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Occupational skill mismatch in self-employment: prevalence and income implications

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Abstract

Purpose – This study explores the relationship between occupational skill mismatch and self-employment, examining both the likelihood of self-employment among those experiencing skill mismatches and the subsequent impact on entrepreneurial earnings.

Design/methodology/approach – We analyze data from the REFLEX Project involving 17,623 respondents across 13 countries, complemented by a post-hoc analysis of 43,536 respondents from the PIAAC dataset spanning 24 countries. Our methodology combines logistic regression to examine self-employment choice and OLS regression to analyze income effects.

Findings – Our analysis reveals three key findings: (1) in the REFLEX data, individuals reporting higher skill differences are more likely to be self-employed; (2) among self-employed individuals in the REFLEX sample, higher skill differences are associated with significantly lower income levels (negative interaction effect) and (3) in the PIAAC data, we find consistent effects.

Originality/value – This research provides an analysis of how occupational skill mismatches influence both self-employment choices and income outcomes across diverse geographic contexts. Our findings contribute to understanding the entrepreneurial earnings puzzle and offer practical implications for policymakers designing support programs for self-employed individuals.

Keywords Skill mismatch, Self-employment, Human capital, Entrepreneurial earnings gap

Paper type Research paper

1. Introduction

The literature on human capital broadly categorizes skill mismatches into two types: educational and occupational skill mismatch. Educational skills mismatch, also known as field-of-study mismatch, occurs when an individual's skills and qualifications do not align with the specific requirements of their job or industry. Occupational skill mismatch refers to a misalignment between an individual's level of skills and the level demanded by their job. McGuinness's comprehensive examination provided insights into the overarching effects of skill mismatch on various labor market outcomes (McGuinness *et al.*, 2018; Somers *et al.*, 2019; Guvenen *et al.*, 2020).

Occupational skill mismatch may be more prevalent among self-employed (Li *et al.*, 2018). One significant factor is the phenomenon of necessity entrepreneurship, where individuals may venture into self-employment due to economic circumstances or a lack of viable job opportunities. In such cases, individuals may find themselves in entrepreneurial roles possessing less than the ideal skill set for their chosen venture (Mühlböck *et al.*, 2018). The self-employment literature has given limited attention to the prevalence of and implications of skills mismatch (Stenard and Sauermann, 2016; Albiol-Sánchez *et al.*, 2021). Exploring how skills mismatch affects self-employment is important for several reasons. Lowering skills mismatch can improve economic efficiency by aligning individual skills with the demands of self-employment (Velciu, 2017).

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Relatedly, skills mismatch could be an additional explanation for the entrepreneurial earnings puzzle, that is, entrepreneurs and business owners, on average, do not earn higher incomes than their counterparts in wage or salaried positions (Åstebro and Chen, 2014; Hyytinen *et al.*, 2013). Occupational skill mismatch poses operational challenges for self-employed individuals, manifesting in difficulties related to fundamental business operations such as marketing, financial management, and overall business strategy. Inherent risks and resource constraints associated with entrepreneurship may limit the ability of self-employed individuals to invest in formal skill development (Kodithuwakku and Rosa, 2002). Self-employed with higher occupational skill mismatch may encounter difficulties in securing financial resources, as potential investors and lenders may perceive a lack of expertise. Client acquisition and retention present additional challenges, as client trust is crucial in establishing and maintaining relationships a perceived skills mismatch may deter clients, thereby leading to lower earnings.

Examining skill mismatch among the self-employed is particularly crucial because, unlike traditional employees who can rely on organizational structures for skill development and role specialization, self-employed individuals must independently manage diverse business functions while often lacking formal support systems for skill acquisition and utilization. Self-employment context creates a heightened vulnerability to skill mismatches, as self-employed individuals must simultaneously serve as both employer and employee, requiring them to possess and effectively deploy a broader range of competencies. Furthermore, understanding skill mismatch in self-employment is essential because these individuals' productivity and earnings directly impact economic growth through their roles as job creators and innovators.

In this study, we ask whether occupational skill mismatch is associated with self-employment? and whether such mismatches are associated with earnings gap among self-employed. The purpose of this study is to examine the relationship between occupational skill mismatch and self-employment, as well as its impact on earnings among the self-employed. We employ a quantitative approach using logistic and OLS regression analyses on data from the REFLEX project, which includes 17,623 respondents across 13 countries [1]. We complement this with a post-hoc study using PIAAC data to provide additional insights into skill usage patterns.

Addressing these research questions contributes to human capital self-employment and entrepreneurial earnings puzzle literature. First, skills mismatch literature has seldom focused on the intersectionality between self-employment and skill mismatch (Li *et al.*, 2018; McGuinness *et al.*, 2018). The closest study to our study is work by Albiol-Sánchez *et al.* (2021) who use eight waves of the European Community Household Panel covering the period 1994–2001 and find that individuals who transit from salaried employment to self-employment reduce their probability of reporting being skill mismatched after the transition. Focusing on occupational skill mismatch can inform researchers about its prevalence in self-employment and its association with earnings gaps.

Second, for the entrepreneurial earnings puzzle literature, the inclusion of skill mismatch is an important extension for two primary reasons (Åstebro and Chen, 2014; Hyytinen *et al.*, 2013). Skill mismatch introduces a dimension to the entrepreneurial earnings puzzle by recognizing the potential impact of skill disparities on the productivity of self-employed individuals. When an entrepreneur's skills are misaligned with the demands of their business, it can impede their ability to effectively leverage their capabilities for productive outcomes. Skills mismatch relevant to their industry may face obstacles in optimizing operational efficiency, leading to suboptimal productivity levels. Third, for policymakers comprehension of skill mismatch in the context of self-employment is essential. Knowledge about how specific skill mismatch correlates with income outcomes informs the formulation of targeted policies. Skill mismatch guides the development of relevant curricula and training initiatives aligned with the demands of self-employment, ultimately impacting earnings potential.

This study unfolds as follows. First, we present a theoretical framework that explores the relationship between occupational skill mismatch and self-employment, drawing on human capital theory, entrepreneurship literature, and labor market dynamics. We then develop two key hypotheses: one addressing the prevalence of skill mismatch among the self-employed, and another examining its association with income levels. Next, we present our sample and the results. We further complement our main findings with a post-hoc study using PIAAC data, which provides additional insights into skill usage patterns. Finally, we discuss the implications of our findings for theory and practice, outline limitations, and suggest directions for future research.

2. Theoretical development and hypotheses

Skill mismatch relates to the incongruity between the skills possessed by an individual and the skills demanded by their job or the broader labor market. We present our conceptual framework in two parts. Table 1(a) outlines the types of skill mismatches and their extension to the self-employment context, while Table 1(b) presents our proposed conceptual model linking occupational skill mismatch to self-employment outcomes. Unlike educational mismatch, which primarily centers on the misalignment between formal education and job requirements, skill mismatch delves into the adequacy or excess of specific skills, irrespective of academic credentials (McGuinness *et al.*, 2018). This mismatch can manifest in various forms, each with its unique implications. Over-skilling occurs when an individual's skills surpass the requirements of their current job, potentially leading to underutilization or mismatch in specific skills, where an individual may excel in certain technical competencies but lacks vital interpersonal or communication skills necessary for their job (McGuinness *et al.*, 2018). Under-skilling arises when an individual lacks certain essential skills for their job, leading to decreased performance and limited opportunities for career advancement.

McGowan and Andrews (2015), based on data from the OECD Survey of Adult Skills, establish a link between higher skill mismatch and lower labor productivity. Skills mismatch not only challenges the matching of workers to jobs but also hinders the reallocation of resources, resulting in prolonged adjustment periods and higher search costs. Moreover, research on job satisfaction reveals that skills mismatch can lead to increased absenteeism, frequent job changes, and reduced investment in training, collectively impacting productivity. Wage inequality emerges as a significant outcome of skills mismatch, as evidenced by Slonimczyk (2011) study on rising over-qualification rates and premia in the United States. Identification of skill mismatches relies heavily on subjective measures, where individuals self-report whether they perceive themselves as over-skilled (Guvenen *et al.*, 2020; McGuinness *et al.*, 2018). Despite potential biases due to individual overconfidence, studies consistently show that subjective measures align with objective measures in capturing the impact of skill mismatches on job satisfaction, job changes, and wages (Guvenen *et al.*, 2020; McGuinness *et al.*, 2018).

2.1 Hypotheses development

We present our theoretical framework in Table 1. Hypothesis 1 higher levels of skill mismatch are likely to exhibit a greater prevalence among self-employed individuals. Several mechanisms may explain the proposed relationship. Role complexity in self-employment often requires individuals to perform a diverse array of tasks beyond their core expertise. Self-employed workers frequently manage various aspects of their business, including operations, marketing, and financial planning, in addition to their primary service or product delivery. The jack-of-all-trades requirement (Lazear, 2004) may lead to a perceived mismatch between specialized skills and the broad demands of running a business. While wage-employed individuals typically focus on specific role-related tasks, self-employed workers must navigate a more complex skill landscape, potentially increasing their likelihood of experiencing and reporting skill mismatches.

Human capital theory provides a theoretical foundation for understanding skill mismatch in self-employment contexts (Sala, 2011). Self-employed individuals invest in their human

Table 1. Conceptual background

(A). Types of skill mismatches and their extension to self-employment context

Mismatch type	Definition	Example	Impact on income gap	Causes	Impact on self-employment earnings
Educational mismatch	Occurs when there is a misalignment between the skills possessed by an individual entrepreneur and the skills demanded in work	An artisan with exceptional carpentry skills starting a business in a market where there is a high demand for modern, custom-designed furniture using computer-aided design (CAD) technology	Can lead to reduced success and profitability of the self-employed venture. The entrepreneur may struggle to meet the demands of the market, resulting in lower income and business growth	Limited adaptability of skills, lack of awareness about market trends, or insufficient understanding of the skills required in a specific niche within self-employment	Support programs and resources that focus on enhancing the adaptability of self-employed individuals, providing market-oriented training, and fostering awareness of emerging trends
Occupational skill mismatch	Occurs when the skills possessed by an individual entrepreneur are not aligned with the hierarchical demands or management requirements of their own business	A highly skilled software developer launching a tech startup but lacking managerial skills to lead a growing team and handle business operations effectively	Can hinder the growth and sustainability of the self-employed venture. The entrepreneur may struggle to manage the increasing complexity and demands of their business	Limited focus on developing managerial and leadership skills, rapid business growth that outpaces skill development, or underestimating the importance of occupational skill mismatch in entrepreneurship	Entrepreneurial education and support programs should include components that enhance managerial and leadership skills. Encouraging self-employed individuals to invest in their professional development can mitigate occupational mismatch challenges

(*continued*)

Table 1. Continued

(B). Proposed conceptual model

Occupational	Definition and key findings from human capital	Implications for employment	Implications for self-employment	Implications for income gap
Vertical skill mismatch	Skill Mismatch in the realm of human capital refers to a disparity between the skills possessed by an individual and the skills demanded by their job or the broader labor market. Unlike educational mismatch, which primarily focuses on the misalignment between educational qualifications and job requirements, skill mismatch centers on the inadequacy or excess of specific skills, irrespective of formal education Skill mismatch can take various forms Over-skilling: This occurs when an individual's skills surpass the requirements of their current job. Over-skilled workers may find themselves underutilized or performing tasks that do not fully leverage their skill set. Under-skilling: Conversely, under-skilling happens when an individual lacks certain skills essential for their job. This situation may lead to decreased job performance and limited opportunities for career advancement Mismatch of Specific Skills: It's also possible for there to be a mismatch in specific skills. For instance, a worker may possess strong technical skills but lack necessary interpersonal or communication skills for their job Difference from Educational Mismatch The key distinction between skill mismatch and educational mismatch lies in their focus *Educational Mismatch*: Primarily concerns the misalignment between an individual's educational qualifications and the requirements of their job. It addresses the level and type of education an individual has obtained *Skill Mismatch*: Focuses on the specific skills possessed by an individual and whether these skills align with the demands of their job. It is more granular and considers competencies and capabilities beyond formal education	Skills misaligned with job needs, leading to over/ underqualification	Higher skill differences may lead to self-employment as individuals seek entrepreneurial opportunities when their skills differ significantly from job requirements Individuals might be driven towards self-employment due to the belief that their unique skills or expertise are best utilized in an entrepreneurial setting. However, challenges in effectively leveraging these skills may result in lower income	Self-employed individuals with higher skill differences might face challenges in effectively utilizing their skills, potentially affecting business success and income outcomes The income gap between self-employed and employed individuals may be influenced by the degree of skill mismatch

(*continued*)

Table 1. Continued

(B). Proposed conceptual model

Occupational	Definition and key findings from human capital	Implications for employment	Implications for self-employment	Implications for income gap
Post-hoc study skills usage	Skill Usage in the context of human capital refers to the effective application and deployment of an individual's skills within their job or occupation. It is concerned with how well a person's acquired skills, whether through formal education or practical experience, are actively and productively utilized in their work tasks and responsibilities A high level of skill usage implies that an individual is leveraging their skills effectively in their job, contributing to better job performance, job satisfaction, and potentially higher productivity. On the contrary, low skill usage suggests that the individual may not be fully utilizing their acquired skills in the workplace, which can impact performance and job satisfaction Examines how well an individual applies and utilizes their skills in their day-to-day work. Evaluates the effectiveness of skill deployment, aiming to understand if the individual is actively using their skills to perform tasks and contribute to the success of their role	Effective use of skills in the workplace	Individuals reporting higher skills relative to expected skills may prefer traditional employment where their skills are actively utilized	Self-employed individuals with higher skills relative to expected skills may exhibit effective skills usage, leveraging their abilities to enhance their businesses The income gap between self-employed and employed individuals may be narrower if skills are effectively utilized in self-employment

Source(s): Author's own work

capital with the expectation of returns through their ventures. However, the diverse skill requirements of entrepreneurship may lead to suboptimal utilization of specific skills, resulting in perceived mismatches. Additionally, the theory of occupational choice (Blau *et al.*, 1956) suggests that individuals select self-employment based on expected utility. The realization that certain skills are underutilized or that new skills are required may lead to higher reported mismatches among the self-employed.

The dynamic and often isolated nature of self-employment may contribute to rapid skill obsolescence. Unlike wage-employed individuals who often benefit from organizational structures that support ongoing training and development, self-employed workers are typically responsible for their skill maintenance and enhancement (Malchow-Møller *et al.*, 2010). The absence of formal organizational mechanisms for skill development may exacerbate this issue, leaving self-employed individuals more vulnerable to skill mismatches as they struggle to keep pace with changing industry requirements.

Self-employed individuals' direct exposure to market forces and competitive pressures may heighten their awareness of skill deficiencies. The need to constantly compete for clients or contracts in a rapidly changing business environment could make self-employed workers more critical of their capabilities. Heightened sensitivity to market demands might result in a more acute perception and reporting of skill gaps compared to wage-employed individuals who may be more insulated from direct market pressures (Camasso and Jagannathan, 2021). The constant need to adapt and evolve in response to market signals may lead self-employed workers to more frequently question the adequacy of their skill set. Self-determination theory (Ryan and Deci, 2000) provides a framework for understanding how the autonomy associated with self-employment might influence skill mismatch perceptions. While autonomy is often cited as a benefit of self-employment, it may also lead to increased pressure to develop and maintain a diverse skill set. The responsibility for one's own skill development, coupled with the desire for competence, may result in higher reported skill mismatches among the self-employed.

The self-selection process for self-employment may play a role in the higher reporting of skill mismatches among self-employed individuals (Rocha *et al.*, 2015). Those who choose self-employment often have higher aspirations or more ambitious career goals, potentially leading to a persistent sense of skill inadequacy. Aspirational gaps could result in self-employed workers consistently striving for higher levels of expertise, thereby increasing the likelihood of perceived skill mismatches (Astebro *et al.*, 2014). The discrepancy between current skills and ambitious targets may be more pronounced than among wage-employed individuals, contributing to higher reported rates of skill mismatch.

The absence of clear job descriptions and standardized performance metrics in self-employment contexts may contribute to a higher incidence of reported skill mismatches. Unlike wage-employed individuals who often have defined roles and performance indicators, self-employed workers must navigate a more ambiguous professional landscape. Lack of structure may lead to uncertainty about the adequacy of one's skills, resulting in higher rates of perceived and reported skill mismatches.

H1. Self-employed are more likely to report occupational skill mismatch.

Hypothesis 2 posits that occupational skill mismatch is correlated with diminished income levels among self-employed individuals. Drawing from entrepreneurship and human capital theories, we propose six reasons to support this hypothesis. First, human capital theory (Becker, 1964) posits that individuals invest in skills to maximize their economic returns. In the context of self-employment, occupational skill mismatch may lead to suboptimal allocation of human capital resources. Entrepreneurs experiencing skill mismatch may invest time and effort in activities that do not align with their core competencies, potentially reducing their productivity and, consequently, their income. This misallocation of human capital resources can impede the efficient operation of the business, leading to lower overall performance and reduced financial returns (Unger *et al.*, 2011).

Second, entrepreneurship theory emphasizes the importance of identifying and exploiting market opportunities (Shane and Venkatraman, 2007). Self-employed individuals experiencing occupational skill mismatch may struggle to effectively recognize or capitalize on these opportunities due to a misalignment between their skills and market demands. This misalignment can result in reduced competitiveness, as these entrepreneurs may be less equipped to deliver products or services that meet customer needs efficiently. Consequently, their ability to command premium prices or secure a stable customer base may be compromised, leading to lower income levels (Teece, 2007).

Third, the theory of entrepreneurial bricolage (Baker and Nelson, 2005) suggests that entrepreneurs create value by recombining available resources in novel ways. However, occupational skill mismatch may lead self-employed individuals to engage in less efficient forms of bricolage. Time and effort spent attempting to overcome skill deficiencies represent opportunity costs that could otherwise be invested in more productive, income-generating activities. This inefficient allocation of time and resources can result in lower overall income for self-employed individuals experiencing skill mismatch (Davidsson and Honig, 2003).

Fourth, rooted in social cognitive theory (Bandura, 1997) plays a crucial role in entrepreneurial success. Occupational skill mismatch may negatively impact an entrepreneur's self-efficacy, as the perceived gap between required and possessed skills can undermine confidence in one's ability to successfully manage a business. Lower entrepreneurial self-efficacy can lead to reduced risk-taking, less ambitious goal-setting, and decreased persistence in the face of challenges. These factors can collectively contribute to lower income levels among self-employed individuals experiencing skill mismatch.

Fifth, human capital theory extends to the concept of social capital, which is crucial for entrepreneurial success (Davidsson and Honig, 2003). Self-employed individuals with occupational skill mismatch may struggle to effectively leverage their professional networks due to a misalignment between their skills and the expectations or needs of their contacts. This impaired ability to utilize social capital can result in missed opportunities for collaborations, referrals, or knowledge exchange, all of which are vital for income generation in self-employment contexts. Consequently, skill mismatch may indirectly lead to lower income through reduced social capital effectiveness (Stam *et al.*, 2014).

Sixth, self-employed individuals experiencing occupational skill mismatch may face higher transactional costs in their business operations (Williamson, 1981). These increased costs can manifest in various forms, such as the need to outsource tasks they cannot efficiently perform themselves, longer learning curves for new business-related skills, or inefficiencies in client interactions due to skill gaps (Michael, 2007). Higher transactional costs can erode profit margins and ultimately result in lower income for self-employed individuals with skill mismatches (Chiles and McMackin, 1996). These reasons, grounded in entrepreneurship and human capital theories, provide a theoretical foundation for the hypothesized negative relationship between occupational skill mismatch and income among self-employed individuals. Based on this discussion we propose:

H2. Among self-employed individuals, higher levels of occupational skill mismatch are associated with lower income levels relative to those with lower levels of skill mismatch.

3. Sample and methods

To investigate these hypotheses, we utilize data from the REFLEX (Research into Employment and Professional Flexibility) project, a large-scale survey of higher education graduates across 16 European countries and Japan. We operationalize occupational skill mismatch using respondents' self-reported assessment of their competencies relative to job requirements. Respondents rated 19 different skills on a 7-point scale (1 = very low, 7 = very high) for both their level and the level required in their current job. Our analytical approach employs two main strategies. First, we use logistic regression to examine the relationship between skill mismatch and the likelihood of self-employment (Hypothesis 1). Second, we employ OLS regression to investigate the association between skill mismatch and income among self-employed individuals (Hypothesis 2). In both models, we control for various demographic and human capital factors, including age, gender, education level, and work experience. Additionally, we include country fixed effects to account for potential cross-national differences. We provide more details on the sample, measures, analysis, and results below.

3.1 Sample

The REFLEX project, which stands for The Flexible Professional in the Knowledge Society, spans sixteen diverse countries, including Austria, Belgium-Flanders, Czech Republic, Estonia, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK This major initiative involves a large-scale survey encompassing around 70,000 higher education graduates across these nations. Each country drew a representative sample of graduates from ISCED 5A who earned their degrees in the academic year 1999/2000. The data collection occurred in 2005, precisely five years after their departure from higher education.

The survey, conducted through mail questionnaires, delves into various aspects, including educational experiences before and during higher education, the transition to the labor market, characteristics of the first job, features of the occupational and labor market career up to the present, attributes of the current job and organization, assessment of required and acquired skills, evaluation of educational programs, work orientations, and some socio-biographical information.

Complementing the survey is a country study that identifies key structural and institutional factors shaping the transition from higher education to work. Additionally, a qualitative study sheds light on primary developments in higher education and the economy, offering insights into factors affecting the acquired and required competencies.

The REFLEX project was recently launched with the aim of contributing to the assessment of the feasibility of ambitious goals and identifying potential challenges. It primarily focuses on providing a detailed description of the demands placed on higher education graduates by the modern knowledge society. These demands, intensified by an emphasis on education and training, the volatility of labor market processes, and the globalization of markets, particularly stress areas such as professional expertise, functional flexibility, innovation, knowledge management, mobilization of human resources, and international orientation.

The project's second major focus evaluates the preparedness of higher education institutions in Europe to equip graduates with the competencies required to meet these demands. A third aspect examines how work organization in firms and organizations influences the realization of demands and graduates' abilities. Furthermore, the project explicitly addresses the broader motivations of graduates, beyond their professional sphere, including their goals, aims, and orientations. Finally, it scrutinizes the transition from higher education to work and subsequent occupational outcomes, considering specific characteristics of graduates, higher education institutions, employers, and the broader institutional, structural, and cultural context within which these actors operate. Based on casewise deletion our sample includes 17,623 respondents from 13 countries.

3.2 Measures

For our earnings variable, we use the log of gross earnings current job per (contract-) hour (in Euros) (variable: F7EPHREX). For the self-employment indicator, we code those reporting as employed as 0 and those reporting as self-employed as 1 (variable: *F3SELEMP*).

Measuring skill mismatch involves self-reported assessments or realized-matches approaches. Self-reported measures rely on workers reporting if they possess the skills for a more demanding job or need training for their current job (McGuiness *et al*., 2017). Realized-matches approaches measure cognitive skills like literacy and numeracy, comparing them with occupation-specific averages or medians (McGuiness *et al*., 2017; Allen and van der Velden, 2001; Green and McIntosh, 2007; Hartog, 2000; Sala, 2011; Quintini, 2011). The definition of job requirements significantly influences measured skill mismatch. Pellizzari and Fichen (2017) demonstrate differences between self-reported mismatch and realized matches using Survey of Adult Skills data. They find workers are often considered over-skilled using self-reports but well-matched using realized matches. Recent work combines both methods, creating a quantitative scale of required skills for each occupation based on workers reporting good matches (Pellizzari and Fichen, 2017). This two-step approach identifies over and under-skilled workers by comparing their proficiency scores to established threshold values.

Skill difference in current job is based on "Below is a list of competencies. Please provide the following information: How do you rate your own level of competence?" "The respondents evaluated each item for A: What is the required level of competence in your Own level vs. B Required level in current work current work?" for 19 items (1-very low to 7-very high): i. Mastery of your own field or discipline; ii. Knowledge of other fields or disciplines; iii. Analytical thinking; iv. Ability to rapidly acquire new knowledge; v. Ability to negotiate effectively; vi. Ability to perform well under pressure; vii. Alertness to new opportunities; viii. Ability to coordinate activities; ix. Ability to use time efficiently; x. Ability to work productively with others; xi. Ability to mobilize the capacities of others; xii. Ability to make your meaning clear to others; xiii. Ability to assert your authority; xiv. Ability to use computers and the internet; xv. Ability to come up with new ideas and solutions; xvi. Willingness to question your own and others' ideas; xvii. Ability to present products, ideas, or reports to an audience; xviii. Ability to write reports, memos, or documents; xix. Ability to write and speak in a foreign language.

We take the difference for each item by subtracting its level from the required level, suggesting that a higher difference indicates a higher gap. We take the mean of these differences across the 19 items.

We control for gender is represented by a binary variable where 1 denotes male and 2 denotes female. This control is included to account for potential gender-based variations in the dependent variables, ensuring a comprehensive examination of the study outcomes. Age is included to control for the potential influence of age-related factors on the dependent variables. Age is recognized as a significant determinant in various aspects of life. We control whether the respondent is partnered to address the potential impact of relationship status on the dependent variables, acknowledging that individuals in relationships may experience different outcomes compared to those without partners. We include several children measured as: those with 1 child, 2 children, 3 or more children, and those without children. This control is included to control for the potential influence of parental responsibilities on the outcomes under investigation. The years required to receive the highest degree (after high school) is the years of education after high school.

To control for effects in Study 1, we include two variables on assessment of skills (1-yes; 0-no): (1) Undereducation: current job relative to study programme; and (2) Undereducation: current job relative to highest sublevel currently attained.

We further control for the importance of the following (not at all important (1) to very important (5)): the perceived importance of work autonomy, job security, the opportunity to learn new things, high earnings, encountering new challenges, good career prospects, having enough time for leisure activities, social status, the chance to do something useful for society, and the ability to combine work with family tasks are considered.

We include country dummies for 52 countries: Angola (1); Australia (4); Austria (998); Belgium (977); Canada (11); Cape Verde (1); China (2); Czech Republic (1); Denmark (6); Estonia (585); Finland (1,754); France (1,030); Gabon (1); Germany (1,081); Greece (2); Guatemala (1); Hong Kong (1); India (1); Indonesia (1); Iraq (1); Ireland (14); Italy (1,448); Japan (1,706); Kenya (1); Kuwait (1); Latvia (1); Liechtenstein (1); Luxembourg (10); Mexico

(1); Monaco (1); Netherlands (2,352); Norway (1,562); Peru (1); Poland (2); Portugal (433); Qatar (1); Romania (1); Russia (3); San Marino (1); Saudi Arabia (1); Serbia and Montenegro (2); South Africa (1); Spain (2,656); Sweden (16); Switzerland (23); Taiwan (1); Thailand (2); Uganda (1); United Arab Emirates (3); United Kingdom (997); United States (27); Venezuela (1)

3.3 Results

Sample descriptives are presented in Table 2. Table 3 and Figure 1 present the results. In Table 3 model 1, those reporting higher skill differences were more likely to report self-employment (H1: odds ratio = 1.077). In model 2 and Figure 1, self-employed reporting higher skill differences were more likely to report lower income (H2).

4. Post-hoc Study—PIAAC

In the previous two studies, we focused on skill mismatches. To further build on reported mismatches, the examination of skill usage is complementary in the context of occupational skill mismatch. While skill mismatches may lead to the underutilization of skills, impeding overall productivity, skill usage directly impacts individual and firm productivity. When employees can effectively apply their acquired skills to their roles, it contributes to heightened efficiency and superior task performance. Prolonged skill mismatches, however, can act as impediments to career advancement and limit opportunities for skill development. Beyond individual considerations, skill usage patterns offer valuable insights into the broader dynamics of the labor market.

4.1 Sample

We assessed our proposed hypothesis using the latest release of three rounds of The Programme for the International Assessment of Adult Competencies (PIAAC). The dataset encompasses 24 countries that participated in Round 1 of the Survey of Adult Skills (PIAAC) from August 1, 2011, to March 31, 2012. In Round 2, data collection involved participants from 9 countries spanning from April 2014 to March 2015. Finally, Round 3 data collection occurred between July and December 2017. Covering adults aged 16 to 65 in Europe, Asia (including Korea and Japan), Israel, and Chile, PIAAC provides a comprehensive survey measuring various respondent characteristics, including cognitive skills, demographic details, and work-related features. The cognitive tests in PIAAC are thoroughly described in OECD (2013). Our study utilizes a diverse array of variables from multiple countries, enabling us to examine the impacts of variations in skill regimes and the returns to vocational training for self-employed individuals. For detailed information on sampling, data collection procedures, and the public use file employed in this study, visit https://www.oecd.org/skills/piaac/data/. The total sample comprises 43,536 participants from 24 countries.

4.2 Measures

Our outcome measure is the log of Monthly earnings including bonuses, corrected for purchasing power parity. Self-employment is operationalized using the question "Current work employee or self-employed" (1 = self-employed, 0 = employed).

In addition to the discussion on the measurement of skill mismatch in the main study, The concept of skill is multifaceted, encompassing cognitive and non-cognitive abilities, as well as technical skills specific to particular jobs (OECD, 2017; Margolis, 2014). Cognitive skills involve understanding complex ideas, adapting to the environment, learning from experience, and various forms of reasoning, including literacy, numeracy, and abstract problem-solving. Non-cognitive skills encompass social, emotional, and behavioral traits, while technical skills combine cognitive and non-cognitive abilities for specific tasks (Margolis, 2014). Skill usage is based on the first computing factor score based on In our analysis, we utilized rotated

Table 2. Reflex sample descriptives

Summary statistics	Mean	SD	Min	Max
Log of hourly earnings in Euros	2.635	0.465	0.543	4.377
Self-employed	0.072	0.259	0	1
Skill difference	−0.097	0.936	−6	4.667
Gender (1-male; 2-female)	1.588	0.492	1	2
Age	30.895	4.732	25	64
Partner (1-yes; 0-no)	0.099	0.299	0	1
Children	3.405	1.105	1	4
Years required to receive highest degree (after high school)	4.111	0.958	3	7
Undereducation current job relative to study programme	0.153	0.360	0	1
Undereducation current job relative to highest sublevel currently attained	0.092	0.289	0	1
Importance: work autonomy	4.223	0.800	1	5
Importance: job security	4.279	0.875	1	5
Importance: opportunity to learn	4.439	0.687	1	5
Importance: high earnings	3.808	0.901	1	5
Importance: new challenges	4.113	0.825	1	5
Importance: good career prospect	3.84	0.986	1	5
Importance: enough time for leisure	4.177	0.870	1	5
Importance: social status	3.246	1.056	1	5
Importance: chance of doing something useful for society	3.749	1.042	1	5
Importance: good chance to combine work with family tasks	4.024	1.069	1	5

Pairwise correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	Log of hourly earnings in Euros	1									
2	Self-employed	−0.073*	1								
3	Skill difference	0.017*	0.003	1							
4	Gender (1-male; 2-female)	−0.155*	−0.054*	0.044*	1						
5	(N) Age	0.135*	0.073*	−0.102*	−0.049*	1					
6	Partner (1-yes; 0-no)	−0.011	−0.001	−0.042*	−0.017*	−0.015*	1				

(*continued*)

Table 2. Continued

Pairwise correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
7	Children	−0.088*	−0.018*	0.026*	−0.007	−0.263*	0.132*	1			
8	(N) Years required to receive highest degree (after high school)	0.040*	0.091*	0.019*	−0.081*	0.195*	−0.016*	−0.033*	1		
9	Undereducation current job relative to study programme	−0.007	0.021*	0.091*	−0.036*	−0.044*	0.025*	0.007	−0.059*	1	
10	Undereducation current job relative to highest sublevel currently attained	−0.005	0.031*	0.071*	−0.041*	−0.003	0.019*	−0.015	−0.033*	0.749*	1
11	Importance: work autonomy	0.038*	0.092*	−0.034*	0.023*	0.120*	−0.004	−0.024*	0.125*	0.057*	0.043*
12	Importance: job security	−0.136*	−0.096*	0.036*	0.138*	−0.036*	−0.053*	−0.029*	−0.030*	−0.014	−0.009
13	Importance: opportunity to learn	−0.076*	0.001	−0.005	0.106*	−0.002	0	0.031*	0.045*	0.053*	0.030*
14	Importance: high earnings	−0.086*	0.003	0.030*	−0.033*	−0.055*	−0.032*	0.020*	0.043*	0.018*	0.021*
15	Importance: new challenges	0.041*	0.012	−0.042*	0.027*	0.006	0.026*	0.018*	−0.014	0.045*	0.028*
16	Importance: good career prospect	−0.096*	−0.027*	−0.034*	−0.027*	−0.105*	−0.014	0.105*	−0.006	0.051*	0.027*
17	Importance: enough time for leisure	−0.067*	−0.044*	0.022*	0.075*	−0.080*	−0.051*	0.015*	−0.034*	−0.037*	−0.027*
18	Importance: social status	−0.108*	0.007	0.034*	0.006	−0.038*	−0.020*	0.026*	0.021*	0.042*	0.038*
19	Importance: chance of doing something useful for society	−0.143*	0.009	0.047*	0.144*	0.007	−0.024*	0.022*	0.014	0.056*	0.042*
20	Importance: good chance to combine work with family tasks	−0.105*	−0.002	0.032*	0.141*	−0.023*	−0.142*	−0.172*	0.065*	−0.01	−0.008

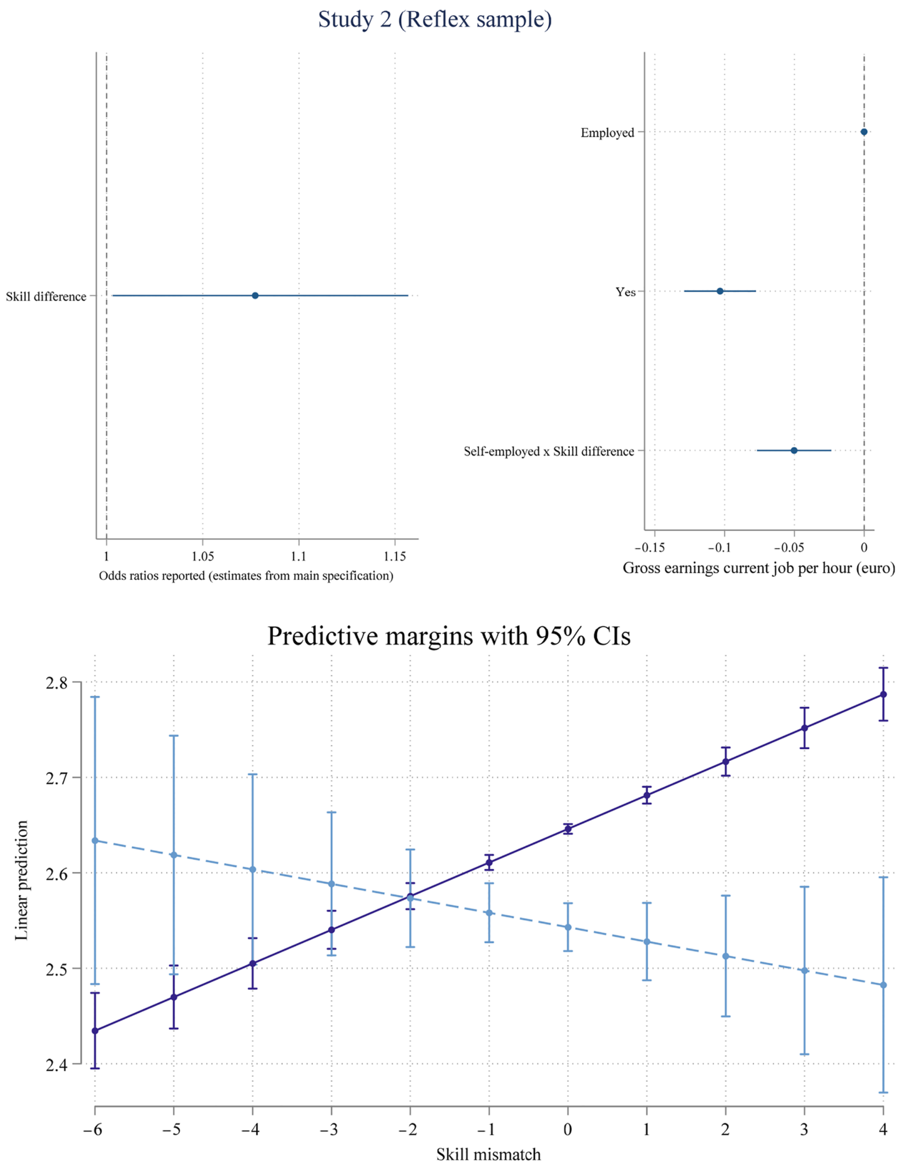
	Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
11	Importance: work autonomy	1.000									
12	Importance: job security	0.090*	1.000								
13	Importance: opportunity to learn	0.266*	0.127*	1.000							
14	Importance: high earnings	0.114*	0.263*	0.177*	1.000						
15	Importance: new challenges	0.232*	0.014	0.494*	0.208*	1.000					
16	Importance: good career prospect	0.137*	0.154*	0.326*	0.444*	0.417*	1.000				
17	Importance: enough time for leisure	0.067*	0.245*	0.114*	0.178*	0.052*	0.104*	1.000			
18	Importance: social status	0.099*	0.189*	0.143*	0.357*	0.166*	0.349*	0.151*	1.000		
19	Importance: chance of doing something useful for society	0.130*	0.142*	0.232*	0.011	0.186*	0.112*	0.175*	0.240*	1.000	
20	Importance: good chance to combine work with family tasks	0.108*	0.254*	0.129*	0.148*	0.043*	0.088*	0.383*	0.161*	0.267*	1.000

Note(s): $N = 17{,}623$; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Source(s): Author's own work

Table 3. Reflex sample estimates

Variables	(1) DV = self-employed [logit]	(2) DV = log of hourly earnings in Euros
Skill difference	1.077**	0.0352***
	(0.0392)	(0.00339)
Self-employed		−0.103***
		(0.0131)
Self-employed x Skill difference		−0.0502***
		(0.0136)
Gender	0.757***	−0.108***
	(0.0481)	(0.00551)
Age	1.620***	0.0144
	(0.207)	(0.0115)
Age-square	0.991***	−8.29e−05
	(0.00259)	(0.000249)
Age-cubic	1.000***	−5.68e−07
	(1.62e−05)	(1.68e−06)
Partner (1-yes; 0-no)	0.845	−0.0243***
	(0.0903)	(0.00793)
Children	0.979	−0.00747***
	(0.0280)	(0.00238)
Years required to receive highest degree (after high school)	1.178***	0.0550***
	(0.0466)	(0.00286)
Undereducation current job relative to study programme	0.924	0.0663***
	(0.121)	(0.0106)
Undereducation current job relative to highest sublevel currently attained	1.412**	−0.0195
	(0.216)	(0.0132)
Importance: work autonomy	1.659***	0.0145***
	(0.0887)	(0.00360)
Importance: job security	0.671***	−0.0147***
	(0.0232)	(0.00342)
Importance: opportunity to learn	0.876**	−0.0117**
	(0.0467)	(0.00465)
Importance: high earnings	1.053	0.0355***
	(0.0441)	(0.00357)
Importance: new challenges	1.093*	0.0198***
	(0.0498)	(0.00413)
Importance: good career prospect	0.822***	−0.000865
	(0.0313)	(0.00350)
Importance: enough time for leisure	0.911**	0.00224
	(0.0349)	(0.00343)
Importance: social status	1.069**	−0.000431
	(0.0350)	(0.00278)
Importance: chance of doing something useful for society	1.020	−0.0164***
	(0.0332)	(0.00275)
Importance: good chance to combine work with family tasks	1.032	−0.00490*
	(0.0359)	(0.00294)
Country dummies	Included	Included
Constant	1.27e−05***	1.474***
	(2.74e−05)	(0.168)
Observations	17,623	17,623
R-squared		0.478

Note(s): Robust seeform in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Author's own work



Dashed line represents self-employed, and solid line represents employed

Figure 1. Point estimates—reflex sample. Source: Author's own work

Principal Component Analysis (PCA) to examine work-related variables, including learning at work, information processing, planning at work, decision-making, and scores on three cognitive skills tests—literacy, numeric, and decision making. Using the resulting factor, we compute expected skills by averaging the factor at the country-occupation-income quartile. We then subtract the individual factor score from the expected skill measure. The resulting measure of skills mismatch is based on the difference between individual skill usage and the country-occupation-income quartile level. Higher scores indicate greater use of skills and lower scores indicate lower use of skills.

We include a variety of controls. We control for age, sex (1-male; 2-female), living with partner; Education: medium (ref. low); Education: high; Years of work experience; Hours worked per week; and occupational skill level (Skilled occupations; Semi-skilled white-collar occupations; Semi-skilled blue-collar occupations; Elementary occupations). We also include industry country dummies x occupational dummies [2]. We use robust standard errors.

4.3 Results

Sample descriptive is presented in Table 4. Table 5 and Figure 2 present the results. In Table 5 model 1, those reporting higher skills relative to expected skills were less likely to report self-employment (odds ratio = 0.989). In model 2 and Figure 2, self-employed reporting higher skill differences were more likely to report lower income (left side of the figure) relative to those with higher-than-expected skills (the right side of the figure).

5. Conclusion

Table 6 presents a summary of our results. Our empirical analysis provides evidence for both hypotheses. Supporting Hypothesis 1, the REFLEX data shows that those reporting higher skill differences have a higher likelihood of being self-employed. This finding aligns with our theoretical framework about how the jack-of-all-trades requirement (Lazear, 2004) and role complexity in self-employment lead to skill mismatches (Mühlböck *et al*., 2018; Li *et al*., 2018). The relationship between skill mismatch and self-employment reflects the challenges of necessity entrepreneurship, where individuals may venture into self-employment possessing less than ideal skill sets (Mühlböck *et al*., 2018). For Hypothesis 2, the REFLEX analysis demonstrates that self-employed individuals reporting higher skill differences experience significantly lower income levels, as shown by the negative interaction effect (−0.0502). This finding supports our theoretical predictions grounded in human capital theory (Sala, 2011) and aligns with research on entrepreneurial earnings gaps (Åstebro and Chen, 2014; Hyytinen *et al*., 2013). The income effect reflects how skill mismatches can impede effective resource allocation and market competitiveness among self-employed individuals.

The post-hoc PIAAC analysis provides complementary insights. We find that individuals with higher skills relative to expected levels were less likely to be self-employed (odds ratio = 0.989), though self-employed individuals who reported higher skill usage showed higher earnings (interaction effect of 0.223). This nuanced finding suggests that while skill differences may deter self-employment, effective skill utilization in self-employment can lead to positive income outcomes. These results align with theories about the importance of skill deployment and human capital utilization in entrepreneurial success (Unger *et al*., 2011).

5.1 Practical implications

Our findings yield several actionable implications for stakeholders. For policymakers, the results call for implementing targeted interventions to address occupational skill mismatches through specialized training programs and support mechanisms for self-employed individuals (Velciu, 2017). Educational institutions should integrate entrepreneurial skills into their curricula, focusing on both managerial and technical competencies to reduce potential skill mismatches. Government agencies and business support organizations can play a crucial role by offering guidance, training, and mentorship programs tailored to self-employed individuals' specific needs, particularly in areas where skill gaps are most prevalent (Davidsson and Honig, 2003). Infrastructure development, both physical and digital, is essential for facilitating knowledge spillover and skill development among entrepreneurs (Stam *et al*., 2014). Additionally, the development of skill assessment tools tailored to self-

Table 4. Post-hoc study, PIAAC sample descriptives

Summary statistics

	Mean	SD	Min	Max
Log of monthly earnings (PPP, US $)	7.561	0.872	0.1	16.29
Self-employed	0.043	0.204	0	1
Skill usage	0	0.668	−2.445	2.754
Age (5-year intervals)[a]	5.555	2.470	1	10
Living with partner	1.278	0.448	1	2
Education: medium (ref. low)	0.453	0.498	0	1
Education: high	0.4	0.490	0	1
Years of work experience	17.774	12.120	0	55
Hours worked per week	38.127	12.845	1	125
Occupational skill level (Skilled occupations; Semi-skilled white-collar occupations; Semi-skilled blue-collar occupations; Elementary occupations)	1.938	0.980	1	4

Note(s): [a]Aged 16–19; Aged 20–24; Aged 25–29; Aged 30–34; Aged 35–39; Aged 40–44; Aged 45–49; Aged 50–54; Aged 55–59; and Aged 60–65

Pairwise correlations

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log of monthly earnings (PPP, US $)	1.000								
1	Self-employed	0.089*	1.000							
2	Skill usage	−0.022*	−0.039*	1.000						
3	Age (5-year intervals)	0.340*	0.101*	0.007	1.000					
4	Living with partner	−0.316*	−0.077*	0.025*	−0.426*	1.000				
5	Education: medium (ref. low)	−0.185*	−0.008	0.031*	−0.083*	0.074*	1.000			
6	Education: high	0.282*	0.008	−0.066*	0.119*	−0.128*	−0.806*	1.000		
7	Years of work experience	0.346*	0.094*	0.001	0.903*	−0.388*	−0.027*	0.030*	1.000	
8	Hours worked per week	0.443*	0.168*	−0.058*	0.126*	−0.142*	0.000	0.082*	0.124*	1.000
9	Occupational skill level (Skilled occupations; Semi-skilled white-collar occupations; Semi-skilled blue-collar occupations; Elementary occupations)	−0.294*	−0.021*	0.078*	−0.178*	0.166*	0.314*	−0.474*	−0.139*	−0.065*

Note(s): N = 43,536; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Author’s own work

Table 5. Post-hoc study, PIAAC

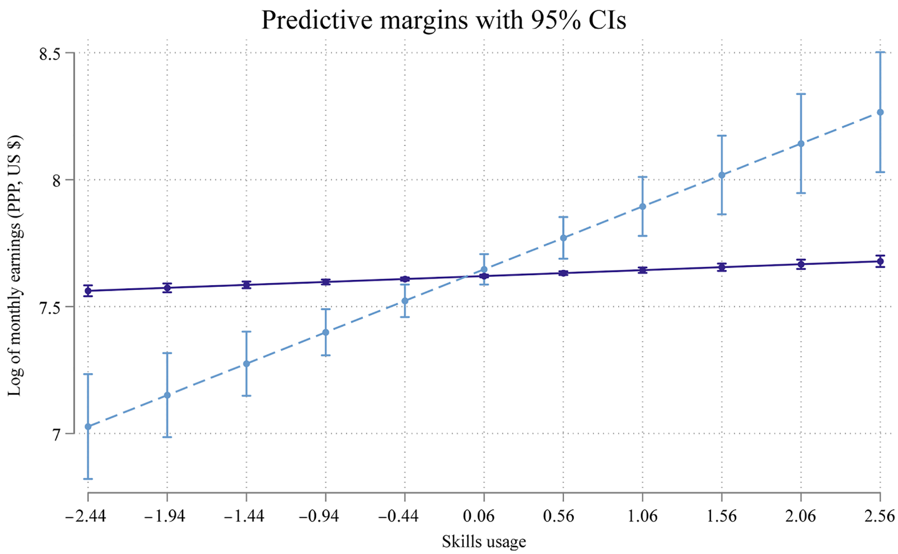
Variables	(1) Self-employed	(2) Log of monthly earnings (PPP, US $)
Skill usage	0.989***	0.0276***
	(0.00125)	(0.00430)
Self-employed		0.0222
		(0.0301)
Self-employed x Skills usage		0.223***
		(0.0438)
Age	0.981***	0.380***
	(0.00478)	(0.0193)
Age-square	1.004***	−0.0580***
	(0.00103)	(0.00368)
Age-cubic	1.000***	0.00254***
	(6.35e−05)	(0.000215)
Living with partner	0.984***	−0.0833***
	(0.00187)	(0.00721)
Education: medium	0.998	0.101***
	(0.00316)	(0.0103)
Education: high	0.997	0.267***
	(0.00379)	(0.0117)
Years of work experience	1.001***	0.0112***
	(0.000203)	(0.000657)
Hours worked per week	1.002***	0.0263***
	(0.000122)	(0.000408)
Occupational skill level	1.009***	−0.136***
	(0.00293)	(0.00829)
Country x occupation fixed effects	Included	Included
s.e.	*robust*	*robust*
Constant	0.955***	6.609***
	(0.00847)	(0.0289)
Observations	43,536	43,536
R-squared	0.290	0.639

Note(s): Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Author's own work

employment contexts could help individuals better evaluate and address their skill mismatches before and during their entrepreneurial journey.

5.2 Limitations and future research directions

Our study has several limitations that suggest directions for future research. First, our reliance on cross-sectional data from both REFLEX (collected in 2005) and PIAAC limits our ability to establish causal relationships and examine how skill mismatches evolve over time. Future studies should employ longitudinal designs to track the dynamic nature of skill mismatches in self-employment. Second, our measures of skill mismatch rely primarily on self-reported assessments, which may be subject to individual biases. While this approach aligns with established research practices (McGuinness *et al.*, 2018), future research could complement these with objective skill assessments or employer evaluations. Third, while our study spans multiple countries, deeper investigation is needed into how cultural and institutional factors influence the relationship between skill mismatch and self-employment outcomes. Future



Dashed line represents self-employed; and Solid line represents employed

Figure 2. Post-hoc study—PIAAC. Source: Author's own work

Table 6. Summary of results

Study	Data	Sample Size	Key findings	Future research directions
Main study	REFLEX Project (13 countries)	17,623	A positive association between higher skill difference and self-employment. Higher skill differences are linked to lower income among self-employed	1. Examine the cross-cultural differences in the relationship between skill differences and self-employment 2. Investigate the role of gender and other demographic factors in moderating the impact of skill differences on self-employment 3. Explore policy implications for supporting self-employed individuals with varying skill differences
Post-hoc study	PIAAC (Programme for the International Assessment of Adult Competencies) sample from 24 countries	43,536	The negative association between higher skills relative to expected and self-employment. Self-employed with higher skill differences are more likely to report lower income	1. Explore the intersectionality of cognitive skills and vocational training on self-employment outcomes 2. Investigate how national education policies influence the relationship between skills and self-employment 3. Analyze the potential moderating effects of technological advancements on the observed patterns

Source(s): Author's own work

research could explore how different institutional contexts and support systems moderate the effects of skill mismatch on entrepreneurial success, particularly focusing on the mechanisms through which skill differences influence business performance and income generation.

Notes

1. Portugal; Spain; Italy; France; Austria; Germany; Netherlands; Belgium; United Kingdom; Norway; Finland; Estonia; Japan.
2. Using a combination of country-occupation-industry dummies led to similar inferences.

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