Estimating Gender Wage Gap and Its Decomposition In Pakistan

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ABSTRACT

This study estimates the gender wage gap in Pakistan by applying Nopo's decomposition procedure. This technique is a non-parametric alternative to the Blinder-Oaxaca (B-O) technique of decomposition. It addresses the issue of gender wage gap in the common support and decomposes the total wage gap into four components. One of these components focuses on gender discrimination, while the other three explain individual characteristic differences. For this purpose, the study used Pakistan Social and Living Standard Measurement Survey data for the years 2013-14 and 2018-19. The results of the non-parametric procedure revealed that there was an 18.91% gender wage gap in Pakistan in 2013-14. This figure increased to 29.48% in 2018-19. Furthermore, the results of the decomposition technique showed that about 17.7% and 27.54% of the total wage gap was due to gender discrimination in the labor market in 2013-14 and 2018-19, respectively. In the same time periods, almost 2% was due to the differences in individual characteristics. The policy implication is that the government should chalk out and implement such policies that can decrease gender discrimination in the labor market.

Keywords: discrimination, education, gender wage gap, individual characteristic differences

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Introduction

Gender equality is a central human right and it is an important foundation for a developed, prosperous and sustainable world (UNDP, 2014). It increases the productivity of workers which ultimately leads to an increment in earnings. It was included in the United Nation's Millennium Development Goals (MDGs) and later on is the fifth goal of the Sustainable Development Goals (SDGs) to be accomplished by 2030 and implemented by the United Nation's member states at the Sustainable Development Summit which was held on September 2015. Despite so much importance, gender disparities still happen in developing countries, especially in employment and education (Malhotra et al., 2003). When workers do not receive equal pay for their equal productivity, it is regarded as the gender wage gap (Aigner & Cain, 1977). The gap between the earnings of men and women is a composite of many factors including the women's level of schooling and skills, motherhood, unpaid care work, or family responsibilities leading to part-time and direct or indirect discrimination based on sex. But there are two main causes of the gender wage differential: a productive characteristic which includes different levels of profitable skills such as education, experience, capability, labor market, and occupations; and other by default disparities, and such differences may be inspired by culture, geographic locality, historical reasons, and so on. Such differences are observable and known as explained. The second cause of the wage gap is gender discrimination. Wage inequality may occur even in the existence of equal levels of productive skills if owners give different rewards to male workers and female workers depending on their gender due to favoritism and gender biases for similar productive skills. Such reasonable justification of wage differential is generally known as discrimination at the workplace and this is as a result of favorable behavior with male workers, this is known as unexplained part (Blinder, 1973; Oaxaca, 1973). The male-female pay gap has attracted attention in the developed and the developing countries; but it is a critical problem in developing countries (Richard, 2007). Owing to gender wage inequalities, women lose their efficiency. The lower wages for women due to discrimination reduce economic growth and cause a reduction in per capita GDP (Esteve-Volart, 2004). Gender disparities affect economic growth (Alam, 2011). Regardless of the application of antidiscrimination programs, policies, and improved contribution of women in the labor market, it is a reality and it is generally observed that women's earnings are less than those of men (Polachek & Xiang, 2009).

Female citizens are a major part of our society and can perform an important part in accelerating the economic development of the economy. But mostly in developing countries, women are rewarded less as compared to males are rewarded. In developing countries, less attention is paid to women's education. Women who are participating in the labor market don't have sufficient education to get a proper job and earn well. Women's physical characteristics are also different from men's. Physical attributes may also cause less wages for women (Ahmed & McGillivray, 2015).

The Hausmann et al. (2012) shows the observed gender wage gap in different countries from 2012-18. In 2012 Pakistan and Iran had the same trend which showed 79 % of women's earnings were less than men's. In Bangladesh, about 48%, India 72%, Sri Lanka 63%, Nepal 58%, and Turkey 7% of women's earnings were less than that of men in 2012. During 2014-15 women in Pakistan and Iran earned 83% less than men, In Nepal, about 47%, Turkey and Sri Lanka 6% of women's earnings were less than men. But in 2018 this gender wage gap reduced and became 19% in Pakistan.

Gender discrimination in Pakistan appears to be ironic in respect of females when it is seen that a female popular political leader, i.e., Prime Minister Benazir Bhutto, was the first lady to lead the Islamic Republic of Pakistan. The gender gap in literacy is growing, the rate of cruelty against females is disturbing and according to World Bank, female's participation rate in the labor force is 25.12 percent. The average value of this participation rate for Pakistan during the span of 1990 to 2018 was 18.66 percent with a least of 12.51 percent in the year 1995. This value shows the women's low participation as compared to other nations with the same Gross Domestic Product (GDP) per capita. An indication regarding gender discrimination in Pakistan's labor market is well-acknowledged by (Ashraf and

Ashraf (1993), Siddiqui et al. (1998), Nasir and Nazli (2000), Siddiqui et al. (2006), Yasin et al. (2010), Ñopo et al. (2011), and all confirm that men's earnings are higher than women even after controlling for characteristics which are measurable and affect their efficiency and productivity.

Significance of the Study

A few studies have been conducted in Pakistan on the estimation of gender wage differential using the Blinder-Oaxaca Decomposition procedure (Ali and Akhtar (2014), Ali and Akhtar (2016), Ashraf (1996), Ashraf and Ashraf (1993), Ashraf et al. (1993). This decomposition technique was developed by Blinder (1973) and Oaxaca (1973). This method needs the linear regression estimation of wage equations for male workers and female workers. The male worker's and female worker's average wage differences are divided into two components or parts, explained and unexplained part: first is attributable to differences in male-female average characteristics or we can say the difference in productive characteristic or endowment; and second is due to the differences in average reward of male-female similar characteristics known as unexplained part. The unexplained part comprises two effects-the unobservable difference in endowments and labor market discrimination (Blinder, 1973; Oaxaca, 1973).

B-O technique has certain restrictions and limitations (Neumark, 2004). It is a summary measure; in which it clarifies just the conduct around the mean. Concentrating just on the mean can lose out on some helpful data. For example, there is proof of a connection between the wage differential and the wage levels, which will not be seized by just watching at the conduct around the mean (Albrecht, Björklund, & Vroman, 2003). Known as the part of the distribution which has the maximum wage gap can be important for policy design. The second restriction of the B-O approach is that it needs a parametric description of the contingent work connecting income with individual qualities. The potential issue related to B-O decomposition is misspecification because of the difference in the supports of the empirical distributions of males' and females' characteristics. It has not been considered in the wage gaps analysis.

B-O decomposition flops to identify gender differences in the supports by calculating wage equations for all employed males and females by not confining the comparison just to those people with similar attributes. By not thinking about this limitation, the B-O decomposition certainly works in light of an "out-of-support assumption. It is important to assume that the linear estimators of the wage equations are appropriate out of the supports of individual attributes for which they were evaluated. Practical evidence recommends that this assumption overvalues the unexplained component of the gap which is due to differences in labor market rewards. The misspecification problem is connected with gender differences in supports, the B-O method only talks about the average unexplained wage gap. It is consequently not helpful for addressing the distribution of such unexplained gaps. This fresh study uses matching to highlight the issue of the gender wage gap in the supports and addresses the distribution of the unexplained wage gaps. Thus this study uses Ñopo's (2008) decomposition technique that addresses all these issues (Agrawal & Vanneman, 2014). There is little evidence to use this technique in Pakistan. Furthermore, the present study uses the Pakistan Social and Living Standard Measurement survey PSLM 2013-14 and the recent data set of 2018-19.

Scheme of the Study

After the introduction the remaining part of the paper is as follows: the second section discusses the literature review. The third section explains the data and methodology. The fourth section explains the results. The final section concludes and suggests some policy implications.

Literature Review

Ñopo (2008) presented a matching instrument to decompose the gender wage difference by using data for Peru 1986-2000. The non-Parametric decomposition approach suggested that the issue of non-comparability was 23% and 30% due to the men and women of employed populations correspondingly. It allowed us to compute the outcome of clearly identifying these disparities in supports that also found the 45% male-female earning gap in Peru that was disintegrated in four parts that were 11% wage gap is due to change in the supports of both genders, 6% described by differences in the male-female specific attributes and the lasting 28% was mainly due to discrimination or may be due to difference in unobservable attributes. Around half of the last portion was due to unexplained changes in the upper quintile of earning dispersal.

Ahmad et al. (2008) addressed the gender wage gap in Bangladesh and checked the part of wage gap owing to individual characteristics, discrimination, and also due to selectivity bias in both rural and urban areas of Bangladesh. This analysis used the LFS 1990-1995 and B-O was employed to draw results. The findings of the study showed that gender wage differentials were larger in urban areas than rural areas and a significant portion of this gender wage gap resulted from discrimination.

Ñopo (2008) addressed the gender wage differences by using matching comparisons or a non-parametric approach. This approach emphasized gender differences in the support of distributions of observable characteristics and provided insights into the distribution of the unexplained gender pay gap. Data used in this study was a Ministry of Labor and Social Promotion 1986-95 and the National Institute of Statistics and Informatics 1996-1999. Results suggested that a substantially higher unexplained wage gap was the main cause of the total wage gap.

Kapsos (2008) investigated determinants of earnings and estimated gender wage differentials of non-agricultural workers in the country. The study used Bangladesh Occupational Wage dataset 2007. The Mincerian regression model and B-O results revealed that an increase in education played an important role in decreasing the gender wage gap in Bangladesh

Cudeville and Gurbuzer (2010) evaluated the income discrimination in Turkey depending on the method of selectivity-adjusted male-female earning gap. Dataset used in this study was Household Budget Survey 2003. Results of the B-O decomposition procedure observed an average pay difference of women earning was 38%, and 63% of that part was due to discrimination against a female in the labor market. An assessment of outcomes found in European countries, by using the same methodological procedure, disclosed that even the earning gap in Turkey was amazingly decreasing, near to that detected in France and Italy, the discrimination element was higher as compared to that in Spain and Greece.

Hoyos et al. (2010) studied the gender wage gap in Colombia from 1994 to 2006, utilizing the matching approach to show the degree to which people with comparable human capital attributes gain distinctive wages. Three sub-periods were viewed as 1994-1998; 2000- 2001; and 2002-2006, comparing to the monetary sequence of the Colombian economic sector. The male-female earning gap remained to a great extent unexplained after controlling for various mixes of socio-socioeconomics and work-related characteristics. That gap was brought down at the center of the earning disseminations than the limits, perhaps because of a gender equality impact of the lowest pay permitted by law. In addition, the difference was more articulated for low-efficiency laborers and those individuals who required adaptability to take an interest in labor markets.

Ñopo et al. (2012) analyzed the gender gaps in employment wages for a complete group of 64 countries by using the methodological decomposition tool proposed by Nopo. Data sources had been any kind of nationwide demonstrative household review accessible with evidence on labor wages and noticeable attributes of the entities and their professions. The gender wage gap was calculated only of those individuals who had the same observable characteristics and attributes and only those male workers and female workers who were matched had similar socio-demographic features. Gaps were also qualified for gender gaps in noticeable and work attributes. After conducting identical men and women with similar attributes results suggested that the wages difference decrease within an array among 8% and 48% of average women's wages. The unexplained wage breaks were more explained between those laborers who worked part-time and those who had a low level of education.

Longhi et al. (2012) examined the distinction in normal wages, the supposed wage difference of indicated ethno-religious gatherings in Great Britain at the mean and over the income dissemination with the point of clarifying why such wage gap varies crosswise over minority gatherings. Labor force surveys 2002 and 2009 were used in this analysis. It was recognized that minorities by their ethno-religious foundation, as well as by nation, in which individuals grew up and gained their capabilities. B-O decomposition suggested that inside all minority ethno-religious gatherings the second age group accomplished higher earnings than the original, but the quantity that was clarified by attributes did not rise with age.

Ali and Akhtar (2016) analyzed the gender earning gaps existing in urban areas of Pakistan by using Household income and expenditure survey 2010-11. Variables used in this study were level of education experience, experience square, and marital status while the dependent variable was a log of wages. OLS, Quantile regression, and B-O techniques were employed. Results showed that higher were earnings for males as compared to that of females but higher incremental returns to investment in human capital for females at all levels of education.

Sinden (2017) explored the gap between male and female employment in the South African workforce, in terms of employment numbers as well as employment in different sectors. The nature of the data used in this study was primary & sourced from the South African Department of labor's 14th commission for Employment Equity Annual Report. Secondary data were obtained from books, journals, and relevant government departments. Findings showed that despite South African' progressive law and policy measures, women remained underrepresented in the workplace & men continued to dominate, especially in the top and senior management positions.

Combet and Oesh (2019) analyzed the gender wage gap in Switzerland. This study explained that the gender wage gap existed not only because of employer's discriminating behavior against female workers, but it was due to parents and household's differential investment paid work. They made an experiment of this argument by comparing the growth of wages between male workers and female workers before talking about family formation and gendered household specialization. The study used the data of young adults of Switzerland for cohort study (TREE 2000-2014) and compared the two genders based on intellectual ability and educational achievement before they went into the labor market. The study also used the ensuing survey waives to explain job characteristics along with human capital and their values towards work and family. They reproduced an analysis along with second-panel study graduate students of Swiss. In both cohort studies, they found a gender wage gap between 3 to 6 % in favor of men. This outcome suggests that young females earn low wages than young males with the same specification and same productive characteristics and skills. In the calculation of annual wages, this means that young females had to lose half of their monthly wage each year in comparison to men.

Seneviratne (2020) examined the gender wage gap in Sri Lanka from 1992 to 2014, a period of tough economic growth following pro-market improvements. The wage gap between men and women diminished gradually over the period. Unconditional Quantile regression showed that the decrease in gender wage was due to developments in females' observable human capital characteristics, but the pay structure became more inadequate, representing spreading gender wage gaps in the labor market. The study also revealed selection bias overestimated the gains inequality over time and underestimated the gender wage gap.

Data and Methodology

Data

The present study uses the Pakistan Social and Living Standard Measurement (PSLM) Survey 2013-14 and 2018-19 collected by the

Pakistan Bureau of Statistics (PBS). These data provide enough information on social indicators along with information about Income and Consumption, the number of working people with their employment status, consumption patterns, and income, etc. The universe in this survey is rural and urban zones of four provinces along with Gilgit Baltistan and AJK. The excluded areas from the scope of the survey are Military limited areas and FATA. The total sample size of data sets PSLM 2013-14 and 2018-19 was 17989 and 24809 households, respectively, from all four provinces. For this survey, a two-stage stratified sample design has been espoused which are primary sampling units and secondary sampling units.

Methodology

Gender wage gaps and returns to human capital can be assessed by following the Mincerian approach as a baseline framework (Pastore et al., 2013). As the Mincerian model yields more stable and good results than one can assume (Montenegro & Patrinos, 2014). The modified form of basic earning function used in this study is as under.

$$\mathrm{lnY_i} = \mathrm{a} + \mathrm{bX_i} + \mathrm{e} \tag{1}$$

lnY_i is a natural log of the male-female monthly earning and function of male and female characteristics in form of different variables. To correct for possible skewness and heteroscedasticity, the dependent variable has been used in form of log-transformation (Vassil et al., 2014). General wages are considered in this analysis. bX_i *is* set of male-female characteristics and e is error term.

The econometric form of the model is as follows which describes the gender-related attributes on that basis difference in wages can be calculated.

$$\mathrm{lnY_i} = \mathrm{b_0} + \mathrm{b_1Edu_i} + \mathrm{b_2Exp_i} + \mathrm{b_3Exp^2{}_i} + \mathrm{b_4MS_i} + \mathrm{b_5Prov_i} + \mathrm{ei} \tag{2}$$

Edu Stands for the level of education, Exp is male-female labor market experience in completed years. The squared term of Experience is Exp^2 which is incorporated in the earning function to capture nonlinearity in male-female earnings during their life period (Pastore et al., 2013; Willis, 1986). MS is Marital Status, Prov is

Provinces of Pakistan and ***e*** is error term which represents other variables. It is assumed independent to the other explanatory variables.

By using education dummies for a different level of education, returns are estimated by earning function. According to the education system of Pakistan, eight dummy variables are generated which EduUp (under primary), Edu5 (primary), Edu67, Edu89, Edu10, Edu12, Edu14, EduMA. These dummy variables show the specific level of education achieved by males or females (Montenegro & Patrinos, 2014). The dummy variable of never attended is used as the reference category. Dummy variables for the province are Punjab, Baluchistan, and Sindh. KPK is the reference category of the province. Such as married, widow, and divorced are dummies for marital status, and unmarried is the reference category. All omitted categories are not included in the model to avoid the issue of singularity in the matrix. The econometric model with dummy variables is as under.

$$\begin{aligned} \ln Y_i = {} & b_0 + b_1 EduUP_i + b_2 Edu5_i + b_3 Edu67_i + b_4 Edu89_i + b_5 Edu10_i + b_6 Edu12_i + b_7 Edu14_i + b_8 EduMA_i + b_9 Exp_i + \\ & b_{10} Exp^2{}_i + b_{11} Married_i + b_{12} Widow + b_{13} Divorced + b_{14} Punjab + b_{15} Sindh + b_{16} Baluchistan + e_i \end{aligned} \tag{3}$$

The definitions of the variables are presented in Table 1.

Table 1

Operational Definition of Variables

Lnwage	The dependent variable is the Logarithm of the monthly wage earned from employment
Education	
EduUp	Education under primary
Edu5	Primary education
Edu67	Under middle education
Edu89	Blow secondary education
Edu10	Secondary education
Edu12	Higher secondary/college education
Edu14	13 or more years of schooling graduates

Lnwage	The dependent variable is the Logarithm of the monthly wage earned from employment
EduMA	Master degree in education Reference category is never attendant
Experience	
Exp Exp^2	Experience is calculated as age - completed years of schooling - 6 Exp. * Exp. (Experience square)
Marital status	= 2 otherwise zero
Married	= 3 otherwise zero
Widow	= 4 otherwise zero
Divorced	Unmarried is a reference category
Province	
Punjab	= 2 otherwise zero
Sindh	= 3 otherwise zero
Baluchistan	= 4 otherwise zero KPK is the reference category

Source: Author's calculations

Non-Parametric Decomposition Approach.

The non-parametric approach was first introduced by Ñopo (2008) and it has no need for estimation of any wage equation and out of support assumption has no validity†. This study uses a new decomposition of the gender wage gap that is not used in Pakistan before. This decomposition will check the differences in the distribution of individuals' attributes and wage gap due to that difference. It also tells about the part of the wage gap which is due to discrimination or favorable behavior in the labor market for similar male-female characteristics.

The idea of non-parametric decomposition is to compare the wages of a male workers with female workers' wages, those male-

† B-O procedure worked under the out of support assumption, which means he estimates earning equation for all working female and male without restricting the comparison only those men and women have same and comparable characteristics.

female workers having the same observable attributes. We have a male (M) and female (F), two gender groups. The expected values of male and female earnings are given respectively in the following equations.

$$E(Y|M) = \int_{S^M} g^M(x)\, dF^M(x) \tag{4}$$

and

$$E(Y|M) = \int_{S^F} g^F(x)\, dF^F(x) \tag{5}$$

Y represents their wages and X is a vector of individual characteristics or attributes. S^M and S^F are Support of distribution of characteristics of male and female respectively. F^M and F^F denote the conditional distribution functions of individuals' characteristics. dF^M and dF^F are Corresponding probability measures. g^M and g^F represent expected value of the wages, which are conditional on male-female gender and their characteristics i-e

$$E(Y|M,X) = g^M(x) \text{ and } E(Y|F,X) = g^F(x) \tag{6}$$

The wage gap Δ is defined as

$$\mathbf{\Delta} \equiv E(Y|M) - E(Y|F) \tag{7}$$

For males and females, the support of the distribution of characteristics is different. Each integral is fragmented into two parts, within the intersection ($S^M \cap S^F$) and out of the common support ($S^F \cap \overrightarrow{S^M}$) and ($\overrightarrow{S^F} \cap S^M$).

$$\mathbf{\Delta} = \left[\int_{\overline{S^F} \cap S^M} g^M(x) dF^M(x) + \int_{S^M \cap S^F} g^M(x) dF^M(x)\right] - \left[\int_{S^M \cap S^F} g^F(x) dF^F(x) + \int_{S^F \cap \overline{S^M}} g^F(x) dF^F(x)\right] \text{ .... } (8)$$

Nopo (2008), demonstrates that the above equation can be expressed as a sum of four elements:

$$\mathbf{\Delta} \equiv \Delta_X + \Delta_M + \Delta_F + \Delta_0 \tag{9}$$

Δ is the raw wage gap or the total wage gap which is the sum of explained and unexplained wage differential.

$$\mathbf{\Delta_X} \equiv \int_{S^M \cap S^F} g^M(x) \left[\frac{dF^M}{\mu^M(S^F)} - \frac{dF^F}{\mu^F(S^M)}\right](x) \tag{10}$$

$\mathbf{\Delta_X}$ displays the portion of the wage gap that can be described by a difference in males' and females' distributions of characteristics of 'on the common support'. In linear B-O, decomposition setup, this component corresponds to the part $\left(X'_m - X'_f\right)B_m$.

$$\mathbf{\Delta_M} \equiv \left[\int_{\overline{S^F}} g^M\,(\mathrm{x})\,\frac{dF^M(x)}{\mu^M(\overline{S^F})} - \int_{S^F} g^M\,(\mathrm{x})\,\frac{\mathrm{d}F^{M(x)}}{\mu^M(S^F)}\right]\mu^M(\overline{S^F}) \tag{11}$$

$\mathbf{\Delta_M}$ the component is the part of wage difference that explains the difference of characteristics between two males' groups, matched males and unmatched males. Matched males are those who have characteristics that are similar and matched to female characteristics. This part can be calculated as the weighted difference between the expected wages of two groups of people, those who are out of the common support and in the common support. This part can disappear if all males have the same combination of characteristics as females have, or all males' characteristics matched to females (there is no man out of common support). This part also disappears if those males out of common support (with unmatched characteristics) are paid as much as matched males in common support.

$$\mathbf{\Delta_F} \equiv \left[\int_{S^M} g^F\,(\mathrm{x})\,\frac{dF^F(x)}{\mu^F(\overline{S^M})} - \int_{\overline{S^M}} g^F\,(\mathrm{x})\,\frac{\mathrm{d}F^{F(x)}}{\mu^F(\overline{S^M})}\right]\mu^M(\overline{S^M}) \tag{12}$$

$\mathbf{\Delta_F}$ the component is the part of wage difference that explains the difference of characteristics between two females' groups, matched females and unmatched females. Matched females are those who have characteristics that are similar and matched to male characteristics**.** This part can disappear if all females have the same characteristics as the matched males and there is no female out of common support. It could also disappear if unmatched females are paid on average as much as matched females.

$$\mathbf{\Delta_0} \equiv \int_{S^M \cap S^F} [g^M(\mathrm{x})\text{-}g^F(x)]\,\frac{dF^F(x)}{\mu^F(S^M)} \tag{13}$$

The component of $\mathbf{\Delta_0}$ shows part of the wage gap that is known as unexplained and it is attributed to the difference in unobservable characteristics and due to discrimination in the labor market against any gender. In Blinder-Oaxaca decomposition, this component corresponds to this term $X'_f(B_m - B_f)$.

Consequently, the raw wage gap can be decomposed into four additive parts.

$\Delta \equiv (\Delta_X + \Delta_M + \Delta_F) + \Delta_0$

The sum of the first three parts of the wage gap is known as the explained part which is due to the difference in characteristics. With this background, the present study will highlight the matching decomposition method for estimating the above four components. All women will be resampled without replacement and match each individual to one artificial male, with the same noticeable attributes, and with a wage got from averaging all men with the very same qualities x. The above procedure has two core restrictions: first is that the matching variable essentially discrete; second, it may have the problem of dimensionality, i.e., the usage of many matching attributes reduces the probabilities of conducting an acceptable figure of matched characteristics and also the extent of the common supports.

Matching Algorithm of Nopo (2008), Approach.

The non-parametric procedure adopts the following method. step1: choose one woman from the sample and do not replace it. Step 2: choose all males who have the same characteristics as the female which is selected in the previous step. Step:3 construct a synthetic male with all males which are chosen in the second step, whose wage is the average of all selected men, and match that male to the female selected in the first step. Step 4: Put the data of synthetic male and the female in their separate new sample of matched people. Step5: repeat these 4 stages to the point when the first female sample is depleted (Ñopo, 2008). However, it might be noticed that the above methodology has two fundamental conditions or limitations. The first condition is that matching variables ought to be discrete. Second, is a perfect matching, i.e. the utilization of many matching attributes brings down the probabilities of finding a sufficient number of matched observations.

Results and Discussion

Descritive statistics (in form of percentages) of both genders, male and female separately are discussed in table 2. In the 2013-14 overall sample 11.2% of people have received EduUp education as compared to13.3% of male and 9.1% of female. Only 7.8% male and 6.4% female receive Edu5. Similarly, 3.9% male and 2.8% female attain Edu12 and at the level of EduMA only 1.7% both genders as compare to 2.1% male and 1.3% female reach and get a master degree. 34.6% of male and 39% of female workers are found to be married and only 1.7% of male and 5% of female occur in the widowed category. Conversely, male workers 0.1% and 0.3% of female workers are divorced. In the case of provinces 39.2%, 27.8%, and 11.7% (of both genders) are residents of the Punjab, Sindh, and Baluchistan respectively. The descriptive statistics in 2018-19 in overall sample 5% people have received EduUp education as compared to 5.2% of male and 3.8% of female. Only 11.1% male and 8.3% female receive Edu5, similarly, 4.8% male and 1.5% female attain Edu12 and at the level of EduMA only 4.2% both genders as compare to 4.4% male and 3.5% female reach and get a master degree. 86.7% of male and 71% of female workers are found to be married and only 2.5% of male and 8.7% of female occur in the widowed category. Conversely, male workers 0.27% and 1.3% of female workers are divorced. In the case of provinces 56.2%, 18.3%, and 6.5% (of both genders) are residents of the Punjab, Sindh, and Baluchistan respectively. The descriptive statistics are given in table 2.

Table 2

Percentage Distribution of Variables

	2013-14			2018-19		
Variables	**Over All**	**Male**	**Female**	**Over All**	**Male**	**Female**
EduUp	11.2	13.3	9.1	5.0	5.2	3.8
Edu5	7.1	7.8	6.4	10.7	11.1	8.3
Edu67	4.5	5.7	3.3	3.4	3.9	0.9

	2013-14			2018-19		
Variables	**Over All**	**Male**	**Female**	**Over All**	**Male**	**Female**
Edu89	.6.9	8.9	4.9	11.2	11.4	3.4
Edu10	5.7	7.1	4.2	10.8	12.3	2.2
Edu12	3.4	3.9	2.8	4.3	4.8	1.5
Edu14	2.5	2.9	2.1	1.3	1.5	0.6
EduMA	1.7	2.1	1.3	4.2	4.4	3.5
Married	36.8	34.6	39.0	84.3	86.7	71.0
Widow	3.4	1.7	5.0	3.4	2.5	8.7
Divorced	0.2	0.1	0.3	0.4	0.27	1.3
Punjab	39.2	38.5	39.9	56.2	52.1	80.6
Sindh	27.8	28.5	27.1	18.3	9.9	8.6
Baluchistan	11.7	12.4	11.1	6.5	7.3	0.7

Source: Author's calculations

The results are presented in Table 3. The table shows the decomposition results in 2013-14 and 2018-19 which are achieved by using the matching decomposition method. There are four specifications[‡]. The total wage gap (Δ) is 18.91%, and 29.48% in 2013-14 and 2018-19, respectively. The total wage gap in both years is the same till the fourth specification. The wage gap is taken as a percentage of the average female wages so this advocates that men

[‡]Note. All numbers are in percentage form. Different four specifications are in columns (1-4). 1. Controls for all dummies of education. 2 specification controls for experience and experience square along with education. 3rd specification includes education, experience, experiences q and marital status. 4th include province along with all variables such as education, experience, experiences q and marital status. $\Delta_X + \Delta_M + \Delta_F$ is the total explained wage gap which is due to the difference in male and female characteristics. % of male and female in common support shows the percentage of people on common supports and those having similar characteristics such as same level of education, same experience and same status of marriage also living in same province.

earn 18.91% and 29.48% accordingly more wages as compared to women. These results for the year 2013-14 are consistent with the Global Gender Gap Report 2018 which has an estimated 19% total gender wage gap.

As we include more variables, the wage gap due to characteristics at support changes. The total wage gap which is also known as the raw wage gap is divided into four components: Δ_X, Δ_M, Δ_F and Δ_0. In the first specification of both years, a large part of the wage gap is unexplained which is 18.09% in 2013-14 & 28.78% in 2018-19 and is

Table 3

Gender wage gap decomposition results (2013-14 & 2018-19)

		Specifications			
Components	**year**	**1**	**2**	**3**	**4**
ΔX	2013-14	0.81	1.15	0.97	0.82
	2018-19	0.71	0.98	1.46	1.22
ΔM	2013-14	0	0.19	0.58	1.13
	2018-19	0	0.74	0.84	1.05
ΔF	2013-14	0	-0.01	-0.52	-0.09
	2018-19	0	0.11	0.11	-0.24
Explained gender wage gap ΔX+ΔM+ΔF	2013-14	0.81	1.33	1.03	1.86
	2018-19	0.71	1.84	2.41	2.03
Unexplained gender wage gap (Δ0)	2013-14	18.09	17.57	17.88	17.7
	2018-19	28.78	27.65	27.07	27.54
Total gender wage gap (Δ)	2013-14	18.91	18.91	18.91	18.91
	2018-19	29.48	29.48	29.48	29.48

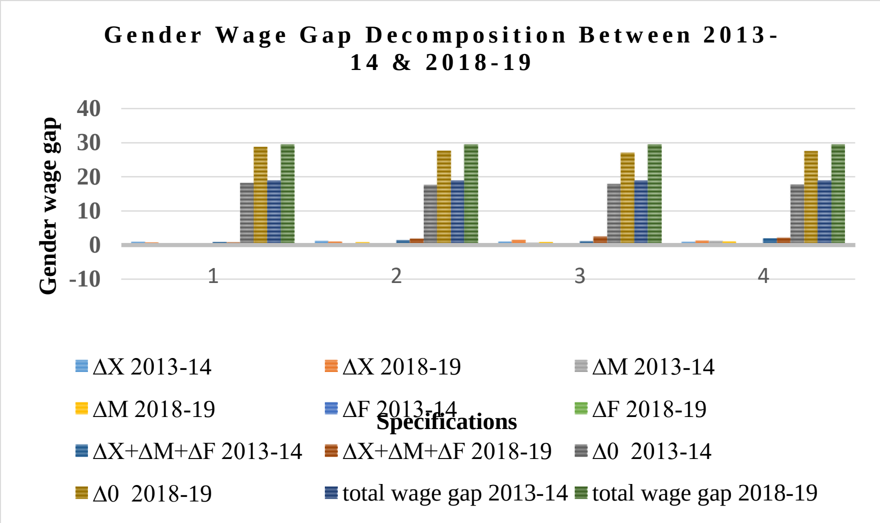
Source: Author's calculations

Considered mainly due to discrimination in the labor market. The wage gap which is due to the difference in characteristics on support is 0.81% and 0.71% in both years accordingly. Here Δ_{M}, and Δ_{F} are 0.00 because there 100% of males and females have similar characteristics and they all are in common support. In the second specification of 2013-14, the component of Δ_{X} increases from 0.81% to 1.15%, Δ_{M} is 0.00% to 0.19% and Δ_{F} changes 0.00% to -0.01%. Positive sign of Δ_{M} shows that unmatched males earn on average more than those of matched males. But the negative sign of Δ_{F} shows unmatched females earn on average more than matched females. In 2018-19 the second specification results indicate that the component of Δ_{X} increases from 0.71% to 0.98%, Δ_{M} increases 0.00% to 0.74% and Δ_{F} 0.00% to 0.11%.

By adding marital status in the third specification and province in the fourth specification the unexplained part of the wage gap does not change greatly in both years. Results show that Δ_{X} reduces from 1.15% to 0.97% and 0.82% in 2013-14. In 2018-19, the same specification results explain that Δ_{X} increases from 0.98% to 1.46% and 1.22%. This matching decomposition method has two additional parts: Δ_{M} and Δ_{F}. These components show the gap that can be explained by individuals' characteristics that are in and out of the common support. Δ_{M} increase from 0.19% to 0.58% and 1.13% in 2013-14 and similarly in 2018-19 it increases from 0.74% to 0.84% and 1.05% which is showing that unmatched males earning on average higher wages than the matched males and Δ_{F} decreases from -0.01 to -0.52 and -0.09 in 2013-14 and 2018-19. Δ_{F} remains same 0.11% but it decreases -0.24%. As well as more variables are included the percentage of persons in the common support decreases. Increasing part of Δ_{M} shows the big portion of the wage gap can be enlightened as men get access to certain groups of employment attributes that females fail to grasp. The negative value of Δ_{F} also explains that there are some other profitable sectors in which females have contact and males do not (Ñopo et al., 2011). These results are in line with NNANYIBU (2014), Ñopo et al. (2012), Hoyos et al. (2010), Ñopo (2008), Nopo (2003), Ñopo et al. (2003).

Figure 1:

Gender wage gap Decomposition (2013-14 & 2018-19)



Source: Author's calculations

The graph is showing the extent of the gender wage gap. Different sizes of the bar in the graph are showing the part of the wage gap in four specifications during 2013-14 and 2018-19. The smaller part is wage difference due to difference in characteristics in common support and out of the common support but the unexplained wage gap is very high which is 18.09% in the first specification 17.75%, in second 17.88%, 17.7% in the third and fourth specification of 2013-14. This unexplained wage gap in 2018-19 in c and this unexplained wage gap in both years is mainly due to the favorable behavior for men against women in the labor market.

This wage gap exists when all the men and women have similar characteristics but they are awarded in the labor market differently based on their gender, known as discrimination against women in the labor market. The part of wage gap due to the difference in characteristics is very small but it changes with the addition of more control variables. The explained wage gap part which is due to the sum of three components, increases due to the major part of Δ_M. This indicates that men have access to such combinations of employment opportunities that females can't get access to. The total wage gap is based on the sum of four components. The raw wage gap has a major portion of wage differential due to the unexplained part. If Δ_M is negative it shows that those noticeable attributes that females flop to attain are not related to higher wages as compared to the matched males and Δ_F is positive. It recommends the separation of females in the labor market where earnings are less than average (Ñopo et al., 2011)

The matching approach also provides two portions of the wage gap like the B-O, the explained wage gap, and the unexplained wage gap. The sum of the first three components (Δ_X+ Δ_M+Δ_F) becomes the explained wage gap which is basically due to the difference in characteristics and remaining part Δ_0 is due to discrimination in the labor market. The figure also shows the extent of the total wage gap along with explained and unexplained wage gaps. During four specifications the unexplained wage gap does not vary greatly. However, the major part of the total wage gap is due to an unexplained wage differential. Higher unexplained wage indicates extensive wage discrimination against females in the labor market and favors the males. It explains that females are earning 18.09%, 17.57%, 17,88 %, and 17.7% fewer wages as compared to the male in 2013-14 and similarly women are earning 28.78% 27.65%, 27.07%, and 27.54% fewer wages than men in 2018-19. The major part of the wage gap that is higher can be divided into two parts, some unobservable characteristics of the individual that are rewarded by the labor market.

Conclusion

This study investigates the determinants of gender wage gap using non-parametric decomposition. For this purpose, it used the data set PSLM over the periods 2013-14 and 2018-19. Non-parametric decomposition checks the differences in the distribution of individual characteristics and wage gap due to gender discrimination by comparing the wages of male and female workers with those male-female workers that have the same observable attributes. Four specifications show the extent of the wage gap and each specification focuses on a different aspect of the wage gap. As more control variables are included, the explained component of the wage gap increases. The total wage differential is decomposed into four parts. The sum of the first three parts is known as the explained component. The fourth component is known as the unexplained wage gap which demarcates the differences caused due to unobservable attributes and gender discrimination in the labor market. The results suggest that the greater unexplained part of the wage gap is mainly due to discrimination against women at the workplace. The total wage gap was 19% in 2013-14 and it increased up to 29% in 2018-19. These results are consistent with the Global Gender Gap Report 2018, which estimated a total gender wage gap of 19%. This study proved that the gender wage gap reported in the Global Gender Gap Report 2018 is neither overestimated nor underestimated. The results showed that wages are higher for male workers as compared to their female counterparts. To raise the effective and fruitful participation of the total population in the economic progress of a country, it is necessary to abolish discrimination in the labor market.

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