Climatic Variations and Spatial Price Differentials of Perishable Foods in Nigeria

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ABSTRACT: In this study, we attempt to examine the factors that explain the spatial price differentials of selected perishable food crops across Nigerian markets. Based on monthly market prices of onions and tomatoes across different States, we examine the implications of climatic variations, cost of transportation and differences in economic sizes on the price spread of these items. The empirical findings from the dynamic heterogeneous panel regressions show that these factors have significant long-run impacts on the difference in food prices across markets. The results highlight climatic differences and transportation costs are important factors in regional price spreads for agricultural commodities and hence the need for specific policies to reduce the prices variability. Policies geared towards improving agriculture value-chain could offer pathways towards mitigating food loss and waste associated with changing climate and transfer costs, and thereby reduction in prices.

JEL classification: C21, C23, Q11, Q54

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1 Introduction

The focus of the second item of the sustainable development goals (SDG-2) is centred around ending hunger and achieving food and nutrition security for all. The target is not just about ending hunger prevalence but also achieving a nutritious and food-healthy society. The severity of malnutrition is more pronounced in the global statistic of food and nutrition security. For instance, the 2019 report on the state of food insecurity (SOFI) documents that about 821 million people globally suffer from hunger. However, an estimated 2 billion people are affected by severe and moderate levels of malnutrition and food insufficiency. Therefore, the nutrition and calorie content of food consumed is an important focus for the achievement of a hunger-free and nutritious world.

Perishable foods account for an increasingly large proportion of food items with strategic importance of improving the nutrition content and calories intake from non-perishable, staple food items. Most of these nutrition contents and calories are contained in fruits and vegetables, all of which have high tendencies for simultaneous quantitative and qualitative deterioration. The causes of deterioration of perishable foods have both environmental and human aspects. The environmental reasons include temperature, humidity, air velocity and insect infestation which all make fresh produce subject to loss in weight or volume. The human behaviour include improper transportation, poor handling, and inappropriate storage (Duan and Liu, 2019). In most developing and less developed countries, there is limited capacity for handling and storage for these food items. This is coupled with huge reliance on weather, through rain and sunshine, for food production, processing, and preservation. In addition, food markets in these countries are mostly not well integrated due to heavy transport and telecommunication infrastructural gaps which often lead to information asymmetry and missing institutions (Rashid and Minot, 2010). Hence, perishable food items are more susceptible to food loss and waste.

The economic value of food loss and waste has implications for both producers and consumers (Sheahan and Barrett, 2017). As a result of food loss, income and investment returns for farmers and value chain actors can be reduced, while it could translate into higher prices for the consumers. Besides food losses can also trigger food price volatility, with severe adverse consequences for poor and marginalized consumers. Overall, the losses resulting from food loss and waste could have disproportionate effects in developing and underdeveloped countries. These countries are mostly characterized by large poor agricultural producers and consumers that are highly vulnerable to climate change with high prevalence of food insecurity and undernourishment (FAO, 2016). As a consequence, food loss and waste could further increase the existing burden of hunger, poverty and climate change by hampering development progress and poverty alleviation (Wieben, 2017).

Furthermore, agricultural policy intervention and attention are mostly placed on production, storage, distribution and consumption of non-perishable, staple foods, crops and tubers such as rice, wheat, maize, millet and yam among others. Besides, food security has been mostly associated with the vision of abundance of these grains, roots, and tubers

(Schreinemachers et al., 2018) and these items are mostly insulated from the effects of high price volatility and market variations (Benson et al., 2008). On the contrary, policy responses towards managing price instability of perishable foods are obscured with lack of clarity on the triggers of price shocks and price transmissions along their supply chains (Dorward, 2012). With the increasing awareness of the nutritional benefits of fruits and vegetables, managing price stability in these food items with high-value is a matter of policy concern (Birthal et al., 2019).

More importantly, there is increasing awareness in less developed and developing nations on the influence of shifts in climate patterns and weather events on domestic food production, consumption and prices since farmers largely rely on rainfed locally produced food for the majority of their caloric intake (Brown and Kshirsagar, 2015; Grace et al., 2014). Changes in climatic conditions are driving an increase in the intensity and frequency of heatwaves and declining average rainfall and cool days. Agricultural output is continuously constrained by water scarcity, heat stress, and increased climatic variability.

Understanding the pathways linking climate change and nutrition is critical for developing effective interventions towards ensuring the world's population has access to sufficient, safe, and nutritious food. The effects of climate change on agriculture could occur in a number of ways. For example, increase and variability in temperature can promote crop disease and increase crop sensitivity to pests, thereby affecting crop development and potential yield (McCarl et al., 2008). In a similar vein, precipitation could also affect agricultural production and yield. Variability in rainfall is a key element that determines the agricultural sector performance in many countries, especially with heavy reliance on rainfed production. Low or excessive rainfall can affect crop production yield (Sivakumar et al., 2005). The decline in yield can act as a disincentive for future production and negative supply response leading to higher prices.

Perhaps owing to limited data, much that has been written in the past about climate change implications on agriculture and food security are largely conceptual in nature with limited empirical literature analytically examining the quantitative relationship between climatic factors and aspects of food security. However, recent improvements in data and modelling approaches have allowed for the evaluation of outcomes of changes in climate to agricultural production (food availability), although there is room for more studies on the other components of food security – access, utilization, and stability. It is worthy of mention that quite a number of studies have also examined the relationship between climate and food access (through food prices). The bulk of these studies are focused on the prices of food in the international markets with limited studies mainly focused on the domestic prices of staples and grains.

From the foregoing, this study aims to provide an analysis of the implications of climatic variations on perishable food prices. Specifically, we evaluate the implications of climate change variability on differential prices of perishable food across Nigeria. Following the spatial market model which is based on the law of one price or market integration theory, a large body of literature on spatial price has highlighted a number of factors responsible for price differentials across markets. A few among these factors include import tariffs, tariff-rate quotas, export subsidies or taxes, intervention mechanisms, and exchange rate policies. However, these factors largely reflect the extent to which domestic agricultural markets respond to international prices (Rapsomanikis et al., 2006). Within the domestic markets, the main factor evaluated in the literature include the transfer costs or transportation costs across markets. Only very few studies evaluate the implications of climate variations on price difference and market performance. For example, (Essam, 2013) applied a price dispersion model to analyse the effects of exogenous weather shocks on price spreads between millet markets in Niger. The results of the price dispersion modelling suggest that positive (negative) shocks to weather increase (decrease) price dispersion across markets and as the extent of weather shocks grow, absolute price disparity across markets declines.

Using monthly price data for two major perishable crops, onions and tomatoes, we evaluate the implications of climatic variations, transportation costs and market size on the variation of prices across markets. The choice of tomato and onion is informed by the important roles they play in food and nutrition for many households. Besides, there are data limitations on other types of perishables, especially fruits and vegetables. Although the empirical findings of the study should be generalized to explain the overall factors explaining price spreads of these items, however, it presents an analytical evaluation of spatial price differential accruable to transportation costs, climatic variations, and market size. The remainder of the paper is structured as follows: the next section presents the analytical framework for the empirical analyses. Section 3 presents and discusses the empirical results, while section 4 concludes the paper with some implications.

2 Analytical framework

The empirical framework for the study is premised on the modified spatial market integration model. Spatial price relationships for agricultural commodities have been widely used to indicate market performance (Faminow and Benson, 1990). The spatial market integration model draws implication from the law of one price and it is concerned with the physical flow of commodities across markets and the degree of shocks transmission between these markets. The model postulates that at all points of time, the relationship between prices for an agricultural commodity in two spatially separate markets, $p_{i,t}$ and $p_{j,t}$, is explained by the transfer costs for transporting the commodity between the two markets. This relationship takes the form of:

$$p_{i,t} = p_{j,t} + tc_t \tag{1a}$$

$$p_{i,t} - p_{j,t} = tc_t \tag{1b}$$

where tc is transportation costs. If the relationship as expressed in Equation (1a) holds, the two markets are said to have trade relations and as such integrated. However, even when there are no trade relations, markets may still be integrated (Barnett et al., 2016). Equation (1a) could be re-specified into estimable econometric form as follows:

$$fp_{ij,t} = \alpha + \beta \cdot tc_t + \varepsilon_t \tag{2}$$

where $fp_{ij,t} = p_{i,t} - p_{j,t}$ is the difference between prices in the two markets, i and j; α and β are constant and slope terms, respectively, and ε is an error term.

The relationship between the two prices above expresses the weak form of the law of one price and a spatial arbitrage condition (Fackler and Goodwin, 2001). The relationships between prices across markets have been extended and explained using multimarket and regional specific factors such as trade volumes, food-related transaction costs, and other unobserved time-varying market heterogeneous factors. Brown (2014) and Essam (2013) in different studies both conclude that using observable weather information alongside food prices in a quantitative model could improve the estimation of food price changes most especially in regions where food security is of concern. Therefore, we extend the model to account for the variability in the climatic conditions in the two markets on the price differentials. In addition, current price spreads between market pairs may also be affected by unobserved or latent influences that are not captured in the exogenous covariates. The modified model becomes:

$$\begin{gathered} fp_{ij,t} = \alpha + \lambda \cdot fp_{ij,t-1} + \beta \cdot tc_{ij,t} + \varphi \cdot cc_{ij,t} + \theta \cdot Z_{ij,t} + \phi_t + \delta_{ij} + \varepsilon_{ij,t} \\ \forall i \neq j; \quad i = 1, \ldots, n-1 \end{gathered} \tag{3}$$

where $fp_{ij,t-1}$ is one-period lag of difference between prices in the two markets; the subscript ij refers to market-pair from originating market (i) to destination (j); cc_{ij} represents variations in climate change between markets and Z_{ij} is a vector of control variables and it includes relative market size; ϕ_t is a general time trend which captures the unobserved temporal changes that may also affect the dependent variable; δ_{ij} captures the time-invariant fixed effects common to both markets; $\varepsilon_{ij,t}$ is the idiosyncratic and independently distributed error term.

2.1 Variables measurement and data

Food price spread is measured as the natural log of the absolute difference between the month-end values of food between two market pairs. As discussed in the introduction, the perishable food items considered are onions and tomatoes. Monthly data on the prices across all the thirty-six states and federal capital territory of Nigeria. This gives a total of thirty-seven (37) markets[1].Data on prices for both food commodities are collected from the National Bureau of Statistics (NBS) database between January 2016 and December 2018.

Transportation cost is measured as the natural log of the product of pump price of petrol per litre in a given market at time, t, and the distance in miles to another market. Data on petrol prices are collected from NBS while information on miles between the capital of the two states is extracted from the distance calculator website[2]. Relative size is computed as the simple average of the logarithm of the markets' monthly internally generated revenue.

Climatic variation is measured as the standard deviation of the log of monthly changes in climate between the two markets. Following extant literature, changes in climate is proxy using the Normalized Difference Vegetation Index (NDVI) derived from sensing observations to measure agriculture yield changes. NDVI provides a measure of the greenness of plants on a landscape and has been widely used as a proxy for the productivity of crop and yield (Becker-Reshef et al., 2010; Brown and Kshirsagar, 2015; Funk and Budde, 2009). Unlike rainfall datasets that are poorly calibrated due to lack of ground observations and crop models that report unrealistic variations in production due to massive reduction in the baseline production from land redistribution (Brown and Kshirsagar, 2015), vegetation remote sensing has made significant contribution globally on the estimates of cropland distribution, crop development and yield estimation. Hence, it remains a better proxy for weather changes on agricultural production. We use the monthly vegetation dataset from the moderate resolution imaging spectroradiometer (MODIS) for different regions across the country considered from the 0.05° resolution climate modelling grid data downloadable from NASA[3].

2.2 Estimation procedure

Analysis of panel data usually commences with the use of pooled ordinary least squares estimator (Pooled OLS). Meanwhile, as pooled OLS fails to account for individual specificities of the cross-sectional units, the use of fixed effect and random effect models have been introduced to account for this heterogeneity effect. The pooled OLS, fixed effect and random effect models are however static models, implying that they ignore short run dynamics or lag effects. Heterogeneous panel has been developed to capture both short run and long run dynamics of such models. Developed by Pesaran and Smith (1995) and Pesaran et al. (1997, 1999), the Panel autoregressive distributed lag (ARDL) model relies on the asymptotic of large cross-sectional units (N) and large time periods (T). The Panel

[1]The number of cross-section units (ij) is made up 666 pairs of markets' price-differentials, that is market i to market j for all $i \neq j$. This is computed using the combinatorial formula $\binom{N}{C_n}$; where the number of markets (N) is 37 and price pair (n) is 2.

[2]Downloadable from `www.distancecalculator.net`

[3]See `https://mars.jrc.ec.europa.eu/asap/download.php`

ARDL representation of Equation (3) is expressed as:

$$fp_{ij,t} = \sum_{k=1}^{p} \lambda_{ij,k} \cdot fp_{ij,t-k} + \sum_{k=0}^{q} \beta'_{ij,k} \cdot X_{ij,t-k} + \mu_{ij} + \varepsilon_{ij,t} \tag{4}$$

where $X_{i,t} = (tc_{ij,t}, cc_{ij,t}, \text{size}_{ij,t})$ is a vector of explanatory variables; ij represents the number of cross-section units; t is the number of periods; p and q are the optimal lag for the dependent and explanatory variables respectively, and β_{ij} is the vector of the (lagged and contemporaneous) explanatory variables. $\varepsilon_{ij,t}$ is a serially uncorrelated error process across all and it is defined as:

$$\varepsilon_{ij,t} = \sum_{l=1}^{m} \gamma_{ij,l} \cdot f_{ij,l} + \mu_{ij,t} \tag{5}$$

where $\mu_{ij,t}$ is a cross-section unit (market-pair) specific idiosyncratic and independently distributed error term; $f_{ij,t}$ is an unobserved common factor; and, $\gamma_{ij,l}$ are factor loadings and l ranges from 1 to m.

The panel ARDL specification assumes that the errors are independently distributed across cross-section. However, the assumption that errors are independently distributed when in fact they are not would lead to parameter inconsistency as the factors and the regressors are correlated (Chudik et al., 2015). Besides, from equation (1a) the nature of relationships across markets could imply spatial dependence following some observable and unobservable dependence[4]. The presence of spatial interactions in this context implies that variations in the factors that determines prices differences across two hypothetical markets would not only affect prices in these markets but also for other markets, and these effects may differ from one market to another (Bouayad-Agha and Védrine, 2010). This also implies that the common factors are correlated with the regressors, and leaving such out leads to omitted variables bias and inconsistent estimates (Ditzen, 2019). Thus, we extend the panel ARDL model to accommodate cross section dependence which is modelled as a common factor and part of the error term following (Chudik et al., 2013, 2015). Accounting for cross-sectional dependence, Equation (4) becomes:

$$fp_{ij,t} = \sum_{k=1}^{p} \lambda_{ij,k} \cdot fp_{ij,t-k} + \sum_{k=0}^{q} \beta'_{ij,k} \cdot X_{ij,t-k} + \sum_{l=0}^{m} \tau'_{ij,l} \cdot \overline{W}_{t-l} + \varepsilon_{ij,t} \tag{6}$$

where $\overline{W_t} = \left(\overline{f}p_{t-1}, \overline{X}_t\right)$ are the cross section averages of explanatory variables. To separate long run from short effect, equation (6) can be rewritten in error correction form

[4]The cross-sectional dependence test is also carried to formally confirm the presence or otherwise of cross-sectional dependence and the result is reported in Section 3 the next section.

as:

$$\Delta fp_{ij,t} = \phi_{ij}\cdot fp_{ij,t-1} - \varphi_{ij}\cdot X_{ij,t} + \sum_{k=1}^{p-1}\lambda^{*}_{ij,K}\cdot\Delta fp_{ij,t-k} + \sum_{k=0}^{q-1}\beta^{*}_{ij,k}\cdot X'_{ij,t-k} + \sum_{l=0}^{m}\tau'_{ij,l}\cdot\overline{W}_{t-l} + \varepsilon_{ij,t}, \quad (7)$$

where

$$\phi_{ij} = -\left(1-\sum_{k=1}^{p}\lambda_{ij,k}\right), \varphi_{ij} = -\frac{\sum_{k=0}^{q}\delta_{ij,k}}{\left(1-\sum_{k=1}^{p}\lambda_{ij,k}\right)} = \frac{\sum_{k=0}^{q}\delta_{ij,k}}{\phi_{ij}}, \lambda^{*}_{ij,k} = -\sum_{m=ij+1}^{p}\lambda_{ij,m},$$

and $\beta^{*}_{ij,k} = -\sum_{m=ij+1}^{p}\delta_{ij,m}$.

The first term in Equation (7), $\phi_{ij}fp_{ij,t-1} - \varphi_{ij}X_{ij,t}$, captures the adjustment in dependent variable to the deviation from its long-run relationship with the explanatory variables, while the second and third terms capture the short-run dynamics. The vector φ_{ij} represents the coefficients of the explanatory variables in determining the long-run growth and the coefficient ϕ_{ij} measures the error-correcting speed of the adjustment term. If $\phi_{ij} < 0$, the model suggests the existence of a long-run relationship between the dependent variable and its determinants. The greater the absolute value of ϕ_i the faster the rate of convergence toward the long-run equilibrium. However, if $\phi_{ij} \geq 0$, no stable linkage exists among the variables in the long run. Therefore, the speed of adjustment parameter ϕ_{ij} and the long run coefficients φ_{ij} will be our focus in the estimation output.

3 Discussion of results

We begin the empirical analysis by considering the stationarity properties of the series. Each of the variable of the specified model is subjected to unit root tests. We conducted four variants of panel unit root tests based on variations in the hull hypothesis and for robustness purposes, namely: (i) unit root with common process (Harris-Tzavalis [HT]), Breitung and Levin Lin & Chu [LLC] tests); (ii) unit root with individual unit root process (Im, Pesaran & Shin [IPS] and Fisher tests); (iii) no unit root with common process (Hadri unit root test) and, (iv) unit root with cross section dependence (Pesaran (2007) unit root test). The results are summarised in Table 1. The results from the various unit root and stationarity tests reveals that the series are either stationary at levels [$I(0)$] (that is no unit root) or at first difference [$I(1)$]. The mixed result motivates the choice of ARDL-based estimation model as the preferred modelling framework because of its consistency in estimating variables that are both $I(0)$ and $I(1)$. In addition, the panel ARDL approach can be used for analysis of long-run cointegration (Pesaran and Smith, 1995).

Table 1: Panel Unit Root Tests

	fp_o	fp_t	tc	cc	size
Null hypothesis: unit root with common process					
Harris-Tzavalis rho					
Breitung t-stat	$-45.328^{***,a}$	$-49.2801^{***,a}$	$-68.717^{***,a}$	$-54.317^{***,a}$	$-4.653^{***,a}$
Levin Lin & Chu t-stat	$-39.756^{***,a}$	$-69.3004^{***,a}$	$-97.102^{***,a}$	$-108.48^{***,a}$	$-2.372^{***,a}$
Null hypothesis: unit root with individual unit root process					
Im, Pesaran & Shin W Stat.	$-61.899^{***,a}$	$-64.5919^{***,a}$	$-125.20^{***,a}$	$-115.88^{***,a}$	$-120.325^{***,b}$
ADF Fisher Chi-Square	$7332.59^{***,a}$	$6527.28^{***,a}$	$13654.9^{***,a}$	$13077.5^{***,a}$	$12581.7^{***,b}$
Null hypothesis: no unit root with common process					
Hadri Z-Stat.	20.514^{a}	29.963^{a}	10.1058^{a}	14.5921^{b}	39.531^{a}
Null hypothesis: unit root with cross-sectional dependence					
Pesaran CADF	$-10.058^{***,a}$	$-11.545^{***,a}$	$-31.581^{***,a}$	$-27.671^{***,a}$	$-55.179^{***,a}$

Note: *** indicate statistical significance at 1% level; while a and b denote stationarity at level and at first difference respectively; fp_o, fp_t, tc, cc and size respectively are acronyms for onion price differential, tomato price differential, transportation cost, climatic variations and market size; CADF represents cross-sectionally adjusted Augmented Dickey Fuller.

Next, we perform cross-sectional dependence (CD) tests on each of the series as a pre-estimation analysis to confirm the validity of the choice of estimator. The need for testing for cross-sectional dependence is more relevant when the structure of the panel data is large such that $N > T$ (Chudik et al., 2013). Besides, the construction of food price differentials may imply the presence of strong spatial connections across markets and shocks may be transmitted between markets. For robustness purpose, we apply two variants of CD tests – the Breusch and Pagan (1980) LM and Pesaran (2004, 2015) CD tests. The differences in these tests lie in the approach and null hypothesis under which the tests are conducted. The Breusch-Pagan test is conducted under the general null hypothesis of no cross-sectional dependence, while for Pesaran tests, the null hypothesis is that there is strict cross-sectional independence or weak cross-sectional dependence (Pesaran, 2004, 2015). The results are summarised in Table 2. Both test results confirm the presence of cross section dependence across all the series for both tests. Although, for tc, the Pesaran CD statistics is not statistically significant. However, the Breusch-Pagan LM test shows otherwise. The presence of cross-sectional dependence in the series further validates the choice of cross-sectional adjusted ARDL model.

Table 2: Cross-sectional dependence test

	fp_o	fp_t	tc	cc	size
Breusch-Pagan (1980) LM	420904.1***	516684.9***	227506.8***	913685.0***	5055182***
Pesaran CD Stat.	49.0838***	190.6518***	1.5468	471.9067***	2171.376***

Note: *** indicate statistical significance at 1%; fp_o, fp_t, tc, cc and size respectively are acronyms for onion price differential, tomato price differential, transportation cost, climate variations and market size.

Having established mixed stationarity among the series as well as the presence of cross-sectional dependence in the series, we proceed to the estimation using the cross-sectionally augmented ARDL (CS-ARDL) estimator. The merit of this approach is in its ability to produce estimates for both short-run and long-run coefficients as in the traditional panel ARDL model. We begin the estimation with the panel ARDL using Pooled Mean Group (PMG) estimator[5] for robustness purposes and to further test for the presence of unobserved common factors (cross section dependence) in the residuals. Table 3 summarizes the estimation results based on both the panel ARDL and CS-ARDL estimator. The automatic lag length selection criteria which based on the Schwarz Criterion (SC) supports one lag for both the dependent and independent variables in the estimation. Hence, we estimate an ARDL(1,1,1,1) model. The long-run estimates are summarized in the upper pane, while the short-run estimates are in the lower pane for both estimators.

The estimated coefficients for the panel ARDL model show that transportation costs, climatic variations and market size are significant long-run factors that determines the variations in prices of onions and tomatoes across the different markets in Nigeria. The results show positive and significant long-run coefficients for transportation cost and economic size for both commodities. However, the long-run coefficient for climate variations is significant and negative for tomato. The short-run estimates report that transportation costs are significant determinants of onions price differentials, while market size is negative and significant for tomatoes prices in the short-run.

The distinction between short run and long run price transmission is important and the speed by which prices adjust to their long run relationship is essential in understanding the extent to which markets are integrated in the short run. The negative signs and the significance of the error correction coefficients (cointegration variable) for the panel ARDL results show theoretical and empirical consistency. This implies that price spreads across markets in the short run adjust to long-run equilibrium. Lastly, the significance of the CD test statistic for the panel ARDL estimator shows the presence of cross-section dependence which further strengthens the choice of cross-sectional adjusted estimator in order to account for the dependence caused by common factors.

The CS-ARDL estimator shows slightly varied estimates both in the magnitude and significance, from the panel ARDL estimates. The estimates after adjusting for the common factor dependence for both transportation costs and size have significant long-run and positive influence on the differences in price of onions across Nigerian markets. However, for tomatoes, climatic variations and size are both significant in the long-run. Although, climate differences across markets have a negative long-run impact on price differences. The finding is similar to previous finding by Shinyekwa and Ijjo (2016) for Ugandan markets. The authors also found that wide range of food price differences across markets are attributed to interaction between physical infrastructure and remoteness of markets. The short-run dynamics are mixed and similar to the panel ARDL estimates.

We extend the estimation by comparing the CS-ARDL estimates using the CS-DL estimator. The CD-DL method directly estimates the long-run coefficients and its merits

[5]The choice of PMG as the efficient estimator as against the mean group (MG) estimator is validated using the Hausman test

Table 3: Panel regression results

	Panel-ARDL		CS-ARDL		CS-DL	
	Onions	**Tomatoes**	**Onions**	**Tomatoes**	**Onions**	**Tomatoes**
Long-run estimate						
tc	0.2873**	0.0350**	0.1504*	0.0273	0, 2473*	0.3351**
	(0.1147)	(0.0173)	(0.0748)	(0.0707)	(0.1390)	(0.1522)
cc	0.2089***	−0.1740*	0.1340	−0.2702*	−0.0350	0.4010
	(0.0742)	(0.1045)	(0.1836)	(0.1629)	(0.3304)	(0.3923)
size	0.1637***	0.1710***	0.0746**	0.2273***	0.1464***	0.4351***
	(0.0392)	(0.0088)	(0.0349)	(0.0859)	(0.0490)	(0.1584)
Short-run estimate						
Δtc	−0.2170***	−0.0185	−0.2374***	−0.0590	−0.2587**	−0.1252
	(0.0517)	(0.0546)	(00852)	(0.0828)	(0.1060)	(0.1150)
Δcc	−0.0955	−0.1909	−0.1239	0.1629	−0.1155	−0.7924***
	(0.1164)	(0.1176)	(0.2216)	(0.1957)	(0.2734)	(0.2737)
Δ size	−0.1259	−0.1892**	0.1284	−0.0821	0.2601	−0.1837
	(0.0900)	(0.0878)	(0.1218)	(0.1795)	(0.1580)	(0.2715)
Cointegration variable	−0.6223***	−0.4522***	−1.7410***	−1.8198***		
	(0.0076)	(0.0103)	(0.0095)	(0.0102)		
No of cross-sections	666	666	666	666	666	666
No of periods	35	35	35	35	35	35
Included observations	23310	23310	23310	23310	23310	23310
CD test stat.	40.30***	117.70***	0.2889	0.3335	0.2252	0.7381
Hausman test	2, 54[0.3162]	2.27[0.5187]				

Note: ***, **, and * respectively denote statistical significance at 1%, 5% and 10% level. Standard errors are presented in parenthesis, while probability values are in squared brackets. The cointegration variable is the same as the error correction term in the Panel ARDL estimation; CD test is statistic for the cross-sectional dependence test on the residuals; The cointegration variable is the same as the error correction term in the Panel ARDL estimation;

is that it exhibits better small sample performance when the time dimension, t, is not very large (Chudik et al., 2015). The estimated results are summarized in the lower pane of the last columns of Table 3. The estimates using CS-DL estimator show that both transportation costs and economic size significant predictors of food price differential, while climatic variations are not statistically significant, unlike the panel-ARDL estimate and CS-ARDL in the case of tomato.

To check the robustness of both the CS-DL and CS-ARDL approaches, we evaluate the post-estimation error cross-sectional dependence. Using the CD test, the results show that the statistics are not statistically significant, hence the null hypothesis of cross-sectional independence in error terms could not be rejected for both food commodities. Overall, these results lend support for the complete price transmission between two spatially separated markets, as postulated by the Law of One Price (Balcombe and Morrison, 2002). Although, there are differences in the signs and magnitudes of the estimates both in the short-run and long-run for both food items. The long-run convergence to equilibrium depicts equilibrium in the long-run from the short-run imbalances in the estimates. Besides, price transmission is incomplete in the short run, but complete in the long run, as implied by the spatial arbitrage condition. Price changes are passed-through across markets after some periods and not instantaneously.

4 Conclusion

This study attempts to evaluate the underlying factors responsible for price spread of perishable foods across markets in Nigeria. Using monthly data on retail prices of onions and tomatoes across markets between 2016 and 2018, we evaluate the implications of climatic variations, transportation costs, and market size on price differential for these items across markets. To account for the mixed stationarity of the series based on the tests of their unit root properties, we apply the panel ARDL estimator which accommodates both $I(0)$ and $I(1)$ series. Specifically, the Hausman test shows strong support for the pooled mean group estimator as the efficient estimator. However, to deal with econometric issues that could arise as a result of significant cross-sectional dependence observed both in the series and residuals, we apply cross-sectionally adjusted dynamic heterogenous panel estimator (CS-ARDL), which accounts for cross-sectional dependence caused by common factors.

The estimation results show significant long-run impacts mainly from transportation costs and market size to food price differentials across markets in Nigeria. However, the estimated coefficients for climatic variations is found significant and negative on tomatoes price spreads in the short-run. While, the factors responsible for price spreads accounted for in the estimation are exhaustive, overall, we find from the empirical results that inter-market price spreads for perishable foods are largely explained by the market size of the market, transportation cost and variations in vegetation index across markets both in the short-run and long-run. The results point towards some important policy implications. First, climatic differences are inevitable and important determinants of agricultural production strengths across locations. Second is the importance of transport and distribution infrastructure in curtailing price imbalances across markets. Constraints generated across markets as a result of geography and distance could be ameliorated through effective infrastructure.

Reduction in food price differentials can be achieved through concerted agriculture policies geared towards improving the entire agriculture value-chain, most especially, production, processing, storage and distribution. Efforts should be made to adopt sophisticated system of production, contrary to the rainfed production currently dominant in the country. This could ameliorate the impact of climatic changes on the production and hence, reduction in price and difference across markets. In addition, improved storage and distribution system will further reduce the associated food loss and waste, thereby increasing farmers return and reduction in prices for consumers.

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