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Food Prices Over Space vis-à-vis Transport Cost

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ABSTRACT:
The study examined economic geographic separation on food prices via space. Spatial price dependence was modelled with data from 300 amaranth-green marketers. Evident from the study were spatial price clustering (Moran test $\chi^2=8.34, p<0.0001$), price dependence ($\hat{\rho}=0.077$, $p<0.0039$) with transport costs significantly impacting price differentials. Distance-related Road transport costs depended on market visits frequency, transport cost of amaranth green from farm to central market, and from central market to other markets for resale. Overall, increased transport costs across space also increases retail market food prices. Addressing transport costs and market distances is essential for mitigating price imbalances and ensuring fair pricing.

KEYWORDS: Spatial Models; Transport Cost; Spatial Prices; Spatial spillover effects, Food prices

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INTRODUCTION

Between the mid-1960s and the mid-2010s, global transport costs decreased 33–39% and 48–62% by weight and value respectively (Ganapati & Wong 2023), impacting positively on trade volumes, productivity, household income and consumption, decrease in the price of goods and their variation across space, job opportunities, access to markets, and improved welfare (Ghani et al., 2016; Storeygard, 2016; Donaldson et al., 2017; Donaldson, 2018; Duranton & Venables, 2018; Kebede, 2021; Lall et al., 2022; Herrera et al., 2024). Contrarily, real transport costs per unit of final consumption more than doubled between 1965 and 2020, increasing 100% and 160% by weight and value respectively (Ganapati & Wong 2023) such that food prices increased globally by 6.7% between 2019 and 2021 with a notable single-year increase of 4.3% in 2021. This is because transport cost reductions are uneven between countries, and the inequalities persist also at the domestic level (Dappe et al., 2024). However, transport cost for agricultural foods in and out of origin remain much higher for low- and middle-income countries than in developed countries. Using the price-gap methodology, Atkin and Donaldson (2015) finds cost of transport in Ethiopia and Nigeria as approximately 4–5 times as large as in the United States. Between January 2001 and July 2010 for example, such transport costs in Nigeria were about 9% of the final price of goods (Dappe et al., 2024). In a world of changing transport costs, prices may appear to have a low degree of spatial integration even though the law of one price is not evident. Road transportation as a prominent mode of shipment in developing countries, eliminates unnecessary waste of products in supply-chain (Mei & Afli, 2017), accounts for 80–90% of passenger and freight traffic (Lipińska et al., 2019; Dappe et al., 2024), specifically reduces unsuitable environment that hamper fruits and vegetables (Iordachescu et al., 2019). Distance-related Road transport costs resulting from economic geographical market separation add to staple food prices in local markets (Gollin & Rogerson 2016), creating differences in price between markets (Brectova, 2016; Bondarenka et al., 2017), and food price heterogeneity (Gibson et al., 2017; Yang, et al., 2017; Gitau & Meyer 2018; Sobczak et al., 2018; Hamulczuk et al., 2019; Pan & Li 2019; Tan et al., 2022; Xu et al., 2022). This is especially significant in West Africa, where food prices tend to be 30-40% higher compared to the rest of the world and more than 90% of households with limited budgets express high food prices as among their top concerns (Green, 2024) for a healthy diet, who devote up to 32.6% of their budget to food, and are more accustomed to foods that cannot be grown in region of demand (Suweis et al., 2015; Wang et al., 2016; Kumar & Rojani, 2017; Roman, 2020) rely on markets to buy food. Besides foreign aid agencies who distribute food to the poor being vulnerable to fluctuations in the price of stable commodities, commodity price fluctuations also result in financial risk and planning uncertainty for farmers, food processors and other agribusiness firms.

The questions of "where, within the food supply-chain, will food markets choose to locate?", "How large are distance-related Road transport costs?", "How much do such transport costs contribute to price difference among markets?" are important for policy thrust particularly for fruits and vegetables. A healthy diet relies on a variety and abundance of vegetables including amaranth green-leaf, with the household demand and household expenditure share on them growing fastest after meat and fish in market value (Allen & Heinrigs, 2016; Dolislager *et.al.,* 2023). Like most vegetables, amaranth green-leaf is highly price sensitive, characterized by an inelastic short-run market supply, short shelf-life, lack of import, significant influence of producer-consumer distance, and timing of growing seasons while the fresh produce undergoes minimal processing and packaging. The most important component of marketing costs, therefore, is likely to be in transport. This study utilizes spatial cross-section amaranth green-leaf market price-transport costs data to examine the extent to which rising transport costs, and location issues contributes to food prices estimates as a substitute to the typical time-series framework food prices analysis approach. Firstly, using the latest available district-level cross-section data for the 2022-2023 period, this paper confirms that regional price variation occurs in amaranth green market. Secondly, the paper highlights significant differences in the spatial prices, specifically with regards to the impact of transport costs. Thirdly, it demonstrates that increasing spatial dependence is associated with increasing regional price disparities. The results of the study updates stakeholders with information on the degree of spatial influence on food prices, equipping them with valuable insight on spatial market price differentials, *ceteris paribus*.

LITERATURE REVIEW

The existent economic literature extensively discusses the differences in food prices across different areas (Gitau & Meyer 2018; Sobczak et al., 2018; Hamulczuk et al., 2019; Pan & Li 2019; Gaigné & Gouel, 2022). Other studies have identified challenges facing the transportation of urban fresh fruits and vegetables in the supply-chain (Agarwal, 2017; Wadhwa, 2018; Issa & Munishi, 2021). Many more studies have been traditional on global food price analysis using a time-series framework (Ojogho & Egware, 2015; Mani et al., 2018 and Onwusiribe et al., 2020). Time series data have some drawbacks which makes cross-sectional data ideal for price variations in retail marketing. Time series data may not capture as broad a range of variables and characteristics, as the focus is typically on tracking a specific set of variables over time. Yang et al., (2017) argues that a spatial approach to analyzing price dispersion is more appropriate on the grounds that price differences can occur when the product is sold at varying prices in different markets due to factors including economic geographic separation, *ceteris paribus*.

Interestingly, with elasticity of price differentials with respect to distance ϵ_{pd}, in the range of $0.001 \leq \epsilon_{pd} \leq 0.02$, earlier empirical results provide little to no variability in food prices across different locations, and that distance-related trade costs may not be significant compared to other sources of price dispersion (Ceglowski, 2003; Engel et al., 2003; Anderson & Smith, 2004; Crucini et al., 2005). However, there seems to be no consensus among the studies to spatial price variation arising from differences in methodology, commodities, periods, and countries. These results are also especially more worrisome, considering other literature that shows significant transport costs attributed to distance in other regions (Conforti, 2004; Coondoo *et al.,* 2004; World Bank, 2009; Coondoo et al., 2011; Majumder et al., 2012; 2015; Gibson et al., 2017; Harrigan et al., 2015; Gorg et al., 2017). A study by the World Bank (2009) demonstrates that the average transport cost tends to be considerably higher in sub-Saharan Africa than in other regions. The results indicated that the cost of long-distance transportation in sub-Saharan Africa ranges between US$0.06 and US$0.11 per Km-ton, compared to rates of US$0.02-0.05 per km-ton in other regions. Another study examining the cost of agricultural marketing in eastern Africa estimated the cost of marketing over shorter distances, including from the farm to local markets, indicate that short-distance marketing has a much higher cost on a per kilometer-ton basis (World Bank, 2009). In a study of patterns and determinants of transport prices in 60 low- and middle-income countries in 2019–20 for 53,106 shipments of food transport contracts across 4,659 different routes, Dappe et al., (2024) identifies the role of distance, and economic geography border frictions associated with the ability of foreign shippers to access the market.

METHODS

This study adopted cross-sectional research designs to obtain data from 300 amaranth-green marketers from New-Benin, Uselu, Oba, and Santana markets in the urbanized parts of Oredo, Egor, Ikpoba-Okha and Uhunmwunode Local Government Areas of Benin Metropolis in Edo State, Nigeria for the duration of October 2022 to September 2023. From the selected markets, a simple random sample of 356 amaranth-green marketers, consisting of 79, 92, 50 and 105 marketers respectively from New-Benin, Uselu, Oba market, and Santana markets were selected using the Krejcie and Morgan (1970) small sample-size estimator at 95% confidence interval and 0.05 degree of accuracy as used by Ojogho and Izekor (2023). Though the handiest 325 copies of questionnaire were retrieved from the marketers, only about 92% had useful information for data analysis.

To account for cross-market spillover price effects and spatial autocorrelation of the residuals, the econometric approach from regional economics perspective (Tobler, 1970) was adapted to model cross-unit spatial dependence and spatial heterogeneity *via* the so-called spatial weights matrix (Cliff & Ord, 1973, 1981, Anselin 1988). This was used after an oversimplified linear regression model of amaranth green-leaf price on level unit-level price on daily transport cost, transport cost of green-leaf from farm to New-Benin market (assembling point), transport cost from New-Benin market (Central Market for green-leaf) to other markets for resale, selling price of green-leaf and weekly visit to market was fitted to determine whether the residuals of the model are spatially correlated. The study estimated the Manski (1993) general nesting spatial (GNS) simultaneously determine the weighted average cross-market price dependence. The general nesting spatial (GNS) econometric model for spatial cross-section as used in the study is given in vector form as:

$$P = \alpha i_N + \rho WP + X\beta + WX\theta + \mu, \qquad [1]$$
$$\mu = \lambda W\mu + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_N)$$
$$W = \begin{bmatrix} 0 & w_{1,2} & w_{1,3} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & 0 & w_{2,3} & \cdots & w_{2,n-1} & w_{2,n} \\ w_{3,1} & w_{3,2} & 0 & \cdots & w_{3,n-1} & w_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{n-1,1} & w_{n-1,2} & w_{n-1,3} & \cdots & 0 & w_{n-1,n} \\ w_{n,1} & w_{n,2} & w_{n,3} & \cdots & w_{n,n-1} & 0 \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix}, \quad \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \vdots \\ \mu_n \end{bmatrix}, P = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \\ p_n \end{bmatrix}$$

In general, [1] simplifies to Ordinary Least Square (OLS) if on $\rho = 0, \theta = 0$ and $\lambda = 0$, to SAC that combines endogenous interaction effects and interaction effects among the error terms, if $\theta = 0$, to Spatial Durbin Model (SDM) if $\lambda = 0$, Spatial Durbin Error Model (SDEM) if on $\rho = 0$, SAR if $\theta = 0$ and $\lambda = 0$, to Spatial Error Model (SEM) if $\rho = 0$ and $\theta = 0$, to Spatial Lag exogenous Model (SLX) if $\rho = 0$ and $\lambda = 0$. WP is the spatial lag in price of green-leaf such that p_i observed in cross-sectional unit *i* is explained by p_j in other cross-sectional units *j*, $i \neq j$, and units *j* which are included depend on the specification of the spatial weight matrix W, WX is the spatial lag in the independent variables such that X observed in cross-sectional unit *i* is explained by x_j in other cross-sectional units $j,\ i \neq j$, and units *j* which are also included depend on the specification of the spatial weight matrix W that defines dependence between the cross-sectional market prices. $W\mu$ is the spatial lag in the idiosyncratic term such that μ_i observed in cross-sectional unit i is explained by μ in other cross-sectional units $j,\ i \neq j$, and units *j* which are also included depend on the specification of the spatial weight matrix W, ρ is the spatial lag coefficient reflecting the importance of spatial dependence, i_N is an $N \times N$ vector of ones associated with the constant term parameter α to be estimated, λ coefficient reflects the spatial autocorrelation of the residual, P represents an $N \times 1$ vector consisting of one observation on the selling price of amaranth green for every unit in the sample $(i = 1, \dots, N)$, X denote an $N \times K$ matrix of exogenous explanatory variables, with the associated β contained in a $K \times 1$ vector with unknown parameters to be estimated, θ , like β, is a $K \times 1$ vector of lag explanatory variable parameters. W is the spectral normalized inverse-distance matrix with its elements as the inverse of the distance between each pair of markets with $w_{i,j} = \left(\frac{1}{d}\right) W$ where d is the largest of the moduli of the eigenvalues of the un-normalized nonnegative spatial-weighting matrix W, describing the structure of dependence between units in the sample using the geographic coordinates of each observation. All distances were on a great circle basis in kilometers. p_i is the selling price of amaranth green-leaf in the i^{th} market. X is a vector of number of visits to market per week, cost of transport to sell green-leaf, the cost of transportation of green-leaf from farm to market, transport cost from New Benin Market (the central market) as the explanatory variables. The spatial weight matrix was generated using the 'mata' language, and estimation was done using *spregress, geodist* and *georoute* packages all in Stata 17.

Taking clue from LeSage and Pace (2009), the estimated indirect effects of the independent explanatory variables was used to test the hypothesis as to whether spatial spillovers exist. The estimated direct and indirect effects of the independent explanatory variables were used to predict the own- and across-market effects, derived from the matrix of partial derivatives of the expected value of *P* with respect to the k^{th} explanatory variable of *X* in unit 1 up to unit N after rewriting the general nesting spatial (GNS) model in [1] as:

$$P = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}(\alpha i_N + \mu) \qquad [2]$$

The matrix of partial derivatives of the expected value of *P* with respect to the k^{th} explanatory variable of *X* in unit 1 up to unit N was expressed as:

$$\left[\frac{\partial E(P)}{\partial X_{1k}} \cdots \frac{\partial E(P)}{\partial X_{Nk}}\right] = \left[\frac{\partial E(P)}{\partial X_{11}}\ \frac{\partial E(P)}{\partial X_{12}} \cdots \frac{\partial E(P)}{\partial X_{1,k}}\ \frac{\partial E(P)}{\partial X_{21}}\ \frac{\partial E(P)}{\partial X_{22}} \cdots \frac{\partial E(P)}{\partial X_{2k}}\ \frac{\partial E(P)}{\partial X_{31}}\ \frac{\partial E(P)}{\partial X_{32}} \cdots \frac{\partial E(P)}{\partial X_{3k}}\ \vdots \vdots \ddots \vdots\ \frac{\partial E(P)}{\partial X_{N,1}}\ \frac{\partial E(P)}{\partial X_{N,2}} \cdots \frac{\partial E(P)}{\partial X_{Nk}}\right] = (I - \rho W)^{-1}\left[\beta_k\ w_{1,2}\theta_k \cdots w_{1,n}\theta_k\ w_{2,1}\theta_k\ \beta_k \cdots w_{2,n}\theta_k\ w_{3,1}\theta_k\ w_{3,2}\theta_k \cdots w_{3,n}\theta_k\ \vdots \vdots \ddots \vdots\ w_{n,1}\theta_k\ w_{n,2}\theta_k \cdots \beta_k\right] \quad [3]$$

Diagonal elements, β_k of the $N \times K$ matrix of partial derivatives measures the direct effect that reflects own-partial derivatives showing how changes in own-market *j* prices lead to changes in own-market *j* prices while the off-diagonal elements represents cross-partial derivatives, the indirect effect, which quantify the magnitude of spatial spillover price impacts that arise in other-markets *i* as a result of changing the price explanatory variables in market *j*. $\frac{\partial E(P)}{\partial X_{ii}}$ represents the contemporaneous direct effect on market *i's* price arising from a change in market price operating in market *i*. $\frac{\partial E(P)}{\partial X_{ij}}$ measures the contemporaneous spatial spillover price effect on market *j***.** Indirect effects are identically zero if both $\rho = 0$ and $\theta_k = 0$. The direct and indirect effects for the SAC/SAR are $(I - \rho W)^{-1}\beta_k$, for the SLX/SDEM are respectively β_k and θ_k, and for the SDM/GNS are $(I - \rho W)^{-1}(\beta_k + W\theta_k$. The magnitude of the covariate interaction effects are expected to be significant in the SDEM model but similar to the SLX in magnitude.

RESULTS AND DISCUSSIONS

The mean travel-time and distances between markets for the study are presented in Figure 1. The distance is greatest between Oba market and Santana market (11.20Km). This is followed by that between Oba market and Uselu market (7.69Km), then between Santana market and New-Benin market (5.87Km) and least between Uselu market and New Benin market (2.40Km). The least average travel-time is that between Uselu market and New Benin market (6.06 minutes). This is followed by average travel-time between Uselu market and Santana market (9.4minutes), and Santana market and Uselu market (10.48 minutes). These suggest that, in the event of buying from other markets, consumers would shuttle purchase between Uselu and New Benin market with the least distance and travel-time between them, or Uselu market and Santana market. This would be expected as most people are rational patrons who seek the more proximate option between two similar amaranth green markets to reduce commuting costs unless there is some compelling reason to patronise markets farther away. In agreement with Tan et al., (2022) and Xu et al., (2022), this may suggest a clustering of consumers around markets such that buyers purchase amaranth green in markets closest to them. Similarly, marketers are expected to sell amaranth green in nearby markets from point of purchase to make optimal benefits of low transport costs except where there is arbitrage, and/or other various endogenously generated non-market spatial externalities.

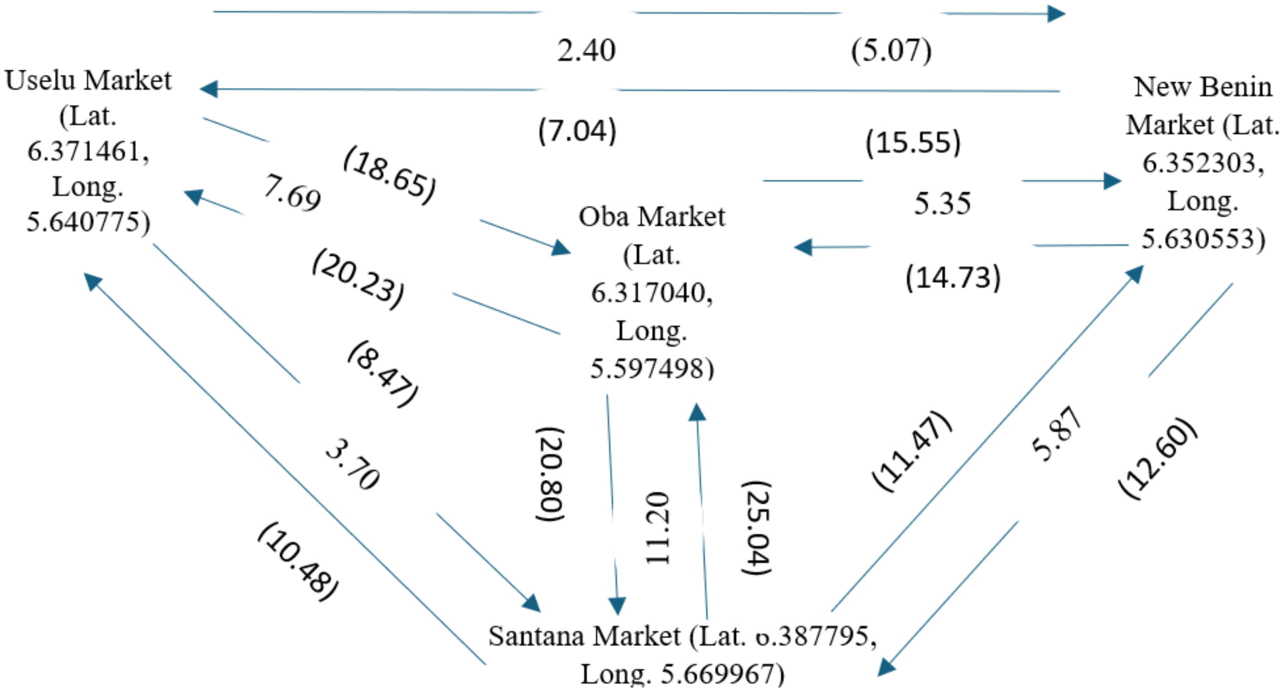

Figure 1. Travel-time by Car and Distance between Markets in Benin Metropolis of Edo State, Nigeria; values in parentheses are travel-time between markets.

Source: Authors' Computation from 2023 Survey Data.

Figure 2 shows the spatial prices of amaranth green in markets of Benin Metropolis in Edo State, Nigeria. It shows group of marketers in Oba market, Uselu, and Santana market, with unique distances separating the various markets, purchase amaranth green-leaf from New-Benin market given that the price difference exceeds the marginal transport costscheck fi.

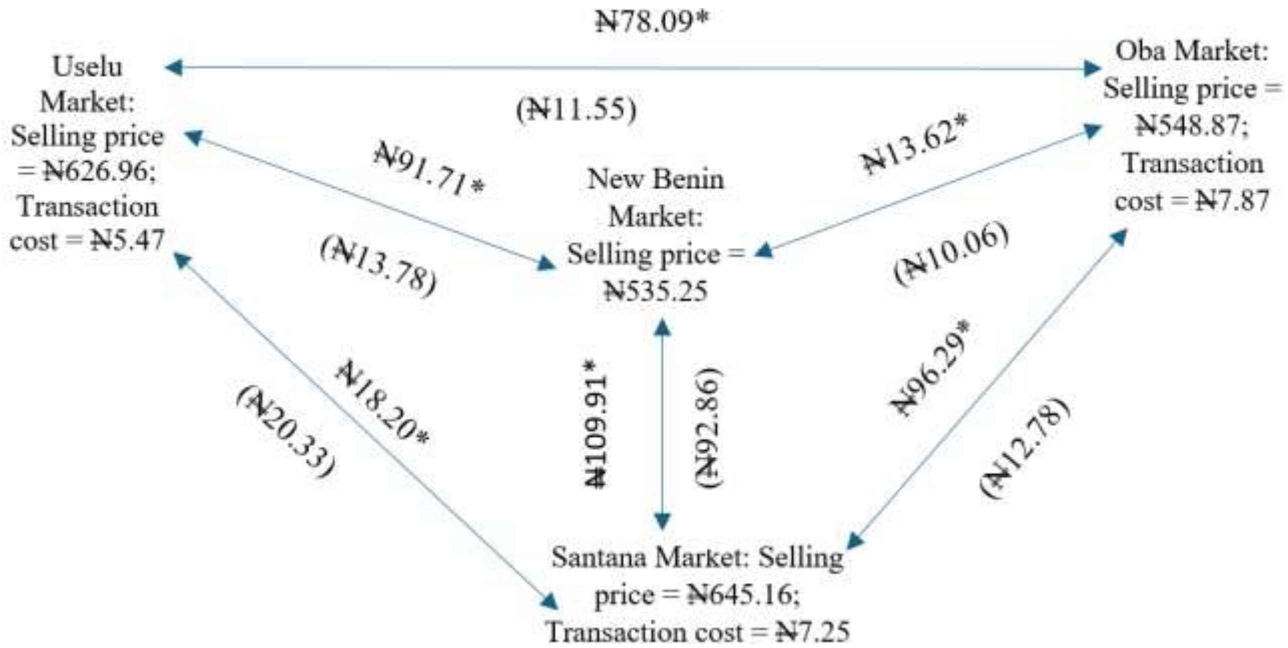

Figure 2. Spatial Prices of Amaranth Green in Markets of Benin Metropolis in Edo State, Nigeria; *price difference between markets, values in parentheses are transport costs for consumer between markets.
Source: Authors' Computation from 2023 Survey Data.

Specifically, amaranth green is cheapest in the central market (₦535.25), cheaper in Oba market (₦548.89) while Santana market sells at the highest price (₦645.16). The high price in Santana market may be attributed to the transport cost and distance between it and the central market. The difference in selling price is also highest in Santana market, however, the marketers could also profitably purchase amaranth green from Oba market and resell to consumers at a lower price of ₦642.57 after ₦3.59 margin of all costs. Similarly, the marketers in Uselu market could also profitably purchase amaranth green from Oba market and resell to consumers at a lower price of ₦624.71 provided the opportunity cost is not higher ₦2.25 margin of all costs, narrowing the difference in selling price between them and marketers in Oba market to the advantage of marketers in Uselu market. In either case, consumers in the market environs pay higher price for the same quantity amaranth green in the metropolis.

Table 1 presents the summary statistics of variable used in the spatial model estimation of price of amaranth green-leaf. Generally, mean price in the markets of Benin metropolis in Edo State is ₦577.24 among marketers who sell green-leaf vegetable about 6 days in a week, spending ₦62.40 per Kg weekly on transport. It cost ₦482.38 per Kg to transport amaranth green-leaf from farm to market but ₦193.81 to transport same amount from the central market to other markets, on average. Specifically, amaranth green is cheapest in the central market (₦535.25), cheaper in Oba market (₦548.89) while Santana market sells at the highest price (₦645.16). The high price in Santana market may be attributed to the distance between it and the central market. Among the variables, the selling price of amaranth green-leaf was similar among markets with a 0.082 price variation. The transport cost from New-Benin Market had the highest variation (1.094). This may affect the marketers in an unequal way as it suggests existence of rising spatial inequalities

Table 1. Summary Statistics of the Spatial Price Model Variables of Amaranth Green Leaf in Benin Metropolis

Variables	**Mean and Coefficient-of-variation**					
	Oba	New-Benin	Uselu	Santana	Pooled	
Spricegleaf	548.87	535.25	626.96	645.16	577.24	11.73*
	[0.012]	[0.014]	[0.024]	[0.000]	[0.082]	[7.204]
	7.913E-03	5.267E-03*	68.379*	0.034*		
Nmktvisit	6.061	5.970	6.111	5.190	5.867	0.114*
	[0.130]	[0.089]	[0.111]	[0.277]	[0.159]	[7.306*]
	8.71E-05*	5.89E-05*	0.667*	2.336E-04*		
Salestport	7.87	5.62	5.47	7.25	6.40	0.981*
	[0.931]	[0.828]	[0.927]	[0.912]	[0.925]	[7.300*]
	8.71E-05*	5.89E-05*	0.667*	2.336E-04*		
Ctportgleaf	527.27	0.000	336.11	395.24	419.38	0.114*
	[0.408]	-	[0.283]	[0.108]	[0.996]	[7.306*]
	2.190E-03*	5.04E-05*	16.667*	2.927E-02*		
tportNbenin	10.06	0.000	72.78	92.86	58.81	2.864*
	[0.106]	-	[0.077]	[0.030]	[1.094]	[7.194*]
	1.194E-03*	5.775E-04*	5.7145*	5.147E-03*		

Source: Authors' Computation from 2023 Survey Data, nmktvisit is number of visits to market per week, salestport is sales transport cost, ctportgleaf is the transport cost of green-leaf from farm to New-Benin market, tportNbenin is transport cost from New-Benin market (Central Market for green-leaf), spricegleaf is selling price of green-leaf, *spatial-lag values, values in brackets are coefficient of variation

Also presented in Table 1 are the spatial lags of the variables. The mean spatial-lag of amaranth green-leaf selling price, visit-to-market frequency count, transport cost from farm to market, transport cost from New Benin market and transport cost to sell amaranth green were respectively ₦11.73, ₦0.11, ₦0.11, ₦2.86 and ₦0.98. These suggest potential cross-market effects including the selling price of amaranth green-leaf. In addition, they suggest that the price of amaranth green-leaf and the covariates are not independent across amaranth green-leaf markets. The high selling price (₦626.96) and the inconsistencies (0.024) in Uselu market may, therefore, be tied to the greater spatial-lag effects of both price of amaranth green-leaf (₦68.38) and its explanatory variable particularly transport cost to markets (₦5.72) among the markets rather than might be under a random experiment.

Parameters estimates of the model shown in [1] are presented in Table 2. The Moran test with $\chi^2 = 8.34$ and a $p = 0.0039$ conducted after a linear regression with explanatory variables indicate that the hypothesis of independent and identically distributed residuals from the model is rejected. The parameters $\hat{\rho} = 0.077$ at $p = 0.0010$. These implies that residuals are not only correlated with cross-market residuals but the evidence of positive spatial dependence. The coefficient estimates of transport cost transportation from the farm to the market and from New-Benin Market are statistically significant at the 5% level across all model specifications. While the transport cost from the farm to the market has a negative effect on the selling price of green-leaf, the transport cost from New-Benin Market has a positive effect.

When exogenous interaction effects are included in the OLS model, the log-likelihood value increases from -495.862 to -492.785, resulting in the SLX model. The LR-test between the SLX and OLS models gave a value of 6.15 with 4 degrees of freedom (df) and a $p < 0.1880$ so that the OLS model remain the maintained hypothesis against the SLX model. Similarly, when the SAR model is created by including amaranth-green price interaction effects, the log-likelihood value increased from -495.862 to -492.833. The LR-test between the SAR and OLS models gave a value of 6.06 with 1 df and a $p < 0.01$ so that we reject the OLS model in favor of the SAR model. With error terms interaction effects included (SEM), the log-likelihood value increases further. The LR-test between the SEM and OLS models yields a value of 4.20 with 1 df and a $p < 0.01$ so that the SEM was the maintained hypothesis against the OLS model. When comparing these models with the SAC model, which considers both amaranth-green price interaction effects and interaction effects among the error terms, the SAC model produces coefficient estimates for amaranth green interaction effects that do not significantly differ from those of the SAR model. However, the coefficient estimates for interaction effects among the error terms significantly differ from those of the SEM model.

The coefficient for the spatially autoregressive term in the SAC model is 0.0766. However, the corresponding t-value is very low that the 95% confidence interval [0.0506, 0.1026] includes the coefficient estimate of 0.0766 from the SAR model, even though it is significant. Similarly, the LR-test of the SAC model versus the SAR model has a value of 0.00 with 1 df, and the LR-test of the SAC model versus the SEM model has a value of 1.86 with 1 df, both of which are not significant at the 5% level. This creates a problem in choosing among the three models. However, the coefficient of the interaction effects of the amaranth-green price is significant in the SAC model, while the coefficient of the interaction effects among the error terms is not significant.

Table 2. Parameter Estimates of Greenleaf Spatial-Price Models

Variables	OLS	SAR	SLX	SEM	SDM	SAC	SDEM	GNS
Nmktvisit	0.130	0.127	-0.0559	0.113	-0.0559	0.127	-0.190	-0.185
	(0.969)	(0.969)s	(0.987)	(0.972)	(0.987)	(0.969)	(0.955)	(0.983)
Salestport	-0.0226	-0.0198	-0.0204	-0.0202	-0.0204	-0.0198	-0.0243	-0.0242
	(0.663)	(0.695)	(0.686)	(0.689)	(0.686)	(0.695)	(0.635)	(0.742)
Ctportgleaf	-0.0435**	-0.0441**	-0.0446**	-0.0440**	-0.0446**	-0.0441**	-0.0447***	-0.0447*
	(0.010)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.031)
tportNbenin	0.273***	0.275***	0.276***	0.274***	0.276***	0.275***	0.276***	0.276***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	546.0***	544.8***	545.9***	545.1***	545.9***	544.8***	546.6***	546.5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
sigma	27.21***							
	(0.000)							
W*spricegleaf		0.0766*			0.00284	0.0766*		0.00339
		(0.013)			(0.997)	(0.013)		(0.994)
W*nmktvisit			800.1		800.0		800.1***	800.3***
			(0.781)		(0.810)		(0.000)	(0.000)
W*salestport1			93.33		93.31		93.34***	93.37***
			(0.781)		(0.810)		(0.000)	(0.000)
W*ctportgleaf			-75.09		-75.09		-75.09***	-75.10***
			(0.770)		(0.825)		(0.000)	(0.000)
W*tportNbenin			136.6		136.6		136.6***	136.6***
			(0.796)		(0.846)		(0.000)	(0.000)
W*error term				0.647*		0.000209	-1385.0*	-1384.9
				(0.014)		(1.000)	(0.065)	(0.066)
Var (ε)		698.8***	698.2***	704.0***	698.2***	698.8***	713.6***	713.6***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-likelihood	-495.862	-492.833	-492.785	-492.764	-492.785	-492.833	-479.812	-479.812
Wald chi-square		228.59***	228.88***	222.37***	228.84***	228.58***	69616.44***	21447.88***
Pseudo R^2		0.6852	0.6855	0.6665	0.6855	0.6852	0.6855	0.6855
AIC	1003.7	999.7	1005.6	1001.5	1007.6	1001.7	979.6	981.6

Source: Authors' Computation from 2023 Survey Data; P-values in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001; W = spectral-normalized inverse-distance matrix, nmktvisit is number of visit to market per week, salestport is cost of transport to sell greenleaf, ctportgleaf is the transport cost of green-leaf from farm to market, tportNbenin is transport cost from New Benin Market (Central Market for green-leaf), spricegleaf is selling price of green-leaf

Additionally, the log-likelihood function value of the SAR model is higher than that of the SEM model. Based on these criteria, the SAR model seems to be the better choice. When considering the SDM model, which includes the SAR, SEM, and SLX models, the SDM does not outperform any of these models. The LR-test has a value of 0.000 with 1 df and $p < 0.9968$ for the SLX model, a value of 0.10 with 4 df and $p < 0.9989$ for the SAR model, and a value of 1.96 with 4 df and $p < 0.7436$ for the SEM model. However, the SDEM model outperforms the SEM model with an LR-test value of 27.90 with 3 df and $p < 0.001$. It is difficult to determine whether the SDM model or the SDEM model provides a better description of the data, as these are non-nested models. The LR-test of the SDEM model versus the SDM model has a value of -25.95 with 1 df and $p < 1.00$. Unfortunately, the GNS model, which nests the SDM and SDEM models, does not provide a clear answer. The decrease in the log-likelihood function value when estimating this model is so small that it is impossible to draw any conclusion from the results in Table 2. However, the results indicate that only the GNS and SDEM models produce acceptable results based on the AIC values reported in Table 2.

The estimated coefficient on the spatial lag explanatory variables and the autoregressive error term for selling price of amaranth green in the SDEM and GNS models are significant at $p < 0.001$ and $p < 0.1$ respectively, indicating correlation between the exogenous variables and interaction effects among the error terms such that the selling price in one particular market depends on cross-market price explanatory variables, and that the unobserved heterogeneity has cross-market effects in amaranth green markets. The coefficient estimate of the error interaction is only positive and significant in the SEM model, not in the SAC, SDEM, and GNS models, although it is substantially higher in absolute terms in the SDEM and GNS models. The covariate interaction effects in the SDEM model have the same sign as in the GNS model. Hence, the SDEM and GNS models were used to explain the local and global spillover effects respectively.

Presented in Table 3 are the SDEM and GNS estimates for the average indirect effects of visit-to-market frequency, transport cost from farm to market, transport cost from New Benin market and transport cost to sell amaranth green. The estimates are similar in magnitude and are significant at $p < 0.001$. The results show that the cross-market effects, except for transport cost of amaranth green-leaf from farm to market, are positive and significant at $p < 0.001$. The own-market spillover effect is highest with a unit increase in the number of visits to market per week increasing the price of green-leaf (₦15.25) on average and least with transport cost to sell amaranth green (₦1.76). On average, the spatial lag of the number of visits contributes ₦91.53 to the price of amaranth green-leaf. Similarly, the across-market spillover effect of a unit increase in the cost of transport from New Benin market (the central market) would increase the price of green-leaf, and that increase spills over to further increase the price of green-leaf. Hence, consumers would pay an additional significant amount of ₦17.01 imposed by the marketers, partly due to transport costs. At the average, consumers would pay additional significant ₦16.58 attributed to the spatial lag of amaranth-green selling price explanatory variables. This implies that consumers of amaranth green in the study area would have to pay additional significant ₦2.60 build-in by the marketers resulting from marketing transport cost. At its average, spatial lag of the transport cost from New Benin market (the central market) contributes ₦391.20 to the price of green leaf.

Table 3: Marginal Effects of Explanatory Variables on Greenleaf Price

Variables	OLS	SAR	SLX	SEM	SDM	SAC	SDEM	GNS
	Direct Effects							
Nmktvisit	0.1300	0.1267	-0.0559	0.1131	-0.0126	0.1267	-0.1897	-0.1329
	(0.969)	(0.969)	(0.987)	(0.972)	(0.999)	(0.969)	(0.955)	(0.992)
Salestport	-0.0226	-0.0198	-0.0204	-0.0202	-0.0154	-0.0198	-0.0242	-0.0182
	(0.663)	(0.695)	(0.686)	(0.689)	(0.990)	(0.695)	(0.635)	(0.982)
Ctportgleaf	-0.0435**	-0.0441***	-0.0447***	-0.0440***	-0.0487	-0.0441***	-0.0446	-0.0495
	(0.010)	(0.007)	(0.007)	(0.008)	(0.962)	(0.007)	(0.008)	(0.936)
tportNbenin	0.273***	0.2747***	0.2763***	0.2744***	0.2838	0.2747***	0.2763	0.2851
	(0.000)	(0.000)	(0.000)	(0.000)	(0.877)	(0.000)	(0.000)	(0.800)
	Indirect or Spatial Spillover Effects							
Nmktvisit		0.0001	15.255		15.252	0.0002	15.255***	15.258***
		(0.969)	(0.781)		(0.810)	(0.969)	(0.000)	(0.000)
Salestport		-0.00003	1.779		1.779	-0.00003	1.755***	1.780***
		(0.697)	(0.781)		(0.810)	(0.697)	(0.000)	(0.000)
Ctportgleaf		-0.00006*	-1.432		-1.432	-0.00006*	-1.432***	-1.432***
		(0.071)	(0.770)		(0.825)	(0.071)	(0.000)	(0.000)
tportNbenin		0.00040**	2.604		2.604	0.00040**	2.6035***	2.6035***
		(0.020)	(0.796)		(0.846)	(0.020)	(0.000)	(0.000)
	Total Effects							
Nmktvisit		0.1269	15.199	0.1131	15.239	0.1269	15.065***	15.126
		(0.969)	(0.779)	(0.972)	(0.811)	(0.969)	(0.000)	(0.269)
Salestport		-0.0198	1.759	-0.0202	1.764	-0.0198	1.755***	1.762**
		(0.695)	(0.783)	(0.689)	(0.814)	(0.695)	(0.000)	(0.019)
Ctportgleaf		-0.0441***	-1.476	-0.0440***	-1.480	-0.0441	-1.476***	-1.481**
		(0.007)	(0.763)	(0.008)	(0.822)	(0.007)	(0.000)	(0.015)
tportNbenin		0.2751***	2.880	0.2744***	2.888	0.2751	2.880***	2.888***
		(0.000)	(0.775)	(0.000)	(0.832)	(0.000)	(0.000)	(0.009)

Source: Authors' Computation from 2023 Survey Data; P-values in parentheses * p <0.05, ** p <0.01, *** p <0.001; W = spectral-normalized inverse-distance matrix, nmktvisit is number of visit to market per week, salestport is cost of transport to sell green-leaf, ctportgleaf is the transport cost of green-leaf from farm to market, tportNbenin is transport cost from New Benin Market (Central Market for green-leaf)

At its average, spatial lag of cost of transport to sell green-leaf in the market contributes ₦91.59 to the price. However, the across-market spillover effect of an increase in the cost of transport of green-leaf from farm to market decreased the price of green-leaf, and that decrease spills over to further decrease the price of green-leaf. The result is a ₦1.43 decrease in the price of green leaf resulting in a total effect of ₦1.48 decrease on average. At its average, spatial lag of cost of transport of green-leaf from farm to market contributes negative ₦ 8.59 to the price of green-leaf. Practically, the cost of transport from New Benin market, cost of transport to sell green-leaf in the market, and the number of visits to market per week had significant spillover effects on the price. The spatial heterogeneity led to natural monopolies in local food markets, directly impacting price levels and variations, and the quantity of food consumers purchase. These results agree with Gieri et.al, 2015; Allen, 2017; Beck & Hensher, 2020; Kassouri & Okunlola, 2022; Munir & Ameer, 2022; Ojogho & Izekor, 2023.

CONCLUSION

This study investigates food spatial prices using retail prices between October 2022 and September 2023 from 300 amaranth-green marketers across four markets in Benin Metropolis, Nigeria. It addresses gaps in distance-related transport costs and their contribution to retail prices, using spatial econometric models, particularly the Spatial Durbin Error Model (SDEM) and the General Nesting Spatial (GNS), to account for spillover effects and spatial autocorrelation of residuals. The models incorporate variables such as weekly market visits, daily transport costs, and transport costs from farm to market and from the central market to other markets.

The results of the study reveal significant insights into the spatial price dynamics of amaranth green in Benin Metropolis. The Moran test indicated price clustering and spatial price dependence, confirmed by the spatial-lag coefficient parameters. The Spatial Durbin Error Model (SDEM) and the General Nesting Spatial (GNS) model were identified as the most appropriate data-generating processes for explaining local and global spillover effects on amaranth-green market prices. The study demonstrates that reducing distance between markets and transport costs are crucial for addressing price imbalances. Spatial parameters were significant, indicating similarities in neighboring markets performance. Key findings include evidence of price clustering and spatial price dependence, with transport costs significantly impacting price differentials. The SDEM and GNS models were identified as the most appropriate for explaining local and global spillover effects on amaranth-green market prices. There were price differentials resulting from both own-market and cross-market price effects. Transport costs also play a crucial role, with a spillover price increase attributed to distance-related transport costs. Specifically, the transport cost from the farm to the market has a negative effect on the selling price, while the transport cost from central Market has a positive effect. The study concludes that addressing transport costs and market distances is essential for mitigating price imbalances and ensuring fair pricing. Policy recommendations include avoiding price policies that undervalue marketers near consumers and overvalue those further away to prevent supply scarcity and address price disparities.

The research contributes to the literature by confirming regional price variations, highlighting the impact of transport costs, and demonstrating the association between increasing spatial dependence and regional price disparities. These findings carry several significant policy implications for addressing food price imbalances and improving market efficiency in Benin Metropolis and similar urban areas. Firstly, the study found that distance between markets is a crucial determinant of food commodity prices. The study also highlights the importance of reducing transport costs to address price imbalances. Decreased transport costs can reduce the price of goods substantially and their variation across space. To achieve a decrease in transport costs, governments in collaboration with stakeholders need to ensure that transport markets and food commodity markets are efficient to reduce economic distance. This could involve upgrading road networks, promoting efficient transportation systems, strengthening competition for and in the market, and establishing strategically located market centers to minimize distribution distances. Facilitating connections between smallholder farmers and SMEs can also help reduce transport costs by enabling more direct access to local, regional, and global markets. Secondly, the findings of the study suggest that a price policy should carefully consider the location of marketers relative to consumers. Rather than undervaluing marketers near consumers and overvaluing those further away, which can lead to supply scarcity and price disparities, policies should aim to create a level playing field that ensures fair compensation for marketers regardless of their location, promoting a more even distribution of food commodities and preventing regional price imbalances. Finally, the evidence of spatial dependence and spillover effects indicates the need for improved market information systems. Thus, providing accurate and timely information on food market economic geography to both marketers and consumers can help facilitate price signals for economically efficient decisions, reduce information asymmetry, and promote more competitive market dynamics.

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