BIRZEIT UNIVERSITY

Gender Wage Gap Analysis in Palestine

"تحليل فجوة الأجور بين الذكور والإناث في فلسطين"

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Palestine, Birzeit

March 2023

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DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Date: **March 4th, 2023**

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Date: **March 4th, 2023**

STATEMENT 2

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Abstract

One of the most vastly discussed topics in the economic literature is discrimination, particularly gender discrimination, which, presents itself in different aspects of the labor market. Wage discrimination has stayed a primary topic of interest globally, because of the need for equity, sustainable development of the nation, and reducing poverty. Several serious efforts have been made in recent years, and some resolutions have been adopted by international organizations and countries. For example, in 2018, Iceland[1] became the first country in the world to enforce equal pay for men and women by law. Companies with 25 or more employees must obtain a certification from the government proving that they pay all their employees equally, regardless of gender. Only a few countries, however, have achieved a high level of gender equality, such as Iceland, which has been consistently ranked as the most gender-equal country in the world for over a decade. Women in Iceland have equal rights and opportunities to men in terms of education, employment, and political participation. Also, Sweden is another country that has made significant progress in achieving gender equality. It has implemented policies such as paid parental leave, subsidized child care, and flexible working hours that enable women to balance their work and family responsibilities[2]. Despite the existence of laws such as the Equal Pay Act of 1963 and the Lilly Ledbetter

[1] "Iceland becomes first country in the world to enforce equal pay" (The Guardian, 2 Jan 2018)
"Iceland has made it illegal to pay men more than women" (BBC News, 2 Jan 2018)

[2] World Economic Forum, "The Global Gender Gap Report 2021", https://www.weforum.org/reports/global-gender-gap-report-2021

Fair Pay Act of 2009, the gender pay gap in the United States remains significant, with women earning only 82 cents for every dollar earned by men, according to the National Women's Law Center[3].

According to new studies from various countries, gender wage inequality is not constant throughout the wage distribution. Furthermore; the average pay disparity gives only limited details on women's labor-market status. Using micro-level data from the Palestinian Central Bureau of Statistics (PCBS), this study examines the most recent Quarterly Labour Force Survey 2015-2019 data from Palestine to get in-depth insights on the gender wage gap and wage discrimination in the Palestinian labor market.

This study first employs Blinder-Oaxaca decomposition methods, then two different decomposition techniques, the first is conditional quantile decomposition (CQD) proposed by Melly (2006) and unconditional quantile decomposition (UCD) - Recentered Influence Functions (RIF)-by Firpo, Fortin, and Lemieux (2009). Also, quantile regression techniques (CQR, and UQR) are used and sample selection is corrected by using Heckman (1979) based methodology, in order to examine the determinants of wage inequalities at these different points in the earnings distribution, and to understand how these factors change at various levels of earnings. According to the estimates of average wage decomposition by Oaxaca - Blinder, women in Palestine earn 11.8 percent less than men. On the other hand, the quantile regression and

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[3] National Women's Law Center. (2021). The gender wage gap: 2020. https://nwlc.org/issue/equal-pay-and-the-wage-gap/

counterfactual decomposition analyses indicate some interesting aspects of the Palestinian labor market. The first is that at the top of the income distribution, the total wage inequality between men and women has sharply increased in both conditional and unconditional quantile regressions. Furthermore, the results show that educational attainment has a major impact on the gender wage disparity. Finally, the findings reveal that married females face higher discrimination.

This study suggests that the government should monitor wage differences and encourage equal opportunity in the workplace. On the other hand, to encourage women's engagement in the workforce, career development programs for women should be developed.

تحليل فجوة الأجور بين الذكور والإناث في فلسطين

إعداد
محمود عثمان يوسف خصيب

إشراف
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المُلخَّص

يُعتبر التمييز ضد النساء من أكثر الموضوعات التي نوقشت على نطاق واسع في الأدب الاقتصادي. إذ يَظهر التمييز في مناح مختلفة في سوق العمل. وظل التمييز في الأجور، وخاصة ضد المرأة ، نقطة رئيسية عالميا وذلك بسبب الدعوة إلى المساواة ، والتنمية الوطنية المستدامة ، والحد من الفقر. وقد بُذلت عدة جهود جادة في السنوات الأخيرة ، واتخذت دول ومنظمات دولية بعض القرارات، منها على سبيل المثال ، في عام 2018 ، أصبحت أيسلندا أول دولة في العالم تفرض المساواة في الأجور بين الرجال والنساء بموجب القانون. اذ يتعين على الشركات التي تضم 25 موظفًا أو أكثر الحصول على شهادة من الحكومة تثبت أنها تدفع لجميع موظفيها بالتساوي ، بغض النظر عن الجنس. ومع ذلك ، لم يحقق سوى عدد قليل من البلدان مستوى عالٍ من المساواة بين الجنسين ، على سبيل المثال ، تم تصنيف أيسلندا باستمرار على أنها أكثر دول العالم مساواة بين الجنسين لأكثر من عقد من الزمان. إذ تتمتع النساء في أيسلندا بحقوق وفرص متساوية مع الرجال من حيث التعليم والتوظيف والمشاركة السياسية. كذلك الأمر بالنسبة للسويد هي دولة أخرى أحرزت تقدمًا كبيرًا في تحقيق المساواة بين الجنسين. وقد نفذت سياسات مثل إجازة الأمومة مدفوعة الأجر ، ودعم رعاية الطفل ، وساعات العمل المرنة التي تمكن المرأة من تحقيق التوازن بين مسؤوليات العمل والأسرة. على الرغم من وجود قوانين مثل قانون المساواة في الأجور لعام 1963 وقانون (Lilly Ledbetter) للأجر العادل لعام 2009 ، لا تزال فجوة الأجور بين الجنسين كبيرة في الولايات المتحدة، حيث تحصل النساء على 82 سنتًا فقط مقابل كل دولار يكسبه الرجال ، وفقًا للمركز الوطني لقانون المرأة.

ووفقًا للدراسات الحديثة من مختلف البلدان ، فإن الفجوة بين الجنسين ليست ثابتة عبر توزيع الأجور ،وقد تختلف في المستويات العليا والوسطى والمنخفضة من التوزيع. وتشير بعض الدراسات إلى أن الفجوة بين الجنسين تتسع في المستويات العليا من توزيع الأجور ، مما يعكس صعوبة وصول النساء إلى الوظائف العليا ذات الأجور العالية. ومع ذلك ، يتم الاعتراف بأن متوسط الأجور لا يمكن أن يعكس بالضرورة وضع المرأة في سوق العمل. وبالتالي ، فإن دراسة العوامل الأخرى التي تؤثر على الفجوة بين الجنسين ، مثل التوظيف والتدريب والترقية والحوافز والأجور المعتمدة على الأداء ، يمكن أن تساعد في فهم المزيد من التفاصيل حول الوضع النسبي للمرأة في سوق العمل .

وباستخدام بيانات من الإحصاءات الرسمية للجهاز المركزي للإحصاء الفلسطيني (PCBS) تبحث هذه الدراسة في أحدث البيانات الربعية المتاحة لمسح القوى العاملة الفلسطيني خلال الفترة 2015-2019 لاستخلاص رؤى معمقة فيما يتعلق بفجوة الأجور بين الجنسين والتمييز في الأجور في سوق العمل الفلسطيني. وتم استخدام ثلاث منهجيات في هذه الدراسة وهي منهجية Blinder-Oaxaca ، ثم منهجيتين مختلفتين للتحليل، وهما طريقة "(Conditional Quantile Regression) والتي قدمها(2006) Melly " وطريقة "(Unconditional Quantile Regression-RIF) بواسطة ((2009) Firpo, Fortin and Lemieux)"، اذ تعتبر المنهجية الأخيرة الأولى استخداما في فلسطين ، وقد تم تصحيح اختيار العينة باستخدام منهجية (1979) Heckman من أجل دراسة عوامل التفاوت في توزيع الأجور، ومن أجل فهم كيفية اختلاف هذه العوامل على مستويات الأجور المختلفة.

تظهر نتائج تحليل متوسط الأجر أن متوسط أجور النساء في فلسطين يقل عن متوسط أجور الرجال بنسبة 11.8%. من ناحية أخرى ، تشير تحليلات الانحدار الكمي إلى بعض الجوانب المثيرة للاهتمام في سوق العمل الفلسطيني. منها أن الفجوة في الأجور بين الرجل والمرأة أكثر وضوحا في الجزء العلوي من توزيع الأجور. تقترح هذه الدراسة أن على الحكومة مراقبة الفروق في الأجور وتشجيع تكافؤ الفرص في مكان العمل.

Table of Contents Page

List of Figures Page

List of Tables Page

Abbreviations

Abbreviation	Expression
OLS	Ordinary Least Squares
RIF	Recentered influence functions
NSSO	National Sample Survey Office
CQR	Conditional Quantile Regression
UQR	Unconditional Quantile Regression
US	United States of America
LFS	Labor Force Survey
PCBS	Palestine Central Bureau of Statistics
NGO	Non-Governmental Organizations
IGO	International Governmental Organization
QCD	Quantile Counterfactual Decomposition
Satt.	Settlements
UQCD	Unconditional Quantile Counterfactual Decomposition
NIS	New Israeli Shekel

Gender Wage Gap Analysis in Palestine

1. Introduction

Inequality research is still crucial in economics as well as other areas of study such as psychology and sociology. This is due to the fact that inequality has been demonstrated to have an effect on people's welfare and life satisfaction (Clark and d'Ambrosio, 2015). Inequality is unacceptable because it not only restricts poverty reduction efforts but also leads to ineffective resource allocation (Okojie and Shimeles, 2006). Women have traditionally earned less than males, although this disparity has narrowed in most transition economies in recent years (Badalyan, 2018). Gallego-Granados and Geyer (2015) observe that the differences between men and women are a continuous labor market phenomenon. Female average earnings are less than males in almost all occupations (Hegewisch and Hudiburg, 2014). There is a lack of research on the discrepancy in pay between genders in Palestine. One of these studies, examines the disparity in pay between genders and the involvement of women in the workforce in Palestine, using data from PCBS. The findings show that the proportion of females in the labor force is significantly lower than men (roughly 21.6% among working-age women in 2018 compared to 71.4% for males), which is one of the lowest in the globe, and female unemployment rates are higher than male rates, which is approximately double the rate of males. The study also identifies a significant gap between men and women's earnings, with women earning around 20% less than men. These findings highlight the existence of gender inequality in the labor market in Palestine. The study suggests that policies intended to raise the involvement of women in the workforce and reducing the gender wage pay are necessary to promote gender equality in the Palestinian labor market (Hammoudeh, 2020).

The main factors contributing to the gender wage gap are two-fold. Firstly, occupational segregation leads to women being employed in jobs that require less education, resulting in lower pay. Secondly, women often experience interruptions in their careers due to household and social obligations, which hinder their ability to acquire the same level of experience and skills as men, and thus affect their earning potential.

Blinder (1973) Blinder (1973) is recognized as the pioneer in researching the issue of wage disparity. He focused on the US labor market and studied the gender pay inequality, as well as the differential between white and black workers. According to Blinder's research, approximately 68% of the gender disparity can be explained by personal characteristics. For instance, age is a critical factor in the gender pay gap since male wages tend to rise faster than female earnings. is recognized as the pioneer in researching the issue of wage disparity. He focused on the US labor market and studied the gender pay gap, as well as the differential between white and black workers. According to Blinder's research, approximately 68% of the gender disparity can be explained by personal characteristics such as age, education, and occupation being significant determinants. For instance, age plays a crucial role in the gender pay gap since male wages tend to rise faster than female earnings. Based on the Global Gender Gap Report (2020), the global gender gap score (calculated using a populationweighted average) is 68.6%. This score indicates that there is a remaining gender gap of 31.4% that needs to be narrowed, on average[4].

Pay gap analysis is critical for several reasons; first, equivalent work with equal pay in general is an important anti-discrimination principle. Second, reducing discrimination and giving women equal opportunities will be better for the realization of women's potential, which is necessary from the viewpoint of the aging population and the decreasing numbers of working-age people. In the long run, we should utilize all available opportunities to increase the working-age population's contribution.

The standard approach to analyze the wage gap is the Oaxaca-Blinder (1973) decomposition; and to a lesser degree the quantile regression which outperforms Ordinary Least Squares (OLS) as it does not require assumptions about the residuals as OLS does (Wenz, 2019). New methodologies have recently been developed to examine the disparity not just at the mean, but also over the full distribution. Firpo, Fortin, and Lemieux (2007) are credited with developing the Re-centered Influence Function (RIF) regression, and then introduced to "STATA" and popularized by Rios-Avila and Maroto (2020) to examine distributional changes due to certain interventions. To the best of our knowledge, there is no prior research that has utilized

[4] The Global Gender Gap rankings report reveals that the top ten countries in the world are divided into four northern countries - Iceland (1st), Norway (2nd), Finland (3rd), and Sweden (4th), one Latin American country - Nicaragua (5th), one country from the East Asia and Pacific region - New Zealand (6th), three other countries from Western Europe - Ireland (7th), Spain (8th), and Germany (10th), and one country from Sub-Saharan Africa - Rwanda (9th).

these modern techniques for studying the wage gap in Palestine, indicating a gap in the literature on this specific topic.

To break down the average difference in pay between genders, The traditional Oaxaca-Blinder (1973) method decomposes it into two parts: one resulting from differences in characteristics (characteristic effect) and the other from differences in how those characteristics are rewarded (coefficient effect). To analyze the pay distribution at different points, the Oaxaca-Blinder approach needs to be used alongside conditional quantile regression. Several techniques have been suggested in research, such as Machado and Mata (2005) creation of a hypothetical wage distribution through random sampling of quantiles and observations.

Empirical studies such as Albrecht, Björklund, and Vroman (2003), Arulampalam, Booth, and Bryan (2007), De la Rica, Dolado, and Llorens (2008), Kee (2006), and Koenker and Bassett (1978) have used this method. But, they all share a common drawback: they are unable to consider the impact of individual covariates on the characteristic and coefficient effects. A quantile computation is also considered to be a useful approach for characterizing the distribution of the outcome variable. This played a role in the increasing popularity of conditional quantile regression models. (e.g., Koenker and Bassett (1978), Moore (2018), and Koenker (2005).

Firpo, Fortin, and Lemieux (2009) introduced unconditional quantile regression to address the limitation of quantile regression in estimating the impact of explanatory variables on the corresponding unconditional quantiles. Unlike the conditional mean, the expectation of the conditional quantiles does not equal the expectation of the unconditional quantiles, making it impossible to study the impact of the explanatory variables on the latter using quantile regression estimates

Borah and Basu (2013) examined conditional and unconditional quantile regressions and identified three differences that provided an advantage for the latter,

(1) If only one covariate affects the data generation process, both conditional and unconditional regressions will yield the same estimate of the impact of that covariate on a specific quantile;

(2) If multiple covariates impact the data generation process, conditional quantile regression estimates the effect of a variable on a particular quantile of the dependent variable based on the average values of the other covariates. On the other hand, unconditional quantile regression provides a generalized estimate of the impact of a covariate across the distribution of other covariates, and its interpretation is applicable to the entire population, rather than a specific quantile;

(3) The estimate of an exogenous covariate in unconditional quantile regression is not affected by different sets of explanatory variables because a specific quantile of the distribution is not conditioned on the average values of other covariates.

As compared to other methodologies in the literature, RIF decomposition has several advantages,

(1) The simplicity with which it can be implemented,

(2) The ability to determine specific contributions from individual covariates on aggregate decomposition,

(3) Unconditional quantile regression can extend the analysis to encompass any statistic for which a RIF can be defined,

(4) It enables the path-independent computation of a detailed decomposition and the unconditional mean interpretation of coefficient estimates[5], since the proportions are inverted back to quantiles locally,

(5) It is easy to compute and interpret decompositions at particular points in the distribution,

(6) The primary issue with this method is the accuracy of the linear decomposition approximation[6], which assumes linearity in the relationships between variables (Blau and Kahn, 2017),

(7) Because it just requires OLS regression estimate on the RIF variable, it is computationally efficient,

(8) This method enables the identification of intercepts and the performance of Oaxaca-type decompositions at various quantiles, and

(9) One significant advantage of the UQR model over the CQR model is that it enables the interpretation of unconditional means.

Unconditional quantile regression techniques were recently introduced by Firpo, Fortin, and Lemieux (2009) to address this issue (both Oaxaca-Blinder decomposition and conditional quantile regression decompositions have limitations when it comes to

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5 In contrast to the approach taken by e.g. (Machado and Mata 2005).

6 While the RIF decomposition technique is a useful method for estimating causal effects, its precision depends on the accuracy of the linear approximation used in the decomposition.

explaining differences in outcomes between two groups, such as differences in wages between men and women. The Oaxaca-Blinder method can only explain differences in terms of differences in the group means of independent variables, while conditional quantile regression decompositions allow for the estimation of the effects of independent variables at different points of the conditional distribution of the dependent variable. However, neither of these methods provides a comprehensive understanding of the factors contributing to differences in outcomes between two groups). The coefficients computed in this approach are essentially unconditional partial effects resulting from minor shifts in the location of the covariate (i.e., independent variable) on the unconditional quantile of the dependent variable. Therefore, using the Oaxaca-Blinder approach, decomposing the pay gap between men and women at quantiles is as straightforward as decomposing it at the mean. To estimate the impact of each variable on the gender pay inequality, a decomposition method using unconditional quantile regression, developed by Firpo, Fortin, and Lemieux (2009), was utilized. This research aims at considering the wage disparities in the Palestinian labor markets between men and women[7]; the study will analyze the magnitude of those disparities, and the proportion of which that is explained by the human capital model. In addition, having a long time series of the surveys will enable the researcher to track to what degree we have learned to devise measures to reduce that disparity. The research problem is therefore many fold:

[7] Palestinian Central Bureau of Statistics, 2020. Palestinian Labour Force Survey: Annual Report: 2019. Ramallah - Palestine.

First: What is the magnitude of the gender wage gap in Palestine?

Second: How has that changed overtime?

Third: How much of the wage gap can the human capital model explain?

Fourth: What is the added value of using distributional measures of the gap over the standard measure?

Men and women should have the same chance at success in modern society. The presence of a pay gap between men and women is often regarded as a crucial indicator of unequal opportunities. Women earn less than men on average in most nations do, and the situation is the same in Palestine. Therefore, the goal of this study is to investigate which factors significantly affect the gender wage gap in Palestine.

This study proceeds by providing an up to date literature review in section 2. Section 3 presents the research methodology; and section 4 presents the empirical results. Finally, section 5 concludes.

2. Literature Review

There is a vast and varied body of literature on the gender pay disparity, which employs various techniques and explores different aspects of the issue. A recent study He, Xu, and Men (2020), focuses on analyzing the gender wage gap among Chinese university graduates by decomposing it into different factors. They argue that the composition effect, which refers to the differences in the characteristics of male and female workers, plays a crucial role in explaining the gender pay gap. The study employs a counterfactual decomposition analysis using quantile regression to decompose the wage differences between men and women decomposition method to separate the wage differential into an explained component (due to differences in characteristics) and an unexplained component (possibly due to discrimination or other factors). Using data from the Chinese College Student Career Development Annual Report 2007, they find that the gender pay gap among Chinese university graduates is largely explained by differences in human capital endowments (characteristics), such as majors, industries, and work experience and that the composition effect explains 30-60% of the wage gap at every level of the log wage distribution. The research also shows that female graduates had lower average work capacity than male graduates, and work capacity has a positive correlation with wages. Their findings suggest that policies aimed at reducing the gender pay gap should target the root causes of the composition effect.

Moore (2018) analyzes the relationship between occupational mobility among female wage earners and gender wage inequality. The research utilizes data from the Current Population Survey-Merged Outgoing Rotation Group over the period of 1979 to 2015 to investigate how changes in the composition and wages of occupations related to caring and culturally associated with women, as well as managerial and professional positions outside of the care economy sector, affect the gender pay gap. The findings indicate that the gender pay gap has narrowed as a result of women's admission into high-paying managerial positions and their exit from low-paying private household employment. However, the wage-equalizing effect of occupational changes and associated behavioral changes has decreased with time, and gender wage convergence has stopped after 2007. The findings also indicate that wage disparities continue to disadvantage women, with the majority of the remaining gender pay differential occurring within occupations. The implications of the study's results are discussed with regards to how they can help reduce the gender pay gap.

Recently, Deshpande, Goel, and Khanna (2018) investigated the pay disparity between men and women in India for regular salaried employees using data from a large Indian firm. Based on Blinder - Oaxaca and the Machado – Mata – Melly decompositions, they found a substantial unexplained gender wage gap of 24% despite controlling for various factors, including education, experience, job level, and performance ratings. The gap was higher for more experienced employees and for those at higher job levels. They also found that women were underrepresented in higher-paying job categories and were more likely to leave their jobs, which contributed to the gender pay inequality. They show that the gap is most probably related to gender discrimination. Also, females at the bottom of the wage distribution face greater discrimination than women at the top of the income distribution. They concluded that policies aimed at reducing the pay gap between men and women in India should focus on addressing the factors that lead to occupational segregation and on promoting women's retention and advancement in the workforce.

Another study of Adireksombat, Fang, and Sakellariou (2010) conducted a study to examine the gender earnings gap in Thailand from 1991 to 2007. They used a double decomposition approach to analyze the changes in gender pay differences over time and employed unconditional quantile regression in combination with the Oaxaca-Blinder decomposition. The study found that gender inequality in the Thai labor market had decreased since the 1990s, although changes in characteristics explained only a small portion of the total changes. The research also revealed that gender pay inequality was larger at the lower end of the wage distribution and that the gap had declined more at the higher end of the distribution. The study concluded that policies aimed at promoting gender equality in the labor market should address the underlying causes of the gender wage gap and the persistence of gender segregation in the labor force.

In addition, Badalyan (2018) conducted a study on gender wage differences in Hungary using wage data from the National Employment Office between 1998 and 2011. They employed a decomposition method with the RIF regression technique to analyze the wage gap along the distribution. The study found that the overall wage gap increased over time, but the explained gap was negative in all years, mainly due to differences in firm characteristics, occupation, and residential variables. Another study examined the gender wage gap in the Russian Federation as well as earnings distribution from 1996 to 2011. The study utilizes a reweighted, recentered influence function decomposition, which enables the estimation of each covariate's contribution to wage structure and composition effects throughout the earnings distribution. The study's results show that women's career progression tends to be slower and flatter than men's, and observable characteristics that represent human capital have less impact on the gender pay gap at higher earnings levels. Additionally, if women's pay was determined by their educational qualifications to the same extent as men's pay, the gender pay gap would either disappear or even reverse for those in the highest earnings distribution. According to the study's results, it is suggested that women at the lower end of the earnings distribution could benefit from support in enhancing their labor market skills. Meanwhile, women at the higher end of the earnings distribution would benefit from measures aimed at breaking the glass ceiling and ensuring they receive comparable compensation for their skills as men.(Atencio and Posadas, 2015).

Blau, and Kahn (2017) used data from the panel study of wage dynamics for the US labor market between 1980 and 2010 to analyze the pay gap between men and women. The study includes major characteristics of individual workers, such as education, experience, occupation, industry, and union status. They found that the gender earnings gap decreased during this period. However, by 2010, variables related to human capital, such as education and experience, did not have a significant impact on gender pay inequality. The study also shows that the role of occupation and industry in the gender pay gap remained significant. Furthermore, they discovered that the decrease in the gender wage gap was much slower at the top of the wage distribution than in the middle or at the bottom.

In addition, Ismail, Farhadi, and Wye (2017) study utilizing data obtained from 7,135 working households in Peninsular Malaysia in 2011, researchers examined occupational segregation and salary differentials between men and women in the Malaysian labor market. The study uses the wage decomposition model Brown, Gilroy, and Kohen (1982) developed to analyze the determinants of gender-related wage differentials. According to the findings, differences within occupations are the major driver of the gender wage gap, and wage discrimination within occupations plays a significant role in the disparity. The study also finds that sample selection bias is a significant factor in examining gender wage gaps. Despite an increase in women's participation in the labor market over time, occupational segregation and wage differentials remain prevalent in Malaysia. In a different setting, Chuang, Lin, and Chiu (2018) employed individual data from the Manpower Utilization Survey from 1978 to 2013 to conduct a study on the wage disparity between men and women in Taiwan at the inter-industry level. Their study indicates that the pay disparity between men and women exists across all industries and has decreased over the years. However, the study finds that the size of the wage disparity between men and women differs across industries, with the mining industry having the largest gender wage gap, while the financial industry having the smallest. They suggest that policies aimed at narrowing the pay differences between men and women should take into account the differences in wage gaps across industries. The study conducted by Duraisamy and Duraisamy (2016) is significant as it investigates the gender pay inequality in India across various labor market segments and wage distribution utilizing representative national-level data from 1983 to 2012. According to the study's findings, (i) the gender pay gap has declined over time across the pay distribution, (ii) the pay differences between men and women, which can be attributed to differences in productivity, has increased over time, and there is evidence of the convergence of productive characteristics of men and women, and (iii) the adjusted pay disparity indicates that females at the lower end of the wage distribution face more discrimination than those at the top, and this gap has increased over time. In another study, discrimination against females was found to be the main cause of un-adjusted wage gap between females and males in Romania (Pauna

B. and Pauna C., 2016). A similar study of wage discrimination in Northeast Brazil found evidence that discrimination is twice as large in agriculture than industry sector. both in occupational insertion as in income, and the situation worsens in the industrial sector. Wage discrimination based on gender, even within the service sector. As compared to the classes of employed in the previous year, the remaining workers face the most gender discrimination in the region. Whereas, the lowest discrimination is found in the trade sector (Gomes and Souza, 2016).

Akhmedjonov (2012) conducted a study to examine gender pay inequality in Turkey using the Oaxaca (1973) approach and the OLS method, based on the 2009 Turkish Household Survey of Income. The study controlled for factors such as the type of economic activity, employment status, marital status, and education level of individuals. The findings indicate that there is a significant pay differences between men and women in the Turkish labor market, with females earning less than men on average. The study found that the average wage for women in Turkey is about 28% lower than that of men. Additionally, the study found that the cause of gender pay gap in Turkey's labor market is entirely due to labor market discrimination against women.

Ahmed and Pushkar (2010) have employed Labor Force Survey (LFS) data for Bangladesh, they investigated earnings inequality between men and women from 1999 to 2005. The main finding was that wage difference due to gender is mostly because of discrimination against females. On the other hand, Moral-Arce et al. (2012) Alternatively, Moral-Arce and colleagues (2012) applied Machado and Mata's semiparametric extension to analyze the wage gap in Spain. Their approach involved dividing job positions into quantiles based on pay levels, and their results showed that discrimination is more prevalent in jobs that are relatively low-paid or relatively high-paid, as opposed to those with median wages.

The literature on wage gaps in Palestine is less frequent; a qualitative study ILO (2016) pertaining only to workers in the educational sector found that males enjoy a higher benefit package relative to females, despite the equal wage. In Daoud and Shanti's (2016) quantitative study, they utilized data from the PCBS Labor Force Surveys between (1999, 2001, 2007, and 2010) to investigate gender and sector-based wage inequalities using the Oaxaca-Blinder decomposition. They discovered marked gender disparities in sector selection, returns on education, and the breakdown of pay gaps by gender and sector. Despite low educational returns, which tended to minimize the endowment effect's impact on gender and sector pay disparities, the data indicated that, in the public and "other" sectors, females had higher expected log hourly wages than males for all years compared to those in the private sector. Hammoudeh (2020) conducted a study to examine the extent to which gender wage disparity across various sectors and industries in the West Bank can be attributed to differences in men's and women's characteristics, and how much of that gap remains unexplained and could potentially be due to discrimination. The study analyzed key aspects of women's labor force participation and working conditions and utilized labor force survey data from 2015 to 2017, employing the Oaxaca-Blinder decomposition analysis. The results revealed that the pay differences between men and women is mainly present in the private sector and the NGO/IGO sectors, but not on average in the public sector, which contrasts with earlier research conducted by Blinder (1973) and Daoud and Shanti (2016). In another study about "What Explains the Gender Pay Gap in the West Bank?" Ayyash and Sek (2021) analyze the causes of the West Bank gender wage difference. Using data from the Palestinian Central Bureau of Statistics (PCBS) and the Labor Force Survey (LFS) in 2018, they use the Oaxaca-Blinder decomposition approach to discover that women in the West Bank earn much less than males, even after adjusting for individual and job variables. According to the survey, the key factors contributing to the gender wage disparity in the West Bank include discrimination, occupational segregation, and a lack of access to education and training. They advocate for policies addressing these underlying concerns to promote gender equality and regional economic growth. On the other hand, Jemmali, Morrar, and Rios-Avila (2022) "On Decomposing the Changes in Pay Inequality in Palestine over Time" examines the patterns and determinants of wage disparity in Palestine from 2000 to 2019. They apply an inter-temporal decomposition approach utilizing data from the Palestinian Central Bureau of Statistics (PCBS) to estimate the contributions of several factors, such as changes in skill distribution, job structure, and income returns. The analysis shows that pay disparity in Palestine has risen over time, owing mostly to changes in skill distribution and wage returns associated with those skills. To address the core causes of wage disparity in Palestine, they recommend policies that increase education and training, minimize occupational segregation, and improve employees' bargaining power.

In summary, the literature review reveals that comparing the outcomes of gender-based wage discrimination studies is challenging due to differences in variables such as dependent variables (e.g., annual or hourly, gross or net), estimating techniques (e.g., Mincer regression, Oaxaca-Blinder decomposition, and Recentered Influence Function regression approach RIF), number of controllable variables, and years of inquiry. Despite these variations, it can be concluded that some wage discrimination exists based on gender.

This study makes several contributions to the existing literature. Initially, earlier research on the pay gap between men and women in Palestine predominantly concentrated on the mean pay gap. Nonetheless, concentrating solely on the mean may not provide a comprehensive understanding of the situation. Research from various developed and developing nations shows that the pay gap differs across the whole wage distribution (Ahmed and Maitra, 2015). Second, as far as we know, this is the sole study that utilizes the Recentered Influence Function (RIF) to decompose gender wage gap in Palestine. The study examines both the explained 'endowment' and unexplained 'discrimination' effects across the wage distribution. Third, given that the PCBS data contains rotating panels, our analysis identified repeated interviews and used first-time interviewees only. This has not been done in previous studies, as the questionnaire does not indicate which interviews are first-time interviews or not. The effect of duplicate observation on regression results was analyzed by Sarracino and Mikucka (2016) [8] which makes this study the first that isolates this effect.

3. Research Methodology

The study utilizes a quantitative method that use the decomposition technique developed by Oaxaca and Blinder (1973) to assess the extent to which the overall wage gap between males and females occurs. The Oaxaca and Blinder decomposition approach indicates whether wage gaps between men and women are due to variations in their characteristics or, alternatively, to discrimination. The Heckman (1979) decomposition approach is then used to adjust for the selectivity bias effect. Methods other than Oaxaca and Blinder decomposition, on the other hand, are used. Initially, Melly (2006) developed conditional quantile decomposition approaches. This method is based on the Machado and Mata (2005) decomposition. This study will utilize Firpo, Fortin, and Lemieux's (2009) technique, in addition to Melly's (2006) conditional quantile regression decomposition, to estimate a detailed unconditional quantile decomposition of the gender wage gap in Palestine.

The decomposition method proposed by Firpo, Fortin, and Lemieux (2009) involves a standard regression where the dependent variable, which is the log daily wage of the respondents, is substituted with its re-centered influence function (RIF). This method is estimated using an ordinary least squares (OLS) regression, where the RIF of the log

[8] Sarracino and Mikucka (2016): A Monte Carlo simulation of estimation bias due to duplicated observations.

daily wage's unconditional quantile is represented as a linear function of the explanatory variables.

3.1 Data

The study examines the gender wage gap in Palestine from 2015 to 2019, using “stata” program. It is determined by the results of the Palestinian Quarterly Labor Force Surveys gathered by the PCBS, which estimates the number of employees and average daily wages in NIS according to the type of the economic activities, geographical and occupational classification.

3.2 Variables

Dependent variable: log (Average Daily Wage)

Independent variables:

The predictors were chosen using Becker's (2010) human capital model, which includes the following: Age, Age squared[9], and a group of variables known as control factors, including gender, marital status, workplace, locality type, occupation, region, current job nature, education level, industry, and work sector. A list of explanatory variables is shown in Table 1(Appendix II).

[9] Age squared used in the model as an explanatory variable since the relationship between wage and age is not linear relationship.

3.3 The Empirical Model

3.3.1 Oaxaca – Blinder Method

3.3.1.1 Oaxaca – Blinder Decomposition Method

The first analytical method for investigating the wage difference between men and women is the Oaxaca-Blinder decomposition approach (Oaxaca, 1973) and (Blinder, 1973), which is commonly used to evaluate wage disparities between specific groups, such as sexes. This approach distinguishes between the portion of the pay difference that can be explained by endowments and the portion that cannot be explained. Each explanatory variable, such as education, place of work, industry, etc., is used to separate the wage gap into two components:

1. Differences in the gender endowments "characteristics", and
2. Differences in compensation based on unexplained factors.

This approach allows us to determine to what extent the control variables account for the wage difference and how much of the difference remains unexplained. Furthermore, the contribution of each variable to the wage difference can be assessed individually.

The Oaxaca – Blinder decomposition developed by Jann (2008) for "stata" was used for the analysis. There are two groups, A and B, and an outcome variable, Y, along with a group of predictors. The goal is to analyze the mean outcomes difference between males and females using predictors such as education and job experience. The question is how much of the gap in mean outcomes between the two groups can be attributed to each predictor. Let

$$R = E(Y_A) - E(Y_B) \quad (1)$$

Where the expected value of the outcome variable, E(Y), represents the contribution of the predictor group differences to the mean outcome difference.

In the linear model,

$$Y_\ell = X'_\ell \beta_\ell + \varepsilon_\ell, E(\varepsilon_\ell) = 0, \ell \in (A, B) \quad (2)$$

Assuming X is a vector of predictors and a constant, β contains the intercept and slope parameters, and ε represents the error, the difference in mean outcome can be expressed as the difference in linear prediction at the average values of the predictors for each group. That is,

$$R = E(Y_A) - E(Y_B) = E(X_A)'\beta_A - E(X_B)'\beta_B \quad (3)$$

Since $E\left(Y_\ell\right) = E\left(X'_\ell \beta_\ell + \varepsilon_\ell\right) = E\left(X'_\ell \beta_\ell\right) + E\left(\varepsilon_\ell\right) = E\left(X_\ell\right)'\beta_\ell$

where $E(\beta_\ell) = \beta_\ell$ and $E(\varepsilon_\ell) = 0$ by assumption.

Equation (1) can be rearranged to determine the impact of the differences between the groups in the predictors on the overall difference in the outcome variable, like this:

$$R = \{E(X_A) - E(X_B)\}'\beta_B + E(X_B)'(\beta_A - \beta_B) + \{E(X_A) - E(X_B)\}'(\beta_A - \beta_B) \quad (4)$$

Where R represents the overall mean difference between the reference group A and the comparison group B, and a positive R value indicates that $E(Y_A) > E(Y_B)$. This is a "threefold" decomposition, which means that the difference in the outcome variable is split into three components:

$$R = E + C + I \tag{5}$$

The first component,

$$E = \{E(X_A) - E(X_B)\}'\beta_B \tag{6}$$

amounts to the portion of the difference caused by predictor group differences ("endowments effect"). This means that if the predictor variables' means for both groups are evaluated at group B's coefficients and the endowment effect turns out to be negative, then group B must have had higher characteristics that group A. Therefore, if group B and group A had the same characteristics, the wage gap would increase.

The second component,

$$C = E(X_B)'(\beta_A - \beta_B) \tag{7}$$

estimates how much the differences in coefficients, including the intercept, contribute. The third component is an interaction term that addresses the fact that discrepancies in both endowment and coefficient exist simultaneously between the two groups,

$$I = \{E(X_A) - E(X_B)\}'(\beta_A - \beta_B) \tag{8}$$

3.3.1.2 Oaxaca – Blinder Detailed decomposition

The decomposition of outcome difference into explained and unexplained components is important, as is the analysis of the individual contributions of specific predictors or predictor sets. To better understand wage disparity between genders, it is necessary to determine the extent to which it is caused by differences in education or job experience. Additionally, assessing the portion of the unexplained difference resulting from differences in educational or job experience returns could be useful (Jann, 2008).

3.3.1.3 Oaxaca – Blinder Detailed Decomposition with Selectivity bias adjustment

According to Reza and Manfor (2002), the income equation for women is not straightforward because working women may not represent a random sample of all women and should be viewed as a distinct subgroup. Therefore, working women are considered self-selected, which could lead to a distorted outcome and bias in an unadjusted earning equation. Additionally, the increase in women's work participation may be attributed to factors such as high or low earning potential. Moreover, Neuman and Oaxaca (2004) propose a method to address selection bias in labor market research. Selection bias occurs when employees are not a random sample of the working-age population, and this can be minimized by using the inverse Mills ratio in the wage equation, as suggested by Heckman (1979). Therefore, it is common practice to correct for sample selection bias in pay equations using Heckman's technique. However, earnings are only observed for individuals who are part of the workforce, which may not be a representative group. To address selection bias in the decomposition, one approach is to subtract the selection effects from the total differential and then use the standard decomposition formulae on this adjusted differential, as proposed by (Reimers, 1983). Other methods, such as those proposed by Dolton and Makepeace (1987), Neuman and Oaxaca (2004), and Jann (2008), are also available.

This study uses the Heckman adjustment for sample selection bias because when it is combined with the Oaxaca decomposition technique, the resulting decomposition automatically accounts for selection bias (Jann, 2008).

3.3.2 Conditional Quantile Regression (CQR) and Decomposition

3.3.2.1 Conditional Quantile Regression (CQR) and Decomposition without Selection Correction

Over 40 years ago, Koenker and Bassett (1978) introduced conditional quantile regression (CQR) as an extension of the least absolute deviation estimator in the field of econometrics. CQR focuses on quantiles, which are a set of statistics that better describe the distribution of the outcome. CQR can be used to examine how the outcome of a person rated above a specific quantile (τ %) changes in response to a change in their characteristics, assuming their outcome is still greater than that of (τ %) of the new individuals who share the same (but new) set of characteristics. According to Rios-Avila and Maroto (2020), conditional quantile regression (CQR) cannot be utilized to interpret individual level effects because they depend on an unknown factor.

One significant limitation of the Oaxaca-Blinder decomposition method is that it does not account for wage differences across the earnings distribution. The quantile counterfactual decomposition (QCD) method, which utilizes a bootstrap approach, is another technique used to analyze how the gender wage gap fluctuates across wage distributions. Machado and Mata (2005) suggested this strategy, which employs modeling and inference methods developed by Chernozhukov, Fernández-Val, and Melly (2013).

The following outlines the counterfactual wage decomposition using quantile regression[10]: Consider wage equations for female and male workers as:

$$\log(W_m) = g_m(X_m, \varepsilon_m) \tag{9}$$

$$\log(W_f) = g_f(X_f, \varepsilon_f) \tag{10}$$

Where:

$\log(W_i), i = m, f$: log (daily wage),

Q: quantile,

$X_i, i = m, f$: explanatory variable vector, and

$\varepsilon_i, i = m, f$: the error term.

The pay gap at the quantile (τ th) may be divided into two parts:

$$Q_\tau(\log W_m) - Q_\tau(\log W_f) = [Q_\tau(\log W_m) - Q_\tau(\log W_c)] + [Q_\tau(\log W_c) - Q_\tau(\log W_f)] \tag{11}$$

Where:

$\log W_c$: the counterfactual log (wage) in equation (11) above[11];

The first component of the quantile counterfactual decomposition approach focuses on the counterfactual effect of the conditional distribution, which examines wage gaps due to gender

[10] Stata's "cdeco" command was utilized for this purpose. This can be found at "https://sites.google.com/site/blaisemelly/home/computer-programs/inference-on-counterfactual-distributions/"

[11] Another form:

$$Q_{W(M|M)}(\tau) - Q_{W(F|F)}(\tau) = [Q_{W(M|M)}(\tau) - Q_{W(F|M)}(\tau))] + [Q_{W(F|M)}(\tau) - Q_{W(F|F)}(\tau)] \tag{12}$$

differences in characteristics (endowments effect). The second component exhibits the counterfactual effect of changing the covariate distribution (coefficient effect or composition effect) of the corresponding coefficient between the (τ^{th}) quantile of the male pay distribution and the (τ^{th}) quantile of the female wage distribution. The effect of coefficients reflects the extent of gender discrimination in the labor market. To examine wage disparities, this study also uses the conditional quantile regression model and quantile regression decomposition techniques developed by Koenker and Bassett (1978), and Melly (2006).

3.3.2.2 Copula-Based Approach for Quantile Sample Selection Models

Heckman (1979) suggests a two-stage estimator technique in the literature to handle non-random selection in the labor market, assuming that the errors in the selection and outcome equations are normally distributed. On the other hand, Buchinsky (1998) offers an additive method for correcting sample selection bias in quantile regression. However, this implicit control function approach cannot be used in a quantile regression context because it requires the covariates and error terms to be independent of selection probabilities. Furthermore, in quantile models, the assumption of normally distributed errors is not generally valid, as suggested by Huber and Melly (2015)[12] suggest. Arellano and Bonhomme (2017) introduce a sample selection approach that

[12] The Stata command "qregsel" developed by Melly (2006) currently permits only bootstrapping standard errors. For a sample size of approximately 150,000 observations, estimating standard errors for the explained and unexplained components, as well as the total gap, for a single quantile using this method can consume up to a week.

employs a copula, which is a function that links a multivariate distribution to its marginal distribution functions.

3.3.3 Unconditional Quantile Regression and RIF Decomposition Approach

Koenker (2005) employed conditional quantile regression; however, according to Firpo, Fortin, and Lemieux (2009), this method does not lead to meaningful conclusions because the findings cannot be extrapolated to the entire population. Unlike OLS, where the law of iterated expectations enables us to convert from a conditional ($E[y_i|x_i]$) to an unconditional ($E[y_i]$) expectation, this principle does not apply to quantiles. Therefore, the (τ^{th}) unconditional quantile (y_i) may differ from the (τ^{th}) conditional quantile. Although conditional quantile decomposition methods are better than others at breaking down the gap into explained and unexplained components, they cannot distinguish the influence of covariates on each gap (DiNardo, Fortin, and Lemieux, 1995). Thus Firpo, Fortin, and Lemieux (2009) developed unconditional quantile regressions to examine how changes in the distribution of independent variables affect the quantiles of the dependent variable's marginal distribution. To assess the impact of changes in the explanatory variables' distribution on the quantiles of the dependent variable's marginal distribution, the RIF (Recentered Influence Function) decomposition utilizes unconditional quantile regressions, which involve running a regression of the transformed outcome variable (i.e., its RIF) on the independent variables. However, the RIF coefficients, which show the effect of increasing the mean value of X on the unconditional quintile, can be misleading in conditional quantile regressions because the law of iterated expectations does not apply. The technique consists of two stages. The initial stage involves calculating the Recentered Influence Function (RIF) for a particular quantile q (τ) and substituting this variable for the intended outcome, namely wage (Y). Fortin, Lemieux, and Firpo (2010) define the RIF of the variable Y at quantile (τ) as[13]:

$$RIF(y;Q_\tau) = Q_\tau + \frac{\tau - 1(y \le Q_\tau)}{f_Y(Q_\tau)} \tag{13}$$

Where:

Q_τ : matches to the population in the τ quantile,

$1(\cdot)$: The indicator function determines whether the wage observation (y) is above or below the quantile (τ), and

$f_Y(\cdot)$: calculated using the Kernel density function of Y.

Assuming a linear unconditional quantile regression specification, i.e.

$$\hat{RIF}(Y_i;\hat{Q}_\tau) = X_i\,\hat{\beta} \tag{14}$$

Therefore, under the assumption that all other variables are constant, the OLS estimate (specifically, the RIF-OLS[14] estimator) provides a consistent estimate of the impact of a small displacement in the distribution of X on the unconditional quantile. However,

[13] Firpo, Fortin, and Lemieux (2009) define the Recentered Influence Function (RIF) as RIF(y; v) = v(F_Y) + IF(y; v), which can also be expressed by adding the quantile back $\int RIF(y;v).dF(y) = v(F_Y)$, where IF(y; v) represents the influence function of the observation y for the quantile v(F_Y).

[14] Firpo, Fortin, and Lemieux (2009) propose three techniques: OLS, logistic estimator, and non-parametric estimator.

RIF-OLS estimates may become inconsistent if the unconditional quantile regression is not linear. In such cases, a non-parametric estimator may be necessary as an alternative. Where Y= log(W), $\hat{\beta}$: "the unconditional quantile partial effect" of X (Adireksombat, Fang, and Sakellariou, 2010), The RIF coefficients obtained indicate the impact of increasing the mean value of X on the unconditional quantile. As $\hat{Q}_\tau(Y) = \overline{X}\hat{\beta}$, The analysis of the gender wage gap can be reformulated as the decomposition as:

$$Q_\tau(\log W_m) - Q_\tau(\log W_f) = [\left(\overline{X_m} - \overline{X_f}\right)\hat{\beta}_{m\tau} + \hat{R}_X] + [\overline{X_f}\left(\hat{\beta}_{m\tau} - \hat{\beta}_{f\tau}\right) + \hat{R}_S] \qquad (15)$$

Where:

$\hat{R}_S$: the structure's approximation error, and

$\hat{R}_X$: the composition effect's approximation error, approximation errors that may occur in practice are due to the use of first-order approximations and the construction of the counterfactual pay distribution.

4. Results and Discussions

4.1 Data descriptive statistics

Quarterly data from the Palestinian Central Bureau of Statistics (PCBS) on the labor force survey conducted from 2015 to 2019 is being utilized. The pooled number of observations exceeds 500,000[15], which provides statistical power for a number of analytical tests. The summary statistics were calculated to focus on the differences in

[15] The number of observations used is 28271 because of using first wave interviewees only.

wages and the source of such gaps. Table 3A and Table 3B (Appendix II) show basic descriptive statistics for model variables.

Table 3A (Appendix II) shows that the sample was selected from 27585 observations, 23130 (83.8 percent) of which were male, with on average, males having received 11.6 years of education, while females have received 14.5 years of education. These findings indicate that, on average, men have lower levels of education in the labor market. However, the average age of males is roughly two years less than that of females, while the average daily wage for females is 23.7 NIS lower than that of males.

Table 3B (Appendix II) shows descriptive statistics cover selected variables in Palestine from 2015Q1 to 2019Q4, focusing exclusively on wage employees. The data indicates that the majority of wage employment, at 83.8%, is held by males, which reflects the low participation of females in the labor force. Although both males and females have a similar wage and non-wage employment distribution, around four out of every five employees are male. The age distribution for males and females in the sample used for estimation is mostly similar, except for the 15-24 age group, where the percentage of males is nearly twice as much as that of females. This implies that males tend to finish compulsory education only, and transition to the labor market earlier. This also explains why women have more school years (education) on average. Similar stories are found for marital status, and employment status; however, the sector of employment reveals differences among men and women. The majority of men are employed in the private sector, while women are almost equally distributed between the private and public sectors. Another remarkable difference is the higher proportion of women employed by foreign sector by almost four to one. According to the human capital theory, education is a crucial factor that determines wages. However, this study reveals that a larger proportion of females are in the upper end of the education distribution, while the proportion of males is higher towards the lower end of the distribution. The frequency distribution indicates that females tend to be concentrated in the service industry, whereas men are distributed across various industries. Another significant factor in determining wages is the occupation; three quarters of women are in clerical occupations which are characterized by low wages; on the other hand, men's occupations are more spread out and are in male dominated occupations (service shop, craft, plant machine shops…. etc.).

Figure 2 (Appendix I) indicates that the gender pay gap is around 20% the whole time. Whereas, Table 2 (Appendix II) shows that at the beginning of the period 2015Q1 males enjoyed a 25% wage premium over females; by 2019Q3 the gap decreased to a mere 16%. The reduction may have been due to improvement of female endowments or policy induced changes.

Figure 3 (Appendix I) shows the wage distribution for both men and women reveals that women tend to be more represented towards the far right of the distribution. On the other hand, more men are found towards the right of the center of the distribution (100-150 NIS), where most of the observations lie. However, the wage distribution for males appears to be more right-skewed than that of females, indicating that a larger proportion of males are in the higher end (upper tail) of the distribution.

4.2 Empirical Results

This part investigates the gender wage gap with three different decompositions (Blinder-Oaxaca, quantile regression, and re-centered influence function) to compare their results for the periods of 2015Q1-2019Q4.

4.2.1 Three-folds Oaxaca - Blinder Decomposition Results

The Jann (2008) user-written program in Stata is utilized to perform a decomposition analysis. This method splits the average daily wages of men and women into two parts - one that can be accounted for by factors like education or job experience and another component that cannot be explained by these factors. The unexplained portion is suggestive of gender-based wage discrimination. Additionally, the study investigates the effect of individual variables on the pay gap by utilizing both the threefold and twofold decomposition methods. The results of the Oaxaca-Blinder approach are displayed in a table in "STATA". The table is divided into two sections: the differential panel and the decomposition panel. The differential panel includes ("prediction 1" and "prediction 2")[16]. They measure the log daily wages individually for males and females, but the wage disparity is divided into three components in the second panel of the decomposition output. The first component (endowments) represents the average improvement in wages for females if they have the same characteristics as males. The second component (coefficients) shows the difference in women's wages when men's coefficients are applied to women's characteristics. Finally, the third component, the

[16] These results are not reported in this study

interaction term, estimates the combined impact of differences in endowments and coefficients (Jann, 2008). The overall results of the Blinder-Oaxaca decomposition are displayed in Tables 4 and 5 (Appendix II).

Table 4 shows the findings of the two-part decomposition, which assumes that a non-discriminatory coefficient vector (i.e., pooled regression) is used. The findings are quite similar to those in Table 5, which is the unadjusted model. Table 5 reports both self-selection adjustment and the unadjusted estimation. The first panel of Table 5 indicates that the average of men's log daily wages is 4.573, while the mean for women's log average daily wages is 4.434, yielding a wage gap of nearly 14% $(4.573 - 4.434)$, that is average male wage is higher than female average wage by 14%. However, for the second panel of the table, the first part, which is explained by individual and job characteristics (Endowments) is nearly - 0.104 and statistically significant at 1%. The negative endowments effect means that women have better endowments which is in line with ((Rahman and Al-Hasan, 2019); (Biltagy, 2014); and (Salardi, 2012)), thus if male endowments are applied to females, their wages would fall. It also implies that differences in endowments account for about -75% $\left(\frac{-0.104}{0.139} \times 100\%\right)$ of the wage gap. The endowment effect sign is negative due to the constant coefficient in female model (-3.68) which is greater than the constant coefficient (-3.62) in the male model. When the men's coefficients are applied to the women's characteristics, the second term measures the change in women's wages. Whereas, the third part is the interaction term, which reflects the simultaneous effect of endowment and coefficient differences.

“However, The second and third terms jointly account for the unexplained part (residual) of the wage difference” (Daoud and Fallah, 2014). So, the remaining 175.5% pay gap cannot be explained by these factors, and the coefficient of "unexplained” pay gap is 24.4%, statistically significant at the 1% level.

Surely, an unexplained wage gap for the same values of explanatory variables cannot be interpreted as the amount of the wage difference due only to discrimination. This is due to the fact that additional explanatory variables not included in the regression, such as job experience, may explain for wage differences as well.

The bias adjusted estimates indicate that the total differential is 11.8%, which is lower, indicating that the bias in female wages was downward. However, the endowment effect constitutes -73.7%, which is a bit lower than the unadjusted. Both Table 6, and Table 7 (Appendix II) shows detailed estimation results for the explained part of the wage difference. It is observed that in the "explained" category, age has a non-linear effect on endowment with a negative coefficient for age and a positive but non-significant for age square. The age coefficient is statistically significant at the 1% level (Table 6). Therefore, as age increases, the gender gap increases. As a result, the gender pay gap can be partially explained by age. More precisely, around 46% $\left(\frac{-0.048}{-0.104} \times 100\%\right)$ of the explained earning gap can be explained by age; whereas age contributes nearly 43.7% of the explained gap for the adjusted model (Table 7). On the other hand, in the "unexplained" category, predictor age square has a positive estimated coefficient and is statistically significant at the 1% level (both Tables 6 and 7). This finding indicates that the explained (endowments effects) wage gap grows with age, whereas, the unexplained (coefficients and interactions effects) wage gap declines as age rise due to the effect of the unexplained gap being higher than the explained gap effect. Consequently, we can conclude that the gender wage gap can be partially explained by age. More precisely, around 23.3% $\left(\frac{-0.048+0.014}{-0.104} \times 100\%\right)$ of the gender pay disparity can be explained by age, but for the adjusted model approximately 29.8%.

Turning to education, except for the Illiterate and Ph.D. categories, higher qualifications have a negative estimated coefficient and are statistically significant at the 5% level in the "explained" component. This suggests that the pay difference between men and women is higher for those with secondary education or below, and lower for those with higher education. For example, the negative schooling gap suggests that female workers are more likely to earn more than male workers since their average years of schooling are greater. The remaining negatively explained contributions are interpreted similarly (Ayyash and Sek; 2021).

For marital status, the variable "married" has a positive and statistically significant estimated coefficient in the "explained" category. This indicates that the endowment effect is higher among married people, and the marital status variable explains approximately 3.8% of the wage gap based on just being married. In unadjusted models, females should be earning 3.8% more than males. However, the unexplained difference is positive and not significant, indicating that the wage gap widens with marriage. At the net level, marriage has a positive impact, indicating that the wage gap is wider for the married group.

Regarding the regional variable, the endowment effect shows no significance for both the West Bank or the Gaza strip. However, when it comes to the Locality Type, the endowment effect is negative and significant in the urban areas compared to rural and camp areas. This implies that better endowments decrease the wage gap in urban areas. Moreover, the unexplained difference coefficient is negative, suggesting that urban areas have a lower unexplained gap than rural and camp areas. However, the interaction effect leads to a higher unexplained gap in urban areas. Overall, the net regional effect is negative, indicating that the wage gap is smaller in urban areas.

Regarding the place of work variable, the "West Bank" and "Israel & Satt." have positive estimated coefficients, which are statistically significant at the 1% level in the "explained" category. This finding indicates that the gender wage gap increases for those who work in these regions, and it explains about 82% and 81% of the gender earning inequality, respectively, in the unadjusted model. Whereas, in the adjusted model, the findings also show that the gender wage gap increases for those who work in these regions, and it explains about 95% and 94% of the wage gap, respectively, in the unadjusted model. However, the unexplained gap is insignificant at the 95% level of the confidence interval.

The variable of work sectors (i.e., Private, Foreign, and Public) has a statistically significant negative estimated coefficient at a 1% level in both the unadjusted and adjusted models, explaining approximately 44%, 32%, and 13%, respectively, of the gender pay gap. This suggests that the pay gap decreases in these sectors of work. Moreover, the unexplained gap for the Foreign and Public sectors is negative, indicating that the pay gap reduces in these sectors of work. The impact of the Private, Foreign, and Public sectors is negative, which implies that the wage gap decreases in these sectors of work. As a group of predictors, the work sector contributes to reducing the wage gap in favour of females.

Similarly, both the unadjusted and adjusted models show comparable outcomes for the variable of the current job's nature (i.e., full-time), which is statistically significant at a 5% level and has a negative predicted coefficient in the "explained" category. This suggests that the pay inequality in favour of women reduces with full-time work, and the full-time variable explains around 1% of the wage gap. However, the unexplained gap is not statistically significant for full-time work.

Moreover, both the unadjusted and adjusted models account for the Industry variable (such as Commerce, Hotels and Restaurants, Mining, Quarrying and Manufacturing, and Agriculture, Hunting, and Fishing), which display negative estimated coefficients in the "explained" category. This indicates that the wage gap reduces with the industry of Commerce, Hotels and Restaurants, Mining, Quarrying and Manufacturing, and Agriculture, Hunting, and Fishing. However, the unexplained gap is positive for the Commerce, Hotels and Restaurants, and Mining, Quarrying, and Manufacturing industries, indicating that the wage gap increases with these industries. Conversely, the Construction, Transportation, Storage and Communications, and Services and Other Branches industries all exhibit a positive predicted coefficient in the "explained" category. This implies that the wage gap increases with these industries, but the unexplained gap is negative for the Construction and Transportation, Storage, and Communication industries, while the Services and Other Branches industry has a positive estimated coefficient in the "unexplained" category. This suggests that the wage gap increases with the Services and Other Branches of industry.

Finally, for the Occupation variable that is significant at 1% level and has a negative estimated coefficient for (Proff-Clerks, Craft, and Elementary Occupation) in the “explained” category. These findings for both models unadjusted and adjusted show that wage gap decreases with (Proff-Clerks, Craft, and Elementary Occupation) and it explains about ((64%, 74%), (26%, 31%), and (11%, 13%)) respectively of the gender pay, also the unexplained gap is negative for (Proff-Clerks, and Elementary Occupation), indicating that wage gap decreases with (Proff-Clerks, and Elementary Occupation).

To summarize, the findings of the Oaxaca-Blinder decomposition reveal that the unexplained portion of the pay gap exceeds 100%, some may believe that this is a sign of discrimination against females in Palestine, although it may be a sign of model misspecification. Whether this is the case or not requires further investigation and experimental design.

Nonetheless, at the 95% confidence level, the regression coefficient for several of the factors is significant. Table 8 (Appendix II) provides a thorough overview of the regression coefficients' significance levels.

4.2.2 Selectivity Bias Adjustment for Oaxaca Decomposition Results

The conclusions drawn from the aforementioned figures may be affected by selection bias. To address this issue, we perform a selection correction by utilizing the Heckman (1973) method in our analysis (Jann, 2008). As mentioned earlier, the outcomes of the selection correction can be found in Table 5. The table reveals that the raw earnings of females are somewhat underestimated (the average log daily wage of females is 4.434 as opposed to the corrected 4.455) and the gender pay gap is slightly overestimated (13.9% in comparison to the adjusted 11.8%). Figure 4 in (Appendix I) displays the outcomes of the Oaxaca-Blinder wage decomposition. When all measurable sources of the difference are included, the unexplained part of the gap 24.4% (see Figure 4 Appendix I), becomes larger than the actual gap 13.9% for the adjusted model. This surprising outcome means that, on the whole, observable characteristics of the female labor force suggest that they should be paid more than males. To put it differently, the impact of discrimination not only involves variations in the constant term but also discrepancies in the coefficients.

4.3 Quantile Regression (QR) Results

4.3.1 Quantiles Decomposition Results

The QCD method was utilized in conjunction with the bootstrap method to draw conclusions about the degree to which the disparity in wages between genders fluctuates throughout the wage distribution[17]. This was conducted using the QCD approach given by Machado and Mata (2005), for which Chernozhukov, Fernández-Val, and Melly (2013) provided the modeling and inference tools[18]. The results of the counterfactual analysis of wage decomposition utilizing conditional quantile is presented in Figure 5 (Appendix I), reported in Table 9 (Appendix II).

As can be seen the gap falls to nearly zero for the 40th percentile, then increases with wages, in general male wages are higher for each successive quantile until it reached a maximum of 55% for the top percentile. At the lower end of the distribution, the endowments part (explained) is negative implying that the unexplained part (coefficient and residual) are more than 100% of the gap. But as wages rise, the explained part becomes positive (around the 50th percentile, the total gap is larger than the unexplained gap); for the top quantile, the explained part constitutes 18.2% of the pay gap, the corresponding figure for the fourth quantile is 23.6%. The differences are significant for almost all cases. Not only is the wage gap rising with wages, but also the explained part does so too; however, the explained part remains small throughout the wage distribution. Based on that, one can conclude the degree of discrimination (if

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[17] The Stata software provides fundamental functions for estimating quantile regression estimators and their standard errors. The "qreg" function computes asymptotic standard errors, assuming independently and identically distributed errors. However, in this specific study, the standard errors are derived from pairwise bootstrapping. This involves randomly selecting pairs of observations (yi, xi) , *i = 1, 2..., n,* with replacement from the original sample. Pairwise bootstrapping is appropriate for the independently but not identically distributed setting observed in the study, which resulted from a simple random stratified sampling procedure. To perform simultaneous quantile regressions, the "sqreg" command is used, and 100 re-samplings are conducted to obtain a sample with a covariance matrix that is a consistent estimator of the original estimator's covariance matrix.

[18] Stata's “cdeco” command was used for this purpose. This can be found at https://sites.google.com/site/blaisemelly/home/computer-programs/stata---decomposition-of-differences-in-distribution-using-quantile-regression?authuser=0”

it exists) increases with lower wages and that the endowments' effect becomes more visible as wages rise. As can be seen from Figure 5 (Appendix I), the unexplained proportion is greater than the whole gap owing mostly to differences in the intercepts. The total unexplained component is a major cause of earnings inequalities between the upper, lower, or middle of the wage distribution[19] (Töpfer 2017).

4.3.2 Quantile Regression Detailed Results

4.3.2.1 Quantile Regression (Unadjustment) Results

Table 10A in (Appendix II) displays the outcomes of unadjusted quantile regression, indicating that the gender wage gap that cannot be explained by other factors is larger for lower wage quantiles. (due to the difference in the male/female wage equation intercept). Particularly, in the first quantile of the unadjusted model, females earn approximately 23% less than males. However, as we move up the wage distribution, the difference in wages between men and women becomes smaller. For example, the pay gap between men and women is roughly 19.4% in the 60th percentile for an unadjusted model, but it climbs to over 33% in the 99th percentile. These figures are not in contradiction[20] with those in Table 9 (Appendix II) as the total wage gap is shown at each quantile while Table 10A (Appendix II) gives the female intercept difference which is part of the unexplained gap. Also, the results in Table 10A (Appendix II) warrant the articulation of two observations: The first pertains to the significance (or

[19] The constant term is included in the wage structure component. Differences in the intercept term narrow wage gaps between individuals at the high and low ends of the wage distribution.
[20] The findings of quantile regressions, such as CQR and UQR, differ from those of QCD because the absence of the counterfactual effect is evident (Rahman and Al-Hasan, 2019).

lack of) the coefficients as we move up the pay scale or the educational achievement. Low levels of education do not seem to affect wages regardless of the quantile. But as we move up the educational scale, the impact of schooling on wages becomes evidently non-linear as documented in the literature. This holds no matter which quantile is in question. This shows that education becomes more significant as education increases, and its effect becomes even larger. The second observation concerns place of work. It is common to find university graduates working in Israel and the settlements with similar jobs as the uneducated (which is dominated by male workers), thus getting the same wage. The table mentioned above confirms that the wage premium for working in Israel and the settlements is greater at lower quantiles; this implies workers with lower wages earnt more than 80% than the same workers employed in the West Bank; this figure drops to less than 50% in the top quantile. On the other hand, workers in foreign entities exhibit the opposite trend, that is the premium increases as wages rise.

4.3.2.2 Quantile Regression (Adjustment) Results

In Appendix II, Table 10B presents the outcomes of quantile regression that accounts for selection bias and adjusts the coefficients. The covariates used in the previous section remain the same, with expected signs. The results reveal that, in terms of bachelor's wage growth, education-related factors have a continuous impact when controlling for selection. The education coefficients are positive, indicating that both male and female workers with higher education earn more. However, for males in top-paying positions, education is even more valuable. Moreover, the finding that the return on education for men increases with quantile highlights that having a higher level of education has a favorable effect on wage inequalities. Experience (age squared as a proxy variable) appears to have little influence on female employees across all quantiles. The data shows that being married has a significant positive correlation with wages across the entire pay distribution. However, for female employees, working in Gaza does not appear to have a statistically significant impact across all quantiles.

After correcting for sample selection, the data reveals that the gender wage gap in Palestine is around 30%, as compared to 33% before adjusting for sample selection, particularly at the higher wage levels. Additionally, the results suggest that the gender wage gap is larger in the lower percentiles of the wage distribution when controlling for sample selection. Specifically, in the 20th percentile, women earn approximately 22.2% less than men. As we move up the wage distribution, the difference in wages between genders becomes smaller; for example, the wage difference is roughly 21.3 percent in the 80th percentile, Table 10B (Appendix II). Also, Figures 6, and 7 (Appendix I) indicate that the difference in earnings between men and women without sample correction is relatively narrower than the difference with sample correction.

Table 11 in Appendix II presents the bootstrap inference on the gender pay gap's quantile counterfactual decomposition (QCD). The results show that the functional form of the regression model specified in the previous analysis is accurate, and the null hypothesis of "no impact on observable distributions" is rejected. As a result, the analysis reveals that there is a significant gender wage disparity in Palestine at each percentile of the wage distribution. Moreover, both the "no impacts of characteristics" and "no impacts of coefficients" null hypotheses are rejected. As a result, the study indicates that the gender wage disparity in Palestine is the result of a combination of both coefficient and characteristic effects.

4.3.3 Unconditional Quantile Regressions (RIF) and Decomposition Results

(Firpo, Fortin, and Lemieux, 2009) argue that the RIF-OLS decomposition method offers the significant benefit of being able to calculate more specific decompositions across different quantiles. This approach allows for the evaluation of the influence of each covariate on wage gaps at varying levels of wages. As mentioned earlier, this method allows for the estimation of the contribution of each characteristic to the explained component or the impact of coefficients on the unexplained component of wages.

4.3.3.1 RIF Unconditional Quantile Regressions Results

Before presenting the decomposition findings, some estimates from the RIF unconditional quantile regression coefficients are shown for the different log daily wage quantiles: the 20th, the 40th, the 60th, the 80th, and for the 99th percentile from 2016Q1-2019Q4, which are the bases of the decomposition analyses, along with bootstrapped standard errors. Tables 12, and 13 (Appendix II) present unconditional quantile regression results for the log of earnings (log of daily wage), and Panels A and B report the male and female results, respectively.

The returns to characteristics vary between men and women across all quantiles. This is evident in the Bachelor's degree level of education, where the gender gap decreases from 37.3% at the 20th percentile to approximately 24.3% at the 80th percentile, in comparison to individuals without any education. Specifically, men who obtained a

Bachelor's degree earned 37% more than those without education at the lower end of the wage distribution and 24% more at the 80th percentile, as shown in (Table 12). At the lower end of the wage distribution, women who obtained a Bachelor's degree earned 87% more than those without education, while at the 80th percentile in (Table 13), they earned only 25% more. As a result, The return to education increases with educational attainment, but more so for women. The return also diminishes as the pay scale increases until it becomes insignificant for the top quantile (except for Ph.D. and MA and Ph.D. for women where it increases drastically as you move up the scale).

The UQR in Table 14 (Appendix II) shows that the gender coefficient is negative and decreases in absolute value with higher quintiles. The conclusion that emerges is that higher-paid women have a lower gender wage penalty. The effect of education on wages follows a similar pattern as discussed above, higher education is associated with a higher return, but the effect decays as wages increase.

4.3.3.2 RIF Unconditional Quantile Decomposition Results

In Appendix II, Table 15 presents the decomposition of wage disparities between men and women at the 20th, 40th, 80th, and 99th percentiles. At the top of the table, the overall gap is positive and increases with each quantile (excluding the second quantile), indicating that men enjoy a more significant advantage at the upper end of the wage distribution. The endowment effect is negative for the first three quantiles, but it becomes positive for the last two, and its magnitude varies across the quantiles. However, for the 4th and 5th quintiles, the endowment effect accounts for 70% and 30% of the total gap, respectively.

As previously discussed, (Adireksombat, Fang, and Sakellariou, 2010) have noted that an advantage of unconditional quantile regression is that it facilitates not only the decomposition of gender wage gap into the effects of characteristics and coefficients but also the assessment of the contribution of each covariate in each component of the gender gap. The study's results suggest that gender disparities in place of work, occupation, and industry significantly contribute to wage disparities at the top of the wage distribution. At the 60th percentile, the sector of work is the primary contributor to wage gaps, while education is the significant factor at the lower end. At the bottom of the distribution, unobservable qualities linked to the constant have the most significant impact. The study reveals that the constant has a considerable effect on gender wage disparities, indicating the influence of gender inequalities in various difficult-to-measure characteristics[21].

Women possess more observable educational characteristics compared to men. The gender wage gap is most significant at the top of the wage distribution. Differences in work characteristics, as well as variations in occupations and industries, are significant at the bottom of the wage distribution and remain negative throughout. The explained gap is positive from low-income earners up to earners near the 60th percentile, but negative for top-income earners (80th and 99th percentiles). Regarding the impact of coefficients, educational inequalities between men and women are typically

[21] Eckel and Grossman (2008) discovered in their field studies that women are more averse to taking risks compared to men.

insignificant at the bottom of the wage distribution, negative at the median, and positive at the top. The unexplained gap is statistically significant and negative from the lower to the bottom of the distribution, but positive at the top (as shown in Table 15).

In Figure 8 (Appendix I), it can be seen that there has been a reduction in the pay gap between men and women across the wage distribution, with the most significant reduction happening between the 60th and 99th percentiles. However, this reduction is primarily due to changes in wage structures rather than changes in gender differences in characteristics. The wage structure accounts for almost the entire gender wage gap at the 80th percentile (unexplained gap). Moreover, changes in wage structures in the upper half of the wage distribution have had a negative impact on women, with the line for the unexplained gap dropping below zero at the 80th percentile and rising above zero at the 99th percentile.

4.4 Comparing the Different Approaches Results

Table 16 (Appendix II) presents the Oaxaca-Blinder decomposition results for the average gender wage gap, along with the quantile decomposition results obtained using various methods, which are expected to produce similar results. This section compares the outcomes of these different approaches, focusing on whether there are differences in the estimated decomposition components across methods.

Based on the results of the Oaxaca-Blinder decomposition, it was found that women earn 11.8% less than men on average. This difference can be broken down into two components: the characteristics effect and the coefficient effect. The characteristics effect, which accounts for differences in education, experience, etc., shows that women's wages would be 8.7% lower if they had the same characteristics as men. The coefficient effect, which measures discrimination in the labor market based on gender, is 20.5% in the adjusted model[22]. Whereas, the CQR findings reveal that the gender wage gap varies across different percentiles of the wage distribution. At the 20th percentile, the gap is 4.2%, which decreases to 1.1% at the 40th percentile. However, it then increases to 8.2% at the 60th percentile, 28% at the 80th percentile, and reaches around 55% at the highest percentile (99th). The wage difference at the 80th percentile can be attributed to both the unobserved coefficients effect and the effect of the characteristics, which is 6.6%. Throughout the wage distribution, there is a mix of the characteristics effect and the coefficient effect that drive the gender wage gap. Women have an advantage in the 20th, 40th, and 60th percentiles due to their characteristics, but labor market discrimination is still the main factor explaining the gender pay gap in these percentiles.

On the other hand, UQR[23] findings demonstrate that the gender wage gap decreases as we move from the 20th to the 60th percentile of the wage distribution, but then increases again to reach around 43.6% at the 99th percentile. The gender wage gap is insignificant at the 40th percentile, as shown in Table 16. At the top of the wage distribution, both the characteristics effect and the coefficient effect play a role. However, in the lower to middle percentiles (20th to 60th), women have an advantage in terms of their

[22] The results are significant at a 5% level of significance.
[23] UQR gender wage gap looks U- shaped.

characteristics, but labor market discrimination is still the main factor driving the wage gap in these percentiles.

Table 17 (Appendix II) reports the dummy variable female coefficient estimates of quantile regressions (CQR, and UQR)[24] for the 20th, 40th, 60th, 80th, and 99th percentile. As predicted, the impact of being a woman on log daily wages is consistently negative across the entire wage distribution. This negative effect decreases in absolute terms from the lowest percentile to the 60th percentile, increases at the 80th percentile, and then sharply decreases again at the 99th percentile. On the other hand, the conditional effect shows a slight decrease from the 10th to the 60th percentile and then increases thereafter. The results indicate that the disparity in wages between genders is more significant at the lower ends of the wage distribution. At the 20th percentile, women earn around 22.8% and 38.9% less than men in the CQR and UQR models, respectively. The CQR and UQR indicate that if you are a woman, your earnings are lower in the corresponding percentile of the earnings distribution, whether it's conditional or unconditional. For instance, at the 80th percentile, women earn about 20.4% less in CQR and 22.4% less in UQR.

Figure 9 (Appendix I) provides a detailed depiction of the variation in gender wage gap estimates for conditional and unconditional quantile regression. The figure presents a graph of the wage difference for conditional and unconditional quantile regression

[24] In Appendix II, Tables 10A and 14, display the complete regression results for the log daily wage model using UQR and CQR, respectively. The models use the exact same set of predictors.

estimates at five quantiles, including the 20^{th}, 40^{th}, 60^{th}, 80^{th}, and 99^{th}. According to Table 17 (Appendix II), the impact of the unconditional gender wage gap decreases from around 38.9% at the 20th quantile to 18.6% at the 60^{th} quantile, before increasing and reaching about 22.4% at the 80% quantile, and then sharply decreasing to less than 6% at the 99^{th} quantile. Furthermore, standard (conditional) quantile regression estimates decrease from approximately 22.8% at the 20^{th} quantile to 20.4% at the 80^{th} quantile, but then suddenly increase to about 33% at the 99^{th} percentile.

5. Conclusions and Recommendations

5.1 Conclusions

Gender discrimination is one of the most controversial topics in literature, and there has been extensive theoretical and empirical research on wage discrimination against women from an economic perspective. The level of the gender wage gap is influenced by main factors such as educational attainment, job-related factors, and marital status. This study provides a comprehensive analysis of the gender wage gap using the Palestine Quarterly Labor Force Survey data from 2015 to 2019. To my best knowledge, there have been a few previous applied studies in Palestine on wage discrimination against women, but this is the first study to employ the number of observations in first wave interviewees only, as well as the Recentered influence functions (RIF), which adds importance to our findings. That is why this study focuses on investigating a very important and scantly studied issue. Therefore, the thesis's practical contribution comes from considering wage gap analysis using the entire distribution, not just at the means. While previous studies may have suffered from biases resulting from repeated observations, this study does not suffer from this lacuna. To analyze the gender wage gap, this study employs various methodologies such as the Oaxaca - Blinder (1973) decomposition of the mean wage, both standard and adjusted for potential selection bias, the conditional quantile decomposition technique developed by Melly (2005; 2006), and the unconditional quantile decomposition approach (Recentered Influence Function) developed by Firpo, Fortin, and Lemieux (2009). Additionally, a new regression approach is introduced in this study to evaluate the influence of explanatory factors on the unconditional quantiles of an outcome variable. While the unconditional quantile regression approach has advantages over CQR models, such as intuitive estimation and easy computation, CQRs are the standard approach in the literature on quantile regression (Fortin, Lemieux, and Firpo, 2011). The different methods were used to identify variables contributing to wage inequalities at various points of the distribution.

The findings of this study indicate that the gender wage gap differs according to several factors such as educational attainment, job characteristics, industries, occupations, and demographic characteristics. The contribution to the gender pay gap also differs across different quantiles, especially when the various categories are split into an endowment and a coefficient part. Additionally, other labor market indicators, such as differences in educational attainment, significantly contribute to wage inequalities between men and women across the wage distribution. The results suggest the importance of examining gender wage inequalities across the entire wage distribution, rather than just focusing on the mean. This is especially relevant for policy implications. The study highlights the impact of gender gaps in educational attainment on the wage structure, which is a significant contributor to wage inequality between the top and bottom or median quantiles. The study found that the endowments effects of the set of regressors that account for gender differences in labor market participation are particularly important in creating wage gaps, leading to a positive gender wage gap across all quantiles. Differences in work characteristics, as well as variations in industrial and occupational endowments between men and women, have been shown to be significant near the bottom of the wage distribution. However, in terms of endowments and coefficient effects, gender disparities in characteristics across the wage distribution are less significant. The unexplained component, which refers to how men and women are rewarded, contributes to most of the quantile-specific pay differences. This finding is consistent with previous studies on gender pay gaps, such as those conducted by Blau and Kahn (2017). To account for the potential non-random selection into job participation that affects men's and women's (log) daily wages differently along the pay distribution, the study expands its approach and includes selection factors as second-order polynomials in the wage equation. This adjustment is made in order to improve the estimation findings (Buchinsky, 1998). The study's Oaxaca-Blinder decomposition reveals that in Palestine, the adjusted model's mean gender wage gap is around 12%, with most of the disparity attributable to "discrimination." Moreover, the QCD and UCD show that this gap is smaller at the lower end of the wage distribution but increases towards the higher percentiles in most wage distributions[25]. In addition, the QCD and UCD outcomes reveal that the proportion of the gender wage gap attributable to discrimination is considerably greater at the lower end of the distribution.

On the other hand, the models include a dummy variable for "female," and the coefficient of this variable is typically negative and statistically significant. Additionally, the Blinder-Oaxaca decomposition method reveals a substantial wage gap between men and women's daily wages.

5.2 Recommendations

The gender wage gap in Palestine is a significant issue that requires urgent attention. To address this problem, the following recommendations could be considered:

1. Encourage equal pay: Palestinian policymakers should establish regulations and policies that guarantee equal pay for equal work. This could be done by implementing laws that require employers to disclose salary information and by promoting pay transparency.

2. Promote education and training: Palestinian women must be empowered with the knowledge and skills they need to compete for high-paying jobs. Policies that support education and training programs focused on fields where women are underrepresented could help to close the gender wage gap.

[25] The gender wage gap is often found to be higher in the bottom of the distribution and decreases as we move up the wage distribution, and then increasing again towards the top of the distribution. This pattern is observed in many countries and is known as the "sticky floor, glass ceiling" phenomenon (Blau and Kahn, 2017).

3. Increase women's participation in decision-making processes: Women's participation in decision-making processes related to labor market policies should be encouraged. This could include increasing the number of women in leadership roles and providing opportunities for women to participate in labor unions and other advocacy groups.

4. Raise awareness: Raising awareness about the gender wage gap is crucial. Educational campaigns aimed at both employers and employees could help to promote gender equality in the workplace and increase understanding of the impact of the gender wage gap on individuals, families, and society as a whole.

5.3 Suggestions

Future research should focus on several aspects. Firstly, it should investigate how the selection process of men and women for different job categories affects labor market participation and the wage difference decomposition. Secondly, the study should confirm the results using the combination of the RIF technique and reweighting approach recommended by Fortin, Lemieux, and Firpo (2010). Finally, when new survey data becomes available, it is essential to explore the determinants of the gender wage gap to provide a better assessment of gender equality.

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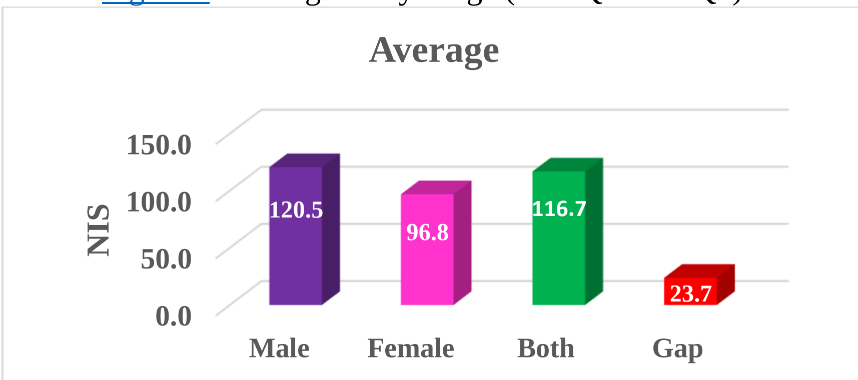
7. Appendices

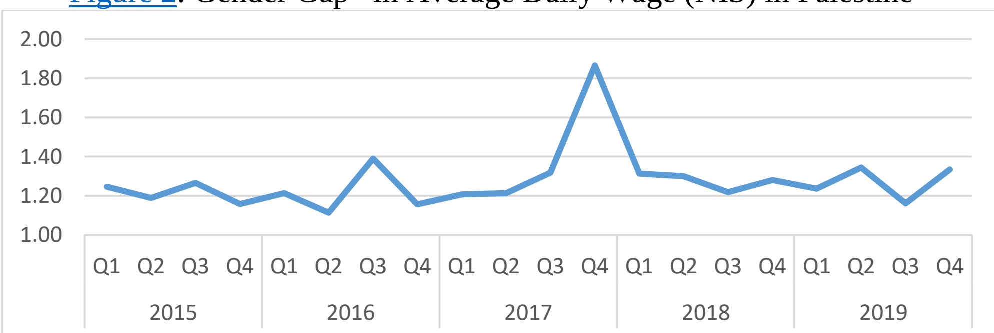
7.1. Appendix I: Figures

Figure 1: Average Daily Wage (2015Q1-2019Q4)



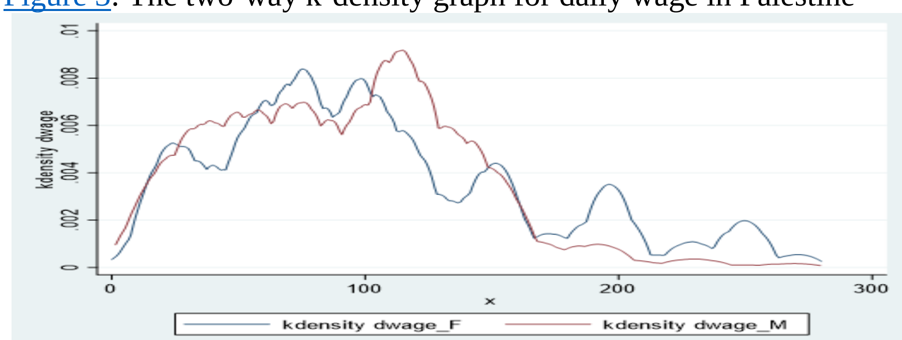
Source: Researcher's calculations

Figure 2: Gender Gap* in Average Daily Wage (NIS) in Palestine



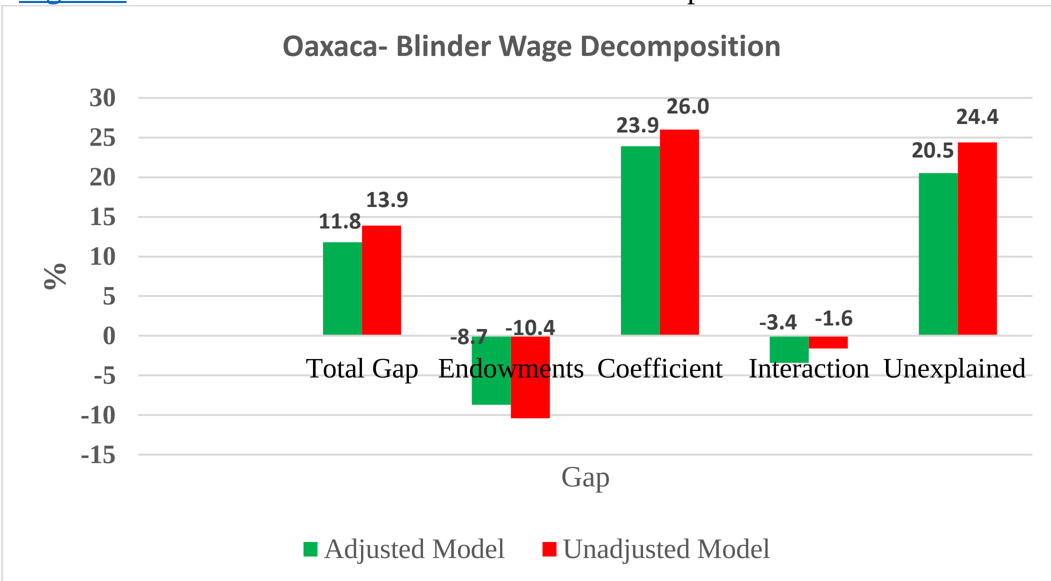
Source: Researcher's calculations
*Male/Female daily wage ratio, the number of females in 2017 quarter 4 in the estimation sample is very low (22 observations) which explains the spike in the gap.

Figure 3: The two-way k-density graph for daily wage in Palestine



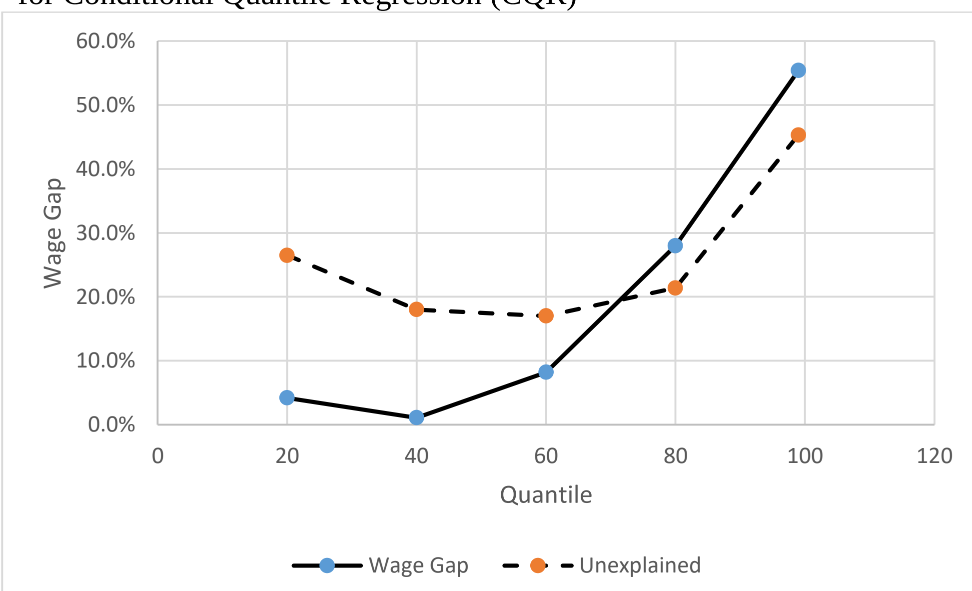
Source: Researcher's calculations

Figure 4: Overall Results of Blinder-Oaxaca Decomposition



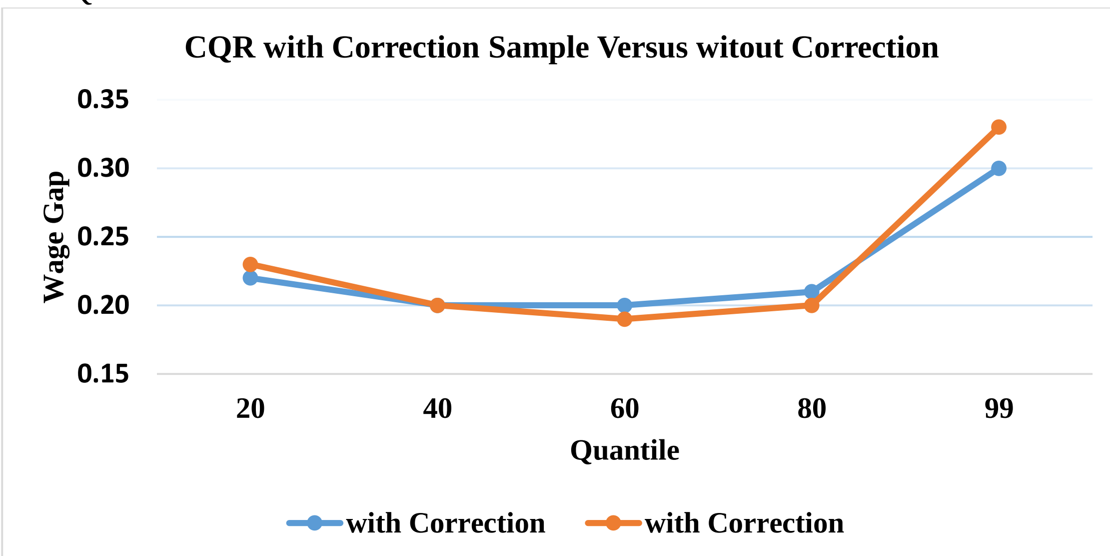
Source: Researcher's calculations

Figure 5: Gender Wage Gap across the Wage Distribution for Conditional Quantile Regression (CQR)



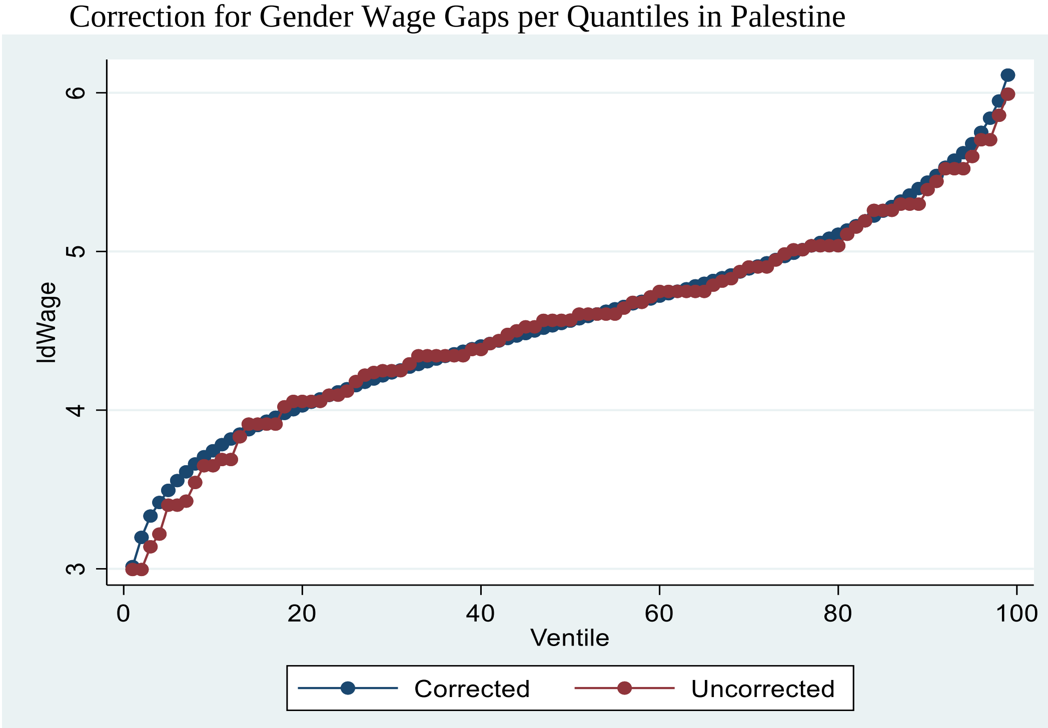
Source: Researcher's calculations

Figure 6: Results CQR with Sample Correction Versus Sample without Correction for Gender Wage Gaps per Quantiles in Palestine for Selected Quantiles



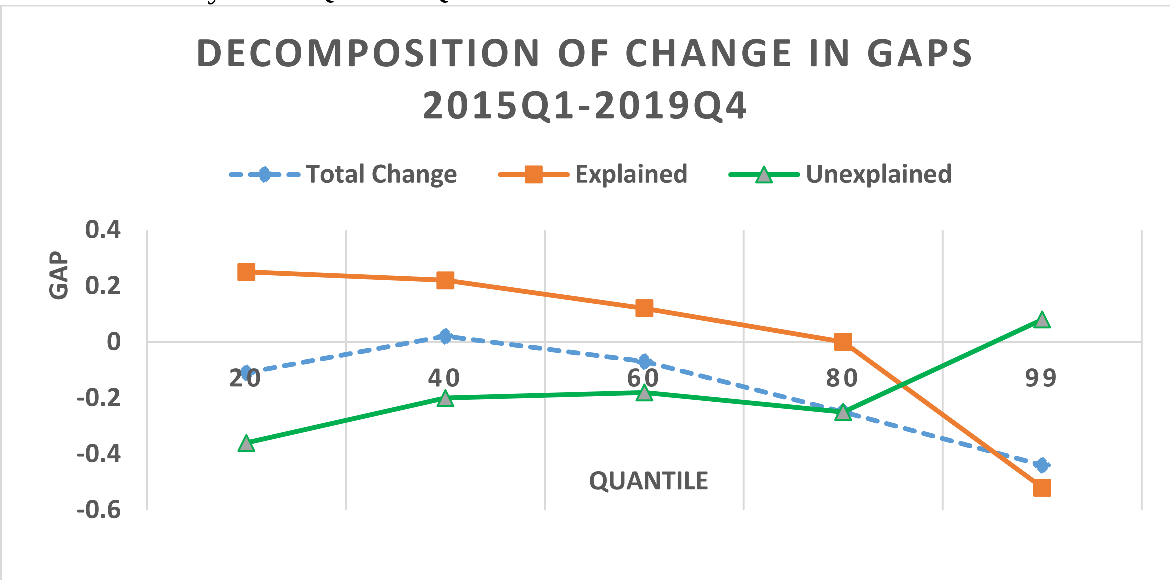
Source: researcher's calculations.

Figure 7: Results CQR with Sample Correction Versus Sample without Correction for Gender Wage Gaps per Quantiles in Palestine



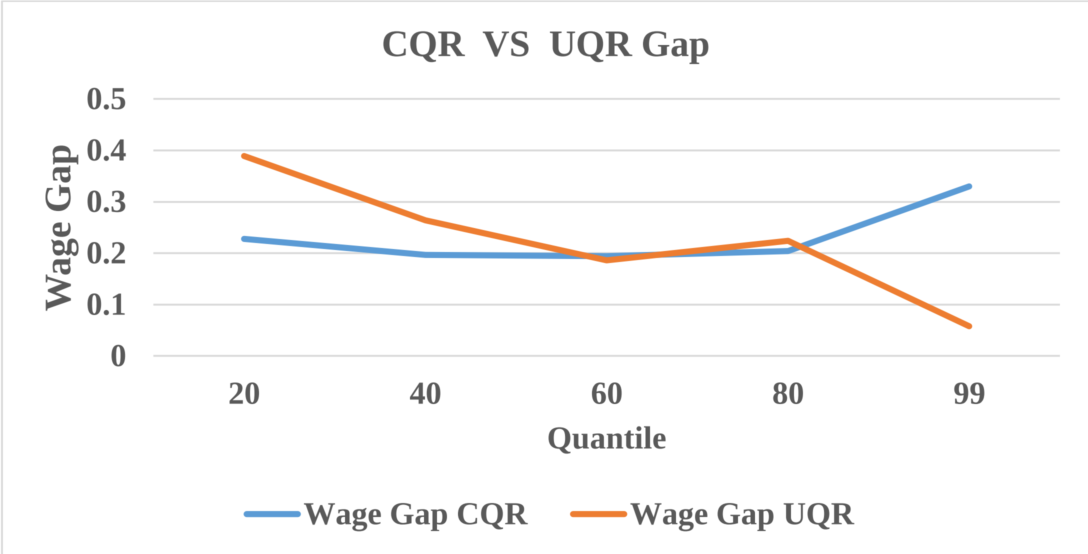
Source: researcher's calculations.

Figure 8: Decomposition of Change in Gaps for RIF Regression Model in Palestine by 2015Q1-2019Q4



Source: researcher's calculations.

Figure 9: Gender Wage Gap for Conditional and Unconditional Quantile Regression Estimates



Source: Researcher's Calculations.

7.2 Appendix II: Tables

Table 1: Classification of the explanatory variables

Variable	Components
Sex	Male, Female
Education Level	Illiterate, Can Read and Write, Elementary, Preparatory, Secondary, Associate Diploma, BA\ BSc, Higher Diploma, Master Degree, PhD.
Nature of Current Job	Full- and part-time worker, Temporary
Marital Status	Never Married, Married, Other
Age	Individuals aged in years.
Age^2	The estimated square of the variable age
Sector of Work	Public, Private, Foreign, Other
Place of Work	West Bank, Gaza, Israel & Satt., Abroad
Region	West Bank, Gaza
Locality Type	Urban, Rural, Camp.
Industry	Agriculture, Hunting & Fishing, Mining, Quarrying & Manufacturing, Construction, Commerce, Hotels & Restaurants, Transportation, Storage & Communication, Services & Other Branches
Occupation	Legis-Senior, Proff-Clerks, Services-Shop Skilled-Agriculture, Craft Plant-Machine, Elementary Occupation

Source: Compiled by the researcher

Table 2: Average Daily Wage Gap in Palestine

Year	Quarter	Male	Female	Both	Difference	M/F Ratio
2015	Q1	111.0	89.1	107.4	21.9	1.25
	Q2	109.2	91.8	106.5	17.4	1.19
	Q3	111.5	88.1	107.8	23.4	1.27
	Q4	105.9	91.5	103.8	14.4	1.16
2016	Q1	113.3	93.3	110.3	20.0	1.21
	Q2	111.0	99.6	109.2	11.4	1.11
	Q3	118.3	85.1	113.3	33.2	1.39
	Q4	112.1	96.9	110.4	15.2	1.16
2017	Q1	121.7	100.8	118.2	20.9	1.21
	Q2	119.1	98.1	115.6	21.0	1.21
	Q3	120.8	91.6	116.4	29.2	1.32
	Q4	136.6	73.2	132.3	63.4	1.87
2018	Q1	127.0	96.7	121.7	30.3	1.31
	Q2	130.1	100.0	125.6	30.1	1.30
	Q3	131.8	108.1	127.7	23.7	1.22
	Q4	130.9	102.2	125.8	28.7	1.28
2019	Q1	131.0	106.0	126.5	25.0	1.24
	Q2	136.8	101.7	130.7	35.1	1.35
	Q3	146.6	126.2	143.5	20.4	1.16
	Q4	138.3	103.6	132.4	34.7	1.33

Source: Researcher's calculations

Table 3A: Descriptive Statistics of Selected Variables (2015Q1-2019Q4)

	Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Male	Age	23130	35.1	11.510	12	82
	Years of Schooling	23130	11.6	3.609	0	27
	Daily Wage (dwage)*	23130	120.5	85.057	20	1518.1
Female	Age	4455	37.4	10.108	16	77
	Years of Schooling	4455	14.5	3.286	0	25
	Daily Wage (dwage)*	4455	96.8	52.401	20	1100.5
Both	Age	27585	35.46	11.326	12	82
	Years of Schooling	27585	12.03	3.722	0	27
	Daily Wage (dwage)*	27585	116.69	81.154	20	1518.1

*: New Israeli Shekels (NIS)

Source: Researcher's calculations depending on the Palestinian Labour Force Surveys from PCBS data from 2015q1- 2019q4

Table 3B: Descriptive Statistics of Selected Variables for the Estimation Sample only (2015Q1-2019Q4)

Variable	%		
	Male	**Female**	**Both**
N	**23130**	**4455**	**27585**
Sex	**83.8**	**16.2**	**100**
Age (Years)			
Less than 15	0.2	0.0	0.2
(15- 24)	21.7	10.4	19.9
(25 – 34)	29.2	32.5	29.7
(35 – 44)	26.3	31.6	27.2
(45 – 54)	16.7	19.7	17.2
(55 – 64)	5.3	5.5	5.3
More than 64	0.6	0.3	0.5
Marital Status			
Never Married	29.7	31.7	30.0
Married	69.8	61.7	68.5
Other	0.5	6.6	1.5
Employment Status			
Full -time	98.0	98.7	98.2
Part-time	0.5	0.7	0.5
Temporary	1.5	0.6	1.3
Work Kind			
Public	30.4	43.9	32.6
Private	66.5	40.6	62.3
Foreign	2.4	12.1	4.0
Other	0.7	3.4	1.1
Place of Work			
West Bank	48.6	70.7	52.2
Gaza	30.2	27.3	29.7
Israel & Satt.,	20.8	1.8	17.7
Abroad	0.4	0.2	0.4
Region			
West Bank	69.8	72.6	70.2
Gaza	30.2	27.4	29.8
Locality Type			
Urban	66.1	69.8	66.7
Rural	22.3	18.3	21.6
Camp	11.6	11.9	11.7

Table 3B: Continued

Education Level	**Male%**	**Female%**	**Both%**
Illiterate	0.3	0.4	0.3
Can Read and Write	3.9	2.0	3.6
Elementary	13.9	4.3	12.3
Preparatory	37.8	10.7	33.4
Secondary	16.7	5.9	15.1
Associate Diploma	6.5	15.1	7.9
BA\ BSc	18.1	55.7	24.1
Higher Diploma	0.2	0.6	0.3
Master Degree	2.0	4.9	2.5
PhD	0.4	0.4	0.5
Industry			
Agriculture Hunting & Fishing	5.7	1.4	5.0
Mining, Quarrying & Manufacturing	13.1	6.7	12.1
Construction	22.0	0.7	18.5
Commerce, Hotels & Restaurants	15.2	6.5	13.8
Transportation, Storage & Communication	4.4	1.9	4.0
Services & Other Branches	39.6	82.8	46.6
Occupation			
Legis-Senior	2.3	4.2	2.6
Proff-Clerks	29.2	75.5	36.7
Services-Shop	13.2	6.9	12.2
Skilled-Agriculture	0.5	0.1	0.4
Craft	19.9	1.4	16.9
Plant-Machine	9.2	4.3	8.4
Elementary Occupation	25.7	7.6	22.8
Wage employment			
Wage Employed	79.6	79.6	79.6
Not Wage Employed	20.4	20.4	20.4

Source: Researcher's calculations depending on the Palestinian Labour Force Surveys from PCBS data from 2015q1- 2019q4, the sample is restricted for the estimation sample only.

Table 4: Overall Results of Blinder-Oaxaca (Two- Fold) Decomposition

Dependent Variable: Log(daily wage)	
Differential	***Coefficients***
Mean value of log(daily wage), Males	4.573***
	(0.004)
Mean value of log(daily wage), Females	4.434***
	(0.008)
Difference	0.139***
	(0.009)
Decomposition of Log(daily wage) Difference	
Explained by Difference in Worker Characteristics	- 0.117***
	(0.008)
log(daily wage Differences due to unobserved effect)/	0.256***
Unexplained	(0.008)
No. of Observations (Male)	23130
No. of Observations (Female)	4455
No. of Observations	27585

Source: Researcher’s calculations.
Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% level respectively

Table 5: Overall Results of Blinder-Oaxaca (Three-Fold) Decomposition

Dependent Variable: Log(daily wage)		
Differential	***Coefficients***	
	Unadjusted Model	***Adjusted Model***
Mean value of log(daily wage), Males	4.573***	4.573***
	(0.005)	(0.004)
Mean value of log(daily wage), Females	4.434***	4.455***
	(0.008)	(0.034)
Difference	0.139***	0.118***
	(0.009)	(0.034)
Decomposition of Log(daily wage) Difference		
Explained by Difference in Worker	- 0.104***	- 0.087**
Characteristics (Endowments)	(0.026)	(0.035)
log(daily wage Differences due to	0.260***	0.239***
unobserved effect (Coefficients)	(0.009)	(0.034)
Interaction	- 0.016	- 0.034
	(0.026)	(0.035)
No. of Observations (Male)	23130	23130
No. of Observations (Female)	4455	4455
No. of Observations	27585	27585

Source: Author's calculations.
Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% level respectively

Table 6: Detailed Blinder-Oaxaca Decomposition Results of the Gender Wage Gap (Unadjusted Model)

Predictors	Endowment Coefficients	Coefficient Coefficients	Interaction Coefficients	Explained Contribution to wage gap
Age	-0.048***	0.605***	-0.037***	46.2%
Age square	0.014	-0.381***	0.034***	- 13.5%
Marital Status				
Never Married	0.001	-0.003	0.000	- 0.5%
Married	0.004***	-0.009	-0.001	- 3.8%
Others	0.001**	0.002	-0.001	- 1.0%
Locality Type				
Urban	- 0.001***	- 0.003	0.000	**1.0%**
Rural	- 0.0004	0.003	0.001	**0.4%**
Camp	0.000	- 0.002	0.000	**- 0.1%**
Region				
West Bank	- 0.006	0.080	- 0.003	**5.8%**
Gaza Strip	- 0.006	- 0.030	- 0.003	**5.8%**
Higher Qualification				
Illiterate	0.001	0.000	- 0.000	**- 0.5%**
Can Read and Write	- 0.005***	- 0.001	- 0.001	**4.8%**
Elementary	- 0.030***	0.004***	0.010***	**28.8%**
Preparatory	- 0.048***	0.000	0.001	**46.2%**
Secondary	- 0.017***	0.002	0.004	**16.3%**
Associate Diploma	0.008**	- 0.008*	0.005*	**- 7.7%**
BA\ BSc	- 0.027***	- 0.027*	0.018*	**26%**
Higher Diploma	- 0.001**	- 0.0001	0.000	**1.0%**
Master Degree	- 0.008***	0.001	0.001	**7.7%**
Ph.D.	0.002*	0.000	0.000	**- 11%**
Place of work				
West Bank	0.085***	0.030	- 0.009	**- 81.7%**
Gaza Strip	- 0.007	- 0.018	- 0.002	**6.7%**
Israel & Satt.	0.084***	- 0.001	- 0.007	**- 80.8%**

Abroad	0.000	0.000	0.000	**- 0.4%**
Sector of Work				
Public	- 0.013***	- 0.034***	0.011***	**12.5%**
Private	- 0.046***	0.026***	0.016***	**44.2%**
Foreign	- 0.033***	- 0.005*	0.004*	**31.7%**
Others	0.007***	0.001	-0.002	**- 6.7%**
Nature of currently Job				
Full Time	- 0.001**	0.030	- 0.000	**1.0%**
Part Time	0.000	0.001	-0.000	**- 0.3%**
Seasonal	- 0.000	- 0.001	- 0.001	**0.1%**
Industry				
Agriculture, Hunting & Fishing	- 0.007***	- 0.001	- 0.002	**6.7%**
Mining, Quarrying & Manufacturing	- 0.009***	0.012***	0.012***	**8.7%**
Construction	0.097***	-0.001**	-0.040**	**- 93.3%**
Commerce, Hotels & Restaurants	- 0.015***	0.008***	0.011***	**14.4%**
Transportation, Storage & Communication	0.003***	-0.004***	-0.006***	**- 2.9%**
Services & Other Branches	0.040***	0.132***	-0.069***	**- 38.5%**
Occupation				
Legis-Senior	- 0.006***	-0.001	0.001	**5.8%**
Proff-Clerks	- 0.066***	- 0.057***	0.035***	**63.5%**
Services-Shop	- 0.006**	0.004	0.003	**5.8%**
Skilled-Agriculture	- 0.0004	0.000	0.000	**0.4%**
Craft	- 0.027***	0.002**	0.027***	**26%**
Plant-Machine	- 0.003	- 0.002	- 0.002	**2.9%**
Elementary Occupation	- 0.011***	- 0.009***	- 0.022***	**10.6%**
Constant		-0.086		
Total difference	**-0.104 [-75%]**	**0.260 [187%]**	**- 0.016 [-12%]**	

Source: Researcher’s calculations.
Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively

Table 7: Detailed Blinder-Oaxaca Decomposition Results of the Gender Wage Gap (Adjusted Model)

Predictors	Endowment Coefficients (s.e)	Coefficient Coefficients (s.e)	Interaction Coefficients (s.e)	Explained Contribution to wage gap
Age	- 0.038**	0.774**	- 0.047**	**43.7%**
Age square	0.007	- 0.461***	0.041***	**- 8.1%**
Marital Status				
Never Married	0.000	0.000	- 0.000	**- 0.8%**
Married	0.004***	- 0.008	- 0.001	**- 4.6%**
Others	0.001	0.001	- 0.001	**- 1.2%**
Locality Type				
Urban	- 0.001***	- 0.002	0.000	**1.2%**
Rural	- 0.000	0.003	0.001	**0.5%**
Camp	0.000	- 0.002	0.000	**- 0.1%**
Region				
West Bank	- 0.006	0.084	- 0.003	**6.9%**
Gaza Strip	- 0.006	- 0.032	- 0.003	**6.9%**
Higher Qualification				
Illiterate	0.001	- 0.000	0.000	**- 0.6%**
Can Read and Write	- 0.004***	- 0.001	- 0.001	**4.6%**
Elementary	- 0.046***	- 0.000	- 0.000	**52.9%**
Preparatory	- 0.048***	0.000	0.001	**55.2%**
Secondary	- 0.017***	0.002	0.004	**19.5%**
Associate Diploma	0.007***	- 0.008	0.004	**- 8.1%**
BA\ BSc	- 0.021*	- 0.018*	0.012	**24.1%**
Higher Diploma	- 0.001**	0.001	- 0.000	**1.2%**
Master Degree	**- 0.008*** **	**0.000**	**- 0.000**	**9.2%**
Ph.D.	0.002*	0.000	0.000	**- 2.3%**
Place of work				
West Bank	0.083***	0.023	- 0.007	**- 95.4%**
Gaza Strip	- 0.006	- 0.020	- 0.003	**6.9%**

Israel & Satt.	0.082***	- 0.000	- 0.005	**- 94.3%**
Abroad	0.000	0.000	0.000	**- 0.5%**
Sector of Work				
Public	- 0.013***	- 0.034***	0.011***	**14.9%**
Private	- 0.047***	0.026***	0.017***	**54%**
Foreign	- 0.033***	- 0.005*	0.004*	**37.9%**
Others	0.007***	0.001	- 0.002	**- 8.1%**
Nature of currently Job				
Full Time	- 0.001**	0.030	- 0.000	**1.2%**
Part Time	0.000	0.001	-0.000	**- 0.4%**
Seasonal	- 0.000	- 0.001*	- 0.001	**0.1%**
Industry				
Agriculture, Hunting & Fishing	- 0.006**	- 0.001	- 0.003	**6.9%**
Mining, Quarrying & Manufacturing	- 0.009***	0.012***	0.011***	**10.4%**
Construction	0.097***	- 0.001***	- 0.040***	**- 111.5%**
Commerce, Hotels & Restaurants	- 0.015***	0.008***	0.011***	**17.2%**
Transportation, Storage & Communication	0.003**	- 0.004***	- 0.005***	**- 3.5%**
Services & Other Branches	0.046***	0.144***	- 0.075***	**- 52.9%**
Occupation				
Legis-Senior	- 0.006***	- 0.001	0.001	**6.9%**
Proff-Clerks	- 0.064***	- 0.054*	0.033	**73.6%**
Services-Shop	- 0.006**	0.004	0.003	**6.9%**
Skilled-Agriculture	- 0.000	0.000	0.000	**0.5%**
Craft	- 0.027**	0.002**	0.027**	**31%**
Plant-Machine	- 0.003	- 0.002	- 0.002	**3.5%**
Elementary Occupation	- 0.011***	- 0.010***	- 0.023***	**12.6%**
Constant		- 0.217		
Total difference	**- 0.087 [-73.7%]**	**0.239 [202.5%]**	**- 0.034 [- 28.8%]**	

Source: Researcher’s calculations.
Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 8: The Status of the Regression Coefficients by Significance

Predictors	Explained		Unexplained			
	Endowment		Coefficient		Interaction	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Age	×	*	×	*	×	*
Age square			×	*	×	*
Marital Status						
Never Married						
Married	×	*				
Others	×					
Locality Type						
Urban	×	*				
Rural						
Camp						
Region						
West Bank						
Gaza Strip						
Higher Qualification						
Illiterate			×		×	
Can Read and Write	×	*				
Elementary	×	*	×		×	
Preparatory	×	*				
Secondary	×	*				
Associate Diploma	×	*	×		×	
BA\ BSc	×	*	×	*	×	
Higher Diploma	×	*				
Master Degree	×	*				
Ph.D.	×	*				
Place of work						
West Bank	×	*				

Gaza Strip						
Israel & Satt.	×	*				
Abroad						
Sector of Work						
Public	×	*	×	*	×	*
Private	×	*	×	*	×	*
Foreign	×	*	×	*	×	*
Others	×	*				
Nature of Currently Job						
Full Time	×	*				
Part Time						
Seasonal				*		
Industry						
Agriculture, Hunting & Fishing	×	*	×			
Mining, Quarrying & Manufacturing	×	*	×	*	×	*
Construction	×	*	×	*	×	*
Commerce, Hotels & Restaurants	×	*	×	*	×	*
Transportation, Storage & Communication	×	*	×	*	×	*
Services & Other Branches	×	*	×	*	×	*
Occupation						
Legis-Senior	×	*				
Proff-Clerks	×	*	×	*	×	
Services-Shop	×	*				
Skilled-Agriculture						
Craft	×	*	×	*	×	*
Plant-Machine						
Elementary Occupation	×	*	×	*	×	*

Source: Researcher's preparation.
Note: × indicates Unadjusted Model Status, *: indicates Adjusted Model Status,

Table 9: Decomposition of Changes in Measures of Gender Wage Gap in Palestine (2015Q1-2019Q4) using Quantile Regression (Three-Folds)

Dependent Variable: log (Daily Wage)

Quantile	Total Change	Effect of: (Explained)		
			(Unexplained)	
		Characteristics	Coefficients	Residuals
20	0.042***	- 0.223***	0.254***	0.011
	(0.015)	(0.009)	(0.014)	(0.010)
40	0.011	- 0.169***	0.221***	- 0.040***
	(0.013)	(0.008)	(0.011)	(0.007)
60	0.082***	- 0.088***	0.189***	- 0.020**
	(0.010)	(0.007)	(0.009)	(0.006)
80	0.280***	0.066***	0.178***	0.036***
	(0.010)	(0.009)	(0.009)	(0.007)
99	0.554***	0.101**	0.243***	0.211**
	(0.027)	(0.027)	(0.019)	(0.038)

Source: Researcher’s calculations.

Notes: Pointwise standard errors are in parenthesis. The conditional model is linear quantile regression. A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 100 times. The reference group is female. The counterfactual group is male.

Table 10A: Quantile Regression Estimates of the Wage Equations Without Sample Correction Selection in Palestine (2015Q1-2019Q4).

Dependent Variable: log (daily wage)					
Variables\Q	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**
Female	- 0.228***	-0.197***	-0.194***	-0.204***	- 0.330***
Age	0.029***	0.029***	0.032***	0.032***	0.030***
Age square	- 0.0003***	-0.0002***	-0.0003***	-0.0003***	- 0.0002***
Marital Status (Reference: Never Married)					
Married	0.092***	0.086***	0.067***	0.054***	0.014
Others	- 0.005	- 0.019	- 0.016	0.019	- 0.099
Locality Type (Reference: Urban)					
Rural	- 0.007	- 0.002	- 0.012*	- 0.029***	- 0.106**
Camp	- 0.063***	- 0.062***	- 0.058***	- 0.049***	- 0.069***
Region (Reference: West Bank)					
Gaza Strip	- 0.579***	- 0.493***	- 0.429***	- 0.375*	- 0.424*
Higher Qualification (Reference: Illiterate)					
Can Read and Write	0.119	0.074	0.050	- 0.056	- 0.203
Elementary	0.178**	0.125	0.101	0.015	- 0.152
Preparatory	0.207**	0.174**	0.151**	0.059	- 0.086
Secondary	0.252***	0.205***	0.197***	0.121*	- 0.046
Associate- Diploma	0.286***	0.259***	0.245***	0.167**	0.023
BA\ BSc	0.406***	0.398***	0.381***	0.293***	0.155
Higher Diploma	0.553***	0.602***	0.518***	0.427***	0.325
Master Degree	0.602***	0.581***	0.583***	0.534***	0.489**
Ph.D.	1.082***	1.055***	1.080***	1.015***	1.204***
Place of work (Reference: West Bank)					
Gaza Strip	0.014	0.007	0.035	0.024	- 0.003
Israel & Satt.	0.813***	0.813***	0.812***	0.750***	0.486***
Abroad	0.449***	0.490***	0.656***	0.687***	0.897***
Sector of Work (Reference: Public)					
Private	- 0.352***	- 0.213***	- 0.093***	0.043**	0.304***

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Foreign	0.193***	0.415***	0.396***	0.362***	0.482***
Others	- 0.415***	- 0.301***	- 0.217***	- 0.131***	0.083
Nature of currently Job (Reference: Full Time)					
Part Time	- 0.139***	- 0.272***	- 0.170**	- 0.123*	0.008
Seasonal	- 0.237***	- 0.320***	- 0.407***	- 0.419***	- 0.105***
***Industry* (Reference: Agriculture, Hunting & Fishing)**					
Mining, Quarrying & Manufacturing	0.343***	0.310***	0.223***	0.179***	0.238***
Construction	**0.623*****	**0.554*****	**0.453*****	**0.404*****	**0.467*****
Commerce, Hotels & Restaurants	0.241***	0.202***	0.139***	0.130***	0.306***
Transportation, Storage & Communication	**0.088**	**0.109**	**0.087*****	**0.168**	**0.351*****
Services & Other Branches	0.230***	0.259***	0.212***	0.244***	0.345***
***Occupation* (Reference: Legis-Senior)**					
Proff-Clerks	- 0.230***	- 0.206***	- 0.199***	- 0.203***	- 0.189***
Services-Shop	- 0.420***	- 0.328***	- 0.286***	- 0.252***	- 0.258***
Skilled-Agriculture	- 0.276***	- 0.233***	- 0.351***	- 0.341***	- 0.468**
Craft	- 0.330***	- 0.277***	- 0.264***	- 0.212***	- 0.190**
Plant-Machine	- 0.433***	- 0.428***	- 0.393***	- 0.318***	- 0.342***
Elementary Occupation	- 0.508***	- 0.450***	- 0.451***	- 0.425***	- 0.397***
Constant	**3.546*****	**3.641*****	**3.759*****	**3.952*****	**4.540*****
Obs.	27585	27585	27585	27585	27585
R-Squared	**42.45%**	**39.75%**	**38.73%**	**38.93%**	**31.96%**

Source: Researcher's calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: standard errors are in parenthesis. Conditional model is linear quantile regression. A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 100 times. Reference group is female. Counterfactual group is male.

Table 10/B: Quantile Regression Estimates of the Wage Equations for Sample in Palestine (2015Q1-2019Q4) With Correction Selection

Variables\Q	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**
Female	- 0.222***	- 0.199***	- 0.198***	- 0.213***	- 0.303***
Age	0.029***	0.029***	0.032***	0.031***	0.018***
Age square	- 0.0003***	-0.0002***	- 0.0003***	-0.0002***	- 0.00001***
Marital Status (Reference: Never Married)					
Married	0.085***	0.081***	0.058***	0.048***	0.029***
Others	- 0.027	- 0.032	- 0.023	- 0.0006	- 0.128
Locality Type (Reference: Urban)					
Rural	- 0.010	- 0.006	- 0.015*	- 0.033**	- 0.135***
Camp	- 0.062***	- 0.064***	- 0.060***	- 0.056***	- 0.128***
Region (Reference: West Bank)					
Gaza Strip	- 0.597***	- 0.497***	- 0.454***	- 0.407*	- 1.146*
Higher Qualification (Reference: Illiterate)					
Can Read and Write	0.117	0.082	0.005	- 0.058	0.245
Elementary	0.178**	0.135	0.051	0.014	0.364
Preparatory	0.206**	0.187**	0.104**	0.064	0.451
Secondary	0.253***	0.219***	0.151***	0.131*	0.484
Associate Diploma	0.292***	0.272***	0.201***	0.176**	0.548
BA\ BSc	0.407***	0.416***	0.335***	0.308***	0.748
Higher Diploma	0.582***	0.616***	0.463***	0.456***	0.681
Master Degree	0.604***	0.606***	0.559***	0.547***	1.104**
Ph.D.	1.124***	1.144***	1.033***	1.043***	1.281***
Place of work (Reference: West Bank)					
Gaza Strip	0.024	0.004	0.046	0.029	0.283
Israel & Satt.	0.008***	0.809***	0.809***	0.744***	0.468***

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Abroad	0.436***	0.489***	0.651***	0.764***	0.550***
Sector of Work (Reference: Public)					
Private	- 0.336***	- 0.198***	- 0.086***	0.058**	0.073***
Foreign	0.212***	0.422***	0.402***	0.369***	0.440***
Others	- 0.412***	- 0.266***	- 0.187***	- 0.122***	0.484
Nature of currently Job (Reference: Full Time)					
Part Time	- 0.146***	- 0.278***	- 0.181**	- 0.110*	0.042
Seasonal	- 0.237***	- 0.316***	- 0.400***	- 0.406***	- 0.196***
Industry (Reference: Agriculture, Hunting & Fishing)					
Mining, Quarrying & Manufacturing	0.332***	0.307***	0.224***	0.186***	0.254***
Construction	0.614***	0.549***	0.453***	0.407***	0.445***
Commerce, Hotels & Restaurants*******	0.232***	0.199***	0.139***	0.135***	0.345***
Transportation, Storage & Communication	0.083	0.112	0.091***	0.171	0.300***
Services & Other Branches	0.228***	0.263***	0.214***	0.265***	0.291***
Occupation (Reference: Legis-Senior)					
Proff-Clerks	- 0.225***	- 0.207***	- 0.207***	- 0.247***	- 0.364***
Services-Shop	- 0.417***	- 0.330***	- 0.299***	- 0.299***	- 0.463***
Skilled-Agriculture	- 0.283***	- 0.225***	- 0.372***	- 0.386***	- 0.442***
Craft	- 0.331***	- 0.281***	- 0.281***	- 0.265***	- 0.524***
Plant-Machine	- 0.434***	- 0.431***	- 0.406***	- 0.377***	- 0.640***
Elementary Occupation	- 0.509***	- 0.456***	- 0.473***	- 0.482***	- 0.744***
Constant	**3.544*****	**3.629*****	**3.827*****	**4.010*****	**4.983*****

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: Copula parameter (Gaussian): 0.63, Conditional model is linear quantile regression. A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 100 times. Reference group is female. Counterfactual group is male.

Table 11: Bootstrap Inference on Counterfactual Quantile Process

Null Hypothesis	P-Values	
	KS-statistic	CMS-statistic
Correct specification of the parametric model 0	**0.00**	**0.00**
Correct specification of the parametric model 1	**0.00**	**0.00**
Differences between the observable distributions		
No effect: QE(τ) = 0 for all τs	0.00	0.00
Constant effect: QE(τ) = QE(0.5) for all τs	0.00	0.00
Stochastic dominance: QE(τ) > 0 for all τs	0.82	0.82
Stochastic dominance: QE(τ) < 0 for all τs	0.00	0.00
Effects of characteristics		
No effect: QTE(τ) = 0 for all τs	0.00	0.00
Constant effect: QE(τ) = QE(0.5) for all τs	0.00	0.00
Stochastic dominance: QE(τ) > 0 for all τs	0.00	0.16
Stochastic dominance: QE(τ) < 0 for all τs	0.00	0.00
Effects of coefficients		
No effect: QE(τ) = 0 for all τs	0.00	0.00
Constant effect: QE(τ) = QE(0.5) for all τs	0.00	0.00
Stochastic dominance: QE(τ) > 0 for all τs	0.76	0.76
Stochastic dominance: QE(τ) < 0 for all τs	0.00	0.00
Effects of coefficients		
No effect: QE(τ) = 0 for all τs	0.00	0.00
Constant effect: QE(τ) = QE(0.5) for all τs	0.00	0.00
Stochastic dominance: QE(τ) > 0 for all τs	0.00	0.29
Stochastic dominance: QE(τ) < 0 for all τs	0.00	0.00

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.

Table 12: The Unconditional Quantile Regression Results of the Wage Equation by Gender in Palestine (2015Q1-2019Q4)

Dependent Variable: log (daily wage)					
Variables\Q	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**
Panel A: Male					
Age	0.058***	0.053***	0.031***	0.017***	0.006
Age square	- 0.0007***	-0.0006***	-0.0002***	-0.0001***	- 0.000
Marital Status (Reference: Never Married)					
Married	- 0.030***	0.119***	0.106***	0.159***	0.058**
Others	- 0.033	0.085	- 0.030	0.019	0.002
Locality Type (Reference: Urban)					
Rural	0.011	0.009	- 0.039***	- 0.049***	- 0.021
Camp	- 0.033**	- 0.097***	- 0.091***	- 0.096***	- 0.097***
Region (Reference: West Bank)					
Gaza Strip	- 0.376**	- 0.379**	- 0.543**	- 1.107***	- 0.829
Higher Qualification (Reference: Illiterate)					
Can Read and Write	0.131	0.012	0.107	0.050	- 0.172
Elementary	0.206	0.093	0.148*	0.077	- 0.092
Preparatory	0.247*	0.154**	0.221***	0.125	- 0.040
Secondary	0.296**	0.208**	0.258***	0.157*	- 0.018
Associate- Diploma	0.266**	0.239**	0.327***	0.103	- 0.072
BA\ BSc	0.373***	0.410***	0.566***	0.243***	- 0.044
Higher Diploma	0.489***	0.589***	0.750***	0.573**	- 0.157
Master Degree	0.436***	0.556***	0.939***	0.756***	0.289
Ph.D.	0.645***	0.752***	1.223***	1.642***	1.519***
Place of work (Reference: West Bank)					
Gaza Strip	- 0.547***	- 0.137	0.195	0.871***	0.757
Israel & Satt.	0.375***	0.634***	1.025***	1.375***	0.569***
Abroad	0.109*	0.331***	0.620***	1.210***	1.813***
Sector of Work (Reference: Public)					
Private	- 0.478***	- 0.163***	0.025	0.285***	0.172***
Foreign	0.010	0.309***	0.564***	0.355***	0.163**

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Others	- 0.532***	- 0.322***	- 0.223***	0.082	0.277*
Nature of currently Job (Reference: Full Time)					
Part Time	- 0.343***	- 0.059	0.063	0.078	0.118
Seasonal	- 0.627***	- 0.160***	0.003	0.095***	0.162*
***Industry* (Reference: Agriculture, Hunting & Fishing)**					
Mining, Quarrying & Manufacturing	0.061**	0.326***	0.331***	0.309***	- 0.244***
Construction	**0.218*****	**0.483*****	**0.473*****	**0.715*****	**0.320*****
Commerce, Hotels & Restaurants	- 0.132***	0.202***	0.332***	0.419***	-0.038
Transportation, Storage & Communication	**-0.237*****	**0.154*****	**0.329*****	**0.540*****	**0.005**
Services & Other Branches	0.040	0.277***	0.333***	0.525***	0.076
***Occupation* (Reference: Legis-Senior)**					
Proff-Clerks	0.027	- 0.171***	- 0.420***	- 0.535***	- 0.285**
Services-Shop	- 0.070**	- 0.335***	- 0.570***	- 0.601***	- 0.301***
Skilled-Agriculture	- 0.191**	- 0.265***	- 0.520***	- 0.701***	- 0.538***
Craft	- 0.170***	- 0.354***	- 0.491***	- 0.431***	0.071
Plant-Machine	- 0.172***	- 0.375***	- 0.558***	- 0.604***	- 0.308***
Elementary Occupation	- 0.275***	- 0.508***	- 0.648***	- 0.707***	- 0.543***
Constant	3.286***	3.179***	3.687***	4.083***	5.804***
Obs.	23130	23130	23130	23130	23130
R-Squared	**40.3%**	**40.7%**	**47.4%**	**46.8%**	**7%**

Source: Researcher's calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 100 times.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 13: The Unconditional Quantile Regression Results of the Wage Equation by Gender in Palestine (2015Q1-2019Q4)

Dependent Variable: log (daily wage)					
Variables\Q	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**
Panel A: Female					
Age	0.037***	0.037***	0.025***	0.011	0.037
Age square	- 0.0003***	-0.0003***	-0.0002***	-0.00002	- 0.0003
Marital Status (Reference: Never Married)					
Married	0.108***	0.092***	0.081***	0.035**	- 0.084
Others	0.023	- 0.038	- 0.012	- 0.009	0.154
Locality Type (Reference: Urban)					
Rural	- 0.005	- 0.025	- 0.047**	- 0.045**	- 0.147*
Camp	- 0.041	- 0.118***	- 0.042**	- 0.042	- 0.063
Region (Reference: West Bank)					
Gaza Strip	- 0.412	- 0.011	- 0.415	- 0.165	-1.289
Higher Qualification (Reference: Illiterate)					
Can Read and Write	0.392	0.035	- 0.053	- 0.002	0.449
Elementary	0.551*	- 0.024	- 0.107	- 0.036	- 0.280
Preparatory	0.630**	0.162	0.45	0.085	- 0.039
Secondary	0.553**	0.224	0.030	0.082	- 0.029
Associate- Diploma	0.662***	0.366**	0.159**	0.135*	0.029
BA\ BSc	0.870***	0.535***	0.255***	0.249***	0.171
Higher Diploma	1.085***	0.757***	0.437***	0.274**	- 0.018
Master Degree	1.044***	0.724***	0.423***	0.456***	1.139**
Ph.D.	1.168***	0.913***	0.656***	1.028***	7.958***
Place of work (Reference: West Bank)					
Gaza Strip	0.017	- 0.286	0.164	-0.057	0.907
Israel & Satt.	0.945***	1.024***	0.695***	0.654***	1.339
Abroad	0.336	0.095	0.251	0.493***	0.957
Sector of Work (Reference: Public)					
Private	- 0.675***	- 0.558***	- 0.178***	0.036**	0.445***
Foreign	- 0.017	0.134***	0.340***	0.457***	0.841***

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Others	- 0.654***	- 0.560***	- 0.288***	- 0.074**	0.062
Nature of currently Job (Reference: Full Time)					
Part Time	- 0.414	- 0.180	- 0.064	- 0.216***	- 0.559***
Seasonal	0.151	- 0.260	- 0.171*	- 0.122**	0.042
Industry **(Reference: Agriculture, Hunting & Fishing)**					
Mining, Quarrying & Manufacturing	- 0.227	- 0.125	0.037	0.097	0.420
Construction	**0.348**	**0.681*****	**0.290*****	**0.513*****	**3.353****
Commerce, Hotels & Restaurants	- 0.429	- 0.094	0.069	0.197***	0.537
Transportation, Storage & Communication	**0.375**	**0.259***	**0.186****	**0.227****	**0.339**
Services & Other Branches	- 0.215	0.034	0.044	0.174***	0.660*
Occupation **(Reference: Legis-Senior)**					
Proff-Clerks	0.102*	- 0.040	- 0.187***	- 0.350***	- 0.812**
Services-Shop	- 0.332***	- 0.285***	- 0.315***	- 0.429***	- 0.996***
Skilled-Agriculture	- 0.319	- 0.704***	- 0.358***	- 0.359**	- 0.442
Craft	- 0.726***	- 0.193*	- 0.241***	- 0.349***	- 1.133**
Plant-Machine	- 0.200	- 0.381***	- 0.342***	- 0.402***	- 0.846**
Elementary Occupation	- 0.047	- 0.500***	- 0.444***	- 0.462***	- 0.873**
Constant	**2.728*****	**3.308*****	**4.003*****	**4.428*****	**4.547*****
Obs.	4455	4455	4455	4455	4455
R-Squared	**26%**	**43%**	**35%**	**26%**	**10%**

Source: Researcher's calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 100 times.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 14: RIF Results of the Gender Wage Gap in Palestine (2015Q1-2019Q4)

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Female	- 0.389***	- 0.264***	- 0.186***	- 0.224***	- 0.058***
Age	0.045***	0.043***	0.028***	0.018***	0.011
Age square	- 0.0005***	- 0.0004***	-0.0002***	-0.0001***	- 0.00001
Marital Status (Reference: Never Married)					
Married	0.031**	0.133***	0.096***	0.099***	0.048*
Others	- 0.088	- 0.014	- 0.034	0.083**	0.009
Locality Type (Reference: Urban)					
Rural	0.009	0.002	- 0.040***	- 0.038***	- 0.020
Camp	- 0.039**	- 0.086***	- 0.077***	- 0.074***	- 0.100***
Region (Reference: West Bank)					
Gaza Strip	- 0.342***	- 0.399***	- 0.497***	- 0.878***	- 0.973
Higher Qualification (Reference: Illiterate)					
Can Read and Write	0.116	0.042	0.038	- 0.043	- 0.166
Elementary	0.210**	0.124*	0.073	- 0.020	- 0.083
Preparatory	0.257**	0.197***	0.149***	0.031	- 0.025
Secondary	0.303***	0.245***	0.188***	0.055	- 0.0003
Associate Diploma	0.313***	0.327***	0.301***	0.035	- 0.060
BA\ BSc	0.428***	0.482***	0.479***	0.168***	- 0.017
Higher Diploma	0.612***	0.701***	0.667***	0.352***	- 0.116
Master Degree	0.501***	0.648***	0.786***	0.586***	0.321
Ph.D.	680***	0.839***	1.048***	1.293***	1.741***
Place of work (Reference: West Bank)					
Gaza Strip	- 0.476***	- 0.0112	0.166	0.673***	0.891
Israel & Satt.	0.434***	0.578***	0.920***	1.172***	0.650***
Abroad	0.145**	0.288***	0.527***	0.992***	2.135***
Sector of Work (Reference: Public)					

Variables\Q	τ(20)	τ(40)	τ(60)	τ(80)	τ(99)
Private	- 0.551***	- 0.271***	- 0.057***	0.198***	0.161***
Foreign	0.128***	0.358***	0.501***	0.389***	0.147***
Others	- 0.523***	- 0.393***	- 0.219***	- 0.002	0.175
Nature of currently Job (Reference: Full Time)					
Part Time	- 0.361***	- 0.095*	0.010	- 0.0002	0.083
Seasonal	- 0.626***	- 0.231***	- 0.009	-0.068***	- 0.165*
Industry (Reference: Agriculture, Hunting & Fishing)					
Mining, Quarrying & Manufacturing	0.034	0.222***	0.288***	0.293***	- 0.267***
Construction	0.222***	0.456***	0.416***	0.589***	0.391***
Commerce, Hotels & Restaurants	- 0.121***	0.105***	0.297***	0.371***	- 0.040
Transportation, Storage & Communication	- 0.175***	0.045	0.287***	0.475***	0.001
Services & Other Branches	- 0.015	0.087*	0.249***	0.430***	0.061
Occupation (Reference: Legis-Senior)					
Proff-Clerks	0.014	- 0.165***	- 0.353***	- 0.494***	- 0.268**
Services-Shop	- 0.160***	- 0.343***	- 0.497***	- 0.575***	- 0.282***
Skilled-Agriculture	- 0.196***	- 0.278***	- 0.442***	- 0.613***	- 0.544***
Craft	- 0.183***	- 0.322***	- 0.418***	- 0.415***	0.154
Plant-Machine	- 0.264***	- 0.367***	- 0.486***	- 0.552***	- 0.270*
Elementary Occupation	0.286***	- 0.469***	- 0.562***	- 0.640***	- 0.533***
Constant	**3.530*** **	**3.508*** **	**3.893*** **	**4.271*** **	**5.669*** **
Obs.	**27585**	**27585**	**27585**	**27585**	**27585**
R-Squared	**36.3%**	**37.7%**	**44.6%**	**46.0%**	**7.0%**

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: Unconditional model is linear quantile regression. A total number of 100 regressions are estimated. The variance has been estimated by bootstrapping the results 50 times. Reference group is female. Counterfactual group is male.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 15: Changes in Measures of Gender Wage Gap using Blinder-Oaxaca RIF-Decomposition, Option (quantile)

Dependent Variable: log (Daily Wage)			
Quantile	Total Change	Effect of:	
		Characteristics (Explained)	Coefficients (Unexplained)
20	0.107***	- 0.262***	0.369***
40	- 0.013	- 0.209***	0.197***
60	0.065***	- 0.112***	0.177***
80	0.250***	0.176***	0.074***
99	0.436***	0.138**	0.298***

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
Notes: Pointwise standard errors are in parenthesis. Unconditional model is linear quantile regression.
The variance has been estimated by bootstrapping the results 100 times.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively

Table 16: Comparing the Decompositions of Oaxaca-Blinder (OB), Conditional Quantile Regressions (CQR), and Unconditional Quantile Regressions (UQR) Estimates of the Wage Equations in Palestine (2015Q1-2019Q4)

Dependent Variable: log (daily wage)						
Quantile	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**	**Oaxaca-Blinder (OB)**
Conditional Quantile Regressions (CQR)						
Total effect	0.042***	0.011	0.082***	0.280***	0.554***	0.118***
Characteristics effect	- 0.223***	- 0.169***	- 0.088***	0.066***	0.101***	-0.087**
Coefficients effect	0.265***	0.181***	0.169***	0.214***	0.454***	0.205**
Unconditional Quantile Regressions (UQR)						
Total effect	0.107***	- 0.013	0.065***	0.250***	0.436***	
Characteristics effect	- 0.262***	- 0.209***	- 0.112***	0.176***	0.138***	
Coefficients effect	0.369***	0.197***	0.177***	0.074***	0.298***	

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 17: Quantile Regressions (CQR, and UQR) of Log daily Wage Equation[26]

Dependent Variable: log (daily wage)					
Variable/Q	**τ(20)**	**τ(40)**	**τ(60)**	**τ(80)**	**τ(99)**
Conditional Quantile Regressions (CQR)					
Female	- 0.228***	- 0.197***	- 0.194***	- 0.204***	- 0.330***
Others Variables included?	Yes	Yes	Yes	Yes	Yes
Obs.	27585	27585	27585	27585	27585
R-Squared	42.5%	39.8%	38.7%	38.9%	23%
Unconditional Quantile Regressions (UQR)					
Female	- 0.389***	- 0.264***	- 0.186***	- 0.224***	- 0.058***
Others Variables included?	Yes	Yes	Yes	Yes	Yes
Obs.	27585	27585	27585	27585	27585
R-Squared	36.3%	37.3%	44.6%	46.0%	7.0%

Source: Researcher calculations depending on the Palestinian Labor Force Surveys from PCBS data from 2015q1-2019q4.
***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively

[26] The quantile regressions (CQR, and UQR) results are different from QCD because the effect of counterfactual is absent.