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VERTICAL PRICE TRANSMISSION IN NIGERIAN RICE VALUE CHAIN: COPULAR MODELS APPROACH

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ABSTRACT
Rice is a staple food consumed by Nigeria's high and low. Rice Prices have experienced strong variations over the last few years, both upwards and downwards. This increased volatility, combined with long-term prospects of rising rice prices due to the rice import ban highlights the necessity to increase the efficiency of the rice supply chain to ensure consumer prices reflect the evolution of inputs prices. This study assesses price transmission along the rice marketing chain in Nigeria. Static and time-varying copula methods were analysed on about 155 weekly price data obtained from different sources. Results suggest a positive link between producer, wholesaler and retailer rice prices. Such positive dependence is characterized by asymmetries during extreme market events that lead price increases to be transferred more completely along the supply chain than price declines. Price transmission asymmetries suggest potential market fragmentation and discrepancies in competition intensity along the chain.

Keywords: Rice, Copula, Market, Competition, Pricing, Poverty

INTRODUCTION
Nigeria is Africa's largest oil producer and relies on the sale of crude oil for about 90% of its foreign exchange earnings. As a way of diversifying the country's economy and reducing its dependence on oil, policies aimed at stimulating the growth of the agricultural sector have been put forward over the past years. Various trade policies that have been adopted in Nigeria in the past include tariffs, import restrictions, and outright bans on rice imports. During the 1970s and early 1980s, increased export earnings coupled with the highly overvalued naira exchange rate made it possible for Nigeria to finance huge food imports. The high naira exchange rate cheapened food imports and consequently, lowered the domestic prices. In 1986, the Structural Adjustment Programme (SAP) was introduced and the main policy instrument in this regard was the ban on food importation, especially rice. Consequently, the index of bias in protection shifted in favour of rice. Even though farmers were able to respond to this policy by way of increased production, the high cost of production could not make them cope with the increasing demand for the product. Hence, to make up for the resulting gap in demand and supply, rice came into the country through illegal importation. The ban continued till 1995 before it was lifted in line with the WTO agreement on trade liberalization. However, because of the weak capacity of Nigerian rice farmers to respond very quickly to policy initiatives, the government resorted to the use of tariff measures as a way of protecting the farmers. Since the ban was lifted, the tariffs on imported rice have increased from an average of 50% during 1996-1999 to 100% in 2002. In 2003 the government increased the tariffs to 150% and proposed to ban the importation of the commodity by 2007. This, however, could not be achieved due to the astronomical increase in prices of rice as a result of the global food crisis. Even then, the proposed policy reversal intended to protect Nigerian rice farmers from foreign competition. Given the experience of the past, one is not sure that the best option for the country today is an outright ban on the importation of the commodity.

In 2015, the Central Bank of Nigeria (CBN) presided over a ban on access to foreign currency for 41 items that the bank felt could be manufactured in the country, including rice and poultry. According to the National Bureau of Statistics (2019), spending on food and drink imports increased from nearly $2.9bn (£2.4bn) in 2015 to $4.1bn in 2017, dipped in 2018 and if the trend from the first quarter of 2019 continues, imports of agricultural products were valued at ₦236 billion (about $640 million) in the first quarter of 2019. These policies are expected to reduce how much is spent on imports and encourage local production of goods. Though sounds commendable, it is feared that restricting food imports should be a gradual process since the country cannot yet meet domestic demand for most food commodities, and the policy risks increasing food price inflation further.

Further, Statistics have shown that Nigeria's large population is fed by subsistence farmers largely in rural communities. Majorly, 80 percent of rice grown in the country which is about 3.7 million tonnes is produced by smallholder farmers while the remaining 20 percent is cultivated by commercial farmers. Yet, local consumption of the staple food stands at 6.4 million tonnes as of 2017. Invariably, this implies an almost 50 per cent deficit in local consumption. This is expected to impact rice prices along the chain. Assessing food consumer price formation requires analysing how food prices are transmitted along the food marketing chain, from agricultural producers to final consumers. Understanding price behaviour along the rice marketing chain is very useful for assessing the functioning of rice production, processing and distribution markets, their competition and integration level. Vertical price transmission analyses can help identifying market -failures and are a good indicator of the degree of competitiveness and effectiveness of market performance. Competitive behaviour is rare in less developed countries, Nigeria for example, due to distinctive market characteristics such as excessive government intervention, corruption, deficient infrastructures etc. Since prices drive resource allocation and production decisions, price transmission information is useful for economic agents when making their economic decisions, policymakers and competition regulatory authorities. Hence, the link between different prices at different levels of the food marketing chain is a very interesting research topic in Nigeria today. This article characterises the relationship between producer and wholesaler price levels and between wholesaler and consumer price levels of rice markets in Nigeria. The analysis is pairwise. Pairwise analyses are usual in the price transmission literature and represent a natural avenue for studying price relationships (Goodwin and Piggott 2001). The lack of food price data in Nigeria is the reason underlying the scarcity of studies on price behaviour in the country. This study aims to investigate the transmission of price changes from the producer through the wholesaler to the retailer who sells rice to the final consumer. This paper contributes to the scarce literature that investigates the effects of trade-oriented policies on domestic food prices.

Description of the Rice Supply Chain

The rice supply chain is composed of a wide diversity of firms which operate in different markets and sell rice and other products. The regulatory framework affects the rice supply chain at all levels from the Producer down to the retail sector. The degree of market power held by the firms along the chain varies by category, depending on the relevant markets in which these firms operate. It has an impact on the contractual relationships between the main players along the chain and can influence the degree of transmission of the increase in the commodity price to consumer prices. Given this complexity, general conclusions regarding the functioning of the rice supply chain have to be drawn with caution. The food supply chain connects three main sectors (see Figure 1): the agricultural sector, the food processing industry and the distribution sectors (wholesale and retail). Basic agricultural commodities undergo, to varying degrees, an often substantial series of intermediate alterations before they are sold as final food products to consumers. A description of the rice supply chain may improve the understanding of how prices are formed along this chain, how input costs are passed on, where interactions between firms take place and where different regulations may have an impact. The first sector considered in the rice supply chain is the Producer. Its activities include rice production through improved cultural practices. Firms or producers primarily sell their output to the food processing industry and to itself (e.g., animal feed), but also sell directly to retailers, final consumers or alternative markets. The rice processing industry is very homogenous and comprises milling, cleaning, sieving and bagging. The processed rice is packaged and dispatched to customers (e.g. distributors, food service). Another important activity of rice processing is to carry out market and product research leading to the development of new products and to engage in marketing. The

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distribution sector (and retail in particular) is the principal outlet for rice and, being the final link in the supply chain, it interacts directly with final consumers. While the sector's main activity is the sale of products, in doing so, retailers may also carry out services for rice processors, such as promotional activities.

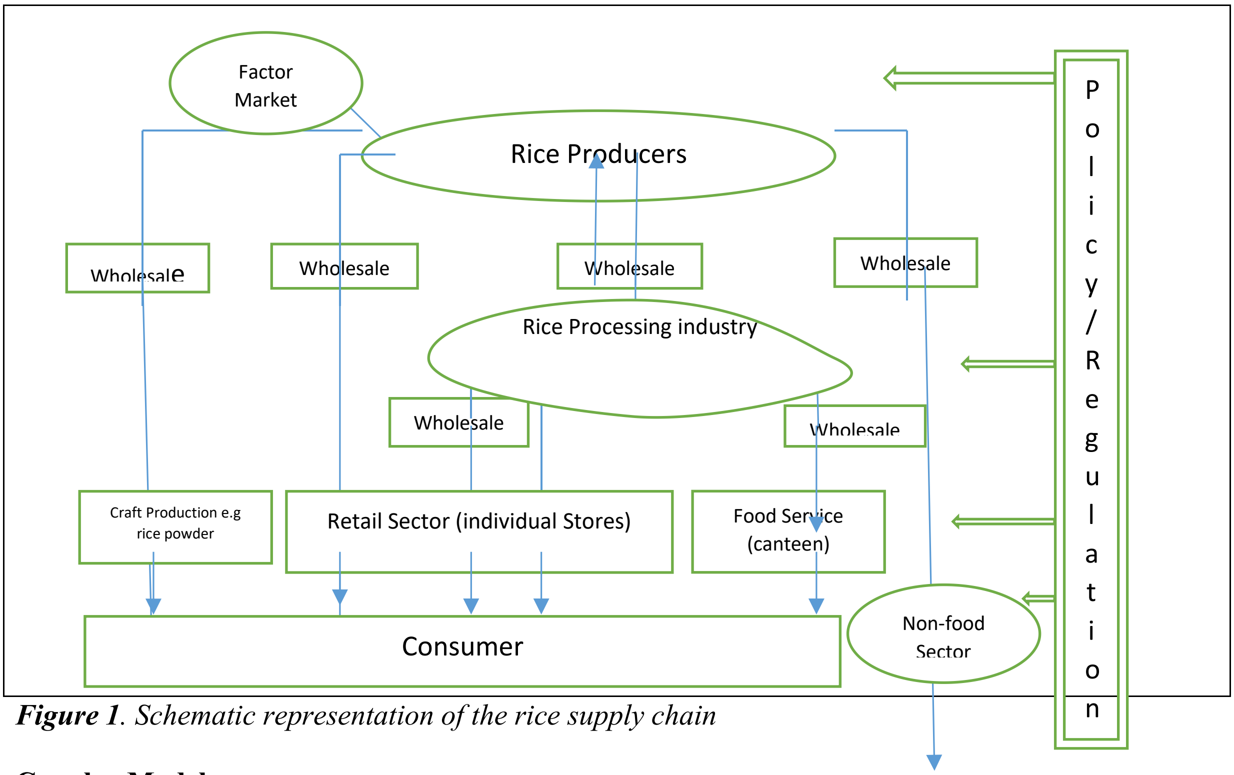

Figure 1. *Schematic representation of the rice supply chain*

Copular Models

Copula models are modern methodologies used by economists to study the dependence between prices. It is one of the models used in the analysis of non-structural time series data. These approaches rely on direct examination of the joint probability distribution function of the variables that are being studied and pay special attention to the nature of cooperation between these variables. Serra and Gil (2012) assessed the dependence between crude oil and biodiesel blend prices, and crude oil and diesel prices during extreme market events in Spain, using statistical copulas. The evidence of asymmetric dependence between crude oil and biodiesel prices was found, extreme increases in crude oil price not likely to be passed to the consumer level, while increases and decreases in crude oil prices likely to move equally to the diesel prices. Goodwin *et al*. (2011) studied the joint distribution of North American lumber prices in different markets (Eastern Canada, North Central US, Southeast US, Southwest US), employing Copula models to assess the dependence between these prices at the different geographical locations considered. Results indicated that market adjustments were generally large in response to large price differences that reflect more substantial disequilibrium conditions. Qiu and Goodwin (2013) rely on the application of static and time-varying copula models to the empirical study of the links between farm–retail and retail–wholesale prices for US hog/pork markets. Results indicated that farm and wholesale markets were closely related to each other, while retail price adjustment was less dependent on the other two markets. Wholesale–Retail price adjustments was relatively constant dependence structures indicating asymmetric price transmission between farm and retail markets. Increases in farm prices were translated to the retail level, while the price declines were less likely passed to consumers. Ahmed and Serra (2015) assessed the correlation between price and yield perils using statistical copula models to determining how the introduction of agricultural revenue insurance contracts in Spain affected the cost of purchasing insurance. Results indicated that revenue insurance likely reduce the price of agricultural insurance in Spain, which tend to result in higher acceptance and demand for agricultural insurance programmes. Fousekis and Grigoriadis (2016) studied the linkage between different qualities of coffee beans prices by using non-parametric copula models. The study relied on monthly spot prices from 2009 to 2015. Results indicated strong relationship between the Arabica beans prices, while the dependence is less between the individual prices of Arabica and the Robusta beans. Results also found evidence of symmetric price transmission.

Multidimensional copula functions were used to assess the dependency between prices along the tomato supply chain in Egypt (Ahmed, 2018). While copulas have been widely used in the financial economics literature (Patton, 2006, 2012; Parra and Koodi, 2006), most empirical studies on rice in Nigeria focused effects of trade liberalization on rice supply (Ogundele, 2012), technical efficiency of rice producers (Okoruwa *et al*., 2006) or adoption of NERICA rice technology as in Nguezet *et al*. (2011). Most studies probably sidestep price transmission issues concerning rice. To our knowledge, no study has used the copulas model to assess dependency along the food marketing chain in Nigeria. Our article contributes to the literature by assessing the dependence between producer–wholesaler and wholesaler–retailer price levels in rice markets in Nigeria. During the political transition period, Nigeria suffered from food insecurity and food price instability. It is thus important to pay special attention to extreme upturns and downturns in the rice market, as these are likely to have a stronger impact on food security and economic issues. Food security is a complex and multi-dimensional phenomenon with poverty. Our study used both static and time-varying copulas in order to allow for changes in price patterns. To our knowledge, this is the first attempt to study vertical price transmission in Nigeria using this methodology.

METHODOLOGY

Data Collection

The study made use of secondary data from various publications of the Central Bank of Nigeria (CBN), National Bureau of Statistics (NBS), Food and Agricultural Organization (FAO), United Nations Centre for Trade Administration and Development (UNCTAD), Ministry of Agriculture and Natural Resources (MANR) and Ministry of Commerce and Trade (MCT). Information sought included total areas of rice (ha) harvested annually, producer and wholesale price and the retail price of rice, the world price and the nominal effective exchange rate among others. The data covered the period between 2015 and 2018.

Analytical Framework

Price transmission analyses can be classified into structural and non-structural studies. While structural models rely on economic theory, non-structural analyses identify empirical regularities in the data. Our approach to studying price transmission along the Nigeria rice marketing chain is based on non-structural time-series models- copular analyses.

Statistical copulas have the advantage of allowing high flexibility when studying the correlation between two or more variables. Copulas are based on Sklar's (1959) theorem that shows how multivariate distribution functions characterizing dependence between *n* variables, where *n* is the number of the variables, can be decomposed into *n* univariate distributions and a copula function, the latter fully capturing the dependence structure between variables. A copula function is a multivariate distribution function defined on the unit cube $[0, 1]^n$ in the parenthesis, two or more variables uniformly distributed marginally. Since our analysis is pairwise, let F_x and F_y be the univariate distribution functions of two random variables (*X, Y*). H (*X, Y*) is assumed to represent the joint distribution function. According to Sklar's theorem, there exists a copula C (.) that can be defined as (Embrechts, Lindskog, and McNeil 2001).

$$H(X,Y) = C(F_X(X), F_Y(Y)) = C(u,v) \quad (1)$$

Where, C (.) is a two-dimensional distribution function with uniformly distributed margins u: *Unif* (0, 1) and v: *Unif* (0, 1). The joint density function can be expressed as

$$h(x,y) = f_x(x) f_y(y) c(u,v) \quad (2)$$

Where c is the copula density and $f_x(x)$ and $f_y(y)$ are the univariate density functions of the random variables.

Different copula families represent different dependence structures and specifications (Patton, 2006), which represent the copula models with different standard normal marginal distributions. Analysis of the price linkage by using copula models can study the prices at higher (lower) levels and move together (Reboredo, 2011). Our analysis considers both elliptical (Gaussian and Student's t copulas) and Archimedean (Gumbel, Clayton and symmetrized Joe-Clayton [SJC] copulas) copulas. Elliptical copulas are copulas that can study the dependency between two or more variables in the central area of the distribution ignoring the distributions in the tails. For such a purpose, we have applied Archimedean copulas to overcome this limitation (Nelsen, 2006; Joe, 1997). Archimedean copulas are commonly used to study the dependence between prices, which can assess the prices during extreme market events (downturns and upturns). Gumbel copula is one of the Archimedean copulas that can study the response to positive price shocks more than negative shocks, while Clayton is the opposite. *SJC* copula has upper and lower tails to study the positive and negative price shocks together that can examine the asymmetric dependence between prices (Patton 2006).

Copulas can be categorized as static and time-varying. A static copula implies parameter constancy over time, while a time-varying copula allows the parameters to change with changing environment. To ensure that the copulas correctly fit our data, a series of time-varying dependence and goodness-of-fit (GoF) tests were conducted. As a result, price dependency along the Nigerian rice marketing chain is modelled using four copulas. The Gaussian copula was selected for being the benchmark copula in economics. The student's *t*, its dynamic version and the *SJC* copula are selected based on statistical selection criteria (the log-likelihood value and *GoF* statistics described below).

The bivariate Gaussian copula can be expressed as:

$$C_R^{Ga}(u,v,R_{12}) = \int_{-\infty}^{\phi-1}(u)\int_{-\infty}^{\phi-1} v\overline{\overline{2\lambda\sqrt{1-R_{12}^2}}}^{1} \exp\left\{\frac{-(S^2-2R_{12}uv+t^2}{2(1-R_{12}^2)}\right\}dsdt \quad (3)$$

where -1 < R12 < 1 is the correlation coefficient of the corresponding bivariate normal distribution, *u* and *v* are random variables, $S = \varphi(U) \big/ [\varphi(U)+\varphi(V)]$ and T=C(U,V), S and T are given by the joint density function *H(s,t)=sKc(t)* for all (*s,t*) in $[1,0]^2$ and ϕ denotes the univariate normal distribution function. While the Gaussian copula represents dependence in the central region of the distribution, it assumes non-dependency in the extreme tails of the distribution. The implication for our analysis is that price transmission along the food market chain does not occur for very high/low market prices. A bivariate student's *t* copula can be expressed as:

$$C_{y,R}^{t}(u,v) = \int_{-\infty}^{\frac{t-1}{y}}(u)\int_{-\infty}^{\frac{t-1}{y}} v\overline{\overline{2\lambda\sqrt{1-R_{12}^2}}}^{1} \exp\left\{\frac{-(r^2-2R_{12}rs+s^2}{2(1-R_{12}^2)}\right\}drds \quad (4)$$

Where R_{12} is the correlation coefficient of the corresponding bivariate *t*-distribution with γ degrees of freedom, and *tγ* denotes the bivariate distribution function. The student's *t* copula assumes positive and symmetric lower and upper tail dependence. As noted above, evidence of AVPT within the food marketing chain is abundant. These asymmetries tend to be more pronounced as we move to extreme tails of the distribution (i.e., when price increases or declines are larger), which we capture through the static SJC specification. The Joe-Clayton copula can be expressed as:

$$C_{r^v,r^L}^{jc}(u,v) = 1-(1-\{[1-(1-u)^k]^{-y}+[1-(1-v)^k-1\}^{-1/y})^{1/k} \quad (5)$$

Where $K = 1 \big/ Log_2(2-ru), \gamma = -1 \big/ Log_2$ $(rL), r^u \in (1,\ 0)$ and $r^L \in (1,\ 0)$, which measure the upper and lower tail dependence, respectively. The Joe-Clayton copula implies asymmetric dependence, even when $\tau^U=\tau^L$. The SJC copula allows overcoming this problem (Patton 2006) and can be specified as:

$$C_{r^v,r^L}^{sjc}(u,v) = 0.5 - C_{r^v,r^L}^{jc}(u,v) + C_{r^v,r^L}^{jc}(1-u,1-v)+u+v-1) \quad (6)$$

Two types of time-varying dependence tests have been used to determine whether time-varying copula. The first focuses on rank correlation breaks between *u* and *v* at some unknown date and is based on the 'sup' test statistic (Patton 2013). The second test is the ARCH LM test for time-varying volatility (Engle 1982). Both tests provide support for the use of time-varying copulas. The dynamic Student's *t* copula is chosen based on the highest log-likelihood values, to capture dependency changes, and defines the correlation parameter to evolve through time as shown in Equation (7) (Patton 2006):

$$P_t = \Lambda\left(\omega_\rho + \beta_\rho \rho_{t-1} + \alpha_\rho \frac{1}{10}\sum_{i=1}^{10} t_y^{-1}(u_{t-i}) t_y^{-1}(v_{t-i})\right) \quad (7)$$

Where t_y^{-1} is the inverse of the t distribution of ε_t with γ degrees of freedom, and $\Lambda = (1+e^{-x})^{-1}$
Is the modified logistic function.

Copulas can be estimated through two-stage estimation processes. The first stage consists of estimating marginal models that filter information contained in univariate distributions and allow deriving standardized, independent and identically distributed residuals from the filtration. The copulas have been estimated in a second stage either through parametric or nonparametric methods. We use the latter which consists of transforming the independent and identically distributed residuals into *Unif*(0,1) using the non-parametric empirical cumulative distribution function (EDF). The empirical EDF method is especially convenient when the true distribution of the data is not known. The maximum likelihood method has been applied to the uniform residuals to estimate copula. Since the theory of copulas applies to stationary time series, tests for unit roots are run on our data. Results support the absence of a unit root in producer, wholesaler and retailer prices.

Univariate ARMA(p_a,q_a)–GARCH(p_g,q_g) marginal models capture univariate price patterns with P_a representing the number of autoregressive parameters of the ARMA model; q_a the number of moving average components, P_g the number of autoregressive terms in the GARCH specification and q_g the number of lags of squared innovations. Residuals have been modelled through GARCH specification to allow for time-varying and clustering volatility:

$$P_t = C + \sum_{i=1}^{\rho a} \eta_{1i} P_{t-i} + \sum_{i=1}^{qa} \eta_{2i} \varepsilon_{t-i} + \varepsilon_t \quad (8)$$

$$\sigma_t^2 = \omega_i + \sum_{i=1}^{\rho g} \omega_{i2} \sigma_{t-i}^2 + \sum_{i=1}^{qg} \omega_{i1} \varepsilon_{t-i}^2 \quad (9)$$

where P_t are the prices considered, c is the constant of the conditional mean model, η_{1i} is the coefficient representing the autoregressive component, η_{2i} is the coefficient representing the moving average component, being ε_t a normally distributed error term, ω_i is the constant in the conditional volatility model, being ω_{i1} and ω_{i2} the coefficients representing the lagged square residuals and variance, respectively. Log-likelihood methods assuming normally distributed errors were used in model estimation.

Following Patton (2013), *GoF* tests were used to assess to what extent an estimated copula model is different from the unknown true copula. Comparison of estimated with unknown copula is made through the Kolmogorov–Smirnov (KS) and the Cramer–von-Mises tests (Genest and Rémillard 2008; Genest *et* al., 2009; and Rémillard 2010). Conducting GoF tests on the marginal models is essential for copula model estimation. To make sure that the residuals obtained from univariate models have no autocorrelation, the Ljung–Box tests are used. The LM tests of serial independence of the first four moments of u_t and v_t are also used. We also rely on the KS test to make sure that the transformed series are *Unif* (0, 1).

RESULTS AND DISCUSSION

The analysis was based on weekly producer, wholesaler and retailer rice price data, expressed in several Nigerian publications on prices of rice in Naira/kg, and observed from the first week of January 2015 to the last week of December 2018, leading to a total of 155 observations.

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Summary of Property Test of the Series

To test for the stationarity properties of the series, a unit root test was performed on each of the variables. The result of the unit root test (DF and ADF test) is presented in Table 1. It is clear from Table 1 that Standard unit root tests show that the series is stationary. Table 2 presents summary statistics for the price series. The skewness and kurtosis and their significance tests were conducted following Kendall and Stuart (1958). The Anderson–Darling is a well-known statistical test for normality. The ARCH LM test of Engle (1982) was conducted using 10 lags. Overall, these statistics provide evidence of non-normal price series, characterized by skewness, kurtosis and ARCH effects, legitimizing the copular analyses adopted for the study.

Table 1. Unit Root Tests for Producer, Wholesaler and Retailer Rice Price Series.

	t-Test	Critical values: 1%	Critical values: 5%	Critical values: 10%
Dickey-Fuller (Dickey and Fuller, 1979) test for unit root with intercept				
Producer prices	-3.834	-3.474	-2.880	-2.577
Wholesaler prices	-4.898	-3.474	-2.880	-2.577
Retailer prices	-4.573	-3.474	-2.880	-2.577
Augmented Dickey-Fuller (Dickey and Fuller, 1979) test for unit root with intercept				
Producer prices	-5.177	-3.460	-2.880	-2.570
Wholesaler prices	-7.051	-3.460	-2.880	-2.570
Retailer prices	-4.574	-3.460	-2.880	-2.570

Table 2. Summary Statistics for Producer, Wholesaler and Retailer Rice Prices expressed in Naira/kg.

	Producer prices	Wholesaler prices	Retailer prices
Mean	1.708	1.977	2.760
SD	0.018	0.047	0.063
T-statistic	89.295	48.643	34.909
Skewness	4.050*	3.023*	1.413*
Kurtosis (excess)	17.864*	13.286*	1.808*
Anderson–Darling test	29.396*	14.091*	6.383*
ARCH LM test	37.300*	15.615*	63.980*
Number of observations	155	155	155

*Indicates rejection of the null hypothesis at the 5% significance level.

Table 3. Univariate ARIMA–GARCH model for Producer, Wholesaler and Retailer rice prices.

Variable	Producer prices	Wholesaler prices	Retailer prices
Conditional mean			
C	0.708**	0.761**	0.127**
	(0.151)	(0.147)	(0.048)
ϕ_1	0.521**	0.529**	1.791**
	(0.099)	(0.071)	(0.059)
ϕ_2	-0.926**	(0.051)	
θ_1	0.291**	0.046**	-0.574**
	(0.106)	(0.098)	(0.095)
θ_2	0.054	0.232**	-0.296**
	(0.085)	(0.087)	(0.089)
θ_3	0.440**	0.067**	
	(0.078)	(0.084)	
θ_4	0.380**	0.282**	
	(0.088)	(0.081)	
Conditional variance			
ω_i	0.002**	0.005**	0.041**
	(2.509e - 07)	(1.439e - 06)	(0.001)
ω_{i1}	0.325**	0.413**	0.437
	(0.026)	(0.017)	(0.031)
ω_{i2}	0.582**	0.554**	0.329**
	(0.009)	(0.004)	(0.016)
Ljung–Box Q (10)	7.829	11.188	8.658

(**) Denotes statistical significance at the 5% level.

Table 3 presents Results from the univariate ARMA–GARCH model, whose specification is chosen through Akaike's information criterion and Bayesian information criterion. An ARMA (1,4)–GARCH (1,1) model was fitted to producer and wholesaler prices, while an ARMA (2,2)–GARCH (1,1) represents retailer prices. Conditional mean model results suggest that current price levels were positively influenced by price levels during the previous week. Univariate GARCH (1, 1) model parameter estimates are all positive for the three prices considered, which indicates that past market shocks as well as past volatility triggered higher current volatility levels. Since $\omega_{i1}+\omega_{i2} < 1$, we can conclude that the three GARCH processes are stationary, being the unconditional long-run variance $\sigma_i^2=\omega_i/(1-\omega_{i1}-\omega_{i2})$ around 0.022, 0.143 and 0.176 for producer, wholesaler and retailer prices, respectively. Hence, in the Nigerian rice market, consumer prices have long-run volatilities that are above the volatilities at the producer and wholesale price level. This suggests most price changes occur at the retail level. Perhaps favourable price changes are not fully transmitted through the value chain to the consumers, as volatility of prices in Nigeria usually translates to price increases. Also in Table 3, the Ljung–Box test results are presented. The result fails to reject the null of no auto-correlated residuals. Table 4 presents the p-values from the LM test of serial independence of the first four moments of u_t and v_t and Kolmogorov–Smirnov (K–S) tests, following Patton (2006) and Ahmed (2018). The LM tests for the independence of the first four moments of the transformed variables provide evidence that the models are well specified. The KS test confirms that the transformed series are Unif (0, 1).

Table 4. LM Tests on the Transformed Prices (u_t and v_t).

Producer prices	Wholesaler prices	Retailer prices	
First moment LM test	0.769	0.527	0.684
Second moment LM test	0.884	0.527	0.812
Third moment LM test	0.897	0.667	0.866
Fourth moment LM test	0.880	0.862	0.982
K–S test			

Table 5 presents p-values from one-time break correlations and autocorrelation (AR) tests for time-varying dependence using 1000 bootstrap replications. The left panel test focuses on rank correlation breaks between *u* and *v* at some unknown date. The right panel is the ARCH LM test for time-varying volatility proposed by Engle (1982) which focuses on autocorrelation independence. The results support the use of time-varying copulas.

Table 5. Time-varying Rank Correlation between Prices

AR(p)

Price pair	Break occurring anywhere	1	5	10
Producer–wholesale	0.002	0.001	0	0.008
Wholesale–retail	0.003	0.002	0	0.008

In Table 6, we present the log-likelihood values for a wide range of copulas. Those copulas yielding the highest log-likelihood (Gumbel, Student-*t*, SJC, time-varying SJC and Student's *t*) values are selected for a more in-depth analysis. The Gaussian copula is also chosen as the benchmark model in economics

Table 6. Log Likelihood Values for Static Copulas

	Producer–wholesaler	Wholesaler–retailer
	Log-likelihood	Log likelihood
Gaussian	12.151	3.363
Clayton	8.217	1.774
Rotated Clayton	12.966	4.726
Plackett	11.034	2.726
Frank	10.792	2.426
Gumbel	13.659	4.822
Rotated Gumbel	11.265	2.938
Student's *t*	13.431	4.919
Symmetrized Joe Clayton	14.662	4.919

The results of the KSC and CvMC GoF tests are presented in Table 7. The table presents p-values from goodness-of-fit tests for four copula models using 100 bootstrap replications. KSC and CvMC tests refer to the Kolmogorov–Smirnov and Cramer–von Misses tests, respectively. Following Rosenblatt's (1952) empirical copula of transformed residuals was applied to the empirical copula of the standardized residuals. The results as shown in the Table suggest that the students *t* constant copula has the best fit, followed by the Gaussian and the SJC constant copulas in the producer–wholesaler pair of prices category. In the wholesaler–retailer category, the SJC constant copula has the first best fit followed by the Student's *t* constant copula. For time-varying copulas, the GoF tests suggest that the Student's *t* better fits the data relative to the SJC copula for both pairs of prices. Given these results, static Gaussian, static and dynamic Student's *t* and static SJC copulas were selected for the copular analysis.

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Table 7. Goodness-of-fit Tests for Copula Models.

KSC	CvMC	KSR	CvMR
Producer–wholesaler			
Gaussian		0.120	0.030
Gumbel		0.020	0.050
SJC		0.030	0.110
Student's *t*		0.120	0.130
Time-varying SJC		0.820	0.360
Time-varying Student's *t*		0.880	0.430
Wholesaler–retailer			
Gaussian		0.190	0.410
Gumbel		0.050	0.220
SJC		0.300	0.590
Student's *t*		0.200	0.470
Time-varying SJC		0.180	0.150
Time-varying Student's *t*		0.320	0.460

Table 8 presents the results from static copulas. Results of Gaussian and Student's *t* copula imply a positive short-run correlation between prices at different market levels. The association is stronger between producer and wholesale prices than between wholesale and retail prices. Furthermore, the inverse of the degrees of freedom of Student's *t* copulas is 0.170 and 0.216 for producer–wholesaler and wholesaler–retailer pairs of prices, respectively.

Table 8. Static Copulas Outcomes.

Producer–wholesaler Gaussian	0.381**	(0.074)
Log likelihood	12.151	
SJC(τ^L,τ^U)	0.141**	0.297**
	(0.081)	(0.095)
Log-likelihood	14.662	
Student's *t* (ρ; v^{-1})	0.388**	0.170**
	(0.071)	(0.101)
Log-likelihood	13.431	
Wholesaler–retailer Gaussian	0.206**	(0.087)
Log likelihood	3.363	
SJC (τ^L,τ^U)	0.002	0.174**
Log likelihood		4.919
Student's *t* (ρ, v^{-1})	0.191**	0.216**
	(0.091)	(0.108)
Log-likelihood		4.919

(**) Denotes statistical significance at the 10% (5%) level

This implies strong dependence in the tail (Wholesaler–retailer price pair), which is not captured by the Gaussian copula. It is thus relevant to estimate a copula that allows for dependency on very high/low market prices. Results of SJC copulas provide support for asymmetric dependency during extreme market events. The SJC copula for the producer–wholesaler price pair shows stronger upper than lower tail dependency, which suggests that price increases tend to be passed from producers to wholesalers more completely than price declines. For the wholesaler–retailer price pair, the lower tail is not statically different from zero while the upper tail was statistically significant, which implies that while price increases will be transferred from wholesalers to retailers, the contrary will happen in the case of price declines. Hence, retailers are more likely to increase prices than to reduce them, which reflects the degree of market power that retail chains have in Nigeria. In particular, bargaining power between wholesalers and retailers for rice.

Time-varying Student's *t* copula shows how dependency among the pairs of prices considered changes over time. Table 10 shows the estimated results for the producer–wholesaler price pair, indicating that dependence was relatively low and fluctuated. The decreasing-increasing dependency is likely to be related to the increased activities of rice processors which resulted from the availability of access to the cottage industry loan of Bank of Industry and Anchor borrower loan scheme of the Central Bank of Nigeria (CBN). Rice production has increased astronomically since the involvement of various levels of Government in its production. Access to finance facilitated by CBN for proprietors of rice mills is meant to proliferate the setting up of modern rice mills and therefore create partnerships to increase trust between producers and processors of rice that stabilize their relationships through forward contracts. Such a relationship leads to an increase in the dependency between the producer of paddy and the wholesaler (off-takers) and sometimes the contrary through competition resulting from forward integration by producers. The Table further shows Time-varying Student's *t* indicates a low dependency between wholesaler and retailer market levels, which is on the order of 0.2 that fluctuates over the period studied, mainly in the range from 0 to 0.4. Low dependency between wholesaler and retailer prices may be explained by retailers' market power and a lack of forward contracts linking these two levels of the marketing chain. Fluctuations are not surprising given the economically tumultuous period studied.

The Ban on the importation of rice by the Buhari administration gave impetus to local rice farmers to increase their investment to maximize output and profit. The seasonal harvesting effects create opportunities for the processor of rice to hike prices since the demand for their services often outweighs what they could meet instantaneously. This scenario is what facilitate a forward contract that led to an increase in the dependency between producer and wholesaler. Increases and decreases in producer prices are transmitted to the wholesalers, but the price increase is passed more completely than reductions in prices because the wholesalers most often do not have other outlets to sell except retailers. The increase in rice prices will be passed to the retail level, while the declines may not be transmitted. This result agreed with Ward (1982) who found retailers exert their market power to prevent price declines from passing through the wholesaler to the retail level. In developing countries, retailers' market power in food supply chains is not surprising because there is a lack of competitiveness, information and forward contracts.

Table 10: Time-varying Student's t copula.

Producer–wholesaler	Wholesaler–retailer	
Student's t ω	0.056	0.459**
	(0.042)	(0.105)
α	0.190**	0.446**
	(0.043)	(0.155)
β	0.950**	0.102**
	(0.179)	(0.026)
γ^{-1}	0.213**	0.168**
	(0.063)	(0.129)
Log-likelihood	18.651	6.598

(**)Denotes statistical significance at the 5% level.

CONCLUSION AND RECOMMENDATIONS

This study is novel in that its pioneer focuses on rice price analyses along the rice chain. The paucity of data is one of the banes of a study like this in developing economies as data on rice prices along the value chain are extremely difficult to come by. This study is of high political, social and economic interest, especially in light of the low-income levels and chronic poverty affecting Nigeria today. The two most important policy variables emanating from this study are that price increases are transmitted in full from the producer to the wholesalers and the retailer, while, price declines if transmitted at all, are not totally transmitted through the same chain to the retailers. This accounts for the high cost of locally produced rice in Nigeria. All incentives injected into the sub-sector, meant to positively affect price and thereby make rice affordable to consumers are not allowed to reach the consumers. This situation, however, requires appropriate and conscious policy decisions. In the light of food self-sufficiency and national food security or poverty reduction, no country would like to embark on a policy that will adversely affect the well-being of its citizens in an attempt to discourage the importation of one food item. Local actors in rice production and processing in Nigeria today are not efficient enough to produce the required quantities of rice to match the local demand. The inability of demand to meet supply will escalate prices. Injected incentives by the government to abate escalating prices are corruptly manipulated from reaching the retailer who is to sell to the final consumer. Similarly, imposing a total ban on the importation of rice will contradict the government's plan to pursue a market-led economy. Therefore, the only viable option is for the government at various levels to concentrate on those factors that can lead to an increase in the local supply of the commodity.

REFERENCES

Ahmed, O. (2018). Vertical price transmission in the Egyptian tomato sector after the Arab Spring, *Applied Economics*, ISSN 1466-4283, Routledge, New York, NY, Vol. 50, Iss. 47, pp. 5094-5109.

Ahmed, O., and T. Serra. (2015). "Economic Analysis of the Introduction of Agricultural Revenue Insurance Contracts in Spain Using Statistical Copulas." *Agricultural Economics* **46**: 69–79. doi:10.1111/agec.12141.

Embrechts, P., F. Lindskog, and A. McNeil. (2001). Modelling Dependence with Copulas and Applications to Risk Management. Zurich: Department of Mathematics.

Engle, R. F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation." *Econometrica* **50**: 987–1007.

Fousekis, P., and V. Grigoriadis. (2016). "Joint Price Dynamics of Quality Differentiated Commodities: Copula Evidence from Coffee Varieties." *European Review of Agricultural Economics* **44**(2): 337–358. doi:10.1093/erae/jbw015.

Genest, C., and B. Rémillard. (2008). "Validity of the Parametric Bootstrap for Goodness-Of-Fit Testing in Semiparametric Models." Annales De l'Institut Henri Poincare: *Probabilites Et Statistiques* **44**: 1096–1127.

Genest, C., B. Rémillard, and D. Beaudoin. (2009). "GoodnessOf-Fit Tests for Copulas: A Review and a Power Study." Insurance, *Mathematics and Economics* **44**: 199–213.

Goodwin, B. K., M. T. Holt, G. Onel, and J. P. Prestemon. (2011). "Copula-Based Nonlinear Models of Spatial Market Linkages." *Working Paper. 2011* Annual Meeting, July 24–26, 2011

Goodwin, B. K., and N. Piggott. (2001). "Spatial Market Integration in the Presence of Threshold Effects." *American Journal of Agricultural Economics* **83**: 302–317.

Joe, H. (1997). Multivariate Models and Dependence Concepts. London: Chapman & Hall.

Kendall, M.G. and Stuart, A. C (1958). The Advance Theory of Statistics. London: Charles Griffin and Company, National Bureau of Statistics (2019) Monthly Price and import statistics. Abuja, Nigeria

Nelsen, R. B. (2006). An Introduction to Copulas. New York: Springer Series in Statistics.

Nguezet, P.M.D, Diagne, A, Okoruwa, V.O and Ojohomon (2011). Impact of Improved Rice Technology (NERICA Varieties) On Income and Poverty among Rice Farming Households in Nigeria: A Local Average Treatment Effect (LATE) Approach. *Quarterly Journal of International Agriculture,* **50**(3): 267-291.

Ogundele, F. (2012) Trade Liberalization and Import Demand For Rice In Nigeria: A Dynamic Modelling. *Journal of Economics and Rural Development,* **16**(1): 587 – 596.

Okoruwa V.O., Ogundele, F., and Oyewusi, B.O. (2006) Efficiency and Productivity of Farmers in Nigeria: A study of Rice Farmers in North-Central Nigeria. A Paper presented at Annual Conference of International Association of Agricultural Economists, August,12-18. Queensland Australia.

Parra, H., and L. Koodi. (2006). “Using Conditional Copula to Estimate Value at Risk.” *Journal of Data Science,* **4**: 93–115.

Patton, A. J. (2006). “Modeling Asymmetric Exchange Rate Dependence.” International *Economic Review,* **47**: 527–556.

Patton, A. J. (2012). “A Review of Copula Models for Economic Time Series.” *Journal of Multivariate Analysis* **110**: 4–18.

Patton, A. J. (2013). “Copula Methods for Forecasting Multivariate Time Series.” *In Handbook of Economic Forecasting*, edited by G. Elliott and A. Timmermann, 899–960. Amsterdam: Elsevier.

Qiu, F., and B. K. Goodwin (2013). “Measuring Asymmetric Price Transmission in the U.S Hog/Pork Markets: A Dynamic Conditional Copula Approach.” Proceedings of the NCCC- 134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, MO.

Reboredo, J. (2011). “How Do Crude Oil Price Co-Move? A Copula Approach.” *Energy Economics,* **33**: 948–955.

Rémillard, B. (2010). “Goodness-of-fit Tests for Copulas of Multivariate Time Series.” *Working paper*, HEC Montreal.

Rosenblatt, M. (1952). “Remarks on a Multivariate Transformation.” *The Annals of Mathematical Statistics,* **3**: 470–472.

Serra, T., and J. M. Gil. (2012). “Biodiesel as a Motor Fuel Price Stabilization Mechanism.” *Energy Policy*, **50**: 689–698.

Sklar, A. (1959). “Fonctions De Répartition À N Dimensions Et Leurs Marges.” Publications *De l’Istitut Statistique De l’Université De Paris*, **8**: 229–231.

Ward, R. W. (1982). “Asymmetry in Retail, Wholesale and Shipping Point Pricing for Fresh Vegetables.” *American Journal of Agricultural Economics,* **62**: 205–212.