Mismatch in the Egyptian labor market

Caroline Krafft[1] and Carmen Armas Montalvo[2]

Abstract

High rates of unemployment and non-participation in the labor market are often attributed to labor market mismatch. This paper examines the mismatch between job seekers' expectations and Egypt's labor market realities. For the non-employed, analyses examine reservation wages and what occupations the unemployed would accept. For the employed, analyses explore skills and educational attainment relative to the skill and educational requirements of their jobs. The results demonstrate that the non-employed generally have reasonable wage expectations and are willing to accept public sector jobs, but these jobs, and to some degree formal private sector jobs, are not readily available. The non-employed, and especially women, are less likely to accept more readily available informal private sector employment. As a result of women being more selective in what employment they accept, among the employed, women's skills and qualifications better match their job requirements than men's, although overeducation and over-skill are substantial issues for both men and women. There are not differences in overeducation by vocational secondary specialization or among most higher education specializations, suggesting a pervasive problem of mismatch throughout the education system.

Keywords: Mismatch, labor markets, education, skills, unemployment, reservation wages, Egypt
JEL codes: J21, J23, J24, J31, J64, I21

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1 Introduction

As education has expanded globally, the potential for mismatch between the skills and education young people acquire and the demands of the labor market has become an increasingly pressing issue (Leuven and Oosterbeek 2011; Cho et al. 2013; Kupets 2016; Handel et al. 2016). Mismatch can be explained in terms of two inter-linked dimensions: structural and aspirational mismatch. The structural dimension results from a fundamental disconnect between labor demand and labor supply, e.g., in terms of skills and specializations (Weaver and Osterman 2017). The aspirational dimension arises from the misalignment between youth aspirations or expectations, such as for high status occupations and high wages, and the realities of the labor market. These structural and aspirational (mis)matches reinforce each other and can play a critical role in the functioning of the labor market. Aspirational mismatches, such as reservation wages that are too high relative to wage offers, contribute to high youth unemployment and long unemployment durations (Levinsohn and Pugatch 2010; Abebe et al. 2025). Mismatch between available jobs and preferences may be a particularly acute employment barrier for women in contexts with low rates of female labor force participation (Fletcher et al. 2017; Caria et al. 2025; Croke et al. 2023). Structural mismatch reduces wages, productivity, and employment satisfaction (Tansel and Lassassi 2023; Mateos-Romero and Salinas-Jiménez 2018; Quinn and Rubb 2006).

The Arab world has the longest school-to-work transitions of any world region (Nilsson 2019) coupled with high rates of educated, youth, and female unemployment (El-Kogali and Krafft 2020; World Bank 2013). These challenges are often attributed to skills and education mismatch, but "with little empirical evidence" (Adely et al. 2021). This paper endeavors to provide some of that evidence, examining mismatch in Egypt. The analyses draw on the Egypt Labor Market Panel Survey (ELMPS) 2023 to assess the extent of mismatch in the labor market. For the non-employed, analyses focus on reservation wages and occupations the unemployed are willing to accept relative to prevailing wages and their qualifications. For the employed, analyses examine the match between the education and skills workers have and those required by their jobs to quantify match versus over- and undereducation and likewise skill. The research thus explores the extent of mismatch and for whom mismatch is particularly acute in Egypt.

The results demonstrate that mismatch is sizeable in the labor market, although complex and heterogenous in its nuances. While the non-employed are willing to accept lower wages in the public sector, such jobs are not readily available. They are also often unwilling to accept occupations and wages that are available in the informal private sector, particularly so for women. Among the employed, there is appreciable education mismatch including substantial over-education, for instance, 51% of the employed are over-educated, as well as some over-skilling. Because women are less likely to accept jobs that do not meet their reservation working conditions, employed women are less likely to be mismatched than employed men. Moreover, among the employed, there are not differences in overeducation by vocational secondary specialization or among most higher education specializations (except medicine, science, and engineering), suggesting a pervasive problem of mismatch throughout most of the education system.

The findings provide an important, multi-dimensional understanding of mismatch from a low- and middle income (LMIC) context. Most of the existing research on mismatch focuses on high-income countries (see Handel et al. 2016 for a review) or focuses solely on one aspect of mismatch,

such as education (e.g., Didier 2024; Fakih and Lizzaik 2024; Pholphirul 2017). The findings on mismatch also have important policy implications for training, education, and career advising systems (Hastings et al. 2016). Furthermore, updating individuals' beliefs on their skills (Kiss et al. 2023) or prevailing wages (Abebe et al. 2025) can potentially help reduce labor market mismatch.

2 Context: Education and labor markets in Egypt

Egypt has substantially and rapidly expanded educational attainment. For example, while only 22% of the adult (aged 25-64) population in 1988 had attained a secondary or higher education, by 2023, 62% of adults had done so (Krafft, Assaad, and McKillip 2024). Among cohorts born since the 1990s, around 40% have attained a secondary education and nearly 30% higher education (Krafft, Assaad, and McKillip 2024). Although educational attainment has expanded rapidly, education quality remains an issue (Elbadawy 2015; Krafft 2012). For instance, in mathematics on the Trends in International Mathematics and Science Study (TIMSS), Egypt ranked 34th of 39 countries in its average mathematics score (Mullis et al. 2020).

One potential driver of low education quality in Egypt is a focus on credentials over skills (Assaad et al. 2018). Historically, Egypt guaranteed public sector jobs to graduates of secondary or higher education, which led to youth queuing in unemployment seeking such jobs (Assaad 1997; 2014). The education system was thus geared towards producing credentials that allowed workers to enter the public sector – not skills demanded in the private sector (Assaad et al. 2018). With structural reform starting in the 1990s, the public sector employment guarantee ended, but young people, particularly educated young people, continued to prefer and queue for public sector jobs (Assaad 1997; 2014; Barsoum 2015). The focus on credentials over skills in the education system is one potential driver of structural mismatch, while the historical public sector employment guarantee may contribute to a mismatch between expectations and aspirations and the realities of the labor market.

Another important factor shaping mismatch is the strong male breadwinner/female homemaker norm (El-Feki et al. 2017; Hoodfar 1997). For men, obtaining employment (preferably a formal job) is a precondition for transitioning to other adult roles, such as marriage (Krafft and Assaad 2020; Assaad et al. 2010). Lengthy and difficult school-to-work transitions in the Arab world and Egypt have led to a common "waithood" (short for wait adulthood) phenomenon (Assaad and Barsoum 2009; Dhillon and Yousef 2009). In contrast, employment prior to marriage is not mandatory for women. If women do undertake employment, and particularly if they wish to continue working after marriage, jobs must be reconcilable with gender norms and caregiving responsibilities (Assaad, Krafft, et al. 2022; Selwaness and Krafft 2021). Therefore, there was and continues to be a strong preference, particularly among young women, for jobs in the public sector (Barsoum 2015).

Although there has been economic growth post structural reform, it has largely been jobless (Assaad, AlSharawy, et al. 2022), with employment rates declining to 15% of women and 69% of men aged 15-64 employed as of 2023 (Krafft, Assaad, and McKillip 2024). While the share of the employed in the public sector fell from 39% in 1998 to 21% in 2023, private sector formal wage employment rose only from 8% to 11% of employment over the same period (Assaad, AlSharawy,

et al. 2022; Assaad and Mahmoud 2024). The nature of job creation in Egypt has largely followed a labor absorbing paradigm, unrelated to productivity, and driven primarily by sectors such as construction that do not tend to employ educated graduates (Assaad et al. 2020; 2019). Thus, particularly for new entrants, informal private sector jobs have become increasingly common for men, as they (eventually) adjust their aspirations and expectations, while women have increasingly withdrawn from the labor force (Assaad, AlSharawy, et al. 2022; Assaad and Mahmoud 2024; Assaad and Krafft 2021; Assaad et al. 2023; Amer and Atallah 2022). The structural and aspirational aspects of mismatch may thus be interacting dynamically.

Past research on labor market mismatch in Egypt has largely focused on education (Roushdy and ElKhouly 2024; Fakih and Lizzaik 2024), and more rarely described skills (Krafft 2023) or reservation wages and working conditions (Barsoum and Abdalla 2022; Dougherty 2014; Majbouri 2025). Overeducation is common for secondary and higher education graduates in the Egyptian labor market, with negative impacts on wages and job satisfaction (Roushdy and ElKhouly 2024; Fakih and Lizzaik 2024). Returns to education in Egypt are low, which is often taken as further evidence of labor market mismatch (Krafft 2018; Salehi-Isfahani et al. 2009; Krafft et al. 2019).

3 Data and methods: measuring and explaining mismatch

3.1 Data: Egypt Labor Market Panel Survey

The analyses in this paper are based primarily on the ELMPS 2023 (OAMDI 2024; Assaad and Krafft 2024). Some analyses also draw on the preceding wave in 2018 (OAMDI 2019; Krafft et al. 2021). The ELMPS is a nationally representative survey. Initially fielded in 1998, with waves in 2006, 2012, 2018, and 2023, it tracks households and individuals over time, even when individuals leave to form new households. The 2023 wave included 70,363 individuals and 17,784 households. Our analyses focus on individuals aged 15-64, who answered the detailed individual questionnaire modules on labor force participation, employment and unemployment. We primarily use the 2023 wave cross-sectionally, but in some specific analyses, described below, use the 2018-2023 panel.

3.2 Data: Covariates related to mismatch

Mismatch may be heterogeneous. Being a woman is associated with higher rates of overeducation in the U.S. (Leuven and Oosterbeek 2011; Capsada-Munsech 2017), Spain (Boto-García and Escalonilla 2022), and other European contexts (Baran 2024). In the U.S., increases in unemployment are more strongly related to mismatch among highly educated workers than among less educated workers (Şahin et al. 2014). Younger workers are generally at higher risk of being overeducated due to not having work experience and temporarily accepting mismatch as a strategy to begin their career path (Boto-García and Escalonilla 2022; Leuven and Oosterbeek 2011; Baran 2024). However, there is also literature showing overeducation has an association with older workers, suggesting a U-shaped relationship between age and overeducation (Green and McIntosh 2007; Baran 2024). Moreover, in Jordan, a country with similar context to Egypt, mismatch is also influenced by geography and socio-economic status (Adely et al. 2021). Other characteristics, such

as nationality, ethnicity and ability, also affect mismatch in the global literature (Leuven and Oosterbeek 2011; Baran 2024).

For this reason, we control for variables related to demographic and job characteristics. The demographic factors include age, geographic location, gender (interacted with marital status and spouse presence), having in the household children[3] under age six or between ages 6 and 17 (interacted with gender), household size, educational attainment, parental educational attainment, and the father's employment status. Job-related characteristics include occupation, job stability, working inside or outside an establishment, job sector, firm size, and work experience.

The variables are categorized in detail below:

- Demographic variables:
    - Sex, marital status, and spouse presence[4] (including interactions)
        - Woman
        - Ever married
        - Spouse presence
        - Woman living with spouse (interaction)
        - Ever-married woman (interaction)
    - Household size (continuous variable)
    - Age and presence of children (including interactions with sex)
        - Has children, youngest under 6
        - Has children, youngest child aged 6-17
        - Woman with youngest under 6 (interaction)
        - Woman with youngest child aged 6-17 (interaction)
    - Age group:
        - 15-19
        - 20-29
        - 30-39
        - 40-49
        - 50-59
        - 60-64
    - Educational attainment:
        - Illiterate
        - Reads and writes
        - Primary
        - Preparatory
        - General secondary
        - Vocational secondary
        - Post-secondary institute
        - University and above

[3] Children are identified based on listing the individual as their mother (for women) or father (for men).
[4] Only married people can have a spouse. Thus, there is not an interaction between spouse and ever-married.

    - Region:
        - Greater Cairo
        - Alexandria, Suez Canal Area
        - Urban Lower
        - Urban Upper
        - Rural Lower
        - Rural Upper
    - Educational attainment of respondent's mother:
        - Illiterate
        - Reads and writes
        - Less than intermediate
        - Intermediate
        - Higher education
    - Educational attainment of respondent's father:
        - Illiterate
        - Reads and writes
        - Less than intermediate
        - Intermediate
        - Higher education
    - Employment status of the respondent's father when the respondent was 15:
        - Wage worker
        - Employer
        - Self-employed or unpaid family worker
        - No job
    - Work experience (non-employed only):
        - No experience
        - 1 year or less
        - More than 1 year, up to 3 years
        - More than 3 years, up to 5 years
        - More than 5, up to 10 years
        - More than 10 years
- Job characteristics (employed only):
    - Job sector
        - Public sector
        - Private formal sector (with social insurance)
        - Private informal sector (without social insurance)
    - Working outside of an establishment
    - Working as an irregular worker
    - Occupation (1-digit, major group):
        - Managers and the armed forces
        - Professionals
        - Technicians and associate professionals
        - Clerical support, service and sales workers

        - Skilled agricultural, forestry and fishery workers
        - Craft and related trades workers
        - Plant and machine operators, and assemblers
        - Elementary occupation workers
    - Firm size (number of workers)
        - 1-4
        - 5-9
        - 10-24
        - 25-49
        - 50-99
        - 100 or more

All the demographic covariates are used in the mismatch model sections for both the employed and non-employed. In the descriptive analyses, we include only sex, education level, and job sector, as the most important divisions and drivers of mismatch. Moreover, as an additional analysis in the multivariate section, we incorporate educational specializations to examine the relationship between skill or qualification mismatch and specialization at the vocational secondary and university levels. We analyze the following specializations of vocational secondary:

- Agriculture
- Commerce
- Industrial
- Other

For university, we analyze the following specializations:

- Medicine, Science, Engineering
- Commerce and law
- Education
- Humanities
- Social sciences
- Other

3.3 Methods: Quantifying mismatch

The 20th International Conference of Labour Statisticians (ICLS) adopted the "Guidelines concerning measurement of qualifications and skills mismatches of persons in employment" (International Labour Organization 2018), which we use as a starting point for our analyses. There is not equivalent guidance for considering mismatch between those who are not employed and the employment available in the labor market, but we follow a similar paradigm to that for the employed when analyzing the non-employed. The ICLS guidelines highlight the importance of mismatch by qualification (level; field) as well as skills. Workers can be over- or under- skilled or educated for their job (International Labour Organization 2018). Because of the nature of the data available for the non-employed, particularly the unemployed, versus the employed, we necessarily organize our analyses and outcomes somewhat differently for these different groups.

3.3.1 Mismatch for the non-employed

For non-employed individuals, we measure mismatch based on the occupations and wages they are willing to accept. Those who are unemployed (using a broad definition of unemployment; not working for even one hour in the past seven days; not attached to a job; wanting to work and available to start within two weeks) in the ELMPS are asked "What is the minimum net monthly income you would need to accept a position in the [specific] sector?"[5], where the specific sectors asked were (1) government or public enterprise (2) formal private or (3) informal private, with a hint explaining the informal sector lacks social insurance. Using this information, we construct a dummy variable for each job sector that takes the value of one if the individual's stated minimum acceptable wage (reservation wage) exceeds the predicted market wage for that individual for 2023. Thus, this indicator serves as a measure of mismatch and proxy for the probability of rejecting a job among unemployed individuals and is available for each job sector. Further details on the construction of the predicted wage market for individuals are provided in Appendix 1.

As a second measure of mismatch, we use the percentage of jobs that unemployed individuals would NOT be willing to accept. This indicator is constructed by dividing the number of occupations to which unemployed respondents answered "no" in a series of yes/no questions, "Would you accept a job as a:", by the total number of occupations asked (17 in total). The occupations are listed in Appendix 2, along with their corresponding International Standard Classification of Occupations (ISCO) codes in parentheses, which are used for descriptively matching specializations with what occupations individuals would accept, as discussed later.

For those outside of labor force (not employed and not unemployed using the broad definition), a series of yes/no questions was asked:

- Would you work in the public sector if you were paid [random wage] per month?
- Would you work in the private formal sector (with social insurance) if you were paid [random wage] per month?
- Would you work in the private informal sector (with no social insurance) if you were paid [random wage] per month?

The [random wage] was generated from the 5^{th} to 90^{th} percentile of the ELMPS 2018 wage distribution, was adjusted for inflation, and varies across questions and individuals. As a final indicator for the non-employed individuals, we use the binary response as the probability of NOT accepting a job for each job sector, as a measure of mismatch.

3.3.2 Qualification mismatch by field of study for the employed

Qualification mismatch by field of study occurs when the field of study of the employed person does not correspond to the field of study required to perform their job (International Labour Organization 2018). We use a measure based on the relationships between occupations and specializations as listed in Appendix 2 (listing matches) for this type of mismatch, focusing only

[5] Surveys measuring reservation wages typically ask some variation on "What is the lowest wage you would be willing to work for?" (Kesternich et al. 2022, 583). Experiments have validated that these reservation wage questions effectively represent labor supply (Kesternich et al. 2022).

on the occupations that were responses to the ELMPS question: "Would you accept a job as a:" described above.[6]

3.3.3 Qualification mismatch by level of education for the employed

There are three approaches to quantifying qualification mismatch by level of education: the normative, statistical, and self-assessment approaches (International Labour Organization 2018). We use primarily the self-assessment (self-report) approach but present the normative approach in Appendix 3 (Appendix Figure 1 and Appendix Figure 2). The normative approach, based on national standards, is not feasible in the context of Egypt where no such standards exist, so we necessarily use international occupational classifications, making this a second-best approach. We eschew the statistical approach, which uses, for example, the modal level of education because in country contexts where over-education is substantial, the modal education level could well be over-education.

For self-assessment of qualification mismatch by level of education, we use the educational attainment along with the question "*What are the minimum education requirements for your job?*" Employed individuals responded with options ranging from no formal schooling to a postgraduate degree.[7] Match is then defined as a categorical variable based on (1) the same education level attained as the minimum required, (2) over-education as more education than required or (3) under-education as less education than required.

3.3.4 Skill mismatch for the employed

To construct the skill mismatch indicators, we use information on the skills individuals possess (available for all respondents) and the skills required by their jobs (available for employed individuals) across 13 skills: Basic literacy, mathematics or statistics, physical fitness, management skills, customer service skills, foreign language skills, basic book-keeping or accounting skills, problem-solving, communication and presentation, manual dexterity, teamwork skills, computer skills, and technical skills.

The skills possessed by individuals are based on responses to the question "To what extent do you have the following skills?" for each skill. Responses are categorical, ranging from 1: Not at all; 2: Very weak; 3: Weak; 4: Strong; to 5: Very strong. We recode these responses into binary variables that are equal to one if the individual reports a level of strong or very strong, and zero otherwise. Regarding the skills required by the job, they are captured through 13 binary variables derived from the question: "Does your job require any of the following specific abilities?" with Yes/No response options.

To create more concise skill mismatch measures, we group the 13 skills into two categories: basic skills and cross-functional skills, adapting the classification criteria of O*NET (Tsacoumis and

[6] Public sector employee response is not incorporated because this term covers a wide range of occupations.
[7] However, this question does not include an option for post-secondary education (a two-year higher education degree), making it impossible to identify a matched worker with post-secondary education. For that reason, we exclude workers with post-secondary education from the classification for qualification mismatch by level of education.

Willison 2010).[8] Basic skills include literacy, mathematics or statistics, physical fitness, manual dexterity, and communication and presentation skills. Cross-functional skills include management, customer service, foreign language, basic book-keeping or accounting skills, problem-solving, teamwork skills, computer and technical skills.

For each skill group, we construct two outcomes: one for being over-skilled and one for being under-skilled, based on job skill requirements. Our measure for over-skilled is the percentage of skills exceeding job requirements, which is calculated by dividing the number of skills that an individual possesses that are not required for his or her job by the total number of non-required skills for that job. The under-skilled measure is the percentage of skills unmet for job requirements and is calculated by dividing the number of required skills that an individual lacks by the total number of skills required for his or her job. Both outcomes are expressed as percentages ranging from 0 to 100.[9]

3.4 Methods: Predicting mismatch

Since we have different groups (employed and non-employed), we use slightly different methods and control variables for the multivariate models for each. However, all models use individual-level weights. Robust standard errors are applied to account for heteroscedasticity.

3.4.1 Predicting mismatch for the non-employed

The probability of rejecting a job is estimated separately by job sector (public, formal private, and informal private), and by non-employed type (separately for the unemployed and individuals outside the labor force). We use logit models and present odds ratios. For individuals outside the labor force, the model also includes an additional control that is the randomly assigned wage that forms part of the survey question. The model of the percentage of jobs that unemployed individuals would not be willing to accept is estimated using OLS.

3.4.2 Predicting mismatch for the employed

To analyze qualification mismatch, we use our categorical variable with three categories: matched (base), undereducated, and overeducated. We use a multinomial logit model and present relative risk ratios. For skill mismatch, we estimate four separate OLS regressions, each with a dependent variable corresponding to one of our four outcomes of being over-skilled or under-skilled, for both basic and cross-functional skills.

[8] According to O*NET, basic skills are defined as "capacities that facilitate learning or the more rapid acquisition of knowledge" (Tsacoumis and Willison 2010, A-1). Based on this definition, we classify literacy, mathematics or statistics, and communication and presentation as basic skills. We also include manual dexterity and physical fitness in this category, as they are commonly required in our dataset. Cross-functional skills refer to "capacities that facilitate performance of activities that occur across jobs" (Tsacoumis and Willison 2010, A-2). The skills we classify as cross-functional align with ONET's definition, with the exception of foreign language, which we include for convenience to maintain a two-group structure.

[9] An individual would not be included in the over-skilled model if all skills are required and would likewise not be included in the under-skilled model if no skills are required.

Additionally, we conduct subgroup analyses for employed individuals with (1) vocational secondary and (2) university education, separately, for each type of mismatch. In these specifications, we restrict the sample to the corresponding educational level, include the same control variables as in the main models, and add indicators for specific specializations at that level.

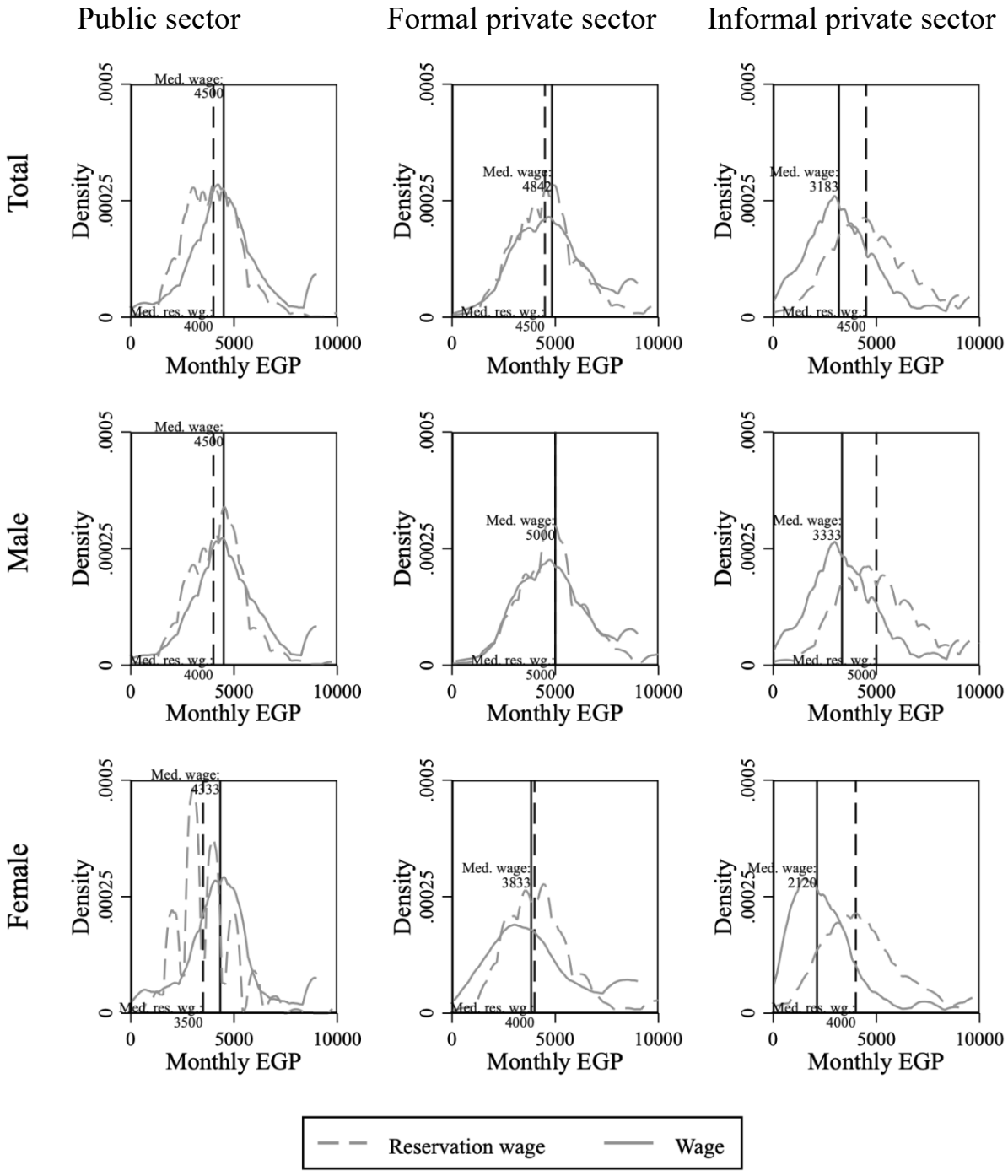
4 Results

4.1 Reservation wages for the non-employed

Current wages are often below those the unemployed would accept, particularly in the informal private sector. Figure 1 compares the distributions of reservation wages of the unemployed and the current wages of wage workers, by sector and sex. The median current wage (4,500 Egyptian pounds [EGP]) is in fact higher than the median reservation wage (4,000 EGP) in the public sector. In the formal private sector, the current median wage (4,842 EGP) is likewise higher than the median reservation wage (4,500 EGP). However, the current median informal private sector wage is much lower (3,183 EGP) than the median reservation wage (4,500 EGP), suggesting substantial scope for mismatch in this sector – which has the greatest share of employment and particularly so for new entrants (Assaad and Mahmoud 2024). Notably, the median reservation wage is 500 Egyptian pounds (EGP) lower in the public sector, at 4,000 EGP, than the formal private or informal private sectors (4,500 EGP); individuals are more willing to accept the public sector's higher-quality, but decreasingly available jobs even if wages are lower.

In all sectors, the median male reservation wage differs substantially from the median female reservation wage, with women willing to accept lower wages than men. Women also earn lower median wages than men in all three sectors. The differences between current and reservation wages vary, although with the same pattern across sectors, for men and women. Reservation wages are below current wages for the public sector, more so for women (by 833 EGP) than men (by 500 EGP). Reservation wages are similar to current wages in the formal private sector (167 EGP higher for women and 0 EGP difference for men). Reservation wages are much higher than current wages in the informal private sector (by 1,880 EGP for women and 1,667 EGP for men). Thus, while women have lower reservation wages than men, in the private sector there is a larger gap between what they are willing to accept and the wages women typically earn, suggesting particularly acute mismatch for women in these sectors. These descriptive analyses do not, however, account for key characteristics that determine wages, such as experience and education; we therefore use predicted wages (see Appendix 1) in our multivariate models.

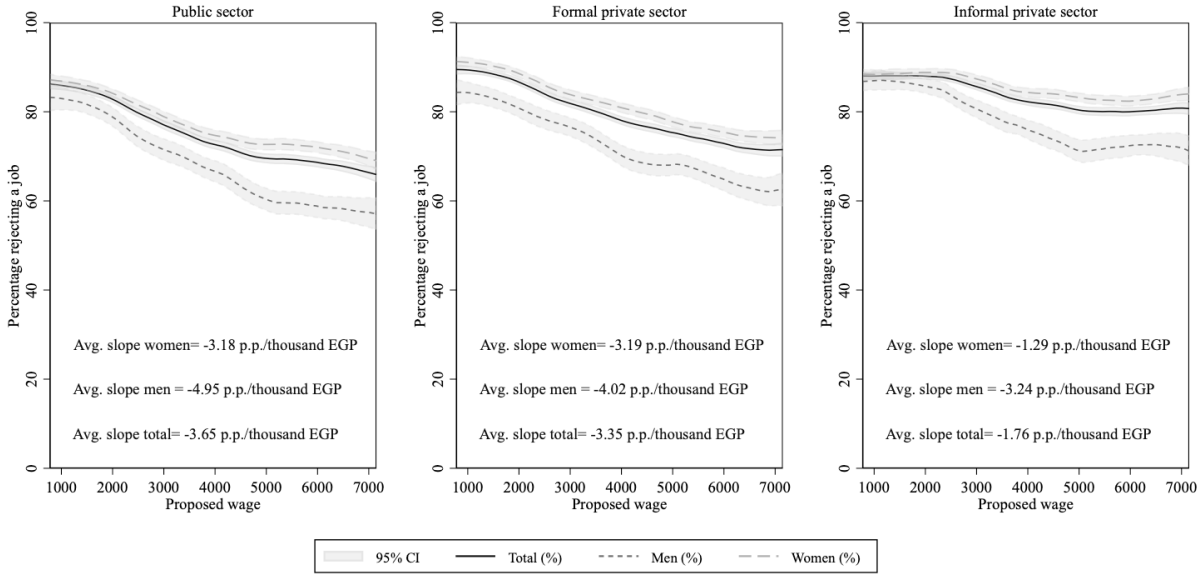
Figure 1. Distribution of monthly wages (employed, wage workers) and reservation wages (unemployed individuals), in 2023 EGP (Egyptian pounds), by sector and sex, ages 15-64



Source: Authors' calculations based on ELMPS 2023.
Notes: Outliers were removed (based on the 99th percentile for public sector reservation wages), restricting reservation and monthly wages to those less than 10,000 EGP per month. Formal jobs are those with social insurance. The figure shows a local polynomial smooth with an Epanechnikov kernel.

For individuals out of labor force, the probability of rejecting a job at a random wage is lower if the wage offer comes from the public sector or the formal private sector, and if the individual is a man (Figure 2). At very low wages, around 1,000 EGP per month, more than 80% of men and women reject jobs. On average, an increase of 1,000 EGP in the random wage offer is correlated with a decrease in the probability of rejecting a job by 3.7 percentage points (p.p.) in the public sector and 3.4 p.p. for the formal private sector, whereas it is 1.8 p.p. in the informal private sector. Even at very high wages, above 6,000 EGP per month, more than half of those out of the labor force would not accept a job. For informal private sector jobs, individuals who are out of the labor force are particularly uninterested in these types of jobs, even when they offer high wages, illustrating the mismatch between aspirations and the most commonly available jobs. Men are generally less likely to reject jobs and more responsive to higher wages than women. Women are particularly non-responsive to wage increases in the informal private sector.

Figure 2. Percentage rejecting a job, by proposed wage, sector and sex, individuals out of the labor force aged 15-64



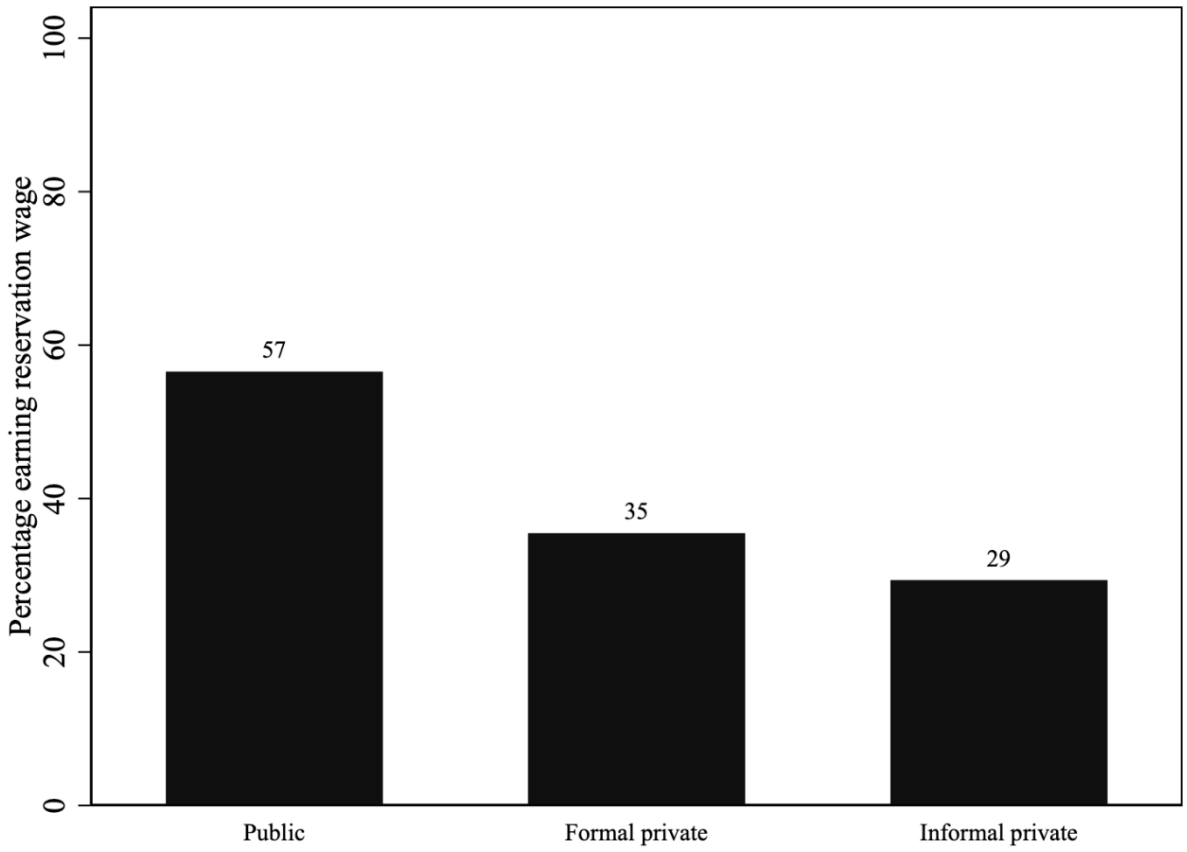
Source: Authors' calculations based on ELMPS 2023.
Notes: The "avg. slope" represents the percentage point (p.p.) change in willingness to accept a job for a 1,000 EGP change in the offered wage based on a linear regression. The figure shows a local polynomial smooth with an Epanechnikov kernel and bandwidth 500.

Tracking individuals who were unemployed in the ELMPS 2018 wave, we can assess whether they obtain employment in 2023 that meets their 2018 reservation wages or if they have to adjust their expectations. In this panel sample, 39% of those who were unemployed in 2018 obtained a job in 2023. Specifically, 28% of the unemployed individuals in 2018 secured a wage job (71% of those who became employed). These new wage workers were distributed across the informal private sector (65%), formal private sector (21%), and public sector (14%).

Figure 3 shows that relationship between the wage individuals earned in 2023 and their reservation wage in 2018, adjusted into real 2023 terms based on the consumer price index (CPI), across

sectors. In part because the unemployed had lower reservation wages for the public sector, 57% of those who obtained public sector jobs received a wage that was at least equal to their reservation wage. For the unemployed who end up in the private sector, workers are typically earning less than their reservation wage (only 29% earned at least their reservation wage in the informal private sector and 35% in the formal private sector). There is thus substantial evidence of initial mismatch in reservation wages and wage adjustment for the unemployed who do become employed subsequently, particularly in the private sector.

Figure 3. Percentage of 2023 wage workers earning at least their 2018 reservation wage (in 2023 EGP), by sector in 2023, aged 15-64 and unemployed in 2018



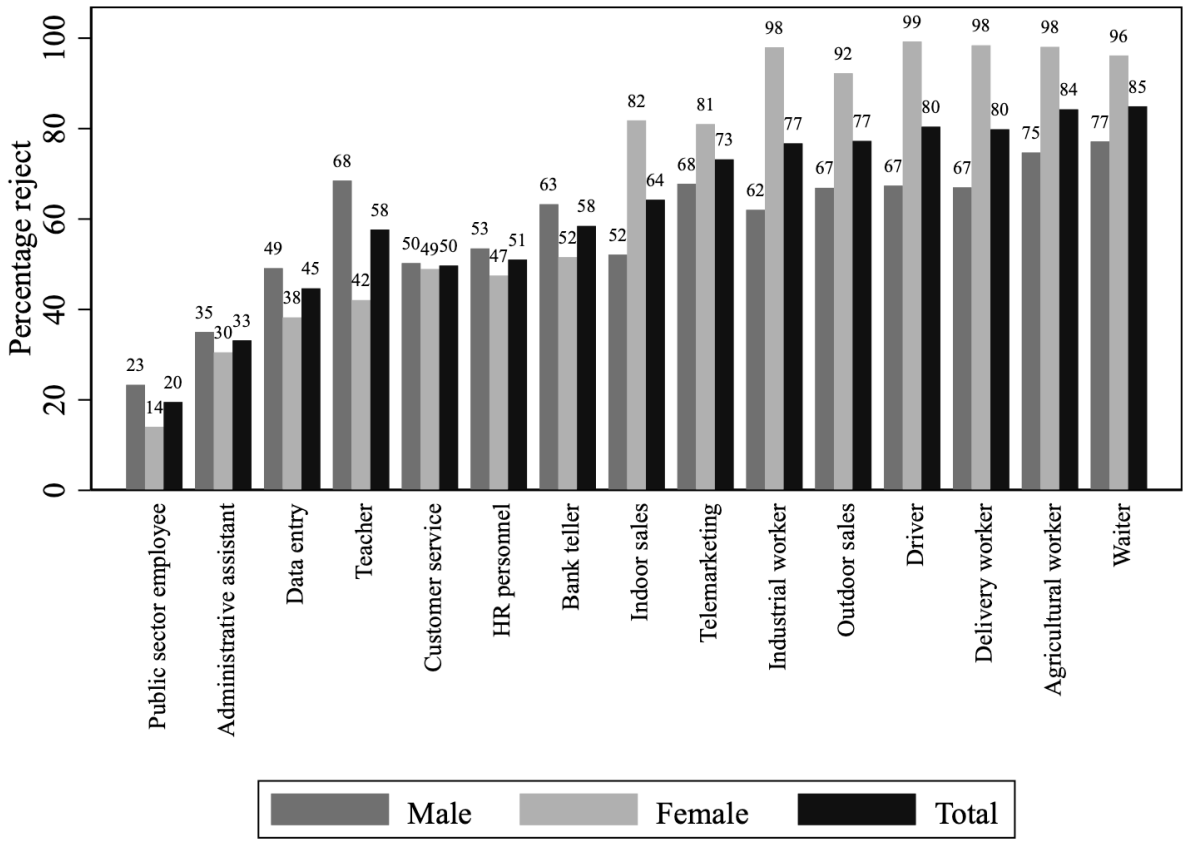
Source: Authors' calculations based on ELMPS 2018 and 2023.
Notes: 2018 wages adjusted into 2023 prices using the consumer price index.

4.2 Reservation occupations for the unemployed

The unemployed, in 2023, would reject the majority of occupations, particularly so for women (Figure 4). The occupations least likely to be rejected for both men and women were the same, with women consistently having a lower willingness to reject: public sector employee (23% reject for men and 14% for women), administrative assistant (35% for men and 30% for women), and data entry (49% for men and 38% for women). However, subsequent rankings of occupations differ between men and women such as teacher (68% reject for men and 42% for women) and

indoor sales (52% reject for men and 82% for women). For the least acceptable jobs, the differences between women and men are more pronounced. While 77% of men reject being a waiter, which is the lowest percentage among occupations for men, 96% of women reject such work. Industrial worker, delivery worker, driver, and agricultural worker are occupations rejected by at least 98% of unemployed women, whereas the percentage of men who would reject these jobs ranges between 62% and 75%. This large discrepancy between men and women suggests strong occupational segregation, as well as substantial mismatch.

Figure 4. Percentage of the unemployed (aged 15–64) who would reject various occupations, by sex, 2023



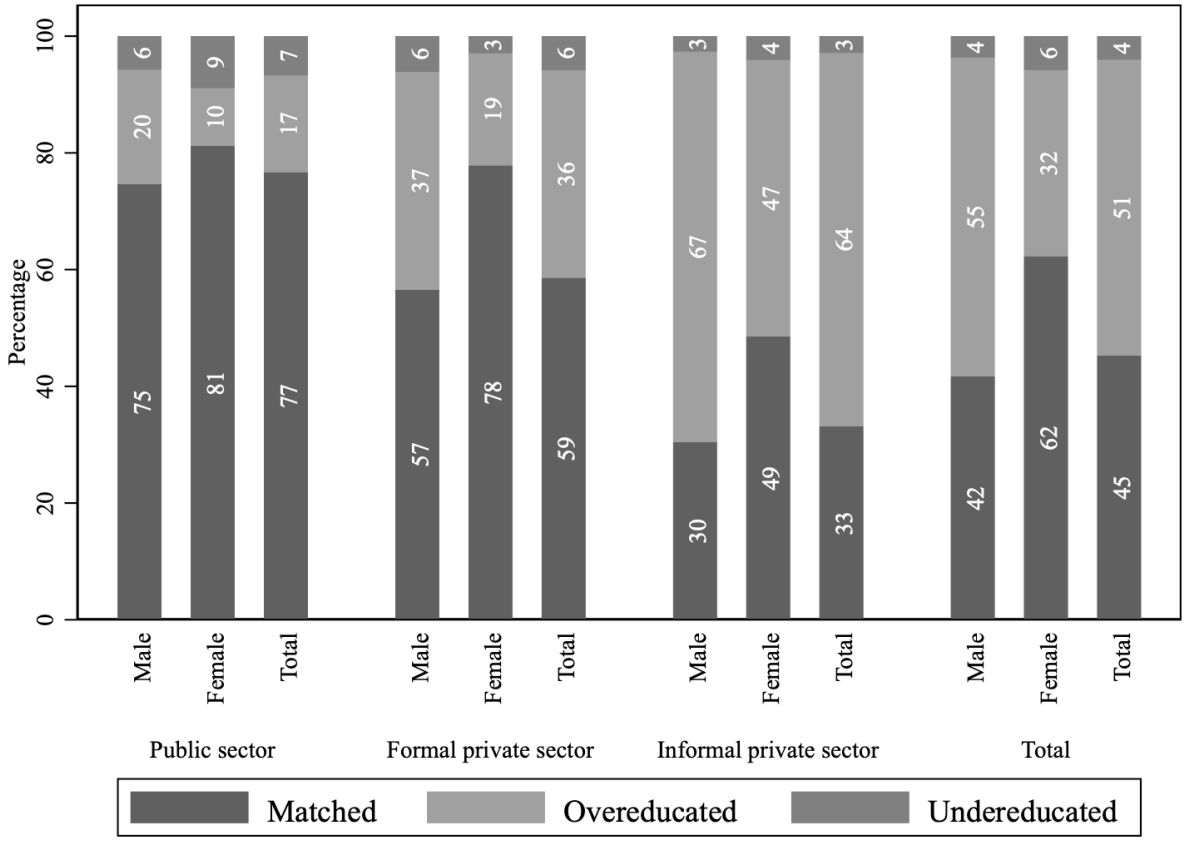
Source: Authors' calculations based on ELMPS 2023.

4.3 Education mismatch for the employed

There is substantial mismatch by education level. Figure 5 shows education level (mis)match by sex and sector. Overall, 51% of workers are over-educated: 55% of men are over-educated and 32% of women. Under-education is rare (4% overall). Workers are more often over-educated in the informal private sector (64%), somewhat in the formal private sector (36%), and less so in the public sector (17%). In all sectors, women are less likely to be over-educated than men. For instance, 47% of women and 67% of men are overeducated in the informal private sector. The

lower over-education among women is likely related to their decision to exit the labor market if they do not find employment meeting their reservation working conditions.

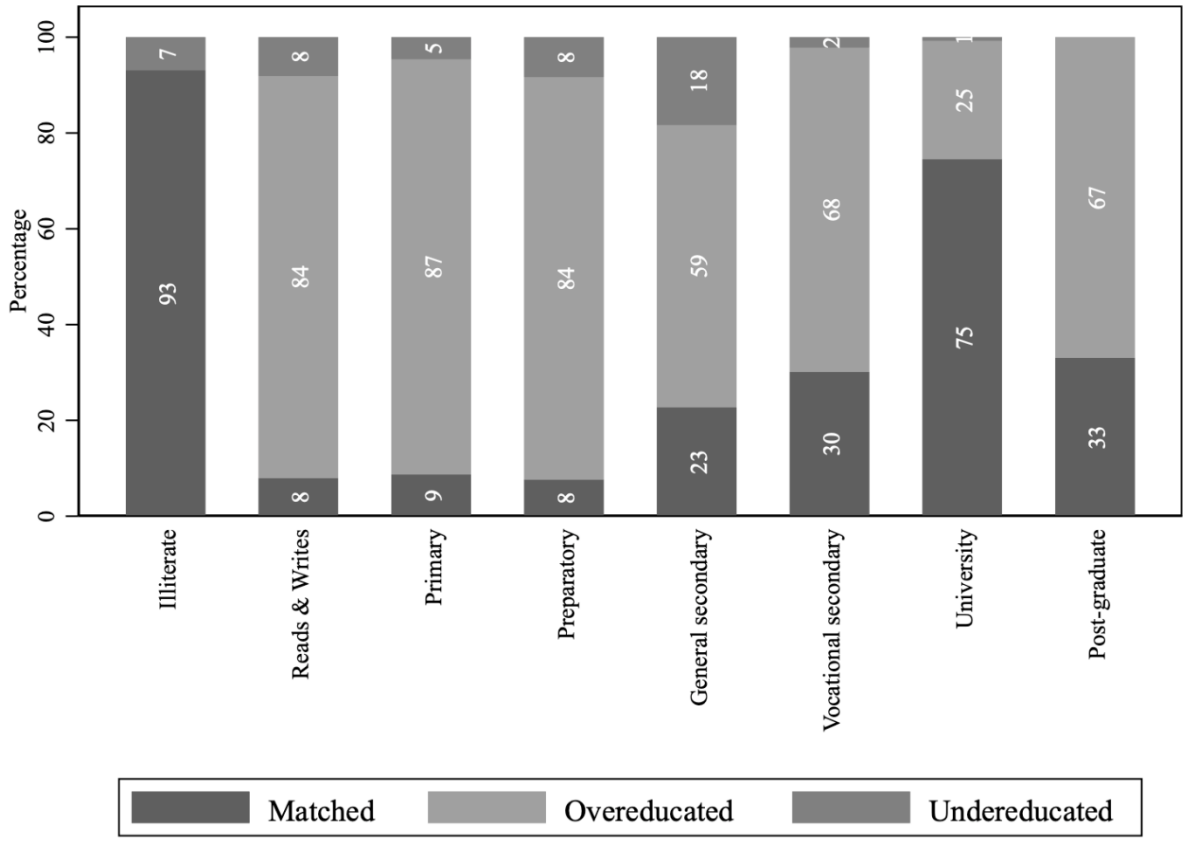
Figure 5. Education level (mis)match for workers aged 15–64, self-assessment approach (percentages), by sex and sector, 2023



Source: Authors' calculations based on ELMPS 2023.

Across education levels, the highest percentages of overeducated workers are among those who are literate but have attained a lower than secondary level of education (84-87%, per Figure 6). In contrast, the highest percentages of matched workers belong to those without any education (illiterate, 93%) or with a university degree (75%). Workers with postgraduate education have a 67% rate of overeducation. Those with secondary degrees are also often over-educated (68% for vocational secondary graduates). Mismatch by sex and education level reaffirms the patterns described above, with overeducation generally higher for men compared to women across education levels (see Appendix Figure 3).

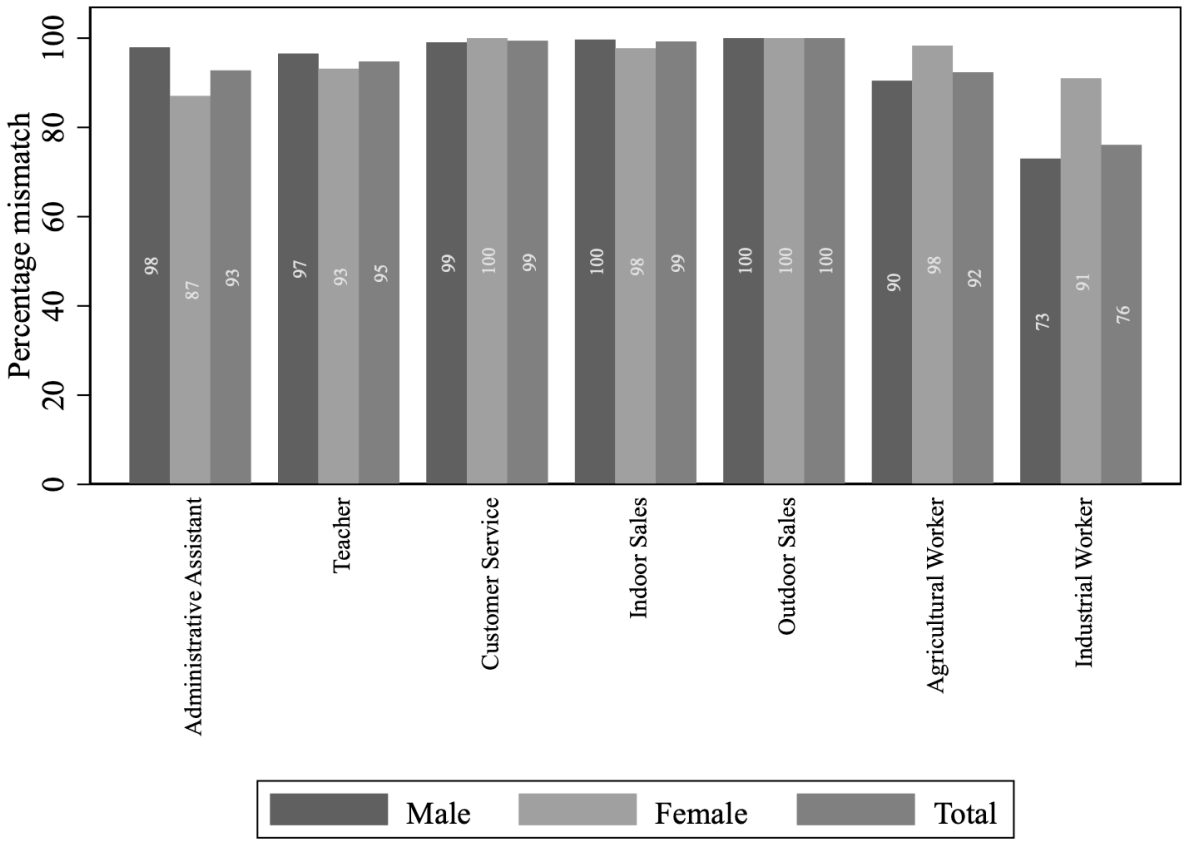
Figure 6. Education level (mis)match for workers aged 15–64, self-assessment approach (percentages), by level of education, 2023



Source: Authors' calculations based on ELMPS 2023.

Analyzing qualification mismatch by field of study, we find that the percentage mismatched is above 90% in most cases (Figure 7). We estimate this mismatch among the employed using the same 14 occupations that unemployed were asked about in Figure 4. We exclude the public sector employee category and categories with fewer than 30 observations for men or women. Thus, these are relatively common occupations. For occupations such as customer service, indoor sales, and outdoor sales, 98% or more, for both men and women, are mismatched by field of study. Industrial worker is the occupation with the least mismatch (76% overall, 73% for men and 91% for women). Only two occupations have a lower percentage of mismatched for women than for men: teaching and administrative assistant. In contrast, men are appreciably less mismatched for agricultural and industrial workers.

Figure 7. Qualification (mis)match by field of study for the employed (percentages), by occupation and sex, 2023



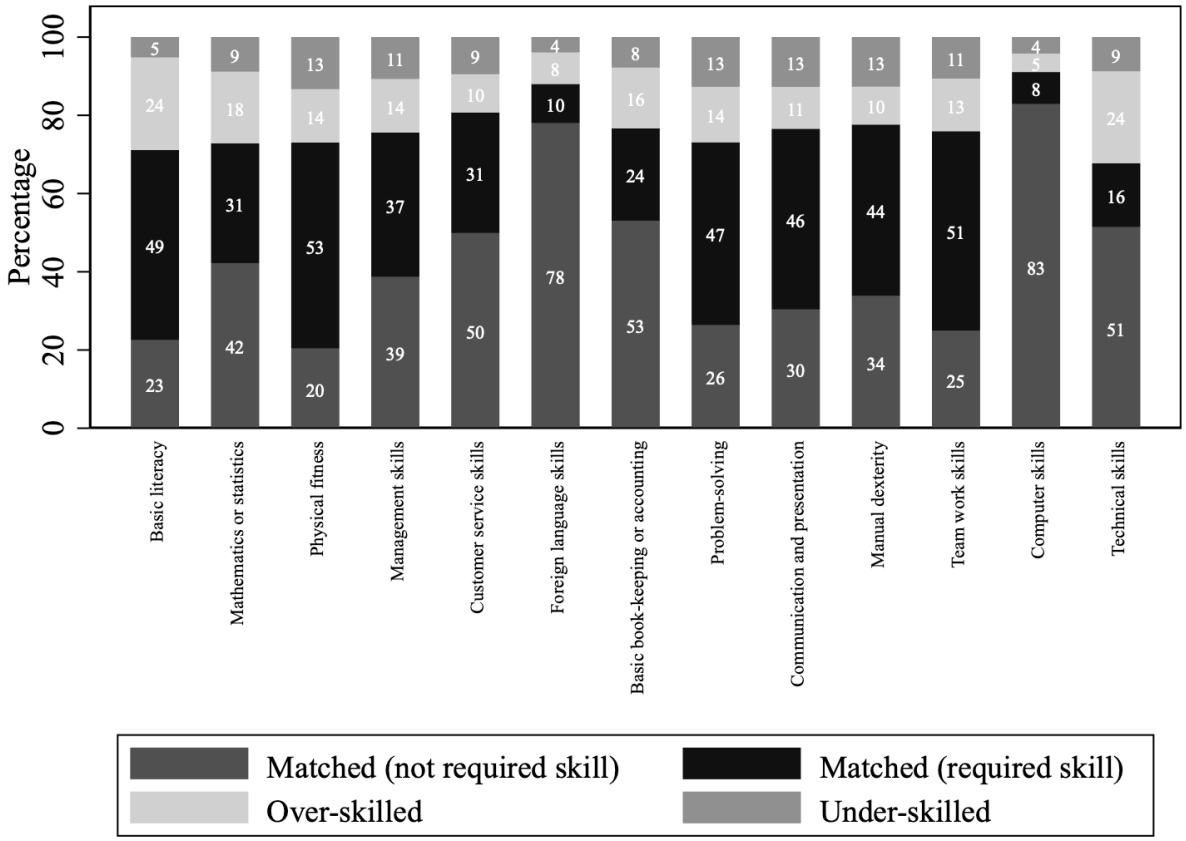
Source: Authors' calculations based on ELMPS 2023.
Notes: Using the same 14 occupations that the unemployed were asked about in Figure 4. We exclude the public sector employee category and categories with fewer than 30 observations for men or women.

4.4 Skill mismatch for the employed

For skill mismatch, we distinguish between mismatches that result from being over-skilled (having a skill when it is not required) and under-skilled (lacking a skill that is required). Figure 8 shows skill mismatch by skill for the employed. Workers are fairly often over-skilled for literacy (49% matched and required, 24% over-skilled, 5% under-skilled) and mathematics or statistical skills (31% matched and required, 18% over-skilled and 9% under-skilled). Foreign language skills are typically not required for most jobs (78% not required and matched, 10% matched and required, 8% over-skilled, and 4% under-skilled). Likewise, computer skills are typically not required for most jobs (83% not required and matched, 8% matched and required, 5% over-skilled, 4% under-skilled). The highest rate of match for a required skill is physical fitness (53% matched and required; 14% over-skilled and 13% under-skilled). Under-skill is highest for physical fitness, problem-solving, communication, and manual dexterity (all 13%). Over-skill is highest for technical skills (24%).

Female workers are more likely than male workers to secure jobs where that require non-physical skills compared to men (Appendix Figure 4). These skills are typically associated with higher-skilled occupations and may be linked to women's greater willingness to select out of the labor market if they do not find jobs meeting their preferences. As with over-education, we observe that male workers are more likely to be in positions where they are over-skilled compared to female workers, particularly so in regard to basic literacy and math/statistics skills.

Figure 8. Skill (mis)match for workers aged 15-64 (percentages), 2023

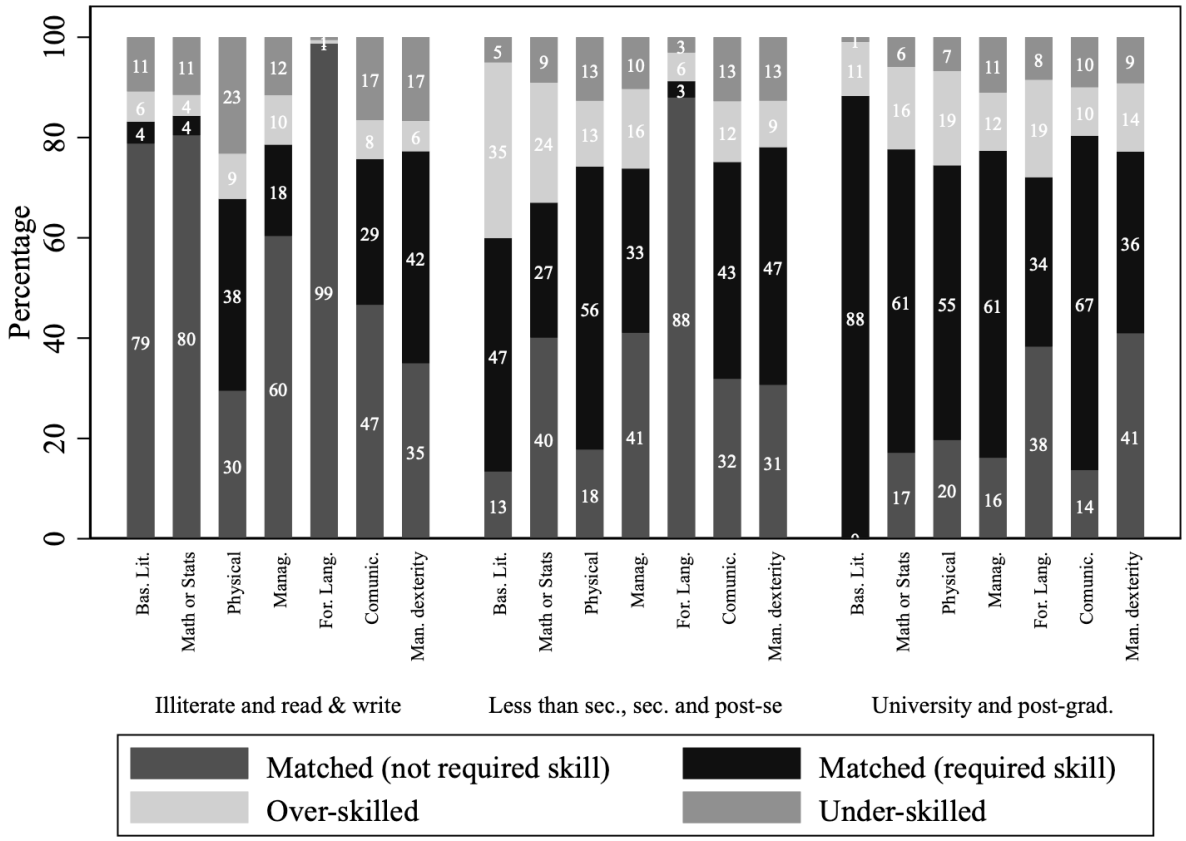


Source: Authors' calculations based on ELMPS 2023.
Notes: An over-skilled person states that they have a strong or very strong level of a skill that is not required for their job, while an under-skilled person states that they have at most a weak level of a skill that is required for their job. Finally, a match occurs when the job requires a skill and the person has it at a strong or very strong level, or when the job does not require a skill, and the person has it in at most at a weak level.

Figure 9 illustrates the distribution of skills match for selected skills by education level. Workers with the lowest levels of education tend to show a high percentage of matched skills, but this is largely because their jobs do not require skills. For workers with university degrees or post-graduate education, the high percentage of matched workers reflects the fact that their jobs specifically demand these skills (e.g., 88% matched on basic literacy). Additionally, workers with education levels ranging from less than secondary to post-secondary education exhibit the highest percentage of over-skill in basic skills like literacy (35%) and mathematics or statistics (24%). In contrast, workers with university degrees or higher show the highest percentage of over-skilled in

other skills, such as foreign languages (19% over-skilled, 34% matched for a required skill). Under-skilled workers are most pronounced at the lowest education levels, as expected. However, when transitioning from any education level between primary and post-secondary to a university degree, there are certain skills for which the over-skilled rate does not decrease drastically. This is the case for communication and presentation, management, and manual dexterity.

Figure 9. Skill (mis)match for workers aged 15-64 (percentages), selected skills, by level of education, 2023



Source: Authors' calculations based on ELMPS 2023.
Notes: An over-skilled person states that they have a strong or very strong level of a skill that is not required for their job, while an under-skilled person states that they have at most a weak level of a skill that is required for their job. Finally, a match occurs when the job requires a skill and the person has it at a strong or very strong level, or when the job does not require a skill, and the person has it in at most at a weak level.

4.5 Models of mismatch for non-employed

Table 1 presents the OLS model of the relationship between demographic characteristics (as well as work experience) and the percentage of jobs the unemployed people would reject. Compared to Greater Cairo, those residing in both urban and rural areas of Lower Egypt and rural Lower Egypt rejected a significantly higher share of jobs (by 6.1-12.5 p.p.). Compared to those aged 15-19, those aged 30-39 rejected 9.2 p.p. more jobs. Moreover, being a woman increases rejections by 8.0 p.p. In contrast, having children reduces rejections by 14-15 p.p. (depending on the child's

age). Compared to vocational secondary, illiterate and preparatory educated unemployed reject a significantly higher share of jobs, although this may reflect that they are not educated enough for such jobs. Additionally, having a father with higher education increases the percentage rejected by 6.6 p.p. Having a father who is an employer rather than a wage worker increases rejections by 6.1 p.p. Finally, having between 3 and 5 years of work experience increases rejections by 17.7 p.p., relative to those without any work experience.

Table 1. OLS estimates for the percentage of jobs the unemployed would reject (of 17 jobs)

Region (Greater Cairo omit.)	
Alexandria, Suez Canal	4.930
	(3.075)
Urban Lower	7.778*
	(3.344)
Urban Upper	5.007
	(2.910)
Rural Lower	12.53***
	(2.734)
Rural Upper	6.135*
	(2.637)
Age group (15-19 omit.)	
20-29	4.768
	(3.589)
30-39	9.224*
	(3.842)
40-49	6.580
	(4.340)
50-59	4.447
	(5.599)
60-64	-7.013
	(11.72)
Sex, spouse presence, and marital status, including int. (Single man omit.)	
Woman	7.956***
	(1.788)
Spouse presence	0.496
	(6.483)
Woman living with spouse (int.)	2.057
	(7.138)
Ever married	6.736
	(5.902)
Ever-married woman (int.)	-1.887
	(6.514)
Kids under 6, including int. (Man w/o kids omit.)	
Kids, youngest under 6	-13.76**
	(5.046)

Kids, youngest aged 6-17	-14.66*
	(5.712)
Woman with youngest under 6 (int.)	5.286
	(5.824)
Woman with youngest aged 6-17 (int.)	7.502
	(6.647)
Household size	0.799
	(0.468)
Education (Voc. sec. omit.)	
Illiterate	14.53***
	(4.024)
Reads & Writes	1.358
	(5.556)
Primary	4.336
	(4.599)
Preparatory	8.879**
	(3.232)
General secondary	5.577
	(3.986)
Post-secondary institute	-2.247
	(4.098)
University & above	5.315
	(2.769)
Father education level (Illit. omit.)	
Reads & writes	3.758
	(2.486)
Less than intermediate	-2.318
	(2.916)
Intermediate	1.202
	(2.529)
Higher education	6.605*
	(3.134)
Mother education level (Illit. omit.)	
Reads & writes	7.484
	(4.317)
Less than intermediate	2.174
	(2.672)
Intermediate	-0.430
	(2.670)
Higher education	3.005
	(3.329)
Father employment status (Wage worker omit.)	
Employer	6.143*
	(2.404)
Self-employed or unpaid family worker	-0.291

	(2.282)
No job	-2.026
	(2.792)
Work experience (Without experience omit.)	
1 yr or less	0.654
	(6.237)
>1-3 yrs	4.266
	(3.509)
>3-5 yrs	17.66***
	(4.765)
>5-10 yrs	-0.388
	(4.636)
>10 yrs	4.741
	(3.763)
Constant	39.74***
	(5.204)
Observations	1308
R^2	0.166

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Dependent variables are 0 to 100. Cells are coefficients and robust standard errors in parentheses.

Table 2 examines the relationship between individual characteristics and the probability of having a reservation wage above the predicted market wage (we shorthand this as rejection) among the unemployed. The probability of rejection, on average, is 64% for public sector jobs, 69% for private formal jobs, and 90% for private informal jobs. Consistent with the descriptive patterns, women are less likely than men to reject public sector jobs, but more likely to reject private sector jobs.

Relative to Greater Cairo, living in Alexandria and rural Upper Egypt is linked with significantly lower odds of rejection for public and formal jobs, while urban Upper Egypt shows significantly lower odds for only public sector jobs. Those in urban Lower Egypt are significantly less likely to reject informal private sector jobs. Compared to ages 15-19, individuals aged 20-29, 50-59, or 60-64 are significantly more likely to reject public sector jobs, but only 50-59 are significantly more likely to reject formal private sector jobs, and there are no age differences for private informal jobs. The only significant differences by spouse presence, marital status, younger children presence or household size are for informal private sector jobs, indicating that married individuals are less likely to accept such jobs, but ever-married women not living with their spouse may resort to such work. Compared to vocational secondary graduates, those with post-secondary institute education are significantly more likely to reject formal private-sector jobs. Read and write and illiterate individuals are more likely to reject public-sector jobs, and illiterate informal private-sector jobs. Those less educated individuals who are unemployed are, however, a selected group (Assaad and Krafft 2023).

The only significant difference by parent's education is a significantly higher rejection of informal private sector jobs if an individual's father has less than intermediate education. Relative to those with a wage-worker father, an employer father is significantly associated with half the odds of

rejection for public sector jobs. Those whose father held no job when they were 15 are significantly more likely to reject formal private sector jobs. Compared to no work experience, one to three years of experience is associated with a lower probability of rejection in the private sector, and seven times the odds for public-sector jobs, while more than ten years of experience corresponds to lower the odds of rejection in the public sector and private informal sector.

Table 2. Logit models of the probability that unemployed individuals have a reservation wage above the market wage (rejection, a form of mismatch), by job sector

	Public sector	Formal Private Sector	Informal Private Sector
Region (Greater Cairo omit.)			
Alexandria, Suez Canal	0.476*	0.425*	0.519
	(0.154)	(0.148)	(0.252)
Urban Lower	0.560	1.190	0.354*
	(0.187)	(0.480)	(0.186)
Urban Upper	0.456**	0.671	0.477
	(0.124)	(0.202)	(0.207)
Rural Lower	0.744	0.650	0.544
	(0.197)	(0.189)	(0.227)
Rural Upper	0.568*	0.450**	0.657
	(0.145)	(0.128)	(0.302)
Age group (15-19 omit.)			
20-29	2.515**	1.453	1.563
	(0.802)	(0.443)	(0.868)
30-39	1.695	1.917	1.834
	(0.635)	(0.724)	(1.100)
40-49	1.642	1.396	2.311
	(0.763)	(0.621)	(1.599)
50-59	3.033*	3.912*	6.407
	(1.661)	(2.435)	(6.576)
60-64	6.866*	0.455	1.453
	(5.853)	(0.329)	(1.807)
Sex, spouse presence, and marital status, including int. (Single man omit.)			
Woman	0.642*	1.142	2.099
	(0.137)	(0.276)	(0.857)
Spouse presence	1.555	0.824	4.990
	(1.101)	(0.495)	(4.647)
Woman living with spouse (int.)	1.016	1.974	0.0596*

	Public sector	Formal Private Sector	Informal Private Sector
	(0.844)	(1.562)	(0.0779)
Ever married	0.525	1.362	0.298*
	(0.346)	(0.721)	(0.181)
Ever-married woman (int.)	0.601	0.783	12.36*
	(0.469)	(0.584)	(13.76)
Kids under 6, including int. (Man w/o kids omit.)			
Kids, youngest under 6	1.576	1.137	0.363
	(0.770)	(0.561)	(0.273)
Kids, youngest aged 6-17	1.077	1.236	0.377
	(0.611)	(0.642)	(0.295)
Woman with youngest under 6 (int.)	1.766	0.885	1.060
	(1.133)	(0.569)	(1.095)
Woman with youngest aged 6-17 (int.)	1.488	0.468	1.004
	(1.145)	(0.350)	(1.148)
Household size	0.999	0.962	1.014
	(0.0481)	(0.0483)	(0.0820)
Education (Voc. sec. omit.)			
Illiterate	8.249***	1.578	3.864*
	(3.365)	(0.596)	(2.107)
Reads & Writes	4.224*	1.143	0.780
	(2.719)	(0.680)	(0.554)
Primary	0.572	1.119	1.425
	(0.200)	(0.405)	(0.743)
Preparatory	1.394	1.137	2.248
	(0.473)	(0.360)	(1.458)
General secondary	1.854	1.868	1.246
	(0.766)	(0.892)	(0.761)
Post-secondary institute	2.026	3.459*	6.722
	(0.832)	(1.867)	(7.390)
University & above	1.373	1.068	1.166
	(0.293)	(0.240)	(0.371)
Father education level (Illit. omit.)			

	Public sector	Formal Private Sector	Informal Private Sector
Reads & writes	1.000	1.423	1.389
	(0.297)	(0.458)	(0.671)
Less than intermediate	1.417	1.503	3.001**
	(0.380)	(0.425)	(1.226)
Intermediate	1.150	1.468	1.342
	(0.291)	(0.388)	(0.500)
Higher education	0.976	1.176	1.050
	(0.322)	(0.431)	(0.599)
Mother education level (Illit. omit.)			
Reads & writes	1.516	1.760	2.567
	(0.586)	(0.884)	(1.638)
Less than intermediate	0.795	0.831	1.180
	(0.223)	(0.246)	(0.535)
Intermediate	1.174	1.265	1.602
	(0.303)	(0.365)	(0.668)
Higher education	1.325	1.719	2.836
	(0.492)	(0.732)	(1.819)
Father employment status (Wage worker omit.)			
Employer	0.528*	1.851	2.711
	(0.162)	(0.586)	(1.524)
Self-employed or unpaid family worker	1.062	1.242	1.986
	(0.250)	(0.309)	(0.805)
No job	1.200	1.812*	1.735
	(0.290)	(0.471)	(0.571)
Work experience (Without experience omit.)			
1 yr or less	0.677	0.747	0.423
	(0.386)	(0.474)	(0.279)
>1-3 yrs	6.698*	0.155**	0.216*
	(5.765)	(0.106)	(0.132)
>3-5 yrs	0.856	1.516	0.555
	(0.970)	(1.896)	(0.768)
>5-10 yrs	0.611	1.095	0.771
	(0.239)	(0.501)	(0.464)
>10 yrs	0.414*	0.493	0.382*
	(0.151)	(0.184)	(0.178)

	Public sector	Formal Private Sector	Informal Private Sector
Constant	1.166	1.371	3.788
	(0.549)	(0.678)	(2.934)
Observations	1306	1301	1295
Pseudo R^2	0.111	0.089	0.143

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Cells show odds ratios, robust standard errors in parentheses. See Appendix 1 for a discussion of the prediction of the market wage.

For individuals outside the labor force, Table 3 analyzes the probability of rejecting a job in each sector at a random wage. An increase of 1,000 EGP reduces the odds of rejecting a job in the public sector (20%), in the formal private sector (20%), and in the informal private sector (13%). Individuals outside of Greater Cairo are significantly less likely to reject jobs, more so in Lower Egypt, while some of the results for Upper Egypt are small and insignificant. Compared to those aged 15-19, while those 20-39 tend to be significantly less likely to reject an offer, those who are older (50-64) are significantly more likely to do so. Women are significantly more likely to reject offers, but there are no differences by the presence of children or household size. Being ever married is associated with three times the odds of rejecting a job in the informal private sector. Compared to those with vocational secondary education, those with less education tend to be significantly more likely to reject jobs. Those from higher socioeconomic status (father or mother with higher education, father employer or self-employed in some models) are significantly more likely to reject jobs. Those with >3-5 or in some cases >5-10 years of work experience are significantly less likely to reject jobs.

Table 3. Logit models of the probability of rejecting a job among people outside the labor force, by job sector

	Public sector	Formal Private Sector	Informal Private Sector
Random offered wage (in thousands)			
Public Sector	0.800***		
	(0.0102)		
Formal Private Sector		0.797***	
		(0.0106)	
Informal Private Sector			0.870***
			(0.0161)
Region (Greater Cairo omit.)			
Alexandria, Suez Canal	0.688**	0.587***	0.511***
	(0.0863)	(0.0792)	(0.0963)
Urban Lower	0.317***	0.299***	0.439***
	(0.0338)	(0.0332)	(0.0769)
Urban Upper	0.853	0.719**	0.742
	(0.0920)	(0.0824)	(0.127)
Rural Lower	0.368***	0.334***	0.363***
	(0.0362)	(0.0349)	(0.0577)
Rural Upper	0.957	0.790*	0.818

	(0.0976)	(0.0874)	(0.134)
Age group (15-19 omit.)			
20-29	0.655***	0.740***	0.704***
	(0.0544)	(0.0606)	(0.0612)
30-39	0.807*	0.812	0.721*
	(0.0871)	(0.0886)	(0.0968)
40-49	0.921	0.954	0.645
	(0.118)	(0.118)	(0.173)
50-59	1.594**	1.788***	1.656*
	(0.229)	(0.264)	(0.351)
60-64	2.533***	3.151***	2.060**
	(0.416)	(0.551)	(0.467)
Sex, spouse presence, and marital status, including int. (Single man omit.)			
Woman	1.572***	1.632***	1.466***
	(0.118)	(0.120)	(0.150)
Spouse presence	1.282	0.556	0.452
	(0.499)	(0.248)	(0.219)
Woman living with spouse (int.)	0.755	1.919	2.126
	(0.302)	(0.878)	(1.053)
Ever married	0.740	1.811	2.851*
	(0.288)	(0.786)	(1.442)
Ever-married woman (int.)	1.677	0.772	0.785
	(0.654)	(0.340)	(0.365)
Kids under 6, including int. (Man w/o kids omit.)			
Kids, youngest under 6	0.818	0.848	0.858
	(0.214)	(0.231)	(0.240)
Kids, youngest aged 6-17	0.759	0.866	0.836
	(0.211)	(0.260)	(0.267)
Woman with youngest under 6 (int.)	1.249	1.099	0.911
	(0.333)	(0.307)	(0.276)
Woman with youngest aged 6-17 (int.)	1.150	1.037	1.092
	(0.333)	(0.327)	(0.365)
Household size	1.002	1.009	1.007
	(0.0139)	(0.0148)	(0.0171)
Education (Voc. sec. omit.)			
Illiterate	1.504***	1.488***	1.392***
	(0.124)	(0.131)	(0.140)
Reads & Writes	0.964	0.880	0.770
	(0.134)	(0.139)	(0.127)
Primary	1.318**	1.556***	1.516***
	(0.130)	(0.157)	(0.163)

Preparatory	1.386***	1.435***	1.563***
	(0.110)	(0.123)	(0.139)
General secondary	1.118	1.229*	1.265*
	(0.0974)	(0.111)	(0.117)
Post-secondary institute	0.730*	0.865	1.046
	(0.114)	(0.157)	(0.181)
University & above	0.960	0.932	0.850
	(0.0826)	(0.0790)	(0.129)
Father education level (Illit. omit.)			
Reads & writes	0.895	0.865	0.883
	(0.0707)	(0.0731)	(0.0878)
Less than intermediate	0.870	0.835*	0.936
	(0.0692)	(0.0705)	(0.0964)
Intermediate	1.091	1.064	1.155
	(0.0846)	(0.0836)	(0.112)
Higher education	1.320**	1.247*	1.392*
	(0.139)	(0.132)	(0.183)
Mother education level (Illit. omit.)			
Reads & writes	0.948	0.996	1.058
	(0.0991)	(0.115)	(0.147)
Less than intermediate	0.917	1.005	1.061
	(0.0829)	(0.0942)	(0.116)
Intermediate	0.980	1.081	1.089
	(0.0830)	(0.0946)	(0.110)
Higher education	1.078	1.447**	1.550**
	(0.134)	(0.179)	(0.229)
Father employment status (Wage worker omit.)			
Employer	1.214*	1.160	1.047
	(0.0932)	(0.0941)	(0.0903)
Self-employed or unpaid family worker	1.112	1.092	1.160*
	(0.0834)	(0.0815)	(0.0873)
No job	1.050	1.059	0.799
	(0.0834)	(0.0847)	(0.108)
Work experience (Without experience omit.)			
1 yr or less	0.681	0.410	0.534
	(0.425)	(0.261)	(0.405)
>1-3 yrs	0.713	1.066	0.715
	(0.329)	(0.610)	(0.366)
>3-5 yrs	0.115**	0.418	0.224*
	(0.0905)	(0.320)	(0.152)
>5-10 yrs	0.353	0.291*	0.958

	(0.247)	(0.173)	(0.574)
>10 yrs	1.134	1.284	1.040
	(0.251)	(0.320)	(0.305)
Constant	7.354***	8.537***	7.355***
	(1.212)	(1.447)	(2.143)
Observations	21372	21372	21372
Pseudo R^2	0.095	0.098	0.077

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Cells show odds ratios and robust standard errors in parentheses.

4.6 Models of qualification and skill mismatch for employed

This subsection presents relative risk ratios (RRR) from a multinomial logit model (Table 4) for the probability of being a qualification (mis)matched worker based on education level (matched [base]; over-educated; or under-educated). There are substantial geographic disparities in being over- and under-educated. Compared to Greater Cairo, those in Alexandria and the Suez Canal region are less likely to be over-educated, while those in rural Upper Egypt are more likely to be over-educated. Those in Alexandria and the Suez Canal and both urban and rural Lower Egypt are more likely to be under-educated. There are no significant differences by age group. Women are significantly less likely to be over-educated than men, and the interaction between ever-married and female increases the risk of under-education. There are no significant differences by household composition, but those with larger households are significantly more likely to be over-educated. Compared to vocational secondary, consistent with Figure 6, those who are illiterate are less likely to be over-educated, and those who read and write, or have completed primary or preparatory are significantly more likely to be over-educated. Those with general secondary or less education are significantly more likely to be under-educated and university graduates are significantly less likely to be over-educated. More educated fathers predict significantly less over-education, but no differences in under-education, nor by mother's education, nor father's employment status.

There are significant differences by occupation, compared to craft and related trades workers, with white collar workers significantly less likely to be over-educated, but other occupations more likely to be over-educated. Professionals are the only group significantly more likely to be under-educated, but a number of other occupations are significantly less likely to be under-educated. Those in the formal private sector, compared to the public sector, have significantly more over- as well as under-education; those in the informal private sector are significantly more likely to be over-educated, with more than double the relative risk of the formal sector (3.478 RRR for informal private vs. 1.634 for formal private). Those working outside establishments are significantly more likely to be over-educated and less likely to be under-educated, while irregular workers are significantly more likely to be over-educated. Over-education but not under-education varies by firm size, with workers in firms of 1-9 workers significantly more likely to be over-educated compared to firms with 100+ workers, and those in medium firms of 50-99 workers significantly less likely to be overeducated.

Table 4. Multinomial logit model of qualification (education level) mismatch

	$\frac{\Pr(\text{Overeducated})}{\Pr(\textit{Matched})}$	$\frac{\Pr(\text{Undereducated})}{\Pr(\textit{Matched})}$
Region (Greater Cairo omit.)		
Alexandria, Suez Canal	0.587***	1.960*
	(0.0901)	(0.614)
Urban Lower	0.946	1.989*
	(0.135)	(0.569)
Urban Upper	1.221	1.136
	(0.168)	(0.336)
Rural Lower	0.998	2.112**
	(0.126)	(0.522)
Rural Upper	1.566**	0.985
	(0.214)	(0.264)
Age group (15-19 omit.)		
20-29	1.116	0.833
	(0.227)	(0.286)
30-39	1.109	1.064
	(0.249)	(0.430)
40-49	1.124	1.298
	(0.264)	(0.586)
50-59	0.839	1.154
	(0.215)	(0.520)
60-64	1.086	0.836
	(0.345)	(0.475)
Sex, spouse presence, marital status, and int. (Single man omit.)		
Woman	0.650*	0.621
	(0.130)	(0.245)
Spouse presence	0.747	2.425
	(0.146)	(1.223)
Woman living with spouse (int.)	1.366	0.394
	(0.413)	(0.236)
Ever married	1.274	0.331
	(0.288)	(0.196)
Ever-married woman (int.)	1.382	6.169**
	(0.468)	(4.354)
Kids under 6 and int. (Man w/o kids omit.)		
Kids, youngest under 6	0.914	0.887
	(0.120)	(0.193)
Kids, youngest aged 6-17	0.873	1.178
	(0.114)	(0.242)

	$\frac{\Pr(\text{Overeducated})}{\Pr(\textit{Matched})}$	$\frac{\Pr(\text{Undereducated})}{\Pr(\textit{Matched})}$
Woman with youngest under 6 (int.)	1.014	0.876
	(0.257)	(0.310)
Woman with youngest aged 6-17 (int.)	0.885	0.570
	(0.228)	(0.219)
Household size	1.075**	0.968
	(0.0266)	(0.0420)
Education (Voc. sec. omit.)		
Illiterate	3.99e-14***	3.784***
	(6.14e-15)	(0.889)
Reads & Writes	3.343***	25.52***
	(0.809)	(7.613)
Primary	2.461***	12.04***
	(0.445)	(3.507)
Preparatory	2.962***	26.16***
	(0.509)	(5.938)
General secondary	1.189	9.588***
	(0.185)	(2.177)
University & above	0.859	0.0401***
	(0.0799)	(0.0167)
Father education level (Illit. omit.)		
Reads & writes	0.786*	1.265
	(0.0820)	(0.230)
Less than intermediate	0.806*	1.123
	(0.0867)	(0.262)
Intermediate	0.659***	0.943
	(0.0741)	(0.259)
Higher education	0.793	1.025
	(0.128)	(0.378)
Mother education level (Illit. omit.)		
Reads & writes	1.052	0.598
	(0.156)	(0.173)
Less than intermediate	1.018	0.794
	(0.153)	(0.228)
Intermediate	0.821	0.913
	(0.105)	(0.345)
Higher education	0.694	1.188
	(0.141)	(0.481)
Father employment status (Wage worker omit.)		
Employer	0.924	0.842

	$\frac{\Pr(\text{Overeducated})}{\Pr(\textit{Matched})}$	$\frac{\Pr(\text{Undereducated})}{\Pr(\textit{Matched})}$
	(0.106)	(0.164)
Self-employed or unpaid family worker	0.963	1.091
	(0.107)	(0.199)
No job	1.022	1.261
	(0.0994)	(0.238)
Major occupational group (craft and related trades workers omit.)		
Managers and armed forces	0.528***	1.095
	(0.0683)	(0.282)
Professionals	0.0909***	6.804***
	(0.0151)	(1.955)
Technicians and associate professionals	0.181***	1.351
	(0.0252)	(0.359)
Clerical support, service and sales workers	0.646***	0.641*
	(0.0655)	(0.125)
Skilled agricultural, forestry and fishery workers	3.359***	0.240***
	(0.702)	(0.0823)
Plant and machine operators, and assemblers	1.566***	0.797
	(0.208)	(0.196)
Elementary occupations	1.988***	0.450**
	(0.328)	(0.136)
Job sector (public sector omit.)		
Formal private sector	1.634***	1.515*
	(0.201)	(0.293)
Informal private sector	3.478***	1.118
	(0.376)	(0.234)
Outside establishment (inside omit.)	1.534***	0.627*
	(0.140)	(0.114)
Irregular (regular omit.)	1.911***	0.850
	(0.216)	(0.193)
Firm size (100+ omit.)		
1-4	2.177***	0.684
	(0.221)	(0.140)
5-9	1.936***	0.651
	(0.235)	(0.162)
10-24	1.133	0.974

	Pr (Overeducated)	Pr (Undereducated)
	Pr (*Matched*)	Pr (*Matched*)
	(0.145)	(0.219)
25-49	0.999	0.987
	(0.135)	(0.216)
50-99	0.659*	0.879
	(0.115)	(0.222)
Constant	0.480*	0.0401***
	(0.140)	(0.0193)
Observations	16405	
Pseudo R^2	0.499	

Notes: p < 0.05, ** p < 0.01, *** p < 0.001. Cells are relative risk ratios, robust standard errors in parentheses. The base outcome category is being a matched worker for level of education.

Table 5 shows the associations of vocational secondary and university specializations with the odds of being overeducated. There is not a significant association of different vocational education specializations with the relative risk of being overeducated compared to the reference industrial specialization. In contrast, university specialization shows a significant relationship with over-education. Relative to those who specialized in medicine, sciences, or engineering, the odds of over-education are approximately two to three times for those who specialized in education (odds ratio 2.0) commerce and law (2.4), humanities (2.5), social sciences (2.9), or others (3.7). There are not, however, significant differences between these different specializations, when testing their joint equivalence.

Table 5. Logit models of educational specializations and qualification (education level) mismatch: over-qualification

	Vocational secondary graduates	University graduates
Vocational spec. (Industrial omit.)		
Vocational secondary-agriculture	1.262	
	(0.216)	
Vocational secondary-commerce	1.183	
	(0.170)	
Vocational secondary-others	1.276	
	(0.207)	
University spec. (Medicine, science or engineering omit.)		
University-commerce and law		2.416**
		(0.664)
University-education		2.045*
		(0.728)

University-humanities		2.510**
		(0.872)
University-social sciences		2.892**
		(0.974)
University-others		3.689***
		(1.088)
Observations	4795	2428
Pseudo R^2	0.321	0.505

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Cells show odds ratios; robust standard errors are in parentheses. We control for the same variables described in the data section for the employed sample, except for the education variable, as the samples are restricted to vocational secondary (column one) and university graduates (column two). Models show only over-education, as under-education is too infrequent to estimate in the vocational secondary or university samples.

Table 6 shows the estimated coefficients from OLS models on skill mismatch. Columns 1 and 2 present the over-skilled percentage (percentage of skills exceeding job requirements) for basic and cross-functional skills. Columns 3 and 4 of Table 6 show the estimated coefficients for the percentage of skills unmet, or the under-skilled percentage, for basic and cross-functional skills. There are substantial geographic disparities in skill mismatch. Compared to Greater Cairo, living in Alexandria and the Suez Canal area or in the urban areas of Lower and Upper Egypt reduces the over-skilled percentage in both basic and cross-functional skills. Being in Upper or Lower Egypt increases the under-skilled percentage in basic skills, but for cross-functional skills only. Alexandria and the Suez Canal area decreases under-skilling while rural Lower Egypt increases it. There are only a few significant differences in skill mismatch by age and none by sex, but some significant differences for the under-skilled percentage in cross-functional skills when the spouse is present (lower main effect), for a woman living with her spouse (higher interaction), and if ever married (higher main effect). There are likewise only a few significant differences by the presence of children, with women with young children having a significantly lower over-skilled percentage in both skill types, likely selection out of the labor market for such women. However, having young children (the youngest under 6) also reduces the under-skilled percentage in cross-functional skills by 3.7 percentage points.

There are large and significant differences in skill mismatch by education level. Being illiterate (–40.4 p.p.), able to read and write (–24.4 p.p.), or having a primary (–22.7 p.p.) or preparatory (–9.9 p.p.) education reduces the over-skilled percentage in basic skills, compared to having a vocational secondary degree. These same educational attainments also reduce the over-skilled percentage in cross-functional skills, though to a smaller extent (from –4.8 to –12.0 p.p.). However, general secondary education, post-secondary, or university education increase the percentage of surplus cross-functional skills (4.9 to 15.3 p.p.). Correspondingly, compared to vocational secondary education, lower levels of education predict increased under-skilling, while higher levels reduced under-skilling. There are only a few significant, mostly small differences by parental background, although a higher educated mother predicts substantially higher cross-functional over-skilling by 11 p.p.

In terms of job characteristics, compared to working as a craft and related trades worker, working in white collar occupations reduces the over-skilled percentage in basic skills along with under-skilled percentage in both basic and cross-functional skills, but there are not appreciable

differences among different types of blue-collar work. Compared to the public sector, the informal private sector has significantly higher basic over-skilling, while both the formal and informal private sector have significantly higher basic under-skilling as well. There are only small differences for outside of establishment, with those outside having a significantly lower over-skilled percentage in cross-functional skills. Irregular workers have a significantly higher under-skilled percentage in both types of skills. Working in smaller firms (with fewer than 50 employees) reduces the over-skilled percentage in basic skills. These same firms, as well as mid-sized firms (50-99), also reduce the over-skilled percentage in cross-functional skills, compared to working in firms with more than 100 employees. There are not, however, clear patterns for firm size and under-skilling.

Table 6. OLS estimates of over-skilled and under-skilled percentages by skill group

	% Skills Exceeding Job Requirements (Over-skilled)		% Skills Deficient in Meeting Job Requirements (Under-skilled)	
	Basic	**Cross-functional**	**Basic**	**Cross-functional**
Region (Greater Cairo omit.)				
Alexandria, Suez Canal	-9.470***	-4.736**	0.932	-5.408**
	(2.191)	(1.651)	(1.604)	(1.697)
Urban Lower	-5.300*	-3.805**	3.509*	0.871
	(2.086)	(1.431)	(1.467)	(1.678)
Urban Upper	-5.006**	-2.954*	4.626**	1.531
	(1.937)	(1.360)	(1.650)	(1.863)
Rural Lower	-3.477	-0.534	5.628***	5.813***
	(1.919)	(1.314)	(1.438)	(1.637)
Rural Upper	-2.365	-1.364	5.572***	2.303
	(1.919)	(1.270)	(1.546)	(1.725)
Age group (15-19 omit.)				
20-29	-3.393	3.155*	-3.360	-2.814
	(2.312)	(1.274)	(2.010)	(2.558)
30-39	-2.830	2.717	0.452	-1.506
	(2.589)	(1.490)	(2.201)	(2.755)
40-49	-3.109	2.728	1.972	-2.736
	(2.705)	(1.590)	(2.250)	(2.844)
50-59	-2.445	3.276	5.632*	-0.700
	(2.883)	(1.722)	(2.476)	(3.031)
60-64	-1.974	4.347*	5.155	-2.757
	(3.245)	(2.052)	(3.265)	(3.800)
Sex, spouse presence, and marital status, including int. (Single man omit.)				
Woman	0.655	1.433	0.203	-2.317
	(2.737)	(2.377)	(1.671)	(2.275)
Spouse presence	5.790	-0.141	0.743	-5.913*

	% Skills Exceeding Job Requirements (Over-skilled)		% Skills Deficient in Meeting Job Requirements (Under-skilled)	
	Basic	**Cross-functional**	**Basic**	**Cross-functional**
	(3.887)	(1.999)	(2.751)	(2.886)
Woman living with spouse (int.)	-1.884	-0.586	0.758	10.49**
	(4.620)	(2.632)	(3.482)	(3.967)
Ever married	-3.598	-0.363	-2.923	6.009*
	(4.100)	(2.235)	(2.785)	(3.028)
Ever-married woman (int.)	3.499	0.819	1.621	-6.403
	(5.233)	(3.479)	(3.706)	(4.241)
Kids under 6, including int. (Man w/o kids omit.)				
Kids, youngest under 6	2.298	2.033	-0.661	-3.706*
	(1.620)	(1.114)	(1.494)	(1.652)
Kids, youngest aged 6-17	1.359	0.425	-1.942	-2.835
	(1.664)	(1.128)	(1.289)	(1.654)
Woman with youngest under 6 (int.)	-6.660*	-5.767**	4.269	4.034
	(2.740)	(2.048)	(2.276)	(2.741)
Woman with youngest aged 6-17 (int.)	-3.825	-2.987	2.962	0.630
	(3.008)	(2.141)	(2.357)	(2.967)
Household size	-0.253	-0.363*	-0.260	0.306
	(0.246)	(0.170)	(0.221)	(0.262)
Education (Voc. sec. omit.)				
Illiterate	-40.44***	-11.62***	19.73***	14.22***
	(1.042)	(0.691)	(1.616)	(1.885)
Reads & Writes	-24.35***	-4.963***	15.14***	2.273
	(1.858)	(1.191)	(2.793)	(2.029)
Primary	-22.67***	-5.877***	11.16***	3.603*
	(1.681)	(0.977)	(1.567)	(1.817)
Preparatory	-9.908***	-4.726***	3.514*	4.130*
	(1.840)	(0.962)	(1.386)	(1.994)
General secondary	3.851	7.766***	-3.459*	-4.461*
	(2.420)	(1.902)	(1.450)	(1.937)
Post-secondary institute	2.915	4.929**	-4.248**	-3.771
	(2.904)	(1.846)	(1.343)	(2.041)
University & above	2.300	15.25***	-5.778***	-4.656***
	(1.947)	(1.193)	(0.945)	(1.188)
Father education level (Illit. omit.)				
Reads & writes	2.680	1.861*	-2.884**	-4.989***

	% Skills Exceeding Job Requirements (Over-skilled)		% Skills Deficient in Meeting Job Requirements (Under-skilled)	
	Basic	**Cross-functional**	**Basic**	**Cross-functional**
	(1.457)	(0.941)	(0.998)	(1.219)
Less than intermediate	-0.937	1.191	-1.209	-0.308
	(1.615)	(1.039)	(1.040)	(1.430)
Intermediate	0.894	1.676	-1.294	-2.926
	(1.728)	(1.133)	(1.023)	(1.497)
Higher education	0.250	2.239	-1.009	-1.311
	(2.343)	(1.832)	(1.342)	(1.764)
Mother education level (Illit. omit.)				
Reads & writes	1.202	0.304	0.154	1.987
	(2.023)	(1.459)	(1.453)	(1.761)
Less than intermediate	0.955	1.644	0.401	0.930
	(1.910)	(1.436)	(1.143)	(1.490)
Intermediate	-0.341	1.608	1.156	2.055
	(1.975)	(1.436)	(1.154)	(1.684)
Higher education	1.731	11.04***	-1.179	-3.291
	(3.361)	(2.653)	(1.473)	(2.039)
Father employment status (Wage worker omit.)				
Employer	-0.414	0.805	-0.937	0.0854
	(1.299)	(0.891)	(1.234)	(1.361)
Self-employed or unpaid family worker	-1.691	0.202	0.785	0.152
	(1.245)	(0.832)	(1.291)	(1.372)
No job	1.151	0.0729	1.805	3.125*
	(1.288)	(0.955)	(0.962)	(1.228)
Major occupational group (Craft and related trades workers omit.)				
Managers and armed forces	-7.867***	-0.302	-5.383***	-6.419***
	(1.979)	(1.372)	(1.508)	(1.780)
Professionals	-10.64***	0.510	-4.887***	-1.306
	(2.340)	(1.791)	(1.267)	(1.747)
Technicians and associate professionals	-5.913*	3.665*	-5.555***	-3.363*
	(2.373)	(1.525)	(1.340)	(1.663)
Clerical support, service and sales workers	-7.557***	0.251	-1.549	-0.510
	(1.437)	(0.895)	(1.224)	(1.476)

	% Skills Exceeding Job Requirements (Over-skilled)		% Skills Deficient in Meeting Job Requirements (Under-skilled)	
	Basic	**Cross-functional**	**Basic**	**Cross-functional**
Skilled agricultural, forestry and fishery workers	-2.377	-0.0696	3.766*	-2.027
	(1.317)	(0.893)	(1.621)	(1.852)
Plant and machine operators, and assemblers	-1.837	-0.554	-1.491	-0.152
	(1.759)	(1.025)	(1.494)	(1.878)
Elementary occupations	2.116	-0.0709	1.468	-1.157
	(1.751)	(1.065)	(1.781)	(2.263)
Sector (public sector omit.)				
Formal private sector	0.364	2.117	3.323**	0.0267
	(1.892)	(1.494)	(1.206)	(1.332)
Informal private sector	8.023***	1.654	2.908**	2.224
	(1.758)	(1.235)	(1.120)	(1.462)
Outside establishment (inside omit.)	-2.058	-1.826*	-1.683	0.816
	(1.198)	(0.765)	(0.999)	(1.272)
Irregular (regular omit.)	0.719	0.462	3.391**	4.106**
	(1.023)	(0.649)	(1.090)	(1.330)
Firm size (100+ omit.)				
1-4	-3.734*	-3.493**	-1.093	2.063
	(1.526)	(1.069)	(1.109)	(1.437)
5-9	-5.827***	-5.181***	-2.750*	0.776
	(1.728)	(1.187)	(1.319)	(1.680)
10-24	-5.738**	-4.133**	0.0830	-0.771
	(1.775)	(1.302)	(1.537)	(1.521)
25-49	-6.028**	-4.175**	-0.241	1.621
	(1.959)	(1.455)	(1.213)	(1.483)
50-99	-3.215	-5.170**	-0.961	1.436
	(2.521)	(1.854)	(1.194)	(1.653)
Constant	52.41***	22.90***	16.70***	24.66***
	(3.715)	(2.383)	(3.025)	(3.700)
Observations	14368	16733	15148	13910
R^2	0.165	0.154	0.131	0.067

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Dependent variables are 0 to 100. Cells are coefficients, robust standard errors in parentheses.

In the same spirit as Table 5, Table 7 shows the relationship between specific educational specializations and the four types of skill mismatch. Once again, vocational education programs appear to have a limited relationship with any type of skill mismatch. Only having a specialization in agriculture or commerce at the vocational secondary level reduces the under-skilled percentage

in cross-functional skills by around 5 percentage points compared to having an industrial specialization.

University specializations, by contrast, have a stronger relationship across the different dimensions of skill mismatch. Compared to holding a university degree in medicine, sciences, or engineering, other specializations often predict lower rates of over-skilling in basic and cross-functional skills and higher rates of under-skilling. For instance, compared to holding a university degree in medicine, sciences, or engineering, having a university degree in commerce and law (-9.8 p.p.), education (-23.5 p.p.), humanities (-15.9 p.p.), the social sciences (-14.8 p.p.), or other fields (-8.4 p.p.) reduces the over-skilled percentage in cross-functional skills. There are not, however, significant differences between these other specializations when testing their joint equivalence for over-skilled in basic skills, but there are for both types of under-skilling and for cross-functional over-skilling.

Table 7. OLS estimates of over-skilled and under-skilled percentages by skill group and education specialization

	Vocational secondary graduates				**University graduates**			
	Over-skilled		**Under-skilled**		**Over-skilled**		**Under-skilled**	
	Basic	**Cross**	**Basic**	**Cross**	**Basic**	**Cross**	**Basic**	**Cross**
Vocational spec. (Industrial omit.)								
Vocational secondary-agriculture	-0.131	0.972	-1.769	-5.638*				
	(2.797)	(1.589)	(1.829)	(2.393)				
Vocational secondary-commerce	3.337	0.645	0.295	-4.639*				
	(2.043)	(1.208)	(1.570)	(1.903)				
Vocational secondary-others	-3.876	-0.632	-0.311	0.0588				
	(2.141)	(1.390)	(1.957)	(2.352)				
University spec. (Medicine, science or engineering omit.)								
University-commerce and law					-8.951*	-9.777**	-1.978	4.110*
					(3.895)	(3.630)	(1.400)	(2.062)
University-education					-9.428*	-23.49***	1.540	11.07***
					(4.461)	(3.737)	(1.674)	(2.980)
University-humanities					-8.335	-15.03***	5.018*	12.54***
					(4.813)	(4.337)	(2.272)	(3.198)
University-social sciences					-1.501	-14.81***	6.301*	11.54**
					(5.153)	(4.336)	(2.655)	(3.646)
University-others					-4.999	-8.418*	2.021	5.660*
					(4.147)	(3.930)	(1.670)	(2.337)
Observations	4119	4825	4332	3992	1728	2303	2359	2300
R^2	0.073	0.039	0.039	0.048	0.124	0.102	0.068	0.072

Notes: *p < 0.05, ** p < 0.01, *** p < 0.001. Dependent variables are 0 to 100. Cells are coefficients, standard errors in parentheses. We control for the same variables described in the data section for the employed sample, except for the education variable, as the samples are restricted to vocational secondary and university graduates.

5 Conclusions

Global increases in education, like those in Egypt, can potentially unlock economic growth and brighter futures – but only if increases in education provide skills that are in demand and pay off in the labor market. Potential mismatch between education, skills, and labor market requirements is thus an increasingly pressing global issue (Leuven and Oosterbeek 2011; Cho et al. 2013; Handel et al. 2016). Challenges in Egypt and the Arab world with high rates of educated youth unemployment, long school-to-work transitions, and low returns to education are frequently attributed to mismatch (El-Kogali and Krafft 2020; Assaad et al. 2018; Krafft et al. 2019). Yet the empirical basis for attributing labor market challenges to mismatch remains limited (Adely et al. 2021). Past research on labor market mismatch in Egypt has identified disparities between levels of education attained and required, with over-education reducing wages and job satisfaction (Roushdy and ElKhouly 2024; Fakih and Lizzaik 2024).

This research expanded our understanding of the scope of structural mismatch with additional insights into not only education level mismatch, but also field of study mismatch and skill mismatch. Over-skill and especially over-education for the employed were fairly common issues, along with field of study mismatch. These mismatches were somewhat less common for women, as they selected out of employment that did not meet their aspirations and often remained non-employed.

Mismatches between reservation wages and predicted wages were particularly an issue for informal private sector work, where 90% of reservation wages exceed predicted informal private sector wages. For those out of the labor force, those with highly educated parents were more likely to reject jobs, suggesting that those from higher socioeconomic status backgrounds may have both higher aspirations and the familial resources to persist in those aspirations. Mismatch of occupations and the types of employment readily available were acute for the unemployed, particularly women, indicating sizeable aspirational mismatch. While the results substantiate that multi-dimensional mismatch is, indeed, an issue in Egypt, the degree to which this mismatch is a causal factor in high rates of unemployment and difficult school-to-work transitions requires further research.

5.1 Policy implications

Both structural and aspirational components of mismatch are inherent in Egypt's labor market. Structural solutions in the education system, labor market, and economy can potentially address both forms of mismatch. Economic reforms that create more jobs, particularly formal jobs with high wages, can close the gaps between aspirations and realities. Ensuring a competitive economy and addressing crony capitalism in the private sector is an important part of improving job creation and quality (Chekir and Diwan 2015). Recent reforms to the social insurance law, such as reducing contribution rates, could help increase access to decent work, but have not, as yet, led to appreciable increases in formal employment (Barsoum and Selwaness 2022; Assaad and Wahby 2023; Krafft and Hannafi 2023).

Better aligning the needs of the labor market with the skills and degrees provided by the education system can help address structural mismatch, and by doing so raise productivity, wages, and job satisfaction (Tansel and Lassassi 2023; Mateos-Romero and Salinas-Jiménez 2018; Quinn and Rubb 2006). Improving labor market information systems can be part of this solution (Angel-Urdinola et al. 2013; El-Kogali and Krafft 2020; Krafft, Assaad, McKillip, et al. 2024). Although information can potentially affect decisions and improve labor market outcomes, its effects are not guaranteed, as illustrated by experiments providing information about job fairs and wages in Egypt, which did not change reservation wages (Crepon et al. 2021). Rigorous research on the impact of labor market information systems, such as Egypt's new "Occupational Outlook" (Ministry of Planning, Economic Development, and International Cooperation 2025) is needed.

Additional training programs, e.g., focused on soft skills, are not necessarily going to be effective at overcoming mismatch (Groh et al. 2012); our results showed over-skill and overeducation are more common than the opposite. Such programs are only likely to be effective when they are apprenticeships or internships responding to labor demand (McKenzie et al. 2016; Krafft 2018), or providing a specific in-demand skill, such as English language skills (Osman and Speer 2022). These additional training programs, however, beg the question of why relevant skills are *not* then taught in the education system.

Structural reforms are, given the global evidence, likely to be more effective than youth-centered interventions around mismatch that try to adjust aspirations and expectations or provide matches without addressing structural issues. High reservation wages can indicate high expectations for labor market prospects (Kesternich et al. 2022). These mismatched expectations can limit the efficacy of individual-level labor market interventions. For instance, in Jordan a job matching program that offered unemployed youth more than a thousand job matches led to only nine actual matches, because the jobs available did not meet youth's reservation working conditions (Groh et al. 2015). Likewise a program offering job matching and child care subsidies to mothers with young children in Egypt did not generate many acceptable matches or increase employment (Caria et al. 2025). In Egypt and India, preferences for women to have part-time work and all-female workplaces lead to strong mismatch with existing jobs (Majbouri 2025; Fletcher et al. 2017). Policies encouraging remote and flexible work may be particularly beneficial for women (Ho et al. 2024; Jalota and Ho 2024).

When youth do not have accurate expectations of the labor market, providing them with information can change their expectations and career aspirations (Osman 2014), ultimately improving labor market outcomes (Fernando and Singh 2025; Kiss et al. 2023; Witte et al. 2025). However, youth can also update their expectations without changing their behavior (Clerici et al. 2024). Furthermore, interventions that raise expectations, such as job matching services, can actually worsen unemployment if reservation wages increase significantly (Kelley et al. 2024). Focusing on youth-centric interventions, rather than addressing the structural mismatch issues in the education system and labor market, is therefore likely to be insufficient (Adely et al. 2021). The effectiveness of information interventions at the systems level (education, training, and labor market systems) needs to be carefully investigated and evaluated in future research.

References

Abebe, Girum, Stefano Caria, Marcel Fafchamps, et al. 2025. "Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment." *The Economic Journal*, ueaf026. https://doi.org/10.1093/ej/ueaf026.

Adely, Fida Issa J., Ankushi Mitra, Menatalla Mohamed, and Adam Shaham. 2021. "Poor Education, Unemployment and the Promise of Skills: The Hegemony of the 'Skills Mismatch' Discourse." *International Journal of Educational Development* 82: 102381. https://doi.org/10.1016/j.ijedudev.2021.102381.

Ahrens, Achim, Christian B. Hansen, and Mark E. Schaffer. 2020. "Lassopack: Model Selection and Prediction with Regularized Regression in Stata." *The Stata Journal* 20 (1): 176–235. https://doi.org/10.1177/1536867X20909697.

Amer, Mona, and Marian Atallah. 2022. "The School to Work Transition and Youth Economic Vulnerability in Egypt." In *The Egyptian Labor Market: A Focus on Gender and Vulnerability*, edited by Caroline Krafft and Ragui Assaad. Oxford University Press.

Angel-Urdinola, Diego F., Arvo Kuddo, Amina Semlali, et al. 2013. *Building Effective Employment Programs for Unemployed Youth in the Middle East and North Africa*. World Bank.

Assaad, Ragui. 1997. "The Effects of Public Sector Hiring and Compensation Policies on the Egyptian Labor Market." *The World Bank Economic Review* 11 (1): 85–118.

Assaad, Ragui. 2014. "Making Sense of Arab Labor Markets: The Enduring Legacy of Dualism." *IZA Journal of Labor & Development* 3 (6): 1–25.

Assaad, Ragui, Abdelaziz AlSharawy, and Colette Salemi. 2022. "Is The Egyptian Economy Creating Good Jobs? Job Creation and Economic Vulnerability from 1998 to 2018." In *The Egyptian Labor Market: A Focus on Gender and Vulnerability*, edited by Caroline Krafft and Ragui Assaad. Oxford University Press.

Assaad, Ragui, and Ghada Barsoum. 2009. "Rising Expectations and Diminishing Opportunities for Egypt's Young." In *Generation in Waiting: The Unfulfilled Promise of Young People in the Middle East*, edited by Navtej Dhillon and Tarik Yousef. Brookings Institution Press.

Assaad, Ragui, Christine Binzel, and May Gadallah. 2010. "Transitions To Employment and Marriage Among Young Men in Egypt." *Middle East Development Journal* 2 (1): 39–88.

Assaad, Ragui, and Caroline Krafft. 2021. "Excluded Generation: The Growing Challenges of Labor Market Insertion for Egyptian Youth." *Journal of Youth Studies* 24 (2): 186–212. https://doi.org/10.1080/13676261.2020.1714565.

Assaad, Ragui, and Caroline Krafft. 2023. "Labour Market Dynamics and Youth Unemployment in the Middle East and North Africa: Evidence from Egypt, Jordan, and Tunisia." *LABOUR* 37 (4): 519–53. https://doi.org/10.1111/labr.12257.

Assaad, Ragui, and Caroline Krafft. 2024. "Introducing the Egypt Labor Market Panel Survey 2023." *Economic Research Forum Working Paper Series* No. 1748.

Assaad, Ragui, Caroline Krafft, Khandker Wahedur Rahman, and Irène Selwaness. 2019. "Job Creation in Egypt: A Sectoral and Geographical Analysis Focusing on Private Establishments, 1996-2017." *Economic Research Forum Policy Paper*.

Assaad, Ragui, Caroline Krafft, and Djavad Salehi-Isfahani. 2018. "Does the Type of Higher Education Affect Labor Market Outcomes? Evidence from Egypt and Jordan." *Higher Education* 75 (6): 945–95. https://doi.org/10.1007/s10734-017-0179-0.

Assaad, Ragui, Caroline Krafft, and Colette Salemi. 2023. “Socioeconomic Status and the Changing Nature of School-to-Work Transitions in Egypt, Jordan, and Tunisia.” *ILR Review* 76 (4): 697–723.
Assaad, Ragui, Caroline Krafft, and Irene Selwaness. 2022. “The Impact of Marriage on Women’s Employment in The Middle East and North Africa.” *Feminist Economics* 28 (2): 247–79.
Assaad, Ragui, Caroline Krafft, and Shaimaa Yassin. 2020. “Job Creation or Labor Absorption? An Analysis of Private Sector Job Growth in Egypt.” *Middle East Development Journal* 12 (2): 177–207. https://doi.org/10.1080/17938120.2020.1753978.
Assaad, Ragui, and Esraa Mahmoud. 2024. “Evolution of the Structure and Quality of Employment in Egypt, 2012-2023.” *Economic Research Forum Working Paper Series* No. 1750.
Assaad, Ragui, and Sarah Wahby. 2023. “Why Is Social Insurance Coverage Falling in Egypt? A Decomposition Analysis.” *Economic Research Forum Working Paper Series* No. 1658.
Baran, Jan A. 2024. “Overeducation in the EU: Gender and Regional Dimension.” *Labour Economics* 90: 102603. https://doi.org/10.1016/j.labeco.2024.102603.
Barsoum, Ghada. 2015. “Young People’s Job Aspirations in Egypt and the Continued Preference for a Government Job.” In *The Egyptian Labor Market in an Era of Revolution*, edited by Ragui Assaad and Caroline Krafft. Oxford University Press.
Barsoum, Ghada, and Dina Abdalla. 2022. “Still the Employer of Choice: Evolution of Public Sector Employment in Egypt.” In *The Egyptian Labor Market: A Focus on Gender and Vulnerability*, edited by Caroline Krafft and Ragui Assaad. Oxford University Press.
Barsoum, Ghada, and Irene Selwaness. 2022. “Egypt’s Reformed Social Insurance System: How Might Design Change Incentivize Enrolment?” *International Social Security Review* 75 (2): 47–74.
Boto-García, David, and Marta Escalonilla. 2022. “University Education, Mismatched Jobs: Are There Gender Differences in the Drivers of Overeducation?” *Economia Politica* 39 (3): 861–902. https://doi.org/10.1007/s40888-022-00270-y.
Capsada-Munsech, Queralt. 2017. “Overeducation: Concept, Theories, and Empirical Evidence.” *Sociology Compass* 11 (10): e12518. https://doi.org/10.1111/soc4.12518.
Caria, Stefano, Bruno Crepon, Caroline Krafft, and AbdelRahman Nagy. 2025. “The Barriers to Female Employment: Experimental Evidence from Egypt.” *G2LM|LIC Working Paper* No. 92.
Chekir, Hamouda, and Ishac Diwan. 2015. “Crony Capitalism in Egypt.” *Journal of Globalisation and Development* 5 (2): 177–211. https://doi.org/10.1515/jgd-2014-0025.
Cho, Yoonyoung, David N. Margolis, David Newhouse, and David A. Robalino. 2013. “Labor Markets in Low and Middle-Income Countries: Trends and Implications for Social Protection and Labor Policies.” *Social Protection & Labor Discussion Paper* No. 1207.
Clerici, Cristina, Iacopo Bianchi, and Dominik Biesalski. 2024. “Information, Expectations and Preferences: Occupational Choices of Young Adults in Uganda.” *Mimeo*.
Crepon, Bruno, Adam Osman, and Mona Said. 2021. *Final Technical Report: Improving the Effectiveness of Job Fairs for Young Jobseekers in Egypt*. American University in Cairo.
Croke, Kevin, Markus Goldstein, and Alaka Holla. 2023. “The Role of Skills and Gender Norms in Sector Switches: Experimental Evidence from a Job Training Program in Nigeria.” *Journal of African Economies* 32 (3): 237–68. https://doi.org/10.1093/jae/ejac007.

Dhillon, Navtej, and Tarik Yousef. 2009. *Generation in Waiting: The Unfulfilled Promise of Young People in the Middle East*. Brookings Institution Press.
Didier, Nicolas. 2024. "Educational Mismatch, Labor Market Completeness, and Gender: Evidence from Chile." *International Journal of Educational Development* 105: 102990. https://doi.org/10.1016/j.ijedudev.2024.102990.
Dougherty, Christopher. 2014. "The Labour Market for Youth in Egypt: Evidence from the 2012 School to Work Transition Survey." *Silatech Working Paper*.
Elbadawy, Asmaa. 2015. "Education in Egypt: Improvements in Attainment, Problems with Quality and Inequality." In *The Egyptian Labor Market in an Era of Revolution*, edited by Ragui Assaad and Caroline Krafft. Oxford University Press.
El-Feki, Shereen, Brian Heilman, and Gary Barker, eds. 2017. *Understanding Masculinities: Results from the International Men and Gender Equality Survey (IMAGES) - Middle East and North Africa*. UN Women and Promundo-US.
El-Kogali, Safaa El Tayeb, and Caroline Krafft, eds. 2020. *Expectations and Aspirations: A New Framework for Education in the Middle East and North Africa*. World Bank.
Fakih, Ali, and Zeina Lizzaik. 2024. "The Incidence and Wage Penalty of Overqualification: The Case of Egypt." *IZA Discussion Paper Series* No. 17247.
Fernando, A. Nilesh, and Niharika Singh. 2025. "The Grass Is Not Always Greener: The Effects of Local Labor Market Information on Search and Employment." *Mimeo*.
Fletcher, Erin, Rohini Pande, and Charity Maria Troyer Moore. 2017. "Women and Work in India: Descriptive Evidence and a Review of Potential Policies." *CID Faculty Working Paper* No. 339.
Green, Francis, and Steven McIntosh. 2007. "Is There a Genuine Under-Utilization of Skills amongst the over-Qualified?" *Applied Economics* 39 (4): 427–39. https://doi.org/10.1080/00036840500427700.
Groh, Matthew, Nandini Krishnan, David McKenzie, and Tara Vishwanath. 2012. "Soft Skills or Hard Cash? The Impact of Training and Wage Subsidy Programs on Female Youth Employment in Jordan." *World Bank Policy Research Working Paper Series* No. 6141.
Groh, Matthew, David McKenzie, Nour Shammout, and Tara Vishwanath. 2015. "Testing the Importance of Search Frictions and Matching through a Randomized Experiment in Jordan." *IZA Journal of Labor Economics* 4 (7): 1–20. https://doi.org/10.1186/s40172-015-0022-8.
Handel, Michael J., Alexandria Valerio, and Maria Laura Sánchez Puerta. 2016. *Accounting for Mismatch in Low- and Middle-Income Countries*. Directions in Development. World Bank.
Hastings, Justine S., Christopher A. Neilson, Anely Ramirez, and Seth D. Zimmerman. 2016. "(Un)Informed College and Major Choice: Evidence from Linked Survey and Administrative Data." *Economics of Education Review* 51: 136–51. https://doi.org/10.1016/j.econedurev.2015.06.005.
Ho, Lisa, Suhani Jalota, and Anahita Karandikar. 2024. "Bringing Work Home: Flexible Arrangements as Gateway Jobs for Women in West Bengal." *STEG Working Paper*.
Hoodfar, Homa. 1997. *Between Marriage and the Market: Intimate Politics and Survival in Cairo*. University of California Press.
International Labour Office, ed. 2012. *Structure, Group Definitions and Correspondence Tables*. International Standard Classification of Occupations, v. 1. International Labour Office.

International Labour Organization. 2018. “Guidelines Concerning Measurement of Qualifications and Skills Mismatches of Persons in Employment.” Paper presented at 20th International Conference of Labour Statisticians, Geneva, Switzerland.
Jalota, Suhani, and Lisa Ho. 2024. “What Works for Her? How Jobs from Home and Local Offices Affect Female Labor Force Participation in Urban India.” *Mimeo*.
Kelley, Erin M., Christopher Ksoll, and Jeremy Magruder. 2024. “How Do Digital Platforms Affect Employment and Job Search? Evidence from India.” *Journal of Development Economics* 166: 103176. https://doi.org/10.1016/j.jdeveco.2023.103176.
Kesternich, Iris, Heiner Schumacher, Bettina Siflinger, and Franziska Valder. 2022. “Reservation Wages and Labor Supply.” *Journal of Economic Behavior & Organization* 194: 583–607. https://doi.org/10.1016/j.jebo.2021.12.031.
Kiss, Andrea, Robert Garlick, Kate Orkin, and Lukas Hensel. 2023. “Jobseekers’ Beliefs about Comparative Advantage and (Mis)Directed Search.” *IZA Discussion Paper Series* No. 16522.
Krafft, Caroline. 2012. “Challenges Facing the Egyptian Education System: Access, Quality, and Inequality.” *Survey of Young People in Egypt Policy Brief Series* No. 2.
Krafft, Caroline. 2018. “Is School the Best Route to Skills? Returns to Vocational School and Vocational Skills in Egypt.” *The Journal of Development Studies* 54 (7): 1100–1120. https://doi.org/10.1080/00220388.2017.1329524.
Krafft, Caroline. 2023. “The Future of Skills in the Egyptian Labor Market.” *ERF Special Policy Research Report* No. SPRR 2023-1.
Krafft, Caroline, and Ragui Assaad. 2020. “Employment’s Role in Enabling and Constraining Marriage in the Middle East and North Africa.” *Demography* 57: 2297–325. https://doi.org/10.1007/s13524-020-00932-1.
Krafft, Caroline, Ragui Assaad, and Zoe McKillip. 2024. “The Evolution of Labor Supply in Egypt through 2023.” *Economic Research Forum Working Paper Series* No. 1749.
Krafft, Caroline, Ragui Assaad, Zoe McKillip, and Esraa Mahmoud. 2024. “The Evolution of Labor Supply in Egypt: Current and Future Challenges.” *Economic Research Forum Policy Brief* No. 135.
Krafft, Caroline, Ragui Assaad, and Khandker Wahedur Rahman. 2021. “Introducing the Egypt Labor Market Panel Survey 2018.” *IZA Journal of Development and Migration* 12 (12): 1–40.
Krafft, Caroline, Zea Branson, and Taylor Flak. 2019. “What’s the Value of a Degree? Returns to Education in Egypt, Jordan, and Tunisia.” *Compare: A Journal of Comparative and International Education*, DOI: 10.1080/03057925.2019.1590801.
Krafft, Caroline, and Cyrine Hannafi. 2023. “The Dynamics of Social Insurance in Egypt.” *Economic Research Forum Working Paper Series* No. 1655.
Kupets, Olga. 2016. “Skill Mismatch and Overeducation in Transition Economies.” *IZA World of Labor* 224: 1–10. https://doi.org/10.15185/izawol.224.
Leuven, Edwin, and Hessel Oosterbeek. 2011. “Overeducation and Mismatch in the Labor Market.” In *Handbook of the Economics of Education*, edited by Eric A. Hanushek, Stephen Manchin, and Ludger Woessmann, vol. 4. Elsevier.
Levinsohn, James, and Todd Pugatch. 2010. “The Role of Reservation Wages in Youth Unemployment in Cape Town, South Africa: A Structural Approach.” *Mimeo*.
Majbouri, Mahdi. 2025. “Preferences and the Puzzle of Female Labor Force Participation.” *IZA Discussion Paper Series* No. 17952.

Mateos-Romero, Lucía, and María Del Mar Salinas-Jiménez. 2018. “Labor Mismatches: Effects on Wages and on Job Satisfaction in 17 OECD Countries.” *Social Indicators Research* 140 (1): 369–91. https://doi.org/10.1007/s11205-017-1830-y.

McKenzie, David, Nabila Assaf, and Ana Paula Cusolito. 2016. “The Demand for, and Impact of, Youth Internships: Evidence from a Randomized Experiment in Yemen.” *IZA Journal of Labor and Development* 5 (1): 1–15. https://doi.org/10.1186/s40175-016-0048-8.

Ministry of Planning, Economic Development, and International Cooperation. 2025. “Occupational Outlook.” https://occupational-outlook.mped.gov.eg/.

Mullis, Ina V. S., Michael O. Martin, Pierre Foy, Kelly, Dana L., and Fishbein, Bethany. 2020. *TIMSS 2019: International Results in Mathematics and Science*. TIMSS & PIRLS International Study Center, Lynch School of Education, Boston College.

Nilsson, Björn. 2019. “The School-to-Work Transition in Developing Countries.” *Journal of Development Studies* 55 (5): 745–64. https://doi.org/10.1080/00220388.2018.1475649.

OAMDI. 2019. “Labor Market Panel Surveys (LMPS). Version 2.0 of Licensed Data Files; ELMPS 2018.”

OAMDI. 2024. “Labor Market Panel Surveys (LMPS). Version 1.0 of Licensed Data Files; ELMPS 2023.”

Osman, Adam. 2014. *Occupational Choice under Credit and Information Constraints*. Working Paper. Yale University.

Osman, Adam, and Jamin D. Speer. 2022. “Are Soft Skills Enough? Experimental Evidence on Skill Complementary for College Graduates.” *Mimeo*.

Pholphirul, Piriya. 2017. “Educational Mismatches and Labor Market Outcomes: Evidence from Both Vertical and Horizontal Mismatches in Thailand.” *Education + Training* 59 (5): 534–46. https://doi.org/10.1108/ET-11-2016-0173.

Quinn, Michael A., and Stephen Rubb. 2006. “Mexico’s Labor Market: The Importance of Education-Occupation Matching on Wages and Productivity in Developing Countries.” *Economics of Education Review* 25 (2): 147–56. https://doi.org/10.1016/j.econedurev.2005.01.003.

Roushdy, Rania, and Nouran ElKhouly. 2024. “Education-Occupation Mismatch Among Vocational Secondary and University Graduates in Egypt.” *Economic Research Forum Working Paper Series* No. 1757.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. 2014. “Mismatch Unemployment.” *American Economic Review* 104 (11): 3529–64. https://doi.org/10.1257/aer.104.11.3529.

Salehi-Isfahani, Djavad, Insan Tunali, and Ragui Assaad. 2009. “A Comparative Study of Returns To Education of Urban Men in Egypt, Iran, and Turkey.” *Middle East Development Journal* 1 (2): 145–87.

Selwaness, Irene, and Caroline Krafft. 2021. “The Dynamics of Family Formation and Women’s Work: What Facilitates and Hinders Female Employment in the Middle East and North Africa?” *Population Research and Policy Review* 40 (3): 533–87. https://doi.org/10.1007/s11113-020-09596-6.

Tansel, Aysit, and Moundir Lassassi. 2023. “Do Educational Mismatches Influence Job Satisfaction and On-the-Job Search in Algeria?” *Economic Research Forum Working Paper Series* No. 1669.

Tsacoumis, Suzanne, and Shannon Willison. 2010. *O*NET Analyst Occupational Skill Ratings: Procedures*. March. https://www.onetcenter.org/dl_files/AOSkills_Proc.pdf.

Weaver, Andrew, and Paul Osterman. 2017. “Skill Demands and Mismatch in U.S. Manufacturing.” *ILR Review* 70 (2): 275–307. https://doi.org/10.1177/0019793916660067.
Witte, Marc, Johanna Roth, Morgan Hardy, and Christian Johannes Meyer. 2025. “Reaching Marginalized Job Seekers Through Public Employment Services: Experimental Evidence from Ethiopia.” *IZA Discussion Paper Series* No. 18005.
World Bank. 2013. *Jobs for Shared Prosperity: Time for Action in the Middle East and North Africa*. June. World Bank.

Appendix 1: Predicting the market wage for the unemployed

We use a lasso model to select the covariates that predict the market wage for unemployed individuals. The model is estimated using the employed sample and used to then predict the market wage for the unemployed.

We include explanatory variables that are potentially exogenous to the determination of the reservation wage among the covariates the lasso model selects from: age group, gender, education level (six categories), work experience group, urban residence, governorate,[10] the interaction between urban residence and governorate, living in a mother village or in a settlement smaller than a village (hamlet) in rural areas, the qism-level unemployment rate (estimated), the qism-level informal private sector rate (estimated), dummies for the number of skills an individual possesses, dummies for each specific skill, and parental characteristics (education level of both parents and employment status of the father). This constitutes the full specification. A restricted specification includes the same variables, except for the parental characteristics, which may be endogenous to the decision to reject jobs.

The dependent variable in the prediction model is the logarithm of the monthly wage, where extreme values are top-coded at the 95th percentile of the population's monthly wage distribution. Due to missing values in some control variables, the final sample includes 1,924 observations for the public sector, 681 for the formal private sector, and 4,496 for the informal private sector.

To select the variables for each sector and specification, we use cross-validation criteria, choosing the penalty parameter for number of variables (lambda) by minimizing the cross-validation function (mean squared error), as this yields the best predictive performance (Ahrens et al. 2020). This selection method requires specifying the number of equal partitions (folds) the program will create for training (folds-1) and testing (1). Given differences in sample sizes across sectors, we specify 5 folds for the public sector, 4 for the formal private sector, and 6 for the informal private sector. After selecting the lambda, the method identifies the corresponding set of variables, grouped by model and category (Table 8).

Table 8. Selected variables for lasso model of wage prediction, by model and sector

Variable categories	Public sector		Formal Private Sector		Informal Private Sector	
	Full	Restricted	Full	Restricted	Full	Restricted
Age group (15-19 omit.)	20-24; 35-39; 50-54; and 55-59	20-24; 35-39; 50-54; and 55-59	35-39 and 50-54	35-39 and 50-54	20-24;25-29;30-34; 45-49; and 50-54	5-year age bands except below 24
Sex (Female omit.)	Male	Male	Male	Male	Male	Male
Education level	Illiterate;	Illiterate;	Preparatory and	Preparatory and	Illiterate; Reads & Writes;	Illiterate; Reads & Writes;

[10] Egypt's administrative structure is organized into 27 governorates, forming the top tier. Qism is the subdivision of a governorate.

(vocational sec. omit.)	Reads & Writes; Preparatory; Post-secondary institute; and University & above	Reads & Writes; Preparatory; Post-secondary institute; and University & above	University & above	University & above	Primary; Preparatory; General Secondary; Post-secondary; and University & above	Primary; Preparatory; General Secondary; Post-secondary; and University & above
Work experience group	Less than 1 year; 1-3 years; 3-5 years; and more than 10 years.	Less than 1 year; 1-3 years; 3-5 years; 5-10 years; and more than 10 years.	Without experience; less than 1 year; and 3-5 years	Without experience; less than 1 year; and 3-5 years	Without experience; less than 1 year; 1-3 years; 3-5 years; and 5-10 years.	Without experience; less than 1 year; 1-3 years; 3-5 years; and 5-10 years.
Geographic location (Governorate, and interactions with urban areas, and mother village or hamlet).	Urban areas of Cairo, Port-said, Dakahlia, Sharkia, Kalyoubia, Giza, Menia, Qena, Luxur; Rural mother villages of Dakahlia, Kalyoubia, Gharbia, Menoufia, Ismailia, Fayoum, Luxur; and rural hamlets of Beni-Suef and Suhag.	Urban areas of Cairo, Port-said, Dakahlia, Sharkia, Kalyoubia, Giza, Menia, Suhag, Qena, Luxur; Rural mother villages of Damietta, Dakahlia, Kalyoubia, Gharbia, Menoufia, Ismailia, Fayoum, Menia, Qena, Aswan, and Luxur; and rural hamlets of Beni-Suef and Suhag.	Urban areas of Gharbia, Ismailia, Giza, Asyout, and Luxur; rural mother villages of Sharkia, Ismailia, Giza, Asyout, and Luxur; and rural hamlets of Menoufia and Beni-Suef.	Urban areas of Gharbia, Ismailia, Giza, Asyout, and Luxur; rural mother villages of Sharkia, Ismailia, Giza, Asyout, and Luxur; and rural hamlets of Menoufia, Beni-Suef, and Menia.	Urban areas of Cairo, Alexandria, Port-said, Suez, Damietta, Dakahlia, Sharkia, Kalyoubia, Menoufia, Giza, Suhag, and Aswan; rural mother villages of Sharkia, Kalyoubia, Menoufia, Ismailia, Giza, Beni-Suef, Menia, Asyout, Suhag, Qena, Aswan, and Luxur; and rural hamlets of Gharbia, Behera, Beni-Suef, Menia, Suhag, and Luxur.	Urban areas of Cairo, Alexandria, Port-said, Suez, Damietta, Dakahlia, Sharkia, Kalyoubia, Gharbia, Menoufia, Ismalia, Giza, Menia, Asyout, Suhag, and Aswan; rural mother villages of Dakahlia, Sharkia, Kalyoubia, Kafr-Elsheikh, Menoufia, Behera, Ismailia, Giza, Beni-Suef, Menia, Asyout, Suhag, Qena, Aswan, and Luxur; and rural hamlets of Kafr-Elsheikh, Gharbia,

						Behera, Beni-Suef, Menia, Suhag, Qena, and Luxur.
Qism-level labor market indicators	Qism-level informal sector and unemployment rates	Qism-level informal sector and unemployment rates	Qism-level informal sector and unemployment rates	Qism-level informal sector and unemployment rates	Qism-level informal sector and unemployment rates	Qism-level unemployment rate
Skills of workers	1 skill in total; 5 skills in total; 9 skills in total; 11 skills in total; 12 skills in total; Foreign language skills; Basic book-keeping or accounting skills; team work skills; computer skills; and technical skills	1 skill in total; 5 skills in total; 9 skills in total; 11 skills in total; 12 skills in total; Mathematics or statistics skills; Basic book-keeping or accounting skills; team work skills; computer skills; and technical skills.	11 skills in total; 12 skills in total; mathematics or statistics skills; foreign language skills; teamwork skills; and computer skills.	11 skills in total; 12 skills in total; mathematics or statistics skills; foreign language skills; teamwork skills; and computer skills.	0 skills in total; 1 skill in total; 4 skills in total; 10 skills in total; management skills; foreign language skills; basic book-keeping skills; problem solving skills; communication & presentation skills; and technical skills.	0 skills in total; 1 skill in total; 2 skills in total; 4 skills in total; 5 skills in total; 7 skills in total;10 skills in total; 12 skills in total; all skills except physical fitness, customer service and computer skills.
Parent background	Less than intermediate father; higher educated father; and higher educated mother		Wage worker father		Illiterate father; less than intermediate father; illiterate mother; higher educated mother; employer and self-employed father.	

Source: Author's construction based on ELMPS 2023

We use these variables, excluding the penalty parameter, to predict the logarithm of the monthly wage. As a measure of prediction goodness of fit, we report the out-of-sample R-squared from the remaining fold (Table 9). The formal private sector shows the lowest R-squared. Additionally, we include two random samples, each consisting of half of the original sample size. In these subsamples, the R-squared exceeds 10% across all sectors and specifications.

Table 9. Goodness of fit for lasso models of wage prediction, by model and sector

Sector	Sample	# observations for prediction	R-squared for full specification	R-squared for restricted specification
Public	Out of sample	550	0.089	0.092
Public	Random sample 1	1392	0.138	0.136
Public	Random sample 2	1358	0.211	0.209
Formal Private	Out of sample	288	0.108	0.118
Formal Private	Random sample 1	574	0.255	0.238
Formal Private	Random sample 2	576	0.248	0.241
Informal Private	Out of sample	1005	0.072	0.074
Informal Private	Random sample 1	3034	0.127	0.130
Informal Private	Random sample 2	2995	0.121	0.124

Source: Author's construction based on ELMPS 2023

Finally, between the full and restricted specifications, we chose the restricted specification, as it provides the best out-of-sample goodness of fit. While the R-squared values in the random samples are slightly higher for the full specification, the restricted specification yields higher out-of-sample R-squared values, which is the more important indicator for prediction.

Appendix 2: Occupation and specialization mismatch

Table 10. Relationship between current occupation and matched specialization[11]

Answer	Occupation	Specialization
Human Resource Personnel	HR manager (1212)	Facilitation and management – secondary technical stage or higher (3530413, 4530413, 6650413, 6670413, 7670413, and 8640413)
Administrative Assistant	Administrative secretaries and specialized secretaries (3343)	Secretarial and office work- secondary technical stage or higher (3530415, 4530415, 6650415, 6670415, 7670415, and 8640415)
Data entry	Data entry clerks (4132)	Computer use- secondary technical stage or higher (3530611, 4530611, 6650611, 6670611, 7670611 and 8640611)
Bank Teller	Bank and currency tellers and related clerks (4211)	Finance, banking and insurance - secondary technical stage or higher (3530412, 4530412, 6650412, 6670412, 7670412, and 8640412)
Teacher	Vocational teachers (2320) Secondary education teachers (2330) Basic education teachers (2341)	Teacher training without/ with a specialization subject- secondary technical stage or higher (3530113, 3530114, 4530113, 4530114, 6650113, 6650114, 6670113, 6670114, 7670113, 7670114, 8640113, and 8640114)
Customer service	Travel agency clerks (4221) Call center clerks (4222) Telephone switchboard operators (4223) Hotel reception clerks (4224) Clerks respond to inquiries (4225) Reception clerks (4226)	Marketing and advertising - secondary technical stage or higher (3530414, 4530414, 6650414, 6670414, 7670414, and 8640414)
Indoor Sales	Sellers and their assistants in stores and shops (5223) Ticket cashiers (5230) promoters of goods (5242)	Wholesale and retail sales- secondary technical stage or higher (3530416, 4530416,

[11] The columns for occupation and specialization include the Occupational Classification code (2, 3 or 4 digits) and Specialization code (7 digits) in the ELMPS.

Answer	Occupation	Specialization
	Food service assistants at the counter (5246)	6650416, 6670416, 7670416, and 8640416)
Telemarketing	Salespeople in call centers (5244)	Marketing and advertising- secondary technical stage or higher (3530414, 4530414, 6650414, 6670414, 7670414, and 8640414)
Outdoor Sales	Sellers at stalls and markets (5211) Food street vendors (5212) Door-to-door sellers (5243) Vendors and service providers of stations and parking (5245) Street vendors except food items (9520)	Wholesale and retail sales- secondary technical stage or higher (3530416, 4530416, 6650416, 6670416, 7670416, and 8640416)
Waiter	Waiters (5131)	Hotels, restaurants and ready-to-eat food- secondary technical stage or higher (3531013, 4531013, 6651013, 6671013, 7671013, and 8641013)
Agricultural Worker	Skilled agricultural (06) Agricultural, forestry and fishing workers (92)	Agriculture, forestry, fisheries and veterinary medicine for agricultural secondary school- secondary technical stage or higher (35308, 45308, 66508, 66708, 76708, and 86408)
Industrial Worker	Workers operating fixed machinery and equipment (8100)	Engineering, manufacturing and construction for industrial secondary stage- secondary technical stage or higher (35307, 45307, 66507, 66707, 76707, and 86407
Delivery Worker	Motorcyclists (8321)	Transportation services- secondary technical stage or higher (3531041, 4531041, 6651041, 6671041, 7671041, and 8641041)
Drivers	Drivers of private cars, taxis, and light transport (8322) Bus and tram drivers (8331) Truck and heavy transport drivers (8332)	Transportation services- secondary technical stage or higher (3531041, 4531041, 6651041, 6671041, 7671041, and 8641041)

Source: Authors' construction

Notes: An additional question exists for rejecting occupations (public sector employee, matched to all occupations in the public sector) but is not matched with specialization.

Appendix 3: Additional analyses

For the normative approach we approximate the ISCO-08 skill level of the occupation according to ISCO-08 major groups (International Labour Office 2012). To do this, we transform the education level variable into the ISCO-08 skill level using Table 11. Skill levels are then mapped to occupations as per the International Labour Office (2012). Skill level 1 corresponds to occupations where the main tasks are simple, manual or routine physical tasks; occupations at skill level 2 typically involve tasks such as operating machinery or driving vehicles; Skill level 3 requires complex and specialized technical and procedural knowledge. Finally, occupations at skill level 4 "require complex problem-solving, decision-making, and creativity based on an extensive body of theoretical and factual knowledge in a specialized field" (International Labour Office 2012, 13).

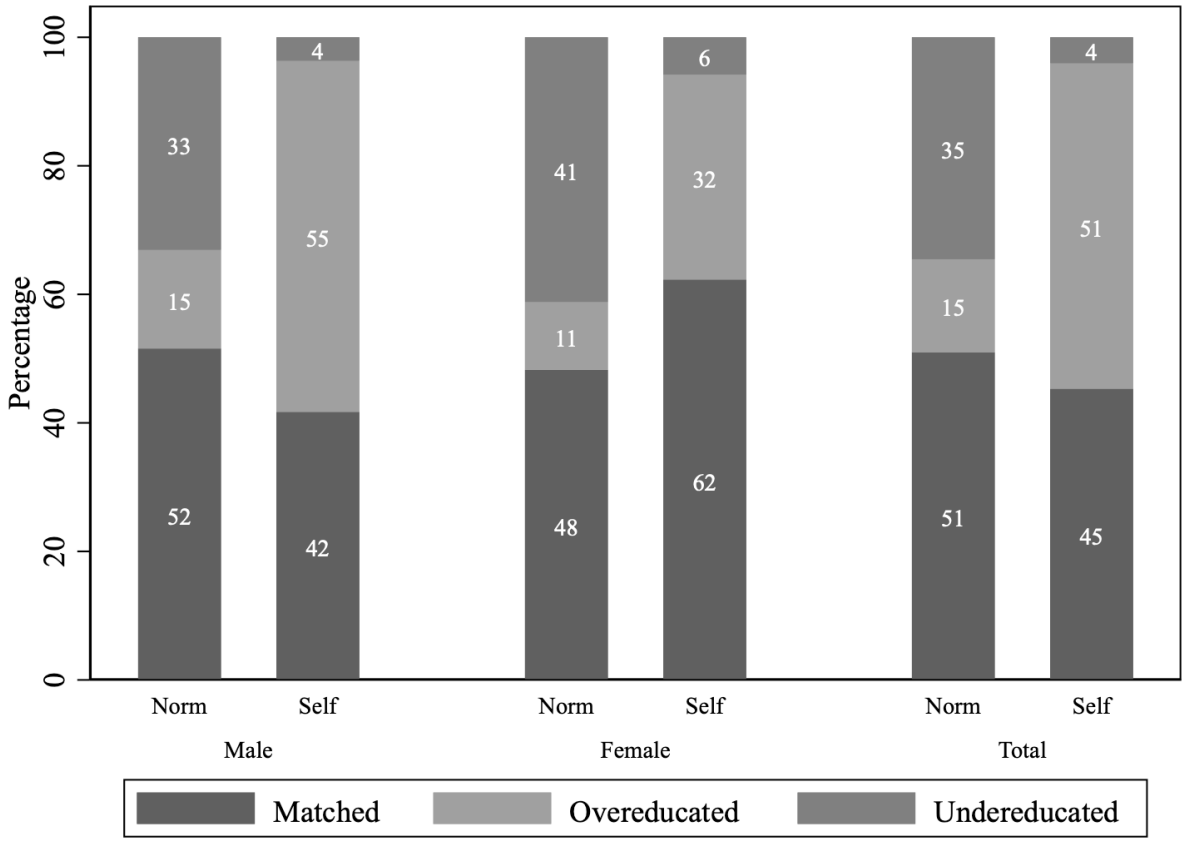
Table 11. Equivalence between the ISCO-08 occupations, ISCO-08 skill level, ISCED-97, and ELMPS 2023 levels of education

ISCO-08 Occupation (1-digit code)	ISCO-08 skill level code	ISCED-97 code	ISCED-97 levels of education	ELMPS 2023 levels of education
Managers (1) Professionals (2) Armed forces (0)	4	6	Second stage of tertiary education (leading to an advanced research qualification)	Post-graduate (doctorate)
		5a	First stage of tertiary education, 1st degree (medium duration)	Post-graduate (master) University
Managers (1) Technicians and associate professionals (3)	3	5b	First stage of tertiary education (short or medium duration)	Post-secondary institute
Clerical support workers (4) Services and sales workers (5) Skilled agricultural workers (6) Craft and related trades workers (7)	2	4	Post-secondary, non-tertiary education	
		3	Upper secondary level of education	Vocational Secondary General Secondary
		2	Lower secondary level of education	Preparatory

Plant and machine operators (8) Armed forces (0)				
Elementary occupations (1) Armed forces (0)	1	1	Primary level of education	Primary

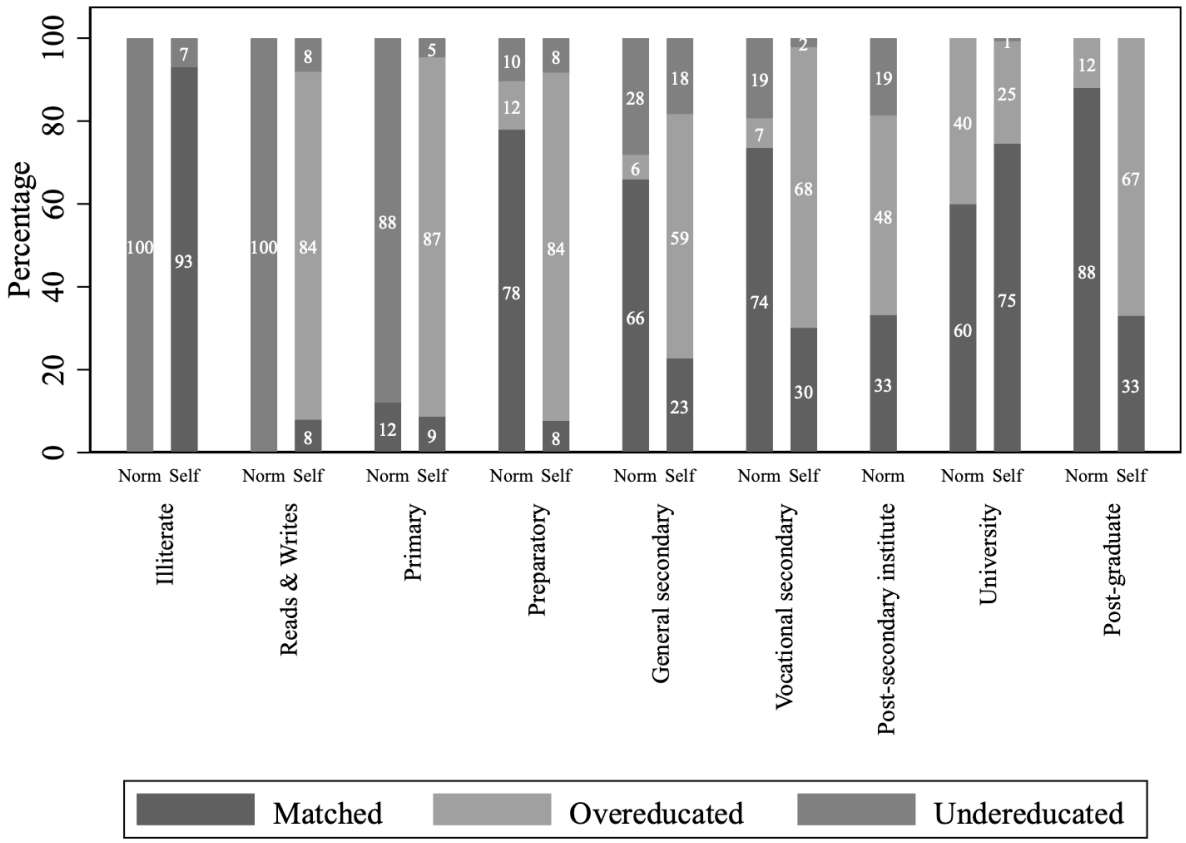
Source: Based on the International Labour Office (2012), own elaboration
Note: Armed forces are excluded from analyses using this correspondence, since it cannot be determined if they are over or under educated.

Appendix Figure 1. Education level mismatch for workers aged 15–64 using normative and self-assessment approaches (percentages), by sex, 2023



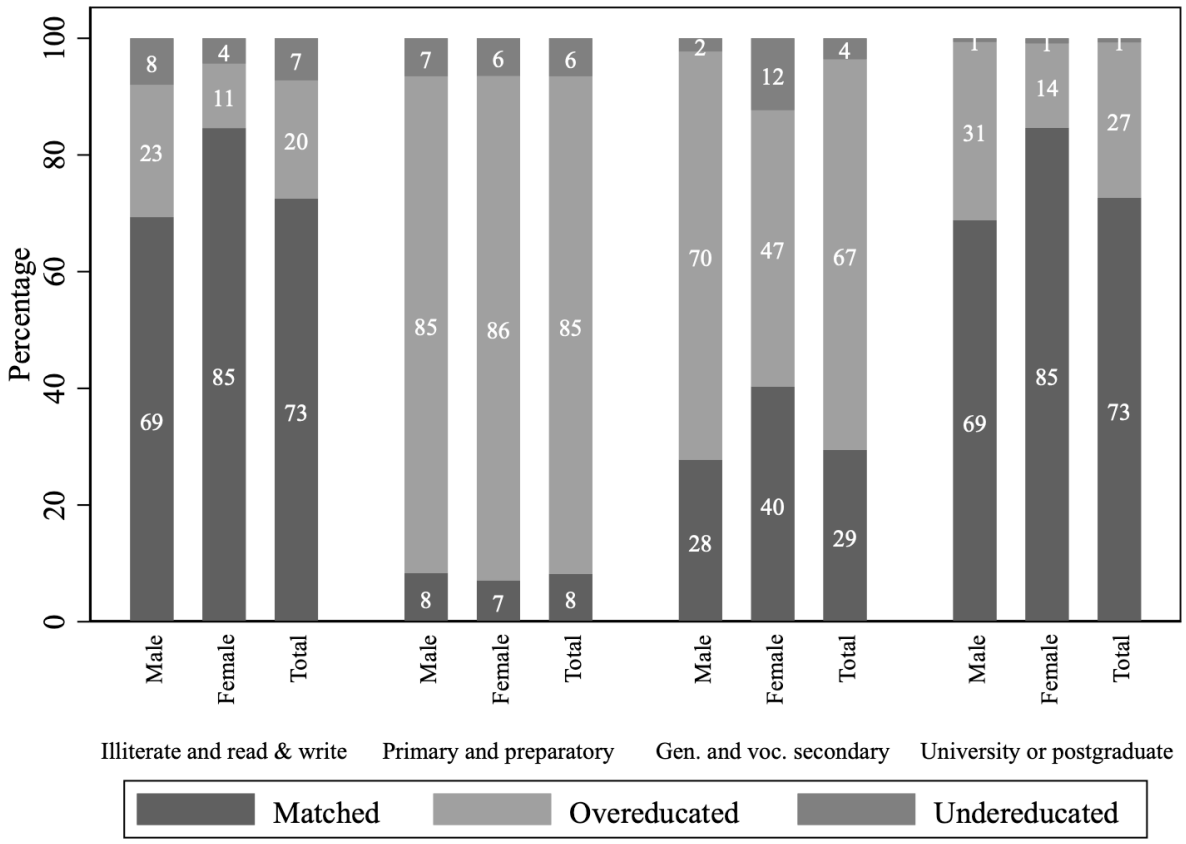
Source: Authors' calculations based on ELMPS 2023.

Appendix Figure 2. Education level mismatch for workers aged 15–64 using normative and self-assessment approaches (percentages), by level of education, 2023



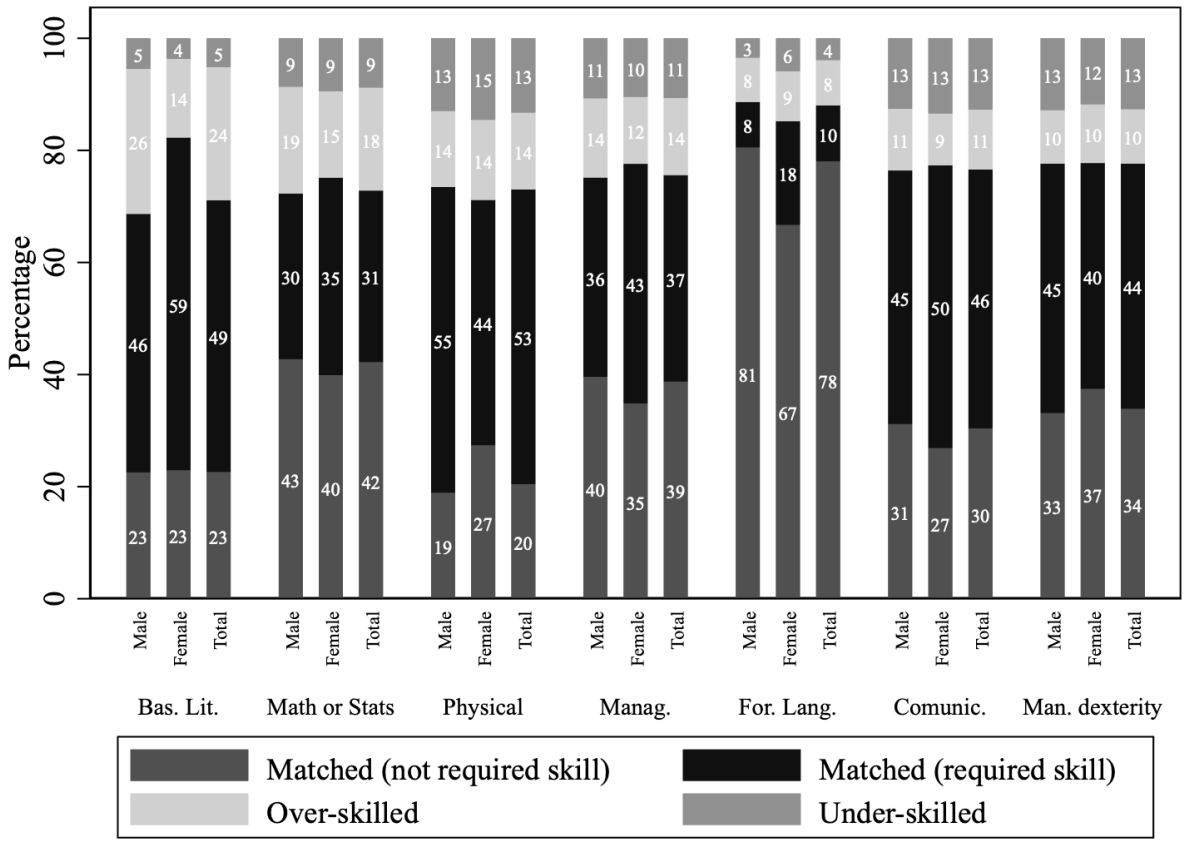
Source: Authors' calculations based on ELMPS 2023.

Appendix Figure 3. Education level mismatch for workers aged 15–64 (percentage), self-assessment approach, by level of education and sex, 2023



Source: Authors' calculations based on ELMPS 2023

Appendix Figure 4. Skill (mis)match for workers aged 15-64 (percentages), selected skills, by sex, 2023



Source: Authors' calculations based on ELMPS 2023.
Notes: An over-skilled person states that they have a strong or very strong level of a skill that is not required for their job, while an under-skilled person states that they have at most a weak level of a skill that is required for their job. Finally, a match occurs when the job requires a skill and the person has it at a strong or very strong level, or when the job does not require a skill, and the person has it in at most at a weak level.