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Rice Price Differentials in Rural Markets of Edo State, Nigeria

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Abstract: The dispersion in price of rice across different markets in exclusive location, and the astronomic annual increase of 30% in the past 7-8 years in Edo state cannot be attributed mainly to transport costs. Consequently, the study examined spatial price variation of rice vis-à-vis beans, garri, and palm oil as typically consumed substitutes/complements food commodities from a segment of 286 food commodity marketers in Ovia North-East Local Government Area (LGA) of Edo state, Nigeria using the spatial lag model of price-cost of transport data set. The outcomes of the descriptive data showed that the price of 1Kg rice under random test became ₦1576.82. The consequences of Moran's I (3.652) and Lagrange multiplier exams (10.753) for spatial lag, and Moran's I (0.175) and Geary's c check (0.460) for spatial autocorrelation suggest evidence of clustering in the spatial price of rice at the nearby markets and spatial price of rice between markets than might be under a random experiment. However, the results confirmed no spatial structure, no spatial dependence in the error term, nor spatial dependence within the costs of garri, beans and palm oil. The effects of the spatial lag model showed a mean price of 1kg of rice as ₦1597.77 with an average total effect of 0.406 comprising 0.274 direct effect and 0.132 indirect effects. Hence, the own-market price of rice in the study area is affected by the across-market price in the nearby markets, in addition to the cost of transportation from market of purchase.

Keywords: Rice; Price; Variability; Spatial-lag; Spatial-dependence; Spatial-autocorrelation.

INTRODUCTION

Rice is the world third most produced and consumed cereal after maize and wheat (FAO, 2012) offering greater than 20% of caloric desires of hundreds of thousands of people on daily basis. It is the fifth-most commonly consumed food after tubers, vegetables, beans, and other cereals. Nigeria is the leading consumer of rice in Africa (FAO, 2015) with rice as the staple dietary household food item (Ojogho and Alufohai, 2010) especially among lower-middle and low-income groups. As at 2013, annual rice consumption rate in Nigeria was 7.2% while annual production rate, on average, was 6.1%. In 2016, the annual consumption was about 5 million MT while quantity supplied was put at 2.7 million MT, leaving a demand–supply gap of about 2.3 million MT (USDA, 2016). This demand-supply gap is mostly filled by importation (Obih and Baiyegunhi, 2017), but without its attendant increase in price of rice. The incessant increase in food price, price of rice inclusive, over recent years has increasingly been of policy concern as a result of the negative outcomes, especially on the poor who spend more than 80% of their earnings on food (Obayelu, 2010; Ayinde et al., 2012; Capuno et al., 2013).

Available statistics on food prices suggests that, on average, price of rice and its substitutes/complements have been rising (Ojogho and Egware, 2015; Onwusiribe et al., 2020). For the period, 2019-21 in Nigeria, the price of commodities like palm oil increased by 28.64%, beans increased by 27.70%, loose solid yellow garri increased by 56.96%, local rice increased by 35.96% (NBS, 2021). In Edo state, palm oil increased by 36.78%, beans increased by 47.05%, solid loose yellow garri increased by 92.84%, solid loose local rice increased by 40.94%. (NBS, 2021). The price of a 50kg bag of rice in Edo state has risen astronomically from N8000 to N50000 (1 USD = ₦700) between December, 2015 and December, 2022, representing 30% increase annual price per Kg of rice. This sudden and large increases in price of rice have been attributed to exchange rate, lending rate, money supply, real GDP per capita, stocks, oil price, seasonal factors, distribution constraints and hoarding attitudes of middlemen CBN, 2021). However, price dispersion of homogeneous product sold at different prices by different marketers in different markets can emerge for different marginal costs (Crucini and Yilmazkuday, 2014; Hakan, 2016), and variations in consumer preferences (Grebitus et al., 2013), entry barriers, different grades of a commodity and geographical separation of markets reasons (Yang et al., 2017).

This study, therefore, aimed at examining price variation of rice *vis-à-vis* other commonly consumed substitutes/complements food commodities (Ojogho and Alufohai, 2010) among markets in Ovia North-east LGA of Edo state, Nigeria using cross section data. To achieve this, the study examined price variability of the food commodities, and price differential of rice vis-à-vis beans, garri, and palm oil between markets in the study area. Previous study have examine the volatility of prices in the Nigerian markets using time-series data (Adekoya et al, 2013; Nwibo, 2013; Ojogho and Egware, 2015; Mani et al., 2018 and Onwusiribe et al., 2020). The study used cross-sectional data to avoid the statistical problem with using time series data in estimation such as auto-correlation and non-stationarity. Besides, the error term is assumed to be an independent draw from a normal distribution with zero mean, contemporaneously uncorrelated and contemporaneous variance-covariance matrix. The outcomes of the study would assist marketers to make effective and efficient decision regarding the marketing of food commodities under study as it relates to price and income risk associated with price variation of homogenous products. It is hoped that this study provides consumers with information on the degree of price variation and also equip them with beneficial records on in which to shop for rice and related substitute/enhances at a cheap price ceteris paribus.

MATERIALS AND METHODS

Study area and Data Collection

The study was conducted in Ovia North-east LGA of Edo state. Edo state has an area of 17,802km2, and is bounded in the North by Kogi state, in the south by Delta state and West by Ondo state. It lies within the geographical coordinate of latitudes 5⁰40` and 7⁰40` North and longitudes 5⁰00` and It has a population size of about 3.2 million (Nigeria Population Commission, NPC, 2006). The state has a tropical climate characterized by two distinct seasons with average minimum and maximum temperature of about 25⁰c and 35⁰c respectively. Ovia North-east is bounded to the North by Owan-west and Ondo state, to the East by Uhunmwonde, Egor and Oredo, to the west by Ovia South-west and to the South by Delta state. Its headquarters is Okada. It has a population size of about 153,849 (NPC, 2006) and an area of 2,301km2. There are some markets within the LGA that sell rice, yellow garri, beans, pepper, and palm oil, amongst other food commodities.

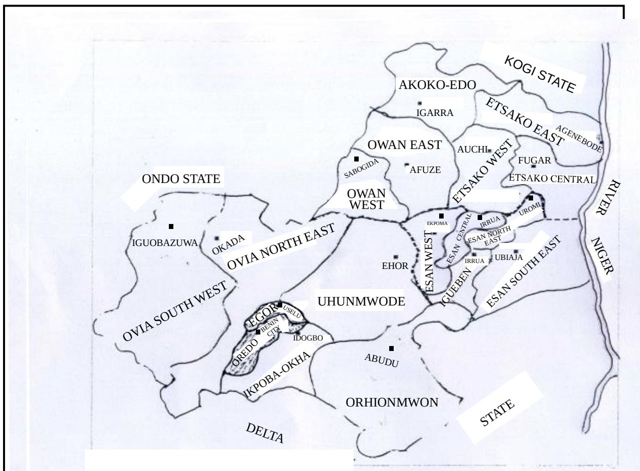

Figure 3.2a: Map of Edo State Showing the Local Government Areas of Study

A two-stage sampling procedure was used to selecting food marketers for the study. For the provision of the chosen food commodities discovered in a few main markets in the location, 4 principal markets had been selected purposively in the first level of the sampling procedure. The markets were Ekiadolor, Oluku, Ugbogiobo and Ugbogui markets. Within the second level of sampling, a simple random of 333 marketers were selected from the selected markets using the Krejcie and Morgan (1970) at 95% confidence interval and 0.05 degree of accuracy as used by Ojogho and Imade (2023). The sample-size estimator is given as:

$$s_i = \frac{\chi^2 N_i P(1-P)}{d^2(N_i-1)+\chi^2 P(p-1)} \quad [1]$$

Where s_i is the sample size of the ith market, N_i is the maximum target marketer in the ith market, P is the proportion marketers in the ith market, $\chi^2{}_{0.05} = 3{,}841,$ and $d = 0.05$. The sample size were respectively 74 from Ekiadolor market, 89 from Oluku market, 79 from Ugbogiobo market, and 91 from Ugbogui market, making a total 333 food marketers from the LGA of the state. Despite the fact that, handiest 300 copies of questionnaire were retrieved from the marketers creating a response rate of

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90%, only 286 of the retrieved copies of questionnaire had useful information for data analysis. The study look at accumulated statistics for the duration of August 2021-April 2022 on rice and its commonly consumed substitutes/complements that have experienced price hike in recent years. The prices of food commodities were measured as the marketplace retail price per unit.

Model Specification

It is far anticipated that food commodity marketers in low-price markets arbitrage in high-price food commodity markets. The study, therefore, assumed a significant sample of spatial clustering within the price of food commodities in the study area, and price spill-over from nearby markets. The values taken on price, in such case, at the different markets are more spatially clustered than they might be under a random assignment. For this reason, the study first anticipated an OLS regression model of the price of the food commodities on transportation cost. It then performed three assessments for spatial error dependence (Moran's I, the simple Lagrange multiplier and the robust Lagrange multiplier tests) and two test for spatial lag dependence (the simple Lagrange multiplier and the robust Lagrange multiplier tests) to ascertain spatial dependence. The spatial lag model treats spatial dependence as substance, assuming that the price of the food commodity in each location is affected by the values taken by it in the neighboring regions.

OLS regression model for the price of food commodity estimated for each commodity was given as:

$$P = T\beta + \epsilon \quad [2]$$

$$\epsilon \sim N(0, \sigma^2 I_N)$$

with

$$P = \begin{bmatrix} p_1 \\ \vdots \\ p_n \end{bmatrix},$$

$$X = \begin{bmatrix} 1 & T_{12} & \cdots & T_{i,n-1} & T_{1,n} \\ 1 & T_{2,2} & \cdots & T_{,2,n-1} & T_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & T_{n-1,2} & \cdots & T_{,n-1,n-1} & T_{n,n-1} \\ 1 & T_{n,2} & \cdots & T_{n,n-1} & T_{,n,n} \end{bmatrix},$$

$$\epsilon = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}$$

T denotes cost of transport from point of purchase. However, when the observations are spatial units, that is, based on markets, the standard OLS regression model may be misspecified/over-simplified because of the presence of spatial dependence among observations, and spatial autocorrelation and heterogeneity among the stochastic terms (Greene, 2018). To overcome that, the following equations, as stated by Anselin (1988) and LeSage (1999), provide the common version of the econometric model that is used for the estimations:

$$P = \rho WP + T\beta + \epsilon \quad [3]$$

$$\epsilon = \lambda W\epsilon + \mu, \quad [4]$$

$$\mu \sim N(0, \sigma^2 I_N)$$

with

$$W = \begin{bmatrix} 0 & w_{1,2} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & 0 & \cdots & w_{2,n-1} & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{n-1,1} & w_{n-1,2} & \cdots & 0 & w_{n-1,n-1} \\ w_{n,1} & w_{n,2} & \cdots & w_{n,n-1} & 0 \end{bmatrix},$$

$$\epsilon = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_n \end{bmatrix}$$

where λ coefficient reflects the spatial autocorrelation of the residuals, ϵ, if the model is spatial error model form, ρ is the spatial lag coefficient reflecting the importance of spatial dependence, WP denotes the spatially lagged dependent variable, W is the spatial weight matrix which indicates the relative position of observations in market space, and all the other terms are defined for [1] and [2]. In general, [3] become spatial lag model, when $\rho \neq \lambda = 0$, spatial error model when $\rho = \lambda \neq 0$, spatial mixed model when $\rho \neq \lambda \neq 0$ and simplifies to OLS model when $\rho = \lambda = 0$

RESULTS

The mean price per unit of rice vis-à-vis beans, garri, and palm oil in the markets of Ovia North-east LGA of Edo State is presented in Table 1. The results show that, generally, garri had the highest price (₦1583.33), followed by rice (₦1562.50), beans (₦1366.23), and least for palm oil (₦1071.94). Specifically, the price of rice was highest in Oluku market (₦1573.56), followed by its price in Ekiadolor market (₦1568.75), then its price in Ugbogiobo market (₦1563.24) and least in Ugbogui market (₦1543.13).

The result also shows the price of yellow garri was highest in Ugbogui market (₦1591.67), followed by its price in Ekiadolor market (₦1584.52), then in Ugogiobo Market (N1583.3) and least Oluku Market (₦1576.28). The price of beans was highest in Oluku market (₦1576.28), followed by its price in Ekiadolor market (₦1375), then in Ugbogui market (₦1373.75) and least in Ugogiobo market (₦1351.47). The price of palm oil was highest in Ugogui market (₦1169.74), followed by Ugogiobo market

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(₦1066.06), then its price in Ekiadolor market ((₦ 1044.92) and least in Oluku market ((₦ 405.13).

Also presented in Table 1 are the standard errors and coefficient of variation of food commodity prices in the markets in the study area. The result shows that, generally, palm oil had the highest standard deviation (294.86) and coefficient of variation in price (0.28%), while garri had the least standard deviation (28.49) and coefficient of variation (2%) in price. These suggest that the inconsistency in the price of palm oil was highest among food marketers in the study area. The standard deviation in price was about the same for the price of beans (54.4) and rice (54.80) with the same coefficient of variation (4%). This may be attributed to the fact that rice and beans are either substitute or complementary food commodities with some degree of price correlation, a priori. Specifically, rice had the highest standard deviation in price in Ugbogui market (88.62) and highest coefficient of variation in price of 0.06% and least in Ugbogiobo market (3.03 and 0% respectively), 1% coefficient of variation in price in Ekiadolor market, and 3% in Oluku market. The results suggest that rice consumers would be better-off buying rice from Ugbogiobo market than the other markets in the LGA. Yellow garri had no price variation in Ugbogiobo markets. Beans had highest variation in Ugbogiobo Market (97.01) with no variation in Ekiadolor market (0.00). Palm oil had the highest variation in Ugbogui market (547.88) with least variation in Ekiadolor market (104.36). These suggest that consumers of garri, beans and palm oil would be better-off buying garri in Ugbogiobo or Ekiadolor, beans in Ugbogui or Ekiadolor and palm oil in Ekiadolor markets in the event of no spatial dependence in price. This suggests that Ekiadolor and Ugbogiobo markets would be better for food consumers in the study area, ceteris paribus.

The results of the OLS parameter estimates and their associated standard errors of rice vis-à-vis beans, garri, and palm oil price-transport cost model are presented in Table 2. The results of the model (see Table 2) indicate R^2 of 0.022, implying that only about 2% of the variation in the price of rice is explained by cost of transportation from point of purchase. It indicates that the cost of transportation is not enough to explain the variation in the price of rice, even under a random assignment. This is contrary to the speculation by CBN (2021) that dramatic rise and variation in the price of rice is attributable to difference in cost of transport either between markets or point of purchase.

Table 1. Price of Food Commodities in Markets of Ovia North-East Local Government of Edo State, Nigeria.

Variable	Mean Price (₦) per Kg				
	Ugbogui	Ugbogiobo	Oluku	Ekiadolor	Pooled
Rice	1543.13 [88.62] (0.06)	1563.24 [3.03] (0.00)	1573.56 [45.73] (0.03)	1568.75 [23.39] (0.01)	1562.50 [54.80] (0.04)
Garri	1591.67 [37.27] (0.02)	1583.30 [0.00] (0.00)	1576.28 [35.95] (0.02)	1584.52 [4.45] (0.00)	1583.33 [28.49] (0.02)
Beans	1373.75 [5.59] (0.00)	1351.47 [97.01] (0.07)	1576.28 [49.03] (0.03)	1375.00 [0.00] (0.00)	1366.23 [54.46] (0.04)
Palm Oil	1169.74 [547.88] (0.47)	1066.06 [19.04] (0.18)	405.13 [137.25] (0.34)	1044.92 [104.36] (0.10)	1071.94 [294.86] (0.28)

Source: Authors' computation from Field Survey, 2022; values in brackets are standard deviation; values in parentheses are coefficients of variation; 1 USD = N700

However, the marginal effect of cost of transport on price of rice is significant at $p < 0.001$. The coefficient of cost of transport was 0.032. This implies that the price of rice increases by ₦0.03 for ₦1 increase in the cost of transport, ceteris paribus. Similarly, the coefficient of cost of transport in the models of garri (0.012), beans (0.012) and palm oil (0.112) were significant at $p < 0.001$, the respective explanatory power, R^2, of the models are too low for cost of transport to be considered as the main cause of variation in their prices.

Table 2. OLS Parameter Estimates and Associated Standard Errors Food Commodity Price Spatial Random Model Prices in Markets of Ovia North-East Local Government of Edo State, Nigeria.

Variables	Parameters	Rice	Garri	Beans	Palm oil
		Coefficients	Coefficients	Coefficients	Coefficients
Intercept	β_0	1576.518*** (7.770)	1577.59*** (5.828)	1383.847*** (14.187)	1010.606*** (25.177)

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Transport cost	β_1	0.032*** (0.003)	0.012*** (0.002)	0.012*** (0.006)	0.112*** (0.010)
	R^2	0.022	0.006	0.046	0.026

Source: Authors' computation from Field Survey, 2022; values in brackets are standard errors; *** significant @ $p < 0.001$

The results of spatial lag, spatial dependence and spatial autocorrelation of food commodities prices in markets of Ovia North-East Local Government of Edo State, Nigeria are presented in Table 3. The result showed that Moran's I z-values for prices of rice, garri, and beans are positive but negative for price of palm oil. The respective estimates for prices of rice, garri, beans and palm oil were 2.783, 1.291, 0.09.and -0.681. It was observed, as expected, that the Geary's c z-values for prices of rice (-2.059), garri (-1.403), beans (-0.930) and palm oil (1.279) had opposite sign as their counterpart Moran's I z-values.

Table 3. Spatial Lag, Dependence and Autocorrelation of Food commodities Prices in Markets of Ovia North-East Local Government of Edo State, Nigeria.

Variable	Without Regressor			Spatial Dependence Test in the OLS Regression		
	Global Spatial Autocorrelation				Spatial error	Spatial lag
	Moran's I	Geary's c	Getis & Ord's G	Moran's I	Lagrange multiplier	Lagrange multiplier
Rice	0.175*** [2.783]	0.460** [-2.059]	0.098 [-1.359]	3.652***	10.490*** (0.087)	10.753*** (0.350)
Garri	0.006 [1.291]	0.428 [-1.403]	0.099 [1.456]	0.119	0.013 (0.024)	0.011 (0.022)
Beans	-0.017 [0.059]	0.706 [-0.930]	0.099 [0.961]	-0.225	0.192 (0.147)	0.141 (0.096)
Palm oil	-0.077 [-0.681]	1.227 [1.279]	0.097 [-1.030]	-0.788	0.946 (2.432)	0.679 (2.166)

Source: Authors' computation from Field Survey, 2022; values in brackets are z-values; values in parentheses are robust values

The positive Moran's I z-values for prices of rice, garri and beans and negative Geary's c z-values indicate positive global spatial autocorrelation. That implies that there is clustering of respective similar prices of rice, garri, and beans among market in the study area, while their negative Moran's I z-values and positive Geary's c z-values for the price of palm oil indicate negative global spatial autocorrelation. This also implies that there is a clustering of dissimilar price of palm oil among the markets in the study area. Specifically, positive Getis and Ord's G z-values of the price of garri (1.456) and beans (0.961) indicate global spatial clustering of high values of price of garri and beans among the markets, while negative Getis and Ord's G z-values of rice (-1.359) and palm oil (-1.030) indicate global spatial clustering of low values of the price of rice and palm oil around the markets in the study area. The above statistics, given the level of significance, show that the price of rice at the different markets in the study area more spatially clustered than would be under a random assignment, ceteris paribus.

Also presented in Table 3 are tests for spatial error model and spatial lag model of spatial dependence. The test comprises of Moran's I, the simple Lagrange multiplier and the robust Lagrange multiplier tests for spatial error dependence, and the simple Lagrange multiplier and the robust Lagrange multiplier tests for spatial lag dependence. The Moran's I (3.652) and simple Lagrange multiplier (10.490) for the spatial autoregressive parameter of the spatial error model test in the price of rice equation are both significant at $p < 0.001$. Positive values of local Moran's I indicate a clustering of high rice price values in the neighborhood of high rice price values.

Also, the simple Lagrange multiplier (10.753) for the spatial autoregressive parameter of the spatial lag model test is significant at $p < 0.001$ in the price of rice equation. The significance of the Moran's I implies that there is spatial autocorrelation, suggesting the presence of very strong positive spatial autocorrelation among the regression residual which undermines the use of OLS criteria for parameter estimator and the interpretation of the related hypotheses testing procedures. This implies that there is the presence of spatial structure. This agrees with the assertion of Green (2018). However, the OLS and the Lagrange multiplier test suggests either the spatial error model or the spatial lag model, the Lagrange multiplier test suggests the spatial lag model for the price of rice model. The test reports that the study rejects that the residuals from the model in Table 2 are independent and identically distributed. In particular, the test considered the alternative hypothesis that residuals are correlated with nearby residuals as defined by the spatial weighting matrix. Hence,

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the clustering in the price of rice is attributable to spatial structure, spatial dependence in the error term and spatial dependence in it price. The results also showed that there is no spatial structure, no spatial dependence in the error term, nor spatial dependence in the prices of garri, beans and palm oil in the study area. Hence, the maintained hypothesis that rice prices change smoothly through space displaying positive spatial correlation, and thus a spatial lag model seemed an appropriate specification, expressing the price of rice as a function of the price observed for the neighboring rice markets.

The maximum likelihood parameter estimates and associated standard errors for food commodity price spatial lag model in markets are presented in Table 4.

Table 4. Parameter Estimates of Food Commodity Price Spatial Lag Model in Markets of Ovia North-East Local Government of Edo State, Nigeria.

Variables	Parameters	Coefficients	dp/dT Direct effect	Indirect effect	Total effect
Intercept	β_0	1597.767*** (15.005)	..	-	-
Transport cost (T)	β_1	0.261*** (0.030)	0.274*** (0.016)	0.132*** (0.021)	0.406 (0.010)
W.price of rice (WP)	ρ	0.607*** (0.145)	-	-	-
Log likelihood		-237.511			
Variance ratio		0.073			
Squared corr.		0.073			
Sigma		33.76			
Log Likelihood		-241.974			
Wald test of rho=0:		χ^2 = 17.463***			
Likelihood ratio test of rho=0:		χ^2 = 11.508***			
Lagrange multiplier test of rho=0:		χ^2 = 10.753***			

Source: Authors' computation from Field Survey, 2022; values in brackets are standard errors; *** significant @ $p < 0.001$

The results showed that the Wald test ($\chi^2 = 17.463^{***}$), likelihood test ($\chi^2 = 11.508^{***}$) and Langrange multiple test $\chi^2 = 10.753^{***}$) of the spatial lag coefficient were significant at $p < 0.001$, reflecting the importance of spatial dependence of price of rice. The likelihood ratio test for the spatial parameter, ρ, shows a significant positive spatial autocorrelation thus indicating a tendency for small markets to locate near to similar small markets The results showed that a variance ratio of 0.073. The results showed that around 5% of the variation in the price of rice is explained by spatial dependence, given that the R^2 is roughly 0.073 in the model that takes spatial dependence into account and 0.022 in the least squares model that ignores this aspect of the spatial data sample (see Table 2).

Similarly, the t-statistic on the parameter for the spatial dependence variable is 4.18, indicating that spatially lagged price of rice has a coefficient estimate that is significantly different from zero. This means that the spillover effects are significant, thus, β_0 and $\beta_1$values are not the same as those from the OLS model (see Table 2). This suggests that the price of rice in one market in the study area is affected by its price in the nearby markets, besides the cost of transportation from market of purchase. Table 4 also reports the average changes for ₦1 increase in transport cost from point of purchase. The own-market effect (direct effect) was 0.274, the spillover effect (indirect effect) was 0.132 with a resultant total effect 0.406. This means that a ₦1 increase in transport cost increases price of rice by ₦0.27, and that reduction spills over to further increase price of rice by ₦0.13, resulting in a total increase in price of rice by ₦0.41. Hence, a N1 increase in transport cost from point of purchase increased the own-market price of rice by ₦0.27 which resulted in across-market price of rice increase by ₦0.13, and a total increase in price of rice by ₦0.41 in the study area. The "direct" effect of increasing transport cost of a Kg of rice by ₦1 is not an increase of price of ₦0.26, but rather a larger increase of by ₦0.41 because of the additional ₦0.13 due to the indirect effect. Indeed, increasing the transport cost of a Kg of rice in one market will increase price of a Kg of rice in that market, but also in the nearby markets which in turn, due to the spatial lag mechanism, will produce a further increase in price of rice. Thus, the impact is greater if in a spatial lag model in

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place of the traditional a-spatial model due to the positive spatial correlation estimated with the parameter, ρ.

CONCLUSION

This study examined price variation of rice vis-à-vis beans, garri, and palm oil as commonly consumed substitutes/complements food commodities from a cross section of 333 food commodity marketers in Ovia North-East Local Government Area (LGA) of Edo state, Nigeria using the spatial lag model on 286 price-cost of transport data set. The study found evidence of clustering in the price of rice at the different markets and spatial price of rice between markets than would be under a random assignment. There is neither spatial structure, spatial dependence in the error term, nor spatial dependence in the prices of garri, beans and palm oil. Nevertheless, not only is there spatial structure in price of rice, spatial dependence in the error term, and spatial dependence in the prices of rice amongst nearby markets, but there is price differentials amongst rural rice markets in Edo state, Nigeria resulting from own-market price effect and cross-market price effect of rice in nearby rice markets in addition to the cost of transportation from market of purchase.

Conflict of Interest

There is no conflict of interest to declare.

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