UNIVERSITÀ
DI PAVIA

Dipartimento di Scienze Economiche e

Aziendali Corso di Laurea magistrale in

Economics, Development and Innovation

Curriculum: International Development and Economic

Policy

MULTIDIMENSIONAL SKILL MISMATCH, JOB MOBILITY AND PRODUCTIVITY: EVIDENCE FROM GERMANY, ITALY AND SWEDEN

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Anno Accademico 2025-2026

Abstract

This thesis develops an occupation-based framework to measure multidimensional skill mismatch by integrating PIAAC Cycle 2 (2022-23) microdata on adult proficiency with occupational requirements from ESCO, harmonized to ISCO-2 classification. The main contribution is to identify and quantify the alignment or misalignment between individual competency profiles and occupational requirement proxies in Germany, Italy, and Sweden, with a particular focus on cross-country comparability and mismatch structures across various cognitive dimensions.

The mismatch is addressed through signed, standardized gaps between individual proficiency and occupational requirements in literacy, numeracy, and adaptive problem-solving skills. The incidence is estimated using a tolerance band that is symmetric around the gap, yielding a classification of individuals into three main categories: under-skilled, matched, and over-skilled, highlighting that the mismatch is intrinsically multidimensional and cannot be reduced informatively to a single synthetic indicator. The APS measures are missing for Italy in the merged public-use files; therefore, they are available only for Germany and Sweden, limiting full comparability across the three countries in this domain.

To support interpretation rather than causal estimation, the analysis focuses on the mismatch and labor-market outcomes: position in the earnings distribution (hourly gross earnings deciles) and occupational stability (short-tenure proxy). The wage associations are substantially weaker when ISCO-2 fixed effects are included, consistent with an interpretation based on occupational sorting. For stability, the mismatch intensity shows a small negative association with the short-tenure probability, suggesting greater persistence of matches in the cross-section. A robustness check for Italy is conducted using hourly earnings with PPP in logs, confirming that the results are sensitive to occupational controls and remain descriptive.

Overall, the findings support using a multidimensional method to measure mismatch and advise caution in causal interpretation, as the empirical framework is transparent for tracking similar skill-occupation pairs.

Key words: skill mismatch; PIAAC; ESCO; ISCO; literacy; numeracy; occupational sorting; cross-country comparison; adaptive problem solving; APS.

Mismatch multidimensionale delle competenze, mobilità lavorativa e produttività: evidenza da Germania, Italia e Svezia

Abstract in Italiano

Questa tesi sviluppa un framework basato sull'occupazione per misurare il mismatch multidimensionale delle competenze, integrando i microdati del PIAAC Cycle 2 (2022-23) relativi alle competenze degli adulti con i requisiti occupazionali derivati dall'ESCO e armonizzati secondo la classificazione ISCO-2. Il contributo principale di questa tesi consiste nell'identificare e quantificare l'allineamento o il disallineamento tra i profili di competenze individuali e i proxy occupazionali in Germania, Italia e Svezia, con particolare attenzione alla comparabilità cross-country e alla struttura di mismatch lungo diverse dimensioni cognitive.

Il mismatch è misurato attraverso gap, segnati e standardizzati, tra le competenze individuali e i requisiti occupazionali nei domini di literacy, numeracy e problem-solving adattivo (APS). L'incidenza è stimata mediante una banda di tolleranza simmetrica attorno al gap, che consente di classificare gli individui in tre categorie principali: under-skilled, matched e over-skilled. I risultati relativi al mismatch indicano che lo stesso è intrinsecamente multidimensionale e non può essere ridotto, in modo informativo, a un unico indicatore sintetico. Le misure relative all'APS non sono disponibili per l'Italia nei file pubblici utilizzati dopo il merge e risultano osservabili solo per la Germania e la Svezia, limitando la piena comparabilità tra i tre paesi in questo dominio.

Ai fini interpretativi e non di identificazione causale, l'analisi mette in relazione il mismatch con alcuni esiti del mercato del lavoro: la posizione nella distribuzione salariale e la stabilità occupazionale, misurata tramite una proxy di short tenure. Le associazioni con i salari

risultano sensibilmente più deboli quando i fixed effects a livello ISCO-2 vengono introdotti, in linea con un'interpretazione basata sul sorting occupazionale. Per quanto concerne invece la stabilità, l'intensità del mismatch mostra una piccola associazione negativa con la probabilità di short tenure, suggerendo una maggiore persistenza dei match nella cross-section. Un controllo di robustezza specifico per l'Italia, basato sui guadagni orari in logaritmi corretti per PPP, conferma che i risultati sono sensibili ai controlli occupazionali e devono essere interpretati in chiave descrittiva.

Nel complesso, i risultati avvalorano l'uso di un approccio multidimensionale alla misurazione del mismatch e invitano alla cautela nell'interpretazione causale, mostrando che il quadro empirico proposto offre uno strumento trasparente e replicabile per analizzare l'allineamento tra competenze e occupazioni.

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1. Introduction

Understanding skill mismatch, defined as the gap between workers' abilities and the skills required for their jobs, is crucial for analyzing productivity and labor-market adjustment. This thesis takes a **multidimensional** approach: skill mismatch cannot be fully described by a single indicator, such as years of schooling or educational attainment, because workers may be well-matched in some domains while mismatched in others. Many empirical approaches rely on education-based and self-reported proxies, which do not fully capture workers' actual competencies or their alignment with job requirements.

This thesis introduces an occupation-based, multidimensional metric for skill mismatch, integrating objective worker proficiency data from the OECD Survey of Adult Skills (PIAAC) with occupational requirements, proxied by ESCO and harmonized to ISCO-2. Concentrating on Germany, Italy, and Sweden, the study develops a continuous index to measure and describe the gap between workers' skills and job demands.

Against this background, this research explores the following question: *How common and severe is multidimensional skill mismatch within occupations in Germany, Italy, and Sweden when assessed using test-based skills instead of education-based proxies?*

The three countries chosen offer a valuable comparative framework because they feature recent PIAAC data alongside diverse labor-market institutions, training systems, and potential adjustment frictions. These differences can influence both the occurrence and duration of mismatches.

To contextualize micro evidence, this analysis employs OECD Skills for Jobs indicators as a macro benchmark for country-level skill shortages and surpluses. These indicators do not measure individual mismatches but help facilitate cross-country comparisons. Additionally, PISA 2022 data is used descriptively as a cross-cohort benchmark to compare country differences in core cognitive skills.

This thesis makes three key contributions to the literature. First, it creates a test-based measure of mismatch that connects individuals' skill profiles to occupation-level requirements. Second, it considers mismatch as a multidimensional issue, capturing both specific domain gaps and overall mismatch intensity. Lastly, it applies this framework across different countries and analyzes various factors such as occupational sorting, institutional contexts, and macro skill imbalances to explain cross-country differences.

The empirical analysis is primarily descriptive, aiming to document mismatch patterns and offer an understandable framework for comparison.

2. Literature Review: Theoretical Framework & Empirical Evidence

Analyzing skill mismatch—the gap between the competencies workers provides and the skills demanded by occupations—is essential for understanding productivity and labor-market adjustments, especially in a context driven by digitalization and the growth of non-routine tasks. Despite extensive research, three main aspects remain particularly important for comparative empirical analysis. First, many mismatch measures depend on educational proxies (e.g., educational qualifications, years of schooling) or self-assessments, which only partially reflect actual competencies in use. Second, mismatch is inherently multidimensional; an individual can be aligned in some areas and misaligned in others. Lastly, observed mismatch patterns can result from allocation mechanisms (sorting and assignment) and information frictions rather than purely mechanical within-occupation outcomes.

This chapter aims to develop a theoretical framework guiding the empirical analysis. It begins with definitions and mismatch taxonomies, then discusses the evolution from a unidimensional view of human capital to a vectorial representation of competencies. Then the chapter concludes by examining the role of micro benchmarks, such as OECD Skills for Jobs, which uses indicators of skills imbalances, shortages, and surpluses and introduces an alternative distance metric from the mismatch literature for comparison with the baseline Euclidean measure.

The European Centre for the Development of Vocational Training taxonomy highlights that the misalignment is not limited to only one dimension: vertical mismatch, where skills and or education are above or below job requirements, horizontal mismatch, where the field of study or the training is not aligned with the job requirements, and the dynamics related to obsolescence and technological change. This heterogeneity shows that an approach based exclusively on educational qualifications is insufficient to describe the allocation of human capital in the contemporary economy (CEDEFOP, 2010).

Figure 2.1 - Types of Mismatches

Overeducation	To have completed more years of education than the current job requires.
Undereducation	To have completed fewer years of education than the current job requires.
Overqualification	To hold a higher qualification than the current job requires.
Underqualification	To hold a lower qualification than the current job requires.
Overskilling	To be unable to fully use one's skills and abilities in the current job.
Underskilling	To lack the skills and abilities necessary to perform the current job to acceptable standards.
Skill shortage	Demand for a particular type of skill exceeds the supply of available people with that skill.
Skill surplus	The supply of people with a particular skill exceeds the demand for it.
Skill gap	The level of skills of the person employed is less than that required to perform the job adequately or the type of skill does not match the requirements of the job.
Economic skills obsolescence	Skills previously used in a job are no longer required or are less important.
Physical (technical) obsolescence	Physical or mental skills and abilities deteriorate due to atrophy or wear and tear.
Vertical mismatch	The level of education or skills is less or more than the required level of education or skills.
Horizontal mismatch	The level of education or skills matches job requirements, but the type of education or skills is inappropriate for the current job.
Crowding out/ bumping down	Better qualified workers are hired to do jobs that less qualified workers could also do, thus replacing (crowding out) less qualified workers from traditional employment possibilities for their level of skill. Bumping down refers to this process working from top to bottom, pushing less qualified workers to even lower level jobs. At the extreme some lower level workers may become unemployed.

Vertical mismatch refers to discrepancies in qualification levels, causing over- or under-qualification, while horizontal mismatch assesses misalignment in the type of education or training. These differences highlight the need to go beyond solely education-focused indicators and adopt measures that directly evaluate how workers' skill profiles align with the specific requirements of occupations.

2.1 The Evolution of Human Capital: from Unidimensional Credential to Multidimensional Skill Vectors

Early human capital theory conceptualized skills as individual assets acquired through investment, with education serving as the main observable indicator. In this framework, schooling is believed to boost productivity and lead to higher earnings (Schultz, 1961; Becker, 1962). However, subsequent research and policy analysis show that educational attainment is an incomplete measure of productive competencies, as workers with similar levels of education may vary significantly in the types and extent of skills they possess. As a result, the labor-market rewards these differences in heterogeneous ways across occupations and tasks.

A key refinement in this discussion is the differentiation between general and specific human capital. General skills can be transferred across employers and roles, whereas specific skills are tied to particular firms, technologies, and job environments (Kessler & Lülfesmann, 2002). This distinction is crucial for understanding mismatch, as the ability to transfer skills influences worker mobility and the pace of correcting misalignments. Training programs that focus on widely recognized and portable skills can help facilitate workers' reassignment to better jobs. Conversely, environments where career development depends heavily on firm-specific or job-specific skills may slow down adjustment, especially when technological advancements change the nature of tasks.

Rapid technological change can also accelerate skill obsolescence and alter occupational demands, raising the risk that job-specific skills lose value and underscoring the importance of multidimensional measurement.

These considerations drive the shift from simple, one-dimensional proxies to a multidimensional view of skills. In today's labor-markets, what counts is not just how much education a worker has, but how well their skill set matches the demands of their tasks. This thesis adopts a vector-based approach where both workers and jobs are characterized by multidimensional profiles, enabling the measurement of mismatch as the distance between a worker's skills and the requirements of their occupation.

2.1.1 The Signaling Challenge and Vertical Mismatch

While Human Capital Theory suggests that education increases productivity, Signaling Theory (Spence, 1973) highlights the role of asymmetric information in the hiring process. Since firms can't perfectly evaluate workers' productivity ex ante, educational credentials serve more as signals of ability and discipline than as direct indicators of productive skills. In equilibrium, education provides useful information only if signaling costs vary systematically among different worker types, enabling employers to use credentials as a screening tool.

Spence explains hiring as an investment under uncertainty, comparing it to buying a lottery ticket that sets the wage. For risk-neutral employers, the wage reflects the individual's marginal contribution to the firm. Applicants cannot fully control these signals, but they can try to influence them, for example, through education. To do so, they incur signaling costs that extend beyond money to include time.

Figures A.1-A.2 illustrate Spence's signaling mechanism; here, the focus is on its measurement implication: education is an imperfect proxy for skills. This view explains why credentials-based proxies might mismeasure skills and lead to a vertical mismatch. When credentials grow more rapidly than high-skill jobs, the labor-market may undergo "credential inflation" and a "bumping down" phenomenon, where more educated workers accept lower-tier jobs, pushing out less-educated workers. Such mismatches often stem from allocation and screening processes rather than a talent shortage.

These insights underpin the empirical approach of this thesis, which does not depend solely on credentials. Instead, mismatch is assessed using objective proficiency data (PIAAC) and occupation-level requirements within a multidimensional vector framework.

2.1.2 The Paradigm Shift: Toward Multidimensional Skill Vectors

The main limitation of the models examined so far is their treatment of human capital as a one-dimensional scalar variable, typically measured by years of education or qualifications. However, horizontal mismatch and wage heterogeneity indicate that formal education is an incomplete proxy for actual productive skills.

A multidimensional approach, where human capital is represented not as a single value but as a vector of diverse skills ($\mathrm{S_i} = S_{i,1}, \ldots, S_{i,D}$) denotes workers i's proficiency across D skill domains

encompassing both cognitive and non-cognitive abilities. Simultaneously, each occupation can be characterized by a vector of requirements or tasks ($\mathrm{R_j} = R_{j,1}, \ldots, R_{j,D}$) needed to perform the job. In this framework, a mismatch is naturally defined as the distance between a worker's skill profile and an occupation's requirements.

The Mismatch is redefined using the 'Euclidean distance" between these two versions. This metric captures not only the quantitative discrepancy—such as whether the worker has "too much" or "too little' education—but also assesses the quality of the alignment between specific competency dimensions analyzed by PIAAC and the requirements of the task. (Guvenen, et al., 2015)

$$Mismatch_{ij}^{Euc} = \sqrt{\sum_{d=1}^{D} \left(S_{id} - R_{jd}\right)^2}$$

This metric summarizes the overall magnitude of misalignment across domains, moving beyond purely qualitative discrepancies to measure the degree of alignment between specific competencies and task requirements.

As a comparison measure, the multidimensional mismatch literature also employs an index that sums the weighted absolute gaps between worker skills and job requirements. In Mismatch Cycles (Baley et al., 2022), mismatch is defined as a weighted sum of the absolute differences across skill and requirement components. Formally, it can be written as:

$$Mismatch_{it}^{Abs} \equiv \sum_{j=1}^{J} v_j |a_{ij} - q_{i,t,j}|$$

Where $a_i = (a_{i,1}, \dots, a_{iJ})$ denote the skill vector of worker i and v_j are "market weights" obtained by the regression coefficients of each mismatch dimension in a Mincer regression, normalized so $\sum_{j=1}^{J} v_j = 1$. Baley and colleagues suggest using weights based on each dimension's importance in the labor-market, and they differentiate between "positive" and "negative" mismatches as potentially weighted sums of these absolute gaps. (See Appendix A §A.2)

The absolute gap index is used for completeness and robustness alongside the baseline Euclidean distance, without changing the central vector framework.

Focusing on objectively measured domains in PIAAC, the analysis captures skill dimensions that education-based proxies may overlook. Including Adaptive Problem Solving (APS) as an extra domain provides a proxy of workers' ability to adapt to new situations, which is increasingly important as job tasks change with technological advancements.

2.2 Micro-foundations: Assignment Models and Search Frictions

Understanding skill mismatch involves analyzing how workers and jobs are allocated within the labor-market. Assignment models emphasize that economic efficiency depends on matching each worker to the task at which their marginal productivity is highest (Sattinger, 1993). In reality, structural frictions hinder perfect matching and can lead to persistent misallocation across occupations.

A primary mechanism behind search frictions is that finding a good match incurs time and resource costs for both workers and firms. Consequently, workers may accept suboptimal matches to avoid long unemployment periods, and firms may hire imperfectly matched candidates when recruitment is expensive. These frictions are particularly relevant in environments with lower reallocation efficiency, where adjustments to better matches are slower, and mismatches may persist.

Information frictions add further complexity because match quality is not fully observable at the time of hiring, especially for young or inexperienced workers. Fredriksson et al. (2018) demonstrate that workers are sorted based on their comparative advantage within occupations, consistent with Roy-type self-selection, and that match quality improves over time through learning. This suggests that observed mismatch patterns may reflect underlying skill distributions and the dynamics of sorting and information updating, rather than solely educational credentials.

These allocation mechanisms are inherently multidimensional, operating within a vector framework in which both workers and occupations are characterized by profiles across multiple skill domains. Mismatch is reflected by deviations between these profiles. The empirical analysis leverages the idea of measuring mismatch intensity using test-based skill vectors and occupational-level requirement vectors to document variation in mismatch across occupations and countries.

2.3 The US empirical measurement tradition: ASVAB & O*NET

A significant body of empirical research explores multidimensional skill mismatches by linking individual ability measures with occupational requirement descriptors. In the US, worker skills are often assessed through standardized tests like the Armed Services Vocational Aptitude Battery (ASVAB), a multi-aptitude test that evaluates developed abilities and predicts success in military careers. It is administered annually to military applicants, high school students, and post-secondary students. Occupational requirements are usually estimated using data from the O*NET database, which offers detailed descriptions of skills, abilities, and tasks associated with each occupation. This approach allows researchers to position workers and occupations within a shared multidimensional space, measuring mismatch as the distance between a worker's skills and the job's requirements.

This requirements-based method closely aligns with the vector framework used in this thesis. Conceptually, the US literature relies on O*NET for requirement content, whereas European microdata typically classify occupations using the ISCO system, which is a coding scheme rather than a requirements database. European studies must source requirement information from separate sources. In this thesis, occupation-level requirements are derived from ESCO and harmonized with ISCO-2-digit codes to match the occupational data reported in PIAAC. Here, ISCO functions as the merge key and classification layer, while ESCO supplies the underlying skill content needed to build requirement vectors.

Finally, the literature on mismatch cycles indicates that multidimensional mismatch indices can be constructed using various distance metrics, including absolute-gap methods, which provide a natural comparison to the baseline Euclidean distance used in this thesis.

The next chapter describes the construction of ESCO-based requirement vectors at the ISCO-2 level and the implementation of the mismatch indices using PIAAC proficiency domains.

2.4 Economic Consequences: Wage Outcomes, Productive and Skill Obsolescence

Research shows that multidimensional skill mismatches can significantly impact both individual and overall economic outcomes. When workers' skills do not align with job demands, productivity can decline due to underused abilities, potentially leading to slower wage growth over their careers.

Studies indicate that larger skill gaps are often associated with lower earnings, although the strength and direction of this relationship can vary by mismatch type and occupational sorting effects. Additionally, because match quality is not fully observable at hiring, wage disparities caused by mismatches may emerge gradually as firms learn workers' actual productivity and adjust pay, or as workers shift to better-fitting roles. (Fredriksson, et al., 2018)

Another channel discussed in the literature is skill obsolescence, which occurs when workers are persistently employed in jobs that do not fully utilize their skills, leading to skill depreciation over time. Additionally, technological advancements can diminish the value of skills linked to specific tasks and production technologies. These mechanisms imply that ongoing mismatch may have long-term effects on human capital development and adaptability.

While this thesis primarily focuses on measuring and describing multidimensional mismatch patterns, these implications highlight the importance of documenting mismatch across occupations and countries. This is crucial for understanding productivity differences and guiding policy discussions.

2.5 Institutional context and macro benchmarks: reallocation ELP and ALMP, Skill Shortages and Surpluses

The occurrence and duration of multidimensional skill mismatches vary across countries not only because of differences in skill endowments and occupational structures, but also because institutional settings influence reallocation and adjustment. A "Varieties of Capitalism" perspective offers a helpful framework for comparing Germany, Italy, and Sweden, as these economies have different mixes of labor-market regulation, training systems, and policy tools that can affect how quickly mismatches are corrected.

2.5.1 Allocative Efficiency and Aggregate Performance

Vandeplas & Thum-Thysen (2019) emphasize that skill mismatch can impact the macroeconomy by lowering overall productivity and GDP growth, particularly if it reflects an inefficient distribution of talent across firms and occupations. The effect largely depends on how effectively reallocation institutions work; efficient frameworks that support shifting from lower- to higher-productivity matches can reduce the macroeconomic costs of mismatches.

2.5.2 Employment Protection Legislation (EPL) and adjustment frictions.

Employment Protection Legislation (EPL) impacts labor-market adjustments by influencing hiring and separation costs. Stricter EPL can decrease workforce flows and hinder the quick correction of poor matches, whereas more flexible policies may ease transitions when mismatches occur. In this thesis, EPL is viewed as part of the institutional environment that can influence the persistence of mismatch patterns, rather than as a direct cause.

2.5.3 Active Labor Market Policies (ALMP) and Training Capacity

Active Labor Market Policies (ALMP) and training systems help address mismatches by promoting reskilling and improving matching through counseling, placement, and requalification programs. Differences between countries in active and passive policies, as well as in training effectiveness, are key to understanding why mismatch patterns vary across Germany, Italy, and Sweden—particularly in areas related to adaptive problem solving. Historically, Italy has emphasized passive income support over active training, often channeling ALMP funds into emergency aid instead. This insufficient focus on active measures hampers under-skilled workers from bridging their skills gaps, contributing to the persistent stagnation in productivity reflected in PIAAC data.

In the empirical chapter, job tenure is used descriptively as an indicator of job stability, which may correlate with the persistence of mismatches.

2.5.4 OECD Skills for Jobs as a Macro Benchmark (Shortage/Surplus)

To complement the micro-level mismatch measures, this thesis uses OECD Skills for Jobs indicators on skills imbalances as a macro benchmark to describe whether specific skills are in relative shortage or surplus within each country. The OECD methodology constructs imbalances in two steps: first, it computes shortages or surpluses at the occupational level and then maps them into skill shortages or surpluses using information on skill requirements by occupation.

In this thesis, Skills for Jobs indicators are used strictly to contextualize cross-country patterns and support the policy discussion; they are not used to measure individual worker-job mismatch.

The literature review emphasizes that multidimensional skill mismatch is a complex phenomenon that cannot be reduced to educational credentials alone. Transitioning from a one-dimensional view of human capital to a vectorial framework suggests that what truly matters is the alignment between workers' actual competencies and the tasks and skills required by their occupations.

Guided by the discussed framework, the empirical analysis is based on three expectations. First, skill-based measures (PIAAC) were expected to reveal mismatch patterns that differ from those of education-based proxies, reflecting the imperfect nature of education as an indicator of productive skills. Second, mismatch intensity is likely to vary across domains and occupations, justifying a vector-based approach and the use of continuous mismatch indices, such as Euclidean distance, with a Bailey-style absolute gap index used for comparison. Third, the prevalence and intensity of mismatch are expected to differ across the three countries analyzed, reflecting variations in skill distributions, occupational structures, and macroeconomic conditions of shortage or surplus.

These considerations lay the foundation for the next chapter, which describes the PIAAC Cycle 2 dataset, the ESCO-to-ISCO mapping strategy, and the development of occupational requirement vectors and multidimensional mismatch indices.

3. Data & Methodology

This chapter proceeds in four steps. First, it describes the PIAAC data and how the analytical sample was constructed. Second, it defines worker skill supply using PIAAC proficiency scores and establishes occupation-level skill requirements using ESCO information harmonized to ISCO-2. Third, it develops domain-specific and multidimensional mismatch measures. Finally, it outlines the empirical strategy used to analyze how these measures relate to earnings rank and job stability.

3.1 The PIAAC Dataset: A Multidimensional Approach

This study uses the OECD PIAAC survey, which is well-suited because it provides directly assessed proficiency measures, allowing comparisons based on actual skills rather than just educational backgrounds. It is a cross-national household survey of adults aged 16 to 65, capturing cognitive skills and background information across different countries. This thesis uses the PIAAC Cycle 2 (2022-23) public-use files (PUF) for Germany, Italy, and Sweden.

PIAAC Cycle 2 assesses Literacy, Numeracy, and Adaptive Problem Solving (APS). Scores from 0 to 500 are based on Item Response Theory (IRT). The dataset includes 10 plausible values (PVs) per domain, accounting for measurement uncertainty. Its complex survey design uses sampling and replicate weights for accurate, representative statistics and analyses.

In Cycle 2, **literacy** is the ability to access, understand, evaluate, and reflect on texts to meet goals, gain knowledge, and engage society (Rouet et al., 2025). **Numeracy** involves applying and reasoning with math in various formats to solve challenges (Tout et al., 2021). **APS** assesses the capacity to achieve goals in uncertain, dynamic environments, requiring cognitive and metacognitive skills such as problem definition, information gathering, and solution application

(Grieff, S. et al., 2021). Unlike Cycle 1's technology-based problem-solving, APS focuses on strategy adjustment and progress tracking via metacognitive processes.

For each country, PUF data are distributed across two datasets, which are merged by respondent ID (SEQID). The unweighted samples include 4,793 in Germany, 4,621 in Italy, and 3,710 in Sweden.

The analytical sample is restricted to employed individuals with complete proficiency data across all three domains. This enables the construction of worker skill vectors, which are matched to occupation-level requirement vectors from ESCO and aligned with ISCO-2, to compute mismatch indices. The analyses of earnings and job tenure are exploratory and presented separately to examine how mismatch patterns are descriptively linked to labor-market outcomes.

3.1.1 Descriptive comparison of Adult Skills across Germany, Italy, and Sweden

Differences in adult skills across countries affect occupational entry and the development of skill gaps. PIAAC data show that Sweden has the highest literacy and numeracy, Germany is in the middle, and Italy has the lowest. APS data confirm this pattern when available.

Beyond average scores, proficiency distributions vary across Italy, Sweden, and Germany: Italy has more low-proficiency adults, Sweden has more high performers, and Germany is intermediate. These differences differ across domains, reflecting the interaction between worker supply and occupational needs. This cross-country heterogeneity justifies using domain-specific mismatch measures, as comparisons must consider each country's skill distribution and occupational demands.

This thesis documents mismatches separately by domain and combines them into indices, showing workers can be aligned in one area and misaligned in another. These patterns imply two main points: (i) mismatch comparisons should consider each country's skill supply distribution, and (ii) domain-level measurement is crucial due to potential differences across domains. For additional descriptive context on the country skill profiles, see Appendix B.2 (Figure B.2).

3.1.2 PISA 2022 as a Macro Benchmark (Reading and Mathematics)

To complement adult proficiency patterns from PIAAC, this thesis uses student performance data from PISA 2022 as a macro benchmark. PISA, an OECD international assessment of 15-year-olds, reports achievements in Reading, Mathematics, Science literacy, and Creative thinking on a common scale, enabling cross-country comparisons. Since these indicators target different populations and age groups, the comparison is interpreted descriptively: it offers a cross-cohort reference for country skill patterns rather than establishing a causal link between schooling outcomes and adult labor-market results.

The main reason for including PISA is to contextualize PIAAC differences across Germany, Italy, and Sweden using an external benchmark that reflects the skills of a younger cohort prior to entering the labor-market. While adult proficiency in PIAAC reflects initial skill development and later-life experiences such as further education, work-based learning, and potential skill depreciation, contrasting PIAAC data with PISA patterns allows for a straightforward check on whether cross-country rankings in core cognitive domains remain broadly consistent across cohorts.

The benchmark empirically examines the 2022 national mean performance in Reading and Mathematics for Germany, Italy, and Sweden. It compares these patterns to sampling-weighted

PIAAC Cycle 2 proficiency means, pooled across plausible values (PVs). OECD official reports (Education, GPS) already incorporate sampling weights and plausible values procedures. These indicators are shown alongside PIAAC proficiency distributions and mismatch measures to improve cross-country interpretability. Table 3.1 lists the benchmark values for both datasets, while Figure 3.1 shows the relationship between PISA mathematics and PIAAC numeracy. Given only three countries, the figure is illustrative and intended to help interpret cross-national patterns rather than to provide statistical inference.

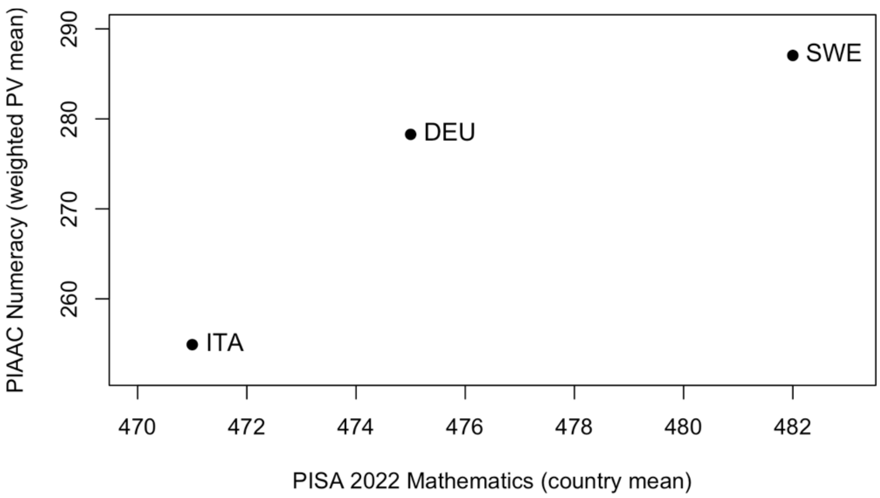
PISA reports country-level mean scores for 15-year-olds (2022); PIAAC proficiency means are computed from Cycle 2 microdata as sampling-weighted averages across plausible values.

Table 3.1 - PISA 2022 v. PIAAC Cycle 2 (Macro Benchmark).

Country	**PISA 2022 Reading (mean)**	**PISA 2022 Mathematics (mean)**	**PIAAC Literacy (weighted PV mean)**	**PIAAC Numeracy (weighted PV mean)**
Germany (DEU)	480	475	273.8	278.3
Italy (ITA)	482	471	254.2	254.9
Sweden (SWE)	487	482	286.8	287.0

Notes: PISA values are OECD official country means (Education GPS, PISA 2022). PIAAC values are sampling-weighted means pooled across plausible values (PV) from PIAAC Cycle 2 microdata.

Figure 3.1 - PISA 2022 Mathematics vs PIAAC Numeracy Proficiency



Overall, Sweden ranks highest in both PISA mathematics and PIAAC numeracy, while Italy records lower performance in both datasets, and Germany lies in between, suggesting broadly persistent cross-country differences in core quantitative skills across cohorts.

3.2 Analytical Sample, Filters, and Missing Data

This section explains how the analytical sample is built, starting from the merged PIAAC public-use files (PUF), selecting the employee sample, and identifying subsamples with valid occupation codes, proficiency measures, and outcomes. It highlights key restrictions for cross-country comparisons and discusses how missing data affects sample sizes.

The analytical sample is constructed sequentially through a set of restrictions.

Merged sample. For each country, the PIAAC PUF are available in two datasets, p1 and p2, which are merged via an inner join on the respondent identifier (SEQID). This forms the "merged" sample shown in Table 3.1 and serves as the basis for all further restrictions. Germany: 4,793; Italy: 4,621; Sweden: 3,710, unweighted counts.

Table 3.2 - Sample construction (PIAAC PUF, merged p1xp2 SEQID)

Country	**Merged sample (p1×p2)**	**Employed (C_D05=1)**	**Wage sample: valid ISCO-2 & EARNHRDCL**	**PPP wage sample: valid ISCO-2 & EARNHRPPP**
Germany	4,793	3,563	2,998	0
Italy	4,621	2,869	1,988	1,988
Sweden	3,710	2,782	2,427	0

Notes: Unweighted counts. Employed defined as C_D05=1. ISCO-2 constructed from ISCO-2C (fallback ISCO-2L); codes ≥ 995 treated as missing. Main earnings outcome is EARNHRDCL; EARNHRPPP only for Italy

Employment filter. The core analysis examines mismatches within jobs; therefore, the baseline analytical sample is limited to employed individuals, identified by the PIAAC employment indicator $C\_D05 = 1$. After applying this criterion, the employed sample comprises 3,563 in Germany, 2,869 in Italy, and 2,782 in Sweden.

Occupation filter. Occupations are categorized at the two-digit ISCO level to compare across sources, ensure consistency, and match the level at which ESCO-based occupational requirements are constructed. ISCO-2 derives from the current occupation (ISCO-2C), using the last occupation (ISCO-2L) as a fallback when ISCO-2C is missing. Codes ≥ 995 are treated as invalid and therefore considered missing. This harmonization is essential for linking PIAAC respondents to ESCO-based occupation requirement vectors.

Analytical sample. Constructing multidimensional mismatch indicators requires (i) valid ISCO-2 codes, (ii) non-missing proficiency measures in literacy, numeracy, and APS, and (iii) the availability of occupation-level requirement vectors after the ESCO → ISCO mapping. These conditions limit the effective mismatch sample compared to the employed sample. For transparency, the missing results report N(valid) for each country is in the relevant tables.

Outcome-specific restrictions. Table 3.1 also shows the size of the earnings sample, based on valid ISCO-2 codes and non-missing earnings deciles (EARNHRDCL). Earnings deciles indicate individuals' positions in the national hourly wage distribution and are comparable across countries; continuous hourly earnings in PPP (EARNHRPPP) are available only for Italy in the PUF used here and are used for country-specific robustness tests.

Treatment of missing values. Baseline estimates are based only on complete cases for each variable. Primary regressions include only complete cases for the dependent and key explanatory variables. Missing data in categorical controls are handled by adding "missing" categories where suitable. Sensitivity analyses show results are unaffected by missing data handling.

Weights, replicate weights, and plausible values: Descriptive statistics and models use the final sampling weight (SPFWT0. x); the sampling variance is handled through replicate weights, while proficiency uncertainty is addressed via PVs combined using standard pooling rules (Appendix A.4).

The following section examines how occupational skill measures and mismatch indicators are integrated into PIAAC microdata using ESCO-based occupational info harmonized with ISCO-2.

3.3 Variables and Measurement Strategy

This section describes how PIAAC microdata combines with ESCO data to create multidimensional skill-mismatch metrics, covering: (i) individual skill supply via PIAAC scores; (ii) occupational skill requirements via ESCO aligned with ISCO-2; and (iii) mismatch as the gap between supply and demand across skill dimensions, calculated both individually and multidimensionally.

To contextualize cross-country patterns, the thesis uses OECD Skills for Jobs indicators of skill imbalances (shortages/surpluses) as the macro benchmark. These indicators do not measure individual work-job mismatch and are not used for individual causal inference; they provide context for interpretation and policy discussion.

Conceptually, the mismatch measure compares a worker’s skill vector with an occupation’s requirement vector in a common multidimensional space.

For a complete variable dictionary, see Appendix A (Table A.1)

3.3.1 Skill Supply: Individual Proficiency in Literacy, Numeracy, and Adaptive Problem Solving (APS)

Individual skill supply is evaluated using PIAAC scores in literacy, numeracy, and APS, as described in § 3.1. PIAAC offers multiple plausible values (PVs) for each domain (e.g., PVLIT1-PVLIT10, PVNUM1-PVNUM10, PVPSL1-PVPSL10), reflecting measurement uncertainty. Descriptive statistics summarize proficiency levels by averaging these PVs. In regression analysis, estimates are derived by repeatedly analyzing these PVs and combining the coefficients and standard errors using PV procedures. This method ensures that inferences include variability from sampling and measurement uncertainty.

3.3.2 Occupational Skill Requirements: ESCO → ISCO

The occupational demand part of the mismatch measure uses ESCO classification as a proxy for skill requirements at the occupation level. ISCO-08 provides the occupational coding for PIAAC and serves as a classification and merging layer, while ESCO supplies the skill content needed to build occupational requirement vectors. To match the sample's occupation detail, occupations are aggregated to the two-digit ISCO-2 level. Although this reduces occupational specificity, it improves data harmonization and supports cross-country comparisons. Requirement indices for each ISCO-2 group are created by aligning ESCO skill content with relevant PIAAC cognitive domains. When multiple ESCO occupations share the same ISCO-2 code, the indices are averaged in the baseline, with robustness checks using the median and other aggregation methods.

3.3.3 Domain-specific Mismatch: Continuous Gaps and Categorical Indicators

For each domain, mismatch measures the difference between workers' observed skills and occupation requirements. A positive value indicates that workers' proficiency exceeds the proxy, while a negative value indicates a skills gap. Both are standardized for comparability across domains and countries.

For each domain $d \in \{literacy, numeracy, APS\}$, a standardized gap is constructed in two complementary ways: a continuous standardized gap maintains information on the magnitude and direction of the mismatch, while a categorical indicator provides a more intuitive classification of workers as under-skilled, matched, or over-skilled groups.

1. *Continuous mismatch – standardized gap.* For an individual i in country c, the domain-specific gap is calculated as the difference between the individual's proficiency and the requirement of the occupation:

$$Gap_{i,c}^{d} = zSkill_{i,c}^{d} - zReq_{occ(i,c)}^{d}$$

   - $Skill_{i,c}^{d}$ denote individual proficiency (PIAAC) in domain d;
   - $Req_{occ(i,c)}^{d}$ is the ESCO-derived requirement for the occupation held by i (harmonized to ISCO-2). To ensure cross-domain and cross-country comparability, both supply and requirements are standardized before computing the gap into z-scores. Positive values indicate over-skilling, while negative values suggest under-skilling.

2. *Categorical mismatch – under, match, over.* A three-category indicator is defined based on a standardized gap: individuals are classified as under-skilled if the gap falls below a negative threshold, over-skilled if it exceeds a positive threshold, and well matched otherwise. The baseline threshold is straightforward and replicable—approximately

one standard deviation of the gap distribution—while alternative thresholds are used for robustness checks. In this case, supply standardization and requirements precede the construction of the indicator to ensure cross-country and cross-domain comparability.

$$MismatchCat_{i,c}^{d} \in \{under, match, over\}$$

Using a symmetric threshold $\tau > 0$ baseline: approximately one standard deviation of the gap distribution, individuals are classified as:

$$MismatchCat_{i,c}^{d} = \begin{cases} under\ if\ Gap_{i,c}^{d} < -\tau, \\ match\ if\ -\tau \leq Gap_{i,c}^{d} \leq \tau, \\ over\ if\ Gap_{i,c}^{d} > \tau. \end{cases}$$

3.3.4 Multidimensional Mismatch: Breadth and Intensity across Domains

Since individuals may be mismatched in one domain but matched in others, the analysis adopts an explicit multidimensional perspective. Two complementary measures are created:

- *Mismatch intensity index – continuous*: A scalar index summarizes overall mismatch across domains by aggregating the absolute magnitudes of domain-specific gaps; it can be calculated either as an average or as a sum of standardized absolute gaps.

  $$Intensity_{i,c} = \frac{1}{D}\sum_{d=1}^{D} |Gap_{i,c}^{d}|$$

  This measure captures the extent of an individual's mismatch, regardless of direction (over- or under-skilling). For robustness, results can also be reported using domain-specific gaps $Gap_{i,c}^{d}$ and categorical indicators $MismatchCat_{i,c}^{d}$.

- *Mismatch breadth indicator – categorical*: Indicates whether the mismatch is concentrated in a single domain or is widespread across multiple domains.

$$Breadth_{i,c} = \sum_{d=1}^{D} \mathbb{1}\,(|Gap_{i,c}^{d}| > \tau$$

Where $\tau > 0$ is the same symmetric threshold used to classify under/match/over in §3.3.3 (baseline: approximately one standard deviation of the gap distribution). Breadth, therefore, measures the number of domains in which the worker is classified as mismatched beyond the threshold, distinguishing domain-specific deviations from more pervasive multidimensional mismatch profiles.

Breadth shows how many domains have mismatches, while intensity indicates the overall level of misalignment across all domains. Essentially, breadth assesses the extent of mismatch across various areas, whereas intensity evaluates how severe the misalignment is.

These indicators are essential for empirical analysis, as they provide a concise view of the magnitude and extent of mismatches across different skill dimensions.

3.3.5 Control Variables and Specification Components

Descriptive models linking mismatch measures to worker attributes typically include a standard set of covariates such as age, gender, and education level, along with labor-market characteristics like part-time or full-time status, and, when available, sector. These models also feature occupation controls at the ISCO-2 level, either as fixed effects or as high-level occupation group controls, to address systematic differences in task content and requirements across occupations. In pooled analyses, country fixed effects are incorporated to account for time-invariant cross-country differences that are not captured by the observable covariates.

For Italy-only checks, geographic controls (e.g., regional fixed effects or macro-area indicators where available) are included to address within-country heterogeneity in skills and labor-market conditions (see Appendix B).

3.3.6 Survey design and inference

All descriptive statistics and estimates consider PIAAC's complex sampling design. Population estimates rely on the final weight SPFWT0, while sampling variance is calculated using replicate weights SPFWT1-SPFWT80, following the PIAAC replication scheme.

For analyses involving proficiency measures, estimation is conducted across all 10 plausible values for each domain, with results combined using standard plausible-value procedures. This method provides point estimates and standard errors that account for both sampling variability (weights and replicates) and measurement uncertainty in skills (plausible values).

PIAAC also includes self-reported indicators of skill match and measured job tenure. These variables are considered only as exploratory supplements and are included in the analysis when relevant.

All descriptive statistics and regression models use the final sampling weights. Sampling uncertainty is addressed with replicate weights, and proficiency uncertainty is handled by pooling plausible values. These methods are applied consistently across the descriptive analysis and regression models.

3.4 Empirical Strategy

This section outlines the empirical strategy for characterizing multidimensional mismatch and its association with labor-market outcomes in Germany, Italy, and Sweden. The core contribution of the thesis is measurement: mismatch is constructed by combining PIAAC test-based skills with ESCO-based occupation requirement proxies harmonized to ISCO-2 (§3.3). Regression models are used to summarize conditional associations between mismatch and outcomes; given sorting and information frictions, results are not interpreted causally.

The empirical analysis uses a baseline mismatch measure and several robustness checks. The baseline employs standardized domain-specific gaps and a multidimensional intensity index, whereas the robustness checks test the sensitivity of results to different thresholds, aggregation rules, and outcome definitions.

The analysis proceeds in two steps: first, documenting cross-country distributions of adult skills (PIAAC) and using PISA 2022 as a macro benchmark for cross-cohort country patterns (§3.1); second, estimating survey-weighted models relating mismatch measures to (i) earnings rank and (ii) job stability, controlling for standard covariates and occupation fixed effects.

3.4.1 Earnings rank (EARNHRDCL): pooled baseline

The primary measure is the decile of gross hourly earnings (EARNHRDCL), which measures an individual's position within the national wage distribution. This choice improves cross-country comparability because coefficients reflect changes in within-country wage rank rather than differences in currencies or price levels across countries. Accordingly, pooled estimates reflect changes in wage rank (decile units) within countries rather than absolute wage-level differences across countries.

The pooled baseline specification is:

$$W_{i,c} = \alpha + \beta Mismatch_{i,c} + X'_{i,c}\gamma + \delta_c + \theta_{occ(i)} + \varepsilon_{i,c}$$

Where:

- $W_{i,c}$ is EARNHRDCL (1-10) for the individual i and country c;
- $Mismatch_{i,c}$ is the mismatch indicator (baseline: intensity; alternative specifications use domain gaps or categorical indicators as robustness);
- $X_{i,c}$ is the control vector: age, gender, education, job characteristic, occupational controls;
- $\delta_c$are the fixed effects for country (pool);
- $\theta_{occ(i)}$ ISCO-2 occupation fixed effects;
- $\varepsilon_{i,c}$ is the idiosyncratic error;
- β indicates the expected change in within-country wage rank, conditional on controls and fixed effects.

EARNHRDCL is the main comparable earnings metric, categorizing individuals into deciles based on gross hourly wages relative to each country's wage distribution. This improves cross-country comparability by providing a common reference for understanding wage hierarchies.

The baseline examines one mismatch measure at a time, with robustness checks using domain-specific gaps and indicators for under-, match-, or over-categories. Since EARNHRDCL is an ordinal rank, the pooled baseline is estimated in deciles. Log transformations are only used when a continuous earnings measure is available, such as in the Italy PPP wage check.

3.4.2 Earnings robustness checks

Two robustness checks assess whether results depend on the treatment of the earnings outcome.

1. **Ordered response model**. Since EARNHRDCL is an ordinal measure, the baseline linear specification is complemented by an ordered response model: ordered logit/probit.

$$Pr\left(W_{i,c} \leq k\right) = F(\tau_k - \beta Mismatch_{i,c} - X'_{(i,c)}\gamma - \delta_c - \theta_{occ(i)}$$

   Where $F(\cdot)$ is logit or probit, and τ_k are the thresholds parameters. This approach preserves the ordinal nature of deciles and is used as a robustness check against the linear baseline.

2. **Italy-only continuous earnings PPP**. For Italy, a continuous PPP-adjusted hourly earnings measure (EARNHRPPP) is available and can be modeled using logarithms; it serves as a robustness check for the linear baseline.

$$\ln(W_i^{PPP}) = \alpha + \beta Mismatch_i + X'_i\gamma + \theta_{occ(i)} + \varepsilon_i$$

   This specific measure allows a semi-elastic interpretation of β. Since the PPPP measure is not available in a comparable way for Germany and Sweden, the robustness test is limited to the Italian case.

3.4.3 Job Stability: proxy based on tenure (C_Q07)

Job stability is proxied using tenure in the current job from PIAAC item C_Q07. The baseline indicator defines short tenure as belonging to the lowest tenure category:

$$ShortTenure_{\{i,c\}} = 1\ (C\_Q07 = 1)$$

Short tenure is coded as a dummy equal to 1 if C_Q07=1, 0 otherwise.

The main specification relates short tenure to mismatch measures and controls using a binary response model:

$$\Pr\left(high_{mobility_{i,c}} = 1\right) = F(\alpha + \beta Mismatch_{i,c} + X'_{(i,c)}\gamma + \delta_c + \theta_{occ(i)})$$

Where $F(\cdot)$ is a logit/probit link, and regressors and fixed effects follow the earnings specifications, including both country fixed effects and ISCO-2 occupation fixed effects. Robustness checks consider alternative definitions of short tenure (C_Q07$\in$ {1,2}) and treat C_Q07 as an ordered outcome when appropriate, using an ordered-response specification.

For transparency, a linear probability model (LPM) can also be reported as a baseline alternative:

$$ShortTenure_{i,c} = \alpha + \beta Mismatch_{i,c} + X_{(i,c)}\gamma + \delta_c + \theta_{occ(i)} + \varepsilon_{i,c}$$

3.4.4 Controls and plausible values inference

Building on the survey design procedure detailed in §3.3.6, the regression models include controls for age, gender, education, job features, and occupational factors; the pooled specifications include country fixed effects. Italian-only models might include geographic controls to account for within-country heterogeneity (refer to Appendix B.4).

All analyses utilize PIAAC's final sampling weights (SPFWT0.x) and account for the complex survey design. Proficiency measures are reported as plausible values (M=10 per domain). Each model is estimated separately for each plausible value, then combined using standard pooling techniques.

The pooled point estimate is:

$$\hat{\beta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\beta}^{m}$$

Standard errors encompass both within- and between-PV variance; see Appendix A.4 for full details.

4. Result Analysis and Discussion

This chapter uses a framework combining PIAAC microdata with ESCO occupational requirements to empirically examine multidimensional skill mismatch in Germany, Italy, and Sweden. Its primary aim is to quantify and describe mismatch across occupations, highlighting patterns and differences across countries and cognitive domains. The countries were chosen for their distinct skill formation systems and labor-market institutions, which shape worker skill profiles and align with occupational tasks. These differences help interpret cross-country patterns, not imply causality.

Mismatch indicators are constructed from PV-based proficiency measures and estimated using the PIAAC sampling design described in Chapter 3.

The chapter is organized as follows. Section 4.1 describes the analytical sample and key coverage patterns. Section 4.2 addresses the main research question by presenting mismatch prevalence across domains and countries. Sections 4.3, 4.4, and 4.5 provide supporting evidence by examining relationships between mismatch measures, earnings rankings, and job stability. These relationships are presented descriptively rather than causally.

To keep the empirical section coherent with the main research question, Table 4.1 summarizes which outcomes are treated as supporting evidence: the sample used and the interpretation of the coefficients. Core descriptive statistics are given in sections 4.1 - 4.2, while sections 4.3 - 4.4 explain mismatch measures for earnings rank and job stability as interpretative associations rather than causal estimates.

Table 4.1 - Empirical roadmap (supporting outcomes)

Component	**Earnings rank models (Section 4.3)**	**Job stability models (Section 4.4)**
Core objective (RQ1)	Describe mismatch incidence/intensity within occupations (RQ1).	Describe mismatch incidence/intensity within occupations (RQ1).
Outcome (supporting)	earn_decile (EARNHRDCL): within-country hourly wage decile (1–10).	ShortTenure: indicator for C_Q07==1 (lowest tenure category).
Main sample	Employed + valid ISCO-2 + non-missing mismatch inputs (ESCO link).	Employed + valid ISCO-2 + non-missing mismatch inputs (ESCO link).
Additional outcome restriction	Non-missing earn_decile (wage coverage differs by country).	Non-missing C_Q07; short tenure defined as C_Q07==1 (robustness: {1,2}).
Key mismatch measure(s)	Panel A (DEU/ITA/SWE): intensity, gap_lit, gap_num, breadth. Panel B (DEU+SWE): gap_aps only.	Intensity (baseline); optional robustness with domain gaps (lit/num; APS DEU+SWE only).
Fixed effects	Country FE + ISCO-2 FE (occupation wage structure).	Country FE + ISCO-2 FE.
Weights	Final sampling weight SPFWT0.x (PIAAC).	Final sampling weight SPFWT0.x (PIAAC).
Interpretation of β	Change in within-country wage rank (decile units), conditional on FE.	Change in probability of short tenure (LPM) or log-odds (logit/probit), conditional on FE.
Role in Chapter 4	Supporting evidence: links mismatch measures to wage rank (descriptive association).	Supporting evidence: whether mismatch correlates with job instability/mobility proxy.
Caveats	Not causal; ESCO requirements are occupational proxies; APS unavailable for Italy in merged PUF.	Not causal; tenure mixes voluntary/involuntary mobility; APS unavailable for Italy in merged PUF.

Notes: This table summarizes the supporting empirical specifications used in Chapter 4. The core research question (RQ1) is addressed by descriptive mismatch patterns; earnings rank and short-tenure models provide interpretative, non-causal associations.

All models use the final PIAAC sampling weight (SPFWT0.x) and include fixed effects for country and ISCO-2. The APS measures exclude Italy because the plausible values are not available in the merged PUF.

4.1 Descriptive profile of the analytical sample

This section examines the structure of the analytical sample across the three countries and clarifies the effective sample sizes for subsequent analyses. Table 4.2 presents key descriptive statistics for the sample used to create the mismatch measure and details the earnings information coverage in the wage analysis. All statistics are calculated using the PIAAC final sampling weight (SPFWT0).

Table 4.2 - Summary statistics by country (PIAAC employed sample)

Country	N	Wage coverage (%)	Mean wage decile	Female (%)	Mean age
Germany	3,470	85.1	5.51	46.0	41.6
Italy	2,786	69.4	5.47	39.7	41.2
Sweden	2,739	87.7	5.49	47.6	41.9

Notes: weighted using SPFWT0.x. Wage coverage is the share of employed observations with non-missing hourly wage decile (EARNHRDCL). Mean wage decile is within-country (1–10).

Sample Definition: The core mismatch analysis focuses on employed individuals with valid ISCO-2 codes and uses constructed mismatch measures. Earnings and job stability outcomes support this analysis, relying on additional non-missing outcome data within the employed sample. The sample sizes are Germany (N=3,470), Italy (N=2,786), and Sweden (N=2,739).

Wage coverage and interpretation: Wage coverage refers to the proportion of individuals with available gross hourly earnings deciles. It is high in Germany (85.1%) and Sweden (87.7%), but lower in Italy (69.4%). This suggests caution when interpreting wage-based associations for Italy, as recorded earnings may reflect only a more formal employment segment. Since earnings deciles are relative within each country, cross-country wage regression comparisons should be understood as differences in individuals' relative positions within each nation's wage distribution, rather than in absolute wage levels across countries.

Basic comparability: The average wage decile and average age are broadly similar across the three samples, with differences largely due to life-cycle effects. Gender composition varies across countries and is included in the regression analysis in the later sections examining earnings ranks and job stability outcomes.

The next section focuses on the incidence of mismatches by domain and country, highlighting the key evidence supporting the main framework of this thesis.

4.2 Incidence of mismatch by domain: Literacy, Numeracy and APS

To characterize multidimensional mismatch, incidence is computed from the signed skill gap between individual proficiency and occupational requirements in each domain. For worker I in country c and domain d, the gap is:

$$Gap_{i,c}^{d} = zSkill_{i,c}^{d} - zReq_{occ(i)}^{d}$$

Where $zSkill^d$ is the standardized PIAAC proficiency measure and $zReq^d$ is the ESCO-derived occupational requirement both standardized as described in Chapter 3. The sign of the gap is economically meaningful: positive values indicate that proficiency exceeds the requirement, hence over-skilling in that domain, while negative values indicate under-skilling.

To avoid classifying small deviations as mismatches, individuals are assigned to three mutually exclusive categories using a symmetric tolerance band τ.

- Matched if $\left|Gap_{i,c}^{d}\right| \leq \tau$
- Over-skilled if $Gap_{i,c}^{d} > \tau$
- Under-skilled if $Gap_{i,c}^{d} < -\tau$

The baseline $\tau = 0.5$ standard deviations. Gap measures are constructed utilizing PV-based proficiency data, as detailed in Chapter 3. For incidence calculations, the baseline methodology employs PV-pooled mean proficiency measures to determine a singular gap for each individual and domain. For incidence the signed gap is calculated for each plausible value, then averaged across PVs to obtain a single gap for each domain. Alternative thresholds are examined in robustness analyses.

Table 4.3 shows weighted shares of matched, over-skilled, and under-skilled workers by country and domain. Notably, the incidence estimates rely on the valid subsample (n_valid), where domain requirements are trackable. Shares are calculated using the final sampling weights and represent the employed population within the subsample where ESCO requirements can be linked.

The APS mismatch index cannot be calculated for Italy because the APS plausible values (PVPSL) are missing from the merged public-use files; as a result, the APS incidence is shown only for Germany and Sweden.

Table 4.3 - Incidence of Skill Mismatch by Domain

Domain	**Country**	**N valid**	**Matched (%)**	**Over-skilled (%)**	**Under-skilled (%)**	**Total (%)**
APS	Germany	3,011	36.2	33.9	29.9	100.0
APS	Italy	0	—	—	—	—
APS	Sweden	2,495	35.3	36.4	28.3	100.0
Literacy	Germany	3,470	34.7	36.3	29.0	100.0
Literacy	Italy	2,786	36.3	34.9	28.8	100.0
Literacy	Sweden	2,739	35.3	38.4	26.3	100.0
Numeracy	Germany	3,470	35.3	34.1	30.6	100.0
Numeracy	Italy	2,786	33.3	34.6	32.2	100.0
Numeracy	Sweden	2,739	32.4	35.2	32.5	100.0

Notes: weighted shares using SPFWT0.x. Classification based on signed gap (row-mean of gap_*_1..10). Matched if |gap| ≤ 0.5, Over if gap > 0.5, Under if gap < -0.5. Percentages sum to 100 within each domain-country among non-missing gaps. APS is not available for Italy in the merged PUF (PVPSL missing), so APS incidence is reported only for Germany and Sweden.

Across literacy and numeracy, the three countries exhibit similar outcomes within the specified tolerance, with each category comprising about one-third of the employed sample. Differences are minor and should be viewed comparatively, as ESCO requirements are proxy-based and normalized at the ISCO-2 level. Results are interpreted relatively, emphasizing cross-country and domain comparisons over deviations from a “zero-gap” benchmark. Focus is on relative under-skilling differences rather than exact prevalence. The APS cannot be reported for Italy due to a lack of plausible values, so incidence is only shown for Germany and Sweden, which have similar levels, including a notable under-skilled share.

Table 4.3 provides a domain-specific descriptive benchmark for the main research question, while subsequent sections use earnings rank and short-tenure associations as supplementary evidence rather than definitive causal estimates. Figures 4.1 and 4.2 offer complementary visualizations of the same incidence rates: stack bars highlight within-cell compositions, while heat maps reveal cross-country and domain comparisons and potential hotspots.

Figure 4.1 - Stacked Mismatch Incidence

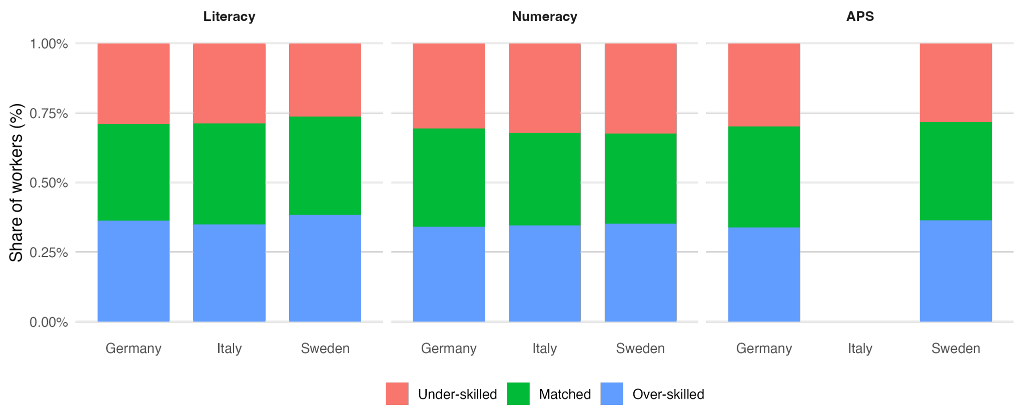


Figure 4.1 — Mismatch incidence by domain and country (100% stacked bars). Shares of under-skilled, matched, or over-skilled workers based on the PV-average signed standardized gap between PIAAC proficiency and ESCO-derived occupational requirements (ISCO-2), using the tolerance band τ=0.5. Weighted quotas (SPFWT0.x).

Figure 4.2 - Heatmap Mismatch Incidence

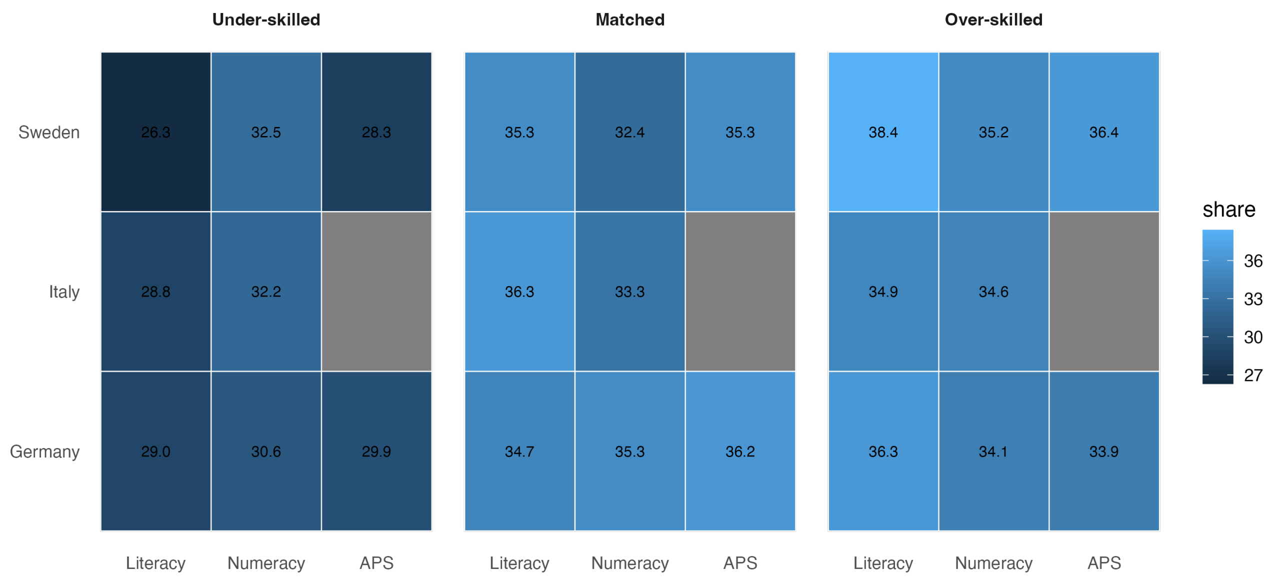


Figure 4.2 presents a heatmap of mismatch rates by domain and country, with darker cells indicating higher quotas. Data is weighted with SPFWT0. x, threshold τ=0.5.

The descriptive results show that mismatch is a multidimensional issue; the gap structure differs across domains. This is important for interpretation in the economics literature because signed gaps help differentiate under-skilling from over-skilling within a common tolerance band. This aligns with existing research on multidimensional mismatch and emphasizes a key limitation of single-index measures: aggregate indices can mask different profiles, such as workers who are aligned in numeracy but not in literacy, or vice versa.

The PIAAC+ESCO framework documents cross-country mismatches by domain using a transparent occupational-demand proxy based on ISCO-2. ESCO requirements are proxies, so comparisons focus on relative differences rather than absolute gaps. The study splits mismatches into domain profiles to aid allocation and skill-use discussions, reflecting misallocations due to sorting processes involving skill supply and workers' distribution across occupations. Using ESCO as proxies and aggregating to ISCO-2 improves comparability; the key contribution is making mismatch composition observable and replicable, rather than estimating absolute gaps.

4.3 Earnings rank and mismatch intensity (supporting evidence)

This section links mismatch measures to earnings outcomes, providing evidence to support interpretation. The dependent variable is the gross hourly earnings decile (EARNHRDCL), which indicates the decile (1-10) of the national gross hourly wage distribution in which an individual is located. The coefficients reflect changes in a person's position within these wage deciles, not their actual earnings. These results display descriptive correlations and should not be taken as causal evidence.

Table 4.4 reports the baseline earnings specification with incremental fixed effects. Moving from the pooled model to country- and ISCO-2-fixed effects clarifies whether the association between mismatch and earnings rank operates primarily through cross-country differences, occupational sorting, or within-occupation variation. Table 4.5, presented subsequently, shows supporting associations for alternative mismatch measures.

Table 4.4 - Main earnings specification (incremental fixed effects)

	(1) Pooled	**(2) + Country FE**	**(3) + Country & ISCO2 FE**
Mismatch intensity	0.880***	0.889***	0.110
	(0.065)	(0.065)	(0.072)
Country FE	No	Yes	Yes
ISCO-2 FE	No	No	Yes
Controls	No	No	No
Observations	6746	6746	6746
R-squared	0.027	0.028	0.300

*Notes: Dependent variable is hourly wage decile (within-country rank). Weighted using SPFWT0.x. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients are in wage-decile units (within-country rank). Column (3) identifies the association net of country differences and occupation wage structure (ISCO-2)*

Table 4.4 shows pooled OLS estimates of how earnings rank relates to mismatch indicators, controlling for country and ISCO-2 occupation fixed effects, using PIAAC weights. Each column displays results for a specific mismatch measure to aid interpretation. The strong positive link between mismatch intensity and earnings rank in the pooled analysis diminishes and becomes less precise when accounting for country and ISCO-2 fixed effects. This indicates that the earnings relationship mainly arises from differences across countries and occupations rather than within them. The reduced effects after including ISCO-2 fixed effects suggest that occupational composition largely drives this association, supporting models where workers sort into occupations with different wages. Therefore, mismatch reflects not only skill gaps but also occupational assignments.

Table 4.5 - Supporting associations between mismatch and earnings rank

	(1) Intensity	(2) Gap LIT	(3) Gap NUM	(4) Breadth
Panel A — Core domains (DEU/ITA/SWE)				
Mismatch intensity	0.110			
Gap (literacy)		0.267***		
Gap (numeracy)			0.383***	
Mismatch breadth				0.065*
	(0.072)			
		(0.033)		
			(0.033)	
				(0.035)
Observations	6746	7316	7316	6746
R-squared	0.300	0.308	0.314	0.301

	(B1) Gap APS (DEU+SWE only)
Panel B — APS only (DEU+SWE)	
Gap (APS)	0.027
	(0.040)
Observations	4804
R-squared	0.344

*Dependent variable is hourly wage decile (within-country rank). All models include country FE and ISCO-2 FE and use SPFWT0.x. Each column includes one mismatch measure. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Panel B excludes Italy because APS PVs are missing in the merged PUF.*

Panel A (Literacy and Numeracy domains, DEU/ITA/SWE).

The overall mismatch intensity index, calculated as the average of the absolute standardized gaps across available domains, is positive but not statistically precise (β = 0.110, s.e. = 0.072). The signed gaps in literacy and numeracy are strongly and positively linked to wage rank (β=0.267 and β=0.383, respectively). Because gaps are signed, positive coefficients primarily capture positive gaps (over-skilling) being correlated with higher wage rank in this proxy-based mapping. This pattern persists even when comparing within the same ISCO-2 occupation and controlling for country differences. The breadth indicator shows a smaller and marginally significant association (β=0.065, p-value<10%).

These coefficients do not mean that a mismatch is beneficial. They show that workers with positive gaps tend to hold higher-wage roles in this occupational proxy due to sorting and composition effects. Caution is advised, as ESCO requirement indices serve as proxies at the ISCO-2 level. The relationships indicate how measured gaps relate to wage rank within this mapping, not a structural penalty for mismatch. With fixed effects at country and occupation levels, the coefficients mainly reflect within-occupation variation and are descriptive.

Panel B reports APS results for DEU+SWE only because PVPSL are missing in the merged Italian files, preventing the calculation of the APS gap for Italy. For Germany and Sweden, the APS gap shows a small, insignificant association with wage rank ($\beta = 0.027$, s.e. = 0.040), indicating that APS-related gaps are not strongly reflected in earnings rank in this pooled analysis.

Tables 4.4 and 4.5 support the mismatch patterns in §4.2. Overall, the wage rank evidence is more informative for signed literacy and numeracy gaps than for aggregate intensity summaries, reinforcing the importance of a domain-specific perspective.

4.4 Job stability (short-tenure proxy) and mismatch intensity (supporting evidence)

This section explores whether measured mismatch is associated with job stability, using short tenure as a proxy for recent job entry and, by extension, recent mobility. The goal is to offer descriptive evidence on whether mismatch correlates with a more “sticky" worker-job allocation, consistent with the search-friction and persistent worker-job matches discussed in Chapter 2.

4.4.1 Outcome definition and specification

Job stability is measured by the length of time in the current job, using the PIAAC item C_Q07. The baseline indicator considers short tenure as falling into the lowest tenure category:

$$ShortTenure_{i,c} = 1(C\_Q07 = 1)$$

The baseline model estimates a Linear Probability Model that links short tenure with mismatch intensity.

$$ShortTenure_{i,c} = \alpha + \beta Intensity_{i,c} + X_{i,c}\gamma + \delta_c + \theta_{occ(i)} + \varepsilon_{i,c}$$

Intensity measures the average absolute standardized gaps across available domains as a non-directional mismatch metric. δ_c represents country fixed effects, while $\theta_{occ(i)}$ indicates ISCO-2 fixed effects. $X_{i,c}$ includes the basic controls outlined in Chapter 3, such as age, job controls, gender, and education, where available. All estimates utilize the PIAAC final sampling weight SPFWT0.x. Coefficients reflect percentage-point changes in the likelihood of being in the lowest tenure category, controlling for fixed effects

4.4.2 Results and interpretation

Table 4.6 presents the baseline results. The coefficient for mismatch intensity is negative and statistically significant in the pooled model, which includes country and ISCO-2 fixed effects: higher mismatch intensity correlates with a reduced likelihood of short tenure. Specifically, a one-unit increase in the mismatch intensity index is linked to approximately a 2.8 percentage-point decrease in the probability of falling into the shortest tenure category ($\beta \approx -0.028, s.e. \approx 0.011$).

The pattern is consistent with slower reallocation in the cross-section: workers with higher mismatch intensity are less likely to appear as recent entrants into their current job.

Table 4.6 - Short-tenure and mismatch intensity (supporting evidence)

	(1) LPM ShortTenure1 + FE	**(2) LPM ShortTenure2 + FE**	**(3) Logit ShortTenure1 + Country FE**
Mismatch intensity	−0.028**	−0.025***	−0.146***
	(0.011)	(0.007)	(0.001)
Country FE	Yes	Yes	Yes
ISCO-2 FE	Yes	Yes	No
Outcome	1(C_Q07=1)	1(C_Q07∈ {1,2})	1(C_Q07=1)
Observations	N1	N2	N3

*Notes: Coefficients reported with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All models weighted using SPFWT0.x. Outcome is ShortTenure based on C_Q07. Estimates are descriptive and not causal.*

Since the logit model is more sensitive to separation and variance estimation under survey weights and fixed effects, the Linear Probability Model (LPM) with country and ISCO-2 fixed effects is treated as the baseline specification, while the logit model is reported as a robustness check.

4.4.3 Robustness: broader short tenure definition

As a robustness check, the short tenure can be refined more broadly as $C\_Q07\epsilon\{1,2\}$. The estimated association remains negative and statistically significant ($\beta \approx -0.025, s.e \approx 0.007$), supporting the stability of the baseline finding to the exact cutoff used for defining short tenure.

APS proficiency (PVPSL) is unavailable for Italy in the merged public-use files due to missing values. The short-tenure models should be interpreted as supporting evidence that complements the descriptive mismatch incidence patterns documented in §4.2 rather than as causal estimates of the effect of mismatch on mobility.

4.4.4 Joint interpretation of earnings rank and short tenure

Together, §§ 4.3 and 4.4 create a coherent interpretative framework. In the incremental fixed-effects earnings models, the initial link between mismatch intensity and wage rank diminishes substantially and becomes less precise statistically when accounting for country and ISCO-2 fixed effects. This indicates that occupational wage structures and sorting processes have a greater influence than within-occupation pay differences. Regarding job stability, higher mismatch intensity is associated with a lower likelihood of short tenure, suggesting that workers with greater deviations from occupational profiles are less likely to be recent arrivals. Overall, these findings are consistent with persistent worker-job allocation under adjustment frictions. Since these results are descriptive, they should be interpreted carefully, given the proxy nature of ESCO requirements, the limitations of cross-sectional data, and the imperfect role of tenure as a mobility indicator: mismatch appears more related to occupational positioning and persistent matching than to quick earnings changes within the occupation.

Taken together, the earnings-rank and job stability results suggest that mismatch reflects occupational allocation and adjustment frictions, not only individual skill shortfalls.

4.5 Robustness: Italy log PPP hourly wages (EARNHRPPP)

To evaluate whether the results on earnings rank in §4.3 are sensitive to using an ordinal wage-decile outcome, this section provides a robustness check using a continuous wage measure for Italy. Specifically, the dependent variable is the logarithm of hourly earnings in purchasing power parity, which captures proportional differences in hourly pay and is less affected by decile-based discretization. The specification follows the same descriptive framework as the supporting model in §4.3 and uses the PIAAC final sampling weight (SPFWT0.x).

Table 4.7 reports two Italy-only models. Row 1 reports the baseline specification; mismatch intensity is positively and strongly associated with log PPP hourly earnings ($\beta \approx 0.123, s.e. \approx 0.018, p < 0.01$). Interpreted descriptively, this coefficient suggests that individuals with higher measured mismatch intensity tend to be observed in higher PPP wage levels within the Italian sample, consistent with the positive associations found for signed literacy and numeracy gaps in Table 4.3.

Table 4.7 - Italy robustness: log PPP hourly earnings

Model	Mismatch.intensity	Std.error	Observations	R.squared
(1) Italy baseline	0.123***	(0.018)	1,942	0.022
(2) Italy + ISCO-2 FE	0.017	(0.022)	1,942	0.231

*Notes: Dependent variable is log (EARNHRPPP). Weighted using SPFWT0.x. *** p<0.01, ** p<0.05, * p<0.10. Descriptive associations only.*

However, once ISCO-2 fixed effects are included in Row 2, the coefficient is small and statistically imprecise ($\beta \approx 0.017, s.e. \approx 0.022$) while the explained variance increases substantially with the increase in R^2. This pattern is consistent with the occupational-sorting interpretation: the association between mismatch measures and earnings primarily reflects differences in the occupational wage structure rather than differences in occupational wage differentials. Mismatch-related differences in earnings seem to operate mainly through occupational allocation, rather than through wage penalties for workers in the same ISCO-2 job.

Overall, the PPP specification confirms that the earnings association is not merely an artefact of the decile outcome, while the strong attenuation under ISCO-2 fixed effects reinforces the role of occupational composition and sorting.

4.6 Summary findings

This chapter provides empirical evidence on multidimensional skill mismatch by integrating PIAAC Cycle 2 microdata with ESCO-based occupational requirements aligned with ISCO-2. Its primary focus is on description and measurement: rather than estimating causal effects, it illustrates how mismatches vary across countries and cognitive domains, and how these patterns can be understood in relation to labor-market outcomes.

The analysis also emphasizes significant coverage differences. Wage data is less complete in Italy, so earnings-related evidence should be interpreted carefully, as it may mainly reflect a more formal segment of employment. By contrast, mismatch incidence is calculated using a larger employment sample with valid occupational links. At the domain level, literacy and numeracy have similar distributions across Germany, Italy, and Sweden within the baseline tolerance band, whereas APS can be reported only for Germany and Sweden because its plausible values are not available for Italy in the merged PUF.

The supporting outcome models aim to interpret mismatch patterns rather than establish causality. The earnings-rank results indicate that positive literacy and numeracy gaps are associated with higher wage ranks within countries, while measures like intensity and breadth are estimated less precisely. Robustness checks specific to Italy, using log PPP hourly earnings, confirm these patterns are not solely due to decile-based outcomes. Additionally, the significant reduction in coefficients after including ISCO-2 fixed effects suggests that occupational composition and sorting account for an important share of the observed earnings relationships. The job-stability models show a small but statistically significant negative relationship between mismatch intensity and short tenure in pooled data, consistent with ongoing work-job matches and adjustment frictions in the cross-section.

More broadly, these findings underscore a key concept in the mismatch literature: using unidimensional measures often obscures important heterogeneity, while a domain-specific approach allows for identifying different types of misalignments. Relative to education-based or self-reported approaches, the main contribution of this thesis is to provide a transparent and replicable framework that integrates test-based skill supply data from PIAAC with occupation-level requirement indicators from ESCO, thereby enhancing understanding of the multidimensional mismatch across countries.

Three main implications emerge from the analysis. First, the evidence indicates that the mismatch should be viewed not only as a problem of individual skill deficits but also as an issue of allocation influenced by occupational structure. The reduction in wage correlations under ISCO-2 fixed effects supports the idea that a significant portion of the differences is driven by occupational sorting with varying pay structures. Second, the negative link with short tenure aligns with ongoing mismatches and adjustment delays, implying that training policies alone may be insufficient unless combined with measures that improve job matching, mobility, and occupational transitions. Third, the limitations in coverage highlight that mismatch measurement depends on domain availability and the accuracy of occupational requirement proxies, underscoring the need for triangulation and more frequent, detailed data on task and skill use, as well as occupational demand.

Overall, Chapter 4 addresses the main research question by illustrating multidimensional mismatch patterns across countries and domains. It uses earnings rank and job stability as additional evidence to interpret these patterns. The goal is not to estimate the causal effect of mismatch, but to make its multidimensional structure empirically visible and to demonstrate that its associations with labor-market outcomes align with occupational sorting and adjustment frictions.

5. Conclusions

This thesis develops an occupation-based empirical framework to measure multidimensional skill mismatch, integrating PIAAC (Cycle 2) microdata with ESCO proxy occupational requirements harmonized to ISCO-2. The main contribution is descriptive and focused on measurement: it quantifies and characterizes how adult cognitive skill profiles align (or misalign) with occupational demand proxies across Germany, Italy, and Sweden, primarily emphasizing cross-country comparability and domain-level structure.

Main takeaways.

1. **Multidimensional concept of mismatch.**

   Skill mismatch is better understood as a domain-specific gap structure than as a single label, because different forms of misalignment can coexist within the same occupation.

2. **Measurement and comparability**.

   The main empirical contribution of this thesis is a transparent and replicable PIAAC+ESCO framework, mapped to ISCO-2, that supports cross-country comparisons of relative mismatch patterns rather than absolute gap levels.

3. **Allocation and frictions.**

   The supporting evidence on earnings rank and short tenure suggests that mismatch reflects not only individual skill deficits, but also occupational sorting, wage structure, and adjustment frictions.

5.1 Main findings: mismatch patterns within occupations

The descriptive evidence confirms that mismatch is not a unidimensional construct. The signed gap-by-domain approach reveals that misalignment profiles differ between literacy and numeracy and, where available, adaptive problem-solving (APS). Using a symmetric tolerance band around standardized gaps, the incidence analysis shows that the distributions are largely comparable across countries for both literacy and numeracy. However, cross-country differences are more meaningful when interpreted in relative terms, such as the balance between under-skilling and over-skilling, rather than in absolute figures.

The APS results are only available for Germany and Sweden because the plausible values (PVPSL) variable is missing from the Italian PUF used. Despite this limitation, APS reinforces the idea that a multidimensional approach provides more detailed information than aggregate measures: misalignment can occur in one domain but be relevant in another, and domain descriptions help distinguish different profiles within the same occupation.

In summary, a mismatch should be seen as a domain-specific gap, not just a 'match' or 'mismatch' label. For cross-country comparisons, better insights come from observing relative patterns within domains and their coherence across contexts, rather than treating the initial gap as a "calibrated” benchmark.

5.2 Supporting evidence: earnings rank and job stability

To support the interpretation of the mismatch pattern, this thesis examined descriptive associations between mismatch and two market outcomes: position in the earnings distribution (earnings rank, deciles) and job stability (short-tenure proxy). These analyses are presented as non-causal interpretative evidence.

Models with fixed effects for country and ISCO-2 show that signed gaps in literacy and numeracy are positively linked to earnings rank. In contrast, synthetic measures like intensity and breadth are weaker and less precise indicators. Essentially, the positive correlation of signed gaps aligns with the idea that positive gaps (indicative of over-skilling relative to the occupational proxy) are more common among workers in higher income deciles. APS associations (DEU+SWE) and earnings rank are small and statistically imprecise in the available sample.

Regarding job stability, the mismatch-intensity results, associated with a lower probability of short tenure, suggest a more rigid cross-sectional allocation: workers who are more misaligned with their occupation profiles are less likely to be newly hired into their current job. However, short tenure does not differentiate between voluntary mobility and involuntary turnover; thus, these results should be understood as descriptive indicators consistent with friction and selection mechanisms.

Finally, the Italian robustness with PPP hourly earnings (in log) confirms that the relationship between mismatch and wages is sensitive to the model specification, particularly the inclusion of fixed occupational effects. Much of the association appears to reflect occupational sorting rather than earning differences "within-occupation."

Taken together, these supporting results are more consistent with occupational sorting and adjustment frictions than with a simple within-occupation wage-penalty interpretation.

5.3 Limitations and robustness

The results should be viewed with certain structural limitations.

First, ESCO-based requirements mapped to ISCO-2 provide a transparent and replicable proxy for occupational demand, but cannot capture firm-level task content, within-occupation heterogeneity, or cross-country differences in work organization.

Second, standardization enhances cross-domain and cross-country comparability, but it also makes the absolute gap levels harder to interpret directly.

Third, PIAAC proficiency is measured through plausible values and a complex survey design. Although standard procedures are applied throughout, the estimates remain subject to sampling and imputation uncertainty.

Fourth, APS cannot be analyzed for Italy because the merged public-use files lack relevant plausible values, limiting complete comparability across countries for all three domains.

In addition, the analysis is cross-sectional and cannot disentangle occupational sorting, on-the-job learning, skill depreciation, or selection into employment. Lower earnings coverage in Italy may also reflect stronger selection into more formal segments. Robustness checks support the stability of the main qualitative patterns, but the analysis remains descriptive rather than causal.

5.4 Implications and next steps

Despite these limitations, the developed approach has three key implications. First, a multidimensional perspective improves the identification of mismatch profiles relative to one-dimensional proxies, because domain-specific measures reveal forms of misalignment that aggregate indices may conceal. Second, the supporting evidence suggests that the mismatch should not be interpreted solely as a skills-supply problem, but also as an allocation problem shaped by occupational structure, sorting, and adjustment frictions. Third, future research should more directly combine proficiency data, task-use information, and occupational demand measures, and ideally rely on longitudinal evidence to distinguish persistent mismatch from temporary adjustment.

Overall, this thesis proposes that understanding skill mismatch requires moving beyond single indicators and viewing mismatch as a multidimensional, partly allocative phenomenon shaped by both workers skills and the occupational structures.

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Data Sources and Reproducibility Note

This section briefly describes the datasets used and explains how they were obtained and integrated. The empirical analysis combines internationally harmonized sources that provide comparable data on adult cognitive skills and labor-market variables, including occupational skill relationships used as proxies for skill requirements, and an external macro benchmark for cross-country skill patterns. Integrating these sources is crucial to developing multidimensional mismatch measures that compare individual skill supply to occupational-level demand proxies and to interpret cross-country patterns transparently.

PIAAC Cycle 2 (OECD) – Core Microdata for Skill Supply and Outcomes.

The primary dataset is the OECD Survey of Adult Skills (PIAAC), Cycle 2 Public Use Files (PUF) for Germany, Italy, and Sweden. PIAAC provides individual measures of literacy, numeracy, and problem-solving skills, along with socio-demographic details, employment status, occupation codes (ISCO), and labor-market outcomes like earnings deciles and job tenure categories. Proficiency is assessed through plausible values (PVs), and the survey's complex design requires sampling and replicate weights for representative statistics and valid inference. The analytical sample merges PUF components p1 and p2 via respondent ID, applying harmonized restrictions across countries as detailed in Chapter 3.

ESCO (European Commission) – Occupational Level proxies for skill requirements.

The analysis uses the ESCO (European Skills, Competencies, Qualifications and Occupations) classification to measure "skill demand" at the occupational level. ESCO links occupations and skills, enabling the creation of requirement indices that aggregate occupation-skill relations. PIAAC reports occupations in ISCO, while ESCO is mapped to ISCO-08 and aggregated at the two-digit ISCO-2 level to match the occupational resolution used in this thesis. These ESCO-based requirement measures serve as proxies for typical skill profiles associated with occupations, not firm-specific tasks. This mapping provides a transparent, replicable method for comparing individual proficiency and supply with occupation-level demands and proxies across multiple cognitive domains, forming the basis for mismatch indicators in the analysis and outcome models.

PISA 2022 – Macro Benchmark for Cross-Cohort Comparison.

Used to contextualize cross-country differences in adult skills. PISA 2022 uses country means in Reading and Mathematics as macro benchmarks. PISA measures the performance of 15-year-old students, and there is no causal link to adult labor-market outcomes. It is used in this thesis descriptively to verify if broad cross-country rankings in core cognitive domains are broadly consistent across cohorts. The benchmark is presented in the descriptive chapter, with sampling-weighted PIAAC proficiency means pooled across plausible values.

Output datasets and reproducibility.

All data processing steps generate intermediate and final datasets, including the merged PIAAC sample, ESCO-to-ISCO skill links, and the mismatch dataset used in Chapter 4. The workflow comprises scripts that clean and harmonize data, build ESCO-based occupational requirement indices, construct mismatch measures, and reproduce the tables and figures presented in this thesis. Key operational details—such as variable definitions, mapping choices, handling of plausible values, and robustness variants—are documented in the following appendices. All data sources are publicly available, with methodological documentation provided by the OECD and the European Commission. This thesis employs these sources within a consistent framework to support a multidimensional, descriptive analysis of skill mismatch.

Appendix A provides technical documentation on variable definitions, measures such as mismatch indices, and handling plausible values and survey weights. Appendix B presents supplementary descriptive evidence for Italy's territorial heterogeneity and robustness tables for mismatch incidence under various tolerance thresholds.

TABLE OF FIGURES & TABLES APPENDIX

APPENDIX A - MEASUREMENT DETAILS

This section provides technical details supporting the measurement framework used in this thesis. It collects short theoretical bridges on signaling (Spence, 1973). It uses them to motivate the interpretation of education/skills as informative signals, an alternative mismatch formulation from the literature for conceptual comparability, variable dictionary and operational definitions used in the empirical sections, and a compact note on plausible values and pooling rules clarifying uncertainty measurement handled in PIAAC.

A.1 - Signaling framework (Spence, 1973) – figures A.1-A.2

Figure A.1 - Informational Feedback

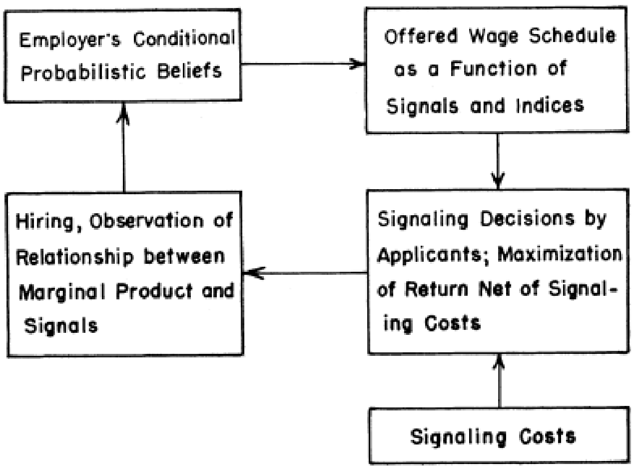


FIGURE I
Informational Feedback in the Job Market

Spence states the signal won't distinguish applicants unless signaling costs are negatively correlated with productivity. If not, everyone invests equally, preventing differentiation. He assumes that such costs are negatively correlated with productivity, making this a prerequisite for a characteristic that can serve as a consistent, informative market signal, linked to one job or product but not others (Spence, 1973).

Figure A.2 – Optimal choice of education

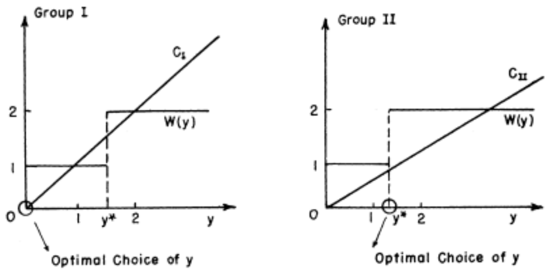


FIGURE III
Optimizing Choice of Education for Both Groups

The signaling mechanism separates applicants by productivity: Group I has lower potential, Group II has higher. Education filters with a steeper cost curve for Group I, needing less effort for high-ability individuals. Wages depend on education, with a threshold for high productivity. For Group II, investing is rational as wages exceed signaling costs, but not for Group I due to high costs, making education an effective screening tool.

A.2 – Alternative mismatch metric

To document comparability with multidimensional mismatch approaches in the literature, this appendix presents an alternative formulation that splits mismatch into positive (over-supply) and negative (under-supply) components across skill dimensions, with importance weights.

$$m_{i,t}^{+} \equiv \sum_{j=1}^{J} v_j \max\{a_{i,j} - q_{i,t,j}, 0\} \; m_{i,t}^{-} \equiv \sum_{j=1}^{J} v_j \max\{q_{i,t,j} - a_{i,j}, 0\}$$

While this thesis used a domain-based approach from PIAAC domains to occupational-level ESCO requirement proxies, Bailey's alternative helps interpret mismatches as a multidimensional object in which direction can matter separately from magnitude.

A.3 – Variable definitions and coding

It defines the operational definitions of the principal variables used in the estimations, giving each variable its source, the variable name as coded, and the transformations and rationale.

Table A.3 – Variable definitions

Construct	Variable name(s)	Definition	Coding / Unit	Source
Respondent identifier	SEQID	Unique respondent identifier used to merge PUF part 1 and part 2.	string/integer	PIAAC PUF (p1/p2)
Country	CNTRYID / CNTRYID_E	Country identifier.	categorical	PIAAC PUF
Final sampling weight	SPFWT0	Final sampling weight used for population-representative estimates.	continuous weight	PIAAC PUF
Replicate weight scheme	SPFWT1–SPFWT80 (replicate weights), indicator: VENREPS	Replicate weights for variance estimation under complex survey design.	continuous weights / replication scheme	PIAAC PUF
Employment status	C_D05	Dummy/indicator for being employed at the time of the interview.	1 = employed; else non-employed	PIAAC PUF
Occupation (ISCO-2)	ISCO2C; fallback ISCO2L; drop codes >= 995	Two-digit ISCO code for current occupation; last occupation used if current missing; invalid codes treated as missing.	ISCO-08 2-digit; NA if missing/invalid	PIAAC PUF

Construct	Variable name(s)	Definition	Coding / Unit	Source
Wage rank (main outcome)	EARNHRDCL	Decile position of gross hourly earnings within the national wage distribution.	integer decile (typically 1–10)	PIAAC PUF
Hourly wage PPP (robustness, IT only)	EARNHRPPP	Hourly earnings in PPP (available in Italy PUF used here) used for robustness checks.	continuous (PPP-adjusted)	PIAAC PUF (Italy only in used files)
Literacy proficiency (PV)	PVLIT1–PVLIT10	Plausible values for literacy (latent proficiency).	scale 0–500 (10 PVs)	PIAAC PUF
Numeracy proficiency (PV)	PVNUM1–PVNUM10	Plausible values for numeracy (latent proficiency).	scale 0–500 (10 PVs)	PIAAC PUF
Adaptive problem solving (PV)	PVPSL1–PVPSL10	Plausible values for adaptive problem solving (latent proficiency).	scale 0–500 (10 PVs)	PIAAC PUF
ESCO occupational requirements (derived)	ESCO occupation Skill Relations → aggregated to ISCO-2	Skill requirements at occupation level obtained from ESCO and mapped to ISCO-2.	constructed (standardized/aggregated indices)	ESCO v1.2.0 + mapping to ISCO
Skill o R2 R3mismatch (derived)	constructed from (PIAAC skills) vs (ESCO requirements) by domain	Mismatch indicators comparing individual proficiency to occupational requirements by domain; multidimensional mismatch derived from domain-specific mismatch.	constructed (domain dummies/indices; overall indicator)	Own construction (PIAAC + ESCO)

Construct	Variable name(s)	Definition	Coding / Unit	Source

Notes: Skills are measured using 10 plausible values (PVs) for each domain (literacy, numeracy, adaptive problem solving). All descriptive statistics and regressions account for the complex survey design using final weights (SPFWT0) and replicate weights (SPFWT1–SPFWT80. ISCO-2 codes are based on current occupation (ISCO2C) with fallback to last occupation (ISCO2L); codes>=995 are treated missing. ESCO requirements are derived from ESCO occupation-skill links mapped to ISCO-2.

This table outlines variables such as the outcome (salaries), key variables (mismatch, mobility), controls (demographics, job factors), and clarifications on recoding/standardization. Transformations such as dummy variables and standardization aid cross-country comparisons and interpretation.

A.4 – Plausible values and pooling note

Moving from theoretical to empirical data in PIAAC skills assessments requires handling measurement uncertainty. PIAAC competencies are estimated using plausible values (PVs), which should not be seen as exact figures. Rubin's Rule (Rubin, 1987) combines estimates from multiple PVs, yielding consistent coefficients and variances that account for sampling error and imputation variability. This process involves a rigorous statistical approach to manage PV uncertainty, pooling results from multiple imputations to yield accurate estimates and standard errors that reflect missing data and measurement uncertainty delays.

The parameter $\hat{\beta}$ is estimated, separately for each of the M datasets, where M=10 corresponds to the PVs. The pooled estimates are: $\hat{\beta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\beta}_m$

The total variance is the sum of two components: within-imputation variance (W), which is the average of the estimated variances across imputations and represents the sample standard errors. Between-imputation variance (B) is the average estimated variability across imputations, highlighting the uncertainty in competency measurement.

$$Var(\hat{\beta}) = \underbrace{\frac{1}{M}\sum_{m=1}^{M}\hat{\beta}_m}_{W} + \underbrace{\left(1+\frac{1}{M}\right)\frac{1}{M-1}\sum_{m=1}^{M}\left(\hat{\beta}_m - \hat{\beta}\right)^2}_{B}$$

This appendix summarizes the theoretical benchmark on information frictions (Spence, 1973) and measurement choices, including the roles of PIAAC PVs and survey weights in shaping domain-specific gaps and indices. It emphasizes that the mismatch measures are reproducible and comparable across countries, are proxy-based, and should be interpreted comparatively across different domains and settings. Additional supplementary evidence is provided in the following appendix.

APPENDIX B – SUPPLEMENTARY DESCRIPTIVE EVIDENCE

This appendix provides details on the sample construction and data coverage supporting the results in Chapters 3 and 4. The analysis uses the merged PIAAC PUF for each country, created by joining two PUF components (p1 and p2) on SEQID. The baseline sample includes employed respondents and occupations harmonized to ISCO-2 to match ESCO occupational requirement proxies.

Earnings rank and job-stability outcomes are included as supporting evidence, but this imposes restrictions because wage models require non-missing gross hourly earnings deciles, and job-stability models require non-missing tenure. As a result, effective sample sizes differ across outcomes.

B.1 -Data coverage and sample filters (PIAAC)

Earnings comparability across countries uses the gross hourly earnings decile (EARNHRDCL) to place workers within their national wage distributions across three countries. The wage sample includes employed respondents with valid ISCO-2 codes and non-missing earnings deciles. For Italy, only PPP-adjusted hourly earnings (EARNHRPPP) are used as a robustness check. Since EARNHRDCL is a relative rank, pooled results should be interpreted as changes in wage position rather than absolute differences.

Job mobility cannot be reliably compared through occupational changes (ISCO2C versus ISCO2L) due to frequent missing or specially coded values of ISCO2L, especially in Italy. For cross-country comparisons, mobility is estimated using job tenure C_Q07, with the baseline set at C_Q07=1 and a broader robustness definition $C\_Q07 \in \{1,2\}$.

B.2 – Additional descriptive tables

This section presents supporting descriptive tables to complement the main assumptions. They are included for readability and transparency, while the discussion in Chapter 4 depends on the main incidence table and figures.

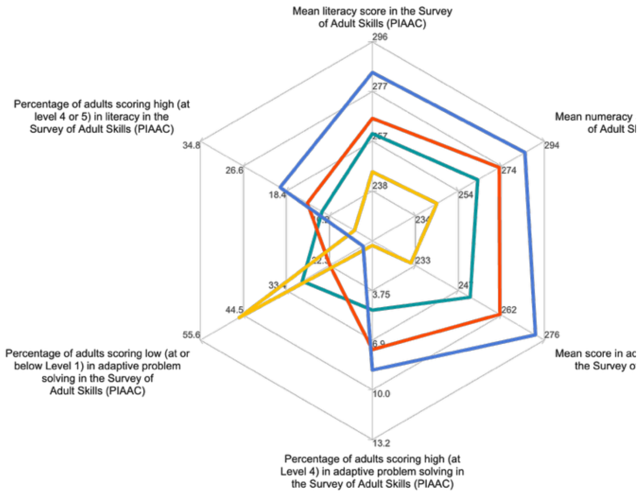
Table B.2 – Incidence of mismatch by domain (wide)

	Matched			**Over**			**Under**			**n_valid**
Country	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	
Germany	22.09856	17.05823	11.83370	77.35260	80.49272	84.46782	0.5488416	2.449052	3.698482	212
Italy	37.96940	18.53809	16.88320	50.29750	71.66547	76.15719	11.7331039	9.796446	6.959609	179
Sweden	25.74040	19.38546	14.59292	69.63644	74.09113	79.65471	4.6231598	6.523405	5.752364	257

Notes: weighted shares using SPFWT0.x. Band = 0.5 on the signed gap.

If preferred, this table can be used to cross-check domain patterns immediately, while the main text emphasizes the long-format incidence table and the graphical summaries.

Figure B.2 - OECD Education GPS (PIAAC): adult skills profile (OECD, 2026)



Descriptive benchmark only. Indicators combine mean proficiency scores and the share of low/high performers in different scales. Used to contextualize cross-country rankings, not for causal inference.

B.3 – Sensitivity and robustness for incidence threshold

Mismatch incidence is defined as the proportion of individuals assigned to under-skilled and over-skilled categories using a symmetric tolerance band around the signed standardized gap. The baseline uses τ = 0.5. Alternative thresholds can be explored to verify that results do not depend on a single cutoff and that the qualitative cross-country patterns stay stable. Where reported, these sensitivity checks are intended to support the robustness of descriptive patterns rather than to provide additional inference.

Table B.3a - Sensitivity (τ = 0.25). Weighted shares (%) by domain and country

Country	Matched (%)			Over-skilled (%)			Under-skilled (%)			N valid		
	APS	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**
Germany	18.9	17.1	17.7	43.3	46.0	43.6	37.8	36.8	38.7	3,011	3,470	3,470
Italy	—	18.9	16.6	—	44.3	43.2	—	36.8	40.2	0	2,786	2,786
Sweden	18.5	17.8	15.9	46.1	49.4	44.2	35.3	32.8	39.9	2,495	2,739	2,739

Table B.3b - Sensitivity (τ = 1) of mismatch incidence. Weighted shares (%) by domain and country

Country	Matched (%)			Over-skilled (%)			Under-skilled (%)			N valid		
	APS	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**	**APS**	**LIT**	**NUM**
Germany	65.8	64.6	63.0	16.2	18.2	19.2	18.0	17.2	17.8	3,011	3,470	3,470
Italy	—	63.7	60.5	—	19.0	19.4	—	17.2	20.1	0	2,786	2,786
Sweden	63.7	65.3	61.4	17.9	18.8	18.8	18.3	15.8	19.8	2,495	2,739	2,739

Sensitivity checks with different tolerance thresholds confirm consistent cross-country and cross-domain patterns. Varying the tolerance band increases the matched quota and reduces over- and under-skilling, with a similar pattern across countries and domains. Conclusions are unaffected by specific cutoff choices.

B.4 – Italian Geographic Heterogeneity

Italy shows regional differences in adult skills, crucial for understanding mismatch patterns and outcome regressions. INAPP PIAAC data (Cycle 2, 2022-2023) reveal territorial skill gradients, which justify the use of geographical controls in Italy-specific analyses. These patterns help interpret cross-sectional results influenced by regional labor-markets and sectoral mixes. (INAPP, n.d.)

Figure B.4a – Italy: Literacy proficiency by region (PIAAC Cycle 2, 2022-23)

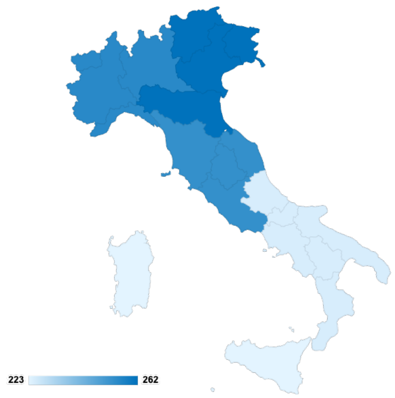


Figure B.4b -Italy: Numeracy proficiency by region (PIAAC Cycle 2, 2022-23)

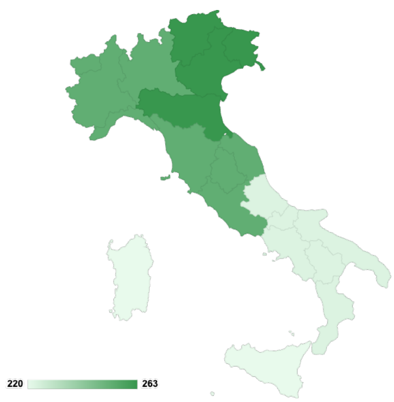
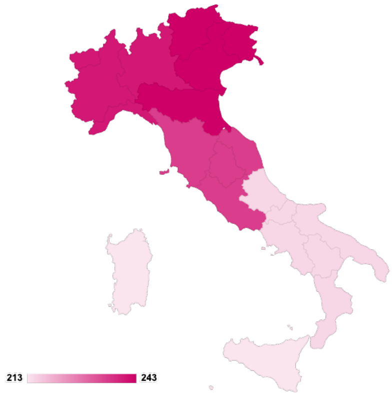


Figure B.4c – Italy: Adaptive Problem-Solving proficiency by region (PIAAC Cycle2, 2022-23)



Across the three domains, the maps clearly highlight a North-South differentiation: higher average proficiency is more prevalent in the Northern regions, especially the North-East. At the same time, lower scores are more prevalent in the Southern areas. This heterogeneity matters because regional labor-market conditions and sectoral composition can jointly influence both skill utilization and labor-market outcomes, potentially leading to misleading conclusions about the relationship between mobility and wages.

This appendix provides additional evidence supporting the main results without altering the core analysis. It includes supplementary patterns for Italy, explaining the role of geographic controls and robustness checks for mismatch-incidence classification under different thresholds.

All statistics use the same conventions as the main text, relying on PIAAC final sampling weights (SPFWT0. x) and mismatch measures combining PIAAC proficiency with ESCO-based occupational requirement proxies at the ISCO-2 level. APS-related results are included only when available, which is why they are not specified for Italy, as the PVPSLs are missing from the public-use files used in this thesis. (OECD, 2026)