Multilevel Analysis of Wage Inequality in Palestine

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Historical data exhibit the imbalance participation rate between genders in the Palestinian labour market in which female participation is among the lowest worldwide. On the other hand, occupational discrimination and wage inequality still exist between males and females. Combining both issues, this study seeks to examine the gender pay gap across occupational groups in Palestine. The data are collected from the Palestinian Labour Force Survey (PLFS) for the year 2017. The multilevel linear regression is applied to model the wage equation. For the robustness purpose, three estimation techniques are applied which are maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian estimation. The results reveal that occupational groups account for about 23.6% of wage differentials. The gender wage gap varies significantly across occupational groups, where it is decreased after correcting for self-selection bias. Moreover, the Bayesian estimation method provides more efficient estimates than ML and REML methods. Schooling, age, and other socioeconomic variables also contribute significantly to wage inequality in Palestine.

Keywords	***JEL code***
Multilevel modelling, maximum likelihood, restricted maximum likelihood, Bayesian estimation, wage inequality, intra-class correlation coefficient	*C01, C10, C11, E24, J31*

INTRODUCTION

Over the past decade, the Palestinian labour market has exhibited an imbalance participation trend in the labour market. As reported in the first quarter 2018 labour force conducted by the Palestinian Central Bureau of Statistics (PCBS), the women's participation rate was 19.9% compared to that of men 70.3% exhibiting a decreasing trend in the gender participation gap. Although this gap has improved over time, the women's participation rate of Palestine still remains among the lowest in the world. In addition, Palestine is also experiencing a high pay gap in the labour market. The wage gap between males and females was 29% with males earn 119.1 New Israeli Shekels (NIS) while women only earn 84.6 NIS daily pay on average (PCBS, May 2018). According to Brown et al. (1980), occupational gender discrimination is considered as a potential source of wage differentials. The facts and data reveal that the imbalances of gender participation and the higher rates of wage inequality are the two major issues/ phenomena faced by Palestine for a long time. Therefore, there is a need to identify the problems/ reasons behind them follow by appropriate policy action to overcome the problems.

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The studies focused on examining the wage inequality are broad, covering different countries and periods as well as applying different decomposition methods. Some studies relied on individual-level variables to study gender pay gaps such as human capital and some socioeconomic variables (Mincer, 1974; Card, 2001). Other studies relied on examining the effect of occupational gender composition on wage inequality; these studies tried to address the sources of inequality such as between occupation gender inequality and within occupation gender inequality (Huffman and Velasco, 1997; Huffman, 2004; de Ruijter and Huffman, 2003; de Ruijter et al., 2003; Bunel and Guironnet, 2017). In term of modelling approaches, many studies applied the classical estimation approaches to model wage inequality decomposition. Such approaches suffered from the inefficiency estimate (Heckman and Vytlacil, 1998; Card, 2001). In addition, many studies applied the single level modeling, which provided limited information and less accurate estimate.

This study seeks to fill the gaps from the previous studies in occupational gender wage inequality and has the following objectives. First, this study seeks to find out which econometric technique provides more efficient estimates in studying the gender pay gap across occupational groups using a multilevel linear model. Second, the study also examines to what extent the occupational gender discrimination contributes to the gender pay gap in Palestine by utilizing the cross-sectional data from the Palestinian labour force survey for the year 2017 conducted by the Palestinian Central Bureau of Statistics (PCBS). Furthermore, this study follows the guide of Boedeker (2017) to carry out the multilevel analysis.

To highlight, this study contributes to the previous literature in several ways. First, this is the first study that analyses the occupational gender wage gap in Palestine to the best of our knowledge. It does not limit to investigate the between-occupation groups and within-occupation groups variability but also investigates between-gender-within occupation groups wage differentials. This study is focused in Palestine as Palestine exhibits very unique structures/features in its social-economy and labour market which make it stand out differently from the other neighbouring countries. The extremely high gap in the participation rate among males and females and the wage inequality in Palestine are the main issues worth to be explored.

Second, we propose a Bayesian estimation technique and demonstrate that the Bayesian approach provides a better estimate as compared to ML and REML approaches. The third contribution can be considered as an empirical contribution to the literature in the debate on wage inequality. This study demonstrates that gender has contributed significantly to wage inequality across occupational groups in Palestine. The gender wage gap is reduced after corrected for self-selection bias.

Finally, our results are important for policy decision and implication. The results reveal that most occupational sectors in the Palestinian labour market are dominated by males and males receive much higher wages than their females counterparts. Such inequality may lead to unsustainable social-economic growth. The government should play its role through legislation and cooperation with the private sectors as its effort to improve the wage gap and occupational participation gap by genders in Palestine.

The organization of the paper is as follows: Section 1 provides an overview of the Palestinian labour market, Section 2 is the summary of literature review, Section 3 is the description of the data and methodology, Section 4 presents the results and discussion and the last section is the conclusion.

1 AN OVERVIEW OF THE PALESTINIAN LABOUR MARKET

According to the World Bank, the Palestinian economy is classified as a lower-middle income developing country. Its labour market is segmented geographically into two regions i.e., West Bank and Gaza Strip. Moreover, after the political division of 2007 between the West Bank and the Gaza Strip, each region has generated its own stumbling block. Thus, Palestine becomes a unique situation with an underdeveloped labour market.

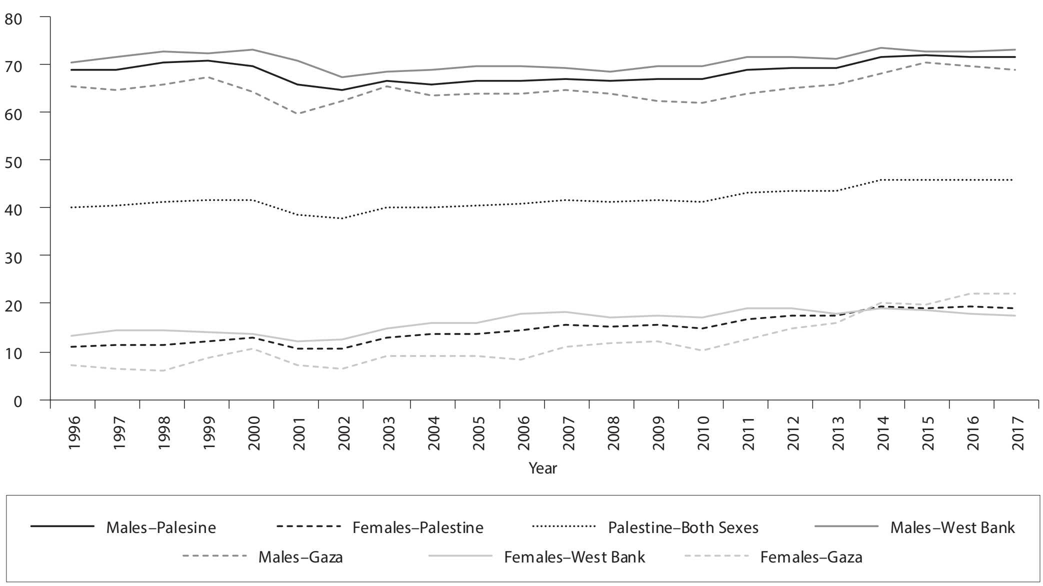
The Palestinian labour market exhibits lower participation rates compared to some neighbouring and developed countries, with extremely lower rates of female participation. The labour force participation rate for individuals aged 15 years or more is approximated as 45.7% in 2017. The participation rate of males was 71.6% while it was 19.2% for females. That is, there is a high gender participation gap. During the period from 1996 to 2017, Palestine exhibits an increasing trend in its labour force participation rate. The females' participation rate has increased slowly. However, this rate is still extremely lower than the world average. Meanwhile, males' participation rate stands near the worldwide average as shown in Table 1 (PECS, 2018).

Table 1 Labour force participation rates and unemployment rates in Palestine and some selected overseas countries by gender for individuals aged 15 years or above, 2017 (%)

Country	Males	Females	Total
Palestine	71.6 (23.2)	19.2 (48.2)	45.7 (28.4)
United States	69.1 (4.4)	57.0 (4.3)	62.9 (4.4)
Canada	70.2 (6.8)	61.5 (5.8)	65.8 (6.3)
United Kingdom	68.9 (4.5)	58.2 (4.2)	63.4 (4.4)
Germany	66.7 (4.1)	55.9 (3.3)	61.2 (3.7)
Czech Republic	68.5 (2.3)	52.3 (3.6)	60.2 (2.9)
Turkey	72.5 (9.4)	33.6 (14.1)	52.8 (10.9)

Note: Unemployment rates are in parentheses.
Source: Palestinian Central Bureau of Statistics, labour force survey (2018) and OECD labour force indicators (2018)

Figure 1 Labour force particiaption rates in Palestine by sex and region,1996–2017 (%)



Source: PCBS labour force surveys, different issues

In terms of geographical region, the labour force participation rate in West Bank was 45.8%, which is a little bit higher than that in Gaza Strip, 45.5%. Males in the West Bank showed a higher participation rate than those in Gaza's. However, females in the Gaza Strip showed a higher participation rate than that in the West Bank (PECS, 2018). This is probably due to the bad economic conditions in the Gaza Strip caused by the Israeli siege and the political division since 2007. Thus, there is a higher attempt by the females to join the labour market in order to compensate for the loss of the males' income (ILO, 2018).

Furthermore, the labour force participation rate reached its peak for females aged 25 to 34 years while for males it was highest between those in the age category between 35 to 44 years as shown in Table 2. This may be explained by the fact that females decide to exit the labour force after married or after having their first child at least. The labour force participation rate for married females was 52.9% while it was 62.3% for married males in 2017.

Table 2 Percentage distribution of individuals aged 15 years and above from Palestine by sex, age and labour force status, 2017 (%)

	Unemployed	**Inside LF**	**Outside LF**
Males			
15–24	47.5	52.5	38.7
25–34	8.5	91.5	24.4
35–44	7.5	92.5	12.8
45–54	13.2	86.8	13.6
55–64	42.7	57.3	15.4
+65	87.9	12.1	6.9
Total	**28.4**	**71.6**	**23.2**
Females			
15–24	87.4	12.6	70.8
25–34	67.7	32.3	59.0
35–44	75.9	24.1	29.5
45–54	82.1	17.9	12.2
55–64	91.0	9.0	7.8
+65	98.6	1.4	-
Total	**80.8**	**19.2**	**48.2**
Both Sexes			
15–24	67.0	33.0	44.7
25–34	37.7	62.3	33.3

Table 2 (continuation)

	Outside LF	Inside LF	Unemployed
35–44	41.4	58.6	16.2
45–54	46.7	53.3	13.3
55–64	66.3	33.7	14.5
+65	93.7	6.3	6.0
Total	**54.3**	**45.7**	**28.4**

Source: Palestinian Labour Force Survey, Revised Annual Report (2018)

Based on the education qualification, the majority of Palestinians in the labour market are educated, with 59.9% have completed at least 13 years of education. Among them, 74.4% were males and 46.5% were females as shown in Table 3. Females with higher education levels are associated with higher chances to join the labour force. Thus, education can be considered as a key determinant for the female to get a job. In general, the lower participation rates among females may be attributed to different factors such as family tie after married and carrying out housekeeping (63.1%) or study and training (24.7%). However, the reasons that hinder males to stay outside the labour force include further study (49.7%) or due to older age or do not have the chance to get a job i.e. 37.0% (PECS, 2018). Moreover, Al-Botmeh and Sotnik (2007) showed that lower rates of females' participation were attributed to social and cultural factors, Israeli restriction on movement, vertical and horizontal segregation and low average female wages.

Table 3 Distribution of individuals aged 15 years or more from Palestine by sex, schooling and labour force status, 2017 (%)

Sex and Years of Schooling	Outside LF	Inside LF	Unemployed
Males			
0	80.1	19.9	22.8
1–6	32.8	67.2	26.8
7–9	28.8	71.2	23.2
10–12	27.0	73.0	24.6
13+	25.6	74.4	20.1
Total	**28.4**	**71.6**	**23.2**
Females			
0	97.3	2.7	9.7
1–6	92.0	8.0	14.8
7–9	92.9	7.1	25.5

Table 3			(continuation)
Sex and Years of Schooling	**Outside LF**	**Inside LF**	**Unemployed**
10–12	92.3	7.7	37.3
13+	53.5	46.5	54.6
Total	**80.8**	**19.2**	**48.2**
Both Sexes			
0	93.1	6.9	18.9
1–6	59.7	40.3	25.8
7–9	56.6	43.4	23.4
10–12	59.1	40.9	25.8
13+	40.1	59.9	34.1
Total	**54.3**	**45.7**	**28.4**

Source: Palestinian Labour Force Survey, Revised Annual Report (2018)

The rate of unemployment in Palestine has increased continuously since 2000 because of Israeli closure and barriers restrictions. The unemployment rate was 14.3% in 2000 and it has increased to the highest world level of 28.4% in 2017 with 48.2% and 23.2% for females and males respectively (see Table 1). In Gaza Strip, it reached 44.4% (i.e. 36.6% for males and 69.1% for females) while in West Bank it was 18.7% (i.e. 15.6% for males and 32.1% for females). That is, unemployment is more severe in Gaza Strip as compared to the West Bank especially for females. Moreover, it reached its highest level among youth for both males and females in the age category between 15 and 24 years. Moreover, females with post-secondary education showed a higher rate of unemployment i.e., 54.6% while males who completed 1–6 years of schooling had a higher rate of unemployment i.e., 26.8% as shown in Table 3 (PECS, 2018).

Moreover, wage inequality in Palestine was evident based on the survey data reported for the year 2017. The average daily wages for workers was 101.8 NIS in the West Bank with 105.4 NIS for males and 87.7 NIS for females. However, it was 59.4 NIS in the Gaza Strip, where males received 57.4 NIS and females received 71.3 NIS. This is probably due to the very small sample size, which is not able to represent females in the Gaza Strip. On the other hand, the average daily wage for workers in Israel and its settlements was 226.9 NIS distributed as 228.1 NIS for males and 154.4 NIS for females (PECS, 2018).

2 LITERATURE REVIEW

The wage inequality among males and females has attracted many studies on revealing the causal factors. These studies used various decomposition methods. Blinder (1973) and Oaxaca (1973) applied the decomposition measuring the difference in mean wages, DiNardo et al. (1996) relied on the density distribution of wages, and Fields (2000) decomposed wage inequalities using the regression-based method. Some other studies introduced other types of decomposition. For instance, Lemieux (2006) proposed quantile decomposition models and Huffman (2004) proposed multilevel decompositions.

Budig (2002) applied a fixed effect and OLS regressions to examine the effect of gender composition in jobs on wages. The study concluded that occupations dominated by females showed lower wages than occupations with mixed-gender and male-dominated and the effect on men and women was different in these occupations. Similar results also found from these studies (England, 1992; England et al., 1994; Huffman et al., 1996; and Tomaskovic-Devey, 1995). Therefore, the wage gap was not only attributed to the worker's attributes, but also on the job's attributes to which the worker belongs.

More recently, Xie et al. (2016) conducted a study in examining the earning inequalities between and within occupation groups among the U.S college graduated workers. They decomposed earning inequality into between and within occupation groups for each education level separately. Their results revealed that rising education premium and the variation of earnings due to occupational groups were constant within all education categories. Coelli (2014) studied the occupational differences and gender wage gap in Australia. He showed that occupations have high positive effects on the wage gap in the Australian labour market. The results revealed that occupational groups contributed significantly to wage inequality. However, its effect of decreased markedly after controlling for industrial groups.

A number of studies applied multilevel modelling to analyse wage inequalities. A study by de Ruijter and Huffman (2003) included gender composition effect to study occupational wage inequality in Netherland using Dutch occupational data for the year 1997. The study applied a two-level model to wage equation and compared between gender composition occupational effect and within-occupation gender inequality as a percentage of their influence on the overall pay gap. They found that most of the wage gap was explained by both occupational and individual levels with male dominance the occupation pay. Males received higher wages across all occupations in which occupational gender composition was neglected and this gap was declined across female-dominated occupations. However, de Ruijter et al. (2003) proposed multilevel analysis to analyze the size and the causes of occupational gender inequality in the Netherlands and they showed that both males and females received lower wages in occupations that are dominated by females in the Dutch labour market. Their results were similar to those found by England (1992). In the jobs that demand high skills, high educational levels, and responsibility, their results revealed that in the occupations dominated by females there is a large wage penalty other than occupations dominated by males.

Moreover, Huffman (2004) applied five different multilevel models to investigate the gender wage inequality, taking into account jobs ranking in the hierarchy structure of local wages in the US labour market. He showed that occupational groups account for about 36% of wage differentials. He also showed in the occupations dominated by females, the wage for women is lower than those male-dominated counterparts. The wage gap in female-dominated occupations increased in which males receive wages higher than females when the number of females increased in these jobs.

Meanwhile, Bunel and Guironnet (2017) applied multilevel analysis to explore the influence of gender, occupation, and localization wage inequalities among recently graduated French workers using Génération 2004 survey data. Besides occupational gender compositions, they also included occupational age compositions. They showed that wage inequality due to occupational groups was about 40%, while due to localization (employment area) it was about lower than 10%. They also showed that young workers received higher wages in occupations dominated by seniors and dominated by males. Moreover, in these latter groups, the gender wage gap was also higher.

3 METHODOLOGY AND DATA

3.1 Econometric models

This paper applied the analysis of wage inequality on wage employed workers nested by occupation groups aged 15 years old or more to explore the contributing factors of wage inequality in the Palestinian labour market. Many dummy variables are created to classify for occupational groups. Raudenbush and Bryk (2002) showed that the use of classical linear regressions such as OLS technique to investigate the effect of each dummy group on both intercept and slope would involve many parameters in the model and thus may lead to misleading results. Such a problem is avoided by using multilevel models.

Multilevel (hierarchical) model is applied to help researchers in identifying the variability at both individual and group levels. Intra-class correlation (ICC) can be used to determine the amount of variation due to the group level. The large variability at the group level is associated with higher values of ICC, which means that the independence assumption is violated and hence the use of multilevel models is justified.

3.1.1 Unconditional model

At the very first step, the initial value of the ICC is generated to help in the decision between single level or multilevel model. Starting from the simplest two-level model (model I), which allows for occupation groups effects on daily wages with no explanatory variables at both levels. This model is the so-called unconditional or varying-intercept model and is written as:

$$\begin{aligned} &\textit{Level } 1\text{: } \ln (w_{ij}) = \beta_{0j} + e_{ij}\,, \qquad e_{ij} \sim N(0, \sigma_{lnw}{}^2)\,, \\ &\textit{Level } 2\text{: } \beta_{0j} = \gamma_{00} + u_{0j}\,, \qquad u_{0j} \sim N(0, \sigma_{\beta 0}{}^2)\,, \end{aligned} \tag{1}$$

where w_{ij} is the daily wage of individual i in the occupational group j, γ_{00} is the overall mean across occupational groups, β_{0j} is the mean of $ln\ (w_{ij})$ for occupation group j, u_{0j} is the effect of occupation group j on daily wages (i.e., the residuals for the group level), $\sigma_{\beta 0}{}^2$ is its variance, e_{ij} is the individual level residual, and $\sigma_{lnw}{}^2$ is its variance. The ICC for Equation 1 can be written as:

$$ICC = \frac{\sigma_u^{\ 2}}{\sigma_u^{\ 2} + \sigma_e^{\ 2}}\,, \tag{2}$$

where $\sigma_u{}^2$ is level 2 residual variance and $\sigma_e{}^2$ is the total residual variance. In other words, it can be estimated by dividing the variance of between-group; the variance of random intercept, by the overall variance. It is the percentage of the residual variance that is due to the group level. The ICC is ranging between 0 and 1. The value of 0 implies no difference among groups. When $\sigma_u{}^2 = 0$, there is no need to employ for multilevel analysis. On the other hand, the value of one exhibit that there is no within-group and between individual differences; $\sigma_e{}^2 = 0$. Meanwhile, the justification for the use of multilevel models has no such rule constraint on the value of the ICC. However, lower values of ICC may be satisfactory (Kreft and de Leeuw, 1998; Boedeker, 2017).

3.1.2 Conditional model

In this model, predictor or independent variables are included in the fixed part (i.e., individual level) sex is allowed to vary across occupational groups (i.e., second level). Adding a set of the covariate in the fixed as well as in the second level will reduce the intra-class correlation. The conditional model is also can be called a varying-intercept and varying-slope model (model II). Thus, Formula 1 can be generalized as:

$$\textit{Level } 1\text{: } \ln (w_{ij}) = \beta_{0j} + \beta_{1j} sex_{ij} + \sum_p \beta_p X_{ij} + e_{ij}\,, \qquad e_{ij} \sim N(0, \sigma_{lnw}{}^2),$$

$$\textit{Level } 2\text{: } \beta_{0j} = \gamma_{00} + u_{0j}\,, \tag{3}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}\,,$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{01}{}^2 & \tau_{11} \\ \tau_{11} & \tau_{11}{}^2 \end{bmatrix}\right).$$

Raudenbush and Bryk (2002) and Snijders and Bosker (1999) provided more detailed assumptions of the above model. w_{ij} is the same as in Formula 1, the sex dummy is coded 1 for females and 0 for males, β_{0j} is the mean of $ln\ (w_{ij})$ for occupation group j, β_{1j} is the effect of sex on $ln\ (w_{ij})$ in occupation group j, γ_{10} is the coefficient of sex dummy, X_{ij} is the set of predictors such as years of schooling, age, marital status, etc., β_p is the set of parameters for these predictors, e_{ij} is level-1 residual, $\sigma_{lnw}{}^2$ is its variance, u_0j is the intercept (group) residual and $\tau_{01}{}^2$ is its variance, u_{1j} is the gender slope residual and $\tau_{11}{}^2$ is its variance, and τ_{11} is the covariance between u_{0j} and u_{1j}. Schooling and age are continuous variables and we centered them about their means, which allow us to interpret the intercept as the expected value of the response variable when these predictors have their mean values and zero values of all binary individual-level predictors. Hox (2002) showed that grand mean centering help us to differentiate between-group variability from within-group variability, demonstrating worker's daily wages relative to others. According to Kreft et al. (1995), the group means centering leads to an increase in the complexity of the model and thus extends the interpretation of the results. Huffman (2004) and Bunel and Guironnet (2017) showed that the mean estimates of the coefficient for group mean centering slightly different from those resulting from grand mean centering. For the predictors in level one, their results suggested relative homogeneity between the group and grand mean values. Thus, we use the grand mean centering to simplify our results and since the use of group means centering was not based on theoretical intuition for our research.

We allow for sex to varying across occupation groups to see whether there is a gender wage gap in each group. That is, for each occupational group, there are two slopes for both males and females.

3.1.3 Model with a selection

Sample-selection or self-selection is a common problem encountered when studying wage inequality. This problem appears when the wage is conditionally observed on the value of the reservation wage. Heckman (1979) two-step procedure is a well-known framework that has been applied to the single linear regression and panel data linear models (Vella, 1998), where the bias due to self-selection occurred when the selection is influenced by the unobserved characteristics that are correlated with error terms. Such a procedure was employed to find consistent estimates of wage inequality factors. In multilevel setting, the selection will be more complex than in the single level models which involves different patterns at different levels, a more complex structure of the variance-covariance matrix as well as alteration of the multilevel structure of the data in terms of cluster sizes (for more details, see Grilli and Rampichini, 2005).

This paper considers the case when the selection equation is single level and the wage equation is two-level in which this procedure can be applied by two-step econometric technique. First, the probability that an individual is employed in the labour market is estimated using the following probit model:

$$H_i = \alpha_0 + \textstyle\sum_k \alpha_k X_{ik} + u_i\ . \tag{4}$$

It is known as the participation equation, where H_i is a dummy variable that represents the individual's employment status; 1 is coded for employed and 0 for those who are unemployed and out of the labour force, α_0 is the intercept, X_{ik} is a set of k predictors, which may affect an individual's decision for participation like age, schooling, and marital status, α_k is the coefficient of k^{th} predictor, and u_i is the error term. From the probit model expressed in Formula (4), we calculate the inverse Mills ratio (IMR), λ, which is the ratio of the probability density function over the cumulative distribution function of a distribution. Second, Formula (3) will be adjusted to include the inverse Mills ratio as a predictor variable in the fixed part component, which can be expressed as follows:

$$Level\ 1\text{: } \ln\ (w_{ij}) = \beta_{0j} + \beta_{1j} sex_{ij} + \sum_p \beta_p X_{ij} + \alpha\lambda_{ij} + e_{ij}\ , \qquad e_{ij} \sim N(0, \sigma_{lnw}{}^2)\ ,$$

$$Level\ 2: \beta_{0j} = \gamma_{00} + u_{0j}\,,$$

$$\beta_{1j} = \gamma_{10} + u_{1j}\,, \tag{5}$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{01}{}^{2} & \tau_{11} \\ \tau_{11} & \tau_{11}{}^{2} \end{bmatrix}\right).$$

Model III expressed in Formula (5) is then implemented on wage employees only. All the parameters are the same as described in Formula (3), but λ_{ij} is the IMR in the fixed part calculated from Formula (4) and α is its coefficient. The significance of the IMR is very important to determine if the self-selection exists. If it is significant, then self-selection is evident. The negative value of this ratio indicates that the unobservable attributes are negatively affecting wages while positive values mean that wages are positively influenced by these unobservable attributes. Moreover, the marginal effect of each predictor in the fixed part can be estimated by differentiating level one equation of model III with respect to each predictor. In other words, it is the estimated coefficient for each predictor.

Finally, the former models will be estimated via three different econometric techniques, i.e., ML, REML Bayesian estimation methods for the purpose of comparisons where each one of them has its own assumptions and limitations (for more details see Boedeker, 2017). Bayesian estimation method, in particular, requires specifying the type of the prior distribution; informative or uninformative in which it can be specified based on past researches or researcher's beliefs. Since we have a small number of groups, the present study will use an uninformative prior distribution because of its low credibility to extreme values, where it has a higher influence on the posterior distribution. In this case, an uninformative prior will lead to lower standard errors and thus wider highest density intervals (HDIs) compared with ML and REML because of its low credibility to extreme values. Moreover, the posterior mode should be interpreted instead of the posterior mean (Boedeker, 2017).

3.2 Data Description

The empirical analysis is based on the Palestinian Labour Force Survey (PLFS) carried out by the department of economic statistics in the Palestinian Central Bureau of Statistics (PCBS) for the year 2017. Since October 1995, the department provides both a quarterly and yearly basis for the data, where the present study uses the yearly data. The population is comprised of all individuals aged 10 years and above. The sample is a two-stage stratified cluster random sampling in which the first stage consists of selecting a systematic random sample of size 494 enumeration areas, excluding the areas that constitute lower than 40 households. In the second stage, a random sample of an average of 16 households from each selected area is selected randomly. This data provides useful information about the structure and the size of the labour market in Palestine and offers inclusive measures of individual wages in Palestine.

One limitation of the data is that the Palestinian PCBS do not provide some variables like household total wages, household size and number of children due to their own privacy and confidentiality of the data. The lack of such variables will limit our attempts to correct for self-selection bias as is known in the literature (see Heckman, 1979). The data cover a total of 91 230 persons aged from 10 to 98 years. We eliminate individuals aged less than 15 years to avoid inferring with child labour and those who are out of the labour force. We exclude working abroad workers to study inside country differences and to avoid external factors. As a result, the sample size dropped to 76 111, which is used to estimate the probit model to correct for self-selection bias. Such bias that appeared after we restrict our analysis on individuals aged 15 years or more and wage employed. There are 28 758 individuals in the labour force aged 15 years or more. Among them, we select wage employed individuals and thus, the sample size dropped to 14 061 workers, which constitutes 11 878 males and 2 183 females. This high number of drops are the sample is attributed to about 16.5% who aged less than 15 years or work outside the country in addition to the lower labour force participation rate, which is about 37.78% as estimated from the data in our hands. Table 4 provides a description of the variables used in this study. These variables are included as the factors contributing to the gender pay gap across occupations. The dependent variable used in this study is the natural logarithm of daily wages measured in New Israeli Shekels. The study includes continuous predictors of age and years of schooling centered about their means measured in years. Moreover, the data in categorical type (qualitative) are coded either 1 or 0 represented by a set of dummies. These variables include gender, marital status, region, locality type (camp), refugee status, place of work, employment sector, industry, and employment contract.

Table 4 Weighted descriptive statistics for individuals(a) aged 15 years or more variables for the year, 2017

Continuous Variables	**Definition**	**All**		**Wage employment**	
		Mean	**SD**	**Mean**	**SD**
Daily wages	In New Israeli Shekels (NIS)	-	-	111.3	82.3
Natural logarithm of daily wages	Dependent variable in (NIS)	-	-	4.44	0.78
Age	In years	36.32 (76 111)	12.8	34.87 (14 061)	11.8
Years of schooling	In years	11.38 (76 111)	3.7	11.78 (14 061)	3.7
Categorical variables	Definition	No. obs.	Percent	No. obs.	Percent
Employed	1 if employed; 0 for unemployed and out of LF	23 677	31.1	-	-
Gender	Male ref. category	37 958	49.9	2 183	16
Marry	1 if married; 0 if not married	49 625	65.2	8 795	62.6
Region	1 if West Bank; 0 if Gaza Strip	51 070	67.1	9 930	70.6
Camp dwellers	1 if camp locality; 0 if urban or rural	8 068	10.6	10.7 1 505	10.7
Refugee	1 if registered refugee; 0 if not refugee	30 386	39.9	5 456	38.8
National Government	1 if works in national gov.; 0 if other sectors	13 167	17.3	3 199	22.8
Construction	if industry is construction; 0 if other	18.9 14 385	18.9	2 912	20.7
Work in Israel and settlement	1 if works in Israel or settlements; 0 if West Bank or Gaza	10 351	13.6	2 740	19.5
No contract	1 if worker has no employment contract; 0 if yes	17 658	23.2	6 488	46.1

Note: (a) individual aged 15 years or more and work in Palestine or in Israel and settlement. Weighted by the Palestinian central bureau of statistics (PCBS) sampling weights.
Source: Authors calculations based on Palestinian Labour Force Survey (PLFS, 2017)

Another limitation of the data is that most occupations are dominated by males and none of them is dominated by females. Table 5 shows the distribution of employment and daily wages by occupational groups and gender of waged individuals aged 15 or more in 2017. It appears that the females' employment percentage is higher in professional, technical, associates and clerks occupations, while males mainly get employed in elementary occupations. However, among the lowest employed jobs for females are legislators, senior officials and managers and plant and machine operators and assemblers, while those for males are legislators, senior officials, and managers. However, males earn daily wages higher than those females' counterparts across all occupational groups. The gender pay gap is higher for craft and related trade workers' occupational group. The low pay is found in jobs like professional, technical, associates and clerks.

Table 5 The distribution of employment and daily wages by occupation group and gender for individuals aged 15 or more in Palestine, 2017

Occupation Group		Employment (%)	Average daily wage (NIS)
Legislators, senior officials and managers	Male	3.5	180.56
	Female	3.9	135.85
Professional, technical, associates and clerks	Male	20.7	112.29
	Female	54.1	95.00
Service, shop, and market workers	Male	19.4	81.41
	Female	16.3	47.95
Skilled, agricultural and fishery workers	Male	3.6	86.10
	Female	8.1	56.67
Craft and related trade workers	Male	20.4	170.17
	Female	5.5	51.18
Plant and machine operators and assemblers	Male	10.7	97.64
	Female	3.9	56.55
Elementary occupations	Male	21.7	98.60
	Female	8.2	66.06
Group total	Male	100.00	115.07
	Female	100.00	87.97

Source: Authors calculations based on the Palestinian Labour Force Survey (PLFS, 2017)

Palestine has its own country-specific factors that affect worker's wages and the gender pay gap. These factors can be related to social or cultural factors and economic factors. Among the social factors are: males can receive bonus on behalf of their family members while females did not receive this type of bonus, women are more likely to focus on taking care of their families after marriage, employers believed that women are not the ones who are the breadwinners for their families and therefore paid them less, and females in higher paying jobs were paid less than those males counterparts despite they have equal education levels because of their time off for family or childcare, which justifies their lower employment rates in these jobs. Meanwhile, some sector job specifications are more suitable for males like construction and manufacturing sectors is attributed among the economic factors (Al-Botmeh, 2013; ILO, 2018).

4 RESULTS AND DISCUSSION

Tables 6, 7 and 9 show the results of the estimated multilevel models in our study. For reliability, we report estimated coefficients with their respective confidence (highest density) intervals in parenthesis. We mainly propose two different models: Model I is a two-level model, which contains no explanatory variables and we call it the unconditional model. This model can be used as a preliminary step to check if the value of the intra-class correlation coefficient (ICC) supports the use of multilevel analysis. Moreover, it allows decomposition of the variations in the wages into within-and between-occupation group variances, which is equivalent to one way ANOVA. Model II is a two-level model, which consists of several predictors in the fixed part such as age, education, region, etc. in addition to gender dummy in the random part. These models were estimated by the maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian methods for the purpose of comparisons. Moreover, Model II is extended to control for the self-selection bias, which is termed as Model III.

First of all, the values of the intra-class correlation coefficients (ICCs) based on the model I estimated using the three methods reveal that there are substantial differences in daily wages. Such differences are due to between occupational group differences and thus multilevel modelling is an appropriate approach to advance our analysis. From this model, the value of ICC estimated by the Bayesian method suggests that about 23.6% of the overall variability in daily wages is attributed to variations between occupation groups, while the remaining 76.4% variation is attributed to the variations among workers i.e., within-occupational group differences (see Table 6). Our results are in line with the literature such as Huffman (2004) and Bunel & Guironnet (2017). The intercept shows that the overall average natural logarithm of daily wages across all occupational groups is estimated as 4.46.

Table 6 ML, REML, and Bayesian estimation results for model I, 2017

Estimation Techniques

	Component	ML [95% CI]	REML [95% CI]	Bayesian Mean [95% HDI]	Bayesian Mode
Fixed	Constant	4.46** [4.19, 4.74]	4.46** [4.21, 4.74]	4.47** [4.08, 4.83]	4.46
Random	Intercept	0.335** [0.143, 0.485]	0.362** [0.165, 0.564]	0.450** [0.231, 0.921]	0.389 0.151321
	Residual	0.731** [0.725, 739]	0.731** [0.722, 0.741]	0.707** [0.701, 0.710]	0.699
ICC		0.173** (0.012)	0.197** (0.014)	0.280** [0.091, 0.481]	0.236
Model fit		AIC = 31 151.6	REML criterion = 31 147.8	DIC = 31 134.1	

Note: Estimates were weighted by the Palestinian central bureau of statistics (PCBS) sampling weights. ** significant at 1%, * significant at 5%.
Source: Authors calculations based on the Palestinian Labour Force Survey (PLFS, 2017)

We also compare the results obtained using the three econometric techniques, specifically for Model II. As shown in Table 7, it is found that the estimated level-two residual standard deviations for intercept and gender using Bayesian approach are higher than those obtained from ML and REML methods. Furthermore, the residual standard deviations for both intercept and gender obtained by REML are greater than those obtained from ML. This reflects the negative bias of the estimated standard deviations resulted when the number of groups is small; which is in our case (Peugh, 2010; Raudenbush and Bryk, 2002). However, the estimated level-one residual standard deviations, as well as the estimated coefficients in the fixed part, are almost the same or identical using these techniques. Additionally, it is evident that the highest density intervals obtained from the Bayesian method for all estimated coefficients and standard deviations are wider than from the bootstrap confidence intervals found in both maximum likelihood (ML) and restricted maximum likelihood methods (REML). This is probably because we use an uninformative prior in case of a small number of groups; this leads to wider HDIs because of its low credibility to extreme values. Therefore, Bayesian estimation method provides a better fix with more efficient estimates overall. On this occasion, the below explanation is interpreted based on the posterior mode estimates instead of the posterior mean for all models in our study (Boedeker, 2017).

Table 7 ML, REML, and Bayesian estimation results for model II, 2017

Estimation Techniques

	Component	ML [95% CI]	REML [95% CI]	Bayesian Mean [95% HDI]	Bayesian Mode
Fixed	Constant	3.855** [3.757, 3.958]	3.855** [3.742, 3.961]	3.854** [3.740, 3.971]	3.855
	Years of schooling	0.0335** [0.0306, 0.0360]	0.0335** [0.0312, 0.0360]	0.034** [0.0310, 0.0362]	0.0342
	Squared years of schooling	0.00298** [0.0026, 0.0034]	0.00298** [0.0025, 0.0034]	0.00294** [0.0023, 0.0041]	0.00297
	Age	0.01089** [0.0099, 0.0118]	0.01089** [0.0099, 0.0]	0.01087** [0.0098, 0.0134]	0.01089
	Squared age	−0.0003** [−0.0003, −0.0002]	−0.0003** [−0.0003, −0.0002]	−0.0003** [−0.0004, −0.0002]	−0.0003
	Gender	−0.3901** [−0.517, −0.264]	−0.3905** [−0.515, −0.260]	−0.3901** [−0.517, −0.259]	−0.3904
	Marry	0.0906** [0.065, 0.117]	0.0905** [0.068, 0.115]	0.0903** [0.065, 0.117]	0.0905
	Region	0.662** [0.644, 0.681]	0.662** [0.644, 0.680]	0.661** [0.640, 0.689]	0.662
	Camp dwellers	−0.0645** [−0.091, −0.038]	−0.0646** [−0.090, −0.037]	−0.0644** [−0.093, −0.033]	−0.0646
	Refugees	0.0112 [−0.005, 0.029]	0.0111 [−0.006, 0.029]	0.0112 [−0.007, 0.041]	0.0111
	National government	0.166** [0.143, 0.187]	0.166** [0.144, 0.189]	0.164** [0.140, 0.192]	0.165
	Construction	0.339** [0.318, 0.362]	0.339** [0.315, 0.363]	0.337** [0.313, 0.369]	0.338
	Work in Israel	0.8235** [0.802, 0.846]	0.824** [0.803, 0.843]	0.823** [0.799, 0.851]	0.824
	No Contract	−0.282 ** [−0.301, −0.264]	−0.282** [−0.300, −0.262]	−0.284** [−0.304, −0.267]	−0.282
Random	Intercept	0.1251** [0.043, 0.182]	0.1359** [0.0669, 0.2122]	0.1402** [0.0662, 0.2101]	0.1395
	Gender	0.1440** [0.0362, 0.2234]	0.1576** [0.0305, 0.2516]	0.1596** [0.0299, 0.2509]	0.1581
	Residual	0.4297** [0.4245, 0.4345]	0.4299** [0.4248, 0.4352]	0.4298** [0.4244, 0.4348]	0.4299
Correlation		0.21 [−0.871, 1.000]	0.20 [−0.778, 0.922]	0.20 [−0.911, 1.000]	0.20
ICC		7.8%**	9.1%**	9.6**%	9.5%
Model fit	0.01966	AIC = 16 237.5	REML criterion = 16 328.1	DIC = 16 316.8	

Note: Estimates were weighted by the Palestinian central bureau of statistics (PCBS) sampling weights. ** significant at 1%, * significant at 5%.
Source: Authors calculations based on the Palestinian Labour Force Survey (PLFS, 2017)

However, after adding predictors in the fixed part as well as adding gender dummy in the random part, the value of the ICC declines to 9.5% as indicated by the results of Model II. Huffman (2004) and Bunel and Guironnet (2017) found that the ICC has declined after accounting for level-one predictors, which is confirmed with our finding. The gender dummy is negative and highly significant. That is, females received daily wages 39.04% lower than those males' counterparts with a significant standard deviation of 0.1581. Moreover, the residual standard deviation of the gender dummy in the random part is highly significant, which indicates that the gender pay gap is significant in each occupational group. The intercept is estimated as 3.855 and we may interpret it as the average natural logarithm of daily wages of workers with an average age (35.87) and average years of schooling (11.31) and zero values of the qualitative variables since we use grand mean centering. Additionally, it seems that all predictors in the fixed part are significant and contribute to wage inequality. That is, wage inequality among workers can be explained by several attributes such as age, education, geographical region, marital status, etc. The results are confirmed by the descriptive statistics discussed above based on PECS (2018) report.

To correct for self-selection bias, we estimate a probit model using the classical generalized linear model (for REML) and Bayesian methods. We find that the estimated coefficients are almost the same in both methods. However, the standard error of estimated coefficients obtained from the Bayesian method is lower than those obtained from the classical method as shown in Table 8. It appears that all variables have significant effects on participation decision using both the classical generalized linear model and Bayesian methods. For example, the effect of years of schooling is significant and positively affects the participation decision, which implies that participation increases as the schooling increase. This result is in line with the labour market specific factors in Palestine as discussed earlier and with the study by Al-Botmeh and Sotnik (2007) that have been examined the determinants of female labour force participation in Palestine.

Table 8 Estimated probability that an individual is employed in the labour market, 2017

Component	Probit (S.E)	Bayes probit
Constant	0.249** (0.041)	0.254** [0.161, 0.334]
Years of schooling	0.0197** (0.003)	0.0201** [0.0139, 0.0286]
Squared years of schooling	0.0016** (0.0006)	0.0015** [0.0125, 0.0158]
Age	0.012** (0.001)	0.014** [0.011, 0.018]
Squared age	–0.0005** (0.00006)	–0.0005** [–0.0006, –0.0004]
Gender	–0.416** (0.029)	–0.413** [–0.472, –0.352]
Marry	0.177** (0.033)	0.179** [0.111, 0.247]
Region	0.815** (0.026)	0.817** [0.765, 0.874]
Camp dwellers	–0.190** (0.038)	–0.038** [–0.053, –0.024]
Refugees	–0.051* (0.026)	–0.048* [–0.067, –0.025]
National government	2.521** (0.077)	2.524** [2.368, 2.678]
Work in Israel	–0.349** (0.035)	–0.345** [–0.419, –0.271]

Table 8 (continuation)

Component	Probit (S.E)	Bayes probit
Construction	–0.736** (0.028)	–0.730** [–0.791, –0.668]
No contract	3.476** (0.087)	3.472** [3.297, 3.639]
Log. Likelihood	–9 274.363	–9 282.725
N	76 111	76 111

Note: ** significant at 1%, * significant at 5%.
Source: Authors calculations based on Palestinian Labour Force Survey (PLFS, 2017)

The coefficient of self-selection; IMR, is negative and highly significant as shown in Table 9, which means that the unobservable characteristics negatively affect the daily wages. In other words, the sample selection bias plays a substantial role in the examination of gender wage gaps. After controlling for self-selection, the gender pay gap decreases to 38.14% and the ICC decreases to 8.5%, which is confirmed with the finding by Bunel and Guironnet (2017). That is, REML and Bayesian methods overestimate the gender pay gap and the ICC in the case without self-selection control.

Table 9 REML and Bayesian estimation results for model III corrected for self-selection, 2017

		Estimation Techniques		
	Component	REML [95% CI]	Bayesian Mean [95% HDI]	Bayesian Mode
Fixed	Constant	3.991** [3.881, 4.122]	3.992** [3.871, 4.138]	3.991
	Years of schooling	0.0316** [0.0292, 0.0339]	0.0315** [0.0284, 0.0348]	0.0316
	Squared years of schooling	0.00247** [0.0021, 0.0029]	0.00246** [0.0018, 0.0045]	0.00247
	Age	0.0122** [0.0113, 0.0130]	0.0120** [0.0095, 0.0136]	0.0121
	Squared age	–0.0003** [–0.0003, –0.0002]	–0.0003** [–0.0004, –0.0002]	–0.0003
	Gender	–0.3815** [–0.499, –0.251]	–0.3812** [–0.511, –0.242]	–0.3814
	Marry	0.0725** [0.053, 0.095]	0.0724** [0.048, 0.115]	0.0726
	Region	0.562** [0.545, 0.579]	0.560** [0.539, 0.594]	0.562
	Camp dwellers	–0.0374** [–0.058, –0.016]	–0.0372** [–0.067, –0.011]	–0.0373
	National government	0.197** [0.159, 0.230]	0.196** [0.153, 0.241]	0.196
	Work in Israel	0.854** [0.832, 0.877]	0.851** [0.825, 0.887]	0.853
	Construction	0.362** [0.336, 0.388]	0.359** [0.325, 0.421]	0.361
	No contract	–0.346** [–0.384, –0.308]	–0.348** [–0.405, –0.287]	–0.346

Table 9 (continuation)

Estimation Techniques

	Component	REML [95% CI]	Bayesian Mean [95% HDI]	Bayesian Mode
Fixed	IMR	–0.0699** [–0.137, –0.001]	–0.0697** [–0.141, –0.001]	–0.0698
Random	Intercept	0.1296** [0.0533, 0.2028]	0.1328** [0.0423, 0.2094]	0.1314
	Gender	0.1600** [0.0433, 0.2649]	0.1634** [0.0421, 0.2851]	0.1619
	Residual	0.4299** [0.4255, 0.4347]	0.4298** [0.4234, 0.4352]	0.4299
Correlation		0.07 [–0.88, 0.96]	0.07 [–1.021, 1.005]	0.07
ICC		8.3%	8.7%	8.5%
Model fit		REML criterion = 16 326.3	DIC =1 319.6	

Note: ** significant at 1%, * significant at 5%.
Source: Authors calculations based on Palestinian Labour Force Survey (PLFS, 2017)

For robustness checking, we have performed the analysis for the year 2016 in which the results are not attached. We find the results from both years are very similar, which confirm our results that the gender pay gap across occupational groups is the main determinant to the wage inequality in Palestine.

CONCLUSIONS

In this paper, we investigate the gender pay gap across occupational groups based on the PLFS data for the year 2017 obtained from the Palestinian central bureau of statistics (PCBS). The study applies the multilevel linear model and seeks to compare the results using three estimation approaches which are maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian estimation. The results of this study reveal that the Bayesian estimation method provides more efficient estimates than ML and REML.

Moreover, the present study finds various important empirical results yielded by the multilevel analysis. First, the results show that wage inequality due to between occupation groups is evident and it is estimated as 23.6% and the remaining is due to disparities among observed and unobserved worker's attributes. This proportion is less than those found in the United States by Huffman (2004) and in France among recently graduated workers by Bunel and Guironnet (2017). However, it was estimated at 18% in the UK by Olsen et al. (2018).

Second, allowing gender to vary across occupational groups, the results reveal that the gender pay gap is significant and varies across occupation groups. Moreover, adding predictors in the fixed part, the results reveal that variables such as schooling, age, region, marital status, locality, sector, industry, place of work, and work contract contribute significantly to wage inequality among workers. Third, the gender pay gap reduces to 38.14% after correcting for self-selection bias. However, this gap is still persistent and high. The empirical analysis of the present study is confirmed with the country-specific factors mentioned earlier.

Since there is pay discrimination among genders and the wage gap persists across occupation groups, immediate action from the policymaker is of atmos. This issue needs to be resolved as it may lead to gender unequal treatment and bad practices in the society and labour market, as well as barriers to economic growth. Women could contribute to significant economic growth and their skills and efforts should be appreciated and encouraged. The enforcement of equal pay through enforcement and equity laws could be one of the ways to close the gender pay gap. Also, the awareness of equal pay and treatment in the labour market, the encouragement of women to enter the job market through campaign and education day can be another good practice.

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