Journal of Developing Economies Vol. 10 No. 1 (2025): 73-89

JOURNAL OF DEVELOPING ECONOMIES
https://e-journal.unair.ac.id/JDE/index

THE ROLE OF INTERNET USAGE ON GENDER WAGE GAP: EVIDENCE FROM INDONESIA

Martina Nurma Dewi*[1]

Arie Damayanti[1]

[1] Economics, Economics & Business, University of Indonesia, Depok, Indonesia

ABSTRACT

This study analyzes the effect of internet usage on the gender wage gap within Indonesia's labor market. Using data from the 2022 National Labor Force Survey (Sakernas), the research employs robust least square regression, quantile regression, and the Oaxaca-Blinder Decomposition Method to assess the differential effects of internet use on wages across genders. The findings indicate that internet usage in main job significantly increases wages for both men and women while also narrowing the gender wage gap which varies by income level and job type. This effect is more pronounced in white-collar jobs and among higher-income groups compared to blue-collar jobs and middle-income groups. Additionally, the study underscores that unexplained factors, including discrimination, play a significant role in perpetuating the gender wage gap.

Keywords: *Gender, Wage Gap, Decomposition, Oaxaca-Blinder*

JEL: J31; J71

ARTICLE INFO

Received: July 16th, 2024
Revised: October 7th, 2024
Accepted: October 24th, 2024
Online: June 28th, 2025

*Correspondence:
Martina Nurma Dewi

E-mail: martina.nurma@ui.ac.id

To cite this document: Dewi, M. N. & Damayanti, A. (2025). The Role of Internet Usage on Gender Wage Gap: Evidence From Indonesia. *Journal of Developing Economies*, *10*(1), 73-89. https://doi.org/10.20473/jde.v10i1.60467

Introduction

In addition to driving economic growth, the internet has the potential to exacerbate inequality (Chamwong et al., 2024; DiMaggio et al., 2004; Mariniello, 2022; Wang & Shen, 2024; Woźniak-Jęchorek & Kuźmar, 2023). One significant aspect of this inequality is the wage disparity between genders. Internet usage, which does not inherently provide equal benefits or returns to men and women, can alter the gender wage inequality. Empirical evidence on the relationship between internet use and the gender wage gap is mixed. Some studies suggest that internet usage reduces the wage gap (Qi & Liu, 2020; Wu, 2021; Xiliang et al., 2021), while others indicate that it exacerbates the disparity (Lukyanova, 2021; Ma, 2022), including contributing 26.73% to the overall gender wage gap in China (Gao & Liu, 2023a). Although the effect of internet use, as part of job characteristics, on the gender wage gap is a growing area of global study, research specifically focusing on Indonesia remains limited.

There is a notable lack of detailed analysis regarding job characteristics, such as internet usage, in Indonesian literature. To our knowledge, empirical research examining the role of internet use as a job characteristic influencing the gender wage gap in Indonesia is still void. In today's digital era, internet usage has become a crucial factor to consider when analyzing this wage gap due to its potential to affect productivity. Existing studies in Indonesia primarily focus on human capital and labor market regulation such as minimum wage (Hallward-Driemeier et al., 2017; Hennigusnia, 2014; Jamielaa, 2018; Lidya & Kadir, 2019; Simamora & Widyawati, 2022; Suharyono & Digdowiseiso, 2021). Meanwhile, the empirical findings in other more advanced countries may not be relevant to developing nations like Indonesia (Gao & Liu, 2023a; Lukyanova, 2021; Ma, 2022; Qi & Liu, 2020). To address this gap in the literature, this study investigates the effect of internet usage on gender wage disparity in Indonesia. It aims to determine whether internet use in the main jobs positively impacts wage levels by gender and whether it serves to widen or reduce the wage gap.

This study has two primary objectives: first, to estimate the effect of the internet usage on wage levels by gender, and second, to decompose the gender wage gap to quantify the contribution of internet use to this disparity. The decomposition results will help identify the main factors contributing to the gender wage gap. Additionally, the role of internet usage will be analyzed across various groups based on income levels and job types, an aspect that has been rarely explored in previous research. This approach enables a more comprehensive understanding of the dynamics at play in the gender wage gap.

We utilize cross-sectional data from the 2022 National Labor Force Survey (Sakernas) conducted after the pandemic. The study employs a robust least squares regression to handle potential issues with outliers or rectify violations of the standard assumptions in ordinary least squares (OLS) regression analysis (Dietz et al., 1987; Olive, 2008; Wilcox, 1998) and a quantile regression method to analyze the impact of internet usage on gender earnings at different wage levels. To further assess the extent to which internet usage contributes to the gender wage gap, the gender wage equation is decomposed using the Oaxaca-Blinder decomposition method. The focus is on workers classified as wage labor/employees, individuals who work for an employer and are compensated based on hours worked or the volume of work performed, as defined by ICLS 13 with no missing wage data.

The remainder of the paper is organized as follows. The next section reviews the mechanisms through which internet use in jobs affects wages and its potential impact on the gender wage gap, along with relevant empirical literature. This is followed by an explanation of the data and the empirical methods used in the analysis. Next, the findings are presented and discussed. The final section concludes the study.

Literature Review

Gender wage inequality can be explained through four channels: first, differences in endoGender wage inequality can be explained through four channels: first, differences in endowments between men and women; second, gender occupational segregation; third, statistical discrimination; and fourth, direct discrimination. The first channel posits that disparities in wages or returns to internet use between genders arise from endowment factors, as outlined by human capital theory (Becker, 1964; Mincer, 1974; Solomon, 2023). According to this theory, individual wages are influenced by labor productivity, which is closely linked to education and skills, key components of human capital (Borjas, 2013; Solomon, 2023). In the context of internet use, individual internet skills, as indicated by internet usage, are perceived as reflecting higher skills and productivity compared to those who do not use the internet.

Consequently, if men possess better internet skills, they are likely to command higher wages, thereby exacerbating the gender wage gap (Ma, 2022).

A newer concept, known as Skilled-Biased Technological Change (SBTC), attempts to explain how technological advancements can contribute to wage inequality between men and women (Acemoglu & Autor, 2011; Ilmakunnas, 2023). Skilled-biased technological change can be understood as an exogenous shift in the production function that increases the demand for skilled labor relative to unskilled labor at the existing wage level (Acemoglu & Autor, 2011; Berman et al., 1998). As technology advances, certain groups of workers may be perceived as more proficient than others. In this context, employers may view female employees, who typically have less education or lower proficiency in technology or internet skills, less favorably than their male counterparts. These dynamics can exacerbate wage disparities between genders.

The second channel, occupational segregation by gender, contributes to wage disparities due to the concentration of men and women in specific occupations. According to the crowding hypothesis (Bergmann, 1974), wage differences arise not from variations in endowments but from disparities in job types. Men are more likely to dominate internet-intensive roles, resulting in higher returns to internet use for men compared to women. This dynamic further exacerbates the gender wage gap.

The third channel, statistical discrimination, can lead to lower wages for women. According to the statistical discrimination hypothesis (Phelps 1972), employers, faced with asymmetric information, make hiring and wage decisions for both male and female employees based on average values of certain unobservable factors, such as work effort and job retention likelihood. This approach results in differing wage levels and contributes to the gender wage gap.

The fourth channel, direct discrimination, pertains to unexplained discrepancies in the return to internet use based on individual characteristics. This implies wage discrimination when men and women possess the same characteristics or endowments related to internet use (Ma, 2022). In other words, wage differences cannot be attributed to variations in productivity (Jacobsen, 1994; Ma, 2022). Theories supporting this form of discrimination include Arrow's theory of discrimination (1973), the Phelps's statistical theory of racism (1972), and the monopsony power hypothesis. Various empirical studies indicate that discrimination is a significant contributor to the gender wage gap.

In existing empirical literature, the effect of internet use on the gender wage gap is generally viewed from two perspectives. The first perspective suggests that internet use has the potential to reduce the wage gap (Qi and Liu, 2020; Wu, 2021), while the second posits that it widens the gender wage gap (Gao & Liu, 2023a; Lukyanova, 2021; Ma, 2022). The variations observed in these studies can be attributed to differences in estimation methods, periods of analysis, and the heterogeneous groups studied, all of which affect wage gaps across regions. Studies indicating that internet use reduces the gender wage gap often rely on cross-sectional data and ordinary least squares (OLS) estimation methods (Qi and Liu, 2020; Wu, 2021). However, these approaches may encounter endogeneity issues, such as omitted variable bias and reverse causality. Conversely, research that uses panel data and addresses endogeneity typically finds that the gender wage gap tends to widen.

From the first perspective in empirical studies, the internet significantly reduces the gender wage gap due to its positive impact on wages. There are at least three mechanisms through which internet use can help close the gender wage gap. The first mechanism is skill enhancement (Gao & Liu, 2023b). Access to the internet at work allows employees to develop and refine their digital skills. Both men and women can leverage these skills to improve job performance and productivity, potentially leading to wage increases. If women benefit more from these opportunities, it could help narrow the gender wage gap. The second mechanism is the provision of timely and relevant information (Gao & Liu, 2023b). Internet use enables employees to stay updated on advancements and best practices, which is essential for making informed decisions and excelling in their roles. This knowledge contributes to career growth and higher wages. The third mechanism involves exposure and networking (Gao & Liu, 2023b; Losh, 2004). Email and other online communication tools enhance connectivity and collaboration among employees, facilitating efficient information exchange and networking opportunities. This is particularly advantageous for women, as it helps them expand their professional networks and gain greater visibility in their fields, further supporting their career progression (Qi & Liu, 2020; Wu, 2021).

From the second perspective, the internet is seen as widening the wage gap due to disparities in both endowments and returns derived from internet usage (Gao & Liu, 2023a; Lukyanova, 2021; Ma, 2022). Internet usage exacerbates the gender wage gap, in part due to ongoing gender discrimination in cyberspace, which disproportionately impacts women. While the internet offers both men and women greater access to resources and opportunities, men tend to experience more substantial wage benefits. This discrepancy is often linked to gender bias that favors men's activities and advancements in both online and broader labor markets. As a result, men's wages increase more significantly through internet use, contributing to a growing gap between men's and women's earnings, particularly at the lower and higher ends of the wage scale where discrimination is often more pronounced (Gao & Liu, 2023a). Furthermore, Lukyanova (2021) shows that while digital technology positively impacts income, it also widens the wage gap when gender decomposition is applied. Similarly, Ma (2022) finds that internet use leads to greater wage increases for men compared to women, especially among older age cohorts and those with lower educational levels. The differences in wage structures tend to increase the wage gap among highly educated groups, while internet access exacerbates income inequality across cohorts, with the greatest disparities observed among middle-aged individuals.

The mechanism behind this widening gap involves two main factors: the disparity in internet access between genders and the differential returns on internet usage. Men generally benefit more from internet usage in terms of wage increases than women, possibly due to the types of internet-related skills that are more valued in the job market or due to gender biases in professional environments (Morahan-Martin, 1998; Sinha, 2018). Additionally, men often have higher rates of internet access, further contributing to wage disparities by providing them with more opportunities for career advancement and skill enhancement that are not equally available to women (Bustelo et al., 2019).

Data and Research Methods

Data

This study utilizes the Sakernas survey conducted in August 2022 by BPS-Statistics Indonesia, which is specifically designed to collect labor force data, thus representing the condition of the Indonesian labor market. The total number of household samples in the Sakernas for August 2022 is 752,688. For this analysis, the sample selected is restricted to paid workers who have complete wage/salary information, resulting in a final sample size of

140,064 individuals. To estimate the population, this study applies sampling weights from the Sakernas data, yielding a total figure of 44,324,790 individuals.

In this analysis, the primary variable is the hourly wage rate by gender, calculated by dividing the monthly wage by the total monthly working hours. Wage refers to the income an individual received during the previous month from their main job, which may be paid either in cash or in kind. The main job is defined as the employment that generates the highest monthly income, with monthly working hours determined by multiplying weekly hours by four. The key variable of interest is internet usage in the workplace.

This study controls for other characteristics that influence wages, including the worker's age, education level (divided into four categories: no education as the reference, primary education up to junior high school, secondary education up to senior high school, and tertiary education for qualifications of diploma level and above), certified training experience, marital status with not married as reference, the presence of household members under the age of five, the sector of employment (classified into three categories: agriculture as the reference, manufacturing, and services), and the classification of rural-urban and Java/ non-Java regions. We then decompose the total wage disparity into two components: the explained component, which relates to the differences between men and women in these characteristics, and the unexplained component, which accounts for differences in returns to internet use. A proportion of the unexplained component serves as an indicator of gender-based wage discrimination.

Empirical Model Framework

The effect of internet use on wages will be analysed using robust least squares and quantile regression methods. The robust least squares method is used to address potential outliers' issues or resolve violations of standard ordinary least square (OLS) assumptions, such as heteroscedasticity (Dietz et al., 1987; Olive, 2008; Wilcox, 1998). This can handle the issue of non-constant variance in residuals, which may affect the accuracy of the OLS standard errors by adjusting the standard errors but does not change the estimated coefficients to ensure more precise statistical inference. This method makes the estimates more reliable even when the assumptions underlying OLS are not fully met.

Furthermore, the gender wage gap will be explored through the Oaxaca-Blinder decomposition method. The objective of the Blinder (1973) decomposition method is to break down differences in mean wages between two groups—in this case, males and females. The wage-setting model is assumed to be separable and linear in terms of both observable and unobservable characteristics (additive linearity). Other assumptions include a zero conditional mean (Fortin et al., 2011). For the gender wage gap, the model is set up as follows. Let Y denote wage, which is a function of covariates X:

$$Y_g = X\beta_g + \nu_g, \; for \; g = male(m), female(f) \tag{1}$$

where $E[\nu_g | X] = 0$. Letting $D_f = 1$ represent the female group, and considering the expectation over X, the overall mean wage gap Δ_O^{μ} may be expressed as:

$$\begin{aligned} \Delta_O^{\mu} &= E[Y_f | D_f = 1] - E[Y_m | D_f = 0] \\ &= E[E(Y_f | X, D_f = 1) | D_f = 1] - E[E(Y_m | X, D_f = 0) | D_f = 0] \\ &= (E[X | D_f = 1]\beta_f + E[\nu_f | D_f = 1]) - (E[X | D_f = 0]\beta_m + E[\nu_m | D_f = 1]) \end{aligned} \tag{2}$$

where $E[\nu_f|D_f=1]=E[\nu_m|D_f=1]=0.$

Applying the addition and subtraction operations on the average counterfactual wages that women would get based on the wage structure for males $(E[X|D_f=1]\beta_m)$, equation (1) becomes

$$\begin{aligned}\Delta_O^\mu &= E[X|D_f=1]\beta_f - E[X|D_f=0]\beta_m + E[X|D_f=1]\beta_m - E[X|D_f=1]\beta_m \\ &= E[X|D_f=1](\beta_f-\beta_m) + (E[X|D_f=0]-E[X|D_f=1])\beta_m\end{aligned} \tag{3}$$

$$\Delta_O^\mu = \Delta_S^\mu + \Delta_X^\mu \tag{4}$$

By substituting the sample averages $\bar{X}_g$ for the predicted value of the variables $(E[X|D_f=1]\beta_m)$ for = 0,1, we can estimate the decomposition as follows:

$$\hat{\Delta}_O^\mu = \bar{X}_f(\hat{\beta}_f-\hat{\beta}_m)+(\bar{X}_f-\bar{X}_m)\hat{\beta}_m \tag{5}$$

$$\hat{\Delta}_O^\mu = \hat{\Delta}_S^\mu + \hat{\Delta}_X^\mu \tag{6}$$

The first term $(\hat{\Delta}_S^\mu)$ in equation 6 represents the wage structure effect, which is the unexplained component of wage differentials, partly attributed to discrimination. The second term $(\hat{\Delta}_X^\mu)$ refers to the composition effect, reflecting the differing characteristics between male and female employees. A limitation of the Oaxaca-Blinder decompositions, as noted by Oaxaca & Ransom (1999) and Barsky et al. (2002), is that the contribution of each covariate to the wage structure effect can be sensitive to the choice of the reference group. In this study, we used the pooled sample, combining both male and female participants, as the reference group.

The estimation model is specified as follows:

$$\begin{aligned}\ln W_i^j &= \alpha^j + \beta_1^j age_i + \beta_2^{j\prime} educ_i + \beta_3^j tenure_i + \beta_4^j training_i + \beta_5^j married_i + \beta_6^j child_i + \\ &\beta_7^{j\prime} sector_i + \beta_8^j internet_i + \beta_9^j rural_i + \beta_{10}^j java_i + \varepsilon_i^j\end{aligned} \tag{7}$$

In this equation, $\ln W_i^j$ represents the natural logarithm of the wage for an individual i. The wage value is derived from the salary question in the Sakernas survey, reflecting the earnings individuals have received over the past month, either in cash or in kind, converted to a real hourly wage. The explanatory variables affecting wages include internet use $(internet_i)$, age, a vector of education levels, where the reference category is no education, tenure as the length of time working in the main job (measured in years), certified training experience (1: if an individual has experienced certified training before and 0: otherwise), married status, household members under the age of five, a vector of sectors, with agriculture sector as the reference category, and the classification of rural-urban and Java-non-Java areas, along with the error term ε_i. Equation 7 is estimated for j (j= men, women) workers separately. The primary focus of equation (7) is to estimate β_1, which captures the returns associated with internet usage.

In the second stage, the wage difference between genders is calculated by subtracting the estimated average wage of men from that of women, as formulated in equation (3). This study hypothesizes that internet use will have a positive impact on wages while widening the gender wage gap, due to differing wage increases between men and women, with women's earnings continuing to lag behind. This hypothesis aligns with findings from Lukyanova (2021), Ma (2022) and Gao & Liu (2023a).

Findings and Discussion

Summary Statistics and Regression Analysis

The findings revealed that male workers, on average, earn higher wages than female workers. There are noticeable differences in the mean values of variables between men and women. Figure 1 presents the kernel density plot for both internet users and non-internet users in their main occupation. The blue line represents the log real wage distribution for men, while the red line represents that for women. Overall, both groups exhibit similar wage distributions. However, men's wages are generally higher, as evidenced by the rightward shift of the male wage distribution. The peak of the wage distribution curve for men is higher than for women, suggesting that a greater proportion of men earn at or above a certain average wage level. Additionally, the male wage distribution is narrower and higher, indicating that men's wages are more concentrated around the mean compared to women's.

Interestingly, internet usage in the main job is associated with higher wages compared to non-internet users, as indicated by the slightly longer tail on the right side of the distribution. In contrast, non-internet users tend to exhibit a longer tail on the left side. Additionally, the average wage for internet users is higher than that for non-users. These differences contribute to disparities in the wage gap between genders within both groups.

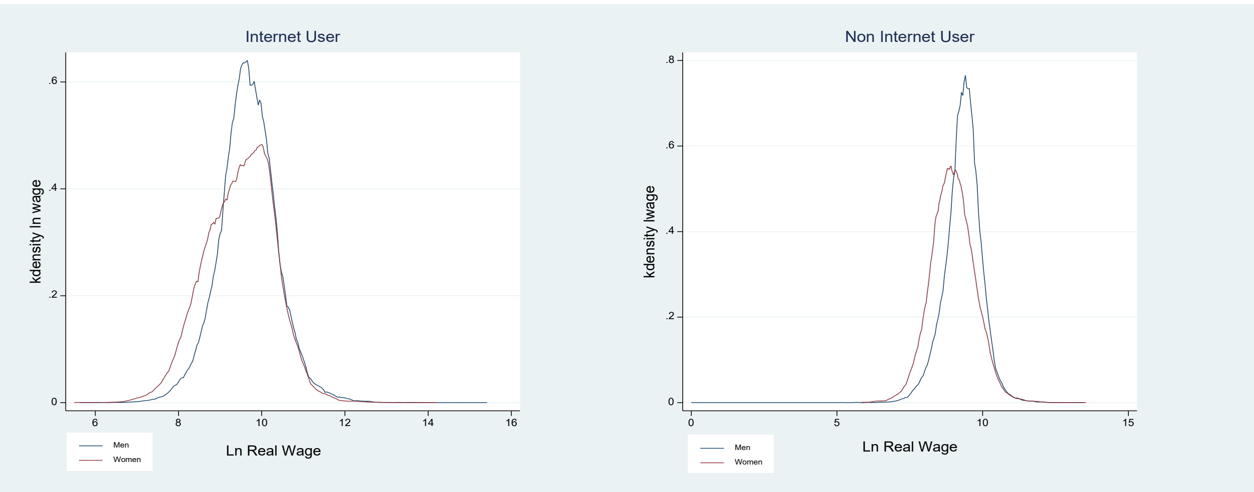

Figure 1: Kernel Density of Log Wage by Internet Usage and Gender

Table 1 provides summary statistics from Sakernas 2022 data for both male and female wage workers. The statistics reveal that men earn a higher mean wage than women, with a ratio of 117.5%. Additionally, men's wages exhibit greater variability, as reflected in the higher standard deviations. Age distributions for both genders are comparable, with average ages around 34-35 years. Notably, men have a higher percentage of secondary education, while women surpass men at the tertiary level. Average tenure is similar for both genders, although men have slightly longer tenure. In terms of industry, more men are employed in agriculture and industry, whereas a larger proportion of women work in the services sector. Internet usage is also higher among women (66.56%) compared to men (62.54%).

Table 2 presents the benchmark regression results for both least squares and quantile regression. Robust least squares in column 2 reveal a marginal coefficient for internet usage of 0.2099, significant at the 1% level. This finding indicates that internet usage significantly boosts workers' overall real wage income across genders by 20.99%. To explore gender differences, the study also conducts separate robust least squares analyses for males and females, assessing the differential impact of various characteristics on wage equations for each gender. Columns 3 and 4 of Table 2 show the estimated results for male and female observations, respectively. For males, the marginal coefficient for internet usage is 0.1787, which is also significant at the 1% level, suggesting that internet use increases male wage income by 17.87%. In contrast, internet usage raises women's wages by 20.59%, indicating a more significant impact on female wages than male wages.

Table 1: Summary Statistics

Continuous variables								
Variable	**Male**				**Female**			
	Mean	**St. dev.**	**Min**	**Max**	**Mean**	**St. dev**	**Min**	**Max**
Hourly wage[1] (Rp)	16,524.67	24,618.13	0	2,341,450	14,052.23	16327.35	215.7043	664,599.9
Lwage_Real	9.5696	0.6957	0	14.78	9.3361	0.8232	5.4974	13.55
Age (years)	35.9522	11.0547	15	65.00	34.1566	11.2548	15	65.00
Tenure (years)	8.6349	8.7368	0	57.17	7.3182	8.2451	0	54.17
Categorical variables								
Variable	**Male**				**Female**			
	Proportion	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**
No Education	0.0355	0.1849	0	1.00	0.0305	0.1718	0	1.00
Primary Educ	0.2917	0.4545	0	1.00	0.2143	0.4103	0	1.00
Secondary Educ	0.4787	0.4995	0	1.00	0.3744	0.4839	0	1.00
Tertiary Educ	0.1942	0.3956	0	1.00	0.3808	0.4856	0	1.00
Certified training	0.2487	0.4322	0	1.00	0.3174	0.4654	0	1.00
Married	0.7257	0.4462	0	1.00	0.6729	0.4691	0	1.00
Child	0.2939	0.4555	0	1.00	0.2226	0.4159	0	1.00
Agriculture	0.0785	0.2690	0	1.00	0.0272	0.1626	0	1.00
Manufacturing	0.3583	0.4795	0	1.00	0.2358	0.4245	0	1.00
Services	0.5632	0.4959	0	1.00	0.7370	0.4402	0	1.00
Internet use	0.6254	0.4840	0	1.00	0.6656	0.4717	0	1.00
Rural	0.2899	0.4537	0	1.00	0.2653	0.4415	0	1.00
Java	0.5992	0.4901	0	1.00	0.6138	0.4868	0	1.00
Observation	28,408,265				15,916,525			

Columns 5, 6, and 7 of Table 2 present the estimated partial effects of the explanatory variable on the male wage equation through quantile regression, specifically at the 25th quantile (lower wage level), the 50th quantile (median wage level), and the 75th quantile (higher wage level). Columns 8, 9, and 10 provide the corresponding estimates for females. The results indicate that internet usage has a significant positive effect on wages at the 1% significance level across all quantiles. Notably, the premium associated with internet use decreases as wage income increases, suggesting that the impact of internet usage on wages varies by wage level and suggesting that its benefits are broadly inclusive as they are more pronounced for lower income groups.

[1]Hourly wage rate refers to the real hourly wage by dividing the nominal hourly wage by given district/city Consumer Price Index (CPI) base year 2018, calculated from 82 inflation districts and cities and applies the CPI from the nearest neighboring districts/cities to those areas outside the inflation-affected cities.

Table 2: Robust Least Square and Quantile Regression Result of Internet Usage on Wage

Variables	Robust Least Square			Quantile Regression					
	All	Men	Women	Men			Women		
				Q 25	Q 50	Q 75	Q 25	Q 50	Q 75
Age	0.0053***	0.0031***	0.0051***	0.0013***	0.0026***	0.0029***	0.0041***	0.0040***	0.0050***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Primary	0.1430***	0.0936***	0.1918***	0.0984***	0.0825***	0.0696***	0.2324***	0.2003***	0.1575***
	(0.0006)	(0.0006)	(0.0011)	(0.0009)	(0.0006)	(0.0008)	(0.0016)	(0.0013)	(0.0015)
Secondary	0.4416***	0.3586***	0.5353***	0.3534***	0.3483***	0.3495***	0.5691***	0.5510***	0.5403***
	(0.0006)	(0.0007)	(0.0012)	(0.0009)	(0.0007)	(0.0008)	(0.0017)	(0.0014)	(0.0016)
Tertiary	0.7609***	0.7573***	0.8923***	0.6889***	0.7351***	0.8183***	0.8854***	0.9694***	0.9585***
	(0.0007)	(0.0007)	(0.0012)	(0.0010)	(0.0007)	(0.0009)	(0.0017)	(0.0014)	(0.0016)
Tenure	0.0133***	0.0095***	0.0183***	0.0103***	0.0093***	0.0089***	0.0212***	0.0184***	0.0173***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Certified training	0.1243***	0.1215***	0.1224***	0.1208***	0.1143***	0.1077***	0.1384***	0.1249***	0.1127***
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0006)	(0.0005)	(0.0006)
Married	0.0995***	0.1956***	0.0049***	0.2406***	0.1890***	0.1709***	-0.0120***	0.0324***	0.0300***
	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0008)	(0.0006)	(0.0007)
Child	0.0164***	-0.0170***	-0.0385***	-0.0239***	-0.0079***	-0.0147***	-0.0620***	-0.0327***	-0.0089***
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0007)	(0.0006)	(0.0007)
Manufacturing	-0.0698***	-0.0116***	-0.1035***	0.0596***	-0.0216***	-0.0970***	0.0194***	-0.0877***	-0.2571***
	(0.0005)	(0.0005)	(0.0013)	(0.0006)	(0.0005)	(0.0006)	(0.0017)	(0.0014)	(0.0017)
Services	-0.3278***	-0.2013***	-0.3823***	-0.1640***	-0.1966***	-0.2206***	-0.3111***	-0.3988***	-0.5195***
	(0.0005)	(0.0005)	(0.0012)	(0.0007)	(0.0005)	(0.0006)	(0.0017)	(0.0014)	(0.0016)
Internet use	0.2099***	0.1787***	0.2059***	0.1679***	0.1658***	0.1578***	0.2089***	0.2091***	0.1905***
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0006)
Rural	-0.2099***	-0.1569***	-0.3038***	-0.1554***	-0.1366***	-0.1393***	-0.3518***	-0.2848***	-0.2512***
	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0006)
Java	0.0365***	0.0209***	0.0883***	-0.0005	0.0162***	0.0424***	0.0831***	0.0955***	0.1164***
	(0.0002)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0006)	(0.0005)	(0.0005)
Constant	8.7808***	8.9014***	8.6083***	8.5803***	8.9671***	9.3423***	8.1338***	8.6387***	9.1544***
	(0.0008)	(0.0009)	(0.0018)	(0.0012)	(0.0009)	(0.0011)	(0.0025)	(0.0020)	(0.0024)
Observations	44,324,790	28,408,265	15,916,525	28,408,265	28,408,265	28,408,265	15,916,525	15,916,525	15,916,525

Standard errors in parentheses
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Decomposition Result

In Table 3, the results of the gender wage gap decomposition are presented, utilizing male, female, and combined wage structures. The mean log wage for males is 9.56, compared to 9.33 for females, resulting in an overall wage gap of 0.23, which is statistically significant at the 1%level. This suggests that men earn real wages that are approximately 23.35% higher than those of women. The explained or characteristic gap is negative, indicating that differences in endowments can reduce the wage gap by 0.048 log points, contributing -20.94% to the overall gap. On the other hand, the unexplained gap is 0.282 log points, accounting for 120.94%of the gender wage gap. This underscores that the primary driver of the wage gap lies in the unexplained component, which may include gender discrimination and other unmeasured factors that significantly exacerbate the disparity.

Table 3: Decomposition Result of Gender Wage Gap

Variable/Wage Structure	Combined wage structure		Male wage structure		Female wage structure	
Male	9.5696***		9.5696***		9.5696***	
	(0.0001)		(0.0001)		(0.0001)	
Female	9.3361***		9.3361***		9.3361***	
	(0.0002)		(0.0002)		(0.0002)	
difference	0.2335***		0.2335***		0.2335***	
	(0.0002)		(0.0002)		(0.0002)	
explained	-0.0489***		-0.0368***		-0.0556***	
	(0.0001)		(0.0002)		(0.0001)	
unexplained	0.2824***		0.2703***		0.2891***	
	(0.0002)		(0.0002)		(0.0002)	
Observations	44,324,790		44,324,790		44,324,790	
Components	**Explained**	**Unexplained**	**Explained**	**Unexplained**	**Explained**	**Unexplained**
Age	0.0070***	-0.0699***	0.0092***	-0.0720***	0.0056***	-0.0684***
	(0.0000)	(0.0011)	(0.0001)	(0.0011)	(0.0000)	(0.0010)
Primary	0.0095***	-0.0233***	0.0148***	-0.0286***	0.0072***	-0.0210***
	(0.0000)	(0.0003)	(0.0001)	(0.0004)	(0.0001)	(0.0003)
Secondary	0.0433***	-0.0720***	0.0558***	-0.0846***	0.0374***	-0.0661***
	(0.0001)	(0.0005)	(0.0001)	(0.0006)	(0.0001)	(0.0005)
Tertiary	-0.1492***	-0.0435***	-0.1665***	-0.0262***	-0.1413***	-0.0514***
	(0.0002)	(0.0005)	(0.0003)	(0.0003)	(0.0002)	(0.0005)
Tenure	0.0164***	-0.0682***	0.0241***	-0.0759***	0.0126***	-0.0643***
	(0.0000)	(0.0003)	(0.0001)	(0.0003)	(0.0000)	(0.0002)
Certified training	-0.0085***	-0.0002	-0.0084***	-0.0002*	-0.0083***	-0.0003*
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0002)
Married	0.0061***	0.1325***	0.0003***	0.1383***	0.0103***	0.1283***
	(0.0000)	(0.0004)	(0.0000)	(0.0005)	(0.0000)	(0.0004)
Child	-0.0012***	0.0048***	-0.0027***	0.0063***	-0.0012***	0.0048***
	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0000)	(0.0001)
Manufacturing	-0.0053***	0.0255***	-0.0127***	0.0329***	-0.0014***	0.0217***
	(0.0001)	(0.0003)	(0.0001)	(0.0005)	(0.0001)	(0.0003)
Services	0.0465***	0.1219***	0.0665***	0.1019***	0.0350***	0.1334***
	(0.0001)	(0.0009)	(0.0002)	(0.0007)	(0.0001)	(0.0009)
Internet use	-0.0077***	-0.0176***	-0.0083***	-0.0170***	-0.0072***	-0.0181***
	(0.0000)	(0.0003)	(0.0000)	(0.0003)	(0.0000)	(0.0003)
Rural	-0.0052***	0.0403***	-0.0075***	0.0426***	-0.0039***	0.0390***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Java	-0.0007***	-0.0410***	-0.0013***	-0.0404***	-0.0003***	-0.0414***
	(0.0000)	(0.0003)	(0.0000)	(0.0003)	(0.0000)	(0.0003)
Constant		0.2931***		0.2931***		0.2931***
		(0.0020)		(0.0019)		(0.0019)

Standard errors in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

The negative values of the explained component suggest that, based on observable characteristics, women should earn more than men. This paradox implies that other unmeasured factors, possibly discrimination, are causing the wage gap to favor men. An unexplained component exceeding 100% indicates that the wage gap is due to factors not captured by the measured characteristics. Basic Oaxaca decomposition results reveal that while observable characteristics suggest women should have higher wages than men, the actual wage gap shows men earning more, largely due to unexplained factors likely related to discrimination.

The partial effects from the decomposition results indicate that several factors contribute to reducing the wage gap, as reflected in the negative values of both the explained and unexplained components. These factors include tertiary education, certified training, and internet usage in the main job. The role of tertiary education and certified training in narrowing the wage gap is consistent with previous studies (Akbar, 2022; Hennigusnia, 2014; Lidya & Kadir, 2019; Sohn, 2015). Additionally, internet usage also appears to mitigate the gender wage gap, evidenced by negative values in both components. Overall, internet usage contributes 2.53%to the wage gap, with explained and unexplained contributions of 0.77 and 1.76%, respectively. Notably, these findings contrast with those of Gao & Liu (2023a) and Ma (2022), who suggested that internet use actually widens the gender wage gap.

When analyzed by income groups, the wage gap decreases with rising income levels. Income groups are divided into three equal segments or quantiles. The first group contains workers with the lowest income, the second group includes those in the middle, and the third group represents the workers with the highest income. This division allows for the comparison of equivalent wage data at different income levels. The Table 4 below provides a summary of the statistics for each group, highlighting the decomposition result of gender wage gap in wage distribution among them. Disparities where men earn more than women are evident only in low and middle-income groups. In contrast, in the high-income group, women typically earn more than men, leading to a negative wage gap of -0.01.

Furthermore, internet usage exhibits a negative contribution in both the explained and unexplained components exclusively within the middle-income group. In contrast, for low- and high-income groups, only the endowment component shows potential for reducing gender wage inequality. This suggests inconsistencies in the results when the decomposition is performed without accounting for income groups. Detailed decomposition results by income level are presented in Table 4.

The data in Table 5 shows that there is a gender wage gap for both blue-collar and white-collar workers, with men earning significantly more than women in both categories. The wage gap is slightly more prominent among blue-collar workers, measuring 0.34 log points or 34.84 percentage points. Both the explained and unexplained components contribute to this gap. When looking at the partial effects, internet usage in the main job widens the wage gap for blue-collar workers but narrows it for white-collar workers.

These results align with previous analyses based on income levels, as white-collar workers generally earn higher incomes than their blue-collar counterparts. At higher income levels, internet usage can help reduce the wage gap, especially among white-collar workers. This suggests that within this group, internet usage may improve women's endowments and returns, potentially reducing the wage disparity between men and women. Overall, these findings indicate that internet usage affects the wage gap differently across income levels and job categories (Ma, 2022; Murray, 2023).

Table 4: Decomposition Result of Gender Wage Gap by Income Level

Variables	Lower		Middle		Higher	
Male	8.7334***		9.4704***		10.2504***	
	(0.0002)		(0.0001)		(0.0001)	
Female	8.5602***		9.4615***		10.2604***	
	(0.0002)		(0.0001)		(0.0002)	
difference	0.1731***		0.0088***		-0.0100***	
	(0.0002)		(0.0001)		(0.0002)	
explained	0.0151***		-0.0062***		-0.0792***	
	(0.0001)		(0.0000)		(0.0001)	
unexplained	0.1581***		0.0150***		0.0692***	
	(0.0002)		(0.0001)		(0.0002)	
Observations	13,886,196		14,987,961		15,450,633	
Components	**Explained**	**Unexplained**	**Explained**	**Unexplained**	**Explained**	**Unexplained**
Age	-0.0005***	0.0208***	0.0007***	0.0149***	0.0064***	-0.0985***
	(0.0000)	(0.0011)	(0.0000)	(0.0005)	(0.0000)	(0.0015)
Primary	0.0042***	-0.0093***	0.0012***	0.0038***	-0.0037***	-0.0009***
	(0.0001)	(0.0004)	(0.0000)	(0.0002)	(0.0001)	(0.0002)
Secondary	0.0035***	-0.0188***	0.0021***	0.0071***	0.0065***	0.0039***
	(0.0000)	(0.0005)	(0.0000)	(0.0003)	(0.0002)	(0.0007)
Tertiary	0.0009***	-0.0152***	-0.0141***	0.0008***	-0.0849***	0.0680***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0014)
Tenure	0.0037***	-0.0122***	0.0018***	-0.0055***	-0.0005***	0.0215***
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0004)
Certified training	-0.0004***	-0.0019***	-0.0009***	-0.0022***	-0.0059***	0.0113***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0002)
Married	-0.0021***	0.0390***	0.0015***	0.0084***	0.0009***	0.0234***
	(0.0000)	(0.0005)	(0.0000)	(0.0002)	(0.0000)	(0.0005)
Child	-0.0004***	0.0101***	-0.0000***	-0.0006***	-0.0001***	0.0020***
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Manufacturing	0.0041***	0.0246***	-0.0031***	0.0117***	-0.0077***	-0.0042***
	(0.0001)	(0.0003)	(0.0000)	(0.0002)	(0.0001)	(0.0005)
Services	0.0057***	0.0486***	0.0072***	0.0286***	0.0164***	-0.0417***
	(0.0001)	(0.0009)	(0.0000)	(0.0004)	(0.0001)	(0.0016)
Internet use	-0.0018***	0.0025***	-0.0020***	-0.0021***	-0.0045***	0.0159***
	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0005)
Rural	-0.0020***	0.0288***	-0.0013***	0.0040***	-0.0016***	0.0031***
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Java	0.0001***	0.0036***	0.0007***	-0.0050***	-0.0005***	-0.0188***
	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0003)
Constant		0.0374***		-0.0488***		0.0844***
		(0.0019)		(0.0009)		(0.0029)

Standard errors in parentheses
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5: Decomposition Result of Gender Wage Gap by Job Type

Variables	Blue Collar		White Collar	
Male	9.4537***		9.8991***	
	(0.0001)		(0.0003)	
Female	9.1054***		9.5888***	
	(0.0002)		(0.0003)	
difference	0.3484***		0.3103***	
	(0.0003)		(0.0004)	
explained	0.0651***		0.0437***	
	(0.0001)		(0.0002)	
unexplained	0.2833***		0.2666***	
	(0.0003)		(0.0004)	
Observations	29,334,461		14,990,329	
Components	**Explained**	**Unexplained**	**Explained**	**Unexplained**
Age	-0.0021***	0.1189***	0.0491***	-0.2157***
	(0.0000)	(0.0012)	(0.0001)	(0.0024)
Primary	-0.0018***	-0.0139***	-0.0044***	0.0024***
	(0.0000)	(0.0005)	(0.0002)	(0.0003)
Secondary	0.0141***	-0.0409***	0.0148***	0.0301***
	(0.0001)	(0.0007)	(0.0006)	(0.0034)
Tertiary	-0.0095***	-0.0156***	-0.0589***	0.0774***
	(0.0001)	(0.0001)	(0.0008)	(0.0071)
Tenure	0.0282***	-0.0427***	0.0080***	-0.0552***
	(0.0001)	(0.0003)	(0.0001)	(0.0006)
Certified training	0.0030***	-0.0014***	-0.0033***	0.0064***
	(0.0000)	(0.0001)	(0.0000)	(0.0004)
Married	0.0081***	0.0630***	0.0020***	0.1900***
	(0.0000)	(0.0005)	(0.0001)	(0.0009)
Child	-0.0003***	0.0022***	-0.0010***	-0.0012***
	(0.0000)	(0.0001)	(0.0000)	(0.0003)
Manufacturing	-0.0005***	0.0403***	-0.0043***	0.0001
	(0.0000)	(0.0006)	(0.0002)	(0.0004)
Services	0.0206***	0.0958***	0.0357***	0.1146***
	(0.0001)	(0.0007)	(0.0002)	(0.0043)
Internet use	0.0110***	0.0045***	-0.0006***	-0.0560***
	(0.0000)	(0.0003)	(0.0000)	(0.0011)
Rural	-0.0055***	0.0304***	0.0022***	0.0211***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)
Java	-0.0002***	-0.0581***	0.0045***	0.0148***
	(0.0000)	(0.0004)	(0.0000)	(0.0004)
Constant		0.1009***		0.1379***
		(0.0021)		(0.0119)

Standard errors in parentheses
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Conclusion

This study examined the gender wage gap in Indonesia within the context of the digital era, utilizing data from the 2022 Sakernas survey. We employed robust least squares and quantile regression analyses to assess the impact of internet usage on average wage levels by gender. Additionally, we conducted Oaxaca decomposition to quantify the effects of internet use on the gender wage gap, separating the explained and unexplained components.

The key findings are as follows: first, internet usage significantly boosts wages for both men and women, with the wage premium effect increasing from lower to upper distribution levels. However, this premium diminishes as wage quantiles rise. Second, the decomposition analysis indicates that internet usage can help reduce the gender wage gap. The gap varies notably across income levels and job types. As income increases, the wage gap narrows, with men earning more than women only in low and middle-income groups. In high-income groups, women tend to earn more than men. Internet usage is pivotal in this dynamic, effectively reducing the wage gap in white-collar jobs and high-income categories while showing less consistent effects in blue-collar jobs and lower-middle-income groups. This suggests that women's endowments and returns are more favorable in environments where internet use is prevalent, potentially alleviating gender wage disparities.

These findings highlight the need to consider wage levels and job categories when addressing gender wage inequality. To effectively reduce the gender pay gap, efforts should focus on low-income and blue-collar workers, who are disproportionately disadvantaged and often lack access to internet resources in the workplace. Enhancing digital skills for this demographic is crucial to ensure they benefit from reductions in the gender wage gap similar to those experienced by higher-income groups.

Furthermore, the study highlights that unexplained variables, particularly discrimination, are significant contributors to the gender wage disparity. Addressing the prevalence of discrimination is crucial, as it can exacerbate the effects of other unexplained factors such as social norms and cultural influences, which further entrench this disparity. However, tackling these unexplained factors presents a challenge due to the lack of relevant data. This data unavailability hinders a comprehensive understanding of how these variables influence wage differences. More robust data collection and analysis are needed to effectively investigate the impact of these unexplained factors on the gender wage gap. In light of this, the estimated level of discrimination can serve as a useful proxy to account for omitted exogenous factors and other unobserved variables affecting wages. By recognizing discrimination as a key element in the wage gap, we can better understand its interaction with social and cultural influences. Future research should prioritize gathering qualitative and quantitative data on these factors to enrich the analysis and provide actionable insights for policymakers.

Declaration

Conflict of Interest

This research was conducted without any potential biases or conflicts of interest that could compromise the reliability of the findings.

Availability of Data and Materials

This study utilized secondary data obtained from BPS-Statistics Indonesia.

Funding Source

This study was conducted with funding provided solely by the authors.

Acknowledgment

-

References

Acemoglu, D., & Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (pp. 1043–1171). https://doi.org/10.1016/S0169-7218(11)02410-5

Akbar, F. (2022). Gender Wage Gap: Evidence from Employment in Informal Sector. *The Journal of Indonesia Sustainable Development Planning*, *3*(2 SE-Research Paper), 104–117. https://doi.org/10.46456/jisdep.v3i2.301

Arrow, K. (1973). The theory of discrimination. In O. Asehenfelter & A. Ress (eds) *Discrimination in Labor Markets*. Princetown University Press.

Barsky, R., Bound, J., Charles, K. K., & Lupton, J. P. (2002). Accounting for the Black–White Wealth Gap. *Journal of the American Statistical Association*, *97*(459), 663–673. https://doi.org/10.1198/016214502388618401

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

Bergmann, B. (1974). Occupational segregation, wages and profits when employers discriminate by race or sex. *Eastern Economic Journal*, *1*(2), 103–110.

Berman, E., Bound, J., & Machin, S. (1998). Implications of Skill-Biased Technological Change : International Evidence Author (s): Eli Berman , John Bound and Stephen Machin Source : *The Quarterly Journal of Economics , 113* (4), 1245-1279,

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources*, *8*(4), 436–455.

Borjas, G. J. (2013). Labor Economics. In *Labor Economics* (6th ed., pp. 235–287). McGraw-Hill Companies, Inc.

Bustelo, M., Flabbi, L., & Viollaz, M. (2019). *The Gender Labor Market Gap in the Digital Economy*. https://doi.org/10.18235/0001941

Chamwong, S., Chomtohsuwan, T., & Charoenphandhu, N. (2024). Analysis of Inequality in Household Internet Utilization and Policy Implications. *Journal of Demography*, *39*(1). https://doi.org/10.56808/2730-3934.1369

Dietz, T., Frey, R. S., & Kalof, L. (1987). Estimation with Cross-National Data: Robust and Nonparametric Methods. *American Sociological Review*, *52*(3), 380. https://doi.org/10.2307/2095357

DiMaggio, P., Hargittai, E., Celeste, C., & Steven, S. (2004). From Unequal Access to Differentiated Use: A Literature Review and Agenda for Research on Digital Inequality. “ Working Papers 29, Princeton University, School of Public and International Affairs, Center for Arts and Cultural Policy Studies.

Fortin, N., Lemieux, T., & Firpo, S. (2011). Decomposition methods in economics. *Handbook of Labor Economics*, *4*, 1–102. https://doi.org/https://doi.org/10.1016/S0169-7218(11)00407-2

Gao, J., & Liu, Y. (2023a). Has Internet Usage Really Narrowed the Gender Wage Gap?: Evidence from Chinese General Social Survey Data. *Human Behavior and Emerging Technologies*, *2023*. https://doi.org/https://doi.org/10.1155/2023/7580041

Gao, J., & Liu, Y. (2023b). Internet technology usage and female employment: Evidence from a Chinese general social survey. *The Economics and Finance Letters*, *10*(1), 57–68. https://doi.org/10.18488/29.v10i1.3287

Hallward-Driemeier, M., Rijkers, B., & Waxman, A. (2017). Can Minimum Wages Close the Gender Wage Gap? *Review of Income and Wealth*, *63*(2), 310–334. https://doi.org/https://doi.org/10.1111/roiw.12219

Hennigusnia. (2014). Kesenjangan Upah Antar Jender Di Indonesia: Glass Ceiling Atau Sticky Floor? (Gender Wage Gap in Indonesia: Glass Ceiling or Sticky Floor?). *Jurnal Kependudukan Indonesia*, *9*, 83–96.

Ilmakunnas, P. (2023). Skill-biased Technological Change. In T. Eriksson (ed.), *Elgar Encyclopedia of Labour Studies* (pp. 205–207). Edward Elgar Publishing. https://doi.org/10.4337/9781800377547

Jacobsen, J. P. (1994). *The Economics of Gender*. Cambridge, Mass.

Jamielaa, M. (2018). Trade Openness and Gender Wage Gap : Evidence from Indonesia. *Journal of International Cooperation Studies*, *26*(1), 25–40.

Lidya, S. W., & Kadir, K. (2019). Decomposition of the Gender Wage Gap in Indonesia: Analysis from Sakernas Data. *Munich Personal RePEc Archive*, *94930*.

Losh, S. C. (2004). Gender, Educational, and Occupational Digital Gaps 1983-2002. *Social Science Computer Review*, *22*(2), 152–166. https://doi.org/10.1177/0894439303262557

Lukyanova, A. L. (2021). Digitalization and the Gender Wage Gap in Russia. *Ekonomicheskaya Politika*, *2*, 88–117. https://doi.org/10.18288/1994-5124-2021-2-88-117

Ma, X. (2022). Internet use and gender wage gap: evidence from China. *Journal for Labour Market Research*, *56*(1). https://doi.org/10.1186/s12651-022-00320-9

Mariniello, M. (2022). Digital Inequality. In *Digital Economic Policy* (pp. 309–328). Oxford: Oxford University Press. https://doi.org/10.1093/oso/9780198831471.003.0013

Mincer, J. (1974). *Schooling, Experience and Earnings*. New York: Columbia University Press.

Morahan-Martin, J. (1998). The Gender Gap in Internet Use: Why Men Use the Internet More Than Women—A Literature Review. *CyberPsychology & Behavior*, *1*(1), 3–10. https://doi.org/10.1089/cpb.1998.1.3

Murray, S. (2023). A Decomposition of the Relationship Between Internet Access and Earnings. *Journal of Applied Business and Economics*, *25*(6). https://doi.org/10.33423/jabe.v25i6.6583

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International*

Economic Review, *14*(3), 693–709.

Oaxaca, R., & Ransom, M. (1999). Identification in Detailed Wage Decompositions. *The Review of Economics and Statistic*, *81*(1), 154–157. https://www.jstor.org/stable/2646794

Olive, D. J. (2008). *Applied Robust Regression*. Southern Illinois University. http://parker.ad.siu.edu/Olive/run.pdf

Phelps, E. S. (1972). The statistical theory of racism and sexism. *American Economic Review*, *62*(4), 659–661.

Qi, Y. D., & Liu, C. H. (2020). Does the use of internet reduce the difference in gender pay in the context of digital economy? *Economoc Theory and Economic Administration*, *9*, 70–87.

Simamora, L. A., & Widyawati, D. (2022). Dampak Kenaikan Upah Minimum Terhadap Kesenjangan Upah Antar Gender: Kasus di Seluruh Provinsi di Indonesia. *Jurnal Ekonomi Dan Statistik Indonesia*, *2*(2), 147–161. https://doi.org/10.11594/jesi.02.02.03

Sinha, S. (2018). Gender Digital Divide in India: Impacting Women's Participation in the Labour Market. In Y. Kumar (ed.), *Reflecting on India's Development* (pp. 293–310). Springer Singapore. https://doi.org/10.1007/978-981-13-1414-8_14

Sohn, K. (2015). Gender Discrimination in Earnings in Indonesia: A Fuller Picture. *Bulletin of Indonesian Economic Studies*, *51*(1), 95–121. https://doi.org/10.1080/00074918.2015.1016569

Solomon, B. D. (2023). Factor endowment theory. In *Dictionary of Ecological Economics* (pp. 224–224). Edward Elgar Publishing. https://doi.org/10.4337/9781788974912.F.1

Suharyono, & Digdowiseiso, K. (2021). Education and gender wage gap: Evidence from indonesia. *Accounting*, *7*(1), 33–40. https://doi.org/10.5267/j.ac.2020.10.017

Wang, F., & Shen, S. (2024). Does the digital economy development improve or exacerbate income inequality? International evidence. *Managerial and Decision Economics*, *45*(6), 4012–4038. https://doi.org/10.1002/mde.4231

Wilcox, R. R. (1998). The goals and strategies of robust methods. *British Journal of Mathematical and Statistical Psychology*, *51*(1), 1–39. https://doi.org/10.1111/j.2044-8317.1998.tb00659.x

Woźniak-Jęchorek, B., & Kuźmar, S. (2023). Income inequalities in the accelerating digital era: Evidence from EU countries and COVID-time. *Panoeconomicus*, *70*(4), 551–572. https://doi.org/10.2298/PAN2304551W

Wu, E. (2021). Analysis of Internet usage and gender wage difference. *Cooperatives Economics Technology*, *16*, 138–140.

Xiliang, F., Panpan, G., & Rongbo, L. (2021). The impact of internet use on the gender wage earnings gaps of migrant workers. *Population and Economy*, *5*, 111–124.