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BOTSWANA'S GENDER WAGE DIFFERENCES: EVIDENCE FROM CROSS-SECTIONAL QUANTILE REGRESSION ANALYSIS

ABSTRACT

The wage gap between men and women in Botswana is examined in this paper. The paper employs both the unconditional decomposition technique and the quantile regression model. The research shows that returns to schooling differ significantly between males and females using quantile regression models. As one's education level rises, both private returns to education tend to increase. Applying the decomposition analysis also reveals that the pay gap between men and women widens as levels rise along the salary distribution. The data do not support the "sticky floor" effect, while the "glass ceiling" effect suggests that many women may not be in leadership positions. The study's policy implications include the need to continue investing in human capital development and draw men into heavily feminised industries.

Keywords: Wages; Gender; Inequality; Education; Employment
JEL Classification: J01; J08; J31; J71

RIASSUNTO

Differenze salariali di genere in Botswana: evidenze da un'analisi trasversale di regressione dei quantili

L'oggetto di questo studio è la differenza retributiva tra uomini e donne in Botswana. I metodi usati sono la tecnica di scomposizione non condizionale e il modello di regressione dei quantili. La ricerca dimostra che il rendimento dell'istruzione è significativamente differente tra maschi e femmine se si utilizzano modelli di regressione dei quantili. Più è alto il livello di istruzione,

maggiore è il rendimento dell'istruzione sia per gli uomini che per le donne. Applicando l'analisi di scomposizione si scopre che la differenza salariale tra uomini e donne è più ampia man mano che le retribuzioni aumentano. I dati non confermano l'effetto "pavimento vischioso", mentre l'effetto "soffitto di cristallo" suggerisce che non sono molte le donne che ricoprono posizioni dirigenziali. Tra le politiche suggerite da questo studio vi è la necessità di investire sullo sviluppo del capitale umano e di introdurre lavoratori uomini nelle industrie dove vi è forte presenza femminile.

1. Introduction

The labour market is one of the essential components of any market economy (Chopra, 2022). It plays a vital role in shaping and directing an economy's economic, social and political structure. Employment significantly impacts workers' quality of life and, more importantly, their families' survival. The literature consistently shows that women are more educated than men, even though they continue to earn less on average than men. Data demonstrate that most economies have a male-dominated labour market (ILO, 2016; Siphambe and Motswapong, 2010).

Furthermore, laws in certain developed and developing countries restrict women from participating in certain professions to the extent that female labour force participation is lower than that of males (ILO, 2018; Siphambe and Motswapong, 2010). This indicates that gender bias exists in global labour markets against women.

A considerable body of literature on the gender wage gap reveals that females earn less than males globally (Siphambe and Thokweng-Bakwena, 2001; Ntuli, 2007). The gap has been found to close, although it remains a severe issue in many developing countries, especially in the Arab States, Africa, and Southern Asia (ILO, 2018). Despite increased awareness and commitment to gender equality at work and in society, progress in closing the gap has been too slow. In 2017, estimates put the gender wage disparity worldwide at 27 percentage points and 50 percentage points in the Arab States, Northern Africa, and Southern Asia (ILO, 2018). Goals 5 and 8 of the UN's Sustainable Development Agenda call for full and productive employment, fair compensation for equal labour for men and women, and other goals by 2030 (ILO, 2018). The UN contends that all economic actors must work together to address gender inequality to achieve this goal.

Even though women make up a considerable share of the unemployed and impoverished in most developing countries, and the majority labour in unofficial or low-paying occupations, females continue to make significant contributions at home and in the community. Children's survival depends on the mother's ability to participate in the labour market and earn a respectable wage. Therefore, there is a need to draw policy recommendations to improve their wages in the labour market. This can only be possible with empirical evidence on factors that determine their lower salaries in the labour force. The current study, therefore, highlights issues that can help in formulating policies that can address wage inequality in the labour market.

Considering existing literature, there is limited empirical research on gender wage disparities in Botswana. The closest study (Siphambe and Thokweng-Bakwena, 2001) examined the gender wage disparity in Botswana's formal labour market by employing the Oaxaca decomposition methodology, which bases its analysis on mean wages rather than the entire wage distribution. In this context, the current study will add to the existing literature on gender wage gaps in Botswana in several ways. Firstly, this is the first study in Botswana to employ the quantile regression and quantile decomposition techniques to analyse gender wage gaps to the best of the authors' knowledge. These techniques investigate wage gaps along the wage distribution and the factors affecting the wage gap's magnitude. Secondly, the current study differs from Siphambe and Thokweng-Bakwena (2001) regarding the selected period and types of workers. With rising female education enrolments and labour force participation in the past decades in Botswana, the issue deserves an in-depth analysis.

The rest of the paper is organised as follows. First, a brief background on Botswana's labour market and public policies on gender disparities is provided. Then, the related literature is presented. Next, the methodology is discussed, followed by the data used in the study. After that, discussions on the results are discussed. Finally, the paper provides conclusions and draws policy implications.

2. Brief background on Botswana

Since gaining its independence in 1966, Botswana has made notable strides and is one of Africa's few success stories of rapid and sustained economic growth. Even if some programs and policies work toward equality, not all populations have equally benefited from the accomplishment.

Women make up a significant portion of the population that has not benefited from the achievement (Siphambe and Thokweng-Bakwena, 2001). This is despite government initiatives to include women in the development process (Lesetedi, 2018). Botswana has achieved progress toward women's empowerment since the 1995 UN Fourth World Conference on Women, often known as the "Beijing Conference", despite all the obstacles and gaps she had to overcome. The nation established the National Policy on Women in Development in 1996 to act on gender equality and women's progress (Ministry of Labour and Home Affairs, 2000). Eliminating all harmful socio-cultural, economic, and legal norms that support gender inequality was one of the policy's main goals. The National Policy on Gender and Development, established in 2015, replaced the previous regulation. The National Policy of Gender and Development is aligned with the UN Sustainable Development Goals (SDGs), particularly Goal 5 on Gender Equality, the Beijing Platform for Action and its Declaration. The policy as adopted by the Government prioritised the following: i. Economic diversification, prosperity, and poverty eradication to achieve sustainable development; ii. Social Protection and social services (health, adequate sanitation and improved well-being, access to quality education, training and information, safe housing and consideration for addressing energy and climate change issues for a sustainable environment); iii. Political power, democratic governance and decision-making; iv. Access to justice, protection of human rights and freedom from violence; and v. Special measures targeting vulnerable groups of men, women, girls and boys across all four areas.

In 1996 and 1997, the nation additionally ratified the international and regional declaration on gender and development, respectively. By signing these declarations, member states agreed to ensure equal representation of men and women in decision-making and eliminate discrimination. Nevertheless, despite all these initiatives, women still faced obstacles. For instance, there are significant gender gaps in the labour market. Although female labour force participation has increased, the growth rate has lagged behind men. In 2016, 49% more women were working in the economy than in 2008, and their labour force participation rate, which was 56% compared to 67.8% for men, was lower (Khanie, 2019).

Thus far, the policy has made significant strides as there have been several amendments in the legal framework that promote a level ground promoting equality for both males and females. According to Mooketsane *et al.* (2023), despite Botswana's efforts to promote gender equality, it needs significant progress to achieve SDG 5. According to the World Economic Forum's (2022)

Global Gender Gap Index, Botswana ranks 66th among 146 countries regarding gender parity in critical dimensions: economic opportunities, education, health, and political leadership. Within sub-Saharan Africa, Botswana ranks 14th among 36 countries in the index, well behind top-rated Rwanda, Namibia, and South Africa.

Additionally, women are more prevalent in primary occupations and clerical support services than in managerial or administrative decision-making. According to Statistics Botswana (2022), 3% of men and 12% of women work in clerical support services. Additionally, 19% of men and 17% of women work in elementary vocations. According to the data, men make up 6% of those working in managerial or administrative jobs, while women make up 4%. Most female workers are also in the services/sales workers category, accounting for 30% compared to 25% of men.

According to Statistics Botswana (2019), males make an average of more money than females in most of Botswana's industries. Further findings reveal that, on average, women make 84% of the mean male salary across all sectors, whereas non-citizen women make far less money than men (70%); for citizens, women make 88% of what men make across all industries. Overall, it is demonstrated that there are wage differences in the labour market of Botswana; hence, a thorough investigation into the causes of the differences is required.

Considering education attainment between men and women, Botswana achieved gender parity at all levels of the education system. In tertiary education, women outnumber men (Statistics Botswana, 2023). However, when we get to the workplace, women are found to be relatively more in managerial, professional, technician and associate professional, clerical support services, service/sales works and elementary occupations but fewer in Science, Technology, Engineering and Mathematics (STEM) (Statistics Botswana, 2022). Men tend to dominate the STEM-related professional disciplines. STEM-related professions earn more compared to other occupations.

In addition, cultural impediments limit the development and progression of females in the country. For instance, there are cultural practices that disrupt the education of females by having pre-arranged marriages at the puberty stage, forcing them to leave school early. Despite several efforts, the country still needs help retaining girls of different cultures in school.

3. Brief related empirical literature

Several economic theories have been deployed to explain the sources of the gender wage gap. Such explanations can be categorised into the human capital model (differences in qualification) and labour market discrimination (Grybaite, 2006). The human capital theory is an integral theory for wage differentials, as described in the works of Becker (1993) and Mincer (1974). This theory assumes that education is an investment that yields future returns and is vital to any worker. That is, once an individual finishes school, he/she attracts higher wages. Hence, education can lead to wage inequalities, even though it is crucial in determining the workforce's quality. Those with high education are highly paid and viewed as productive, hence wage differences. As a result, wage gaps between workers are due to differences in individual human capital, such as education, training and labour market experience (Villadoniga and Rodríguez-Alvarez, 2017). According to Grybaite (2006), gender differences in qualifications have been analysed within the human capital model, whose basic idea is that every person has some form of human capital. Human capital can be determined as the abilities and skills people have taken through education, training and experience. These skills are the basis for the earnings they receive.

Meanwhile, Polachek (2004) stated that the human capital model links expected lifetime labour force participation to one's incentive to acquire marketable training. This training, acquired in school and on the job, determines earnings potential. Thus, expected lifetime work history is the most crucial motivating ingredient in one's ability to achieve high earnings eventually.

Education is viewed as an investment rather than a consumption, assuming that those undergoing education and training would reap rewards in the future. Even though education is vital in determining the quality of the workforce, it can also lead to some inequalities in the workforce. Those with high education are viewed as productive and paid more; hence, there would be wage differentials between workers.

The work by Mincer (1974) forms the basis for gender wage differentials. The human capital earning function has become a fundamental tool in labour economics research and has played a significant role in education policies worldwide (Chiswick, 1997; Teixeira, 2014). Mincer's theory assumes that all individuals have identical skills and equal opportunities to enter any workplace. However, education is used to differentiate wages between individuals. The model emphasizes that those with higher training would attract higher wages.

Additionally, those who invest in on-the-job training would acquire more skills and experiences; hence, their wages will differ from their counterparts who did not engage in training. These are, however, long-term rewards because one is expected to earn less while at school and earn more after completing school. Becker and Chiswick (1966)'s schooling-earnings function theory assumes that the total earnings of any person after they have finished investing in human capital can be said to equal the sum of returns on their investment and the earnings from their original human capital. The schooling-earnings function has been the pioneer in demonstrating theoretically and empirically several propositions about the distribution of earnings (Becker and Chiswick, 1966; Chiswick, 2003).

Voluminous literature analyses the extent of the male-female wage gap worldwide (Ben Yahmed, 2018; Biltagy, 2019; Mbratana and Fotie Kenne, 2018). Earlier studies relied on the most common method of decomposing the male-female wage gap, the Blinder-Oaxaca decomposition method (Blinder, 1973; Oaxaca, 1973). This method conducts decomposition analysis at the mean. However, new evidence suggested that the mean wage gap decomposition did not represent the entire wage distribution. Hence, analysing the mean wage gap might reveal only some of the story (Ahmed and Maitra, 2015).

Following Oaxaca (1973)'s decomposition method, several authors proposed combining decomposition techniques with quantile regressions (Machado and Mata, 2005; Melly, 2005). Machado and Mata (2005) decomposition procedure combine a quantile regression and a bootstrap approach. Their model parameterised the relationship between wages and skills. Machado and Mata (2005) measured the impact of skills differences and the effect of returns across the wage distribution. Their model involved a tedious job where random samples were generated with 1,000 replications; Melly (2007) then introduced a STATA command to carry out the decomposition technique in a simplified manner. The decomposition method provides different coefficients of gender wage 'discrimination' for the different percentiles of the conditional wage distribution (Ntuli, 2007).

Firpo *et al.* (2009) established the recentered impact functions (RIF) to further analyse unconditional partial effects on quantiles inside a regression analysis framework. Like other approaches, this model divides the wage gap into the "explained" and the "unexplained" to understand wage differences. The model is easily constructed for quantiles and is frequently used

in robust estimation. To the best of the authors' knowledge, the quantile decomposition regression method has yet to be applied to study the wage structure in Botswana; hence, it used in this study. A thorough search of existing literature revealed one study carried out in Botswana by Siphambe and Thokweng-Bakwena (2001); hence the literature review focuses on that paper and other papers on developed countries (Cortes *et al.*, 2020; Meara *et al.*, 2020) and developing countries (Deshpande *et al.*, 2018; Biltagy, 2019; Opoku *et al.,* 2021; Adu Boahen and Opoku, 2021) and on those that employed methodologies to be used in the study. The paper by Siphambe and Thokweng-Bakwena (2001) examined the gender wage gap in Botswana and used Oaxaca's decomposition methodology. Therefore, this paper is an extension of their research, using the latest methods to analyse the wage gap. Their article found that the gender wage gap in Botswana was due to discrimination in the private and public sectors due to differences in workers' characteristics. They attributed this to the public sector's strict and transparent systems, whereas the private sector is decentralised.

Contributing to the gender wage gap literature, Cortes *et al.* (2020) revealed that gender wage gaps in developed countries have substantially reduced in the past decades due to technological changes in labour markets. On the other hand, Deshpande *et al.* (2018) explored gender wage gaps among salaried workers in India and employed Blinder-Oaxaca quantile regressions and Machado and Mata (2005) wage decomposition methods. They found the "sticky floor effect" exists in India, and over ten years, it became "stickier" for women. In their paper on the USA, Meara *et al.* (2020) examined the gender wage gap and employed matching techniques to address the problem of heterogeneity of the sample data. Matching techniques provide a more robust basis for controlling heterogeneity. This study is one of the first to employ a different method to the overly used decomposition methods. This methodology was not considered for this paper because the available data makes it impossible to use.

Adding to the literature on wage differentials, Biltagy (2019) analysed the determinants of the gender wage differentials using the Oaxaca-Blinder and Neuman-Oaxaca decomposition techniques in Egypt. Mbratana and Fotie Kenne (2018) also contributed to the existing literature by using the Oaxaca-Blinder decomposition method and augmenting it with the Machado and Mata decomposition method in Cameroon. In their paper on gender inequalities in Tanzania, Opok *et al.* (2021) further suggested the possibility of gender discrimination against women as it was difficult for them to get employment. Similarly, Adu Boahen and Opuku (2021) showed a

positive average total gender wage gap regardless of the selection model employed, indicating that, on average, females earn less than males. Danquah *et al.* (2021) further contributed to the debate by explaining the effect of gender wage differentials within households on women's empowerment, household welfare, and women's welfare in Ghana. Findings show that a decrease in the household gender wage gap substantially impacted women's empowerment and led to a rise in household and women's welfare. These results speak mainly to the literature on how policies are crafted to address wage inequalities. This study is also insightful because such empirical studies on Africa are lacking.

The empirical literature provided evidence of wage differentials for developed and developing countries with different methodologies and datasets and covered different time intervals. This study contributes to the Botswana literature on wage differentials. It is the first study to analyse the wage differentials across the wage distribution using Botswana's quantile regression and RIF decomposition methods.

4. Methodology

4.1 Methodology

This paper uses the quantile regression model and the decomposition techniques proposed by Firpo *et al.* (2009). The first part of this section discusses the quantile regression model, and the second part explains the decomposition models used in the analysis.

4.1.1 Quantile Regression Model

The quantile regression model is more flexible than the OLS model in that it allows for the analysis of the effects of a covariate on the whole distribution of the dependent variable. In contrast, the Oaxaca model allows looking at the developments at the mean. Quantile regression methods have been widely used to analyse what determines wages, discrimination, and income inequality (Koenker and Hallock, 2001). Consequently, there is a rapidly expanding empirical evidence that numerous researchers have investigated the gender wage gap across the wage distribution. Since earnings functions differ, quantile regressions are run separately for males and females. The analysis shows the differences in returns to male and female characteristics and thus explains the coefficients' size and sign.

Let w_i be the log of the worker's wage i and X_i be a vector of covariates representing the ith individual's characteristics. The econometric model used in this paper specifies the θ^{th} quantile of the conditional distribution of w_i given X_i as a linear function of the covariates,

$$w_i = X_i\beta_\theta + u_{\theta i} \text{ with } Quant_\theta\left(w_i|X_i\right) = x_i\beta_\theta \quad (1)$$

where $Quant_\theta\left(w_i|X_i\right)$ denotes the θ^{th} conditional quantile of w given X and subscript i=1... n indexes individuals.

The θ^{th} sample quantile, 0 < θ <1, as shown in Koenker and Hallock (1978), may be defined as any solution to the minimisation problem,

$$\beta_\theta = \arg\min\left[\sum_{i:w_i \geq X_i\beta} \theta|w_i - X_i\beta| + \sum_{i:w_i < X_i\beta} (1-\theta)|w_i - X_i\beta|\right] \quad (2)$$

Increasing θ continuously from 0 to 1 can trace the entire distribution of w_i conditional on X_i (Melly 2005).

4.1.2 Wage Decomposition Models

The most common wage decomposition approach in the literature was introduced by Oaxaca (1973) and Blinder (1973); it is famously referred to as the Blinder-Oaxaca model. Using natural logs, the process breaks sample average wage differences between males and females into two parts.

Suppose the wage determination function for males is given as:

$$w_i^m = \beta^m X_i^m + \varepsilon_i^m \quad (3)$$

where w denotes the log of wages, m denotes males, β is the vector of coefficients of the explanatory variables to be estimated in the equation, the subscript i indicates the i^{th} wage earner, X represents vectors of explanatory variables, and ε denotes the error term, which disappears because the expected sum of OLS errors is zero.

Likewise, the wage determination for females is given as follows:

$$w_i^f = \beta^f X_i^f + \varepsilon_i^f \tag{4}$$

where *f* denotes females. Therefore, the difference between male and female mean wages can be written as:

$$\overline{w}^m - \overline{w}^f = \hat{\beta}^m \overline{X}^m - \hat{\beta}^f \overline{X}^f \tag{5}$$

Adding and subtracting $\hat{\beta}^m \overline{X}^f$ results in:

$$\overline{w}^m - \overline{w}^f = \hat{\beta}^m \overline{X}^m - \hat{\beta}^f \overline{X}^f + \hat{\beta}^m \overline{X}^f - \hat{\beta}^m \overline{X}^f \tag{6}$$

Therefore, equation 6 becomes:

$$\overline{w}^m - \overline{w}^f = \hat{\beta}^m \left(\overline{X}^m - \overline{X}^f \right) + \overline{X}^f \left(\hat{\beta}^m - \hat{\beta}^f \right) \tag{7}$$

The resulting equation decomposes the mean gender wage difference into two parts. The first part on the right-hand side can be explained by differences in average characteristics of males and females, as outlined in the descriptive statistics table. In contrast, the second component is the part of the wage gap that is left unexplained. It may indicate unobservable differences in the quality of characteristics between males and females. This is what is referred to as discrimination in the literature.

Firpo *et al.* (2009) introduced recentred influence functions (RIFs) to analyse unconditional partial effects on quantiles in a regression analysis framework[1].These are statistical tools used to analyse the robustness of distributional statistics, or functional, to minor disturbances in data (Cowell and Flachaire, 2007). The model is simple, flexible, and implemented as OLS regression; hence, it is called RIF-OLS. Furthermore, as with the Blinder-Oaxaca model and other models, this method allows for a decomposition of the wage gap into different categories based on observable characteristics, unobservable effects, and the interaction term between the differences in the two points of the wage distribution (Fortin *et al.*, 2011). This analysis aims to answer this counterfactual: how much would female workers be paid if they were paid according to the wage structure of their male counterparts? The analysis compares the observed wage

[1] This estimation allows one to obtain partial effects of explanatory variables on any unconditional quantile of the dependent variable.

structures with counterfactuals, which capture alternative potential wage structures. The study adopts the model used by Canedo (2019), which is given as follows:

$$RIF(W, Q_\theta) = Q_\theta + \frac{\theta - I\{W < Q_\theta\}}{f_w(Q_\theta)} \tag{8}$$

where $f_w(Q_\theta)$ is the density function calculated at a given quantile and $I\{W < Q_\theta\}$ is an indicator function taking the value of 1 when W (log of the wage) is less than Q_θ. Thus, the expected value of the RIF is an unconditional quantile regression (Canedo, 2019). To get decomposition results, the coefficients of the unconditional quantile regression for male and female groups are calculated by employing the Blinder-Oaxaca decomposition approach for each quantile. All these are implemented by imputing the STATA commands provided (see Rios Avila, 2019).

5. Data description and descriptive statistics

5.1 Data Descriptions

This study uses raw data from the 2015/16 Botswana Multi-Topic Household Survey, a nationally representative survey collected by the National Statistics Office. It is one of the comprehensive sources of socio-economic information on Botswana's population. The sample is restricted to only those aged between 18 and 65 who were employed and earned a wage. The study does not include those older than 65 (the retirement age) but still work because they may have a different wage structure from other workers. In choosing the sample, the labour market characteristics of Botswana were considered.

The final dataset has 4,504 observations after all restrictions, 2,269 being males and 2,235 being females. Table 1 shows variables chosen to estimate the model, and they incorporate Botswana's labour market's specific characteristics. The human capital model developed by Mincer (1974) informed the variables and followed Siphambe and Thokweng-Bakwena (2001), with few added variables. These variables included monthly wage income, tenure, education, marital status, employment sectors, union membership, areas of residence, nature of the job, and nationality of the individual.

TABLE 1- *Explanation of Variables*

Variable	Description
Wage	Average monthly wage income
Ln (wage)	The natural logarithm of the wage
Age	Age in completed years
Age squared/100	To cater for non-linear effects
Tenure	Number of years with current employer and divided into 8 categories, starting with those with less than 5 years to those with more than 35 years
Education level	Different educational levels attained:
Non-formal education	Dummy; 1 if non-formal education
Primary education	Dummy; 1 if primary education
Secondary education	Dummy; 1 if secondary education
Vocational training	Dummy; 1 if vocational training
University/college education	Dummy; 1 if university/college
Post-Graduate	Dummy; 1 if post-graduate
Marital status	Status of marriage:
Married	Dummy; 1 if married
Sectors of Employment	The sectors where individuals work:
Public	Dummy; 1 if public
Private	Dummy; 1 if private
Parastatal	Dummy; 1 if parastatal
Non-governmental organisation (NGO)	Dummy; 1 if NGO
Member of trade union	Dummy; 1 if trade union
Area of residence	Where an individual stays:
Cities	Dummy; 1 is a city
Urban villages	Dummy; 1 if an urban village
Rural areas	Dummy; 1 if rural areas
Nature of the job	The status of the current job:
Permanent	Dummy; 1 if permanent
Nationality	Dummy; 1 if a citizen

5.2 Descriptive Statistics

Descriptive statistics provides a summary of all variables used in the model. Table 2 presents means and standard deviations for all observations, separately for males and females. The sample is approximately 50.4% males and 49.6% females. From Table 2, using males' wages as a reference, males, on average, earn more than females; males (W_m) earn P6, 483.46, whereas females (W_f) earn P5, 835.50. Using the usual procedure for measuring the male-female wage gap by Gardeazabal and Ugidos (2005), the raw wage gap $(W_m - W_f)$ was P647.96. Using the monthly wage's natural logs, the wage gap was 16.9% [8.054 - 7.885 = 0.169]. The main question that ought to be answered is what explains the gap. Gardeazabal and Ugidos (2005) noted in their study that the gap was partly due to differences in productivity between males and females. Figure 1 shows a kernel density function curve that indicates that male and female wage distributions are distinguishable. It depicts that at the lower wage distribution, female wage distributions lie to the left of the male wage distributions.

FIGURE 1- *Distribution of Wages for Males and Females*

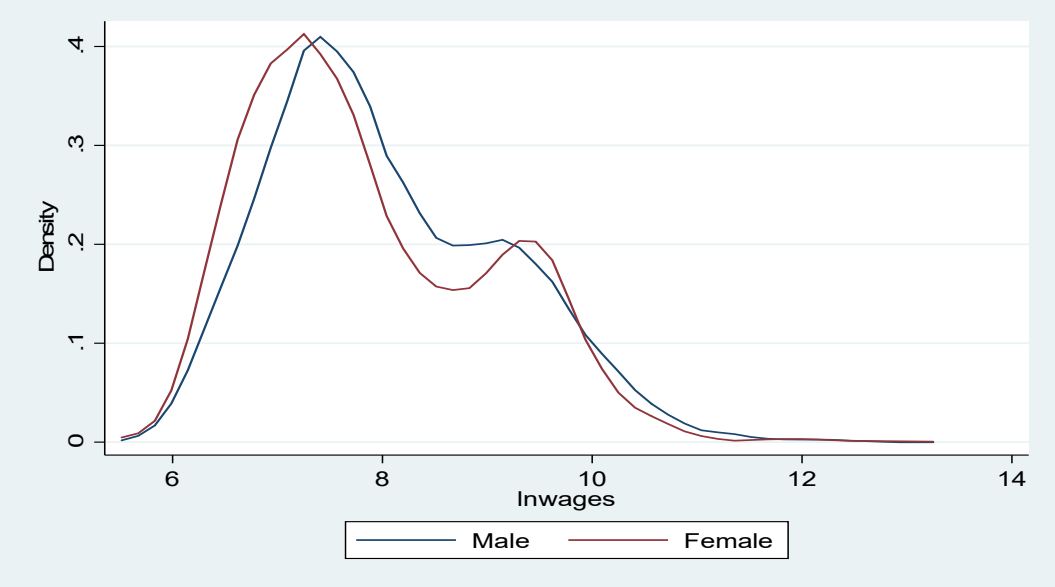

TABLE 2 - *Descriptive Statistics*

Variable	All Obs.		Males		Females	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Wage	6161.93	14245.95	6483.46	12823.46	5835.50	15553.73
Ln(wage)	7.970	1.130	8.054	1.114	7.885	1.139
Age	36.052	10.049	35.665	10.201	36.446	9.880
Age^2/100	14.007	7.798	13.760	7.863	14.258	7.725
Tenure < 5 years	0.552	0.497	0.555	0.497	0.550	0.498
5 < Tenure < 10 years	0.193	0.394	0.194	0.396	0.191	0.393
10 < Tenure < 15 years	0.097	0.296	0.093	0.290	0.102	0.302
15 < Tenure < 20 years	0.066	0.248	0.064	0.245	0.068	0.251
20 < Tenure < 25 years	0.044	0.204	0.043	0.203	0.044	0.205
25 < Tenure < 30 years	0.029	0.168	0.033	0.180	0.025	0.155
30 < Tenure < 35 years	0.012	0.110	0.010	0.100	0.014	0.119
Tenure ≥ 35 years	0.007	0.083	0.007	0.081	0.007	0.084
Non-formal education	0.008	0.087	0.008	0.089	0.007	0.084
Primary education	0.158	0.365	0.187	0.390	0.129	0.335
Secondary education	0.509	0.500	0.508	0.500	0.511	0.500
Vocational training	0.062	0.241	0.062	0.241	0.062	0.242
University/college education	0.242	0.428	0.218	0.413	0.266	0.442
Post-Graduate	0.021	0.144	0.017	0.130	0.025	0.156
Married	0.215	0.411	0.230	0.421	0.199	0.399
Public	0.351	0.477	0.293	0.456	0.411	0.492
Private	0.412	0.492	0.433	0.496	0.391	0.488
Parastatal	0.069	0.254	0.086	0.280	0.052	0.223
NGO	0.016	0.125	0.015	0.120	0.017	0.131
Private Household	0.150	0.357	0.173	0.378	0.127	0.333
Member of trade union	0.260	0.439	0.237	0.425	0.283	0.451
Cities	0.351	0.477	0.363	0.481	0.339	0.473
Urban villages	0.413	0.492	0.373	0.484	0.453	0.498
Rural areas	0.236	0.425	0.264	0.441	0.208	0.406
Permanent	0.686	0.464	0.690	0.463	0.682	0.466
Non-Permanent	0.314	0.464	0.310	0.463	0.318	0.466
Citizens	0.953	0.212	0.936	0.245	0.970	0.169
Non-Citizens	0.047	0.212	0.064	0.245	0.030	0.169
Number of Obs.		**4,504**		**2,269**		**2,235**

In addition, the average age was 36.67 and 36.45 for males and females, respectively. Regarding the years an employee has been with the same employer, more than 50% of all the samples have worked at the same employer for less than five years. Regarding education, 51% of males and females have secondary education, and 22% and 27% have university/college education, respectively. Furthermore, 1.7% of males have post-graduate education, while 2.5% of females have post-graduate education. This is in line with what Siphambe and Motswapong (2010) who found, that, on average, employed females are more educated than their male counterparts in Botswana. Table 2 also shows that 23% of males and 20% of females were married. It is also concluded that 29% and 41% of males and females in the sample, respectively, were in the public sector, whereas 43% of males and 39% of females were in the private sector. The remaining were spread across parastatals, NGOs, and private households. The table further shows that 24% of males and 28% of females were union members, and 69% and 68% of males and females, respectively, were employed permanently. In addition, 36% of males and 34% of females live in cities, 37% and 45% of males and females, respectively, live in urban villages and the rest live in rural areas.

Evidence from Table 2 suggests that males in the public sector earn more than females, and females in the private sector earn more than males. On the other hand, females in parastatals earn considerably less than males (67%), but females earn convincingly more than males in NGOs, 3 times as much on average. This gap is partially unexpected because most NGOs are built on fighting for equal rights and are dominated by females. Furthermore, females earn 1.1 times more than males in rural areas and less than males in cities and urban villages.

6. Empirical results and discussion

This section reports the outcomes of the regression models. Results from quantile regression and decomposition models are reported. The first part of the discussion is the quantile regression results reported at different percentiles, and the second section discusses the unconditional decomposition results. As mentioned in section 5.1, regressions include omitted variables and are run separately for males and females. The coefficients capture the differing returns to male-female characteristics across the wage distribution and observe which aspects yield the most significant differences between male and female returns. The standard errors in quantile regressions were bootstrapped with 200 replications.

6.1 Quantile Regression Results

Tables 3 and 4 show OLS regression results combined with quantile regression results for males and females at the 25th, 50th,75th and 90th percentiles. The OLS regression results are included for comparison purposes. Most of the coefficients are significant and carry the right signs. Results show that the returns to education significantly differ between males and females. First, for both males and females' private returns to education tend to increase as the education level increases and from the lower part of the wage distribution (25th percentile) to the higher positions. These findings are consistent with those of Ncube (2012) and Ntuli (2007). Secondly, across the education level, females have higher returns to education than males in lower and upper wage distribution levels. In terms of experience, these results show that private returns for years spent working increase across the wage distribution for both males and females, implying that experience leads to higher returns.

Furthermore, the table shows that living in areas other than cities generally leads to lower wages. The negative coefficients of the variables for urban villages and rural areas show this. Results also show that males and females with union membership show similar results to those without union membership. The private returns increase across the wage distribution and decrease at the upper part of the wage distribution.

In the case of marital status, being married offers relatively higher returns for males than females, similar to Ncube (2012) and Ntuli (2007). One possible explanation is that married females are negatively affected by being away from work due to maternity duties. Therefore, parenthood and childbearing may serve as potential career interruptions to female employees (Ncube *et al.*, 2011). The results further show that working in the parastatal sector, instead of the public sector, increases wages for both males and females. When comparing the public sector and private households, working for the public sector yields better returns than working in the latter for both males and females.

TABLE 3- *Results from Quantile Regressions for Males*

Variable	OLS	Quantile Regression			
		0.25	0.50	0.75	0.90
Age	0.068	0.056	0.046	0.066	0.094
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Age^2/100	-0.068	-0.058	-0.040	-0.064	-0.097
	(0.000)***	(0.000)***	(0.005)***	(0.000)***	(0.000)***
5 < Tenure < 10	0.220	0.147	0.256	0220	0.175
	(0.000)***	(0.004)***	(0.000)***	(0.000)***	(0.025)**
10 < Tenure < 15	0.275	0.229	0.319	0.327	0.314
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.007)***
15 < Tenure < 20	0.300	0.324	0.311	0.281	0.375
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.010)***
20 < Tenure < 25	0.335	0.327	0.380	0.403	0.358
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.006)***
25 < Tenure < 30	0.525	0.313	0.455	0.606	0.665
	(0.000)***	(0.005)***	(0.000)***	(0.000)***	(0.000)***
30 < Tenure < 35	0.659	0.384	0.485	0.619	1.301
	(0.000)***	(0.041)**	(0.004)***	(0.001)***	(0.013)**
Tenure ≥ 35	0.643	0.419	0.469	0.677	1.547
	(0.001)***	(0.065)*	(0.021)**	(0.001)***	(0.007)***
Non-formal education	0.073	0.064	-0.079	-0.033	0.046
	(0.658)	(0.752)	(0.663)	(0.860)	(0.923)
Secondary education	0.437	0.396	0.430	0.425	0.530
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Vocational training	0.780	0.748	0.833	0.915	0.996
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
University/college education	1.448	1.346	1.501	1.518	1.683
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Post Graduate	1.883	1.817	1.796	1.879	1.816
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Marital status	0.366	0.351	0.306	0.342	0.356
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.002)***
Private	-0.030	0.033	-0.086	-0.111	0.066
	(0.471)	(0.512)	(0.059)*	(0.020)**	(0.387)
Parastatal	0.539	0.513	0.560	0.568	0.459
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
NGO	-1.117	0.064	-0.170	-0.231	-0.187
	(0.347)	(0.673)	(0.209)	(0.103)	(0.411)
Private Household	-0.450	-0.346	-0.477	-0.512	-0.543
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Member of trade union	0.201	0.353	0.196	0.090	0.028
	(0.000)***	(0.000)***	(0.000)***	(0.064)*	(0.698)
Urban villages	-0.134	-0.074	-0.115	-0.221	-0.179
	(0.000)***	(0.079)*	(0.002)***	(0.000)***	(0.012)***
Rural areas	-0.266	-0.218	-0.236	-0.389	0.288
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***

TABLE 3 - *continued*

Variable	OLS	Quantile Regression			
		0.25	**0.50**	**0.75**	**0.90**
Permanent	0.150	0.214	0.103	0.081	0.033
	(0.000)***	(0.000)****	(0.006)***	(0.037)**	(0.637)
Citizenship	-0.109	0.020	-0.068	-0.205	-0.187
	(0.082)*	(0.792)	(0.317)	(0.004)***	(0.171)
Constant	5.853	5.491	6.205	6.470	6.227
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
R^2	0.640				
Adj. R^2	0.636				
Pseudo R^2		0.388	0.451	0.471	0.419

TABLE 4- *Results from Quantile Regressions for Females*

Variable	OLS	Quantile Regression			
		0.25	0.50	0.75	0.90
Age	0.042	0.029	0.025	0.038	0.050
	(0.000)***	(0.016)**	(0.023)**	(0.008)***	(0.048)**
Age^2/100	-0.037	-0.026	-0.017	-0.027	-0.033
	(0.010)*	(0.097)*	(0.023)	(0.154)	(0.324)
5 < Tenure < 10	0.338	0.310	0.389	0.221	0.270
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.004)***
10 < Tenure < 15	0.372	0.382	0.396	0.290	0.382
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.004)***
15 < Tenure < 20	0.471	0.374	0.440	0.385	0.400
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.037)**
20 < Tenure < 25	0.508	0.535	0.405	0.288	0.540
	(0.000)***	(0.000)***	(0.000)***	(0.009)***	(0.009)***
25 < Tenure < 30	0.391	0.547	0.482	0.470	0.361
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.022)**
30 < Tenure < 35	0.666	0.701	0.614	0.363	0.275
	(0.000)***	(0.000)***	(0.000)***	(0.046)**	(0.470)
Tenure ≥ 35	1.158	1.184	0.945	1.114	1.226
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.004)***
Non-formal education	-0.144	0.013	-0.155	-0.328	-0.515
	(0.410)	(0.944)	(0.360)	(0.148)	(0.395)
Secondary education	0.393	0.306	0.319	0.510	0.535
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Vocational training	0.719	0.457	0.656	0.966	1.124
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
University/college education	1.577	1.180	1.742	1.827	1.810
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Post Graduate	2.098	1.966	2.149	2.176	2.004
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Marital status	0.168	0.145	0.157	0.115	0.135
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.159)
Private	0.123	0.125	0.214	-0.031	0.087
	(0.002)***	(0.004)***	(0.000)***	(0.544)	(0.359)
Parastatal	0.426	0.337	0.443	0.565	0.577
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
NGO	0.255	0.269	0.289	0.164	0.285
	(0.027)**	(0.031)**	(0.010)**	(0.275)	(0.350)
Private Household	-0.328	-0.181	-0.127	-0.393	-0.479
	(0.000)***	(0.002)**	(0.015)**	(0.000)***	(0.000)***
Member of trade union	0.320	0.396	0.338	0.250	0.222
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.020)**
Urban villages	-0.129	-0.119	-0.103	-0.129	-0.164
	(0.000)***	(0.001)***	(0.002)***	(0.003)***	(0.012)**
Rural areas	-0.171	-0.200	-0.138	-0.172	-0.184
	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.053)**

TABLE 4 - *continued*

Variable	OLS	Quantile Regression			
		0.25	**0.50**	**0.75**	**0.90**
Permanent	0.299	0.257	0.305	0.262	0.268
	(0.000)***	(0.000)****	(0.000)***	(0.000)***	(0.000)***
Citizenship	-0.136	-0.050	-0.124	-0.192	-0.288
	(0.132)	(0.609)	(0.155)	(0.102)	(0.238)
Constant	5.835	5.766	6.018	6.246	6.375
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
R^2	0.659				
Adj. R^2	0.655				
Pseudo R^2		0.417	0.483	0.505	0.424

6.2 Wage Decomposition Results

Table 5 reports quantile wage decomposition results. The decomposition results used the same variables as the quantile regression analysis. However, completed years rather than categories were used for the tenure variable. These present three decomposition results: endowment coefficients and interaction. Endowments report the predicted change in females' disparity given the same levels of all the variables as males.

In contrast, the coefficients capture the expected change of both groups if endowments are kept identical. Lastly, the interaction component captures the interaction between endowments and coefficients. The results indicate statistically substantial wage differentials across the wage distribution at most levels, except at the 90th percentile. This finding is similar to what Ncube (2012) found.

As evident from the coefficients of raw difference, table 5 shows that the wage gap increases across the wage distribution from the 10th percentile to the median and decreases after. The wage gap increased from 10.3% at the 10th to 25.5% at the 50th percentile, implying that at lower wages, the gap is small and gradually increases as wages increase across the distribution. These results differ from Canedo (2019), where the wage gap decreases across the wage distribution. Findings from the table show that the characteristics (explained) component denotes a small percentage at the lower end of the wage distribution. The share of the characteristics component also increases across the wage distribution. While evidence from the table shows that the coefficients (unexplained) component remains stable, it offers a marginal decline at the 90th percentile. The

RIF-OLS decomposition method also illustrates the extent of the contribution of each variable to the overall gap at different quintiles. The results show that most explanatory variables for the characteristics and the coefficients components are not statistically significant when examined separately.

In contrast, when taken together, they become essential. In terms of the explained component, the results show that the percentage of university/college education characteristics increases steadily from the 10^{th} to the 75^{th} percentile and decreases at the 90^{th} percentile. These results suggest that observable wage differentials due to the university/college education characteristic account for a significant proportion of the wage gap at all wage distribution levels. The results further show similar evidence regarding post-graduate education and parastatal characteristics. Most of the unexplained component's coefficients are statistically insignificant across percentiles; hence, caution is needed when interpreting their effect on the wage gap.

TABLE 5- *Unconditional Quantile Wage Decomposition Results*

Quantile	**⊙=.10**	**⊙=.25**	**⊙=.50**	**⊙=.75**	**⊙=.90**
Wage Differences	0.103	0.220	0.255	0.169	0.083
	(0.001)***	(0.000)***	(0.000)***	(0.028)**	(0.112)
Characteristics					
Age	0.001	-0.041	-0.028	-0.030	0.014
	(0.934)	(0.045)**	(0.087)*	(0.241)	(0.436)
Ageˆ2/100	0.001	0.028	0.015	0.010	-0.030
	(0.931)	(0.097)*	(0.236)	(0.632)	(0.165)
Tenure	-0.002	-0.003	-0.006	-0.005	0.001
	(0.769)	(0.764)	(0.763)	(0.769)	(0.825)
Tenure squared	0.001	0.002	0.004	0.002	-0.003
	(0.793)	(0.783)	(0.781)	(0.813)	(0.793)
Non-formal education	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.862)	(0.794)	(0.956	(0.953)	(0.781)
Secondary education	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.855)	(0.857)	(0.854)	(0.853)	(0.853)
Vocational training	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.995)	(0.995)	(0.994)	(0.994)	(0.995)
University/college	-0.023	-0.029	-0.070	-0.191	-0.076
education	(0.001)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***
Post-Graduate	-0.004	-0.005	-0.012	-0.036	-0.021
	(0.086)*	(0.079)*	(0.070)*	(0.068)*	(0.075)*
Marital status	0.001	0.000	0.006	0.013	0.004
	(0.270)	(0.761)	(0.049)**	(0.049)**	(0.264)
Private	0.013	0.022	-0.005	-0.015	0.004
	(0.010)***	(0.006)***	(0.124)	(0.045)**	(0.260)
Parastatal	0.006	0.010	0.012	0.020	0.014
	(0.005)***	(0.001)***	(0.005)***	(0.034)**	(0.032)**
NGO	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.474)	(0.481)	(0.774)	(0.892)	(0.559)
Private Household	-0.002	-0.013	-0.029	-0.021	0.005
	(0.703)	(0.012)**	(0.000)***	(0.003)***	(0.107)
Trade union	-0.004	-0.011	-0.011	-0.035	-0.006
membership	(0.094)*	(0.002)***	(0.012)**	(0.005)***	(0.262)
Urban villages	0.007	0.008	0.011	0.019	0.017
	(0.009)***	(0.019)**	(0.013)**	(0.022)**	(0.006)***
Rural areas	-0.014	-0.017	-0.008	-0.016	-0.006
	(0.002)***	(0.001)***	(0.037)**	(0.038)**	(0.214)
Nature of the job	0.003	0.003	0.002	0.002	0.001
(1=Permanent)	(0.555)	(0.554)	(0.559)	(0.584)	(0.662)
Citizenship	0.002	0.008	0.006	-0.008	-0.004
	(0.553)	(0.083)*	(0.208)	(0.306)	(0.535)
Total	-0.014	-0.041	-0.115	-0.293	-0.087
	(0.324)	(0.051)*	(0.000)***	(0.000)***	(0.002)***

TABLE 5 - *continued*

Coefficients					
Age	3.043	0.970	2.043	1.561	1.052
	(0.003)***	(0.224)	(0.008)***	(0.204)	(0.325)
Age^2/100	-1.199	-0.485	-1.014	-0.962	-0.596
	(0.017)**	(0.217)	(0.009)***	(0.142)	(0.327)
Tenure	-0.096	-0.173	-0.138	-0.137	0.037
	(0.230)	(0.014)**	(0.127)	(0.386)	(0.790)
Tenure squared	0.033	0.081	0.066	0.081	-0.029
	(0.363)	(0.016)	(0.160)	(0.352)	(0.737)
Non-formal education	0.000	0.005	0.002	0.000	0.004
	(0.916)	(0.111)	(0.463)	(0.912)	(0.156)
Secondary education	0.018	0.057	-0.018	-0.043	-0.010
	(0.782)	(0.256)	(0.743)	(0.608)	(0.865)
Vocational training	0.001	0.010	0.001	-0.008	0.009
	(0.908)	(0.214)	(0.931)	(0.664)	(0.435)
University/college	0.006	-0.013	-0.067	-0.008	0.152
education	(0.858)	(0.616)	(0.038)**	(0.000)***	(0.004)***
Post-Graduate	-0.001	-0.004	-0.010	-0.029	0.045
	(0.792)	(0.194)	(0.021)**	(0.001)***	(0.002)***
Marital status	-0.012	0.023	0.036	0.038	0.095
	(0.305)	(0.034)**	(0.032)**	(0.261)	(0.003)***
Private	0.020	-0.159	-0.083	0.020	0.087
	(0.556)	(0.000)***	(0.022)**	(0.770)	(0.089)*
Parastatal	-0.002	-0.013	-0.007	0.020	0.044
	(0.655)	(0.001)***	(0.316)	(0.187)	(0.002)***
NGO	-0.002	-0.010	-0.005	-0.007	-0.006
	(0.619)	(0.026)**	(0.272)	(0.333)	(0.318)
Private Household	-0.056	-0.079	-0.023	0.021	0.037
	(0.008)***	(0.000)***	(0.108)	(0.336)	(0.019)**
Trade union	0.018	-0.033	0.004	-0.081	-0.043
membership	(0.249)	(0.027)**	(0.870)	(0.152)	(0.335)
Urban villages	0.050	0.043	-0.009	0.015	-0.009
	(0.015)**	(0.091)*	(0.795)	(0.790)	(0.852)
Rural areas	-0.051	-0.032	-0.018	0.012	0.000
	(0.006)***	(0.063)*	(0.341)	(0.713)	(0.995)
Nature of the job	-0.091	-0.239	-0.044	-0.033	-0.003
(1=Permanent)	(0.096)*	(0.000)***	(0.415)	(0.688)	(0.960)
Citizenship	0.072	0.147	-0.038	-0.127	-0.231
	(0.629)	(0.294)	(0.801)	(0.633)	(0.347)
Constant	5.843	0.232	-0.298	0.275	-0.507
	(0.000)***	(0.608)	(0.501)	(0.690)	(0.372)
Total	0.191	0.327	0.380	0.360	0.130
	(0.000)***	(0.000)	(0.000)***	(0.000)***	(0.008)***

TABLE 5 - *continued*

Interaction					
Age	-0.065	-0.021	-0.044	-0.033	-0.023
	(0.056)*	(0.297)	(0.072)*	(0.280)	(0.386)
Age^2/100	0.042	0.017	0.035	0.034	0.021
	(0.127)	(0.321)	(0.113)	(0.258)	(0.412)
Tenure	0.001	0.002	0.001	0.001	-0.000
	(0.819)	(0.780)	(0.802)	(0.846)	(0.940)
Tenure squared	-0.001	-0.001	-0.001	-0.001	0.000
	(0.853)	(0.796)	(0.821)	(0.851)	(0.931)
Non-formal education	0.000	0.000	0.000	0.000	0.000
	(0.975)	(0.795)	(0.859)	(0.974)	(0.803)
Secondary education	-0.000	-0.000	0.000	0.000	0.000
	(0.961)	(0.889)	(0.954)	(0.933)	(0.975)
Vocational training	-0.001	-0.000	-0.000	0.000	0.000
	(0.999)	(0.996)	(1.000)	(0.998)	(0.997)
University/college	-0.001	0.002	0.012	0.047	-0.028
education	(0.863)	(0.631)	(0.075)*	(0.004)***	(0.023)**
Post-Graduate	0.001	0.001	0.003	0.009	-0.014
	(0.816)	(0.325)	(0.163)	(0.114)	(0.117)
Marital status	-0.002	0.004	0.006	0.006	0.015
	(0.370)	(0.116)	(0.113)	(0.331)	(0.058)*
Private	0.002	-0.017	-0.009	0.002	0.009
	(0.558)	(0.011)**	(0.083)*	(0.784)	(0.160)
Parastatal	-0.001	-0.008	-0.004	0.012	0.028
	(0.655)	(0.008)***	(0.336)	(0.212)	(0.011)**
NGO	0.000	0.002	0.001	0.001	0.001
	(0.774)	(0.491)	(0.605)	(0.632)	(0.625)
Private Household	-0.020	-0.029	-0.008	0.008	0.013
	(0.025)**	(0.001)***	(0.138)	(0.358)	(0.041)**
Trade union	-0.003	0.005	-0.001	0.013	0.007
membership	(0.289)	(0.067)*	(0.875)	(0.197)	(0.368)
Urban villages	-0.009	-0.008	0.002	-0.003	0.002
	(0.028)**	(0.111)	(0.798)	(0.793)	(0.854)
Rural areas	-0.014	-0.009	-0.005	0.003	0.000
	(0.022)**	(0.093)*	(0.363)	(0.720)	(0.995)
Nature of the job	-0.001	-0.003	-0.001	-0.000	-0.000
(1=Permanent)	(0.624)	(0.561)	(0.731)	(0.845)	(0.980)
Citizenship	-0.003	-0.005	0.001	0.005	0.008
	(0.636)	(0.310)	(0.805)	(0.640)	(0.362)
Total	-0.074	-0.067	-0.010	0.104	0.041
	(0.000)***	(0.000)***	(0.478)	(0.000)***	(0.127)

Note: ***, **, *: statistically at 1%, 5%, and 10%, respectively. Values in parentheses below parameter estimates are p-values. Standard errors were bootstrapped with 200 replications.

7. Conclusions and policy implications

Gender wage differentials have received increasing attention in developing and developed countries. Earlier studies focused on wage differentials at the mean pioneered by Oaxaca's seminal work. More recent studies focused on wage differentials along wage distribution. This paper's primary focus was to assess gender wage differentials in Botswana using the quantile regression and wage decomposition methods. The study contributes to the existing literature on gender wage differentials by using a methodology that captures the differentials across wage distribution. Overall, the findings of this study are two-fold. First, empirical evidence shows that gender wage gap exists in the Botswana labour market. The raw gender wage gap between males and females is 17%. The quantile regression results show that returns to education are significantly different between males and females. Private returns to education for both tend to increase as the education level increases and from the lower part of the wage distribution (25^{th} percentile) to higher parts, with females getting higher returns than males. These results confirm the importance of education. Additionally, as education level increases, females have higher returns to education than males in the lower and upper levels of wage distribution.

Second, the unconditional quantile wage decomposition results indicate that female employees were paid less on average than their male counterparts. The gap increased across the wage distribution, from 10.3% at the 10^{th} percentile to 25.5% at the median and fell to 16.9% at the 75^{th} percentile. These results imply that the gap at lower wage levels (10^{th} percentile) is smaller than at high wage levels (50^{th} and 75 percentiles), showing that the gap is felt at high wage levels, hence the presence of the "glass ceiling" effect. The evidence described in the paper has significant policy implications. This paper concludes that reasonable access to education leads to higher returns on wages; hence, continuing investing in education and improving the education system is crucial for the country. Higher education gives females a competitive edge over their male counterparts. In addition, the society should promote female empowerment to change common perceptions of female workers in the labour market. There is also a need for employers to attract males into highly feminised sectors to help address the wage gap problem and occupational segregation. This paper reviewed the status of male-female wage differentials in Botswana to stimulate debates and further research.

8. LIMITATIONS OF THE STUDY

Due to limited availability of longitudinal data over time, this study could not examine the gender wage gap where a worker is tracked for some time. Therefore, the study used the available independent survey. Further, the study is descriptive and could not account for issues of potential endogeneity of choice of the sector and the option to participate in the labour force. Therefore, the wage gap estimates could be biased upwards. Due to the potential bias, the study has reported OLS estimates and compared them with the quantile regression results to show that OLS is inappropriate when estimating determinants of the wage gap.

Further, the study could have benefited from other labour market characteristics such as experience, years of schooling, on-the-job training information and the role played by unions over time. Additionally, for the gender wage differentials, there is a need to include more individual characteristics such as maternity or paternity leave information, promotion and secondment attachments to other sectors. Such information does not exist in Botswana at the moment.

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