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Does Gender Wage Gap Exist among Farm Workers in Nigeria? Evidence from Decomposition-Matching Analysis

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Abstract. Using a cross-sectional survey data of agricultural farms, we investigate gender-based differences in farm wages among farm workers by randomly allocating farm workers into treatment (female) and control (male) groups with a simple random sampling technique. We used the Blinder–Oaxaca decomposition method to establish the gender wage gap and Propensity Score Matching to address assumptions and heterogeneity difficulties that plague the decomposition technique. Results show that female farm workers earn ₦9,170.83 less compared to their male counterparts, which indicates an unadjusted gender gap. This gender gap in farm wages is explained by the specific factors included in our model, so upgrading these variables could reduce gender inequalities in farm wages. Matching results indicate that the gender gaps estimated with nearest neighbour matching and kernel-based matching are 9.8% and 21.6% higher, respectively, than the gaps measured by the decomposition technique. Thus, the matching procedure was successful in identifying a sizeable proportion of gender gaps that are unexplained due to discrimination between male and female farm workers.

Keywords: decomposition, farm workers, gender wage inequality, labour, matching, wage gap

JEL Classification: J01, J16, J31

1. Introduction

Most people in Africa, south of the Sahara, work in agriculture. The phenomenon known as "casualization" occurs as a result of decreased pressure on labour costs brought on by the increased industrialization of agriculture and increased global competition. In order to supplement their revenue, independent smallholder farmers are becoming more and more dependent on paid labour. For women, these patterns have important implications. The increasing proportion of women in the labour market is one of the most obvious current trends. For example, women make up more than 45% of the Nigerian workforce (World Bank, 2019). In both rural and urban areas between 1990 and 2009, women's participation in the formal and informal labour market increased, but it remained lower than that of men (Olowa and Adeoti, 2014). There is a significant gender education gap, with net enrolment rates for boys and girls of 70 percent and 58 percent respectively (World Bank SCD, 2018). A lack of investment in women limits their ability to enter the labour market, work successfully, and advance into more secure, high-paying employment (Enfield, 2019).

Both men and women work in agriculture as wage or family workers. Unlike wage labour, which is remunerated, family labour is not, but family members always appreciate it (Ajah, 2012). According to FAO (2011), the amount of family labour that a household can mobilize and the amount of labour that can be hired in local labour markets affect labour availability. According to the data, the wage gap between men and women is the highest and lowest at the top of the income distribution, while wages for hired farm workers are low (Blau and Kahn, 2017). Several studies have been undertaken to estimate the value of work in agriculture (Haruna et al., 2010; Jirgi et al., 2011; Lawal et al., 2008; Anyanwu, 2010; Iheke and Nwaru, 2009; Okoye et al., 2009). According to all research results, labour input has a significant impact on agricultural production and productivity (Ajah, 2012). Because of their position and responsibilities within the family, both men and women can own farms. Housekeeping is by far the most widespread form of employment in agriculture, while employment is rare. Households without paid labour, whether agricultural or non-agricultural, produce primarily for their own use (subsistence) or for modest profits, from which households purchase their essentials for consumption. According to the World Bank SCD (2018), most women are stuck in low-paying jobs due to the high proportion of women in agriculture (73.5 percent). It is evident from the value of labour in agriculture that work, whether performed by men or women, has a substantial impact on the growth of agriculture. But this is also one of the key reasons why men and women fight, particularly in poor nations like Nigeria. The gender wage gap, or the discernible discrepancy between men's and women's wages, has been the subject of political debate and economic research for several decades (ILO, 2009). Suffragettes and feminists have argued that wages for women's work are lower than for men's work. Despite the fact that women are seen as more involved in agricultural production, they claimed that women were underpaid in agriculture, as men earned more than women. According to several studies (Fontana, 2009; ILO, 2009; Ahmed and Maitra, 2010), typically women are paid less than males for jobs with equivalent levels of education and experience (Ajah, 2012).

The evidence attempts to explain wage differentials in the workplace in terms of observable individual characteristics (such as education, experience, occupation and occasionally motivation, expectations, and field of study) and horizontal and vertical employment segregation. While the wage gap has decreased generally in size over time, Blau, Lawrence, and Kahn (2006) found that the percentage of the disparity that cannot be accounted for by characteristics connected to human capital is growing. These factors can account for a sizeable portion of the gender pay gap, although most analyses, according to the OECD (2009), leave out a sizeable portion of the disparity. The unexplainable aspect of the gender pay gap demonstrates the impact of covert problems such as discrimination against women in the workplace. Since it is rarely obvious and there are measurement challenges, it is challenging to determine just how much it contributes to the magnitude of the wage gap. Gender wage gaps, segregation, and inequality in productive sectors, including agriculture, are significant global challenges that require gender mainstreaming in policy frameworks (Adam, Osano, Birika, Amadi, and Bwisa, 2017; Bryant, 2006; Holmes and Slater, 2008; Kilu, 2017; Mbilinyi, 2016; Orr et al., 2016; Peterman, Quisumbing, Behrman, and Nkonya, 2011; Mensah-Bonsu et al., 2019). Some studies in Nigeria have examined pay disparities across a range of occupations, but they have not specifically focused on gender (Aderemi, 2015; Aromolaran, 2006; Ogwumike et al., 2006). Aminu (2010) evaluated the effects of government wage review policies on the pay difference for urban male and female workers in the public and private sectors in his most recent and sole study on gender pay gap. Furthermore, to the best of our knowledge, none of these studies have attempted to close or at least narrow the gender pay gap in agribusiness.

This study would add to the existing body of literature on gender and wage gaps among Nigerian farm workers. Reducing the wealth gap between men and women is high on the Nigerian government's policy agenda, as evidenced by a series of induction programmes. Understanding these differences is crucial to achieving gender equality and tackling wage stagnation and poor pay more generally. Given that women are paid equally for an equal amount of work, determining the gender pay gap among hired agricultural workers is crucial for social justice (Fisher et al., 2021). However, for economic growth, the importance of labour as a factor of production and the gender wage gap among agricultural workers are particularly relevant to discussions about sustainable food policy in sub-Saharan Africa.

The remainder of this work is structured as follows. Section 2 focuses on a global review of relevant literature, and Section 3 presents the methodology, sampling technique, data collection, and estimation strategy. In Section 4, we report the results of the empirical findings and discussion, while Section 5 concludes the study and draws policy recommendations.

2. Review of Relevant Literature

Women in Nigeria have advanced significantly in the workplace during the past three decades, with higher labour force participation, notable increases in educational attainment, growth in employment in higher-paying occupations, and notable increases in real income. Despite these improvements, there is still a gender pay gap that favours men in almost all occupations (Fapohunda, 2013). The prevalent consensus is that salaries for men and women are different. Equal pay laws were passed in Nigeria about 40 years ago. Gender equality laws have been strengthened by the Equality Act 2010 and the Gender Equality Duty 2007, which is mandatory for all public organizations. However, Nigeria still has a long way to go to achieve equality in the workplace. Nigeria, where women are underrepresented in higher-paying, more prestigious positions, has one of the largest gender pay discrepancies in the world, according to the UNDP (2009). The lower pay for women adversely affects their families and children due to the resulting financial instability. When workers are well rewarded, they are driven to perform better (Fapohunda, 2013). Nigerians perceive unemployment as being considerably more urgent than poverty despite the fact that it is estimated that one third of the country's population lives in poverty (World Bank, 2015). Prior to 2015, the country saw a very high and sustained economic growth although this had minimal effect on the poverty rate. Nigeria has emerged from its 2016 recession, according to the magazine Enhancing Financial Innovation & Access (EFInA, 2018). The formal economy employs only 8% of adults, and thus even modest gains in economic growth have not had a favourable effect on employment rates. 11.2 percent work in their own businesses unrelated to farming, 16.7 percent own their own firms, and 23.4% rely on farming as their primary source of income (EFInA, 2018). Olowa and Adeoti (2014) assert that women's engagement in the job market is greatly impacted by their level of education. Olowa and Adeoti (2014) used data from the Harmonized National Living Standard Survey to analyse the effects of education on women's labour market involvement in rural Nigeria (NLSS, 2010). Women work in non-farm enterprises in 26.85% of the cases and on farms in 73.15 percent. The primary agricultural, forestry, and fishing activities on these farms are agriculture and angling. Non-farm activities include, among other things, manufacturing, sales, and services (Enfield, 2019).

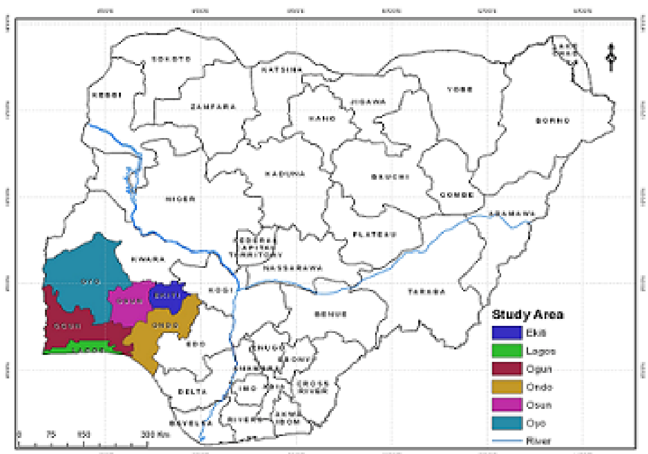
In Nigeria, a person's career path is mostly determined by their birth circumstances, including their residence, gender, and the line of employment of their parents. For instance, general Household Survey panel statistics show that 50% of the children of agricultural workers are employed in the industry (Enfield, 2019). This demonstrates how factors like skills, effort, and talents – which should generally have an impact on job outcomes – are typically unrelated to personal opportunity and employment outcomes (World Bank, 2015). Discrimination against women is pervasive in the workplace. They make less money for the same amount of education and experience, are less likely to be active than men are, and are more likely to work in low-paying fields like agriculture and unofficial occupations (World Bank, 2015). Ekerebi and Adeola (2017) stress how male and female farmers' crop values differ from one another. Women do a wide range of duties and make up between 60 and 80 percent of the labour force, making them the backbone of the agricultural industry. Despite the importance of their work, female farmers have less access to resources and less control over their plots than male farmers (FAO, 2011). A gender discrepancy in crop value was noted in both the southern and northern regions. Female farmers use less fertilizers and are less likely to use irrigation or automated farming techniques despite the fact that male farmers have more household wealth and better crop values (Enfield, 2019). Differences in wealth, education, and access to irrigation may contribute to some of the variations in crop value (Ekerebi and Adeola, 2017).

According to Hertz et al. (2009), men in Ghana made 31% more money than women in urban areas and 58% more money in rural areas. The Women on Farms Project (WFP) and the Centre for Rural and Legal Studies (CRLS) conducted research on this in 2009. According to the survey, women received 457 rand on a monthly basis, while men received an average of 667 rand. With the exception of rural Panama, where women made an average of 11% more than men, Hertz et al. (2009) found that women in rural regions earned on average 28 percent less than men. Economic and gender inequality are interrelated and reinforce each other. In Nigeria, women are subjected to a wide range of traditional and sociocultural discriminatory practices that have an impact on their lives and disadvantage them relative to males in a number of circumstances. For instance, just 28% of the wealthiest males and 75.8% of the poorest women never attended school. Women are much less likely than men to own land. Additionally, women favour low-paying, unskilled employment (British Council, 2012). Men typically occupy permanent positions in export value chains, whereas women are typically hired as temporary or casual employees (Deutsche Gesellschaft für Internationale Zusammenarbeit, 2013). The growth and productivity that are fuelled by agriculture can be significantly impacted by empowering women. Given equal access to supplementary resources such as education, women would be equally productive as agricultural producers as men and could provide comparable returns (USAID, 2011).

3. Data and Methods

The Study Area

We conducted our research in southwest Nigeria. The region, which is presented in *Figure 1*, is located between latitudes 6N and 4S and longitudes 4W and 6E and is made up of six states: Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo. It covers roughly 114,271 km^2 in size. South-west Nigeria experiences 1,200–1,500 mm of annual rainfall on average, with monthly average temperatures that range from 18–24 °C in the rainy season to 30–37 °C in the dry season (Adepoju et al., 2011). Due to the rich alluvial soil, agriculture predominates in this region of the country. Cassava, corn, yam, coconut yam, cowpea, vegetables, and cash crops such as cacao, kola nut, rubber, citrus, coffee, cashew, mango, and oil palm are among the main food crops.



Source: authors' compilation (2022)

Figure 1. *Map of Nigeria showing the south-western region*

Sampling Method

A three-stage sampling process was used to select respondents for this study. The first phase involved a random selection of 50% of the states in the south-west region of the country (i.e. Ogun, Osun, and Oyo). In the second phase, 8 agricultural companies (including crop production, poultry/livestock farming, and agro-processing) were randomly selected from each state, amounting to a total of 24 companies. The list of registered agricultural workers was retrieved from the respective national associations of agricultural companies (arable farmers, poultry/

livestock, and agro-processing). In the third phase, 30 farm workers (15 male and 15 female) were randomly selected from each of the farms, totalling 720 (360 male and 360 female) respondents.

Data Collection and Analysis

The World Bank Survey Solutions application was used to collect empirical data via a survey questionnaire that was deployed on tablets running the Android operating system. The questionnaire was divided into categories according to our study's objectives. Before answering questions posed by the surveyors, respondents were required to sign a consent form. All respondents were encouraged to leave at any moment during the survey if they felt uncomfortable. Every respondent received sufficient information regarding our study's goal and the benefits of participating. To quantify the gender pay gap and determine how much of it is due to socioeconomic factors, various agricultural activities (farming, livestock, poultry, and agricultural processing and marketing) and how much is not accounted for and may be the result of discrimination, we used parametric (Blinder–Oaxaca decomposition) and non-parametric (Propensity Score Matching, PSM) methods. The gender wage gap was determined using the Blinder–Oaxaca decomposition analysis (Blinder, 1973; Oaxaca, 1973), but the PSM has the advantage of avoiding the parametric assumptions of the Blinder–Oaxaca method and addressing the heterogeneity problems that plague the parametric decomposition methods (Ñopo, 2008). As a result, PSM encourages comparable comparisons. In short, the two methods are complementary, and their combination allows for a robustness check of the results.

Estimation Strategy

Blinder–Oaxaca decomposition: The Blinder–Oaxaca decomposition technique has been extensively used in the literature (Fisher et al., 2021) to investigate the possible reasons of intergroup differences in outcome variables. We used the Blinder–Oaxaca decomposition technique (Blinder, 1973; Oaxaca, 1973) to measure and explain gender differences in wage payments in this study. This has become a standard method for separating "gaps" in outcome variables such as farm workers' wages among different population groupings. Estimating the wage pay equation for male and female subsamples is the first step in the Blinder–Oaxaca decomposition method:

$$Y_i = \beta_i X_i + \varepsilon_i, \tag{1}$$

where Y is the wage's natural log, i represents male (m) and female (f) hired farm workers, X represents a vector of control variables, and β shows the average change in Y that corresponds to a unit change in X. The statistical error term ε, which is a random variable that explains why the model cannot fit the data perfectly, is used to correct for the other explanatory factors in the model. Our specification of X followed Barham et al. (2020), who examined the key variables affecting wages, annual income, and poverty levels of US farm workers, and Fisher et al. (2021), who analysed farm workers and the gender pay gap in US agriculture. The vector X includes the socioeconomic characteristics (such as age, marital status, education, household size), farm job characteristics (job tenure, hours worked, various farm job tasks such as land preparation and cultivation, harvest and post-harvest handling, or processing), and the state fixed effects. The estimated male–female wage disparity is then divided into components that can be explained and that remain unexplained:

$$\bar{Y}_m - \bar{Y}_f = \hat{\beta}_m(\bar{X}_{\boldsymbol{m}} - \bar{X}_{\boldsymbol{f}}) + \bar{X}_f(\hat{\beta}_{\boldsymbol{m}} - \hat{\beta}_{\boldsymbol{f}}) = E + U, \tag{2}$$

where $\bar{Y}$ and $\bar{X}$ indicate the dependent and explanatory variables' means, $\hat{\beta}_m$ and $\hat{\beta}_f$ are the estimates of the parameters in equation (1) for male and female farm workers separately, $\bar{Y}_m$ and $\bar{Y}_f$ are the expected mean values of the dependent variable for the subsamples of male and female farm workers, $\bar{X}_m$ and $\bar{X}_f$ represent the average values of vector variables for male and female farm workers that determine their wage pay, and $\hat{\beta}_m - \hat{\beta}_f$ denotes the vector of estimated returns to the wage gap factors for male and female farm workers respectively. The percentage of the average salary gap between men and women that is due to variations in the measurable attributes of men and women is shown in the first set of terms following the first equal sign in Equation (2); this is often referred to as the "Explained Gap", or "Endowment Effect" (E). The second set of terms following the first equal sign in Equation (2) stands for the fraction of the gender pay difference caused by changes in returns on unmeasured qualities, also known as the "Unexplained Gap" (U). However, some studies have linked the unexplained gap to women's increased demand for time flexibility in the workplace (Goldin, 2014; Fisher et al., 2021), weaker bargaining skills (Babcock and Laschever, 2009), and less competitive nature (Niederle and Westerland, 2007). The impact of discrimination as well as any unmeasured traits that are correlated with both gender and farm wages are included in the upper measure of pay discrimination known as U. This measure also takes into account the influence of unmeasured factors.

Propensity Score Matching (PSM): Due to differences in the empirical distribution of attributes, the Blinder–Oaxaca decomposition could not be accurate when used between male and female farm workers (Frlich, 2007; Ñopo, 2008). According to Frlich (2007), this misspecification can be addressed by Propensity Score Matching (PSM), which enables us to distinguish between and compare farmers taking account of the observations between men and women. According to Frlich (2007), PSM is well suited to distinguish between wage differentials caused by discrimination and other unobserved factors and those caused by unequal human capital endowments. Meara et al. (2020) and Fisher et al. (2021) published two recent studies that used PSM to examine the gender wage gap among agricultural workers. PSM was therefore employed to evaluate the common disparity in farm pay between male and female agricultural labourers. A binary choice model calculates the propensity score, which in this example indicates the likelihood that a farm labourer is female, in the first PSM step. We employ a logit model to regress the binary female variable on the previously mentioned explanatory variables, *X*. Then, using a matching algorithm, we matched each female farmworker to one or more male farmworkers depending on how close their propensity scores were. After estimating the propensity for each group of farmworkers, we estimated the average treatment on the treated (ATT) adopting the most widely used matching approaches in the literature, such as nearest neighbour matching (NNM) and kernel-based matching (KBM), pioneered by Heckman (1997). We were able to compare the propensity values between the treatment and control groups using nearest neighbuor matching. Then, using these modified controllers, the counterfactual is built for the treated entities. Using the weighted average of the outcomes, kernel matching determines the difference between each outcome observation in the treated group and the control group. Each control group is given a weight based on their distance from the treatment unit. An overview of how to understand various matching estimators is provided by Heckman et al. (1998), Dehejia and Wahba (2002), and Frölich (2004). Following Hosny (2013), we represent the two ATT matching estimators as follows:

$$ATT = \frac{1}{n^1}\sum 1\left\{(Y_{1i}|T_i = 1) - \sum jr_1(Y_{0i}|T_i = 0)\right\}, \tag{3}$$

where n^1 is the total number of treatment cases, and *r* stands for a system of scaled weights that calculates how far apart each control unit and the intended treatment unit are from one another. According to Morgan and Harding (2006), the main differences between these estimators are the weight given to multiple matches (r) when more than one is employed and the number of matches determined for each target case to be matched. The mean treatment effect on those treated (ATT) is estimated using Equation (4) and by averaging the within-game variations in the outcome variable (farm wages) between the treated and control groups (Rosenbaum and Rubin, 1985; Dehejia and Wahba, 2002), as follows:

$$E(Y_1 - Y_0|T = 1, P(x))] = E[E(Y_1|T = 1, P(x)) - E(Y_0|T = 0, P(x))] \tag{4}$$

In the final PSM phase, differences between matched treatment and control cases are calculated for the outcome variable (log of farm earnings). The average treatment effect, a measurement of the unexplained gender pay disparity in farm wages, is the sum of these changes.

Results and Discussion

Descriptive Statistics Results

Table 1 presents the descriptive statistics of all variables of interest for our sample of farm workers. We use the t-test statistics technique to estimate the descriptive statistics of our selected samples. Using this technique, we were able to examine whether there are indeed differences between the treatment and control groups with regard to the explanatory variables. For this study, our treatment variable is a female farm worker, while a male farm worker was used as a control and was constructed as a binary variable taking values of 1 and 0 respectively. Significant differences existed in both the binary and continuous variables included in our descriptive analysis for the sampled farm workers. Our outcome variable is farm wages, which was measured in term of naira per month. Our outcome (farm wages) was supported by Fisher et al. (2021), who examined farm workers and gender wage gap in US agriculture and used real wage per hour as a measure of outcome variable. By average, our results show that the farm wage was ₦38,320.83/month for men and ₦29,150.00/month for female farm workers. Female farm workers were likely to receive about 24% less monthly wages than their male counterparts. This finding shows a gender gap in wages among farm workers, which is statistically significant ($p < 0.01$), and this could be influenced by some socioeconomic and institutional factors. Our result corroborates the work of Fisher et al. (2021), who revealed a gender difference in real wage among US farm workers. Our results show that farm workers are on average 37.54 years old for the full sample. When comparing the age of agricultural workers between men (38.49 years) and women (36.65 years), there was no significant age difference between the two categories at 0.01%. However, this finding suggests that they are all at a young and active age. Results indicated that the average number of years of schooling was 7.54 years for male and 6.34 years for female farm workers, respectively, in the entire sample. The educational levels of male and female farm workers are not significantly different. This finding supports the earlier work of Fisher et al. (2021), where no significant difference was found among US agricultural workers. The high rate of transition from basic to higher education observed among male and female farm workers suggests why education is more valued especially in southwest Nigeria. This supports the FAO's (2013) claim that Nigeria's literacy rate has been rising since 1991; from 66.4 percent in 2008 to about 80 percent in 2015. In addition, the average household size of farm workers in the male subsample was 8.13 people, while in the case of the female colleagues was 6 people. In comparison, there is a significant difference between the two categories at 1%. Results in *Table 1* show that the majority of male and female farmworkers had more than 10 years of farming experience, with a significant difference observed between the two groups ($p < 0.01$).

Table 1. *Descriptive statistics, overall and by gender*

Variable	Total sample (N = 720)		Male farm workers (n = 360)		Female farm workers (n = 360)		Mean difference	t-values	p-values
	1		2		3				
	Mean	S.D.	Mean	S.D.	Mean	S.D.	(2-3)		
Dependent variable									
Farm wage (₦/month)	33735.42	8395.42	38320.83	8480.92	29150.00	5206.449	9170.83	14.277	0.000***
Socioeconomic characteristics									
Age of farm worker (years)	37.54	7.522	38.49	8.097	36.65	6.800	1.775	2.601	0.004***
Marital status (1 = married, 0 = otherwise)	1.16	0.365	1.21	0.407	1.11	0.311	0.100	3.023	0.000***
Education (years of schooling)	6.94	5.695	7.54	5.710	6.34	5.628	1.200	2.319	0.925
Household size (number)	7.06	1.533	8.13	1.251	6.00	0.939	2.121	20.996	0.002***
Farm work experience (years)	13.07	4.151	13.34	5.134	12.79	2.833	0.554	1.464	0.000***
Membership of labour union (1 = yes, 0 = otherwise)	0.78	0.417	0.88	0.331	0.68	0.468	0.196	5.292	0.000***
Number of years of residence in the village	14.51	6.085	13.2	7.689	15.81	3.417	-2.604	-4.795	0.000***
Job characteristics									
Job status (1 = permanent, 0 = otherwise)	0.48	0.501	0.54	0.499	0.42	0.495	0.121	2.663	0.114*
Job skill (1 = skilled, 0 = otherwise)	0.62	0.486	0.70	0.457	0.53	0.499	0.171	3.906	0.000***
Lives on farm (1 = yes, 0 = otherwise)	0.31	0.462	0.37	0.483	0.25	0.434	0.117	2.784	0.000***
Average work hours (hours/month)	41.71	9.366	47.95	7.244	35.48	6.726	12.471	19.544	0.688
Farm work/activities									
Crop farming	0.25	0.432	0.23	0.424	0.26	0.469	-0.029	-0.739	0.140*
Poultry	0.29	0.457	0.33	0.469	0.27	0.443	0.058	1.400	0.005**
Livestock	0.23	0.422	0.29	0.454	0.18	0.381	0.113	2.943	0.000***
Agro-processing	0.22	0.412	0.15	0.354	0.29	0.454	-0.142	-3.816	0.000***

Source: field survey (2022)

Notes: T-test was performed to test differences in socioeconomic characteristics between male and female farm workers; *, **, *** means significance at 10, 5, and 1% respectively.

This was consistent with the results of Tsue et al. (2014), who found that the majority of arable farms have more than 10 years of experience. In addition, *Table 1* shows that 88% of male and 68% of female farm workers for the respective subsample are members of labour unions. A statistically significant difference was observed between male and female farm workers ($p < 0.01$). Further results in *Table 1* showed that the average number of years of residence in the community was 14.51 years for the entire sample. To compare the two groups, 13.2 years was the average length of stay in the community among male farmworkers, while that of their female counterparts was 15.81 years. This difference is also statistically significant at 1%. *Table 1* reveals gender-based disparities in the job status of male and female farm workers, which are statistically significant ($p < 0.1$). Also, statistically significant gender-based disparities are found in some job characteristics. For instance, half of the male farm workers are members on the permanent staff of their respective farms compared to 42% of female farm workers. This gender-based difference suggests that temporary/casual labour is more common among female farm workers. The use of casual labour as observed among the majority of female farm workers is against the International Labour Law. The job skill is also far lower among female farm workers, with about 25% lower than male farm workers who live on farms. Female farm workers were slightly (26%) more involved in crop farming activities than male farm workers (23%), which reflects a significant difference at 0.01. In comparison to male farm workers, female farm workers were less engaged in poultry (27%) and livestock (17%) firms but worked more (29%) in agro-processing farms.

Blinder–Oaxaca decomposition

The results of the Blinder–Oaxaca decomposition are presented in *Table 2* and show the estimated gender difference for our outcome variable (farm wages) and the net explained and unexplained proportions of the measured differences. *Table 2* shows that female farm workers earn ₦9,170.83 less compared to their male counterparts and thus indicate an unadjusted gender gap. The overall percentage of the unadjusted gender gap explained was 10.79%, and most of this gender gap in farm wages can be accounted for by the variables included in our model. In the unexplained gap, our results show that female farm workers earned ₦8,181.33 less in monthly farm wages compared to male farm workers. This unexplained component indicates that some of the gender farm wage gap is due to unmeasured factors and/or discrimination against female workers, while the explained difference may be due to variables included in our model, suggesting that the observed difference might be due to differences in endowments between male and female farm workers. The results of our unexplained gender gap confirm previous findings by other researchers, who observed several reasons underlying the unexplained gap, such as: Goldin (2014) – women's greater demand for flexibility at work; Babcock and Laschever (2009) – lower negotiation skills; Niederle and Vesterland (2007) – lower desire for competition.

Table 2. *Summary of the results of the Blinder–Oaxaca decomposition*

Wage decomposition	Coefficient	Robust Standard Error
Predicted male farm workers' wage mean	38320.83***	546.939
Predicted female farm workers' wage mean	29150.00***	335.746
Difference (unadjusted gap)	9170.833***	641.769
Explained gap	989.509	1055.693
% Explained gap (% of total)	10.79	
Unexplained gap	8181.325***	1233.414
% Unexplained gap (% of total)	89.21	

Source: authors' computation (2022)

Note: *** means statistically significant at 0.001 significance level.

Contributions of Individual Covariates to Explained Gender Gap

The contributions of each covariate included in our model to the explained part of the gender difference in farm wages are shown in *Table 3*, where the positive percentages indicate variables that increase gender inequality, while negative percentages indicate the opposite. In our results, we found that seven variables explained most of the gender difference in farm wages among farm workers. These variables are reflected in socioeconomic (age, marital status, household size, and number of years in the village) and occupational characteristics (occupational status and average hours worked per month). The majority (90%) of the explained gender gap in farm wages shows that female farm workers earn lower wages, have fewer people in their household, and have less farm work experience compared to their male counterparts. In addition, female farm workers work fewer hours and are less involved in farming activities than men.

Our results show that female farm workers are on average 1.78 years younger compared to their male counterparts (*Table 1*), and farmers' age accounts for about 6.76% of the explained gap (*Table 3*). In addition to socioeconomic differences, 6.96% of the explained gender gap in farm wages is due to female farm workers marrying less often than their male counterparts. In addition, female farm workers have on average fewer family members (*Table 1*) than male farm workers, explaining about 38.94% of the explained gender gap in farm wages (*Table 3*). Female farm workers are most involved in temporary or casual work, meaning they are less permanently employed in farm work compared to their male counterparts, accounting for 12.37% of the declared gender gap in farm wages. *Table 1* shows that female farm workers worked on average 12.47 hours less than their male counterparts, and this is directly responsible for a large proportion (60.09%) of the explained gender gap in farm wages. Our findings are in line with those of Cha and Weeden (2014), who demonstrated that one major factor contributing to the persistence of the wage gap between men and women was the higher prevalence of long hours for men compared to women, along with a higher profitability for overwork compared to full-time work. As observed in recent studies (Fisher et al., 2021; Kiefer et al., 2020; Fairlie and Robb, 2009), most of the gender difference in outcome variables can be strongly explained by demographic/socioeconomic, human, and physical characteristics.

Table 3. *Detailed estimates of the Blinder–Oaxaca decomposition analysis: model variables and their percentage contribution to the explained gap*

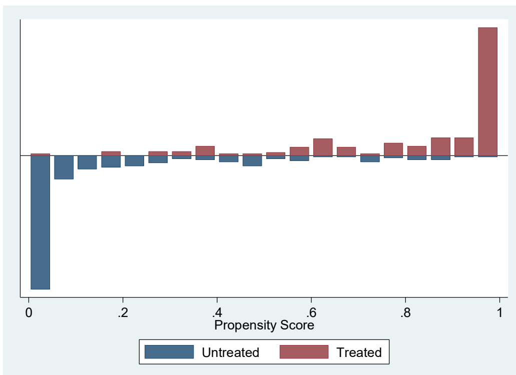
Variable	Coefficient	Standard Error	% Contribution
Socioeconomic characteristics			
Age of farm worker (years)	66.906*	87.701	6.76
Marital status (1 = married, 0 = otherwise)	68.873**	95.293	6.96
Education (years of schooling)	17.752	69.320	1.79
Household size (number)	385.330*	738.573	38.94
Farm work experience (years)	-11.039	48.068	-1.12
Membership of labour union (1 = yes, 0 = otherwise)	-74.564	142.815	-7.54
Number of years of residence in the village	243.690	170.247	24.63
Job characteristics			
Job status (1 = permanent, 0 = otherwise)	122.376***	89.881	12.37
Job skill (1 = skilled, 0 = otherwise)	-319.507**	141.721	-32.29
Lives on farm (1 = yes, 0 = otherwise)	88.017	94.994	8.89
Average work hours (hours/month)	594.606*	574.958	60.09
Farm work/activities			
Crop farming	-0.419***	28.607	-0.04
Poultry	6.767***	57.322	0.68
Livestock	-145.687**	130.134	-14.72
Agro-processing	-53.591*	127.682	-5.42

Source: authors' computation (2022)

Note: *, **, *** mean significant at 10, 5, and 1%, respectively.

Propensity Score Matching

To ensure a consistent and reliable matching, we performed some diagnostic tests before proceeding with our matching and addressing the heterogeneity difficulties that plague the Blinder–Oaxaca method's parametric assumptions. We also looked at how well the covariate distribution used to forecast the propensity score model was balanced by the matching technique (Rosenbaum and Rubin, 1983). After generating propensity scores for the farm workers in the treatment (female) and control (male) groups, the overall support condition was assessed to confirm that the covariates did not differ (*Figure 2*). The common support graph in *Figure 2* presents the similarities in characteristics between the treatment (female) and control groups (male) of farm workers. This *Figure 2* depicts the distribution of propensity scores and the common support region between female farm workers (upper portion) and male farm workers (lower portion).



Source: authors' computation (2022)

Figure 2. *Propensity score matching and common support region between treated and control cases: kernel-based with outcome variable (farm wages)*

The computed propensity scores' distribution reveals that the common support condition is satisfied, as there is a significant overlap in the propensity scores of both treated and untreated. Since selection bias in the treatment group has been addressed due to observed covariates and heterogeneity difficulties, our findings could now attribute any change in farm wage to gender gap. In addition, we further carried out a covariate balancing test for the matching technique to ensure that both treatment (female) and control (male) farm workers are similar under the same characteristics and the quality of common support condition. *Table 4* presents the results of the covariates' balancing property test. Our results show that none of the covariates are significant after matching, meaning that our quality of matching is satisfactory for all covariates used in the model. Therefore, both female and male agricultural workers exhibited similar characteristics of their covariates.

Table 4. *Test of equality of the means of variables before and after matching*

Variable	Unmatched Sample				Matched Sample			
	Mean		% Bias	p > |t|	Mean		% Bias	p > |t|
	Female (treatment)	Male (control)			Female (treatment)	Male (control)		
Age of the farm worker	38.43	36.65	23.70	0.010***	36.95	36.97	-0.40	0.988
Marital status	1.21	1.11	27.60	0.003***	1.24	1.19	14.90	0.578
Education	7.54	6.34	21.20	0.021**	8.89	8.05	14.80	0.467
Household size	8.13	6.01	191.70	0.000***	6.95	6.92	2.40	0.883
Farm work experience	13.34	12.79	13.40	0.144	14.38	13.84	13.00	0.637
Membership of labour union	0.88	0.68	48.30	0.000***	0.89	1.00	-26.70	0.240
Number of years of residence in the village	13.20	15.81	-43.80	0.000***	13.76	14.14	-6.40	0.812
Job status	0.54	0.42	24.30	0.008***	0.59	0.65	-10.90	0.637
Job skill	0.70	0.53	35.70	0.000***	0.57	0.65	-16.90	0.482
Lives on farm	0.37	0.25	25.40	0.006***	0.27	0.19	17.70	0.414
Average work hour on farm	47.95	35.48	178.40	0.000***	43.65	44.32	-9.70	0.613
Crop farming	0.23	0.26	-6.70	0.46	0.19	0.16	6.20	0.764
Poultry	0.33	0.27	12.80	0.162	0.41	0.54	-29.60	0.250
Livestock	0.29	0.18	26.90	0.003***	0.19	0.22	-6.50	0.776
Agro-processing	0.15	0.29	-34.80	0.000***	0.22	0.11	26.60	0.212

Source: authors' computation (2022)

Note: Levels of significance represented by the symbols *, **, and *** are 10%, 5%, and 1% respectively.

The results of the overall covariate equalization test showing the unaligned (before matching) and the equal (after matching) are shown in *Table 5*. Pseudo-R^2 shows the significance of the explanatory variables in explaining the likelihood of female farm workers earning less wages compared to their male counterparts. The combined importance of equality between the genders of farm workers in the covariate distribution was represented by the p-values of the probability ratio test. In addition, *Table 5* shows a significant reduction in the value of the pseudo-R^2 from 0.946 (94.6%) unmatched to 0.058 (5.8%) matched. A low pseudo-R^2 after matching, according to Caliendo and Kopeinig (2008), does not necessarily indicate systemic changes in the distribution of variables between the treated and untreated groups. Thus, our results show that the matching procedure was able to identify a control group with similar observable characteristics as the treatment group. The *p*-values from the likelihood ratio test show that the joint significance was accepted for both the unmatched and matched samples (*p*-value = 0.000). Also, the standardized mean bias for all covariates decreased from 52.8% before matching to 13.5% after matching. Our results show that matching reduces bias by 83.2%. Therefore, the successful balancing of the distribution of covariates between the treatment and control can be seen by the decrease in high overall bias, the insignificant p-values of the likelihood ratio test after matching, the decreased Pseudo-R^2, and a significant decrease in the mean standardized bias.

Table 5. *Indicators of the overall matching quality both before and after matching*

Sample	Pseudo- R^2	LR χ^2	p > (χ^2)	Mean standard bias	Bias	Total % bias reduction
Unmatched	0.946	629.48	0.000***	52.8	328.6	
Matched	0.058	96.81	0.000***	13.5	55.1	83.2

Source: authors' computation (2022)

Note: *** means significance level at 1%.

Results in *Table 6* show the estimated differences in outcome (farm wages) between female and male farm workers. The average treatment effect (ATE) across the two matching methods is reliable for our outcome variable (farm wages). *Table 6* shows that the average treatment effect (ATE) is 9070.833 for nearest neighbour matching (NNM) and 10433.33 for kernel-based matching. The gender gaps/ differences estimated with Nearest Neighbour Matching (NNM) is 9.8 percentage point higher (farm wages) and 21.6 percentage points higher with Kernel-Based Matching (KBM) than those measured with the Blinder–Oaxaca decomposition technique. The disparities could be attributed to many factors, and one of the factors contributing to low wages among farm workers is second shift, which is expected to burden rural farm workers disproportionately, as they are likely to have less flexibility in the workplace and less access to high-quality daycare (Budig, 2014). Therefore, the unexplained component of the gender gap is relatively robust for both parametric and non-parametric approaches used to measure it.

Table 6. *Results of the propensity score matching estimation*

Sample	Average Treatment Effect (ATE)		
	Coefficient	**Robust Standard Error**	***z*-statistic**
Nearest Neighbour Matching (NNM)	9070.833	759.274	11.95***
Kernel-Based Matching (KBM)	10433.330	1036.411	10.07***

Source: authors' computation (2022)

Note: *** means significance at 1%.

Conclusions

In our study, we estimated and explained the gender differences in farm wages among farm workers in Nigeria using a cross-sectional survey data of agricultural farms. We employed a randomized controlled experiment by randomly allocating farm workers into treatment group (female) and control group (male) with a simple random sampling technique. To measure the size of the gender gaps, we employed both parametric (Blinder–Oaxaca decomposition) and non-parametric (Propensity Score Matching, PSM) approaches to estimate how much of the wage gap is explained by socioeconomic characteristics and various agricultural jobs (farming, livestock, poultry, and agro-processing) and how much is unexplained and could be due to discrimination and other factors. While our study used the Blinder–Oaxaca (Blinder, 1973; Oaxaca, 1973) decomposition to measure the gender wage gap, PSM, which has the advantage of eliminating the Blinder–Oaxaca method's parametric assumptions and addressing the heterogeneity difficulties that plague parametric decomposition methods (Ñopo, 2008), was employed to test for the robustness of the decomposition results, and we found an unexplained gender gap very close to the Blinder–Oaxaca estimate. Our results of the Blinder–Oaxaca decomposition analysis show that female farm workers earn ₦9,170.83 less compared to their male counterparts and thus indicate an unadjusted gender gap. The explained total percentage of the unadjusted gender gap was 10.79%, and most of this gender gap in farm wages is explained by the variables included in our model. The percentage of the gender wage differential, as explained by variables included in our model, would be decreased if female farm workers had the same socioeconomic, job/task, farm characteristics as their male counterparts. With regard to the unexplained gap, our findings show that female farm workers earned ₦8,181.33 less in monthly farm wages compared to male farm workers.

Our matching results indicate that the average treatment effect (ATE) is 9,070.833 for Nearest Neighbour Matching (NNM) and 10,433.33 for Kernel-Based Matching. The gender gaps when estimated with Nearest Neighbour Matching (NNM) were 9.8% points higher (farm wages) and when using Kernel-Based Matching (KBM) were 21.6 percentage points higher than the gaps measured with the Blinder–Oaxaca decomposition technique.

Our policy recommendations are: female farm workers' earnings can be improved by increasing their work hours per month, which have been the main factor contributing to inequalities in farm wages, and this may be due to household responsibilities and childcare. Improving women farm workers' access to affordable, quality childcare and domestic work will increase their labour force participation and experience or lengthen their working hours, making it easier for them to participate on equal terms with men.

In terms of the contribution of individual characteristics (such as the average work hours/month, household size, job status, marital status, and age) to the proportion of the gender difference explained, the role of these variables is therefore noteworthy. Upgrading these variables would reduce gender inequalities in farm wages. Also, since workers' educational attainment is closely linked to labour market possibilities, increased female educational levels would also increase their representation in managerial and farm occupations, which will thus eventually contribute to bridging the gender pay gap over time. Finally, the use of casual labour by agricultural private firms should be discouraged, and labour standards, including strong antidiscrimination laws, need to be promoted in order to close the gender gap in farm wages. Such a legislation would promote equality and a regulation prohibiting discrimination in job positions, salary scales, and criteria for entering the agricultural labour market.

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