ISIC 1-digit. These finer cells provide sharper within-job comparisons but reduce average cell sizes from approximately 270 to 95 workers. The core pattern remains quantitatively similar: immigrant-native gaps in abstract tasks are -0.24 standard deviations in the baseline specification and attenuate to -0.08 (statistically insignificant) after controlling for within-job skill positioning. Routine tasks display comparable patterns (-0.29 baseline, -0.11 with controls), while manual tasks show no systematic differences. These results confirm that findings are not artifacts of job-cell granularity and that the skill-mediated mechanism operates even when jobs are defined more narrowly.

Second, we vary the empirical Bayes shrinkage parameter κ that pools job-cell task means toward occupation averages. We test $\kappa \in \{5, 10, 15\}$ and specifications without shrinkage, where lower κ values apply more aggressive pooling and higher values preserve more cell-specific variation. Across all parameterizations, baseline task gaps remain in the range of -0.22 to -0.26 standard deviations for abstract tasks and -0.26 to -0.31 for routine tasks, attenuating to -0.06 to -0.10 and -0.09 to -0.13 respectively once within-job skill gaps are controlled. Coefficients are statistically insignificant in all fully specified models regardless of shrinkage intensity. The consistency across specifications indicates that our central finding, that within-job task gaps are explained by cognitive skill differences rather than discriminatory assignment, is not sensitive to the degree of statistical smoothing or to job-cell definition. Manual task use shows no immigrant-native differences under any specification, reinforcing that the skill-mediated pattern is specific to cognitively demanding activities. These robustness exercises strengthen confidence that the documented relationship represents a genuine feature of within-job allocation rather than a methodological artifact.

4 Discussion and Conclusion

This paper examines the sources of immigrant-native disparities in cognitive skills and task assignments using PIAAC Cycle 2 data from eight European countries. We document large overall differences in literacy and numeracy (35 to 40 points, or 0.7 to 0.8 standard deviations) that persist across the working-age population and are only partially explained by occupational sorting. Approximately 70 to 75 percent of overall skill gaps remain when comparing workers within narrowly defined occupation-industry cells, indicating that occupational sorting accounts for approximately 25 percent of total disadvantage. Immigrants perform fewer abstract and routine tasks than natives within the same jobs (0.2 to 0.3 standard deviations), but these task gaps effectively disappear once we condition on within-job differences in literacy and numeracy. In contrast, manual task use shows no systematic immigrant-native differences. These findings indicate that immigrants' reduced exposure to cognitively demanding tasks is driven primarily by cognitive skill deficits rather than discriminatory task allocation.

Our analysis makes three contributions to research on immigrant labor market integration. First, we provide the first systematic evidence that immigrant-native task gaps within jobs are explained by skill differences rather than discriminatory assignment. Our within-job design, combined with PIAAC's direct assessments of cognitive proficiency, enables identification of whether observed task differences reflect productivity gaps or unequal treatment. By showing that task gaps are skill-mediated, we reconcile the persistence of wage and job-quality disparities (Bratsberg et al., 2012; Hermansen et al., 2025) with limited evidence of discrimination in task assignment conditional on proficiency. This extends recent evidence that task assignment within occupations responds to skill supply (Bittarello et al., 2024), showing that skill-responsive allocation also operates across immigrant-native comparisons and is consistent with efficiency considerations in internal labor markets (Gibbons & Waldman, 2006). Second, we introduce a unified decomposition framework that traces disadvantage across three interconnected stages: overall skill gaps, within-job skill positioning, and within-job task allocation. This reveals that occupational sorting explains approximately 25 percent of overall cognitive skill gaps, while the remaining 75 percent operates through within-job skill positioning and its translation into task assignment. This quantitative decomposition clarifies that policies targeting job access alone can address only a minority of total disadvantage. Third, we provide the first analysis of immigrant task allocation using PIAAC Cycle 2, extending established task classifications (De La Rica et al., 2020) to exploit enhanced measurement while ensuring methodological continuity.

The within-job perspective developed here distinguishes between disadvantage arising from barriers to job access and disadvantage stemming from skill deficits that persist after job placement. Our findings demonstrate that the latter mechanism dominates. The absence of residual task gaps conditional on cognitive proficiency indicates that task assignment responds to workers' skills rather than to demographic characteristics, ruling out systematic discrimination in access to complex work given proficiency levels. This redirects policy attention from workplace assignment practices toward skill formation, recognition, and maintenance. These findings yield four key implications. First, credential equivalence systematically overstates true skill similarity across origin and destination countries. Our finding that occupational sorting explains approximately 25 percent of skill gaps suggests that most immigrants work in jobs broadly consistent with their education levels, but substantial proficiency differences remain within those jobs. More rigorous assessment mechanisms that directly evaluate competencies rather than relying on credential labels may be necessary (Hanushek & Woessmann, 2008). Second, targeted language training and skill development should address cognitive proficiency gaps early in the integration process. We find no evidence of convergence in within-job skill positioning across age groups, indicating that workplace exposure alone does not remediate proficiency deficits and that interventions must occur during formal schooling and early career stages (Cunha & Heckman, 2007; Heckman, 2006).

Third, policies should address the striking life-cycle pattern among highly educated immigrants, who exhibit near-parity with natives when young but develop substantial skill gaps by prime working ages. This deterioration may reflect skill atrophy due to prolonged occupational mismatch, selective return migration, or cohort differences in educational preparation. Interventions could include facilitating earlier labor market entry, providing bridging programs during credential recognition processes, and creating pathways to skill-appropriate employment. Fourth, while our findings indicate that interventions targeting workplace discrimination in task assignment are unlikely to address the primary source of within-job disadvantage documented here, this does not imply that discrimination is absent from immigrant labor market experiences. Our analysis focuses specifically on task allocation conditional on cognitive proficiency within narrowly defined jobs. Discrimination may operate at other margins, including hiring, promotion, wage-setting, or access to training opportunities. The skill-mediated mechanism we identify complements rather than contradicts evidence of discrimination in these other domains.

Several limitations merit consideration. Our skill measures are based on PIAAC's literacy and numeracy assessments, which may not capture all dimensions relevant to workplace performance, including oral fluency, workplace-specific terminology, or non-cognitive skills such as communication abilities. However, the null result for manual tasks suggests that the skill-mediated mechanism is specific to cognitive proficiency rather than reflecting general unmeasured heterogeneity. Both skill measures and task reports derive from the same cross-sectional survey, raising concerns about common-method bias or reverse causality. The progressive attenuation pattern where task gaps decline systematically as we add detailed skill controls is more consistent with skills causing task allocation than with reverse causation, and the differential patterns across task types further suggest genuine relationships rather than measurement artifacts. Our within-job comparisons rely on occupation-industry cells that provide substantial refinement but still permit heterogeneity in actual job content. Robustness checks using finer cells yield consistent results, and controlling for observable job characteristics produces minimal attenuation of our estimates, suggesting that unmeasured job sorting is limited.

Our analysis conditions on employment and therefore may be subject to selection bias if immigrants with particularly low cognitive skills sort out of employment entirely. PIAAC's high response rates and broad coverage mitigate these concerns, and such selection would likely attenuate rather than generate our findings. Our cross-sectional design cannot definitively distinguish between mechanisms generating observed patterns. The widening skill gaps among highly educated immigrants over the life cycle could reflect skill atrophy, selective return migration, or cohort effects, and longitudinal data following immigrant cohorts would enable sharper identification. These limitations suggest productive directions for future research, including combining PIAAC data with administrative records to analyze how within-job skill positioning translates into wage outcomes, examining how skill gaps evolve over immigrants' careers to identify critical intervention points, and comparing mechanisms across different immigration systems to establish generality.

This paper demonstrates that immigrant-native differences in workplace task performance are primarily explained by cognitive skill deficits rather than discriminatory assignment, with approximately 70 to 75 percent of overall skill gaps persisting within jobs. These findings redirect policy attention toward skill development, credential recognition, and early-stage interventions that address cognitive proficiency gaps limiting immigrants' access to complex work. While facilitating occupational mobility remains valuable for addressing sorting-based inequality, the larger component of disadvantage requires human capital investments and more effective skill assessment mechanisms. By distinguishing between barriers to job access and skill deficits that persist after job placement, our within-job perspective clarifies the mechanisms through which cognitive proficiency shapes workplace experiences and identifies the margins where policy interventions are most likely to improve integration outcomes.

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Appendix

Table A1 **Sample descriptive statistics**

	Total		Natives		Immigrants	
	Mean	SD	Mean	SD	Mean	SD
Female	0.49	0.50	0.49	0.50	0.48	0.50
Under 24 y.o.	0.10	0.29	0.10	0.30	0.06	0.24
24 - 34 y.o.	0.21	0.40	0.20	0.40	0.22	0.41
35 - 44 y.o.	0.26	0.44	0.25	0.44	0.30	0.46
45 - 54 y.o.	0.27	0.44	0.27	0.44	0.29	0.46
55 y.o. and above	0.17	0.37	0.17	0.38	0.12	0.33
Cohabiting	0.76	0.43	0.76	0.43	0.78	0.42
No children	0.31	0.46	0.32	0.47	0.25	0.43
One child	0.23	0.42	0.23	0.42	0.22	0.41
Two children	0.32	0.47	0.32	0.47	0.33	0.47
Three children	0.10	0.30	0.10	0.30	0.13	0.33
Four and more children	0.04	0.20	0.04	0.19	0.08	0.27
Low education	0.15	0.36	0.13	0.34	0.30	0.46
Medium education	0.53	0.50	0.55	0.50	0.43	0.49
High education	0.32	0.46	0.32	0.47	0.27	0.44
Managers	0.05	0.22	0.06	0.23	0.04	0.19
Professionals	0.19	0.39	0.20	0.40	0.14	0.34
Technicians and associate professionals	0.19	0.40	0.21	0.40	0.12	0.33
Clerical support workers	0.10	0.30	0.11	0.31	0.06	0.24
Service and sales workers	0.18	0.38	0.17	0.38	0.21	0.41
Skilled agricultural, forestry and fishery workers	0.01	0.10	0.01	0.10	0.01	0.12
Craft and related trades workers	0.11	0.31	0.11	0.31	0.13	0.34
Plant and machine operators, and assemblers	0.08	0.26	0.07	0.26	0.11	0.31
Elementary occupations	0.08	0.27	0.07	0.25	0.17	0.38
Permanent contract	0.84	0.37	0.85	0.36	0.79	0.41
Weekly work hours	36.58	9.67	36.74	9.46	35.59	10.86
Literacy skill	262.15	52.79	267.96	49.55	226.05	57.74
Numeracy skill	266.64	55.02	271.70	52.33	235.25	60.62
N	20323		17709		2614	

Notes: Final population weights are used.
Source: PIAAC cycle 2 data. Own calculations.

Table A2 **Literacy gaps - Weighted subsample OLS regression results**

	(1) Total	**(2) Women**	**(3) Men**	**(4) Low education**	**(5) Medium education**	**(6) High education**
Immigrant	-26.673**	-19.641	-32.029**	-13.964	-31.312**	-29.771
	(10.604)	(15.084)	(13.087)	(16.923)	(13.058)	(18.549)
Female	-0.569			4.410	-0.027	-0.996
	(2.823)			(6.094)	(4.110)	(3.853)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	-4.752	-8.024	-2.624	-26.666*	-0.783	1.315
	(4.413)	(6.006)	(6.982)	(15.182)	(5.360)	(9.080)
35 - 44 y.o.	-8.600*	-10.466	-8.045	-28.905*	-5.360	-2.390
	(4.954)	(6.809)	(7.973)	(14.760)	(6.808)	(9.446)
45 - 54 y.o	-14.680***	-18.469**	-12.347	-37.241**	-12.098*	-7.913
	(5.403)	(7.250)	(8.454)	(17.439)	(6.550)	(10.257)
55 y.o. and above	-25.461***	-27.838***	-24.400***	-44.767***	-22.611***	-22.613**
	(5.857)	(8.020)	(8.970)	(16.575)	(7.780)	(11.200)
Immigrant # under 24 y.o.	0.935	-9.646	9.203	-23.277	4.732	21.609
	(17.202)	(26.740)	(19.317)	(26.065)	(21.722)	(59.550)
Immigrant # 25 - 34 y.o	-12.452	-12.720	-12.243	-21.609	-6.998	-13.381
	(12.582)	(15.911)	(16.660)	(22.389)	(19.158)	(22.315)
Immigrant # 35 - 44 y.o	-11.345	-16.138	-8.111	-22.073	-10.877	-6.206
	(13.153)	(16.609)	(17.955)	(21.856)	(17.075)	(23.298)
Immigrant # 45 - 54 y.o.	-10.498	-9.455	-12.474	-20.717	-6.712	1.863
	(12.855)	(16.506)	(17.336)	(19.913)	(17.844)	(22.598)
Cohabiting	3.382	2.747	4.182	-0.580	3.314	6.108
	(3.118)	(4.030)	(5.094)	(8.327)	(4.180)	(5.242)
Number of children *(base - no children)*:						
One child	-2.113	-0.131	-4.175	3.946	-3.544	-3.010
	(3.482)	(5.282)	(5.930)	(10.803)	(4.776)	(6.051)
Two children	-0.401	-0.017	-0.681	2.733	-2.595	-0.261
	(3.670)	(5.424)	(5.970)	(10.437)	(5.413)	(5.636)
Three children	-2.864	-1.064	-4.023	-5.612	-2.652	-2.312
	(5.164)	(6.973)	(7.453)	(12.647)	(6.626)	(8.055)
Four and more children	-4.412	-0.255	-7.162	-3.261	-3.770	-5.477
	(6.695)	(8.260)	(9.624)	(14.906)	(9.030)	(12.024)
Education *(base - ISCED 1 and below)*:						
ISCED 2	22.055***	25.736*	19.096*			
	(8.243)	(14.217)	(10.139)			
ISCED 3	34.706***	38.179***	31.938***			
	(7.660)	(11.666)	(9.465)			
ISCED 4	50.109***	51.531***	50.505***			
	(8.385)	(13.112)	(12.406)			
ISCED 5	45.207***	48.155***	42.738***			
	(7.846)	(11.541)	(9.734)			
ISCED 6	53.574***	57.536***	50.466***			
	(8.423)	(12.418)	(10.593)			
ISCED 7	63.234***	65.934***	60.682***			
	(7.491)	(11.711)	(9.883)			
Permanent contract	0.843	-0.438	2.001	4.412	0.999	-0.032
	(4.091)	(4.584)	(5.874)	(8.886)	(4.650)	(6.750)
Weekly work hours	-0.089	-0.107	-0.010	0.036	-0.208	-0.037
	(0.138)	(0.152)	(0.221)	(0.324)	(0.203)	(0.211)
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	245.022***	259.868***	238.430***	216.469***	268.653***	303.955***
	(34.409)	(61.786)	(36.131)	(83.224)	(38.190)	(58.133)
N	20323	9412	10911	2639	11140	6544
R-squared	0.353	0.349	0.371	0.265	0.221	0.243

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A3 **Numeracy gaps - Weighted subsample OLS regression results**

	(1) Total	**(2) Women**	**(3) Men**	**(4) Low education**	**(5) Medium education**	**(6) High education**
Immigrant	-25.083**	-17.010	-31.460**	-17.815	-27.044**	-28.108*
	(9.922)	(14.718)	(13.154)	(19.080)	(13.604)	(16.428)
Female	-11.143***			-2.959	-10.515**	-12.676***
	(3.031)			(7.096)	(4.270)	(4.041)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	-6.493	-7.676	-5.890	-26.805*	-3.229	1.052
	(4.402)	(6.045)	(7.410)	(14.928)	(5.673)	(9.023)
35 - 44 y.o.	-9.367*	-9.368	-10.177	-31.312*	-6.496	-1.517
	(4.996)	(7.086)	(8.085)	(16.191)	(7.073)	(9.576)
45 - 54 y.o	-12.905**	-13.702*	-13.238	-35.659*	-9.932	-6.229
	(5.252)	(7.250)	(8.602)	(19.029)	(6.986)	(10.168)
55 y.o. and above	-22.892***	-23.008***	-23.771**	-41.830**	-20.251**	-20.090*
	(5.652)	(8.482)	(9.412)	(18.651)	(7.903)	(11.445)
Immigrant # under 24 y.o.	3.428	-9.413	13.053	-13.107	1.717	17.200
	(15.898)	(26.491)	(17.605)	(27.344)	(21.939)	(49.496)
Immigrant # 25 - 34 y.o	-4.526	-8.136	-1.475	-9.957	-3.992	-3.400
	(11.694)	(15.905)	(16.399)	(25.071)	(19.123)	(19.259)
Immigrant # 35 - 44 y.o	-5.937	-9.366	-3.935	-12.047	-7.390	-2.601
	(12.262)	(16.708)	(17.744)	(21.815)	(18.664)	(20.948)
Immigrant # 45 - 54 y.o.	-7.785	-7.048	-9.321	-12.850	-7.941	5.043
	(11.641)	(16.088)	(15.994)	(21.857)	(17.937)	(20.354)
Cohabiting	5.177*	3.729	7.546	-0.365	6.251	6.361
	(3.119)	(4.437)	(4.635)	(8.447)	(4.341)	(4.978)
Number of children *(base - no children)*:						
	-2.113	-0.131	-4.175	3.946	-3.544	-3.010
	(3.482)	(5.282)	(5.930)	(10.803)	(4.776)	(6.051)
	-0.401	-0.017	-0.681	2.733	-2.595	-0.261
	(3.670)	(5.424)	(5.970)	(10.437)	(5.413)	(5.636)
	-2.864	-1.064	-4.023	-5.612	-2.652	-2.312
	(5.164)	(6.973)	(7.453)	(12.647)	(6.626)	(8.055)
	-4.412	-0.255	-7.162	-3.261	-3.770	-5.477
	(6.695)	(8.260)	(9.624)	(14.906)	(9.030)	(12.024)
Education *(base - ISCED 1 and below)*:						
ISCED 2	26.482***	29.502*	23.665**			
	(9.023)	(15.311)	(10.940)			
ISCED 3	43.616***	45.311***	41.719***			
	(8.893)	(12.942)	(11.067)			
ISCED 4	57.636***	56.585***	61.049***			
	(9.528)	(14.059)	(14.128)			
ISCED 5	57.211***	58.405***	55.675***			
	(9.197)	(12.755)	(11.793)			
ISCED 6	64.726***	65.414***	63.512***			
	(9.610)	(13.684)	(12.487)			
ISCED 7	73.007***	73.108***	71.597***			
	(8.630)	(13.236)	(11.350)			
Permanent contract	2.537	2.726	2.488	7.674	3.211	0.161
	(3.923)	(4.658)	(5.607)	(9.516)	(4.907)	(5.551)
Weekly work hours	-0.062	-0.111	-0.001	0.016	-0.194	0.074
	(0.149)	(0.161)	(0.243)	(0.362)	(0.215)	(0.203)
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	255.199***	268.435***	241.375***	276.567***	258.670***	330.193***
	(35.219)	(75.577)	(37.093)	(60.741)	(41.441)	(55.522)
N	20323	9412	10911	2639	11140	6544
R-squared	0.358	0.327	0.392	0.243	0.205	0.282

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A4 **Within-job literacy skill gaps – Weighted subsample OLS regression results**

	(1) Total	(2) Women	(3) Men	(4) Low education	(5) Medium education	(6) High education
Immigrant	-12.179	-3.739	-20.354	-11.686	-12.546	-14.326
	(8.146)	(9.557)	(12.643)	(16.162)	(10.237)	(15.218)
Female	-0.369			3.918	-0.641	0.767
	(1.958)			(5.288)	(2.806)	(3.566)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	-4.647	-7.766	-2.616	-20.735	-1.806	0.786
	(4.109)	(6.393)	(5.985)	(13.989)	(5.042)	(8.325)
35 - 44 y.o.	-11.230**	-12.834*	-10.766	-24.457*	-9.227	-5.221
	(4.901)	(7.028)	(7.369)	(14.100)	(6.158)	(8.845)
45 - 54 y.o	-14.916***	-18.639***	-12.276*	-29.142**	-13.548**	-7.399
	(4.907)	(6.990)	(7.055)	(14.828)	(6.035)	(9.106)
55 y.o. and above	-26.529***	-31.318***	-23.253***	-38.162**	-24.760***	-23.811**
	(5.470)	(8.702)	(8.104)	(15.009)	(7.176)	(10.606)
Immigrant # 25 - 34 y.o	-12.210	-23.468	-1.772	-20.978	-14.354	10.044
	(14.094)	(21.188)	(17.081)	(23.133)	(19.644)	(26.038)
Immigrant # 25 - 34 y.o	-20.471**	-22.020*	-18.029	-21.444	-18.222	-23.883
	(9.905)	(12.531)	(15.956)	(21.914)	(14.191)	(19.278)
Immigrant # 35 - 44 y.o	-18.788*	-23.232**	-14.258	-18.785	-20.643	-16.283
	(9.982)	(11.383)	(16.576)	(20.834)	(15.072)	(17.588)
Immigrant # 45 - 54 y.o.	-15.301	-14.758	-16.220	-18.847	-15.251	-5.714
	(9.781)	(11.997)	(15.829)	(19.755)	(15.577)	(18.492)
Cohabiting	2.852	2.676	3.355	-1.348	1.968	6.828
	(2.879)	(3.864)	(5.006)	(7.997)	(3.901)	(4.714)
Number of children *(base - no children)*:						
One child	-1.945	-0.468	-3.596	3.960	-2.693	-3.413
	(3.251)	(5.128)	(5.492)	(9.492)	(4.637)	(5.605)
Two children	-0.996	-0.733	-1.382	3.468	-2.620	-1.477
	(3.348)	(5.024)	(5.387)	(9.687)	(5.085)	(5.320)
Three children	-3.087	-1.728	-4.638	-4.394	-2.421	-3.655
	(4.466)	(6.337)	(6.646)	(11.448)	(5.704)	(7.829)
Four and more children	-4.040	0.187	-7.302	-5.249	-1.868	-6.060
	(6.030)	(7.525)	(8.594)	(12.695)	(8.089)	(10.540)
Education *(base - ISCED 1 and below)*:						
ISCED 2	18.507***	19.891	17.262*			
	(7.121)	(12.158)	(9.496)			
ISCED 3	26.009***	26.164**	25.631***			
	(6.608)	(10.300)	(8.370)			
ISCED 4	33.200***	32.149***	35.040***			
	(7.242)	(11.403)	(10.753)			
ISCED 5	31.259***	30.995***	31.069***			
	(6.707)	(9.879)	(8.413)			
ISCED 6	33.568***	34.736***	32.337***			
	(6.755)	(10.867)	(8.339)			
ISCED 7	38.821***	38.911***	39.243***			
	(6.271)	(10.035)	(8.543)			
Permanent contract	-0.550	-1.445	-0.080	0.094	-0.413	-0.053
	(3.599)	(4.584)	(4.948)	(8.050)	(4.107)	(6.351)
Weekly work hours	-0.164	-0.238	-0.018	-0.036	-0.260	-0.172
	(0.127)	(0.162)	(0.198)	(0.276)	(0.186)	(0.208)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.578	14.216	-1.131	17.445	36.371***	39.928***
	(9.806)	(13.597)	(13.073)	(21.208)	(10.561)	(12.268)
N	20323	9412	10911	2639	11140	6544
R-squared	0.149	0.154	0.155	0.151	0.101	0.174

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A5 **Within-job literacy skill gaps – Weighted subsample OLS regression results**

	(1) Total	**(2) Women**	**(3) Men**	**(4) Low education**	**(5) Medium education**	**(6) High education**
Immigrant	-15.848*	-6.607	-24.936*	-19.934	-12.846	-18.786
	(9.082)	(11.050)	(14.582)	(20.558)	(11.525)	(14.725)
Female	-12.468***			-5.685	-12.461***	-13.030***
	(2.106)			(5.821)	(3.030)	(3.601)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	-6.343	-7.553	-5.525	-21.270	-3.926	-0.535
	(4.094)	(6.241)	(6.372)	(13.758)	(5.275)	(8.318)
35 - 44 y.o.	-11.785**	-11.588	-12.549*	-27.980*	-9.611	-5.407
	(4.858)	(7.247)	(7.298)	(15.767)	(6.412)	(9.008)
45 - 54 y.o	-13.142***	-14.051**	-12.878*	-28.308*	-11.114*	-6.888
	(4.729)	(7.007)	(7.029)	(16.559)	(6.226)	(9.133)
55 y.o. and above	-22.737***	-25.244***	-21.265**	-34.906**	-20.744***	-22.109**
	(5.568)	(9.138)	(8.796)	(17.605)	(7.049)	(10.382)
Immigrant # under 24 y.o	-4.415	-17.986	7.719	-6.655	-12.791	18.571
	(13.853)	(22.025)	(17.578)	(26.934)	(19.404)	(23.548)
Immigrant # 25 - 34 y.o	-7.262	-12.108	-1.980	-5.532	-11.549	-5.761
	(10.656)	(13.714)	(17.255)	(26.336)	(14.762)	(17.546)
Immigrant # 35-44 y.o	-7.341	-10.616	-3.964	-2.044	-12.536	-4.438
	(10.461)	(12.476)	(18.447)	(22.814)	(15.969)	(16.605)
Immigrant # 45-54 y.o	-7.090	-6.879	-7.590	-6.858	-11.838	5.671
	(10.273)	(12.887)	(16.880)	(23.623)	(16.777)	(17.549)
Cohabiting	4.840*	3.912	6.765	-0.546	5.140	7.250
	(2.893)	(4.188)	(4.555)	(8.050)	(4.149)	(4.584)
Number of children *(base - no children)*:						
One child	-1.287	-0.715	-2.727	4.949	-3.471	-0.534
	(3.335)	(5.394)	(5.428)	(11.068)	(4.499)	(5.265)
Two children	1.015	0.422	1.004	6.589	-1.725	1.781
	(3.698)	(5.154)	(5.754)	(10.410)	(5.300)	(5.111)
Three children	-0.958	-1.301	-1.425	1.911	-1.941	-0.551
	(4.350)	(6.053)	(6.771)	(13.334)	(5.939)	(7.645)
Four and more children	-3.776	1.766	-8.333	-2.873	-3.806	-3.176
	(5.995)	(8.385)	(8.430)	(11.552)	(8.321)	(11.654)
Education *(base - ISCED 1 and below)*:						
ISCED 2	22.175***	23.889*	20.904**			
	(7.622)	(12.927)	(9.828)			
ISCED 3	34.479***	33.866***	34.730***			
	(7.371)	(11.404)	(9.176)			
ISCED 4	39.357***	37.030***	43.678***			
	(7.702)	(12.048)	(11.663)			
ISCED 5	42.758***	41.239***	43.488***			
	(7.643)	(11.014)	(9.721)			
ISCED 6	44.081***	42.652***	44.928***			
	(7.464)	(11.808)	(9.523)			
ISCED 7	48.124***	46.167***	49.726***			
	(6.839)	(11.096)	(9.195)			
Permanent contract	1.773	2.194	1.205	3.381	2.218	0.928
	(3.346)	(4.530)	(4.484)	(8.216)	(4.302)	(5.030)
Weekly work hours	-0.099	-0.199	0.034	-0.022	-0.221	-0.008
	(0.136)	(0.166)	(0.215)	(0.304)	(0.195)	(0.201)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.976	-5.228	-13.841	17.863	33.468***	40.029***
	(10.148)	(14.048)	(13.465)	(23.910)	(10.611)	(12.751)
N	20323	9412	10911	2639	11140	6544
R-squared	0.152	0.119	0.173	0.118	0.086	0.192

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A6 **Abstract job tasks – Weighted subsample OLS regression results**

	(1) Total	(2) Women	(3) Men	(4) Low education	(5) Medium education	(6) High education
Immigrant	-0.057	0.002	-0.119	-0.064	-0.050	-0.089
	(0.129)	(0.137)	(0.207)	(0.207)	(0.214)	(0.295)
Female	-0.095***			-0.071	-0.101*	-0.096*
	(0.036)			(0.090)	(0.056)	(0.056)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	0.010	0.016	0.007	0.002	0.059	-0.019
	(0.066)	(0.081)	(0.099)	(0.185)	(0.100)	(0.141)
35 - 44 y.o.	0.033	0.043	0.020	0.008	0.043	0.058
	(0.082)	(0.105)	(0.114)	(0.200)	(0.113)	(0.147)
45 - 54 y.o	0.055	0.081	0.027	-0.042	0.069	0.096
	(0.081)	(0.103)	(0.126)	(0.202)	(0.117)	(0.150)
55 y.o. and above	-0.007	0.010	-0.035	-0.078	-0.015	0.081
	(0.084)	(0.120)	(0.124)	(0.211)	(0.117)	(0.165)
Immigrant # under 24 y.o	-0.046	-0.086	-0.003	-0.028	-0.093	0.143
	(0.177)	(0.272)	(0.274)	(0.312)	(0.270)	(0.448)
Immigrant # 25 - 34 y.o	0.009	0.070	-0.037	-0.072	-0.006	0.080
	(0.167)	(0.192)	(0.253)	(0.270)	(0.274)	(0.324)
Immigrant # 35-44 y.o	-0.004	-0.002	-0.004	-0.022	-0.072	0.098
	(0.158)	(0.183)	(0.244)	(0.295)	(0.266)	(0.318)
Immigrant # 45-54 y.o	-0.082	-0.043	-0.126	-0.078	-0.046	-0.121
	(0.146)	(0.190)	(0.204)	(0.243)	(0.247)	(0.353)
Cohabiting	0.057	0.024	0.107	0.022	0.072	0.075
	(0.048)	(0.058)	(0.081)	(0.093)	(0.068)	(0.081)
Number of children *(base - no children)*:						
One child	0.021	0.011	0.015	0.129	0.010	-0.022
	(0.060)	(0.073)	(0.093)	(0.137)	(0.089)	(0.085)
Two children	0.023	0.018	0.017	0.131	0.014	-0.008
	(0.058)	(0.075)	(0.085)	(0.154)	(0.084)	(0.079)
Three children	0.010	-0.017	0.026	0.078	0.015	-0.025
	(0.073)	(0.102)	(0.104)	(0.162)	(0.112)	(0.125)
Four and more children	0.005	0.011	-0.008	0.076	-0.023	0.027
	(0.088)	(0.132)	(0.107)	(0.166)	(0.124)	(0.195)
Education *(base - ISCED 1 and below)*:						
ISCED 2	0.080	-0.002	0.134			
	(0.097)	(0.124)	(0.138)			
ISCED 3	0.189**	0.075	0.274**			
	(0.087)	(0.120)	(0.124)			
ISCED 4	0.290**	0.205	0.358*			
	(0.123)	(0.179)	(0.186)			
ISCED 5	0.315***	0.197	0.399***			
	(0.092)	(0.120)	(0.139)			
ISCED 6	0.388***	0.288**	0.455***			
	(0.091)	(0.126)	(0.125)			
ISCED 7	0.443***	0.343***	0.512***			
	(0.090)	(0.125)	(0.134)			
Permanent contract	0.033	0.063	0.001	-0.017	0.087	-0.014
	(0.045)	(0.064)	(0.065)	(0.080)	(0.071)	(0.084)
Weekly work hours	0.011***	0.010***	0.011***	0.004	0.012***	0.014***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
Within-job literacy gap	0.000	0.001	0.000	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Within-job numeracy gap	0.001**	0.001	0.002	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.059***	-0.929***	-1.245***	-1.263***	-1.139***	-0.258
	(0.155)	(0.214)	(0.201)	(0.263)	(0.174)	(0.203)
N	20323	9412	10911	2639	11140	6544
R-squared	0.106	0.092	0.114	0.091	0.079	0.092

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A7 **Routine job tasks – Weighted subsample OLS regression results**

	(1) Total	(2) Women	(3) Men	(4) Low education	(5) Medium education	(6) High education
Immigrant Status	-0.038	-0.037	-0.045	0.026	-0.035	-0.170
	(0.149)	(0.166)	(0.226)	(0.231)	(0.239)	(0.294)
Female	-0.076**			-0.064	-0.106**	-0.042
	(0.034)			(0.107)	(0.048)	(0.039)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	0.042	0.031	0.055	0.037	0.070	0.046
	(0.063)	(0.071)	(0.091)	(0.214)	(0.086)	(0.124)
35 - 44 y.o.	0.038	0.048	0.027	-0.005	0.044	0.087
	(0.071)	(0.091)	(0.101)	(0.214)	(0.092)	(0.129)
45 - 54 y.o	0.036	0.065	0.008	-0.053	0.047	0.091
	(0.070)	(0.088)	(0.103)	(0.220)	(0.095)	(0.138)
55 y.o. and above	-0.038	-0.022	-0.059	-0.122	-0.029	0.027
	(0.084)	(0.115)	(0.114)	(0.244)	(0.102)	(0.139)
Immigrant # under 24 y.o	-0.008	0.112	-0.084	-0.094	0.017	0.144
	(0.185)	(0.305)	(0.277)	(0.338)	(0.299)	(0.363)
Immigrant # 25 - 34 y.o	-0.010	0.043	-0.050	-0.146	-0.012	0.134
	(0.186)	(0.221)	(0.266)	(0.326)	(0.306)	(0.308)
Immigrant # 35-44 y.o	-0.046	-0.002	-0.083	-0.150	-0.108	0.160
	(0.165)	(0.189)	(0.260)	(0.278)	(0.277)	(0.304)
Immigrant # 45-54 y.o	-0.082	-0.041	-0.127	-0.163	-0.074	0.045
	(0.170)	(0.206)	(0.237)	(0.284)	(0.268)	(0.336)
Cohabiting	0.077	0.052	0.111	0.084	0.090	0.067
	(0.047)	(0.055)	(0.073)	(0.109)	(0.067)	(0.070)
Number of children *(base - no children)*:						
One child	0.038	0.025	0.041	0.105	0.032	0.003
	(0.053)	(0.069)	(0.080)	(0.151)	(0.080)	(0.065)
Two children	0.041	0.030	0.045	0.137	0.028	0.018
	(0.047)	(0.069)	(0.066)	(0.163)	(0.071)	(0.057)
Three children	0.019	0.001	0.025	0.101	0.014	-0.006
	(0.057)	(0.080)	(0.082)	(0.166)	(0.098)	(0.089)
Four and more children	0.022	0.012	0.023	0.144	0.000	-0.015
	(0.082)	(0.112)	(0.113)	(0.210)	(0.112)	(0.128)
Education *(base - ISCED 1 and below)*:						
ISCED 2	0.109	0.091	0.123			
	(0.092)	(0.126)	(0.136)			
ISCED 3	0.235***	0.176	0.289**			
	(0.088)	(0.140)	(0.120)			
ISCED 4	0.322***	0.311*	0.320*			
	(0.107)	(0.172)	(0.169)			
ISCED 5	0.337***	0.277**	0.386***			
	(0.089)	(0.139)	(0.126)			
ISCED 6	0.356***	0.353**	0.353***			
	(0.089)	(0.139)	(0.119)			
ISCED 7	0.330***	0.336**	0.310**			
	(0.093)	(0.140)	(0.136)			
Permanent contract	0.064	0.085	0.039	0.051	0.099	0.023
	(0.045)	(0.056)	(0.071)	(0.108)	(0.061)	(0.066)
Weekly work hours	0.011***	0.009***	0.012***	0.007	0.013***	0.011***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
Within-job literacy gap	0.001*	0.001	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Within-job numeracy gap	0.001	0.000	0.001	0.002	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.072***	-1.041***	-1.166***	-1.369***	-1.094***	-0.266*
	(0.134)	(0.201)	(0.182)	(0.299)	(0.150)	(0.153)
N	20323	9412	10911	2639	11140	6544
R-squared	0.125	0.107	0.137	0.114	0.128	0.098

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

Table A8 **Manual job tasks – Weighted subsample OLS regression results**

	(1) Total	(2) Women	(3) Men	(4) Low education	(5) Medium education	(6) High education
Immigrant	0.096	0.154	0.016	0.132	-0.013	0.216
	(0.220)	(0.189)	(0.394)	(0.352)	(0.363)	(0.511)
Female	0.031			0.070	0.029	0.011
	(0.061)			(0.159)	(0.096)	(0.092)
Age *(base - under 24 y.o.)*:						
25 - 34 y.o.	0.058	0.083	0.040	-0.046	0.073	0.077
	(0.117)	(0.159)	(0.142)	(0.276)	(0.158)	(0.203)
35 - 44 y.o.	-0.056	-0.010	-0.105	-0.417	-0.017	-0.005
	(0.114)	(0.165)	(0.173)	(0.316)	(0.146)	(0.215)
45 - 54 y.o	-0.129	-0.011	-0.248	-0.457	-0.091	-0.068
	(0.121)	(0.180)	(0.182)	(0.287)	(0.162)	(0.219)
55 y.o. and above	-0.199	-0.139	-0.252	-0.375	-0.206	-0.191
	(0.157)	(0.242)	(0.212)	(0.342)	(0.206)	(0.277)
Immigrant # under 24 y.o	-0.215	-0.256	-0.165	-0.533	0.118	-0.809
	(0.384)	(0.537)	(0.517)	(0.613)	(0.522)	(0.965)
Immigrant # 25 - 34 y.o	-0.207	-0.219	-0.178	-0.469	-0.095	-0.252
	(0.244)	(0.300)	(0.388)	(0.414)	(0.409)	(0.567)
Immigrant # 35-44 y.o	-0.163	-0.107	-0.196	-0.141	-0.059	-0.249
	(0.273)	(0.243)	(0.456)	(0.434)	(0.454)	(0.547)
Immigrant # 45-54 y.o	-0.110	-0.323	0.101	-0.141	-0.047	-0.020
	(0.266)	(0.336)	(0.423)	(0.452)	(0.409)	(0.635)
Cohabiting	-0.014	-0.079	0.067	-0.048	0.021	-0.067
	(0.086)	(0.102)	(0.138)	(0.213)	(0.107)	(0.126)
Number of children *(base - no children)*:						
One child	0.069	0.055	0.059	0.134	0.075	0.015
	(0.098)	(0.138)	(0.137)	(0.230)	(0.121)	(0.146)
Two children	0.083	0.065	0.087	0.204	0.065	0.047
	(0.091)	(0.128)	(0.120)	(0.236)	(0.130)	(0.141)
Three children	0.052	0.067	0.014	-0.084	0.072	0.078
	(0.129)	(0.195)	(0.171)	(0.299)	(0.182)	(0.201)
Four and more children	0.015	0.070	-0.038	-0.014	0.034	0.036
	(0.174)	(0.262)	(0.201)	(0.341)	(0.224)	(0.334)
Education *(base - ISCED 1 and below)*:						
ISCED 2	0.088	0.102	0.086			
	(0.193)	(0.316)	(0.216)			
ISCED 3	0.023	0.007	0.050			
	(0.157)	(0.289)	(0.181)			
ISCED 4	0.050	0.037	0.021			
	(0.187)	(0.296)	(0.287)			
ISCED 5	-0.068	-0.067	-0.065			
	(0.175)	(0.293)	(0.225)			
ISCED 6	-0.168	-0.169	-0.143			
	(0.161)	(0.287)	(0.192)			
ISCED 7	-0.273	-0.292	-0.252			
	(0.169)	(0.288)	(0.202)			
Permanent contract	-0.114	-0.093	-0.151	-0.089	-0.076	-0.193
	(0.078)	(0.113)	(0.102)	(0.169)	(0.111)	(0.147)
Weekly work hours	0.005	0.004	0.007	0.008	0.006	0.002
	(0.004)	(0.005)	(0.005)	(0.008)	(0.005)	(0.006)
Within-job literacy gap	-0.002*	-0.002	-0.002	-0.003	-0.002	-0.003
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Within-job numeracy gap	-0.001	-0.001	-0.002	-0.000	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.358	-0.413	-0.307	0.560	-0.256	-0.910***
	(0.239)	(0.376)	(0.304)	(0.548)	(0.270)	(0.344)
N	20323	9412	10911	2639	11140	6544
R-squared	0.059	0.065	0.061	0.053	0.039	0.092

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: PIAAC cycle 2 data. Own calculations.

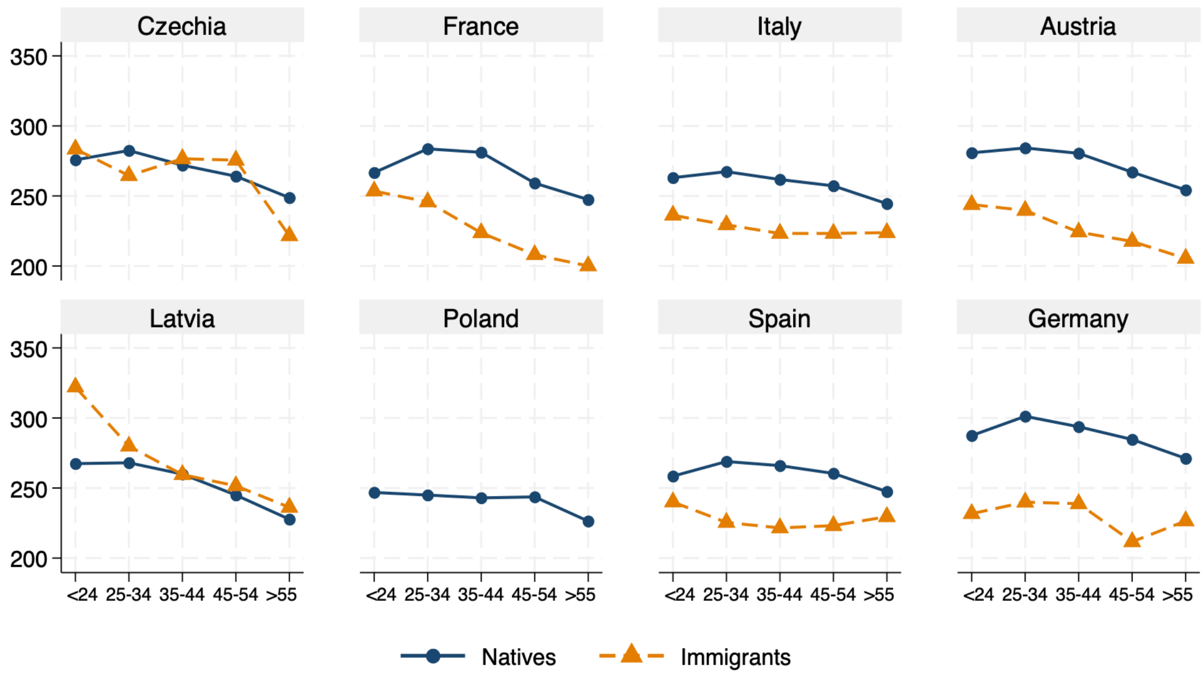
Table A9 **Robustness regressions – Immigrant coefficient**

Job-cell definition	**Smoothing constant** c	(1)	(2)	(3)	(4)
(I) Dependent variable: **Within-job gap in abstract tasks**					
ISCO 2-digit / ISIC 1-digit	No shrinking	-0.17082***	-0.12660**	-0.12344*	-0.10022
		(0.05826)	(0.06062)	(0.06429)	(0.06122)
ISCO 2-digit / ISIC 1-digit	10	-0.17083***	-0.12660**	-0.12345*	-0.10023
		(0.05826)	(0.06062)	(0.06428)	(0.06121)
ISCO 2-digit / ISIC 1-digit	15	-0.17084***	-0.12661**	-0.12345*	-0.10023
		(0.05826)	(0.06062)	(0.06428)	(0.06121)
ISCO 2-digit / ISIC 2-digit	5	-0.13396**	-0.10163*	-0.10213*	-0.06706
		(0.05208)	(0.05353)	(0.05720)	(0.05392)
(II) Dependent variable: **Within-job gap in routine tasks**					
ISCO 2-digit / ISIC 1-digit	No shrinking	-0.17298***	-0.13174**	-0.10968*	-0.09331
		(0.05629)	(0.05949)	(0.05977)	(0.05811)
ISCO 2-digit / ISIC 1-digit	10	-0.17299***	-0.13175**	-0.10969*	-0.09332
		(0.05629)	(0.05949)	(0.05977)	(0.05811)
ISCO 2-digit / ISIC 1-digit	15	-0.17300***	-0.13176**	-0.10969*	-0.09333
		(0.05629)	(0.05949)	(0.05977)	(0.05811)
SCO 2-digit / ISIC 2-digit	5	-0.14420***	-0.11101**	-0.09314*	-0.06681
		(0.05330)	(0.05456)	(0.05460)	(0.05325)
(III) Dependent variable: **Within-job gap in manual tasks**					
ISCO 2-digit / ISIC 1-digit	No shrinking	0.08507	0.04071	-0.03724	-0.02619
		(0.10853)	(0.10415)	(0.10143)	(0.10153)
ISCO 2-digit / ISIC 1-digit	10	0.08508	0.04072	-0.03723	-0.02619
		(0.10853)	(0.10415)	(0.10142)	(0.10153)
ISCO 2-digit / ISIC 1-digit	15	0.08508	0.04072	-0.03723	-0.02618
		(0.10853)	(0.10415)	(0.10142)	(0.10153)
ISCO 2-digit / ISIC 2-digit	5	0.06403	0.03441	-0.02772	-0.03772
		(0.09913)	(0.09330)	(0.09113)	(0.09045)
Additional controls					
Gender			Yes	Yes	Yes
Age			Yes	Yes	Yes
Cohabiting			Yes	Yes	Yes
Number of children			Yes	Yes	Yes
Education			Yes	Yes	Yes
Permanent contract			Yes	Yes	Yes
Weekly work hours			Yes	Yes	Yes
Literacy skill				Yes	
Numeracy skill				Yes	
Within-job literacy gap					Yes
Within-job numeracy gap					Yes
Country		Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Final population weights and a full set of eighty replication weights and Jackknife replication methodology are used in all models. Statistical significance is denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

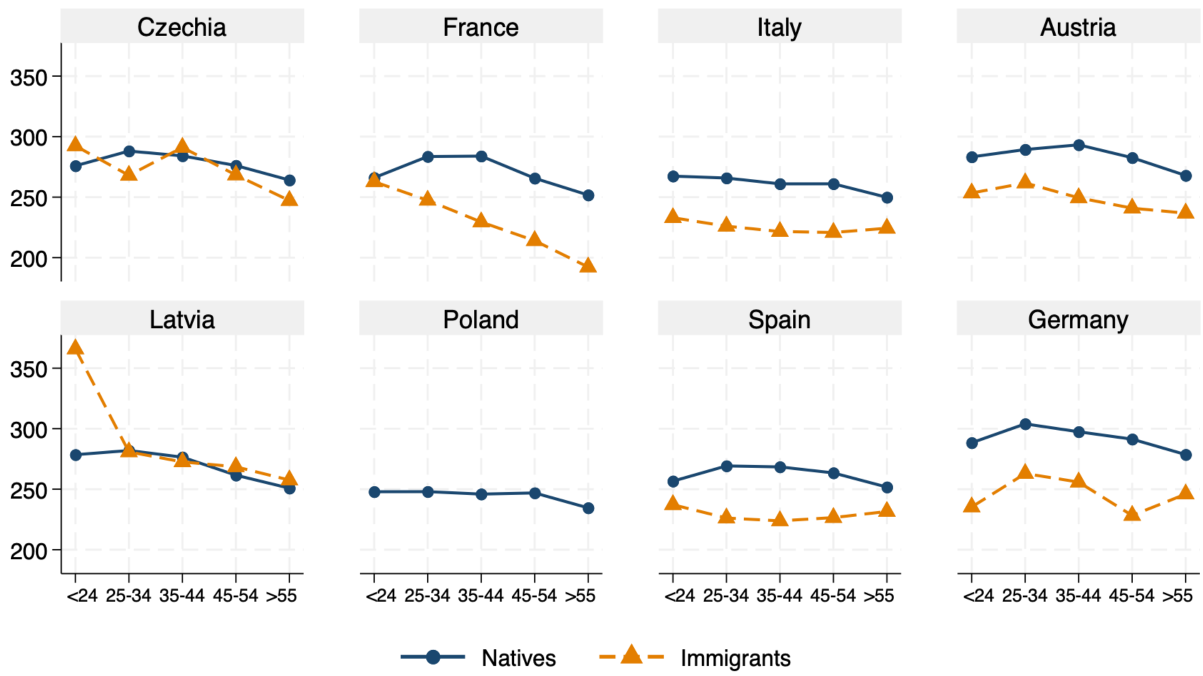
Source: PIAAC cycle 2 data. Own calculations.

Figure A1 **Literacy skill by origin, age group and country**



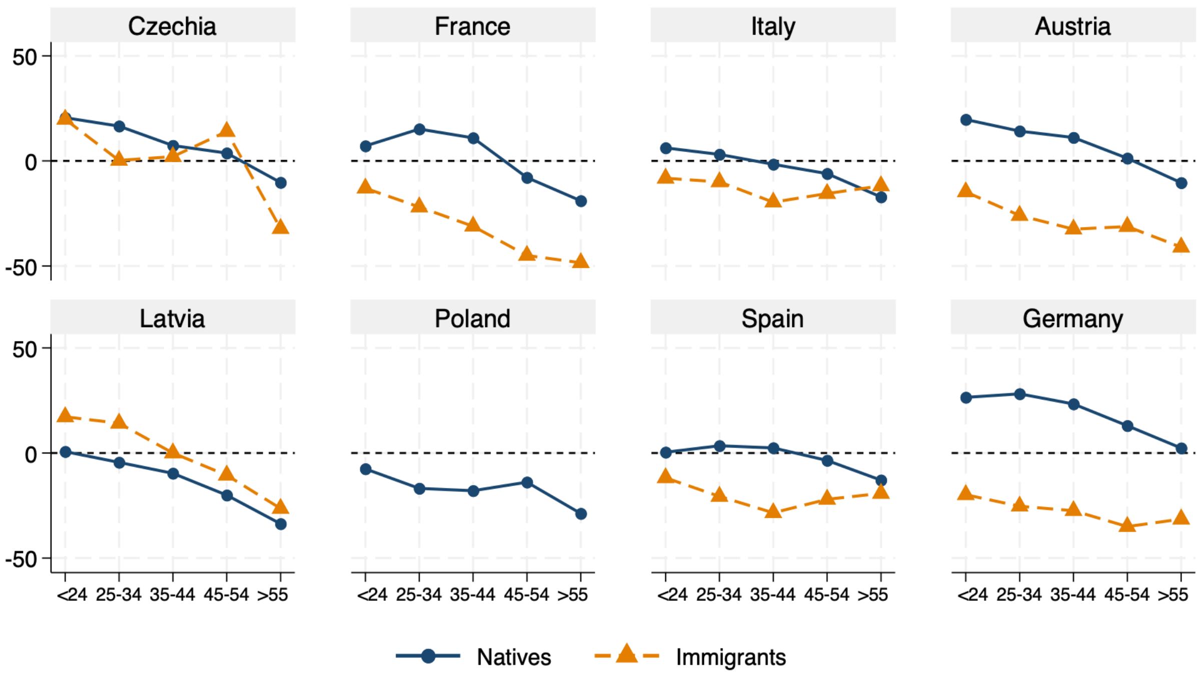
Notes: Final population weights are used in all estimations.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A2 **Numeracy skill by origin, age group and country**



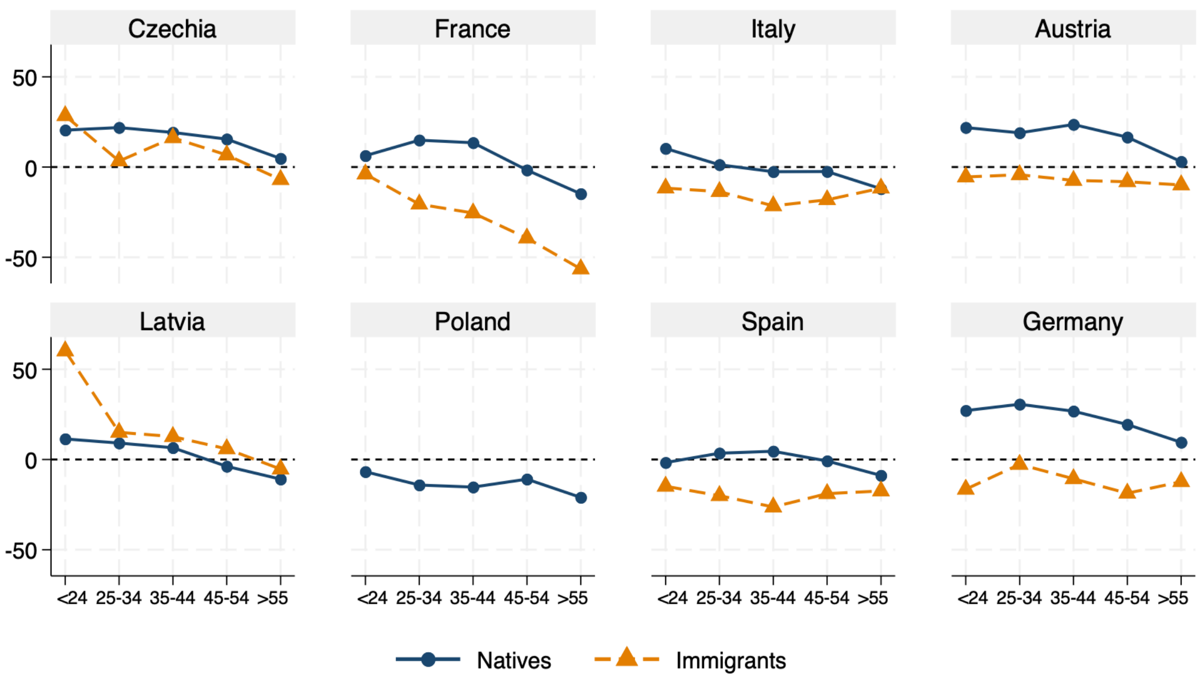
Notes: Final population weights are used in all estimations.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A3 **Average within-job gap in literacy skill by origin, age group and country**



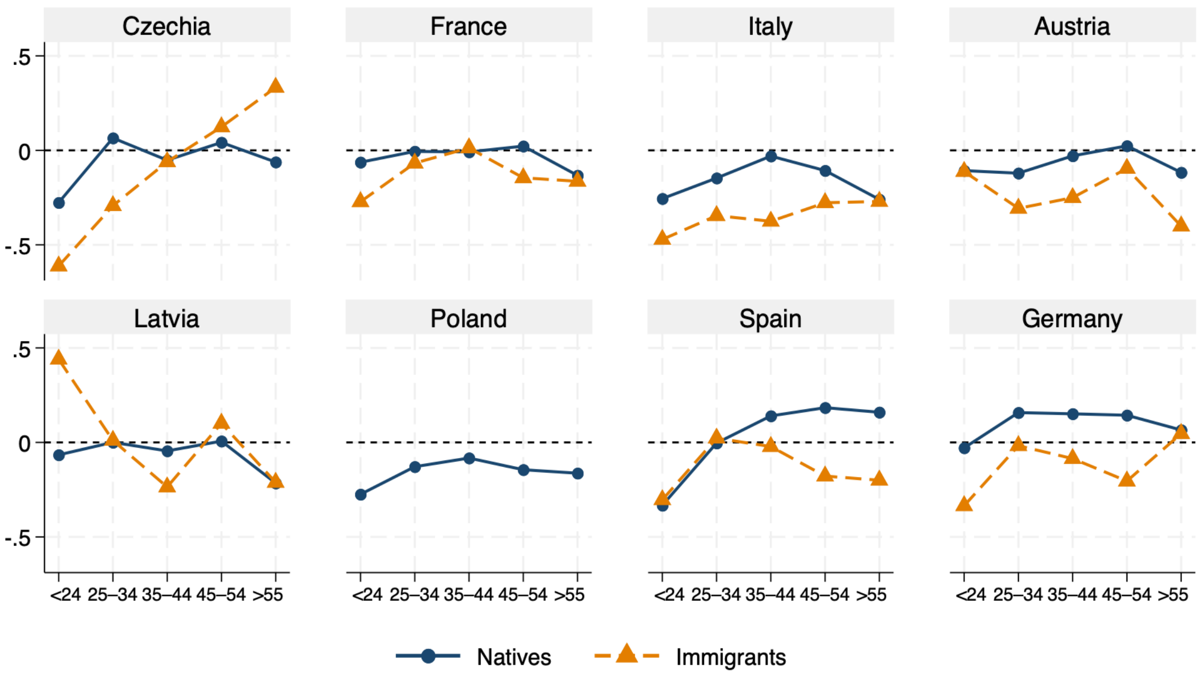
Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual skill level and job-average skill level in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A4 **Average within-job gap in numeracy skill by origin, age group and country**



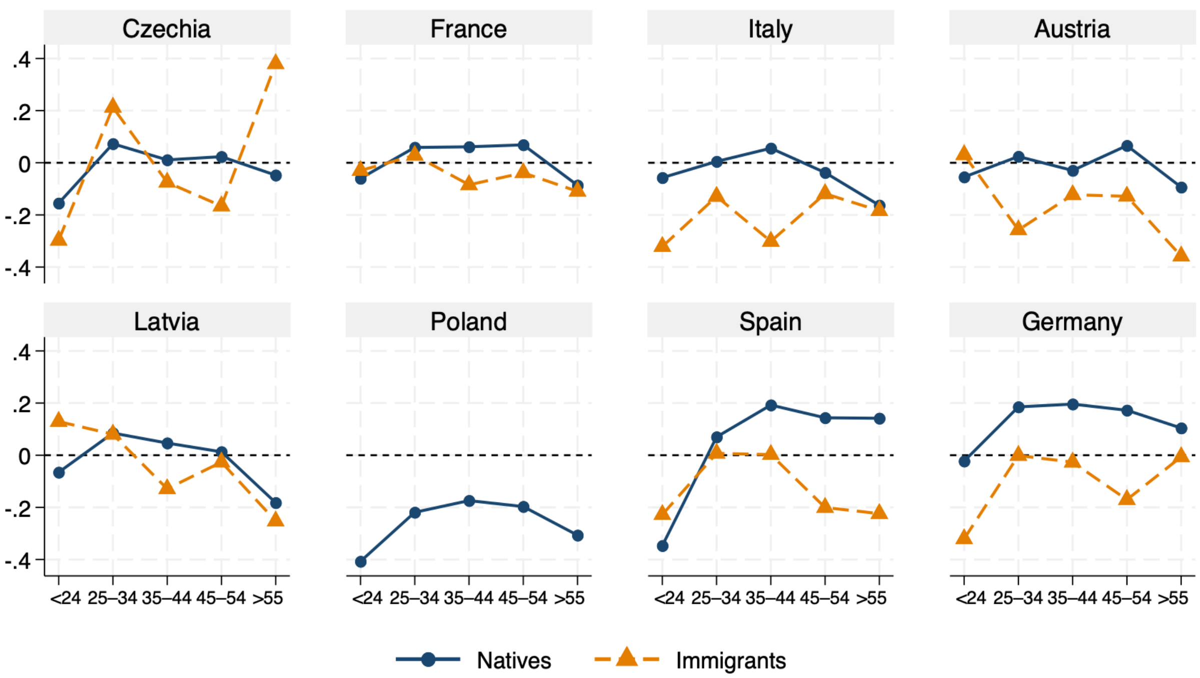
Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual skill level and job-average skill level in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A5 **Average within-job gap in abstract tasks by origin, age group and country**



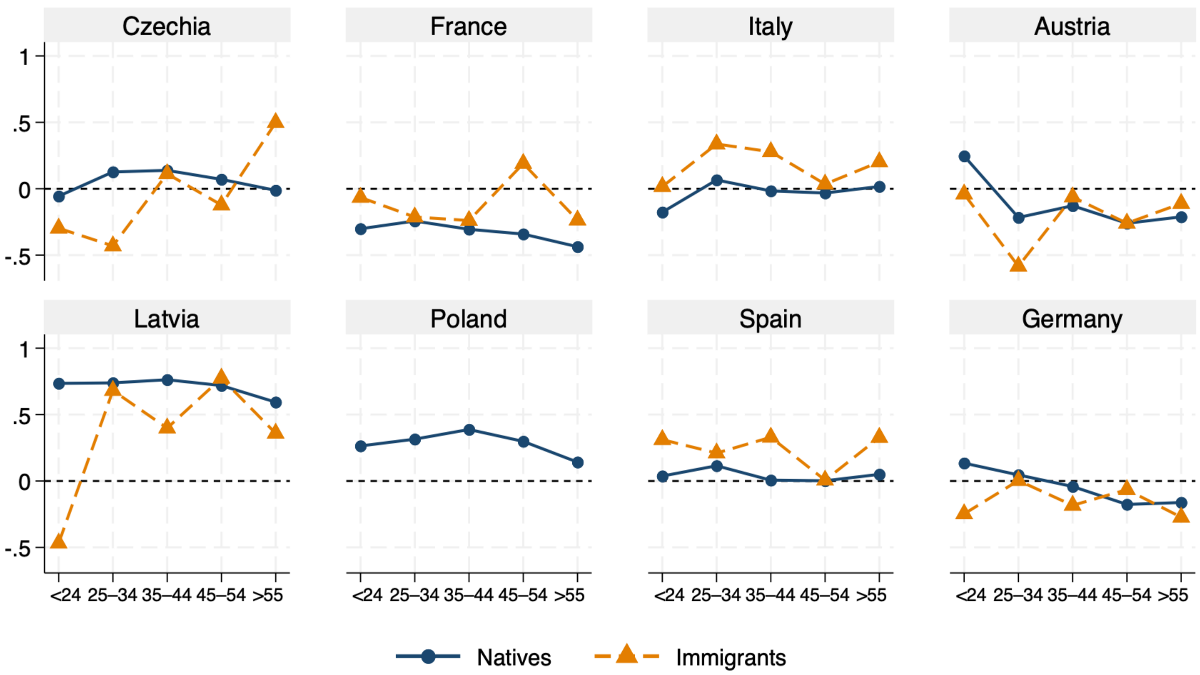
Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual frequency of performing abstract tasks and job-average task frequency in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A6 **Average within-job gap in routine tasks by origin, age group and country**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual frequency of performing abstract tasks and job-average task frequency in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

Figure A7 **Average within-job gap in manual tasks by origin, age group and country**



Notes: Final population weights are used in all estimations. Zero level corresponds to no deviation between individual frequency of performing abstract tasks and job-average task frequency in respective domain.
Source: PIAAC Cycle 2 data. Own calculations.

IMPRESSUM

Herausgeber, Verleger, Eigentümer und Hersteller:
Verein „Wiener Institut für Internationale Wirtschaftsvergleiche“ (wiiw),
Wien 6, Rahlgasse 3

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Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.