Global Science Research Journals

Available online at www.globalscienceresearchjournals.org

Global Journal of Agricultural Economics, Extension and Rural Development

Full Length Research Article Open Access

ISSN: 2408-5480 Vol. 10 (1), pp. 01-07
March, 2022

Gender Analysis of Technology Adoption by Oil Palm Processors in South West, Nigeria

Ajoke Bankole[1*], Oseni JO[2]

[1]Department of Agricultural Economics, Nigerian Institute for Oil Palm Research, Benin City, Edo State, Nigeria.

[2]Department of Agricultural and Resource Economics, Federal University of Technology, Akure, Nigeria.

*Corresponding author. E-mail: ajsbankole@gmail.com

Received: 14-Jan-2022, Manuscript No. GJAEERD-22-47743; **Editor assigned:** 17-Jan-2022, PreQC No. GJAEERD-22-47743 (PQ); **Reviewed**: 31-Jan-2022, QC No. GJAEERD-22-47743; **Revised**: 18-Feb-2022, Manuscript No. GJAEERD-22-47743 (R); **Published**: 25-Feb-2022, DOI: 10.15651/2408-5480.22.10.001

ABSTRACT

The study analyzed gender differential in the adoption of technology among oil palm processors in South West Nigeria. The primary data were collected with the aid of structured questionnaire. Multistage sampling technique was used to select 320 (160 males and 160 females) oil palm processors. Data collected were analyzed using descriptive statistics and endogenous switching regression model. The female adopter (414.968 litres) had higher output than the male adopter (363.290 litres). Factors influencing adoption decision of the female processors are education, access to credit, experience, and awareness of processing technology, extension services and age. Factors influencing adoption decision of the male processors are experience, awareness, ownership of machinery, extension services and education. The study revealed that adoption of technology enhances output of female processors more than the male and also, adoption of technology increases the output of the adopters compared to the non-adopters. Furthermore, under female gender, variables such as educational status, access to credit, extension services, association belong to, experience and family size were statistically significant in influencing output among adopters processors while variables such as age, educational status, access to extension services, marital status and depreciation cost on fixed items had significant impact in influencing output among male gender's adopters.

Keywords: Gender, Technology, Adoption, Oil palm, Processors

INTRODUCTION

Some agricultural products like oil palm, cocoa and rubber cannot be used except when processed; of which majority is cash crop. Oil palm is one of these essential products which has served Nigeria and can serve as foreign exchange earnings for developing countries. The processing of oil palm can be improved on through adoption of improved technology so as to increase productivity. The local/manual method of processing is still being used in some part of the country. Method of processing oil palm in some part of south west Nigeria is still the combination of old traditional method and partly use of the improved technology(semi-mechanized). This semi-mechanizes method involves the use of the digester to pound and ground the fruits while the traditional method is use to extract the palm oil (Figure 1). Doss (2018) opined that gender is an important analytical part for understanding and filtering the impacts of agricultural technologies, development interventions and the impacts of agricultural development investments, irrespective of those (female or male) focused as technology users or beneficiaries. Thus, a gender lens is essential for assessing the effectiveness and impact of an agricultural technology or intervention.

The contributions of women to agricultural productivity cannot be over emphasized. For instance, report has shown that the contribution of women to agricultural production world-wide has been on daily increase over the past decade despite many agricultural programs struggle to capture the difference gender effect (Kanesathasan et al., (2012). Thus, according to Olagunju et al., (2013), it is necessary that policy makers pay attention to the women in agriculture because women were found to be more productive in their output than male.

Figure 1: Local method of extracting palm oil.

Objectives

- Determine and compare the impact of the technology used on output of male and female processors.
- Determine and compare factors influencing the adoption of processing technology of the male and female processors; in south west.

METHODOLOGY

This study was carried out in South Western part of Nigeria. The study adopts a multi-stage sampling procedure. The first stage involved purposive selection of Ondo and Ekiti States out of the six States in Southwest, Nigeria based on the predominance of oil palm processing enterprises. The second stage involved purposive selection of four (4) Local Governments Areas (LGAs) based on concentration of oil palm processing enterprise from each State. The Local Governments Areas were, Okitipupa, Irele, Akure North and Ifedore of Ondo state and Ekiti state were Gbonyi, Ise, Emure and Ikere. The third stage involved purposive selection of four (4) oil palm dominated processing communities from each LGA. The fourth stage involved stratified selection of 10 respondents (5 males and 5 females) from each community in order to adequately capture both genders. This gives a total sample size of 320 oil palm processors but only 275 was valid for the study. Majority of the male from each community are not involved in oil palm processing hence 93 male respondents are used for the analysis of the study [1].

Endogenous Switching Regression Model (ESRM)

Endogenous Switching Regression Model (ESRM) was used to estimate impact of improved technology on processors' output. Given that matching strategies only control for heterogeneity effects due to observable covariates, hence to account for endogeneity bias and effects of unobservable covariates, this study considered ESR model approach most appropriate. Therefore, the study specified the model for impact of technology adoption to comprise: the selection equation that describes the behaviour of the processor as he faces the two regimes of using adoption of improved technology or not [2]. To model adoption decision and its impact on processors' output, two-stage framework was applied following Di Falco et al. (2011), Abdulai (2016) and Oparinde (2019). In the first stage, a selection model for decision to adopt improved technology: a processor takes the decision to adopt if the modern technology generates net benefits. The selection equation is defined as:

$$I_i^* = \alpha Z_i + \mu_i \text{ with } I_i^* = \begin{cases} 1 \text{ if } I_i^* > 1 \\ 0 \text{ otherwise} \end{cases}$$

Where I_i^* is the unobservable variable for improved technology adoption, and I_i^* is its observable counterpart which is the dependent variable (adopters) which equals one, if the processor adopted the technology, and zero otherwise. α is a vector of parameters while Z_i are non-stochastic vectors of observed factors determining adoption of technology and μ_iis random disturbances associated with the adoption of modern technology. The model considered here describes the behaviour of a processor i that faces a decision on whether or not to adopt processing technology. The processor i will choose to adopt if *^*>0 and will choose not to, if otherwise. The vector, $_i$, comprises of variables that affect the expected benefits of adoption. Let the indicator variable be taking a value of 1 for processor who decided to adopt processing technology and 0 otherwise. This leads to two possible situations: a decision to adopt (Z_i= 1) and not to adopt (Z_i= 0), and two population units: adopters and non-adopters. The criterion function, I_i in equation (1) determines which regime the processor will face. Let's denote the benefits to the processor not adopting processing technology by I_0 and the benefit stream from the adoption of processing technology by I_i^*.

Under a random utility framework, a rational processor will choose to adopt if the net benefit is positive i.e. . The net benefit is represented by a latent variable which is itself a function of observed characteristics Z-i and error term μ_i. Conditional on processor's decision to adopt processing technology denoted by a selection function, $_i^*$, there are two potential outcomes to the population units: the outcome of non-adopter $(y_0)$and the outcome of adopter (y_1). This can be put in a 'potential outcome framework' as:

+

$$y_i = \begin{cases} y_{1i} \text{ if } I_i^* = 1 \\ y_{0i} \text{ if } I_i^* = 0 \end{cases}$$

The benefit from treatment (treatment impact) is provided as $y_{1-}y_0$. Nonetheless; the challenge here is that either of the outcomes is observed for a random sample of processors causing a 'missing data' problem. Hence, taking a simple difference and averaging cannot give the effect of the treatment [3]. In the endogenous switching model, the behaviour of a processor is described with two outcome equations and a selection function that determines which regime the processor faces. processor's decision to adopt processing technology is represented by this latent variable framework following Abdulai (2016) and Oparinde (2019).

$$I_i = \begin{cases} 1 & \text{if } \; I_i^* > 1 \\ 0 & \text{if } \; I_i^* \leq 0 \end{cases}$$

Conditional on selection, the two outcome regression equations where processors face the regimes of adopting or not adopting processing technology are defined by a switching regime as follows:

if

$$y_{0i} = \beta_0 X_{0i} + \varepsilon_{0i} \quad \text{if } I_i = 0$$

Z represents a vector of observable variables that determine the decision to adopt such as processor's characteristics and system level variables.

In the continuous equations, are the outcome variables (output);

$_{0i}$ were vectors of explanatory variable assumed to be weakly exogenous

were vectors of parameters to be estimated; and

The random error terms of the continuous $_{0i}$ and the selection equations u_i are assumed to follow a trivariate normal distribution with zero mean vector.

Determination of the impact of technology used on processors' output

The ESRM was used to estimate impact of adoption of processing technologies on processors' output. The likelihood ratio tests for joint independence of the equations in ESR specifications showed that the models are dependent. The correlation coefficients (ρ) in the specifications were significant, indicating that the selection bias due to unobservable factors occurred in adoption. Hence, the use of ESR model, which account for both observable and unobservable factors, is appropriate in this study.

The negative and significant signs for ρ indicate positive selection bias suggesting that processors with above-average annual income have higher probability of adopting the technology. This result is consistent with earlier studies by Abdulai and Huffman (2014) and Abdulai (2016) but contrasts with the result by Kabunga et al. (2012). The log likelihood ratio is significant at 1% indicating that the model has overall a good fit.

Determination of adoption decision among female respondents

The results from the selection equation were presented in Tables 1. The empirical results in the selection equation can be interpreted as normal probit coefficients. Seven variables positively influenced adoption decision of female respondents. The coefficient of age of female processors was negative but statistically significant [4]. This indicates that older female processors are less likely to adopt the technology than the younger female processors. The results were similar to the views of Ullah et al. (2015) and Oparinde (2019) who traced the inverse relationship of age and adoption decision to their inability to cope with the laborious nature of the processing activities and the adoption of risk management strategies. Younger female processors may have better understanding of the processing techniques probably because they may be more enlightened than the older female processors [5].

The coefficient of educational status of the female respondents was positive and significant at 5% level. This indicates that more educated female processors are more likely to adopt the technology than the uneducated female processors. This implied that education will increase the probability of adopting technology. According to Abdulai in his study on adoption of CA technology noted that the estimate of the variable education, which is positive and statistically significant in all specifications at conventional levels, suggesting that more educated and informed processors are more likely to adopt technology on their firms, is a finding that is consistent with the literature that education is important in farmers' decisions to adopt agricultural technologies. In the same vein, this is in line with Olawuyi and Olawuyi, who reported that number of years spent in school increased adoption of technology [6].

Access to credit had positive coefficient and statistically significant at 5%. This means that the female processors who had access to credit are more likely to adopt the technology. This implied that accessibility to credit will increase probability of adopting technology. This result is in support of outcome of the studies by Deressa et al. (2011) and Oparinde (2019) who reported that access to credit will increase adoption of technology [7].

The coefficients of access to extension services was negative and statistically significant at 10%. This means that female processors who had inadequate access to extension services are less likely to adopt the technology. This implied that extension services are very pertinent in adoption of technology. The coefficients of depreciation cost on fixed items were statistically significant and positive in the case of female respondents. The more the depreciation cost of the female respondents the more likely the chance of adopting processing technology [8]. The year of processing experience had positive and significant coefficients at 5% for the female respondents. This indicated that more years of processing experience, the more likely the adoption of technology.

The instrument variable representing awareness of technology was statistically significant at 10% level, meaning that awareness of processing technology will increase the chance of adoption of the technology by the female processors. This is consistent with the finding by Abdulai (2016), who emphasized that awareness on the part of farm operator is a prerequisite for the adoption of technology, but disagreed with the findings of Oparinde (2019) who observed an inverse relationship between the variable awareness and adoption of technology [9].

Variable	**Selection**		**Adopters**		**Non-adopters**	
	Coefficient	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Constant	-1.478	0.231	218.548	0.038	270.731	0.821
Age	-0.006	0.067	19.567	0.123	-1.006	0.11
Education	0.066	0.045	115.556	0.071	3.48	0.04
Credit	0.258	0.012	-719.95	0.034	136.869	0.01
Machinery ownership	0.629	0.456	-32.467	0.432	-13.126	0.122
Land acquisition	0.141	0.209	-103.77	0.211	-18.992	0.345
Extension services	-0.33	0.049	-59.301	0.021	-64.125	0.1
Association	-0.112	0.219	132.244	0.027	7.083	0.089
Marital status	0.162	0.299	372.52	0.43	-5.273	0.111
Depreciation cost	6.96E-07	0.079	-0.004	0.091	0.002	0.5
Experience	0.015	0.022	20.478	0.011	5.337	0.037
Family size	0.005	0.127	-47.51	0.001	-6.833	0.005
Awareness	0.035	0.019				
$\ln\sigma_1$			7.079	0		
ρ_1			-1	0.067		
$\ln\sigma_2$					5.613	0.001
ρ_2					0.714	0.02
Log likelihood	-1480.064					
Likelihood ratio independence: χ^2 (l)	41.75					

Table 1: Full information maximum likelihood estimates of endogenous switching regression model for adoption and impact of adoption on female output.

Determination of adoption decision among male respondents

The results from the selection equation were presented in Tables 2. The empirical results in the selection equation can be interpreted as normal probit coefficients. Six variables positively influenced adoption decision of the male respondents. Age of the male processors had negative coefficients and was not statistically significant. This indicates that older male processors are less likely to adopt the technology than the younger male processors. The coefficient of educational status of the male respondents was statistically significant at 5% but negative. This implied that higher education by male processors will reduce the likelihood of adopting processing technology. The negative relationship of educated male respondents and adoption decision does not follow apriori expectation, and this might affect the adoption of the technologies that could increase revenue among the male processors [10]. The coefficients of ownership of machinery was positive and statistically significant at 1%. This indicates that owners of machinery are more likely to adopt the technology. The coefficients of access to extension services was positive and statistically significant at 5%. This implied that the male processors who have access to extension services are more likely to adopt the technology. Genius et al. (2014) also find extension to be a strong determinant of technology adoption which agreed with the findings. The coefficients of depreciation cost on fixed items were statistically significant at 5% but negative in the case of male. This means that increase in the depreciation cost reduces the likelihood of adopting processing technology. The year of processing experience had positive and significant coefficients at 5% level. This indicates that the more years of processing experience the male processors have the more likelihood of adopting the technology.

The variable awareness of technology was positive and statistically significant at 10% level. This means that the more awareness the male processors have the more likelihood of adopting the technology. This is consistent with the finding by Abdulai (2016), who emphasize that awareness on the part of farm operator is a prerequisite for the adoption of technology, but disagreed with the findings of Oparinde (2019) who observed an inverse relationship between the variable awareness and adoption of technology.

Variable	Selection		Adopters		Non-adopters	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	-1.638	0.269	41.566	0.992	-624.15	0.22
Age	-0.019	0.981	-1.381	0.049	-4.814	0.231
Education	-0.04	0.029	51.973	0.06	2.083	0.05
Credit	-0.22	0.329	24.886	0.034	-122.994	0.714
Machinery ownership	0.747	0.003	-244.541	0.876	-29.391	0.649
Land acquisition	0.012	0.91	-14.061	0.321	6.934	0.213
Extension services	0.657	0.021	-107.135	0.021	197.034	0.099
Association	-0.561	0.033	-15.129	0.984	69.735	0.213
Marital status	1.261	0.411	174.489	0.024	9.522	0.044
Depreciation cost	9.31E-06	0.011	0.005	0.099	0.002	0.067
Experience	0.013	0.058	14.159	0.847	23.733	0.027
Family size	-0.04	0.604	35.964	0.535	29.907	0.008
Awareness	0.051	0.089				
$\ln\sigma_1$			5.86	0.007		
ρ_1			-0.431	0.122		
$\ln\sigma_2$					5.689	0
ρ_2					0.011	0.051
Log likelihood	-710.818					
Likelihood ratio independence: χ^2 (I)	23.15					

Table 2: Full information maximum likelihood estimates of endogenous switching regression model for adoption and impact of adoption on male output.

Impact of determinants

The estimates in the outcome equation representing the columns of adopters and non-adopters were shown in Tables 1 and 2. This showed the impact of socioeconomic factors of the processors on output. The impact results revealed that under female category, variables such as educational level, access to credit, association, experience and family size were statistically significant in addressing output among adopters and non-adopters'. This implies that variables that had positive coefficients among female respondents tend to contribute to increasing output while those variables with negative coefficients tend to contribute to decreasing output. Again, variables such as educational status, access to extension services, marital status, depreciation cost on fixed items, years of experience, and family size had significant impact in addressing output among male respondents' adopters and non-adopters in the study area. This implies that variables that had positive coefficients among male respondents tend to contribute to increasing output, while those variables with negative coefficients tend to contribute to decreasing output [11]. The results on output and adoption technology are in line with other findings like Abdulai and Huffman (2014) for Ghana who indicated that good knowledge and firm understanding of a technology from education may increase the benefits of increasing output. The results are similar to the findings of Abdulai (2016) who also reported that variables like education, access to credit, association belong to and experience had significant impact in output generation as regards to the adoption of technology. Again, this study supports Saqib et al. (2016) who stated that agricultural credit plays vital role as it has significant impacts on farmers' production as well as the annual income of the farmers.

On Table 3 are presented the impact of adoption of technology on output of the processors from the ATT estimates of the ESR specification. To examine the impact, the Average Treatment effects (ATT) on the treated adopters were estimated. It is worthy of note that ATT estimates account for other confounding factors which include selection bias resulting from potential differences between adopters and non-adopters. The results indicated that adoption significantly increases outputs of the female and male respondents in the study area. The expected (mean) output from female respondents' adopters was 414.97litres compared with the non-adopters (238.58 litres), while the male respondents' adopters had 363.29litres compared to 261.82litres of the non-adopters. The indication is that the difference means increase in causal effect in the output of the processors in both female and male respondents [12]. The percentage increase in the female respondents was 73.9% which is far higher than that of male respondents which is 38.8%. Abdulai stated that technology contributes to the enhancement of farm productivity and household returns on investment as well as reduce rural poverty. Likewise, Oparinde (2019) ascertained that adoption of technology strategies is capable of enhancing output and therefore reducing food insecurity and as well bridging supply-demand gaps in food production.

Mean outcome					
	Adopter	**Non-adopter**	**ATT**	**t-value**	**Difference (%)**
Female	414.968	238.583	176.385	33.935	73.9
Male	363.29	261.818	101.472	11.218	38.8

Table 3: Impact of technology adoption.

CONCLUSION

Factors influencing adoption decision of the female processors are education, access to credit, experience and awareness of processing technology, extension services and age. Factors influencing adoption decision of the male processors are experience, awareness, ownership of machinery, extension services and education. The study revealed that adoption of technology enhances output of female processors more than the male and also, adoption of technology increases the output of the adopters compared to the non-adopters.

RECOMMENDATION

- Government and NGOs should provide oil palm improved processing technology at subsidized rate for processors.
- Access to extension services is a pertinent key to decision to adopt processing technology for both male female processors hence government should provide adequate extension services for oil palm processors.
- Policy makers should pay attention to the female processors in agriculture especially in oil palm processing, because female was found to be more productive in their output compared to their male counterpart.

REFERENCES

1. Abdulai AN (2016). Impact of conservation agriculture technology on household welfare in Zambia. Agricul Econ. 47(6):729-741.
2. Abdulai A, Huffman W (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. Land Econ. 90(1):26-43.
3. Deressa TT, Hassan RM, and Ringler C (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. J Agricul Sci. 149(1):23-31.
4. Di Falco S, Veronesi M, and Yesuf M (2011) Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. Am J Agricul Econ. 93(3):829-846.
5. Doss CR (2018). Women and agricultural productivity: Reframing the Issues. Deve Policy Rev. 36(1):35-50.
6. Genius M, Koundouri P, Nauges C, and Tzouvelekas V (2014). Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. Am J Agricul Econ 96(1):328-344.
7. Heckman JJ, Ichimura H, and Todd PE (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. Rev Econ Stud. 64(4):605-654.
8. Kabunga NS, Dubois T, and Qaim M (2012). Yield effects of tissue culture bananas in Kenya: Accounting for selection bias and the role of complementary inputs. J Agricul Econ. 63(2):444-464.
9. Miranda A, and Rabe-Hesketh S (2006). Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables. Stata J. 6(3):285-308.
10. Oparinde LO (2019). Fish output and food security under risk management strategies among women aquaculture farmers in Ondo State, Nigeria. Agris On-line Papers Econ Informat. 11(1):93-105.
11. e Saqib S, Ahmad MM, Panezai S, and Ali U (2016). Factors influencing farmers' adoption of agricultural credit as a risk management strategy: The case of Pakistan. Int J Disast Risk Reduct. 17:67-76.
12. Ullah R, Jourdain D, Shivakoti GP, and Dhakal S (2015). Managing catastrophic risks in agriculture: Simultaneous adoption of diversification and precautionary savings. Int J Disast Risk Reduct. 12:268-277.