Economics Development Analysis Journal Vol. 13 (3) (2024)

Economics Development Analysis Journal

http://journal.unnes.ac.id/sju/index.php/edaj

Qualification Mismatch and Labor Wage Implications

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Article Information

History of Article
Received April 2024
Accepted June 2024
Pusblished August 2024

Keywords:
Wages, Qualification Mismatch, Labor

Abstract

Qualification mismatch is a significant issue in DKI Jakarta's labor market, affecting how wages are distributed among workers. Although DKI Jakarta has the highest Provincial Minimum Wage (UMP) in Indonesia, many employees still receive wages inconsistent with their educational qualifications in terms of level and field of study. This study employs a quantitative regression approach using data from SAKERNAS August 2023 DKI Jakarta to analyze the impact of educational mismatch on labor wages. The results highlight a widespread issue of undereducation, where workers earn less than expected based on their qualifications. On the other hand, overeducation and mismatches in education do not significantly influence wage levels. Key factors such as education level, squared experience, undereducation, and gender have a significant positive effect on wages while working hours exert a significant negative impact. Interestingly, variables like technology use, internet access, and training opportunities show no substantial effect on wage determination. The study suggests that policymakers must address these mismatches by promoting gender equality and enhancing information and communication technology to improve productivity and wage outcomes across the labor force in DKI Jakarta.

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ISSN 2252-6560

INTRODUCTION

Unemployment is a social issue caused by the absence or shortage of jobs. It occurs when the supply of workers exceeds the demand, meaning the number of job seekers exceeds the available job opportunities. Unemployment can arise from a mismatch between workers' education and the needs of the labor market. Educational mismatches, both in terms of skills and qualifications, often contribute to high unemployment rates. A high unemployment rate can, in turn, increase educational mismatches, as workers unable to find jobs in their fields may accept positions in other areas that do not match their qualifications or skills. This contributes to the phenomenon of qualification mismatch in the labor market (Iriondo and Pérez-Amaral, 2016; Rohrbach-Schmidt and Tiemann, 2016; Quang and Tran-Nam, 2019; Hasibuan and Handayani, 2021; Sitorus and Wicaksono, 2022; Quadlin, VanHeuvelen and Ahearn, 2023).

The mismatch between the knowledge and skills needed and those available is indicated by a mismatch in educational qualifications (Allen and Weert, 2007; Iriondo and Pérez-Amaral, 2016; Rohrbach-Schmidt and Tiemann, 2016; Sitorus and Wicaksono, 2022). Research by Wulandari and Damayanti (2021) highlights the relatively high occurrence of educational mismatch (qualification mismatch) and its persistence in Indonesia. When the quality of the labor force improves but is not matched by an increase in labor demand, a mismatch occurs. The mismatch can be categorized by education level (vertical mismatch) and education major (horizontal mismatch).

Vertical mismatch refers to a disparity between the educational qualifications of workers and the requirements of their jobs. This mismatch includes undereducation, where workers have lower education than the job requires, and overeducation, where they have higher education than needed. A horizontal mismatch, or field-of-study mismatch, occurs when there is a discrepancy between a worker’s major or educational background and their job. Qualification mismatches in Indonesia are often due to insufficient educational planning and inadequate facilities to support equitable education across the country (Safuan and Nazara, 2005).

DKI Jakarta is a major economic center and business activity in Indonesia. As the country's capital and the largest city in Indonesia, DKI Jakarta has a vital role in determining the direction of national economic growth. However, economic growth in Jakarta is also characterized by various problems, such as labor problems. The high migration of people from various regions in Indonesia to DKI Jakarta to find work has led to unemployment and income inequality in this city (Hawa, 2023). Based on the report of (Bank Indonesia, 2024), it is known that the increase in labor absorption in DKI Jakarta mainly occurs in the trade services, accommodation providers, and transportation sectors. DKI Jakarta has a population of 10,672,100 people in 2023, with a male population of 5,371,646 people and a female population of 5,371,393. The high number of workers in DKI Jakarta also balances the high population in DKI Jakarta.

The large workforce in DKI Jakarta highlights its status as a metropolitan city and the most significant economic center in Indonesia, with complex workforce dynamics. DKI Jakarta also has the country's highest Provincial Minimum Wage (UMP), attracting many job seekers. According to Keputusan Gubernur Nomor 1153 Tahun 2022 tentang Upah Minimum Provinsi Tahun 2023, the Provincial Minimum Wage in DKI Jakarta for 2023 is IDR 4,901,798. This high wage has been crucial in encouraging people from various regions to move to DKI Jakarta. As Indonesia's leading economic center, DKI Jakarta offers a variety of job opportunities and higher incomes than other regions. The high UMP reflects the local government's commitment to improving workers' welfare and positions DKI Jakarta as a top destination for job seekers, aiming to enhance their living standards and contribute to the city's rapid economic growth.

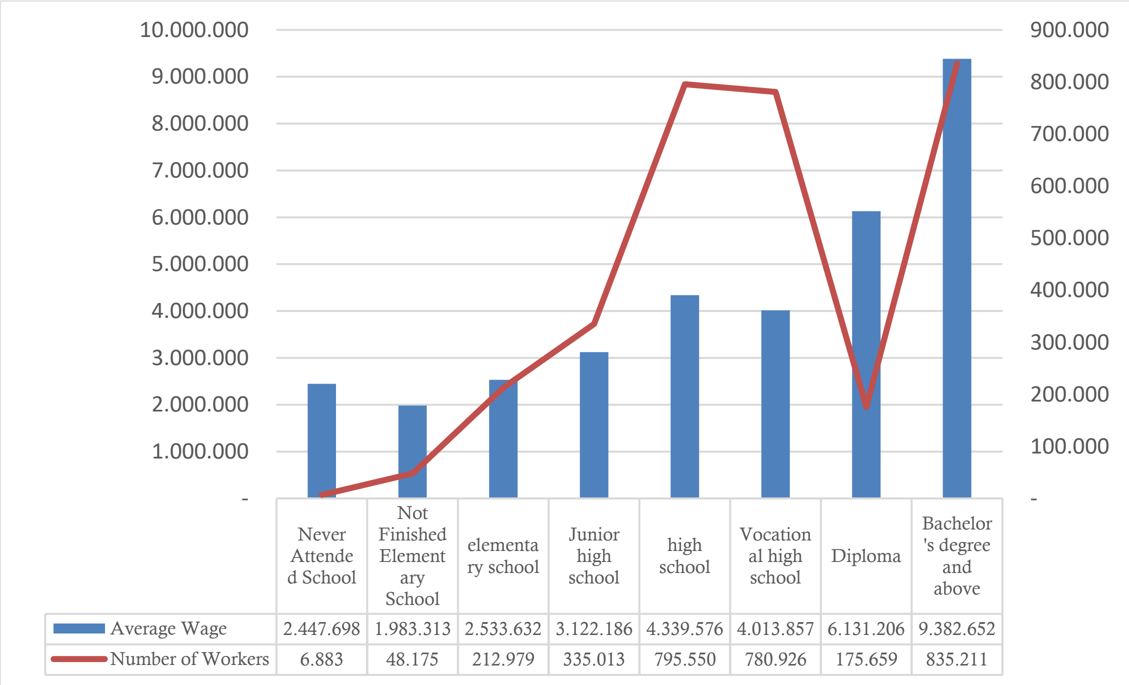

Figure 1. Average Wage/Salary/Net Income Per Month (Rupiah) Based on Education Completed in DKI Jakarta, 2023
Source: BPS-Statistics Indonesia, 2023

Although UMP DKI Jakarta is included in the highest UMP in Indonesia, many workers in DKI Jakarta still need to receive wages by the UMP set. Workers with high school/vocational education and below have an average monthly wage lower than the UMP that has been set. A workforce of high school graduates has a wage of IDR 4,339,576. Meanwhile, workers with a diploma and above education have an average wage of a month higher than the UMP that has been set. The workforce of university graduates has an average monthly wage of IDR 9,382,652. This shows a wage gap in the labor market in DKI Jakarta.

According to Tadjoeddin and Chowdhury (2019), Artamevia, Kafi, and Marpono (2022), and Ganguly and Sasmal (2023), the higher the level of education and productivity of the workforce, the higher the wages that the workforce will receive. However, the wages received by workers also take into account other factors, such as work experience. Mincer (1974) states a close relationship exists between income, education, and experience. The more experience the workforce has, the higher the wages they receive. This aligns with a study by Hutajulu et al. (2021), which found that experience positively and significantly affects wage increases. In addition to the variables of education and experience, the influence of labor wages can also be known through other variables.

Based on previous research, it is known that education and experience influence labor wages. Therefore, this research was conducted to analyze the effect of educational mismatch (qualification mismatch) on labor wages in DKI Jakarta, which is represented through the variables of educational mismatch, experience, demographic factors (gender and marital status), and socioeconomic factors (working hours, computer technology, internet, and training).

RESEARCH METHODS

The method used in this study is a quantitative descriptive method. Quantitative descriptive is a statistical analysis used to describe, summarize, and analyze quantitative data (Sudirman et al., 2023). The data used in this study is cross-section data obtained from the DKI Jakarta National Labor Force Survey (SAKERNAS) in August 2023. The total data is

2,714, sorted based on the workforce's productive age (15-64 years) and wages. Vertical mismatch (overeducation and undereducation) can be identified by comparing the occupational class and level of education required for the job with the last level of education that the workforce has. The International Standard Classification of Occupation (ISCO) 2008 is the basis for the 2014 Indonesian Standard Classification of Occupations (KBJI), which describes the types and classes of occupations in Indonesia. Meanwhile, the International Standard Classification of Education (ISCED) 2011 is a reference for the level of education.

Meanwhile, mapping the 3-digit job classification in KBJI 2014 and the 3-digit education classification was carried out to identify horizontal mismatches. The reference for determining the education major is the International Standard Classification of Education-Fields of Education and Training (ISCED-F) 2013. However, because the classification of education majors in Indonesia does not refer to ISCED-F 2013, adjustments will be made to education majors in Indonesia with those used by the Central Statistics Agency to be by ISCED-F 2013. The undereducation and overeducation data come from the dummy variable mismatch, where the mismatch is given the numbers 1 and 0 for the other. In the field of education mismatch, a dummy of 1 is given if there is a discrepancy and 0 for the others.

The Quantile Regression Model method calculates the influence of qualification mismatch on labor wages in DKI Jakarta. Based on Mincer (1974), the basic equation is known, namely:

$$Q_{yi}(\theta|X) = \alpha_{(\theta)} + X_i'\beta_{\theta.i} \text{ ....(1)}$$

Based on the above formula, it can be explained that the quantile formula with the structure 0 < θ < 1, where: θ is quantity conditions, β_θ is estimated parameter value, and X is the variable that affects the dependent variable under the condition of quantitative regression.

This research uses the basis of (Mincer, 1958) as mentioned in equation (1), which is as follows:

$$\ln[w(s,x)] = \propto_1 + \, p_2 S + \, \beta_0 x + \, \beta_1 x^2 + e \text{ ... (2)}$$

Where, w is wages, S is years of schooling, x is exper (experience), and x^2 is $exper^2$ (quadratic experience).

Ben-Porath (1967) then developed the Mincer (1958) study, which only examined the close relationship between the influence of income on education and work experience. Ben-Porath (1967) added human capital variables and labor investment in his research. So that the following equation is obtained:

$$E_{(t)} = H_{(t)} - I_{(t)} + rK_{(t)} \text{ .... (3)}$$

Where E is income, H is capital, I is the form of investment, r is the rate of return on investment, and K is an overview of the capital stock owned by the workforce.

Mincer (1974) tried to refine his research on wages by updating his previous research and identifying the results of Ben-Porath's research. In this study, Mincer researches the field of income distribution and the development of human resource analysis. Mincer also does not deny that other factors can affect revenue. In this study, Mincer added several variables, such as the type of job, job location, gender, race, and workforce ethnicity. The function of the income equation becomes:

$$Ln(W) = \alpha + \beta_1 Schooling + \beta_2 Exper + \beta_3 Exper^2 + \beta_4 X_4 + \cdots + \beta_k X_k + \varepsilon \text{ .... (4)}$$

Based on Mince's (1974) and Ben-Porath (1967) research, this study uses the same equation function by adding several variables. The basic model of this study, namely:

$$Ln(Wage)_{i(\theta)} = \beta_{0(\theta)} + \beta_{1(\theta)} Schooling_{1i} + \beta_{2(\theta)} Exper_{2i} + \beta_{3(\theta)} {Exper^2}_{3i} + \beta_{4(\theta)} \Sigma X_{n(\theta)} + \varepsilon_i(\theta) \text{ .... (5)}$$

In equation (5), demographic and socioeconomic factors are added to complement the previous research. So the equation becomes:

$$Ln(Wage)_{i(\theta)} = \beta_{0(\theta)} + \beta_{1(\theta)}Schooling_{1i} + \beta_{2(\theta)}exper_{2i} + \beta_{3(\theta)}exper^2{}_{3i} + \beta_{4(\theta)}Demographic\ Factors_{4i} + \beta_{5(\theta)}Socioeconomic\ Factors_{5i} + \varepsilon_i(\theta) \quad (6)$$

The schooling variable, as a proxy for education, includes the level of education and mismatch variables such as undereducation, overeducation, and field-of-education mismatch (Hasibuan and Handayani, 2021; Wulandari and Damayanti, 2021). In this study, demographic factors are represented by the gender and marital status variables (Hossain, Haque, and Haque, 2015; Hasibuan and Handayani, 2021; Hutajulu et al., 2021). Socioeconomic factors are proxied by variables such as working hours, computer technology, internet use, and training (Hasibuan and Handayani, 2021; Hutajulu et al., 2021; Wulandari and Damayanti, 2021). Thus, the empirical model in this study becomes:

$$Ln(Wage)_{i(\theta)} = \beta_{0(\theta)} + \beta_{1(\theta)}educ_i + \beta_{2(\theta)}exper_i + \beta_{3(\theta)}exper^2 + \beta_{4(\theta)}undereduc_i + \beta_{5(\theta)}overeduc_i + \beta_{6(\theta)}field_i + \beta_{7(\theta)}gender_i + \beta_{8(\theta)}married_i + \beta_{9(\theta)}workhours_i + \beta_{10(\theta)}technology_i + \beta_{11(\theta)}intenet_i + \beta_{12(\theta)}certificate_i + \varepsilon_i \quad (7)$$

Where, Ln(Wage) is the amount of wages received by workers in the form of hourly wages (natural logarithms), $Educ$ is level of education attained by the workforce (year), $Exper$ is work experience (years), $Exper^2$ is quadratic work experience, $Undereduc$ is workers with lower educational qualifications than required for their jobs. If educational qualifications are lower than job requirements, it is assigned a dummy value of 1; otherwise, 0, $Overeduc$ is workers with higher educational qualifications than required for their jobs. If educational qualifications are higher than job requirements, it is assigned a dummy value of 1; otherwise, 0, $Field$ is workers whose education major does not align with their field of work. If the education major does not match the field of work, it is assigned value of 1; otherwise, 0, $Gender$ is dummy gender, 1 for males and 0 for others, $Married$ is dummy of marital status, 1 for married workers, and 0 for others.
$Workhours$ is hours of work per week.
$Technology$ is dummy of computer use, 1 for workers who use computers in their jobs and 0 for others, $Internet$is dummy of internet use, 1 for workers who use the internet for their jobs and 0 for others, and *certificate* is dummy training certificates, 1 for workers who participated in training and obtained certificates, and 0 for others, ε is error term, and *i is cross sectiion.*

RESULTS AND DISCUSSION

Descriptive statistical tests are simple statistical analyses used to describe the state of observations presented in the form of tables, graphs, and explanations. This analysis is used to make it easier to explain the research object.

Table 1. Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
LnWage	1415	7.305252	14.08744	9.993289	0.892840
Educ	1415	0.000000	21.00000	11.66996	3.645818
Exper	1415	0.000000	58.00000	22.80636	13.18439
Exper^2	1415	0.000000	3364.000	693.8353	676.7201
Under	1415	0.000000	1.000000	0.130035	0.336461
Over	1415	0.000000	1.000000	0.274912	0.446628

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Field	1415	0.000000	1.000000	0.492580	0.500122
Gender	1415	0.000000	1.000000	0.594346	0.491192
Married	1415	0.000000	1.000000	0.652297	0.476410
Workhours	1415	1.000000	98.00000	45.88339	16.99163
Technology	1415	0.000000	1.000000	0.796466	0.402768
Internet	1415	0.000000	1.000000	0.775972	0.417088
Certificate	1415	0.000000	1.000000	0.289753	0.453808

Source: Data Processed, 2024

Table 2. Multiple Regression Result

Variable	Coefficient	Prob
Constant	8.826190	0.0000*
Educ	0.126378	0.0000*
Exper	-0.008493	0.1330
$Exper^2$	0.000383	0.0004*
Under	0.279034	0.0000*
Over	-0.089183	0.0505***
Field	-0.062877	0.1297
Gender	0.292083	0.0000*
Married	0.072263	0.1151
Workhours	-0.016022	0.0000*
Technology	-0.161712	0.2396
Internet	0.348574	0.0092*
Certificate	0.042868	0.3390
Diagnostic test		
R-Square		0.384402
f-stat		72.95516
Prob f-stat		0.000000*
Classical assumptions		
Normality test		0,0000*
Autocorrelation test		0,0000*
Heteroscedasticity test		0,0000*
Multicollinearity test		Does not pass multicollinearity

Source: Data Processed, 2024

The classical assumption in this study does not show good results, so the analysis will be carried out using quantitative regression to overcome the heteroscedasticity problem. This poor result can occur because the data has outliers, so quantitative regression is considered appropriate because this quantitative regression can overcome the outlier data. Further analysis was carried out because the regression analysis resulted in data that were far from the mean and had large residuals, so it was necessary to estimate the quantitative regression parameters. In addition, estimation with the OLS method often has heteroscedasticity problems, so the analysis continues using quantitative regression (Saidah, Yanuar, and Devianto, 2016; Balami, 2017; Fajar, 2017).

Table 3. Quantitative Regression Estimation Results

Variables	Quantile	Coefficient	Std. Error	t-Statistic	Prob.
C	0.250	8.332916	0.146326	56.94762	0.0000
	0.500	8.949498	0.158626	56.41883	0.0000
	0.750	9.157166	0.135194	67.73348	0.0000
EDUC	0.250	0.116360	0.009360	12.43183	0.0000
	0.500	0.122884	0.010099	12.16793	0.0000
	0.750	0.133630	0.008387	15.93239	0.0000
EXPER	0.250	-0.014382	0.006880	-2.090320	0.0368
	0.500	-0.006965	0.006084	-1.144742	0.2525
	0.750	0.002202	0.005817	0.378459	0.7051
EXPER2	0.250	0.000395	0.000132	2.997151	0.0028
	0.500	0.000260	0.000127	2.041047	0.0414
	0.750	0.000226	0.000123	1.833225	0.0670
UNDER	0.250	0.208959	0.100207	2.085279	0.0372
	0.500	0.188893	0.081156	2.327528	0.0201
	0.750	0.426138	0.081371	5.237007	0.0000
OVER	0.250	-0.018508	0.052070	-0.355456	0.7223
	0.500	-0.064705	0.039904	-1.621494	0.1051
	0.750	-0.089561	0.045348	-1.974978	0.0485
FIELD	0.250	-0.082742	0.049268	-1.679407	0.0933
	0.500	-0.009187	0.036996	-0.248322	0.8039
	0.750	-0.008806	0.042695	-0.206257	0.8366
GENDER	0.250	0.339714	0.054945	6.182855	0.0000
	0.500	0.224473	0.043687	5.138215	0.0000
	0.750	0.111601	0.037091	3.008830	0.0027
MARRIED	0.250	0.137932	0.060340	2.285896	0.0224
	0.500	0.089889	0.052737	1.704462	0.0885
	0.750	0.063221	0.040315	1.568168	0.1171
WORKHOURS	0.250	-0.011738	0.001439	-8.157979	0.0000
	0.500	-0.015421	0.001590	-9.698214	0.0000
	0.750	-0.017156	0.001574	-10.90049	0.0000
TECHNOLOGY	0.250	-0.238517	0.370111	-0.644449	0.5194
	0.500	0.086699	0.201898	0.429422	0.6677
	0.750	0.118130	0.226955	0.520498	0.6028
INTERNET	0.250	0.526294	0.366692	1.435246	0.1514
	0.500	0.046817	0.197541	0.236998	0.8127
	0.750	-0.011995	0.223791	-0.053599	0.9573
CERTIFICATE	0.250	0.037309	0.051022	0.731237	0.4648
	0.500	0.011799	0.038966	0.302804	0.7621
	0.750	0.041142	0.042649	0.964656	0.3349

Source: Data Processed, 2024

The results of the quantitative regression estimate show that education level positively affects labor wages at all wage levels. This supports Mincer's (1958) theory, which states that individuals with higher education earn more than those with lower education. Studies by Chuang and Chao (2001), Hasibuan and Handayani (2021), Hutajulu et al. (2021), Susanto, Engka, and Lapian (2021), and Artamevia, Kafi, and Marpono (2022) also demonstrate that higher levels of completed education lead to higher wages for workers. This confirms that education is a valuable investment for workers seeking better wages.

Undereducation has a significant positive influence on labor wages at all wage levels in DKI Jakarta. The coefficients across all levels are positive, with probability values less than α (5%), indicating that workers with lower education than required by their jobs (undereducation) receive a wage premium. Despite their lower educational attainment, these workers can earn higher wages because they possess the skills and abilities needed by their employers. Social networks also play a role in helping undereducated workers access job opportunities.

In contrast, the regression results show that overeducated workers at low and middle-wage levels do not significantly affect wages in DKI Jakarta. However, at high wage levels, overeducation significantly negatively affects wages. This indicates that overeducated workers in DKI Jakarta often face a wage penalty compared to those with appropriate educational qualifications. This occurs because overeducated workers may possess skills irrelevant to their jobs despite their higher education. These findings align with previous research, which found that overeducated workers receive wage penalties while undereducated workers earn wage premiums (Allen and Velden, 2001; Safuan and Nazara, 2005; Hasibuan and Handayani, 2021).

Education mismatch at the low wage level significantly negatively affects labor wages in DKI Jakarta. However, it does not significantly impact wages at middle and high wage levels. This means that workers with a mismatch between their education and their jobs tend to earn lower wages (wage penalty) than those whose education fields align with their jobs. Discrimination against workers with education mismatches during recruitment and wage determination may also explain why they receive lower wages. These findings are consistent with a study in Malaysia, which found that horizontal mismatch negatively affects labor wages (Zakariya, 2014). Research by Hasibuan and Handayani (2021) similarly shows that workers with an education mismatch experience wage penalties.

Labor experience at the low wage level also significantly negatively impacts wages in DKI Jakarta. This indicates that, for workers at the low wage level, the more experience they have, the lower their wages. In contrast, experience at the middle and high wage levels has little to no effect on wages. There is insufficient evidence to conclude that more experience leads to higher wages for workers in these groups. This phenomenon can occur for high-income workers when their skills have peaked at a certain experience level, which may reduce productivity and, in turn, affect the wages they receive.

It differs from the quadratic experience, which states the positive and significant influence on all levels of labor wages in DKI Jakarta. This decline occurs because labor productivity will decrease as people get older and more experienced, decreasing labor wages. These results confirm Mincer's theory that work experience will show a diminishing marginal return. This research is in line with the results of Hasibuan and Handayani (2021) and Hutajulu et al. (2021), which state that experience significantly positively influences labor wages.

Gender has a significant positive effect on all levels of labor wages. This means that the gender of the workforce at all wage levels significantly influences labor wages in DKI Jakarta. This shows that male workers earn higher wages than female workers at all wage levels. Although, in general, male workers earn higher wages than female workers, the higher the level of labor wages, the smaller the wage gap between male and female workers. The higher the quartile, the lower the value of the coefficient. The difference in wages received by male and female workers is evidence of gender discrimination in the labor market. In addition, the difference in the roles of female workers, who are more likely to take care of the household, and male workers, who are more concentrated in their work, are also factors that affect the wages received by workers. The results of this study are supported by research conducted by Henningusnia (2014), Budiarty and Ramadhan (2016), Hasibuan and Handayani (2021), Hutajulu et al. (2021), and Gunawan, Nainggolan, and Bayu (2022) those who earn below the male workforce earn higher wages than the female workforce. This shows that there is a wage gap between male and female workers.

Workers with married status at low and middle-wage levels have higher wages than workers with unmarried status. Meanwhile, workers with married status at the high wage level do not significantly affect labor wages in DKI Jakarta. Married workers tend to earn higher wages compared to unmarried workers. Married workers have family dependents, so they need a high income to meet their living needs. The high wages of married workers can occur because they are older and have more experience than unmarried workers, so that they can increase wages. Married workers will get higher wages than unmarried workers (Hasibuan and Handayani, 2021). In addition, some studies have shown that marital status does not significantly affect labor wages (Hutajulu et al., 2021; Wulandari and Damayanti, 2021).

Working hours significantly negatively affect labor wages at all levels in DKI Jakarta. Workers who work longer hours tend to earn lower wages across all wage levels. Low wages can result from high working hours, which lead to fatigue and reduced productivity, ultimately impacting wages. This finding supports the research of Hutajulu et al. (2021) and Wulandari and Damayanti (2021) who also concluded that working hours influence the wages workers receive.

The use of computer technology and the internet in daily work has led to lower labor wages in DKI Jakarta. This occurs because computer technology is widely adopted in the labor market in DKI Jakarta. The high usage of computer technology suggests that its implementation is effective and efficient in increasing labor output. Many companies in DKI Jakarta heavily rely on technology in their operations. The results of this study align with the research by Kristal (2020), which found that technology positively impacts the wages workers receive. Additional research also highlights that the internet has a positive influence on increasing labor wages (Paul and Bart, 2008; Atasoy, 2013; Hutajulu et al., 2021; Hötte, Somers, and Theodorakopoulos, 2023).

The training attended by workers at various wage levels only significantly affects labor wages in DKI Jakarta. Training can help the workforce enhance the skills and knowledge needed to perform their jobs. Research by Hutajulu et al. (2021) produced similar results, showing that training did not have a significant impact on increasing labor wages. In contrast, research by Hasibuan and Handayani (2021) found that training has a significant positive effect on labor wages. Through training, the workforce is expected to improve their knowledge and skills.

CONCLUSION

There is a phenomenon of qualification mismatch in the labor market in DKI Jakarta. Education level, undereducation, quadratic experience, gender, and marital status positively influence labor wages in DKI Jakarta. Overeducation, field-of-education mismatch, and working hours negatively affect labor wages. As a result, overeducated workers and those with field-of-education mismatches experience wage penalties, while undereducated workers receive a wage premium.

Meanwhile, computer technology, internet use, and certificates have little effect on labor wages in DKI Jakarta. The workforce is expected to utilize information and communication technology to improve their skills and knowledge, thereby increasing productivity. Additionally, the government needs to emphasize policies that promote gender equality to reduce the impact of wage discrimination between male and female workers. Future researchers are encouraged to separate public sector workers from non-public sector data, as this research combines both. They may also consider using quantile regression analysis with decile division (dividing the data into ten parts) for more detailed insights.

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