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Ali Fakih Zeina Lizzaik

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Ali Fakih Lebanese American University and IZA

Zeina Lizzaik Concordia University

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9	Phone: +49-228-3894-0	
53113 Bonn, Germany	Email: publications@iza.org	www.iza.org

## ABSTRACT

# The Incidence and Wage Penalty of Overqualification: The Case of Egypt

The phenomenon of overqualification is becoming increasingly common across many countries. In this research study, the main objective is to examine factors that determine overgualification, the impact of overgualification on wages, and the earning differences between genders in the case of Egypt. We use a cross-sectional micro-level dataset taken from the Egyptian Labor Force Survey (LFS) conducted by the Economic Research Forum (ERF). We employ a probit model to capture factors determining overqualification. The empirical results reveal that different sociodemographic, economic sector, and job-related factors determine overqualification. Moreover, we apply different matching techniques, radius matching, nearest-neighbor matching, and a weighting method, inverse probability weighting (IPW) to estimate the causal impact of overgualification on wage earnings. The result shows that overqualification affects the hourly wage earnings negatively. For further investigation, we estimate our regression by gender. The coefficients are negative for both genders, with a higher magnitude among females, revealing that overqualified females face higher wage penalties than overqualified males. The paper provides policy recommendations for both the Egyptian educational system and the job market to mitigate overgualification in the country.

JEL Classification:	I21, J23, J31
Keywords:	overqualification, wage penalty, matching techniques, Egypt

**Corresponding author:** Ali Fakih Department of Economics Lebanese American University P.O. Box: 13-5053 Beirut Lebanon E-mail: afakih@lau.edu.lb

### 1. Introduction

In most economies, educational attainment is correlated with job performance, with workers believing that higher education levels will facilitate their job prospects. According to the Organization for Economic Co-operation and Development (OECD) indicators (2018), higher educational attainment is associated with favorable economic and social results. For instance, the more educated a person is, the higher the likelihood of being socially engaged, having greater employment rates, and receiving higher salaries. However, in recent decades, global competition and technological advancement have shifted this trend. Evidence shows that occupations cannot absorb the rising number of educated workers due to the increasing average educational attainment (Dolton and Silles, 2008). These result in overqualification, which occurs when an individual has more academic qualifications than the educational level required by their job.

The overqualification phenomenon is significantly increasing in most countries. That is, there has been a growing trend of workers having levels of education exceeding the levels required by their jobs. Most importantly, developed countries have witnessed a rise in overqualification rates. For instance, the proportion of overqualified individuals in the United States (US) is high, around 48 percent (Li et al., 2015). Additionally, the UK witnessed an increase in overqualification, reaching 16 percent among all employed individuals aged 16-64 years in 2017 and around 31 percent among graduates with a first degree (Office of National Statistics, 2019). Furthermore, according to the International Labour Organization (ILO) (2020), 28 percent of employed individuals are overqualified among 114 developed and developing countries, which validates that the actual global rate of overqualification is much higher.<sup>1</sup>

Overqualification may have a negative effect on the labor market, the production system, and workers. For instance, this phenomenon affects economic growth negatively since overqualification results in a loss of productivity and leads to a loss of opportunity cost (Pascual-Sáez and Lanza-Leon, 2022). From the workers' side, overqualified workers may experience lower job satisfaction, fewer career development opportunities, and reduced engagement in job activities (Turmo-Garuz et al., 2019) since they may not be challenged in the job and may feel unfulfilled with their qualifications not being fully utilized. Specifically, there is evidence that wage penalty

<sup>&</sup>lt;sup>1</sup> https://ilostat.ilo.org/258-million-workers-in-the-world-are-over-educated-for-their-jobs/

exists among overqualified workers, where certain individuals experience lower wages or earnings compared to others with the same qualifications for similar work (Cutillo and Di Pietro, 2006). Therefore, policymakers and researchers need to understand the causes and consequences of overqualification.

This paper examines the factors that determine overqualification and the wage penalty associated with overqualification in Egypt. A rich literature focuses on the determinants of overqualification, and its wage penalty across different countries. Specifically, in Egypt, various studies exist on education-job mismatch. However, to our knowledge, no empirical research has focused only on overqualification, its impact on wage penalty and the earning differences between genders in Egypt. We use the Egyptian Labor Force Survey (LFS) conducted by the Economic Research Forum (ERF, 2021). We apply a probit model to capture the determinants of overqualification. Moreover, the paper identifies the causal effect of being overqualified on wages. The study employs different matching techniques and a weighting method according to the propensity scores. We run our model by gender to see the differences in being overqualified on earnings between males and females. The main results show that different sociodemographic and job characteristics, as well as economic sectors, determine overqualification—furthermore, the incidence of overqualification results in a wage penalty with huge differences between genders.

The remainder of this paper is organized as follows. Section 2 introduces an overview of the related theoretical and empirical literature. In Section 3, we present the data used and the econometric methodologies. The empirical results are discussed in Section 4. Finally, in section 5, we make concluding remarks and provide some policies.

#### 2. Literature Review

In this section, we review the theoretical and empirical literature and discuss the determinants of overqualification and its impact on wage earnings.

## 2.1. Theoretical Consideration

Becker's theory of human capital (Becker, 1964) discusses certain types of human capital, including education and job-specific training, emphasizing their impacts on earnings, employment, and other economic variables. The theory assumes that individuals acquire human capital by investing in education to use it in the job market to increase their utility and wages. At the same time, firms are interested in utilizing workers' skills to achieve higher productivity. Thus, both sides are choosing their best options. Accordingly, overqualification arises from the lack of relevant skills that could have been acquired through relevant work experience rather than skills that could have been achieved through regular education, leading individuals to be responsible for this mismatch (supply-side). The theory explains overqualification as a temporary phenomenon since quick changes may appear, such as the individuals seek jobs that match their skills or the firm utilizes their workers' skills. Besides, Becker (1964) examines this mismatch without accounting for heterogeneous preferences. Finally, this theory suggests that individuals' productivity determines wages. Although overqualified individuals have higher education levels than required, they possess less of other required human capital such as job-specific training, resulting in wage penalty (McGuinness and Pouliakas, 2017).

The job competition model developed by Thurow (1975) stands in contrast to the human capital theory as it focuses on the demand side rather than the supply side. The theory organizes the labor market into two queues: employment opportunities and employees. Accordingly, jobs are arranged hierarchically based on the necessary education level for this job and other relevant job characteristics. On the other hand, workers' place in the queue is based on their educational attainment compared to other workers. This illustration shows that workers continuously compete for jobs, which will always require individuals to invest more in education. To elaborate, overqualification will become permanent if no new jobs are offered for highly skilled workers. Thus, this would explain why firms are responsible for this mismatch (demand-side). Finally, this theory assumes that all individuals have the same job preferences, and only one hierarchy can be applied to occupations. Finally, the model suggests that earnings depend on the job's characteristics.

Sattinger's (1993) assignment theory integrates elements of both the human capital theory and the job competition model. According to this theory, individuals are allocated to specific jobs based on their personal qualifications and the requirements of the job. First, they select a sector based on the individual's preferences regarding the job and wages. Second, individuals get assigned to a job based on their educational level and other personal characteristics such as skills and experience. Therefore, as the job allocation for individuals depends on a specific pattern, the distribution of workers is non-random. The nature of this phenomenon is either temporary, where a match can be achieved if individuals or firms make adjustments, or permanent, where individuals would be willing to remain employed in a job that requires less education as long as it maximizes wages and their utility. In this model, both individuals and job characteristics determine wages.

Spence (1973) proposed the screening theory (also known as signaling theory), in which education is viewed as a signal for employers to allocate labor due to the uncertainty that the employers face regarding the abilities and skills of job applicants. Accordingly, individuals should invest more in their education to secure a well-matched position. This means overqualified workers will be preferred over undereducated workers. Moving to Sicherman and Galor (1990), they developed the career/job mobility theory, where workers choose a job that requires less education than the level they have attained because they face difficulties signaling their skills and abilities or because they lack experience or specific skills required. Thus, overqualified individuals accepting these jobs will gain specific skills or experience, increasing their probability of getting a promotion in the future. This theory may explain why overqualification is seen more among younger individuals. It could be temporary or permanent depending on workers' ability to indicate their skills to employers or obtain firm-specific skills effectively. Accordingly, the theory places the burden of this mismatch on individuals by ignoring the role of job characteristics.

These theories are the main principles that explain the mismatch phenomena. The reality does not fully align with any of these models. However, according to McGuiness (2006), assignment theory offers a more accurate presentation of reality as it accounts for job characteristics, individual preferences, and competition between workers and firms.

## 2.2. Measurements of Overqualification

There has been a debate about the most reliable measuring technique since the emergence of the overqualification phenomenon. According to McGuinness (2006), there is no optimal way of measuring overqualification because it depends on the availability of data. Researchers use three alternative methodologies for measuring overqualification: workers' self-assessment, job analysis, and the realized match. Each method has its advantages and disadvantages; however, the measurement chosen is solely determined by the availability of data (Nieto and Ramos, 2017). First, self-assessment is a subjective method using answers to surveys to gather information from workers. It is done by asking individuals directly whether they believe they are overqualified, or indirectly questioning individuals about the level of education required by their job (Verhaest and Omey, 2006). Second, the job analysis is an objective method; it depends on a classification of occupations drawn by job experts. For instance, the experts developed a categorization system that shows the education level required for each occupation. Accordingly, if the level of education attained is greater than the education level required by the job, the individual will be classified as overqualified (Hartog, 2000). Third, the realized match is an objective method, as well as a statistical approach where the education received is compared to the most common education level for the job (Verdugo and Verdugo, 1989). For example, suppose the individual's educational level is higher than their occupation's mean years of education by one standard deviation. In that case, they will be classified as overqualified individuals.

## 2.3. Determinants of Overqualification

## Socio-Demographic Variables

Several research papers study the factors that determine overqualification in the labor market. Gender plays a role in determining overqualification. Rahim et al. (2021) aimed to investigate the determinants of overqualification and its effect on wages among young individuals in Malaysia. They found that female workers in the Malaysian labor market have a higher probability of being overqualified than male workers. They argued that women are at greater risk of unemployment, which could explain why they accept jobs requiring less education than their actual education attainment, which makes them overqualified. In addition, Pascual-Sáez and Lanza-Leon (2022) explained the gender gap in overqualification by suggesting that women have family and caregiving responsibilities that limit their mobility, leading to accepting jobs that do not match their high educational attainments. In contrast, other studies found that overqualification exists more among male workers. For instance, McGoldrick and Robst (1996), in their research about gender differences in overqualification, found that being a man increases the probability of being overqualified more than a woman by using the range measurement. Cutillo and Di Pietro (2006) found the same result and interpreted it as traditional societies pressure men more than women to get a job. In the context of Egypt, ElKhouly (2022) studied the determinants of educationoccupation mismatch and found that overqualification is more likely to exist among males than females.

Another variable that might impact the overqualification phenomenon is the worker's age. Pascual-Sáez and Lanza-Leon (2022) studied the effect of age on overgualification by dividing the sample into two groups: individuals aged below 30 and those above 30. In both samples, they concluded that a negative relationship exists between overqualification and an individual's age. That is, as the individual becomes older, they will have a lower probability of overqualification. In contrast, Morrar and Syed Zwick (2021) reached the opposite result that one's age positively influences overqualification. Moving to marital status, an individual's marital status might also affect overqualification. According to Rahim et al. (2021), single Malaysian individuals are more likely to be overqualified. However, in Palestine, married or ever married people have a higher probability of being overqualified compared to those who are never married (Morrar and Syed Zwick, 2021). Pascual-Sáez and Lanza-Leon (2022) only reached the same positive results among males in Spain. Furthermore, the phenomenon of overqualification might be affected by the individual's place of residence. Morrar and Syed Zwick (2021) argued that living in rural or camp areas in Palestine increases the probability of being overqualified compared to living in an urban area. Another study done in West Germany by Büchel and Battu (2003) argued that a positive correlation exists between married women living in rural areas and overqualification. Moreover, they controlled for commuting distance and claimed that married men living in rural areas are more likely to be overqualified. They argued that living in rural areas limits job opportunities, leading individuals to become overqualified.

#### Economic Activity

Few studies have included economic activity as a determinant of overqualification. In the case of Malaysia and Palestine, Rahim et al. (2021) and Morrar and Syed Zwick (2021) reached the same conclusion: individuals working in mining, manufacturing, services, and construction sectors have a higher likelihood of being overqualified than individuals working in agriculture-related activities. In his study, Morano (2014) examined the factors determining overqualification in the Italian labor market context. He suggested that overqualification varies across economic sectors in the labor market. He revealed that individuals working in the service sector have a higher probability of being overqualified than workers in the agricultural or industry sector. He explained this by the difference in the economic sector's nature and the skills required in each sector. Moving to Egypt, ElKhouly (2022) found that individuals working in industry, construction, and construction have a lower probability of facing a mismatch than those in the agriculture field.

## Job Characteristics

Different factors allow researchers to capture the impact of job characteristics on overqualification. For instance, being employed in the public sector, holding a part-time job, or having an employment contract may influence overqualification. Starting with the public sector, according to ElKhouly (2022), being employed in the public sector decreases the probability of being overqualified compared to working in the private sector. Similarly, Patrinos (1997) suggested that overqualified Greek workers have a lower probability of working in the public sector. Moving to part-time jobs, according to Turmo-Garuz et al. (2019), individuals holding part-time job are less likely to be overqualified compared to full-time workers. In the context of Palestine, qualification mismatch is higher among full-time workers (Morrar and Syed Zwick, 2021). However, Morano (2014) revealed that overqualification is higher among part-time workers. He explained the result by the fact that workers searching for part-time jobs are more limited in their search, which could result in being overqualified. Lastly, having a contract also influences overqualification. According to Albert et al. (2021), holding a permanent contract decreases the likelihood of being mismatched compared to not holding a contract. Specifically, Charalambidou and McIntosh (2021) found that a permanent contract is negatively associated with overqualification compared to a temporary contract.

### 2.3. Wage penalty of Overqualification

Many researchers have widely studied the effect of being overqualified on wages in the job market. Cutillo and Di Pietro (2006) presented a bivariate probit selectivity model and found that overqualified Italian graduates face wage penalty compared to matched counterparts. In addition, they reported that this penalty is higher when employing the double selectivity approach compared to the OLS approach. A recent study in Spain by Pascual-Sáez and Lanza-Leon (2022) examined the incidence of overqualification and its role on wages, focusing on differences between genders. Using different propensity score matching techniques, they found a rising trend in overqualification with significant differences between genders. Specifically, both overqualified men and women face wage penalty in Spain, while the negative impact on the annual average is higher among women. In China, Wu and Wang (2018) evaluated the effect of overqualification on wage earnings. They found that overqualified workers have a higher probability of facing wage penalty compared to well-matched individuals, especially among individuals with tertiary education. Besides, they reported that overqualified workers with high school education have no significant impact on their wages. Besides, they used other matching techniques and achieved the same results. Moving to Malaysia, Rahim et al. (2021) examined the incidence, determinants, and consequences of overqualification on young Malaysians. They suggested overqualification is higher in the Malaysian economy than other developing economies. Particularly, compared to matched ones, overqualified individuals are more likely to earn less by 21.3 percent. They achieved similar results after employing the Heckit sample correction method to control sample selection bias. Moving to Northern Ireland, McGuinness and Bennett (2007) used quantile regression techniques. It found that overqualified Northern Ireland male graduates with low to moderate levels of ability are more likely to earn less compared to well-matched graduates. They claimed that the wage penalty is higher among females regardless of their skill levels. Similarly, Morrar and Syed Zwick (2021) used the quantile regression as well as the OLS approach in the Palestinian context. They aimed to study the determinants of education-occupation mismatch and the wage effect in the Palestinian labor market, where they found that wage penalty is associated with overqualification.

## 3. Research Methodology

## 3.1. Case Selection

We chose Egypt as the focus of our study for several reasons. According to the World Bank, the current population of Egypt exceeds 107 million people<sup>2</sup>, with a significant rise in school and higher education enrollment over the last ten years. Thus, this country was chosen because of its extensive and complex educational system. It consists of primary, middle, secondary, vocational, and tertiary education.<sup>3</sup> Secondary education was the most frequent level of educational attainment among youth in 2018, accounting for 39 percent of individuals aged 15 to 34 (Amer and Atallah, 2019). Moreover, the share of individuals with no formal schooling decreased significantly from 1988 to 2018, reflecting improved access to schools over this period (Amer and Atallah, 2019). According to UNESCO reports, the number of Egyptians studying abroad has tripled in the last decades, reaching around 32,000 in 2017 compared to 12,300 in 2008.<sup>4</sup> Accordingly, these numbers indicate Egyptian educational enrollment trends, with more educational growth expected over the next ten years.

Although educational growth has improved in Egypt, labor force participation has declined with a higher drop between 2012 and 2018 among those aged 20-24 years and the most educated, particularly among females (Amer and Attallah, 2019). To elaborate, the Egyptian labor market faces two significant challenges in integrating new workers. First, the demographic structure in Egypt is characterized by a large youth population that puts pressure on the Egyptian labor market in both the public and private sectors. For instance, the youth population accounted for around a third of the total population in Egypt (31.2 percent) in 2018, reaching 27.6 million people (Amer and Attallah, 2019). Second, there is a mismatch between an individual's educational attainment and the labor market needs. For example, around 47.7 percent of young people work in jobs unrelated to their educational achievements (Metwally, 2020). Regarding wages in Egypt, the median monthly wages declined by 11 percent from 2012 to 2018, with Egypt being ranked 129 out of 156 countries when considering the gender wage gap, which is considered one of the highest gaps in the world (World Economic Forum, 2021). In conclusion, different indicators, such as the

<sup>&</sup>lt;sup>2</sup> <u>https://data.worldbank.org/indicator/SP.POP.TOTL?locations=EG</u>

<sup>&</sup>lt;sup>3</sup> https://www.scholaro.com/db/countries/egypt/education-system

<sup>&</sup>lt;sup>4</sup> https://monitor.icef.com/2019/05/growing-egyptian-demand-for-education-pressures-domestic-capacity/

steady rise in the number of graduates, high unemployment rates among graduates, employment in jobs that do not align with individuals' qualifications, and restricted labor market opportunities (Ghanaiem and Kamal Abdual Shafy, 2021), show the existence of overqualification in Egypt making it essential to study its determinants and its effect on wages.

### **3.2. Data**

The data used in this paper is taken from the Economic Research Forum (ERF). We use the Egyptian Labor Force Survey (LFS) (2021). The dataset is a cross-sectional micro-level dataset that consists of several questions. The survey aims to gather useful information about the Egyptian labor market by interviewing individuals face-to-face. It includes socio-demographic factors, labor force status, employment status, type of industry, occupation, sector of activity, and wages. The survey utilizes standard definitions developed by the International Labour Organization (ILO). It is conducted on a random sample and generates a dataset of 98 variables. Our study restricts the sample to employed individuals since the overqualification variable arises from the person's employment status and educational attainment.

## 3.3. Variables

#### Dependent Variables

In the first part of the paper, where we aim to study the determinants of overqualification, the dependent variable is a binary variable that equals 1 if the respondent is considered overqualified and 0 if the respondent is well-matched. We apply the objective method, job analyst, which is in our case, a normative measure that is based on the International Standard Classification of Occupations (ISCO) to measure overqualification among individuals since the survey uses the standard definitions of ILO. This measure divides eight occupations into four broad groups. Each group's education level is assigned based on the International Standard Classification of Education (ISCED). Accordingly, overqualification will appear when the individual's level of education exceeds the educational level required by the particular job, while well-matched will appear when the individual has exactly the assigned level of education.

In the second part of this study, where we aim to examine the effect of overqualification on wages, we computed the natural logarithm of the hourly wage, which is determined as the total monthly

wage divided by the number of hours worked in that period. Hence, the dependent variable, hourly wage, is continuous.

#### Independent Variables

We divided our independent variables into three different categories to study whether they determine overqualification. The first category includes the socio-demographic factors, gender, age, marital status, and place of residency. The variable gender is a dummy variable that takes that value of one if the individual is male and 0 otherwise. To control age, we take this variable as a continuous variable. Marital status is a categorical variable that includes never married, married, or other (divorced, separated, or widowed), with never married being the reference group. Also, we included the place of residency as a binary variable that equals one if the respondent lives in a rural area and zero otherwise. The second category includes categorical variables of the economic sector: manufacturing, construction, services, commerce, and transportation, with agriculture and mining as the reference group. Lastly, the third category contains job-related variables, all taken as dummy variables. They are represented as follows: public sector (is equal to 1 if the worker works in a public sector and 0 otherwise), part-time job (equals 1 if the respondent works in a part-time job and zero otherwise), contract (takes the value of 1 if the respondent has a permanent contact and 0 if not).

#### **3.4. Descriptive Statistics**

Table 1 shows the summary statistics of the variables. The number of observations is 15,151 and 11,716 for overqualified and well-matched individuals, respectively. We can observe that overqualified individuals have lower wages compared to their well-matched individuals. We find that 89.8 percent of overqualified individuals are males, and 62.9 percent of well-educated individuals are males. Moreover, overqualified workers have an average of 37 years old, while well-matched workers have an average age of 40 years old. The statistics reveal that most of the surveyed overqualified workers are married, 70 percent, followed by never married workers, 25.5 percent. As for the employment sector, most well-matched workers work in the services sector, while most of the overqualified individuals work in the commerce and transportation sector. Regarding job-related variables, few individuals, whether overqualified or well-matched, work in the public sector, and a low percentage of employed individuals work part-time. When it comes to

contracts, statistics show that 86 percent of well-matched individuals have permanent contracts while only 41.4 percent of overqualified workers have a permanent contract.

#### **3.5.** Collinearity Test

The existence of a correlation between independent variables creates a problem because it increases the variance of the regression coefficients. This, in turn, results in inaccurate statistical significance across variables. Therefore, it is essential to conduct a test to identify collinearity problems. In this study, we conduct the commonly used test, the Variance Inflator Factor (VIF). Hair et al. (1995) recommend a VIF level not exceeding 10, or it will be difficult to accurately assess these variables' contribution in predicting the dependent variable. Table 2 shows that all VIF values are below 10 except for the variable age. The variable services sector also has a high VIF value. Since these are the only two variables with high VIF values, they may be correlated but not with other independent variables. To ensure this is the case in our study, we dropped these two variables and ran the regression again to conclude that no significant changes occurred. In addition, the VIF mean is less than 10, implying that we do not have a multicollinearity problem among the independent variables.

#### **3.6. Econometric Model**

First, this study aims to examine the determinants of overqualification in Egypt. The model carried out to estimate the empirical results is the Probit model since the dependent variable is a dummy variable, and the data is qualitative.

$$Overeducation_{i} = \beta_{1}X_{i} + \beta_{2}Y_{i} + \beta_{3}Z_{i} + u_{i}$$

$$i = \{1, 2, \dots, N\}$$

Where N represents the number of observations, which is 26,867. *Overeducation*<sub>i</sub> is the dependent variable,  $X_i$  is the first set that corresponds to the Sociodemographic factors (gender, age, marital status, and place of residency),  $Y_i$  refers to the employment sectors (manufacturing, construction, services, commerce, transportation, and agriculture). The third set,  $Z_i$ , includes the job-related characteristics (public sector, part-time job, and contract). The error term that follows a normal distribution is represented by  $u_i$ .  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are the perimeters to be estimated. We run three different models to capture the independent variables' effect accurately. The first model

includes the sociodemographic variables, the second model adds to the first economic sectors, and the third combines the previous model with the job-related characteristics.

Second, we use different matching techniques and a weighting method to study the impact of overqualification on wages. We chose these techniques for reducing bias in treatment effects. The matching approach compares the wages between overqualified and well-matched individuals while controlling other observable characteristics. These techniques split the sample into treatment group, overqualified people, and control group, well-matched individuals. Accordingly, we used two techniques: radius matching and nearest-neighbor matching. The main reason for applying different matching techniques is to check for robustness. The first matching approach is radius matching in which each treatment observation is matched with control individuals with a certain radius (r) or range of the propensity score. The second matching technique, nearest-neighbor matching, takes each treatment observation and matches it to the most similar control observations based on the propensity score. After the matching is achieved, the average treatment effect is calculated by taking the average difference between the outcomes of both the observations of the treated and their matched control. The last method is inverse probability weighting (IPW), which assigns weights to each individual in the study based on the inverse probability of receiving the treatment they actually got rather than directly matching individuals from treatment and control groups.

#### 4. Empirical Results

This section is divided into three parts. The first part shows and discusses the results of the probit model for the determinants of overqualification. The second part discusses the different techniques' estimates of overqualification on wage earnings. The third part discusses the estimates of overqualification on wage earnings by dividing by gender.

## 4.1 Determinants of Overqualification

Table 3 presents the estimated marginal effects of the determinants of overqualification. Column (1) shows the impact of the socio-demographic factors. Column (2) presents the results while adding the economic sector variables, and Column (3), the full model, provides results including the job-related characteristics. Starting with the sociodemographic factors, the findings reveal that

being male increases the probability of being overqualified in Egypt. This result is statistically significant in all models. This finding is in line with McGoldrick and Robst (1996) and Cutillo and Di Pietro (2006), who found that being male increases the probability of being overqualified compared to female counterparts. However, this finding opposes the results of Rahim et al. (2021) and Pascual-Sáez and Lanza-Leon (2022), who found a positive relationship between being a female and overqualification as some restrictions and unemployment risks may drive them to accept jobs that require less education. One might argue that in traditional societies, men may face higher pressures than women to obtain employment, resulting in getting jobs for which they are considered overqualified (Cutillo and Di Pietro, 2006).

Moving to the age variable, it is shown that as an individual ages, overqualification decreases. In other words, the probability of being overqualified decreases as the worker's age increases. In all models, the coefficients are statistically significant; however, the impact is weak, standing at only 0.2 percent. This result is consistent with the finding of Pascual-Sáez and Lanza-Leon (2022) and contradicts that of Morrar and Syed Zwick (2021) in Palestine. Various labor market theories can interpret our results. The labor market theories suggest that job matching improves over time (McGuinness and Wooden, 2009). Furthermore, young individuals with additional education and zero experience have a higher likelihood of being overqualified because the additional years of education can balance out the lack of experience at the start of a career, resulting in more overqualification in younger ages (Sicherman and Galor, 1990). Lastly, the career mobility theories present overqualification as an optimal strategy at the early stages since an overqualified person integrating newly into the labor market would acquire skills that will increase the likelihood of getting a promotion and thus decreasing this phenomenon in the long term (Leuven and Oosterbeek, 2011).

As for marital status, the results suggest that married or ever married individuals increase the likelihood of being overqualified compared to those who have never been married. The coefficient is statistically significant in the second and last models. These results align with that reported by Morrar and Syed Zwick (2021) and partially with Pascual-Sáez and Lanza-Leon (2022), who reached the finding that overqualification increases among married people and men married individuals, respectively. The intuition behind these two findings is that married cohorts have more family responsibilities, increasing their pressure to find a job regardless of their qualification

mismatch (ElKhouly, 2022). Regarding the place of residence, our results suggest that residing in a rural area increases the likelihood of being overqualified. This aligns with the study of Büchel and Battu (2003), who demonstrated that place of residency, rural area, positively impacts the likelihood of being overqualified. This finding may be attributed to the fact that rural areas and the costs of traveling to urban areas daily may limit job opportunities available for individuals, resulting in accepting jobs of lower educational achievement (Büchel and Battu, 2003).

Moving to the economic sectors, individuals working in the manufacturing sector increase the likelihood of being overqualified. This result is statistically significant only in the full model. This finding is aligned with Rahim et al. (2021) and Morrar and Syed Zwick (2021) in Malaysia and Palestine. Regarding the other sectors, we achieved negative results for both the construction and services sectors. This means that working in these sectors decreases the probability of overqualification compared to working in the agriculture and mining sectors. These findings are aligned with the study of ElKhouly (2022) in Egypt, which found that individuals in the fields of industry, construction, and services are less likely to be overqualified. Finally, the results were insignificant for the commerce and transportation sectors in both the second and last models.

Regarding the job-related characteristics variables, our findings reveal that being employed in the public sector increases the probability of overqualification by 10.6 percent. The result is statistically significant. This contradicts the effect of Patrinos (1997) in Greece, who suggested that overqualified is less likely to occur in public sectors. One possible explanation for our result is that the public sector might offer more stable employment opportunities with many benefits, encouraging individuals to invest more in education to get accepted or hired. Thus, the competition presented in this sector would increase overqualification in Arab countries (Alattas, 2023). As for part-time jobs, our result suggests that part-time workers have a higher probability of being overqualified by 5.4 percent, with the coefficient being statistically significant. One might argue that part-time individuals are more limited in their search to get a part-time compared to those seeking full-time work. Thus, they may be more willing to accept a position requiring less education as long as it is a part-time job, resulting in overqualification in this sector (Morano, 2014). Moving to the contract variable, individuals with contracts are less likely to be overqualified by 37.1 percent, with the result being statistically significant. This finding is aligned with Albert et al. (2021) and Charalambidou and McIntosh (2021), who suggested that contracts negatively

impact overqualification. The intuition could be that jobs that provide contracts for workers include a clear job requirement; for instance, the qualifications needed would be clearly stated, and accordingly, well-matched individuals are more likely to get this offer. This will decrease the possibility of being overqualified in jobs that offer a contract.

## 4.2 Effect of Overqualification on Wages

We test the causal effect of overqualification on the wages of individuals in Egypt. Table 4 reports the results of the average treatment effect on the treated. All columns are for the full sample, with Column (1) reporting the results using the radius matching technique, Column (2) showing the findings using the nearest-neighbor matching technique, and Column (3) presenting the output using the IPW technique. All models show a negative effect of overqualification on an individual's wage earnings. Looking at the radius technique, the average hourly wage earnings for overqualified individuals is around 18 percent less than that for well-matched individuals. The second method, nearest-neighbor matching, shows that the hourly wage earning for overqualified people is less than that of well-matched individuals by 18.4 percent. The last method, the IPW technique, reveals that overqualification leads to a wage penalty of around 16.8 percent. The results for the three methods are similar, all being statistically significant at a 1 percent significance level. Thus, we find that overqualification is associated with a substantial wage penalty in Egypt. This means that overqualified individuals are paid less than their true worth. In other words, if matched with jobs that require the same level of education they attained, they would be earning more. This finding comes in line with previous theoretical and empirical studies (Wu and Wang, 2018; Rahim et al., 2021; Pascual-Sáez and Lanza-Leon, 2022). Compared to other countries, the results are pretty similar. For instance, in Malaysia, overqualified individuals have a higher probability of earning less compared to well-matched respondents by 21.3 percent. Furthermore, the difference in wage penalty between overqualified males and overqualified females is reported in Table 5. We use radius matching techniques to analyze the gap between genders. The results reveal that overqualified women face a wage penalty of 27.3 percent, while overqualified men face a wage penalty of 16.6 percent. The results are statistically significant. The difference in the average wage earnings shows that women face wage penalty more than overqualified men by around 10 percent. This particular result could explain that although all overqualified individuals face wage penalty, overqualified women are more disadvantaged than men when it comes to wage earnings. This result is consistent with McGuinness and Bennett (2007), who suggested that wage penalty is

higher among females when divided by gender. Our results show that gender bias also exists between overqualified individuals in the Egyptian labor market. That is, overqualified women face a penalty in wage earnings, first for being female and second for being overqualified.

#### 4.3 Results by Economic Sectors

Table 6 represents the impact of being overqualified on wage earnings when dividing by economic sectors: manufacturing, construction, services, commerce and transportation, and agriculture and mining. The findings reveal that overeducation generally leads to lower wage earnings across different sectors. The negative effects are most pronounced and significant in the services, manufacturing, and commerce and transportation sectors. The results indicate that being overqualified in the manufacturing sector is associated with a statistically significant decrease in wage earnings by 15.6 percent. In the construction sector, overeducation is associated with a decrease in wage earnings by 3.2 percent. However, this effect is not statistically significant. For the services sector, the impact of overqualification on wage earnings is highly significant and negative, with overqualified individuals earning 23.5 percent less than their adequately educated counterparts. Moving to the commerce and transportation sector, being overqualified results in a significant wage penalty of 13.6 percent. This indicates that overeducation adversely affects earnings in this sector, although to a lesser extent than in the services sector. Lastly, the agriculture and mining sector shows a decrease in wage earnings that is not statistically significant, suggesting that overeducation does not have a notable impact on wages in this sector.

#### **5.** Conclusion

There has been a rapid spread of the phenomenon of overqualification across many countries. Accordingly, it may have a range of adverse effects, with one of the significant impacts on the wage earnings of individuals. Thus, this paper aims to address factors determining overqualification, the impact of overqualification on wage earnings, and the difference in wage penalty between genders in the case of a developing country, Egypt. We used the Egyptian Labor Force Survey (LFS) conducted by the Economic Research Forum (ERF) to conduct this empirical study. First, we apply a probit model and reveal that sociodemographic variables play a role in determining overqualification. That is, being male, married, having ever been married, or residing in a rural area increases the probability of being overqualified, while as individuals age, the probability of being overqualified decreases. Besides, the economic sectors also determine overqualification, with individuals in the manufacturing sector being more likely to be overqualified compared to other sectors. Furthermore, the job-related characteristics determine overqualification, highlighting overqualification exists more among individuals employed in the public sector or have part-time job and less among those with a job contract. After revealing the factors determining overqualification in Egypt, we employ different matching techniques and a weighting method to identify the causal effect of overqualified overqualification on wage earnings and the earning differences between genders. The results reveal that the incidence of overqualification leads to a wage penalty. Specifically, when dividing by gender, the results reveal that overqualified females face higher wage penalty than their overqualified male counterparts in Egypt.

This empirical study formulates several policies for the educational system and labor market institutions to enhance labor market efficiency and to narrow the gap between attained education and education required by a specific job. First, the educational system should be restructured by developing hybrid curricula that blend theoretical knowledge with practical skills, enabling students to acquire skills to adapt to the labor market requirements (Ma, 2022). Second, the government should strengthen the vocational education and entrepreneurial system, which will allow students to consider those different paths they can enroll in instead of only investing in traditional education, increasing the presence of overqualification (Morrar and Syed Zwick, 2021). Thus, this range of options will allow them to pursue a career aligned with their interests, reducing the risk of education being an unreasonable allocation, thus reducing Egypt's overqualification phenomenon. In addition, career guidance campaigns should be established in schools and universities to provide accurate information and increase awareness of market needs in the country. Accordingly, students would have a broader vision of the available career options and the requirements for each job, allowing them to take the proper steps for their future career, that is, focusing on relevant training to improve their skills to meet the job requirements and avoiding unnecessary more levels of education (ElKhouly, 2022).

From the labor market side, the government could promote or facilitate the creation of new companies that would attract highly educated individuals, which would result in the growth of a high-tech economy on one side and reduce overqualification on the other (Nieto and Ramos, 2017).

It is essential to conduct thorough assessments of the labor market to identify skill gaps and the mismatch between the educational system and industry requirements. Moreover, it is crucial to support collaboration between educational institutions and available industries in the country to guarantee that the curricula match the needs of the current and future endeavors. Regarding the wage penalty, the government should introduce a legal provision that guarantees pay equity between genders. Individuals with the same qualifications and equal work value should be paid the same. Lastly, more independent variables could be included in this empirical study. For instance, if it is added, an individual's skills in their current job could reduce the wage penalty associated with overqualification. In terms of possible directions for future research, this paper could be further extended if further data is collected for variables that could be used as new measures for overqualification, such as years of schooling and years of required schooling, or variables that would directly ask individuals whether they consider themselves overqualified or not. While this paper has employed several matching techniques and a weighting method to determine the causal effects of overqualification on wage earnings of genders, it is crucial to recognize the potential of other methodologies that have not been fully investigated in our paper. Specifically, different matching techniques such as Coarsened Exact Matching (CEM) and Entropy Matching, which have not been widely utilized in studies on overqualification, could offer more insights. Future research could benefit from incorporating these methods to possibly uncover more profound, more nuanced understandings of the dynamics of overqualification and its impact on the labor market. Additionally, if a variable regarding job satisfaction is added in the future, the study could be extended by studying the impact of wage penalty faced by overqualified individuals on their job satisfaction.

## References

Alattas, H. (2023). Overqualification in Arab Labour Markets; Different Measures, Different Outcomes. *European Journal of Sustainable Development*, 12(1), 91-91.

Albert, C., Davia, M. A., & Legazpe, N. (2023). Educational mismatch in recent university graduates. The role of labour mobility. *Journal of Youth Studies*, 26(1), 113-135.

Amer, M., & Atallah, M. (2019). The school to work transition and youth economic vulnerability in Egypt. *Economic Research Forum (ERF)*.

Becker, G. (1964). Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education. *University of Chicago Press*.

Büchel, F. & Battu, H. (2003) The theory of differential overqualification: does it work?, Scottish

Journal of Political Economy, 50, 1–16.

Charalambidou, C., & McIntosh, S. (2021). Over-education in Cyprus: Micro and macro determinants, persistence and state dependence. A dynamic panel analysis. *The Manchester School*, 89(2), 172-189.

Chevalier, A. (2003). Measuring over-education. *Economica*, 70(279), 509-531.

Cutillo, A., & Di Pietro, G. (2006). The effects of overqualification on wages in Italy: a bivariate selectivity approach. *International Journal of Manpower*.

Diem, A., & Wolter, S. C. (2014). Overqualification among Swiss university graduates: determinants and consequences. *Journal for Labour Market Research*, 47(4), 313-328.

Dolton, P. J., & Silles, M. A. (2008). The effects of over-education on earnings in the graduate labour market. *Economics of Education Review*, 27(2), 125-139.

ElKhouly, N. (2022). Education-Occupation Mismatch among University Graduates in Egypt: Determinants and Consequences.

Ghanaiem, M., & Kamal Abdual Shafy, H. (2021). Overqualification in Egypt and its Impact on Labour Market and Unemployment, Higher Education (Case Study). *Sohag University International Journal of Educational Research*, 4(4), 27-35.

Groot, W., & Van Den Brink, H. M. (2000). Overqualification in the labor market: a metaanalysis. *Economics of education review*, 19(2), 149-158.

Hartog, J. (2000). Over-education and earnings: where are we, where should we go?. *Economics of education review*, 19(2), 131-147.

Leuven, E., & Oosterbeek, H. (2011). Overqualification and mismatch in the labor market. *Handbook of the Economics of Education*, *4*, 283-326.

Li, I., Malvin, M., & Simonson, R. D. (2015). Overqualification and employment mismatch: Wage penalties for college degrees in business. *Journal of Education for Business*, 90(3), 119-125.

Ma, W., Baek, J., Qi, M., Li, J., & Liu, B. (2022). The Influence of Overqualification on Chinese Workers' Job Satisfaction from China Household Tracking Survey (2014–2018). *International Journal of Environmental Research and Public Health*, 19(23), 16032.

Morano, C. P. (2014). The determinants of overqualification: Evidence from the Italian labour market. *Investigaciones de Economía de la Educación*, 9, 681-698.

McGoldrick, K., & Robst, J. (1996). Gender differences in overqualification: A test of the theory of differential overqualification. *The American Economic Review*, 86(2), 280-284.

McGuinness, S. (2006). Overqualification in the labour market. *Journal of economic surveys*, 20(3), 387-418.

McGuinness, S., & Bennett, J. (2007). Overqualification in the graduate labour market: A quantile regression approach. *Economics of Education Review*, 26(5), 521-531.

McGuinness, S., & Wooden, M. (2009). Overskilling, job insecurity, and career mobility. *Industrial relations: a journal of economy and society*, 48(2), 265-286.

McGuinness, S., & Pouliakas, K. (2017). Deconstructing Theories of Overqualification in Europe: A Wage Decomposition Approach☆. In Skill mismatch in labor markets (Vol. 45, pp. 81-127). *Emerald Publishing Limited*.

Metwally, S. (2020). Young Workers and the Labor Market in Egypt: Persistent Inequality. Alternative Policy Solution. Retrieved from: <u>Alternative Policy Solutions | Young Workers and the Labor Market in Egypt: Persistent Inequality (aucegypt.edu)</u>

Morrar, R., & Syed Zwick, H. (2021). Determinants and wage penalty of qualification mismatches: the case of Palestine. *Journal of Education and Work*, 34(4), 504-517.

Nieto, S., & Ramos, R. (2017). Overqualification, skills and wage penalty: Evidence for Spain using PIAAC data. *Social Indicators Research*, 134, 219-236.

OECD (2018), Education at a Glance 2018: OECD Indicators, OECD Publishing, Paris, https://doi.org/10.1787/eag-2018-en.

Office for National Statistics. 2019. Overqualification and hourly wages in the UK labour market;2006to2017.Retrievedfrom:https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/compendium/economicreview/april2019/overqualificationandhourlywagesintheuklabourmarket2006to2017

Overqualification and hourly wages in the UK labour market; 2006 to 2017, *Office for National Statistics*, April 2019

Pascual-Sáez, M., & Lanza-Leon, P. (2022). The mismatch of over-education and earnings in Spain: how big are differences?. *Applied Economics*, 1-15.

Patrinos, H. A. (1997). Overqualification in Greece. *International Review of Education*, 43, 203-223.

Rahim, M. A. R. A., Wahab, D. A., & Jani, R. Over-education and its Effect on Wages Among Young Malaysians.

Sattinger, M. (1993). Assignment models of the distribution of earnings. *Journal of Economic Literature*, 31(2), 831-880.

Sicherman, N., & Galor, O. (1990). A theory of career mobility. *Journal of Political Economy*, 98(1), 169-192.

Spence, M. (1978). Job market signaling. In Uncertainty in economics (pp. 281-306). Academic Press.

Thurow, L. C. (1975). Generating inequality: mechanisms of distribution in the U.S. economy. *Basic Books: New York.* 

Turmo-Garuz, J., Bartual-Figueras, M. T., & Sierra-Martinez, F. J. (2019). Factors associated with overqualification among recent graduates during labour market integration: The case of Catalonia (Spain). *Social Indicators Research*, *144*, 1273-1301.

Verdugo, R. R., & Verdugo, N. T. (1989). The impact of surplus schooling on earnings: Some additional findings. *Journal of human resources*, 629-643.

Verhaest, D., & Omey, E. (2006). The impact of overqualification and its measurement. *Social Indicators Research*, 77, 419-448.

World Economic Forum. (2021). Global Gender Gap Report 2021. Retrieved from: <u>https://www3.weforum.org/docs/WEF GGGR 2021.pdf</u>

Wu, N., & Wang, Q. (2018). Wage penalty of overqualification: New micro-evidence from China. *China Economic Review*, 50, 206-217.

	Overqua	lified	Well Matched	
	N=15,15	1	N=11,716	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variable				
Wage	2.667	0.55	2.963	0.638
Socio-Demographic Variables				
Gender	0.898	0.303	0.629	0.483
Age	36.964	11.042	40.365	10.531
Married	0.709	0.454	0.766	0.424
Other	0.036	0.186	0.049	0.215
Never married	0.255	0.436	0.186	0.389
Rural	0.541	0.498	0.431	0.495
Economic Sector				
Manufacturing	0.212	0.408	0.065	0.247
Construction	0.066	0.249	0.04	0.195
Services	0.308	0.461	0.781	0.414
Commerce and Transportation	0.373	0.484	0.103	0.303
Agriculture and Mining	0.041	0.199	0.012	0.109
Job-Related Variables				
Public Sector	0.045	0.207	0.038	0.191
Part-Time Employment	0.136	0.343	0.048	0.213
Contract	0.414	0.493	0.861	0.346

 Table 1. Descriptive Statistics of variables used in the analysis

	VIF	Tolerance
Gender	5.48	0.182478
Age	19.24	0.051962
Married	6.09	0.164224
Other	1.38	0.723190
Rural	1.90	0.526597
Manufacturing	2.79	0.358153
Construction	1.70	0.589014
Services	8.16	0.122577
Commerce and Transportation	4.05	0.247004
Public Sector	1.09	0.920609
Part-time Job	1.18	0.849329
Contract	3.94	0.253981
Mean VIF	4.75	

Table 2. Variance Inflation Factor

Gender (Male=1) $0.392^{***}$ $0.247^{***}$ $0.227^{***}$ $(0.007)$ $(0.009)$ $(0.009)$ Age (years) $-0.007^{***}$ $-0.002^{***}$ $(0.000)$ $(0.000)$ $(0.000)$ Marital Status $(0.000)$ $(0.000)$ Married $0.017^*$ $0.031^{***}$ $(0.010)$ $(0.011)$ $(0.011)$ Ever Married $0.176^{***}$ $0.167^{***}$ $(0.017)$ $(0.018)$ $(0.018)$ Rural Area $0.079^{***}$ $0.123^{***}$ $(base=Agriculture and Mining)$ $(0.007)$ $(0.007)$ Manufacturing $-0.001$ $0.066^{***}$ $(0.023)$ $(0.024)$ Construction $-0.183^{***}$ $-0.173^{***}$ $(0.025)$ $(0.027)$ Services $-0.416^{***}$ $-0.284^{***}$ $(0.019)$ $(0.022)$ $(0.023)$		(1)	(2)	(3)
(0.007)         (0.009)         (0.009)           Age (years)         -0.007***         -0.002***         -0.002***           (0.000)         (0.000)         (0.000)         (0.000)           Marital Status         (base=Never Married)	Socio-Demographic Variables			
Age (years) $-0.007^{***}$ $-0.002^{***}$ $-0.002^{***}$ (0.000)       (0.000)       (0.000)         Marital Status       (0.000)       (0.000)         (base=Never Married)       0.017* $0.031^{***}$ $0.067^{***}$ Married $0.017^*$ $0.031^{***}$ $0.067^{***}$ (0.010)       (0.011)       (0.011)         Ever Married $0.176^{***}$ $0.167^{***}$ $0.161^{***}$ (0.017)       (0.018)       (0.018)         Rural Area $0.079^{***}$ $0.123^{***}$ $0.122^{***}$ (base=Agriculture and Mining) $0.007$ (0.007)       (0.007)         Manufacturing $-0.001$ $0.066^{***}$ (base=Agriculture and Mining) $0.023$ (0.024)         Construction $-0.183^{***}$ $-0.173^{***}$ (0.025)       (0.027)       (0.027)         Services $-0.416^{***}$ $-0.284^{***}$ (0.019)       (0.022)       (0.023)         Commerce and Transportation $0.035$ 0.017         (base]       Use the sector $0.106^{***}$ Public Sector $0.106^{***}$ <td< td=""><td>Gender (Male=1)</td><td>0.392***</td><td>0.247***</td><td>0.227***</td></td<>	Gender (Male=1)	0.392***	0.247***	0.227***
(0.000)         (0.000)         (0.000)           Marital Status         (base=Never Married)		(0.007)	(0.009)	(0.009)
Marital Status         (base=Never Married)         Married       0.017*       0.031***       0.067***         (0.010)       (0.011)       (0.011)         Ever Married       0.176***       0.167***       0.161***         (0.017)       (0.018)       (0.018)         Rural Area       0.079***       0.123***       0.122***         (0.007)       (0.007)       (0.007)       (0.007)         Economic Sectors Variables       (0.007)       (0.007)       (0.007)         Kanua facturing       -0.001       0.066***       (0.023)       (0.024)         Manufacturing       -0.0183***       -0.173***       (0.025)       (0.027)         Services       -0.416***       -0.284***       (0.029)       (0.022)         Services       -0.416***       -0.284***       (0.021)       (0.022)       (0.023)         Services       -0.416***       -0.284***       (0.012)       (0.023)       (0.021)       (0.021)       (0.022)       (0.023)       (0.021)       (0.021)       (0.022)       (0.023)       (0.021)       (0.021)       (0.021)       (0.021)       (0.021)       (0.021)       (0.021)       (0.016)       (0.016)       (0.016)       (0.016)       (	Age (years)	-0.007***	-0.002***	-0.002***
(base=Never Married)       0.017*       0.031***       0.067***         Married       0.010)       (0.011)       (0.011)         Ever Married       0.176***       0.167***       0.161***         (0.017)       (0.018)       (0.018)         Rural Area       0.079***       0.123***       0.122***         (0.007)       (0.007)       (0.007)       (0.007) <i>Economic Sectors Variables</i> (0.007)       (0.007)       (0.007)         Manufacturing       -0.001       0.066***       (0.023)       (0.024)         Construction       -0.183***       -0.173***       (0.025)       (0.027)         Services       -0.416***       -0.284***       (0.019)       (0.022)         Commerce and Transportation       0.035       0.017       (0.023)       (0.023) <i>Job-Related Variables</i> (0.016)       (0.016)       (0.016)         Public Sector       0.106***       (0.016)       (0.016)         Part-time Job       0.054***       (0.013)       (0.013)		(0.000)	(0.000)	(0.000)
Married       0.017*       0.031***       0.067***         (0.010)       (0.011)       (0.011)         Ever Married       0.176***       0.167***       0.161***         (0.017)       (0.018)       (0.018)         Rural Area       0.079***       0.123***       0.122***         (0.007)       (0.007)       (0.007)       0.007)         Economic Sectors Variables       (0.007)       (0.007)       (0.007)         Karal Area       0.007)       (0.007)       (0.007)         Manufacturing       -0.001       0.066***       (0.023)       (0.024)         Construction       -0.183***       -0.173***       (0.025)       (0.027)         Services       -0.416***       -0.284***       (0.019)       (0.022)         Commerce and Transportation       0.035       0.017       (0.022)       (0.023)         Job-Related Variables       (0.016)       (0.016)       (0.016)       (0.016)         Part-time Job       0.054***       (0.013)       (0.013)	Marital Status			
(0.010)         (0.011)         (0.011)           Ever Married         0.176***         0.167***         0.161***           (0.017)         (0.018)         (0.018)           Rural Area         0.079***         0.123***         0.122***           (0.007)         (0.007)         (0.007)         (0.007)           Economic Sectors Variables         (0.007)         (0.007)         (0.007)           Kase=Agriculture and Mining)         -0.001         0.066***         (0.023)         (0.024)           Manufacturing         -0.0183***         -0.173***         (0.025)         (0.027)           Construction         -0.416***         -0.284***         (0.022)         (0.023)           Services         -0.416***         -0.284***         (0.025)         (0.023)           Commerce and Transportation         0.035         0.017         (0.022)         (0.023)           De-Related Variables	(base=Never Married)			
Ever Married         0.176***         0.167***         0.161***           (0.017)         (0.018)         (0.018)           Rural Area         0.079***         0.123***         0.122***           (0.007)         (0.007)         (0.007)         0.007)           Economic Sectors Variables         Use=         Value         Value <t< td=""><td>Married</td><td>0.017*</td><td>0.031***</td><td>0.067***</td></t<>	Married	0.017*	0.031***	0.067***
(0.017)         (0.018)         (0.018)           Rural Area         0.079***         0.123***         0.122***           (0.007)         (0.007)         (0.007)         (0.007)           Economic Sectors Variables         (0.007)         (0.007)         (0.007)           Kase=Agriculture and Mining)         -0.001         0.066***         (0.023)         (0.024)           Manufacturing         -0.183***         -0.173***         (0.025)         (0.027)           Construction         -0.416***         -0.284***         (0.022)         (0.022)           Services         -0.416***         -0.284***         (0.022)         (0.023)           Commerce and Transportation         0.035         0.017         (0.022)         (0.023)           Job-Related Variables         -         (0.016)         (0.016)           Public Sector         0.054***         (0.016)           Part-time Job         0.054***         (0.013)		(0.010)	(0.011)	(0.011)
Rural Area       0.079***       0.123***       0.122***         (0.007)       (0.007)       (0.007)         Economic Sectors Variables       (0.007)       (0.007)         (base=Agriculture and Mining)       -0.001       0.066***         Manufacturing       -0.001       0.066***         (0.023)       (0.024)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)       (0.023)         Job-Related Variables       (0.016)       (0.016)         Public Sector       0.106***       (0.016)         Part-time Job       0.054***       (0.013)	Ever Married	0.176***	0.167***	0.161***
(0.007)       (0.007)       (0.007)         Economic Sectors Variables           (base=Agriculture and Mining)       -0.001       0.066***         Manufacturing       -0.001       0.066***         (0.023)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)       (0.023)         Job-Related Variables       (0.016)       (0.016)         Part-time Job       0.054***       (0.013)		(0.017)	(0.018)	(0.018)
Economic Sectors Variables (base=Agriculture and Mining)       -0.001       0.066***         Manufacturing       -0.001       0.066***         (0.023)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)         Job-Related Variables       -0.106***         Public Sector       0.106***         Part-time Job       0.054***         (0.013)       0.013	Rural Area	0.079***	0.123***	0.122***
(base=Agriculture and Mining)       -0.001       0.066***         Manufacturing       -0.001       0.066***         (0.023)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)         Job-Related Variables       (0.016)         Public Sector       0.106***         Part-time Job       0.054***         (0.013)       0.054***		(0.007)	(0.007)	(0.007)
Manufacturing       -0.001       0.066***         (0.023)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)         Job-Related Variables       (0.026)         Public Sector       0.106***         Part-time Job       0.054***         (0.013)       0.054***	Economic Sectors Variables			
(0.023)       (0.024)         Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)         Job-Related Variables       (0.016)         Public Sector       0.106***         Part-time Job       0.054***         (0.013)       0.013	(base=Agriculture and Mining)			
Construction       -0.183***       -0.173***         (0.025)       (0.027)         Services       -0.416***       -0.284***         (0.019)       (0.022)         Commerce and Transportation       0.035       0.017         (0.022)       (0.023)         Job-Related Variables       0.106***         Public Sector       0.106***         Part-time Job       0.054***         (0.013)       0.013	Manufacturing		-0.001	0.066***
$\begin{array}{ccc} & (0.025) & (0.027) \\ -0.416^{***} & -0.284^{***} \\ (0.019) & (0.022) \\ & (0.022) \\ \hline \\ & (0.022) & (0.023) \\ \hline \\ \textit{Job-Related Variables} \\ \\ Public Sector & 0.106^{***} \\ & (0.016) \\ \\ Part-time Job & 0.054^{***} \\ & (0.013) \\ \hline \end{array}$			(0.023)	(0.024)
Services $-0.416^{***}$ $-0.284^{***}$ (0.019)       (0.022)         Commerce and Transportation $0.035$ $0.017$ (0.022)       (0.023)         Job-Related Variables $0.106^{***}$ Public Sector $0.106^{***}$ (0.016) $0.054^{***}$ (0.013) $0.013$	Construction		-0.183***	-0.173***
$(0.019)$ $(0.022)$ Commerce and Transportation $0.035$ $0.017$ $(0.022)$ $(0.023)$ <b>Job-Related Variables</b> $0.106^{***}$ Public Sector $0.106^{***}$ Part-time Job $0.054^{***}$ $(0.013)$			(0.025)	(0.027)
Commerce and Transportation         0.035         0.017           (0.022)         (0.023)           Job-Related Variables         0.106***           Public Sector         0.106***           Part-time Job         0.054***           (0.013)         0.013)	Services		-0.416***	-0.284***
(0.022) (0.023) Job-Related Variables Public Sector 0.106*** (0.016) Part-time Job 0.054*** (0.013)			(0.019)	(0.022)
Job-Related Variables           Public Sector         0.106***           (0.016)         0.054***           (0.013)         0.013)	Commerce and Transportation		0.035	0.017
Public Sector       0.106***         (0.016)       0.054***         (0.013)       0.013			(0.022)	(0.023)
(0.016) Part-time Job 0.054*** (0.013)	Job-Related Variables			
Part-time Job 0.054*** (0.013)	Public Sector			0.106***
(0.013)				(0.016)
	Part-time Job			0.054***
-0.371***				(0.013)
	Contract			-0.371***

 Table 3. Average Marginal Effects for Determinants of Overqualification (Probit Model)

			(0.008)
N	26,867	26,867	26,867
Pseudo $R^2$	0.097	0.202	0.265
Log-Likelihood	-16594.563	-14664.416	-13503.068
AIC	33201.127	29348.831	27032.135
BIC	33250.319	29430.818	27138.718

Notes: The table reports the marginal effects from a probit regression. Robust standard errors are reported in parentheses. \* p<0.100, \*\* p<0.050, \*\*\* p<0.010.

Table 4. Impact	Estimates	of Overqua	alification	on	Wage	Earnings	using	Different	Matching
Techniques and a	Weighting	Method							

	Radius Matching	Nearest-Neighbor Matching	IPW	
	Wage Earnings	Wage Earnings	Wage Earnings	
Overqualification	-0.180***	-0.184***	-0.168***	
	(0.010)	(0.010)	(0.008)	
Observations	26,867	26,867	26,867	

Notes: Statistical Significance: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1. Standard errors are in parentheses. Control variables are the sociodemographic, economic sector, and job-related variables that are used in determining overqualification in table 3.

 Table 5. Impact Estimates of Overqualification on Wage Earnings by Gender using Radius

 Matching Technique

	Full Sample	Male	Female
	Wage Earnings	Wage Earnings	Wage Earnings
Overqualification	-0.180***	-0.166***	-0.273***
	(0.010)	(0.011)	(0.026)
Observations	26,867	20,977	5,890

Notes: Statistical Significance: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1. Standard errors are in parentheses. Control variables are the sociodemographic, economic sector, and job-related variables that are used in determining overqualification in table 3.

	Manufacturing	Construction	Services	Commerce and Transportation	Agriculture and Mining
Overqualification	-0.156***	-0.032	-0.235***	-0.136***	-0.033
	(0.022)	(0.031)	(0.013)	(0.027)	(0.062)
Observations	3968	1469	13805	6860	765
Notes: Stati	stical Significance: ***	p < 0.01, ** p < 0.01	< 0.05, * p < 0	.1. Standard errors	are in
	. Control variables are at are used in determinin			ic sector, and job-	related

**Table 6.** Impact Estimates of Overqualification on Wage Earnings by Economic Sectors using

 Radius Matching Technique