Journal of Agripreneurship and Sustainable Development (JASD)
www.jasd.daee.atbu.edu.ng; Volume 3, Number 3, 2020
ISSN (Print): 2651-6144; ISSN (Online): 2651-6365

FACTORS INFLUENCING PADDY MILLING IN ADAMAWA STATE, NORTH-EASTERN NIGERIA

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ABSTRACT
The research examined the factors influencing paddy milling in Adamawa State, Nigeria based on data generated from 160 paddy millers via multi-stage sampling technique. In the research, four major functional forms of Ordinary Least Squares (OLS) regression were modeled; linear, semi log, exponential and double log functional forms to unravel the predictors of paddy processing in the area. Diagnostic checks revealed the data set as free from heteroscedasticity, multi collinearity and autocorrelation. Having passed the diagnostic checks, the least square regression in the study was adjudged robust; reliable and stable. However, of the four (4) functional forms modeled in the study, the double log function returned best fit in terms economic, statistical and econometric criteria and used to derive the conclusion of the study. The double log result had the highest R^2 value of 74.99%, lowest Root Mean Square Error (RMSE) of 0.348, lowest Akaike Information Criteria and Bayesian Information Criteria of 122.95 and 144.47, respectively. In terms of estimated coefficients, the double log result revealed that paddy (X_1), labor (X_2), firewood (X_3), and milling cost (X_6) were all significant at $P \leq 0.01$. Thus, paddy, labor, firewood and milling cost were adjudged significant factors that influence paddy processing. The study recommended the need for effective allocation of those variables in the right quantities and time for optimum output of milled rice.

Keywords: Adamawa, Akaike information criteria, Bayesian information criteria, Milling, Paddy.

INTRODUCTION

Rice is a global cereal widely cultivated across the world. Globally, two common species of rice abound; *Orza sativa* and *Oryza glaberrimma* in order of popularity (Ajala and Gana, 2015). It is regarded as the most significant staple crop by half of the world's population (Agric. News, 2003) and rice is seen as the major source of calories by these half of world's population (FAO, 2003) and this global population individually consumed an average between 100 – 240kg in year 2000 (FAO, 2003). In Nigerian context, rice consumption rose significantly owing to the dynamics in consumer preferences (Akande, 2003). Furthermore, Ebuchi and Oyewole (2007) unravelled that most Nigerians show preference to foreign rice than domestic rice for consumption owing to the inability of the domestic rice in meeting the standard of the foreign rice. No doubt, this perception is gradually changing with the current ban on foreign rice importation into Nigerian borders and the multiplier effect that stimulates domestic production in the country and further effect on massive investments via establishment of state of the art paddy processing industries across regions of Nigeria to meet the international standard in paddy processing.

Globally, paddy processing is one of the most significant and lucrative value adding activities in the rice value chain that employs several millions in the value chain. Inuwa *et al* (2001) and Lancon (2003) corroborates the foregoing assertion. Different economies of world deploy different techniques and technologies in paddy processing based on the available resource endowment of such economies. Today, in Adamawa State, Nigeria, it is a mixture of the modern, semi-modern and primitive technologies being deployed in paddy processing; few modern processing mills exist in the urban areas, but the preponderance of millers deploys the semi urban technology, while primitive technology is still being practiced in the hinterlands.

Several researches in paddy production abound in literature, but scarcity exists of research in paddy processing. The foregoing argument corroborates Akpokodje *et al*. (2001). In the light of the foregoing and considering the significance of paddy processing in its value chain, this study aimed to unravel the factors affecting paddy processing in the area to enhance productivity of milled rice for increased revenue and subsequent increase in welfare of paddy millers in the value chain.

MATERIALS AND METHODS

The Study Area

The study was conducted in Adamawa State, Nigeria. The State is agrarian in nature and vast land across all the local government areas (LGAs) are dedicated for the cultivation of paddy. Geographically, the state is located between Latitudes 8.00^0N and 11.00^0N of the equator and Longitudes 11.50^0E and 13.50^0E of the Greenwich meridian; it also has land mass of 39,742.12 square kilometres (Nigerian Investment Promotion Commission [NIPC], 2020) with a total population 3,161,374 (NPC, 2006). Furthermore, it has mean annual rainfall in the range 700mm to 1000mm and mean monthly temperature in the range 26.7^0C to 27.8^0C (Adebayo, 2012).

Sampling Techniques

A multi-stage random sampling technique was used to select 160 respondents (Table 1). Stratified sampling was employed in the first stage to profile the study area into four strata based on agricultural development project (ADP) zones (zone 1 to 4).

Table 1: Sampling Frame and Sample Size Selection Plan of the Study

Agricultural Zone	Selected LGAs	Selected Settlements	Sample Frame	Sample Size
Zone I	Mubi North	Kolere, Lokuwa and Yelwa	185	18
	Mubi South	Gella, Kabang, Gima and Gaya	156	18
Sub-total			**341**	**36**
Zone II	Gombi	Bakin kogi and Sunu	185	18
	Song	Loko and Song main market area	156	17
Sub-total			**341**	**35**
Zone III	Yola North	Jimeta bypass, Doubeli, Gerio, Bacchure and Jimeta market area	218	18
	Yola South	Dandu and Upper Benue	255	18
	Fufore	Gurin	223	18
Sub-total			**696**	**54**
Zone IV	Numan	Numan main market and Gwallam	250	18
	Lamurde	Lamurde main market	145	17
Sub-total			**395**	**35**
Total			**1,773**	**160**

A purposive sampling was later employed in the second stage to select two local government areas each in zone 1, 2, and 4 and three (3) LGAs in zone 3 based on preponderance of rice processing activities. Another purposive sampling technique was used in the third stage

Journal of Agripreneurship and Sustainable Development (JASD)
www.jasd.daee.atbu.edu.ng; Volume 3, Number 3, 2020
ISSN (Print): 2651-6144; ISSN (Online): 2651-6365

for the selection of wards within the selected LGAs. In the fourth stage, a non-proportionate simple random sampling was used to select 18 processing units in each of the nine (9) LGAs earlier selected. Thus, a total of 160 processing unit were selected for the research.

Method of Data Collection

The study used primary source of data via questionnaire from 160 respondents constituting processing firms. The data collection was conducted in year 2018.

Analytical Techniques

The study used the famous and widely used Ordinary Least Squares (OLS) techniques in its estimation and the following functional forms were estimated as models:

Linear Function:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + u_i \qquad \ldots (1)$$

Semi log Function:

$$Y = \beta_0 + \beta_1 LnX_1 + \beta_2 LnX_2 + \beta_3 LnX_3 + \beta_4 LnX_4 + \beta_5 LnX_5 + \beta_6 LnX_6 + u_i \qquad \ldots (2)$$

Exponential Function:

$$\rightarrow LnY = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + u_i \qquad \ldots (3)$$

Double log Function:

$$LnY = \beta_0 + \beta_1 LnX_1 + \beta_2 LnX_2 + \beta_3 LnX_3 + \beta_4 LnX_4 + \beta_5 LnX_5 + \beta_{6Ln} X_6 + u_i \qquad \ldots (4)$$

where;

Y = Milled Rice (Kg)

X_1 = Paddy (Kg),

X_2 = Labor (Man hour),

X_3 = Firewood (₦),

X_4 = Water (Litres),

X_5 = Transportation (₦) and

X_6 = Milling cost (₦)

The Akaike Information Criteria (AIC) introduced by Akaike (1974) was also used in the study and defined as:

$$\text{AIC} = -2\ln\mathcal{L}_{\max} + 2\text{k} \qquad \ldots (5)$$

where; $\mathcal{L}_{max}$ represents the achievable maximum likelihood by the model and k represents number of parameters in the model. Liddle (2007) stated that a model that minimizes the AIC is termed the best model.

The Bayesian Information Criteria (BIC) which emanates from Bayes factor (Kass and Raftery, 1995) propounded by Schwarz (1978) was also used as analytical model expressed as:

$$\text{BIC} = -2\ln\mathcal{L}_{\max} + \text{k}\ln\text{N} \qquad \ldots (6)$$

where; $\mathcal{L}_{max}$ represents the achievable maximum likelihood by the model, k represents number of parameters in the model and N represents the number of data points used to fit the model. Mcquarrie and Tsai (1998) stated that model that minimizes the BIC is termed as the best model.

The study also adopted the Durbin-Watson-d-statistics in line with Durbin and Watson (1950) to detect the presence of autocorrelation in the paddy processing data. Durbin-Watson-d-statistics is a very old, relevant and widely used test tools for autocorrelation (Baum, 2006). The test is presented as:

$$\text{d} = \frac{\sum_{t=2}^{t=n}(\hat{\mu}_t - \mu_{t-1})^2}{\sum_{t=1}^{t=n}\hat{\mu}_t^2}; \simeq 2(1-\rho);\ 0 \le \text{d} \le 4 \qquad \ldots (7)$$

where; d = Computed Durbin-Watson-d value

The decision criteria for test is to compare the computed d value with the tabular d_L and d_U. If $d < d_L$ = presence of positive autocorrelation, if $d > d_U$ or $d < 4 - d_U$ = No autocorrelation and if $d > 4 – d_L$ = Presence of negative autocorrelation.

Variance Inflating Factor (VIF) Test adopted and used in the study as analytical model. Murray *et al.* (2012) stated that the variance inflating factor (VIF) can be used to test collinearity among independent variables in regression models. The VIF shows how the variance of an estimator is inflated under a scenario of multi collinearity (Gujarati and Porter, 2009). Chatterjee and Price (1977) and Belsley *et al.* (1980) stated that the VIF for multiple regression model with p predictors; X_i; $i = 1 \ldots \rho$, are the diagonal elements (r^{ii}) of the correlation matrix R_{pxp} of the predictors. The VIF for a given predictor variable is expressed and described as:

$$\text{Variance Inflating Factor } (VIF_i) = r^{ii} = \frac{1}{1-R_i^2}; i = 1, \ldots \rho \qquad \ldots (8)$$

where;
R_i^2 = Multiple correlation coefficients. If VIF of a variable > 10; usually occurs when $R^2 > 0.90$ shows that the variable is highly collinear; thus, the larger the VIF value the more worrisome.

The study also used Cook Weisberg test to detect the presence of heteroscedasticity. In line with Yafee (2012), the Cook Weisberg test can be expressed below:

$$Var\ (e_i) = \delta^2 exp(Z_t) \qquad \ldots (9)$$

where; e_i= error in regression model, $Z = X\hat{\beta}$ = variable list supplied by user. The test is whether t = 0

$$e_i^2 = \alpha + Z_i t + V_i \qquad \ldots (10)$$

$$S = \frac{SS\ of\ the\ model}{2} \qquad \ldots (11)$$

$$h_o: S_{df=p} \sim X^2 \qquad \ldots (12)$$

where; p = number of parameter.

RESULTS AND DISCUSSION

Table 2 presented the least square estimates of paddy milling based on the four functional forms (linear, semi log, exponential and double log functions). The probability of F-test in all the four models was 0.000; an indication that overall model fit was significant for all the four models. Evaluation of the estimates on the basis of economic, statistical and econometric criteria adjudged the double log model (equ. 4) as the best fit based on the following reasons and hence, its output (double log model result) was used to derive the inference and conclusion of the study. First, the double log function (equ. 4) had five of the independent variables as significant, which was the highest of all the four models; note, models 1 and 3 each had three (3) independent variables as significant, while equ. 2 had the least significant variables (two). The coefficient (0.811) of paddy (X_1) was significant at 1%; indicates that a 1% increase in paddy adds 0.8% of milled rice. Other positive significant variables include firewood (X_3) (0.137) and cost of milling (X_6) (0.104) and both significant at 5%; indicates that a unit increase in firewood and cost of milling increases milled rice by 0.14% and 0.1%, respectively. On the other hand, labor (X_2) (-0.112) and water (X_4) (-0.083) and both significant at 5%; implies that a percent increase in labor and water decreases milled rice by 0.1% and 0.08%, respectively. The negative coefficient on labor and water could be due over utilization of such inputs in the milling process; thus, over utilization of inputs to be avoided by millers. It is imperative to note that paddy (X_1) had the highest coefficient relative to all the independent variables; an indication of the most important variable in the rice milling process. Secondly, the double log function (model 4) predicted the highest R^2 value (74.99); indicating

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www.jasd.daee.atbu.edu.ng; Volume 3, Number 3, 2020
ISSN (Print): 2651-6144; ISSN (Online): 2651-6365

that 75% of the variation in milled rice explained by the six (6) independent variables incorporated in the model. Thirdly, the root mean square error (RMSE) for the double log model was the least (minimum) value (0.348) than the other models. The RMSE as a measure of the dispersion of the residual around the predicted value holds the smaller the better; thus, RMSE with low values are better fit than those with high value. Barnston (1992) stated that the RMSE is popularly used in regression analysis and even climatology to forecast and to verify experimental results and in comparison for model selection, models with lower RMSE often results to better models than those with higher RMSE.

Table 2: Ordinary Least Squares Regression Results across the Four Functional Forms

Variables	Linear Function		Semi Log Function		Exponential Function		Double Log Function	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Paddy (X_1)	0.07***	0.02 (3.99)	464.78***	63.24 (7.35)	$1.0x10^{-5}$ ***	$2.4x10^{-5}$ (4.25)	0.811***	0.062 (13.14)
Labour (X_2)	-0.01	0.02 (-0.48)	-58.09	55.51 (-1.05)	$-6.4x10^{-6}$	$2.1x10^{-5}$ (-0.31)	-0.112**	0.054 (-2.07)
Firewood (X_3)	0.05	0.03 (1.51)	109.10	69.93 (1.56)	$7.3\ x10^{-5}$	$4.5x10^{-5}$ (1.63)	0.137**	0.068 (2.00)
Water (X_4)	-0.03	0.09 (-0.28)	-120.70**	47.42 (-2.55)	$1.5x10^{-4}$	$1.2x10^{-4}$ (1.23)	-0.083*	0.046 (-1.79)
Transportation (X_5)	0.15***	0.05 (3.13)	43.31	44.73 (0.97)	$1.9x10^{-4}$ ***	$6.1x10^{-5}$ (3.13)	0.060	0.044 (1.38)
Milling (X_6)	0.01***	0.01 (2.74)	54.33	50.02 (1.09)	$2.3x10^{-5}$ ***	$6.8x10^{-6}$ (3.35)	0.104**	0.049 (2.14)
Constant	57.19	71.31 (0.80)	-3157.80	539.25 (-5.86)	5.147	0.093 (55.28)	-0.771	0.526 (-1.47)
Observation (N)	160		160		160		160	
F (6, 153)	14.17		22.65		21.42		76.47	
P > F	0.0000		0.0000		0.0000		0.0000	
R^2	35.71%		47.04%		45.65%		74.99%	
Root MSE	392.73		356.45		0.513		0.348	
AIC	2372.303		2341.282		247.157		122.948	
BIC	2393.829		2362.808		268.683		144.474	

Note: Figures in parentheses represents t-values

Fourthly, the Akaike Information Criterion (AIC) was the least in the double log function (model 4) and in model selection, theory holds the lower the AIC, the better the model. Liddle (2007) and Mcquarrie and Tsai (1998) reported that the AIC can be used in selecting preferred model (s) in regression by focusing on the model with the lowest AIC value. In terms of Bayesian Information Criterion (BIC), the least magnitude was also the double log function (model 4), similarly, model selection with respect to BIC holds that the lower the BIC value, the better the model. Similarly, Liddle (2007) and Mcquarrie and Tsai (1998) reported the BIC as another selection criterion for different regression models; lower values of the BIC often yields a better model than those with higher values. In summary, the double log function (model 4) was adjudged the best model that best fit the paddy processing data than the other 3 models owing to highest significant independent variables, highest R^2 value, least Root Mean Square Error (RMSE), least Akaike Information Criterion (AIC) and least Bayesian Information Criterion (BIC).

Table 3 displayed the predicted residual types; the normalized, standardized and studentized residuals are all presented in its minimum, maximum, mean and standard deviation to understand the behaviour of the residual and to further enable diagnostic checks on the data. All the predicted residuals have shown low values and very low standard deviation especially for the standardized and studentized residuals, enough evidence that the estimated values did not deviate much from the observed values (Gujarati and Porter, 2009), further, the residuals were used for diagnostic checking.

Table 3: Predicted Residuals for Testing Normality and Other Diagnostic Checks

Variable (residual type)	Observation	Min.	Max.	Mean	Standard Deviation
Normalized Residual	160	-1045.239	3607.093	-2.1×10^{-7}	385.250
Standardized Residual	160	-4.359	9.279	-0.020	1.087
Studentized Residual	160	-4.643	13.987	0.009	1.381

Table 4 shows result of Smirnov-Kolmogorov test for normality of the data. Based on the probability value (0.0000), it showed that the data was not normally distributed. Yafee (2012) stated that if the chi-square probability (0.0000) is less than 0.05, implied a rejection of the null hypothesis and further implied non-normally distributed residuals. In a quest to make the data normal, the data was subjected to transformation.

Table 4: Smirnov-Kolmogorov Result for Testing Normality of the Data

Variable	Observation	Prob.(Skewness)	Prob.(Kurtosis)	AdjChi^2(2)	Prob >Chi^2
Residual	160	0.0000	0.0000	0.0000	0.0000

Table 5 showed the result of the link test to check for model specification; omitted variable bias in the model. The result failed to reject the null hypothesis of no variable omission following a non-significant p-value of _hatsq (0.023). Therefore, the model had omitted variable bias or needed additional variable or a drop in certain variable. Frost (2019) stated that among the limitations of executing regression in the presence of model misspecification is the case of omitted variable bias; where key variable is omitted the model becomes biased. In the research, the presence of model misspecification showed that the model was not correctly specified. Therefore, further research is needed to identify the variable not specified.

Table 6 displayed the Durbin-Watson test result for detection of autocorrelation in data. The computed d-value (1.850) was higher than both lower d-tabulated (dL= 1.651) and upper d-tabulated (dU = 1.817), but less than 4-dU. Thus, do not reject either Ho* or Ho or both. Hence, indicated absence of autocorrelation in the data. Gujarati and Porter (2009) stated that when the computed-d is greater than upper d-tabulated (dU) but less than 4-dU, the data contains no autocorrelation. The implications of using OLS estimator in the presence of autocorrelation leads to producing estimates with wider confidence interval; low t-values leading to insignificant coefficients (Gujarati and Porter, 2009). Thus, the absence of autocorrelation in the study circumvents the aforementioned limitations and therefore a robust result.

Table 5: Result of Link Test for Detecting Model Specification

Milled Rice (Y)	Coeff.	SE	T-value	P-value	95% Conf. Interval	
_hat	1.702	0.324	5.26	0.000	1.063	2.341
_hatsq	-4.1×10^{-4}	1.8×10^{-4}	-2.29	0.023	-7.5×10^{-4}	-5.7×10^{-5}
_Cons	-199.807	103.497	-1.93	0.055	-404.234	4.620
Number	160					
F (2, 157)	47.71					
P > F	0.0000					
R^2	37.80					
Root MSE	381.35					

Table 6: Result of Durbin-Watson D-Statistics for Testing First Order Autocorrelation

Observation	K	Computed d-statistics (value)
160	6	1.850

In Table 7, both variance inflating factor and tolerance showed the absence of multi collinearity among variables. The VIF for all variables were all far less than 10; similarly, the mean VIF was also 1.52; equally less than 10. On the other hand, the tolerance value for all the variables were tending towards one (1); the closer the tolerance to 1, the greater the evidence of absence of multi collinearity. Oscar (2007) stated that the VIF measures the rate of change in variances and co-variances and the magnitude of variances and co-variances are increased in the presence of multi collinearity and vice-versa. The implications of OLS estimation in the presence of multi collinearity includes among others include the predicted coefficients becomes highly sensitive to little changes in the model, thus, reducing precision and yielding and invalid p-values (Frost, 2019). However, the absence of multi collinearity in the study indicated that the results of this study were free of the foregoing limitations; predicted with valid p-values and less sensitive changes in the model.

Table 7: Result of Variance Inflation Factor for Detecting Multicollinearity

Variable	Variance Inflating Factor (VIF)	Tolerance (1/VIF)
Paddy (X_1)	1.72	0.582
Firewood (X_2	1.88	0.532
Labor (X_3)	1.10	0.911
Water (X_4)	1.46	0.683
Transportation (X_5)	1.29	0.777
Milling (X_6)	1.70	0.589
Mean of Variance Inflation Factor (VIF)	1.52	

Table 8 showed the result of the Cook-Weisberg test used to measure the presence or absence of heteroscedasticity in the data. The chi-square probability value (0.0000) indicated the absence of heteroscedasticity in the data. This further means the data for the study were indeed homoscedastic and in line with assumption. Heteroscedasticity should always be assumed in a model (Stock and Watson, 2003). Thus, the null hypothesis that the residuals were heteroscedastic was assumed. The probability (0.0000) was significant, which implied the violations of homoscedastic assumption (Baum, 2006); thus, the residuals were heteroscedastic, while an insignificant result means lack of heteroscedasticity otherwise known as homoscedasticity (Yafee, 2012); a scenario that shows the presence of equal variance of the residuals alone the predicted line. Thus, diagnostic checks indicated the presence of heteroscedasticity in the data. Presence of heteroscedasticity affects the validity of the regression result leading to inefficient estimator and estimates, when the OLS estimator loses its BLUE property (Ullah, 2012). To enhance its validity, data were attenuated and made free of heteroscedasticity via log transformation.

Table 8: Results of Cook-Weisberg Tests for Detecting Heteroscedasticity

Test Type	**Chi^2**	**$P > Chi^2$**
Cook-Weisberg Test for Heteroscedasticity	2360.46	0.0000

CONCLUSION AND RECOMMENDATIONS

Diagnostic checks for autocorrelation, multi collinearity, heteroscedasticity and variable bias (omission of variables) have shown that the data were free of such limitations; this further implied that estimation under Ordinary Least Square (OLS) estimator is sufficient and valid. On the basis of Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Root Mean Square Error (RMSE) and R^2 criteria, of the four functional forms in the OLS regression, the double log result was adjudged the best model, which revealed paddy, firewood, milling cost and water as significant coefficients. Thus, paddy, labor, firewood and milling cost were adjudged significant factors that influence paddy processing. The study therefore, recommended as follows:

1. There is the need for effective allocation of those variables in right quantities and at the right time for optimum output of milled rice.
2. The millers need to avoid overutilization of resources, particularly in labor and water for optimum output.

REFERENCES

Adebayo, A. A., Zemba, A. A., Ray, A. A. and Dayya, S. V. (2012). Climate Change in Adamawa State, Nigeria: Evidence from Agro climatic Parameters. *Adamawa State University Journal of Scientific Research*, **2**(2): 2-19.

Agric. News (2003). Rice is Life. International Year of Rice, 2004 Declaration. In: FAO, 2003: Food and Agriculture Organization Sustainable Rice Based Production and People's Livelihood. *International Rice Commission Newsletter*. (Special Edition), 52

Ajala, A. S. and Gana, A. (2015). Analysis of Challenges Facing Rice Processing in Nigeria. *Journal of Food Processing*, **5**(1): 1- 6.

Akaike, H. (1974). *A New Look at the Statistical Model Identification*. *Institute of Electrical and Electronic Engineering, Transaction on Automatic Control*, **19**(6): 716-723.

Akande, T. (2003). The Rice Sector in Nigeria. United Nation Crop Project (UNCP) Country Agricultural Project on Trade Liberalization in Agricultural Sector and the Environment. *African Crop Science Journal*, **15**(4): 223-235.

Akpokodje, G., Lancon, F. and Erenstein, O. (2001). *Nigeria's Rice Economy: State of the Art*. Paper Presented at the NISER/WARDA, Nigerian Rice Economy Stakeholders Workshop, Ibadan, 8-9 November.

Barnston, A. G. (1992). *Correspondence among the Correlation, RMSE and Heidke Forecast, Verification Measures; Refinement of the Heidke Scores*. Notes and Correspondence, Pp.699-709.

Baum, C. F. (2006). *An Introduction to Modern Econometrics Using Stata*. Department of Economics, Boston College, USA, Stata Press Publication, 341Pp.

Belsley, D. A., Kuh, E. and Welsch, R. E. (1980). *Regression Diagnostics: Identifying Influential Data and Source of Collinearit.* John Wiley and Sons, New York, 292Pp.

Chatterjee, S. and Price, B. (1977). *Regression Analysis by Example.* John Wiley and Sons, New York, Pp.19-22.

Durbin, J. and Watson, G. (1950). Testing for Serial Correlation in Least Squares Regression. *Biometrika,* **37**: 409-428.

Ebuchi, O. A. T. and Oyewole, A. C. (2007). "Effect of Cooking and Soaking on Physical Characteristics, Nutrient Composition and Sensory Evaluation of Indigenous and Foreign Rice Varieties in Nigeria" *African Journal of Biotechnology*, **6**(8): 1016-1020.

FAO (2003). *Food and Agriculture Organization Sustainable Rice Based Production and People's Livelihood*. International Rice Commission Newsletter. (Special Edition), 52.

Frost, J. (2019). *Regression Analysis: An Intuitive Guide for Using and Interpreting Linear Models*, 338Pp.

Gujarati, D. N. and Porter, D. C. (2009). *Basic Econometrics.* 5th Edition, India, 922Pp.

Inuwa, I. M. S., Kyiogwom, U. B., Ala, A. L., Maikasuwa, M. A. and Ibrahim, N. D. (2011). Profitability Analysis of Rice Processing and Marketing in Kano State, Nigeria. *Nigerian Journal of Basic and Applied Sciences*, **19**(2): 293-298.

Kass, R. E. and Raftery, A. E. (1995). Bayes Factors. *Journal of American Statistical Association*, **90**(430): 773-795.

Liddle, A. R. (2007). Information Criteria for Astrophysical Model Selection. *Monthly Notices of the Royal Astronomical Society*, **377**: 74-78.

Mcquarrie, A. D. R. and Tsai, C. L. (1998). *Regression and Time Series Model Selection.*World Scientific Publication Company, Singapore, 455Pp.

Murray, L., Nguyen, H., Lee, Y., Remmenga, M. and Smith, D. (2012). *Variance Inflating Factors in Regression Models with Dummy Variables.* Conference on Applied Statistics in Agriculture, Kansas State University, 19Pp.

National Population Commission [NPC] (2006). *Report of Nigeria's National Population Commission on the 2006 Census.* Population and Development Review, **33**(1): 206-210.

Nigerian Investment Promotion Commission [NIPC] (2020). *Nigerian State, Adamawa, Adamawa State Snapshot*. www.nipc.gov.ng.

Oscar, T. (2007). *Linear Regression using Stata.* Regression: What to Look for? *Data and Statistical Services, Princeton University*, **6**(3): 1-46.

Schwarz, G. (1978). Estimating the Dimension of a Model. *Annals of Statistics*, **6**(2): 461- 464.

Stock, J. H. and Watson, M. W. (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature*, **41**: 788 – 829.

Ullah, M. I. (2012). *Introduction, Reasons and Consequences of Heteroscedasticity. Basic Statistics and Data Analysis.* Lecture Notes. MCQS Statistics, Centre for Teaching Excellence, University of Waterloo, Canada.

Yafee, R. A. (2012). *Robust Regression Modelling with Stata.* Lecture Note. Statistics, Social Science and Mapping Group Academic Computing Services, 93Pp.