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An Econometric Model for Nigeria's Rice Market

Rakiya Yakubu Abdulsalam*, Mad Nasir Shamsudin, Zainalabidin Mohamed, Ismail Abd. Latif, Kelly Kai Seng Wong and Mark Buda

Department of Agribusiness and Bioresource Economics, Universiti Putra Malaysia, 43400, UPM Serdang, Selangor, Malaysia

ABSTRACT

A dynamic econometric model of Nigeria's rice market was designed to serve as a base for future policy analyses. Using time-series data spanning 38 years, the model contains four structural equations representing paddy area harvested, paddy yield, per capita demand, and producer price variables. Estimates for these equations were obtained using the autoregressive distributed lag (ARDL) cointegration approach. Results of the paddy production and yield sub-models showed that paddy area harvested, and paddy yield was price inelastic. Furthermore, the paddy area harvested responded favourably to technological advancement. For the demand sub-model, estimated own price and cross-price elasticities showed that rice has an inelastic demand response, with wheat being a substitute. A series of validation tests strengthened the reliability of the model for use as an empirical framework for forecasting and analysing the effects of changes in policies such as rice import tariff reforms on production, consumption, retail price, and imports.

Keywords: Cointegration, econometric, model, paddy, rice

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E-mail addresses:
rakiyay@gmail.com (Rakiya Yakubu Abdulsalam)
mns@upm.edu.my (Mad Nasir Shamsudin)
zainal.mohamed@gmail.com (Zainalabidin Mohamed)
ial@upm.edu.my (Ismail Abd. Latif)
kellywong@upm.edu.my (Kelly Kai Seng Wong)
markbuda@upm.edu.my (Mark Buda)
* Corresponding author

INTRODUCTION

National level modelling of staple food markets is considered a crucial step in the development process of a country's agri-food system, which is perceived as an indicator of a nation's prosperity and overall development. The development of these models was mostly motivated by the need for decision-makers to follow agricultural economic issues (Carpentier et al., 2015). However, recent events have

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made modelling of food systems a policy priority for many countries. A case in point being the price spikes induced by the global 'food crisis' of the late 2000s, which revived the issue of world food security (Carpentier et al., 2015). Thus, economic models serve to guide policy interventions by examining existing systems and evaluating alternative scenarios for the selection of appropriate policy strategies.

In developing countries where resources are often limited, an important responsibility of the government is to direct these resources to priority areas. In reality, directing these resources is a delicate process that requires adequate information, usually in the form of formal quantitative policy analysis, a failure of which could jeopardise the effectiveness of a policy intervention in achieving its goal. This is compounded by the fact that the selection of an appropriate policy strategy is a complex resource allocation process that is affected by the dynamic interaction of a multitude of financial, social, economic, and political variables. Usually, policy interventions are politically motivated because each government regime develops its own budget for the economy. These interventions require huge financial investments requiring governments to consider some important factors including beneficiaries, available funds, interest rates, and inflation levels before deciding feasible options. Nevertheless, certain well-designed policy interventions can have favourable long-term impacts on members of the developing society. To ease the complexity in the policy-making process and to facilitate choosing policy options optimally, planning efforts would be made easier if there was a valid common framework for evaluating the potential outcomes of a variety of policy proposals. This common framework, in the form of a market model, has been the practice in national-level agri-food sectors for many economies. Therefore, a well-designed market model serves as a reliable tool for evaluating policies either through forecasting current situations or by simulating the impacts of policy alternatives.

Rice is an important staple in Nigeria and the government has been at the helm of its policy affairs in its efforts to boost domestic production, with an ultimate goal of suppressing its import volumes. In 2016, the Nigerian government, through its Agriculture Promotion Policy, set targets of becoming self-sufficient in rice by 2018 and turning to a net exporter by 2020. Three policies regulate the country's rice market: import tariff, input subsidy, and a formal credit guarantee scheme fund. Although these policies were introduced in the 1970s, there is limited time-series study evidence on the impacts of these policies on rice market variables. This is especially true for most of the available studies on the impacts of the credit and the input subsidy policies which have commonly employed a 'with-and-without' evaluation approach. Nevertheless, studies on the impact of fertilizer subsidy program (Alabi & Adams, 2020; Michael et al., 2018; Wossen et al., 2017) and on the impact of the formal credit (Ammani, 2012; Obilor, 2013; Zakaree, 2014) suggests positive outcomes. On the contrary, available statistics (Production, Supply & Distribution Online database) have suggested that perhaps these government's efforts have been quite sluggish in fostering the country's goal of boosting domestic production. Possible reasons could be due to some challenges faced by the policies. In particular, the fertilizer subsidy policy is challenged by politicisation and untimely delivery of inputs (Michael et al., 2018) while higher tariff rates have failed to decrease rice imports but rather encouraged tariff evasions (Dorosh & Malek, 2016) and smuggling (Johnson & Dorosh, 2017). Consequently, as shown in Figure 1, rice production has always remained below consumption, estimated at 4538 metric tonnes in 2018 while rice consumption demand reached 6800 metric tonnes in 2018, representing an average growth rate of 5% annually in the past 10 years. Yield, an important production variable has always hovered around 2 metric tonnes per hectare compared to a potential of 7 to 9 metric tonnes per hectare (Global Rice Science Partnership, 2013). Worth noting is the fact that Nigeria's rice production system is dominated (80%) by small-holder farmers (PricewaterhouseCoopers, 2018). This smallholder system is characterised by a low level of technology adoption and a low mechanisation rate of 0.3 Hp/ha (PricewaterhouseCoopers, 2018). The supply-demand imbalance is likely to continue due to drivers like rising income levels and population growth. Overall, the domestic supply deficit means the country has to rely heavily on imports to compensate for the shortfall. From 2008 to 2018, import volumes averaged 2345 metric tonnes annually. The foregoing presents a rice economy that is underdeveloped but with great potential.

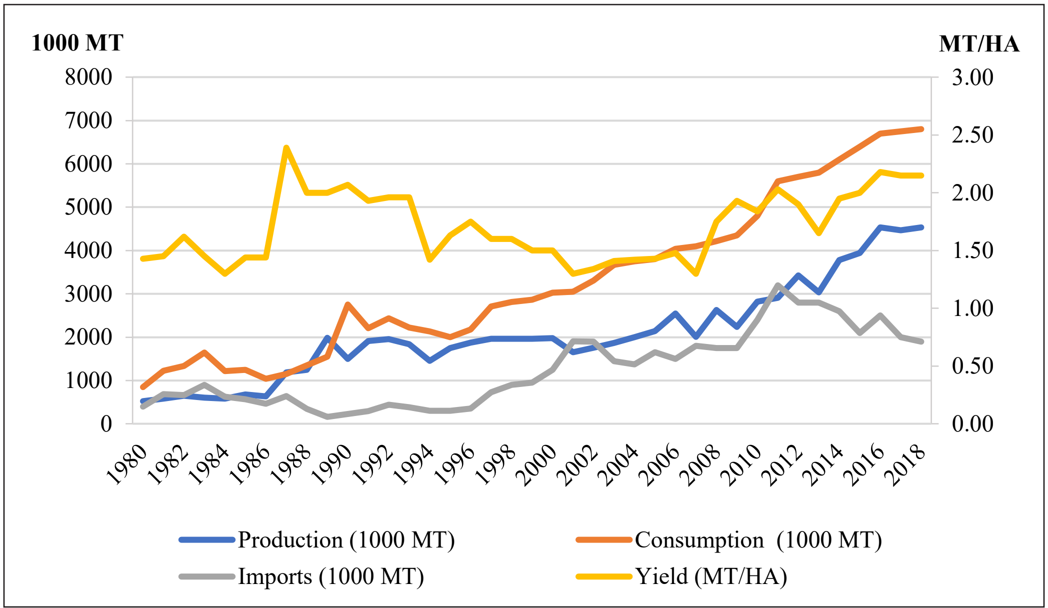

Figure 1. Paddy production, paddy yield, rice import, and rice consumption (Metric Tonnes) in Nigeria, 1980 to 2018

One approach to improving Nigeria's rice market is to review the country's rice policy environment which seems long overdue. As a first step, a well-designed rice market model is important for a number of reasons. First, identifying and understanding key variables, their inter-relationships, and their individual contributions to the functioning of the rice market are critical for preparing policies for improving the market. Secondly, understanding the functioning of each variable can help to identify opportunities that enhance their roles so that policy designs are target-specific. Thirdly, given the lack of a market model for Nigeria, a well-designed framework that approximately represents a market can serve to guide the modelling processes of other staples that have similar policies with rice like wheat.

The present study has the objective of developing a model of Nigeria's rice market that identifies its key determinants and examines their relationships that could serve as a framework for future policy evaluations. The remainder of this paper is organised into four parts. Section 2 explores the methodology and techniques applied to modelling of agri-food systems as employed in previous studies. Section 3 describes the modelling process. In section 4 is a presentation of the results accompanied by their discussions and section 5 concludes the paper.

LITERATURE REVIEW

Agricultural commodity market models find application in understanding structural relationships, policy impact analysis, and forecasting future market prices and quantities (Shamsudin, 2008). Through this market modelling methodology, relationships between key market variables can be quantified by specifying a set of equations (Christ, 1994; Hallam, 1990; Labys & Pollak, 1984). One way of quantifying these relationships is through econometric modelling and therefore, has found extensive application in agriculture. A couple of advantages it offers is that the methodology is less driven by assumptions regarding model parameters and behavioural effects, rather, the effects are calculated based on the observed behaviour of market agents. Additionally, the estimated model can be tested statistically and be validated to ensure their adequacy which is an important feature for policy analyses. The econometric modelling approach as it applies to the agri-food sector can either be of a comprehensive form (Egwuma et al., 2016; Sembiring & Hutauruk, 2018; Yazdanshenas et al., 2011) which encompasses all of the demand, supply, price, and stock components of the market, or a single/multiple components of a market (Chandio et al., 2018; Paul et al., 2020; Yusuf et al., 2020). These variations in scope in addition to differences in included variables in a model, create a challenge for comparisons of studies in modelling agri-food systems. For example, in a study on rice markets, Kozicka et al. (2015) estimated their production variable as a single equation while Sembiring and Hutauruk, (2018) on the other hand, estimated area harvested and yield variables separately, so that their product is an identity for the production variable. However, both studies shared a commonality in the sense that rice production and paddy area harvested were price elastic. This is expected given that producers will be encouraged by higher profits for their produce. When estimation techniques are considered, it is common to find contrasting elasticities in agri-food commodity studies. A case in point is a study on wheat demand in Iran by Yazdanshenas et al. (2015) who employed the autoregressive distributive lag technique (ARDL) and found that the demand for wheat was price elastic and wheat was an inferior good. Similar results were found for a rice study in India (Kozicka et al., 2015) using Ordinary Least Square regression. On the contrary, Essaten et al. (2018) used the seemingly unrelated regressions (SUR) technique on durum wheat demand in Morocco to reveal an inelastic price response to demand. At first, the contrasting results are quite unusual given that wheat and rice are staples in those countries. One explanation for this distorted own price and income elasticities despite wheat and rice being staples in those countries was that the rice retail price in Kozicka et al. (2015) was subsidised. Although each estimation technique has its strengths and weaknesses, the choice of technique ultimately depends on its applicability to a study's objective(s). In particular, the SUR technique has the ability to gain efficiency estimates by combining information on the different equations in a model (Moon & Perron, 2008). In the case of the ARDL technique, it allows for examining the convergence of the relationship between the variables regardless of their static nature, that is whether of I(0) or I(1) (Nkoro & Uko, 2016).

Overall, the econometric estimation technique serves as a way of obtaining elasticities, which are of great value to policymakers and analysts, as they are used in subsequent researches to determine possible impacts of policy changes in the agri-food sector.

METHODS

Model Framework

Models are required to facilitate policy analysis and no single model is capable of serving all policy issues. Rather, the domain of model applicability is guided by the choice of theoretical framework, the extent of regional and sectoral desegregation, and the choice of datasets and estimation methods (Van Tongeren et al., 2001). Bearing this in mind, this study follows the classic commodity market model proposed by Labys (1973), which is based on the neoclassical production function, to investigate commodity supply, demand, and price adjustment. His model specified four general equations adjusted for a typical region i at time t. Mathematically, the model is expressed in its compact form as follows:

$$S_t = s(S_{t-1}, P_{t-1}, N_t, Z_t) \quad (1)$$

$$D_t = d(D_{t-1}, P_t, P_t^c, A_t, T_t) \quad (2)$$

$$P_t = p(P_{t-1}, W_t, \Delta I_t) \quad (3)$$

$$S_t = D_t \quad (4)$$

Where:-
S_t = Supply of a commodity
D_t = Demand for a commodity
P_t = Price of a commodity
I_t = Inventories or stocks
P^c_t = Price of other commodities
P_{t-i} = Price with lag i (i = 1,2,3,….)
N_t = Natural factors
Z_t = Policy variables influencing supply
A_t = Income or economic activity level
T_t = Technical factors
ΔI_t = Change in Inventory
Wt = Shift factors

Where equations [1] and [2] are the supply and demand equations respectively, while equation [3] is the price equation. It is assumed that in the system of equations, the prices adjust to clear the market. The market model is closed using an identity that equates quantity supply minus quantity demand. Although the basic market model framework consists of four equations, in practice a more complex and extended structure can be refined to reflect the features of the commodity and market of interest (Ghaffar, 1986; Hallam, 1990). Guided by Labys' (1973) simple and straightforward theoretical methodology, a modified basic structure explaining rice market equilibrium as an adjustment process among demand, supply, and price variables were designed within a partial equilibrium econometric framework. The model contained four behavioural equations explaining paddy area harvested, paddy yield, rice consumption per capita, and producer price, and three identities that determined rice production, rice imports, and rice retail price. These sub-models are schematically contained in a market model depicted in Figure 2, showing a breakdown of its components.

Rice Supply. For any given year, the total supply of rice is a combination of the total quantity domestically produced and the total quantity imported. The paddy area harvested equation was specified based on the theory of production centred on the producer's supply response to price, which is assumed to depend on profit maximization subject to given production functions, prices, and weather conditions. Accordingly, the paddy area harvested was specified as a function of its lagged paddy area harvested, producer price of paddy, producer price of cassava (substitute crop), and government's guaranteed rice credit scheme (policy variable). Paddy area harvested was expected to be positively related to lagged paddy area harvested, producer price of paddy, and agricultural credit guarantee scheme but negatively related to producer price of cassava.

The yield of paddy is a function of growth-supporting factors which in this study were identified as anticipated producer price of paddy and a trend factor, which reflects productivity growth driven by technology improvements. The producer price of paddy was included based on the assumption that the guarantee of some

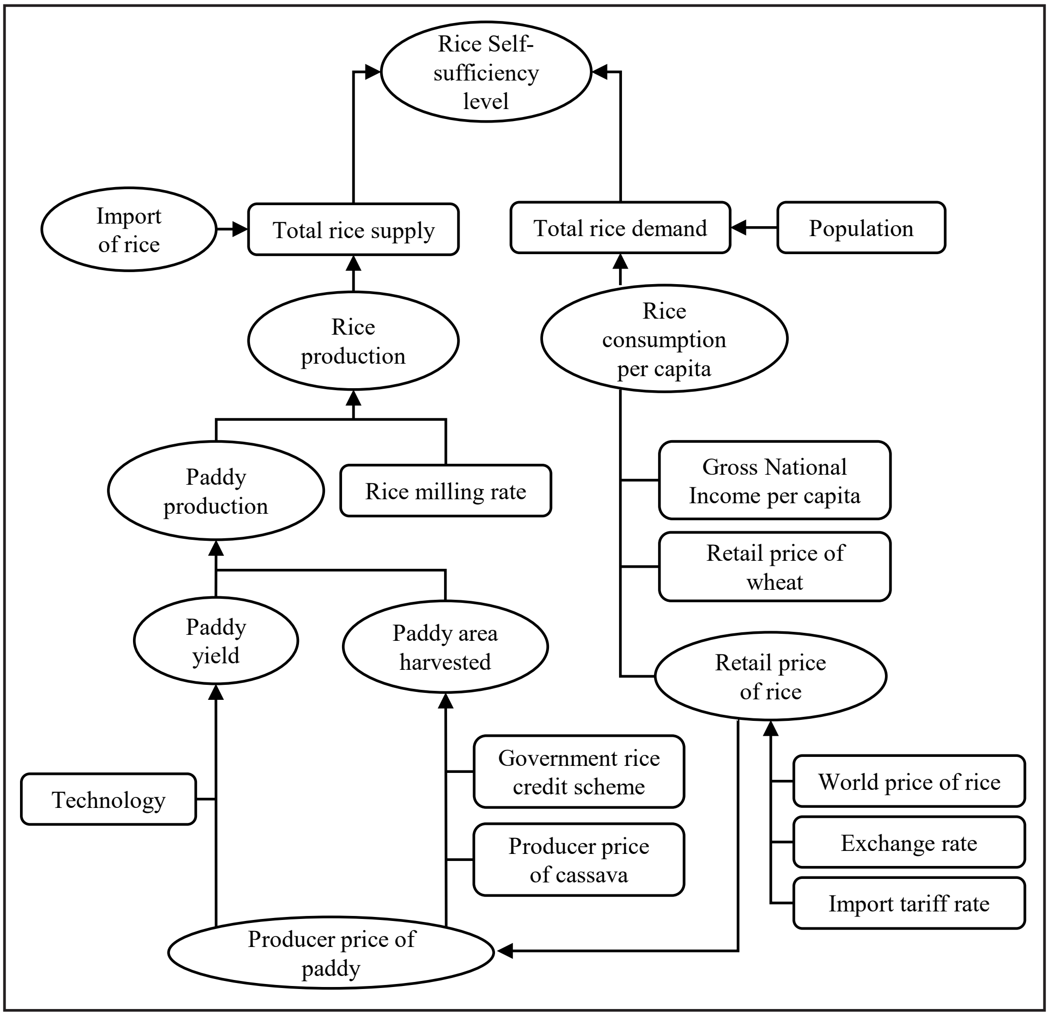

Figure 2. Flowchart of Nigeria's Rice Market Structure
Note. Variables in oval shape are endogenous while variables in the rectangles are exogenous

profit could cushion the effects of the high cost of inputs and ensure timely purchase of adequate amounts of inputs. All the coefficients were expected to carry positive signs.

The product of paddy area harvested, and paddy yield equations form an identity for total paddy produced, which was then converted to rice by a milling rate value. The rice production process consisted of two structural equations and two identities expressed in the following explicit functions:-

$$LPYAH_t = \alpha_0 + \alpha_1 LPYAH_{t-1} + \alpha_2 LPYPP_{t-i} - \alpha_3 LCVPP_{t-i} + \alpha_4 LCGSF_{t-i} + \mu_t \quad (5)$$

$$LPYYD_t = \beta_0 + \beta_1 LPYYD_{t-1} + \beta_2 LPYPP_{t-i} + \beta_3 TECH_t + \mu_t \quad (6)$$

$$PYPN_t = PYYD_t * PYAH_t \quad (7)$$

$$REPN_t = PYPN_t * RCMR_t \quad (8)$$

Where:-
PYAH = Area harvested of paddy in hectares
PYYD = Yield of paddy in tonnes per hectare
PYPN = Production of paddy in tonnes
REPN = Production of rice in tonnes
PYPP = Producer price of paddy in Naira/tonne
CVPP = Producer price of cassava in Naira/tonne
CGSF = National rice credit guaranteed scheme fund in thousand Naira
Trend = Time Trend as a proxy for Technological Change
RCMR = Milling rate of rice in percentage
L = Natural logarithm
$\alpha_1 - \alpha_4$ = Parameters to be estimated
$\beta_1 - \beta_3$ = Parameters to be estimated
μ_t = Stochastic error term
t = Time Period
i = Time Lag

Import Demand. As a net importer of rice, domestic demand and supply are linked to the world market through trade. Import demand is an identity that is determined by the domestic demand equation and total rice production identity. The identity was expressed as the difference between total demand and total domestic rice production, given by:-

$$REIM_t = NTRD_t - REPN_t \quad (9)$$

Where:-
REIM = Nigeria's rice import demand in tonnes
NTRD = Nigeria's total rice demand in tonnes
REPN = Production of rice in tonnes
t = Time Period

Rice Demand. The estimation of demand equations is based on microeconomic theory which suggests that the demand for a commodity is derived from the maximization of a utility function with respect to prices and income (Nicholson & Snyder, 2011). In this study, total rice demand was modelled in two steps because income and population are major variables affecting food consumption and therefore, could be highly correlated. In order to avoid any statistical problems in estimation, a per capita rice demand equation was first estimated, then an identity was expressed for total rice demand as a product of per capita rice demand and population. Rice consumption per capita was specified as a function of its retail price, retail price of wheat (as a potential competing food item), and income. Mathematically, it was expressed as follows:-

$$LREPC_t = \lambda_0 + \lambda_1 LREPC_{t-1} - \lambda_2 LRERP_{t-i} + \lambda_3 LWTRP_{t-i} + \lambda_4 LGNIPC_t + \mu_t \quad (10)$$

$$NTRD_t = REPC_t * POP_t \quad (11)$$

where:
REPC = Per capita domestic demand for rice in Kg/Capita
RERP = Retail price of rice in Naira per tonne
WTRP = Retail price of wheat in Naira per tonne
GNIPC = Gross National Income per capita in Naira
NTRD = Nigeria total rice demand
POP = Population
L = Natural logarithm
$\lambda_0 - \lambda_4$ = Coefficients to be estimated
μ_t = Stochastic error term
t = Time Period
i = Time Lag

Price Linkages. Price relationships were specified to link the demand and supply components of the model. The sub-model was formulated such that the influence of Nigeria's tariff import policy is captured. The Nigerian government imposes a 70% tariff on rice imports as of 2018. Hence, the retail price was expressed to be determined by an identity featuring the world price of rice, Nigeria's currency exchange rate, and tariff rate for rice imports. An equation for producer price of paddy was specified as directly influenced by lagged producer price of paddy and retail price of rice. These relationships were represented by the following equations:-

$$REDP_t = [REWP_t (1 + TARIFF)] * EXRT_t \quad (12)$$

$$LPYPP_t = \delta_0 + \delta_1 LPYPP_{t-1} + \delta_2 LREDP_t + \mu_t \quad (13)$$

Where:-
REWP = World price of rice in US$
TARIFF = Rice import tariff in percentage
EXRT = Nigerian currency exchange rate
PYPP = Producer price of paddy in Naira per tonne
RCRP = Retail price of rice in Naira per tonne
L = Natural logarithm
$\delta_0 - \delta_2$ = Coefficients to be estimated
μ_t = Stochastic error term
t = Time Period

Variable Classification and Sources of Data

Data requirements are determined partly by the level of desegregation in the rice market. Two types of variables were used in this study - endogenous which were determined or generated by the model and exogenous which were not solved for in the model, rather were determined outside it. Data for this study were obtained from multiple sources covering the period of 1980 to 2018. For a breakdown, data on paddy/rice production, consumption, and population were obtained from the International Rice

Research Institute online database, retail prices of rice and of wheat were sourced from FAO'S GIEWS online database, producer prices were sourced from FAO's FAOSTAT online database, Gross National Income per Capita data were obtained from Central Bank of Nigeria database, and Nigeria's currency exchange rate, as well as the world price of rice, were retrieved from UN Comtrade online database.

Model Estimation Technique

Applying the appropriate methodology is the most crucial part of time series analysis, and misspecification or the wrong technique can result in biased and unreliable estimates (Shrestha & Bhatta, 2018). A reliable estimation technique selection for time series analysis is based on stationarity results from a unit root test of the variables (Shrestha & Bhatta, 2018). The stationarity of a time series refers to a feature where its value tends to revert to its long-run average value and the properties of its data series are not affected by the change in time only (Shrestha & Bhatta, 2018). For example, the variance in paddy yield data cannot differ between years. The opposite of this feature is referred to as non-stationarity, meaning that its mean, variance, and co-variance all change over time, and are said to have a unit root. Conventionally, methods used to analyse stationary time series data are inapplicable to analyse non-stationary time series data.

The non-stationarity property of a time series data can be resolved through differencing but using differenced variables for regressions poses the risk of losing relevant long-run properties or information of the equilibrium relationship between the variables under consideration. To overcome such problems, the concept of cointegration was developed to refer to a statistical concept within the regression theory framework that explains long-run equilibrium in economic theories. It integrates short-run dynamics with long-run equilibrium which forms the basis for obtaining realistic estimates of a model (Nkoro & Uko, 2016).

Techniques for establishing cointegration among econometric variables include the autoregressive distributed lag (ARDL) method, advanced by Pesaran et al. (1996) and Pesaran et al. (2001). A desirable feature of the technique is its versatility in analysing time series data regardless of whether all the variables are integrated of I(0) or I(1) or a mix of both, but not I(2). Also, the ARDL technique can test long-run relationships and estimate the long-run parameters. The following model defines the ARDL technique:-

$$y_t = \alpha + \beta_{Xt} + \emptyset_{Zt} + e_t \tag{14}$$

the error correction version of the ARDL model has the following structure:-

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{\rho} \beta_i \Delta Y_{t-i} + \sum_{j=0}^{q} \gamma_j \Delta X_{t-j} + \sum_{k=0}^{r} \delta_k \Delta Z_{t-k} + \emptyset_1 Y_{t-1} + \emptyset_2 X_{t-1} + \emptyset_3 Z_{t-1} + \mu_t \tag{15}$$

Equation (15), Δ symbolises the first difference operator, α_0 signifies the drift component, μ_t is the random error term with its classical attributes, and Y, X, and Z represent the variables in the structural equations. The first part of the equation containing β, γ, and δ represents the short-run dynamics of the model while the part with Øs represents the long-run relationship.

Applying the ARDL approach follows a sequence. In the first step, a long-run relationship is established by calculating the F-statistic and then performing a joint test of the significance of lagged variables. In mathematical notation, the null hypothesis is expressed as:

$$H_0: \emptyset_1 = \emptyset_2 = \emptyset_3 = 0 \tag{16}$$

The null hypothesis of the non-existence of a cointegration relationship is tested against the alternative, that is, the Ø's are jointly different from zero. For the F-test, the critical values provided by Narayan (2005) were applied due to the small sample size of this study (38). In a conclusion, the null hypothesis is rejected if the computed F-statistic exceeds the upper bound. Alternatively, if the computed F-statistic falls below the lower bound, we fail to reject the null hypothesis of no cointegration. The test is inconclusive if the computed F-statistic falls within the bound.

Model Validation

The ability of planners to base policy decisions on modelling outcomes depends on building some level of confidence in the validity of that models. As a necessary requirement in modelling studies, the validation process involves critically examining the model's performance in reflecting the realities of the market in question. Therefore, a number of statistical tests were employed to check the reliability of the model to see if they fall within the acceptable threshold for model strength. They included the Mean Absolute Percentage Error (MAPE) – which measures the mean absolute percentage difference between the actual values and the forecast values (Chu, 2009), the Root Mean Squared Percentage Error (RMSPE) – which estimates the percentage value of the deviation between the forecast value and the mean actual value and the Theil's Inequality coefficient – which measures the fit of the model. For all the tests, the closer to zero the values are, the better. These statistical indicators are generated by:-

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\left(\frac{P_t - A_t}{A_t}\right)\right| \tag{17}$$

$$RMSPE = \left[\frac{1}{T}\sum_{t=1}^{T}(P_t - A_t/A_t)^2\right]^{\frac{1}{2}} \tag{18}$$

$$U^T = \frac{1/T\sum_{t=1}^{T}(P_t - A_t)^2}{1/T\sum_{t=1}^{T}(P_t)^2 + 1/T\sum_{t=1}^{T}(A_t)^2} \tag{19}$$

Where T is the number of periods in the simulation, P is the predicted value, and A is the actual value.

RESULT AND DISCUSSION

Unit Root and ARDL Cointegration Tests

In econometrics, the assumption of stationarity underlies statistical inference and thus, a key aspect of time series analysis is establishing the stochastic properties of all variables (Egwuma et al., 2016). Thus, unit root tests were conducted to establish the stationarity status. Two tests namely the augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1981) and the Phillips Perron (PP) (Phillips & Perron, 1988) tests were conducted. Prior to the tests, the variables were converted to their logarithmic forms so that the estimated parameters can be interpreted as elasticities. Results presented in Table 1 shows that the variables were integrated of order one I(1). Identifying the stationarity status of the variables is crucial because it helps in determining the choice of estimation technique. For example, the ARDL technique crashes in the presence of an integrated stochastic trend of I(2) (Nkoro & Uko, 2016). Therefore, it is important to confirm that the data satisfies the conditions for the ARDL technique so as to obtain reliable estimates that are amenable to subsequent forecasting and policy studies.

The long-run relationships of the variables are determined through the F-statistic of the ARDL bound test of cointegration, the results of which are in Table 2. Based on the results, the null hypothesis of no cointegration was rejected because the computed F-statistics exceeded the critical values reported by Narayan (2005).

Estimated Long-run Coefficients

Table 3 contains a summary of the ARDL long-run parameters of the estimated sub-models with their respective diagnostic statistics. In general, the estimated equations fit the data in a manner consistent with economic theory. The statistical properties of the model are good, and all equations have at least 92% of their historical

Table 1
Results of ADF and PP Unit Roots Tests

Variable	ADF		PP		Conclusion
	Level t-statistic	First difference t-statistic	Level t-statistic	First difference t-statistic	
ln PYAH	-1.792	-8.090***	-1.998	-8.071***	I(1)
ln PYPP	-2.657	-6.801***	-2.616	-6.772***	I(1)
ln CVPP	-0.438	-8.814***	-0.697	-9.428***	I(1)
ln RCGSF	-1.877	-4.033***	-1.593	-4.010***	I(1)
ln PYYD	-1.554	-8.142***	-1.669	-8.126***	I(1)
ln REPC	-1.080	-7.504***	-0.655	-7.709***	I(1)
ln RERP	-1.768	-6.559***	-1.767	-6.845***	I(1)
ln WTRP	0.170	-2.742***	-1.213	-8.859***	I(1)
ln GNIPC	0.453	-4.318***	0.113	-4.343***	I(1)

Note. *** denotes significant at 1% significance level

Table 2
Results of ARDL bound test of cointegration

Equation	K	F-statistic	Narayan (2005) Critical values I(0)	Narayan (2005) Critical values I(1)
PYAH	3	4.081*	2.933	4.020
PYYD	2	4.591*	3.373	4.377
REPC	3	11.023***	5.018	6.610
PYPP	1	6.497**	5.260	6.160

Note. ** and * denote significant at 5% and 10% levels, respectively. K is the number of exogenous variables in the equation.

Table 3
Estimated long-run coefficients of the ARDL approach

Regressor	Paddy harvested area	Paddy yield	Rice consumption per Capita demand	Producer price
Constant	9.520***(3.830)	3.272***(2.724)	-8.799***(-4.350)	-0.622(-0.807)
$PYAH_t$	0.260(1.555)			
$PYPP_t$	0.206***(4.170)	0.220**(2.569)		0.985***(38.915)
$CVPP_t$	-0.076(-1.433)			
$CGSF_t$	0.162**(2.252)			
$PYYD_t$		0.488***(3.557)		
$TECH_t$		0.292***(3.041)		
$REPC_t$			0.493***(5.646)	
$RERP_t$			-0.321***(-5.380)	0.168(1.588)
$WTRP_t$			0.193***(3.754)	
$GNIPC_t$			0.951**(2.693)	
REDP_t				
Adjusted R^2	0.951	0.951	0.920	0.987
BG-LM	0.888[0.422]	0.932[0.437]	0.244[0.786]	2.675[0.084]
JB	19.556[0.000]	1.592[0.451]	1.037[0.595]	2.413[0.299]
RESET	0.084[0.774]	0.008[0.929]	2.633[0.116]	3.447[0.072]
BP-G	1.051[0.406]	0.695[0.601]	0.884[0.542]	1.431[0.253]

Note. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively. Figures in parenthesis () are t-statistics while figures in brackets [] are p-values. BG-LM is the Breusch-Godfrey Lagrange Multiplier test, JB is the Jarque-Bera test, RESET is Ramsey's test, and BP-G is the Breusch-Pagan-Godfrey test.

variation explained. As a prerequisite, the estimated equations were ensured to be in conformity with statistical properties via a series of diagnostic tests, specifically Ramsey's RESET test for specification error, Breusch Godfrey LM test for serial correlation, Breusch-Pagan-Godfrey test for heteroskedasticity, and Jarque-Bera test for normality of residuals.

In the supply component of the model, the paddy area harvested in the next period is significantly influenced by the producer price of paddy and rice credit guarantee scheme fund. As reflected by paddy's own price elasticity, we observed that the paddy area harvested is highly responsive to its price. This is reflected in its own price elasticity value of 0.206 which was statistically significant at 1%, implying that a 1% increase in paddy producer price will induce a 0.206% rise in paddy area harvested, holding other factors constant. Similar rice studies in Nigeria found higher own-price elasticities of paddy. They reported 0.633 (Ayinde et al., 2014), 0.230 (Takeshima, 2016), and 0.340 (Okpe et al., 2018), respectively. As expected, the cross-price elasticity of paddy area harvested for cassava is negative, albeit statistically insignificant to influence paddy area harvested. This means that paddy and cassava substitute each other for land; that is, an increase in the producer price of cassava will cause producers to shift resources away from the paddy area harvested. The rice credit guarantee scheme policy variable also displayed a positive relationship with paddy area harvested with a coefficient of 0.162 and has a statistically significant effect on paddy area harvested at a 5% level. This relationship is crucial, especially for the country's smallholder holder system. As emphasised by Bahşi and Çetin (2020), the benefits of agricultural formal credit extend beyond the monetary value to a deeper consideration where the resources purchased through the credit fund facilitate the enhancement of farmers' entrepreneurial performance. A similar result was reported by Omoregie et al. (2018), who investigated the effect of credit supply on rice output. As for paddy yield, the result showed that a 1% rise in the producer price of paddy results in a yield improvement of 0.220%. With a slight contrast, Boansi's (2014) study observed yield of paddy increased by 0.210% for a 1% increase in the producer price of paddy in the short run. Lagged yield has a positive and a statistically significant (1%) effect upon current yield by about 0.488% because higher volumes of yield may drive producers to invest more in yield-enhancing inputs in the following production season. This relationship was reinforced by the positive elasticity of technology growth which was statistically significant at 1%. It is common logic that technological growth in the form of high yield varieties when combined with appropriate inputs produce dramatic increases in paddy production

Results of the demand component showed that all the featured variables carried their expected signs, more so, significantly. The own price elasticity of rice was -0.321, meaning that the higher retail price of rice diminished its quantity demanded. In a similar study, Makama et al. (2017) found a higher own price elasticity value (-0.55) for rice in Nigeria. It was observed that wheat was a substitute for rice as revealed by a cross-price elasticity of 0.19. The relationship was expected since wheat is also a staple in the country. The relationship between per capita rice demand and income is described by the income elasticity of demand (0.95). Specifically, a 1% increase in income will be reflected by a 0.95% increase in per capita demand while keeping all other factors constant. The income elasticity value is low and means that a rise in income is accompanied by less than a proportional increase in per capita demand for rice. This behaviour is characteristic of a necessary good.

In the producer price of paddy equation, the lagged producer price was positive and statistically significant at 1%. Its elasticity was 0.985, meaning that a 1% increase in the lagged producer price of paddy will cause a 0.985% increase in the current producer price of paddy, in the long run, holding other factors constant.

Short-run Dynamic Error Correction Representation for the Selected ARDL Models

Error-correction models may be thought of as capturing the true dynamics of a system whilst incorporating the equilibrium suggested by economic theory (Granger & Weiss, 2001). The ECM consists of two parts: the first part contains the estimated coefficients of short-run dynamics and the second part consists of the estimate of the error correction term that measures the speed of adjustment whereby short-run dynamics converge to the long-run equilibrium path in the model. For all the endogenous variables, results of the lagged error-correction terms (ECT) have error correction representations. A necessary and sufficient condition for cointegration by virtue of the Granger Representation Theorem (Engle & Granger, 1987; Granger, 1983), which states that the existence of a long-run relationship among a set of variables implies that there exists a valid error-correction representation and vice versa. The magnitude of the ECT reflects the speed of adjustment of any deviation towards the long-run equilibrium path (Egwuma et al., 2016). As shown in Table 4, the coefficients of most of the regressors in the equations have their expected signs. However, only a few of these coefficients were statistically significant. All endogenous variables in our model have a high speed of adjustments judging from the coefficients of their error correction terms. The error correction terms are all negative and statistically significant at 1%. This finding reinforces the long-run relationships of the variables. In each case, the speeds of adjustments are enough (99.7%, 113.0%, 97.2%, and 112.0%) to reach a long-run equilibrium level in response to the disequilibrium caused by short-run shocks of the previous period. For example, the size of the lagged ECT (-0.997) for the paddy area harvested equation indicates that approximately 100% of the previous year's variation between the actual and equilibrium value of the paddy area harvested is corrected for each year. Available studies (Chandio et al., 2018) on grains have found higher ECT values (-1.385). This ability to directly estimates the error correction rate and therefore, account for the rate (whether high or low) of the speed of adjustment in time series as well as the direction it is moving, is an especially attractive feature of the ECM.

Table 4
Short-run dynamic error correction results of the ARDL approach

Regressor	Paddy harvested area	Paddy yield	Rice consumption per Capita demand	Producer price
Constant	0.019(0.600)	0.007(0.195)	0.001(0.069)	0.001(0.014)
$\Delta PYAH_t$	0.538(1.643)			
$\Delta PYPP_t$	0.100(1.096)	-0.012(-0.120)		0.991***(3.287)
$\Delta CVPP_t$	-0.082(1.037)			
$\Delta CGSF_t$	0.005(0.058)			
$\Delta PYYD_t$		0.577*(1.720)		
$\Delta TECH_t$		0.089(0.525)		
$\Delta REPC_t$			0.446***(2.327)	
$\Delta RERP_t$			-0.245***(-3.808)	0.255**(2.114)
$\Delta WTRP_t$			0.091(1.651)	
$\Delta GNIPC_t$			0.384(0.919)	
$\Delta \mathrm{REDP}_t$				
ECT_{t-1}	-0.997***(-2.779)	-1.130***(-2.874)	-0.972***(0.002)	-1.120***(-3.206)

Note. ***, ** and * denote significant at 1%, 5% and 10% levels, respectively. Figures in parenthesis (…) are t-statistics, Δ indicates the first difference of variables and ECT denotes the error correction term

Table 5
Summary of the model validation results

Statistic	Notation	Endogenous variable			
		PYAH	PYYD	RCCP	PYPP
Mean Absolute Percent Error	MAPE	0.533	1.271	2.113	2.541
Root Mean Squared Percent Error	RMSPE	0.763	24.53	2.501	3.030
Theil Inequality Coefficient	U^T	0.004	0.008	0.014	0.014

Overall, the estimation results of Nigeria's rice market model were statistically acceptable and have revealed important relationships associated with the variables in the market. A few of the coefficients were found to miss the threshold for acceptable statistical significance but were retained on basis of their econometric a priori signs.

Model Validation Results

Table 5 contains the results of a series of validation tests employed to assess the model's quality. For all endogenous variables, the values of the MAPE are less than 10%, indicating very good forecast accuracy. The U^Ts are less than 1%, suggesting the non-existence of systematic bias and satisfactory model performance. The yield variable has the highest forecast error (24.5%) which could be reflective of the erratic nature of the growth rates for some periods in the historical data. For example, 100% in 1982 was followed by a -50% in 1983 and then -50% in 1994 proceeded by a 100% in 1995. Based on these statistics, we can conclude that the model offers a fairly accurate representation of the country's rice market and offers a reliable tool for future forecasting and policy analyses.

CONCLUSION

Rice has become the staple food in Nigeria and its position as the main staple is unlikely to change in the near future considering the growing demand. Thus, making it a government's policy priority in recent years, especially considering the volatile nature of the world rice market and the risk of over-reliance on imports. In this paper, a dynamic econometric model of Nigeria's rice market was designed to highlight the key features and describe their relationships in the form of a system of behavioural equations, representing paddy area harvested, paddy yield, rice consumption per capita, and paddy producer price. Using data from 1980 to 2018, the ARDL technique employed was able to produce plausible, and statistically valid results. Most importantly, the technique was able to reveal the existence of long-run relationships among the variables in the model. Based on the elasticities, the pattern and nature of rice consumption in Nigeria were defined. Indeed, the calculated own and cross prices elasticities of per capita consumption of rice suggested that in the long run, the demand for rice was inelastic, a normal staple, and a necessary food item and these relationships were statistically significant at 1% in all cases. Thus, conforming with the economic theory that food goods generally have inelastic demand. It was found that rice consumers displayed a strong sensitivity to changes in its price, consumption of which will increase with rising consumers' incomes. This underlines the need for introducing a regulatory system such as a price ceiling for rice retail price or a price subsidy. Based on the results of the estimates, it turned out that paddy and cassava behave as substitutes, with a cross-price elasticity value of -0.08. Producer price of paddy was found to be a key determinant in the supply and price components of the model and these relationships were found to be statistically significant at 5% at least. This crucial finding coupled with the income elasticity nature (normal good) of rice demand means that the country's demand for rice will continue to increase in a growing economy and therefore makes a case for further research focused on evaluating alternative production supporting policies, like a deficiency payment program, which would boost rice production in line with the country's goal for increasing rice production. Otherwise, falling prices could cause a crowding-out effect of paddy producers that could jeopardise the country's rice self-sufficiency goal. Furthermore, as revealed by the results of the producer price estimation, it seems that the benefits from import tariffs are not significantly transmitted to domestic producers through the retail price. Therefore, policy reforms like lowering tariff rates may benefit consumers at the expense of producers, ultimately stifling production growth in the country.

The econometric approach in this study facilitates the understanding of the behavioural relationships and makes the model flexible to future improvements. The importance of the model lies in the ability of the elasticities to provide an understanding of the relationships that exist in the rice market and to facilitate insights on probable consequences of policy considerations in the rice market so that policymakers and researchers can consider feasible options. Although the study experienced some cases of data gaps in some of the variables, these shortcomings do not undercut the reliability of the model as proven by the model validation tests.

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