

Gender-Based Wage Gap in Thailand

Akkaya Senkrua¹

¹Faculty of Business, Economics, and Communication, Naresuan University (Received: January 24, 2022; Revised: February 2, 2022; Accepted: March 1, 2022)

Abstract

Gender-based wage inequality is prevalent in countries around the globe, and Thailand is no stranger to gender wage discrimination. Specifically, this study is documentary research on pay differentials to investigate the factors contributing to the gender-based wage gap in Thailand by using wage decomposition methods. The findings indicate that the gender pay gap in the country has declined due to higher educational attainment of female workers. The male-female wage differential however remains despite the convergence in individual characteristics and endowments of male and female workers. The study also reveals that gender discrimination contributes to the persistent wage differential.

Keyword: 1) gender wage gap 2) wage decomposition 3) wage discrimination 4) wage inequality

¹ Assistant Professor, Department of Economics; E-mail: akkayas@nu.ac.th



Introduction

The International Labor Organization (ILO) estimates that across the globe women are paid on average about 20 percent less than men, with large variations from country to country ranging from almost no difference to as high as 45 percent (ILO, 2019, p.68). Meanwhile, governments around the world have made efforts to narrow gender-based pay gap with varying degrees of success (ILO, 2019, p.71). The gender-based pay gap is a barometer of the difference in the overall pay between female and male wage earners.

Despite improvement in women's employment opportunities and policy support, Thai women's wages and job opportunities still lag behind their male counterparts'. A recent study by the ILO reports that average wages of male workers in Thailand are higher than for female workers (Liao and Paweenawat, 2019), suggesting the existence of gender wage discrimination and gender wage gaps across industries in the country. Besides, a larger number of women are employed in the low-income occupations (68 percent for female versus 61 percent for male), such as low-level service and sales clerks; agricultural, forestry, and fishery workers; or other elementary occupations (Jithitikulchai, 2016, p.2).

An increasing number of female workers have attained higher education during the past decades, with the proportion of female workers with more than twelve years of formal education having increased significantly (Jithitikulchai, 2016, p.2). The years of schooling of female workers aged 15-64 increased from an average of 9.1 years in 2011 to 10.0 years

in 2020, surpassing that of male workers of an average of 9.0 years in 2011 to 9.7 years in 2020 (National Statistical Office: NSO, 2021). The improvement in education plays a part in narrowing the wage gap between Thai male and female workers. Nakavachara (2010) attributed the decline in gender wage gap in Thailand during 1985-2005 to higher education attainment of Thai women. However, despite higher education and improved work productivity, female workers are being paid less than their male counterparts (Leetrakul, 2011, pp.41-42).

As a result, the issue of gender wagebased inequality, especially in developing countries, warrants thorough investigation. At the micro level, wage inequality discourages female workers from participating in the labor market or disincentivizes them to remain in the labor force. Gender-based wage inequality also exacerbates the living conditions of already impoverished female workers, which in turn aggravates the plight of their offspring given the fact that a majority of female workers in Thailand are single mothers (UNFPA, 2015, p.1). In addition, gender-based wage inequality engenders more poverty and perpetuates other poverty-related social issues, such as limited educational opportunity for poor women and their children, female and child prostitution, and child malnutrition (ILO, 2018, pp.19-20).

At the macro level, gender-based wage inequality lowers economic productivity and growth as qualified and talented women are discouraged from active participation in the labor force. Specifically, wage inequality slows economic growth by reducing labor force participation, working hours, and labor pro-



ductivity (Schober and Winter-Ember, 2009). According to Poggi (2014), gender-based wage inequality adversely influences job satisfaction, leading to lower overall productivity.

Specifically, this paper reviews existing publications related to wage determination and pay differentials in order to provide explanations as to why Thai female workers are compensated substantially below their male counterparts with identical personal characteristics and endowments. The remainder of this study is organized as follows: Section 2 details the theoretical background of wage differentials. Section 3 reviews the methodologies used in the wage determination and wage decomposition in Thailand, and Section 4 discusses the research findings. The concluding remarks along with policy implications and recommendations are provided in the final section.

Theoretical Background

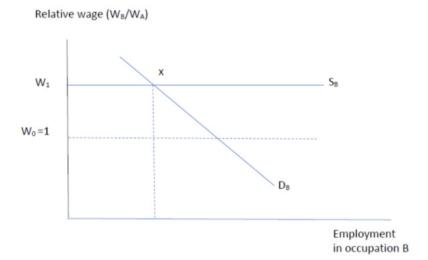
According to the theory of compensating wage differentials, an individual chooses an occupation based on both the financial remuneration and several other negative and positive attributes (Kaufman and Hotchkiss, 2006, p.390). Specifically, a worker compares the advantages and disadvantages of different occupations and chooses the occupation with the highest level of net advantages. Differences in the pay rates among occupations represent the compensating wage differentials because the unequal pay rates equalize the unequal attractiveness of different occupations (Kaufman and Hotchkiss, 2006, p.390).

For example, assuming that occupations A and B are identical in almost all aspects

except that occupation B is somewhat of low social prestige such as butler, janitor, etc. (i.e., negative attribute). People would refuse occupation B and seek employment in occupation A if the wages in both occupations were equal. To establish the equilibrium, the wage for occupation B must rise until it sufficiently compensates for the negative attribute of occupation B, as illustrated in Picture No. 1. In the figure, the difference between W1 and W0 (W1-W0 or compensating wage differential) represents the monetary value required to compensate for the negative utility attributable to the undesirable feature of occupation B.

In Picture No. 1, at the wage (W_1) the supply curve (S_B) is perfectly elastic, indicating that no one would choose in occupation B for any wage below W_1 . The dashed line at W_0 =1.0 is where the wage rates of occupations A and B are equal. Given the low social prestige of occupation B, the wage of occupation B must be sufficiently higher than that of occupation A to equalize the sum of advantages and disadvantages of both occupations. The equilibrium occurs at point X, where the demand curve (D_B) intersects the supply curve (S_D) .





Picture No. 1 The compensating wage differential for a less desirable occupation Source: Kaufman and Hotchkiss, 2006, p.392

According to Becker's theory of labor market discrimination, individuals of equal capabilities competing in the labor market are given unequal job assignments, promotions, or rates of pay on the basis of certain characteristics unrelated to their performance. In addition, there are three theories pertaining to labor market discrimination: employer discrimination, employee discrimination, and customer discrimination (Kaufman and Hotchkiss, 2006, pp.449-450).

For employer discrimination, a discriminatorily-inclined employer would be willing to pay extra to distance him/herself from workers of the minority group. Specifically, a discriminatory employer, when faced with minority workers who could be hired at the wage WB, act as if the actual cost were $W_{\rm B}$ (1+d_i), where d_i is the ith employer's discrimination coefficient against the minority group. The discrimination coefficient (d_i) represents the employer's disutility experience from contact with minority workers.

Becker's labor market discrimination

theory also suggests that the size of the wage differential between majority and minority workers depends on two factors: first, the size of the minority group where the larger the supply of minority workers in the market, the lower their relative wage; and second, the degree of discrimination among employers where the greater the number of discriminatory employers, the lower the relative wage of minority workers.

For employee discrimination, prejudice or discrimination among workers of different races, genders, or ethnicities has its root in their competition for jobs and their close personal contact at work. According to Becker's labor market discrimination model, a worker of the majority group is discriminatorily inclined if a person, when offered a wage W_w for a job that requires working with members of the minority group, acts as if the wage were $W_w(1-d_k)$, where d_k is the k^{th} worker's discrimination coefficient. As a result, the discriminatorily-inclined workers of the majority group (i.e.,



discriminatory workers) would agree to work with the discriminated workers of the minority group (i.e., discriminated workers) only if the former are compensated with a wage premium equal to W_d₁. A firm may be willing to hire both discriminatory and discriminated workers. If workers were prejudiced, the firm would have to pay a wage higher than the market level to maintain an integrated workforce. However, the long-term ramifications of such a practice are as follows: (1) a completely segregated workforce (i.e., hiring all discriminated workers or discriminatory workers to avoid the higher labor costs of an integrated workforce); and (2) discriminatory wage differentials will disappear as the business would switch to an all-discriminated workforce with a lower wage.

For customer discrimination, a discriminatorily-inclined consumer, when faced with an opportunity to purchase a good or service from a discriminated worker at a price of P_s, acts as if the price were $P_{R}(1+d_{m})$, where dm is the discrimination coefficient of the mth consumer. If the discriminated workers are hired to perform tasks that require personal contact with discriminatorily-inclined customers, the workers must be willing to accept a lower wage so that the firm can lower the selling price to overcome the prejudices of the discriminatory customers. Since the discriminated workers could earn more in jobs that required no customer contact, they will in the long run be segregated in jobs that require no interaction with the discriminatory customers.

Wage Determination and Wage Decomposition Methodologies

According to the basic Mincerian wage

model (1974), an individual wage (i.e., the natural log of wage) is a function of the individual's characteristics and endowments, i.e., education, experience, and experience squared. The basic Mincerian wage equation can thus be expressed as

$$\ln(wage_i) = \beta_0 + \beta_1(Education)_i + \beta_2(experience)_i + \beta_3(experience^2)_i + \mu_i$$
 (1)

In the extended Mincerian wage models, the individual's characteristics and endowments are extended to include, e.g., gender, marital status, region of residency, occupation, full time or part time, firm size, in addition o education, experience, and experience squared. Specifically, the extended Mincerian wage equation (equation (2)) takes into consideration both individual and job characteristics. $\ln(wage_i) = \beta_0 + \beta_1(Education)_i + \beta_2(experience)_i$

$$e_i$$
) = $\rho_0 + \rho_1$ (Education)_i + ρ_2 (experience
+ ρ_3 (experience²)_i + $\rho_n X_n + \mu_i$ (2)

where \ln (wage) is the natural log of average monthly wage as the dependent variable; and X_n is individual and job factors including age, age squared, full-time status, occupation, marital status, gender, union status, metropolitan location, and birthplace.

However, ordinary least squares (OLS) regression or multiple linear regression (i.e., equations (1)-(2)) encounters certain limitations: (i) it can only characterize the relationships between variables at the mean of the data, and (ii) it is not robust in the event of outliers since quantile regression is estimated by minimizing the sum of absolute values of residuals instead of the sum of squared residuals (Leetrakul, 2011, pp.44-45).

Unlike OLS regression which characterizes the effects of the explanatory variables



at the mean of the conditional distribution of dependent variable, the quantile regression enables understanding the relationships between variables outside of the mean of the data, making it useful in understanding the outcomes that are non-normally distributed and that have nonlinear relationships with the explanatory or independent variables (Adireksombata, Fangb and Sakellarioub, 2010, pp. 9-11). Besides, quantile regression uses the entire sample to estimate each quantile rather than dividing the sample by arbitrary exogenous sample selection criteria. As a result, there is no sample selection bias problem.

The quantile regression estimates are qualitatively similar to the OLS results, and the median regression results (50th percentile) are very close to the OLS estimates. Specifically, quantile regression enables us to determine whether the wages of female workers in different positions across the conditional distribution (i.e., female workers with higher and lower wages than predicted by observable characteristics) are statistically different from their male counterparts'.

The quantile regression models for wages of female (equation (3)) and male workers (equation 4) can thus be expressed as

$$lnw_f = X_f'\beta_{\theta f} + \epsilon_{\theta f}$$
 (3)

$$lnw_{m} = X'_{m}\beta_{\theta m} + \epsilon_{\theta m} \tag{4}$$

where ln w is the natural logarithm of wage, $X_i^{'}$ is the factors affecting earnings, θ is the th quantile.

The challenge inherent in estimating the wage function is that wage data is available only among employees. Besides, being an employee is not a random process. Some studies (Ninchainan and Osathanankul, 2013) followed Heckman's method (two-stage least squares (2SLS) regression) to correct bias from non-randomly selected samples (i.e., being an employee) in estimating the wage function.

The labor participation equation (equation (5)) is a probit selection equation whether a person will be an employee, given that $Z_i^* = 1$ if $Z_i^* > 0$ (workers decide to work) and $Z_i^* = 0$ if $Z_i^* \le 0$ (workers decide not to work)

$$Z_i^* = Y_i' \gamma + u_i \tag{5}$$

where Z_i^* is a decision to work, Y_i^* is the vector of the explanatory variable in the participation equation (5). The wage equation (equation (6)) is expressed as

$$E(W_i|Z_i^* > 0) = X_i'\beta + \theta\lambda_i + \varepsilon_i$$
 (6)

where $W_{_{_{i}}}$ is the natural logarithm of wage, and $X_{_{i}}$ is the vector of the explanatory variable in the wage equation (equation (6)), $\lambda_{_{i}}$ is the inverse Mills ratio.

The labor force participation equation (equation (5)) is estimated by using maximum likelihood method to obtain inverse Mills ratio (λ). If λ is statistically significant, the explanatory variables that influence the probability of being an employee and the wage rate are not independent of each other. If λ is negative, it implies that those who choose to be employed (i.e., being employees) have lower earnings ability than the average person with similar personal characteristics and endowments; and vice versa if λ is positive.

The dependent variable (W_i) in equation (6) is the monthly wage for those who are employees, and the explanatory variables can be experience, experience squared, education, marital status, occupation, industry type, sec-



tor. Specifically, the wage equations for male (m) and female (f) workers using ordinary least squares regression can be written as

$$\overline{W_{\rm m}} = \overline{X_{\rm m}} \beta_{\rm m} + \widehat{\theta_{\rm m}} \overline{\lambda_{\rm m}} \tag{7}$$

$$\overline{W_f} = \overline{X_f} \beta_f + \widehat{\theta_f} \overline{\lambda_f}$$
 (8)

where \bar{W} is the natural logarithm of mean wage, \bar{x} is the vector of the mean of personal characteristic variable, β is the vector of the coefficient of personal characteristic variable, θ^{\wedge} is the coefficient of inverse Mills ratio, and λ^{-} is the mean of inverse Mills ratio.

In essence, both OLS and quantile regression can predict the extent to which the explanatory factors influence the wage rates between male and female workers. However, the regression results fail to indicate the existence of wage discrimination. As a result, the wage decomposition is utilized to measure the gender-based wage discrimination.

In the wage gap decomposition models, it is assumed that there are two groups of workers, i.e., male (m) and female (f) workers, in the labor market with equilibrium wages of W_m and W_f , and the characteristic vectors related to human capital or labor market indicators are denoted as X_m and X_f . Based on the Mincerian wage equation, the difference of the mean wage between male and female workers can be expressed as equation (9) and can also be rewritten as equation (10).

$$\begin{split} \ln &\overline{w}_m - \ln \overline{w}_f = \overline{X}_m \beta_m - \overline{X}_f \beta_f \\ \ln &\overline{w}_m - \ln \overline{w}_f = (\overline{X}_m - \overline{X}_f) \beta^* + \overline{X}_m (\beta_m - \beta^*) + \overline{X}_f (\beta^* - \beta_f) \end{split} \tag{10}$$

where β^* is the non-discriminatory coefficient vector (i.e., reference vector), $(\bar{\mathbf{x}}_{_{\mathrm{m}}} - \bar{\mathbf{x}}_{_{\mathrm{f}}})\beta^*$ is the wage gap attributable to the endowment differentials, and $\bar{\mathbf{x}}_{_{\mathrm{m}}}$ ($\beta_{_{\mathrm{m}}} - \beta^*$) + $\bar{\mathbf{x}}_{_{\mathrm{f}}}(\beta^{*-} - \beta_{_{\mathrm{f}}})$ measures the discrimination. In solving equation (10),

the reference (i.e., male or female) and study groups (i.e., male or female) must be clearly specified because the selected reference group determines the sign (positive or negative) of the coefficient of explanatory variables.

According to the Oaxaca decomposition model (1973), the wage differential model can be written as

$$ln\overline{w}_{m} - ln\overline{w}_{f} = (\overline{X}_{m} - \overline{X}_{f})\beta_{m} + \overline{X}_{f}(\beta_{m} - \beta_{f}) \qquad (11)$$

As a result, Reimers (1983) proposed a method to estimate the reference vector by applying a half-and-half weight to calculating the average coefficients of both groups. The reference vector can thus be calculated by

$$\beta_{R}^{*} = 0.5\beta_{m} + 0.5\beta_{f} \tag{12}$$

Cotton (1988) followed Reimers (1983) with modifications whereby the weight is changed to the sample share of the total wage earners, giving rise to the following equation:

$$\beta_{\rm C}^* = \left(\frac{n_{\rm M}}{N}\right) \beta_{\rm m} + \left(\frac{n_{\rm f}}{N}\right) \beta_{\rm f} \tag{13}$$

where N is the total sample size; and nM and nF are the group sizes of male and female workers, respectively.

Neumark (1988) further modified Oaxaca (1973) by incorporating the employer discrimination. The proposed method overcomes the upper and lower bound limitations inherent in Oaxaca's, Reimers', and Cotton's models. In Neumark (1988), the reference vector is calculated by pooled sample regression and the wage differential can be expressed as $\lim_{\mathbf{w}_m - \ln \mathbf{w}_f = (\bar{\mathbf{x}}_m - \bar{\mathbf{x}}_f)(\mathbf{x}\beta_m + (\mathbf{1} - \mathbf{x})\beta_f) + ((\mathbf{1} - \mathbf{x})'\bar{\mathbf{x}}_m + \mathbf{x}'\bar{\mathbf{x}}_f)(\beta_m - \beta_f)$ (14)

where X is a matrix of observed weight containing the male and female samples and I is the identity matrix.

Furthermore, Oaxaca-Ransom (1994) used $\Omega_{_{\rm N}}$ to represent the fitted value of weight-



ed matrix and expressed the weighted coefficient as, where $\Omega_{\rm N} = (X_{\rm M}{}'X_{\rm M} + X_{\rm N}{}'X_{\rm N})^{-1} X_{\rm M}{}'X_{\rm M}.$ $\beta_{\rm N}^* = \Omega_{\rm N}\beta_{\rm M} + (1-\Omega_{\rm N})\beta_{\rm F} \qquad (15)$

The Oaxaca-Blinder decomposition model (1973) focuses on the conditional mean wage differentials. However, in the real labor market, different wage distributions (e.g., quantiles, deciles, percentiles) affect the gender wage differential differently. The θ^{th} quantile regression predictions of the hourly earnings of male (m) and female (f) workers can be expressed as

$$\widehat{Y}_{\theta}^{m} = X^{m} \widehat{\beta}_{\theta}^{m}$$

$$\widehat{Y}_{\theta}^{f} = X^{f} \widehat{\beta}_{\theta}^{f}$$

$$(16)$$

$$(17)$$

where $\hat{Y}_{\theta}^{\ i}$ (i = m, f) is the quantile regression prediction of the θ^{th} percentile of Y given X.

Therefore, the θ^{th} percentile values of predicted Y of male and female groups (at the mean values of the covariates) are given by, where $\hat{Y}_{\theta,\bar{x}}^{\ i}$ (i = m, f) is the predicted value of the θ^{th} percentile of Y given the mean values of the covariates.

$$\begin{split} \widehat{Y}^{m}_{\theta,\overline{X}} &= \overline{X}^{m} \widehat{\beta}^{m}_{\theta} \\ \widehat{Y}^{f}_{\theta,\overline{X}} &= \overline{X}^{f} \widehat{\beta}^{f}_{\theta} \end{split} \tag{18}$$

The purpose of the Oaxaca-Blinder decomposition is to break down the total wage gap between the two groups $(\hat{Y}_{\theta_{,x}}^{m} - \hat{Y}_{\theta_{,x}}^{f})$ into differences of observable characteristics (i.e., personal characteristics and endowments) and a residual or an unexplained part, assuming that the wages of the non-discriminated and discriminated groups are equal. Specifically, it is assumed that male and female workers with identical personal characteristics and endowments (education and years of experience) in the same job should be compensated the same. In the absence of unexplained differences (i.e., the unexplained part), the wage of the

female group is given by equation (20), and the total wage gap can be decomposed into two components (equation (21)).

$$\begin{split} \widehat{Y}_{\theta,\overline{X}}^{f*} &= \overline{X}^f \widehat{\beta}_{\theta}^m \\ \widehat{Y}_{\theta,\overline{X}}^m &- \widehat{Y}_{\theta,\overline{X}}^f &= \widehat{\beta}_{\theta}^m (\overline{X}^m - \overline{X}^f) + \left(\widehat{\beta}_{\theta}^m - \widehat{\beta}_{\theta}^f\right) \overline{X}^f \end{split} \tag{20}$$

Normalizing equation (21) by the predicted female wage in the respective quantile yields

$$\frac{\widehat{Y}_{\theta,\overline{x}}^{m} - \widehat{Y}_{\theta,\overline{x}}^{f}}{\widehat{Y}_{\theta,\overline{x}}^{f}} = \frac{\widehat{\beta}_{\theta}^{m}(\overline{x}^{m} - \overline{x}^{f})}{\widehat{Y}_{\theta,\overline{x}}^{f}} + \frac{(\widehat{\beta}_{\theta}^{m} - \widehat{\beta}_{\theta}^{f})\overline{x}^{f}}{\widehat{Y}_{\theta,\overline{x}}^{f}} \tag{22}$$

In equation (22), the first term on the right-hand side corresponds to differences in wages in each quantile due to differences in the endowments (education and years of experience) of the two groups. The second term on the right-hand side reflects differences in pay despite the same endowments. The second term of the right-hand side is the unexplained wage differential that corresponds to Becker's labor market discrimination.

Unlike the Blinder-Oaxaca decomposition method which measures the mean of the pay gap attributable to the observable personal characteristics and endowments (or the explained part) of the two groups (i.e., male and female workers) and to the unobserved part (or the unexplained part) at any point in time, the Juhn-Murphy-Pierce (JMP) decomposition method analyzes the change in the pay gap across time (Juhn, et al. 1991, 1993). Besides, the JMP decomposition method is based on the distribution of workers under the wage structure, unlike the Blinder-Oaxaca decomposition method which is based on average workers.

In the JMP decomposition model, the residual (\mathcal{E}_{it}) in the wage equation is replaced by a standardized residual (θ_{it}) with a mean



of zero and variance of one for each year, as shown in equation (24).

$$Y_{it} = X_{it}\beta_t + \sigma_t\theta_{it}$$
 (23)

where Y_{it} is the log wage for individual i in year t, X_i is the vector of explanatory variables, and σ_t is the residual standard error of the baseline group's wages at time t, with a lower σ_t indicating a lower wage differential.

The change in the gender-based wage gap between two time points (t=0,1) can be decomposed into

$$\begin{split} & \Delta \overline{Y_1} - \Delta \overline{Y_0} = (\Delta \overline{X_1} - \Delta \overline{X_2}) \beta_1 + \Delta \overline{X_0} (\beta_1 - \beta_0) \\ & + \sigma_1 (\Delta \overline{\theta_1} - \Delta \overline{\theta_0}) + \Delta \overline{\theta_0} (\sigma_1 - \sigma_0) \ (24) \end{split}$$

In equation (24), the first term on the right-hand side is the observed (explainable) X effect, indicating the changes in the observable characteristics over time. The second term is the observed price effect, which is associated with the changes in the net wage returns to each observable characteristic over time. The third term is the unobserved (unexplained) quantity effect, and the fourth term is the unobserved (unexplained) price effect. The impact of changes in the observed effect (first and second terms) and those in the unexplained effect (third and fourth terms) collectively constitute the observed change in the total wage gap.

Results and Discussion Results on wage equation

The results are similar independent of the methodologies of wage determination. In the wage determination models, the dependent variable is the natural logarithm of wage, and the predictor or explanatory variables are age (experience), age squared (experience squared), marital status, years of schooling, region of residency (Bangkok, Central, North, Northeast, South), area (municipal or non-municipal), firm type (private, government or state enterprise), firm size, and occupation.

The variables age and experience are used interchangeably because experience is defined as age minus years of schooling minus six (i.e., potential experience). The coefficient of age (experience) is positive and statistically significant, suggesting that workers' skills and knowledge increase with years of work experience and thus become more productive, resulting in higher wages. Meanwhile, the coefficient of age squared (experience squared) is negative and statistically significant, indicating that the value of accumulated skills and knowledge decreases after a certain age. This results of age and age squared are consistent with the study of Leetrakul (2011). Married male and female workers have more household-related financial responsibilities than their unmarried (or single) counterparts. The coefficient for marital status is thus positive and statistically significant.

The level of education is positively correlated to workers' earnings, giving the same conclusion as the study of Mahatthanasomboon (1983). In addition, individuals with a bachelor's degree or higher tend to earn more than non-degree holders. This finding can be attributed to the following reasons: first, higher education contributes to more knowledge and sophisticated skills which in turn leads to improved work productivity; and second, due to employer-employee information asymmetry, employers thus primarily rely on formal edu-



cation in the pay decision and the selection of job applicants.

For the region of residency, male and female workers with a residence in the capital Bangkok earn more than those living in the provinces. In other words, workers living in municipal areas earn more than those living in non-municipal areas.

Household heads tend to earn more than other members in the family given the former's greater household-related financial responsibility. Interestingly, government employees receive higher levels of wage or salary than their counterparts in the private sector. The surprising finding is partly attributable to the fact that, in this study, the workers in the private sector are unskilled or low-skilled daily wage earners or laborers. Workers in large firms earn higher wages than those in small firms. The signs of the coefficients of occupations vary, depending on the reference group, e.g., managers and professionals (ISCO level 1) or elementary occupations (ISCO level 9).

Results on wage decomposition

The purpose of decomposing the male-female wage differentials is to determine the factors that influence these differentials. The explained or observable part of the wage decomposition model is related to the differences in personal characteristics and endowments, and the unexplained or unobservable part is attributable to the difference in male and female coefficients.

A positive coefficient of total wage differential indicates that male workers earn higher wages than female workers, and a negative coefficient indicates otherwise but it is not statistically significant (Adireksombata, Fangb and Sakellarioub, 2010, pp.24-25). The JMP decomposition method also yields a negative sign for the total wage differential since the JMP decomposition analyzes the change in the pay gap across time, unlike other decomposition methods which analyze the earnings gap at any point in time (Liao and Paweenawat, 2019, pp.15-16). A negative change in the total wage differential indicates a reduction in the gender-based wage gap between male and female workers, consistent with the Blinder-Oaxaca decomposition model. Specifically, the size of total wage differential would decrease over time.

The explained or observable part indicates the extent to which the wage gap between male and female workers remains, given the same set of coefficients. Furthermore, given the same set of individual characteristics and endowments (i.e., explained part) between male and female workers, the residual wage gap represents the unexplained or unobservable part (i.e., gender discrimination). The result shows that the overall gender wage gap has declined over time. However, the narrower pay gap is primarily attributable to improved endowments of female workers (e.g., higher educational attainment), while the unexplained or unobservable part, particularly gender-based discrimination, plays a role in widening the wage differentials.

The wage decomposition analysis shows that the coefficient of the explained or observable factors can be either positive or negative, depending on the periods (i.e., years) under study and the decomposition methodo-



logy. The positive explained part indicates that male workers enjoy a wage advantage relative to female workers due to the former's observable personal characteristics and endowments. In other words, the observable covariates could partially explain the genderbased wage gap. In addition, the negative explained or observable part indicates that female workers enjoy a wage advantage with respect to the observable characteristics and endowments, vis-à-vis male workers. So that, the negative explained part suggests the inferiority of male workers' personal characteristics and endowments to their female counterparts'.

In Table No. 1, the explained factors (i.e., the personal characteristics and endowments of workers) account for between -0.112 and 0.28 of the total wage differentials. Higher educational attainment is the most important determinant of wage disparity, independent of gender. The findings reveal that differences in individual characteristics and endowments (explained part) have a minimal impact on the gender-based wage differential, while the unexplained part (gender discrimination) accounts for the substantially larger share of the wage differential.

Evidence also shows that the total wage differential between male and female workers decreased from 0.3092 between 1985-1989 to 0.0668 between 2001-2009 (Srisomboon, 2016, pp.20-22). The finding is consistent with Liao and Paweenawat, 2019, pp.18-19), who documented that gender-based wage gap decreased over time from 0.344 in 1985 to 0.033 in 2017. Specifically, the value of the

explained part of the wage decomposition model decreases over time and becomes increasingly negative, indicating that female workers, on average, possess more favorable observed personal characteristics and endowments. Meanwhile, some studies found that the wage gap due to endowments decreased from 0.0281 in 2000 to -0.0184 in 2005 (Poonsab, 2008, pp.26-27).

The unexplained factors of the wage decomposition model account for -0.0942 to 0.199 of the total wage differential. One of the unexplained factors is discrimination in pay or employment in highly paid positions against women. According to Maithongdee (2010), gender discrimination accounted for 94.7 percent of the total wage differential, vis-à-vis 5.3% for the endowments. Other studies found the same result that the unexplained part plays an important role to enlarge the wage differentials. For example, in 2005, males still earn 0.54 more than females even if all characteristics and coefficients of females and those of males are identical (Chirawat, 2008, p.27). The findings have significant policy implications because, despite greater efforts and higher educational attainment, a majority of female workers are struggling with gender-based discrimination in the workplace, leading to lower wages and limited job opportunities

Conclusion and policy recommendation

The wage differential decomposition indicates that the male-female wage gap in Thailand has declined over time as a result of the convergence of individual characteristics and endowments, especially years of school-



ing (i.e., explained factors). Nevertheless, as the differences in personal characteristics and endowments between male and female workers become less apparent, the proportion of the wage differential attributable to gender-based discrimination in pay and employment (unexplained factors) continues to increase. Given the current labor market structure, greater educational opportunity for women alone is unlikely to close the male-female wage gap. This is because a majority of female workers are still struggling with gender-based discrimination in the workplace, despite higher educational attainment.

The result is consistent with other countries' study. The Philippines' study found that although working women have a higher average level of education and are more likely to work in higher paying occupations, they still earn significantly less than men because of high levels of discrimination (Ramos, 2016, p.124). The study in Indonesia concluded that the wage gap tends to be wider among younger workers and Gender wage gap in Indonesia is mainly due to gender discrimination (Taniguchi and Tuwo, 2014, p.33).

As a result, to further narrow the gender-based wage gap, government should channel more resources (financial, personnel and time) into awareness/educational programs and organization-level monetary/non-monetary incentives to combat workplace discrimination against female workers, in addition to more educational opportunities. In addition, since the majority of low-income female workers in Thailand are single mothers, government agencies responsible for social development

and human security should make available heavily subsidized daycare services so that the female workers with young children can actively participate in the labor market. Besides, policymakers should amend or legislate labor laws concerning employment and employee compensation to incorporate the equal employment opportunity and equal work for equal pay principles.

The smaller gender inequalities in the returns of productive characteristics in formal employment are a good thing for women and the country at large. First, women might receive higher wages. Second, given that women need to take maternity leave and sometimes have to neglect their work responsibilities in favor of childcare, the earnings per work output of women are likely to be higher than those of men in formal wage employment if the benefits of maternity leave and time off for childcare and household chores are quantified and added to their wages.

Looking forward, more and better data to understand gender disparities is important for Thailand. Some factors that may result in a wage gap between women and men are difficult to measure. These include the responsibilities of motherhood and family and the effect they have on women's engagement with the workplace when compared with men; gender stereotypes and discrimination. Including these factors may lead to better result in gender pay gap.



Table No. 1 Results of wage decomposition in Thailand

Authors	Methodology		Area of	Rational behind gender wage differentials		
	Wage Determination	Wage Decomposition	Residency/ Period/ Quantile	Endowment	Discrimination	Total
Mahatthana- somboon (1983)	OLS	Oxaca		71.3%	28.7%	100%
Mathana and Nirat (1993)	Two-stage least squares (2SLS)	Oaxaca-Blinder	Municipal area	32.51%	68.49%	100%
			Non-munic- ipal	30.47%	63.53%	100%
Chirawat (2008)	OLS	Oaxaca	2000 2005	0.0281 -0.0184	0.1163 0.1440	0.1444 0.1256
Maithongdee (2010)	2SLS	Neuman & Oaxaca		0.0129	0.2313	0.2442
Adireksom- bata, Fangb and Sakellar- ioub (2010)	Quantile regression	Oaxaca-Blinder	Q10th Q50th Q90th	0.01 -0.048 -0.118	0.199 0.138 0.083	0.208 0.09 -0.035
Leetrakul P. (2011)	Quantile regression	Oaxaca-Blinder	Q10 Q50 Q90	-0.015 -0.033 0.111	0.179 0.0329 -0.0942	0.164 0.00015 0.012
Mutsalklisa- na (2011)	OLS	Oaxaca-Blinder	1997 2006	-0.049 -0.112	0.172 0.184	0.123 0.072
Khorphet C.	2SLS	Oaxaca (male) Oaxaca		-0.06	0.686	0.626
konkarn K. (2011)		(female) Cotton Oaxaca & Ransom		-0.103 -0.08 -0.041	0.729 0.706 0.667	0.626 0.626 0.626
Ninchainan J. and Osathanan- kul R. (2013)	2SLS	Cotton Oaxaca & Ransom		-0.05 -0.046	0.084 0.089	0.024 0.024



Authors	Methodology		Area of	Rational behind gender wage differentials		
	Wage Determination	Wage Decomposition	Residency/ Period/ Quantile	Endowment	Discrimination	Total
Sukti	OLS	Oaxaca-Blinder	2011	0.280	0.116	0.413
Dasgupta,						
Rut tiya						
Bhula-or and						
Tiraphap						
Fakthong						
(2015)						
Minh-Tam	OLS	Oaxaca-Blinder	1996	-0.0041	0.1519	0.1478
Thi Bui and			2006	-0.0708	0.17215	0.10139
Chom-			2013	-0.1160	0.1260	0.0100
poonuh						
Kosalakorn						
Permpoon-						
wiwat (2015)						
Srisomboon		Oaxaca-Blinder	1985-1989	0.0766	0.2326	0.3092
R. (2016)			1990-1996	0.0203	0.2014	0.2217
			1997-2000	-0.0096	0.1454	0.1358
			2001-2009	-0.0676	0.1344	0.0668
Jithitikulchai		Oaxaca-Blinder	2002	-0.0468	0.161	0.114
T. (2016)			2013	0.0103	0.141	0.0027
Liao and		Oaxaca-Blinder	1985	0.182	0.162	0.344
Paweenawat			1995	-0.059	0.2	0.141
(2019)			2005	-0.077	0.183	0.105
			2017	-0.101	0.134	0.033
		John-Murphy-	1985-1995	-0.002	0.002	-0.0203
		Pierce	1995-2005	-0.016	-0.019	-0.035
			2005-2017	-0.021	-0.051	-0.073

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