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Original Research Article

Spatial Price Transmission of Maize Grain Prices among Markets in Kenya, Tanzania, and Uganda: Evidence from the Nonlinear ARDL Model

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Abstract: Despite the commercial links that exist among Tanzania, Kenya, and Uganda, with maize as the most heavily traded agricultural commodity, there is a deficiency in the empirical literature on the price transmission of maize or any other traded agricultural commodity among these countries. This study attempts to fill this gap in the literature by examining the spatial price transmission of wholesale maize grain prices among these countries using the Nonlinear ARDL model. The empirical results indicate that there is no statistically significant relationship between wholesale maize prices in Uganda and those in Tanzania. However, a 1% increase (decrease) in wholesale maize prices in Kenya leads to a 0.8943% (0.7363%) increase (decrease) in wholesale maize prices in Uganda. Similarly, a 1% increase (decrease) in wholesale maize prices in Kenya leads to a 0.6079% (1.1752%) increase (decrease) in wholesale maize prices in Tanzania. On the other hand, a 1% increase (decrease) in wholesale maize prices in Uganda leads to a 0.5652% (0.6487%) increase (decrease) in wholesale maize prices in Kenya, while a 1% increase in wholesale maize prices in Tanzania leads to a 0.3635% increase in wholesale maize prices in Kenya. These findings are relevant for the development of strategies to improve market conditions and enhance growth in trade among the three countries.

Keywords: ARDL model, cointegration, East Africa, maize prices, Nonlinear ARDL model, spatial price transmission.

INTRODUCTION

Maize is the main staple grain consumed in Tanzania, Kenya, and Uganda, and the most heavily traded agricultural commodity among these three countries. Domestic maize production contributes over 50% of the national grain supply of the three countries (FEWSNET, 2022). In terms of production, Tanzania and Uganda are surplus-producing countries, exporting maize between themselves and Kenya. Kenya on the other hand is a major importer of maize from Uganda and Tanzania. According to the Food and Agriculture Organization (FAO) statistics, Tanzania produced 6.71 million tons, Kenya produced 3.79 million tons, and Uganda produced 2.75 million tons of maize in 2020 (FAO, 2022). In terms of annual per capita consumption, Kenya is the leading consumer of maize at 103 kg followed by Tanzania at 73 kg, and Uganda at 31 kg (Kilwake, 2021). This explains why despite being the second largest producer of maize in the East African region, Kenya continues to be the largest importer of the commodity from Uganda and Tanzania. In 2020, Kenya imported 201,308 and 106,813 tons of maize valued at 49.07 and 22.01 million United States Dollars (USD) from Uganda and Tanzania, respectively. Uganda imported 677 and 10,778 tons of maize valued at 1.09 and 1.53 million USD from Kenya and Tanzania, respectively. And Tanzania imported 33,870 and 356 tons of maize valued at 10.8 and 0.5 million USD from Uganda and Kenya, respectively (FAO, 2022). However, informal exports account for a large proportion of the maize export trade among the countries because of intermittent taxes and controls at the borders (Haggblade & Dewina, 2010).

Given this trade, factors such as low production that could drive up maize prices in one country, trigger increases in domestic prices in the other countries as well. Despite these commercial links, there have not been any empirical studies conducted to examine the price transmission of maize or any other agricultural commodity among Tanzania, Kenya, and Uganda. With this background, this study aims at analyzing the spatial price transmission in the maize supply chain among markets in Tanzania, Kenya, and Uganda. Analyzing price transmissions is important in measuring the degree to which markets function

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efficiently thus enhancing the realization of objectives such as developing the food supply value chain, improving the functioning of food markets, facilitating the integration of domestic markets with global and regional markets, and stabilizing domestic food prices (Hassanzoy, Ito, Isoda, & Amekawa, 2017).

Indexing wholesale maize prices among the three countries to a common January 2015 base produces Figure 1, which shows the monthly trends of wholesale maize prices in Tanzania, Kenya, and Uganda from January 2015 to September 2022. According to the figure, Uganda has the highest wholesale maize prices followed by Tanzania while Kenya has the lowest wholesale maize prices. This could be because Uganda and Tanzania are major exporters of maize not only to Kenya but also to other neighboring countries such as South Sudan and the Democratic Republic of Congo (DRC) (FAO, 2022). According to economic theory, an increase in food exports affects domestic supply and increases the demand for the exported items, causing demand-pull inflation (Qayyum & Sultana, 2018; Rehman & Khan, 2015). On the other hand, Kenya being a major importer, importing maize increases the maize supplied on domestic markets thus lowering prices. Additionally, the prices in the three countries follow similar trends and patterns suggesting that there may be a long-term relationship among wholesale maize prices in Tanzania, Kenya, and Uganda.

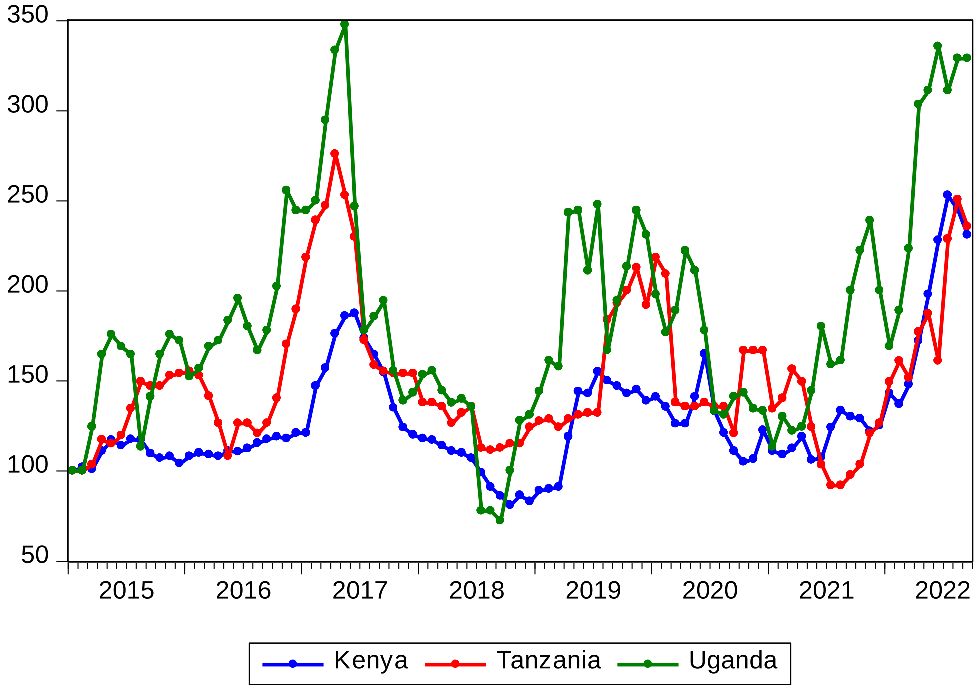

Figure 1: Monthly trends of wholesale maize prices in Tanzania, Kenya, and Uganda
Source: FEWSNET (2022)

The variation in maize prices across the three countries could be a possible indicator of the lack of market integration in the region due to both tariff and non-tariff barriers such as high transportation costs, inefficiencies at border posts, sanitary and phytosanitary regulations, and discretionary exports controls (AUC/OECD, 2022). Another important point to note from Figure 1 is that maize prices in the three countries in 2022 are relatively higher than in the previous years. This is attributed to the high costs of production and marketing brought about by the strengthening of the USD against local currencies, increasing costs of imports, high fertilizer and fuel prices due to the Russia-Ukraine war, and the high international maize prices purchased to compensate for local production shortfalls. The rising prices in surplus-producing countries Uganda and Tanzania are ascribed to the high domestic and regional demand and the below-average maize supplies to markets due to extreme changes in the weather pattern that have led to long dry spells in these countries. It is projected that maize prices in the East African region will remain higher than in the previous years because of the aforementioned factors (FEWSNET, 2022).

There is a bulk of literature examining the spatial price transmission mechanism across markets. These studies include Bakucs, Fałkowski, and Fertő (2012), Ojiako, Ezedinma, Okechukwu, and Asumugha (2013), Acosta, Ihle, and Robles (2014), Zakari, Ying, and Song (2014), Verreth, Emvalomatis, Bunte, Kemp, and Oude Lansink (2015), Wondemu (2015), Hassanzoy *et al.*, (2017), Zhang, Brown, Dong, and Waldron (2017), Helder and Rafael (2020), O. Ozturk (2020), Xue, Li, Wang, and Su (2021) among others. Almost all of these studies employed the Vector Error Correction Model (VECM) to achieve the research objectives. However, the current study employs the

Nonlinear Autoregressive distributed lag (NARDL) cointegration approach to achieve the research objective. To the best of my knowledge, there has been no other published work on spatial price transmission of food commodities using the NARDL model in East Africa, making this the first study in this regard. The NARDL model relies on positive and negative partial sum decompositions of the variables of interest and presents advantages such as easy implementation, it allows for the joint analysis of non-stationarity and non-linearity and, for the detection of asymmetric effects both in the long and in the short run (Fousekis, Katrakilidis, & Trachanas, 2016; Katrakilidis & Trachanas, 2012).

The following sections are organized as follows; Section 2 presents the data, model, and empirical framework. Section 3 presents the empirical results and discussions and section 4 presents the study's conclusion.

MATERIAL AND METHODS

Data and model specification

This study uses monthly wholesale maize prices in Kenya, Tanzania, and Uganda covering the period from January 2015 to September 2022 to examine how price changes in one country are influenced by changes in the other countries in both the short and long run. These prices were extracted from the Famine Early Warning Systems Network (FEWSNET) monthly price bulletin and are expressed in local currency units per kilogram of maize i.e., Kenyan Shilling (KES), Tanzanian Shilling (TZS), and Ugandan Shilling (UGX). All prices were transformed into their natural logarithm to mitigate price fluctuations thus increasing the likelihood of stationarity after the first differencing and allowing the first differences of the prices to be interpreted as growth rates and coefficients in terms of elasticity (Keho, 2021). The models used in this study were specified as:

$$LnUGA_t = \beta_i + \beta_{1i}LnTZA_t + \beta_{2i}LnKEN_t + \varepsilon_{1t} \quad \text{........ (1)}$$

$$LnTZA_t = \beta_{ii} + \beta_{1ii}LnUGA_t + \beta_{2ii}LnKEN_t + \varepsilon_{2t} \quad \text{...... (2)}$$

$$LnKEN_t = \beta_{iii} + \beta_{1iii}LnUGA_t + \beta_{2iii}LnTZA_t + \varepsilon_{3t} \quad \text{... .... (3)}$$

Where UGA, TZA, and KEN denote wholesale maize prices in Uganda, Tanzania, and Kenya, respectively. Ln represents the natural logarithm of the respective variables, β_i, β_{ii}, and β_{iii} are intercepts, β_{1i}, β_{1ii}, β_{1iii}, β_{2i}, β_{2ii}, and β_{2iii} are coefficients of their respective variables, and ε_{1t}, ε_{2t}, and ε_{3t} are the error terms.

Econometric Methodology

The NARDL model employed in this study begins with the formulation of the ARDL model. The primary condition of the ARDL model is that the series examined must be integrated of order 0 or 1 (I(0) or I(1)) or mutually cointegrated (Kamaruddin, Hazmi, Masbar, Syahnur, & Majid, 2021; Keho, 2021). Therefore, as a first step to the empirical analysis, I performed the Augmented Dickey-Fuller, Phillips-Perron, and Elliott-Rothenberg-Stock DF-GLS unit root tests and the Augmented Dickey-Fuller and Phillips-Perron unit root tests with a structural break to ascertain that none of the variables were integrated of order 2 [I(2)]. This was followed by the formulation of the ARDL models presented in equations 4, 5, and 6. In an ARDL model, the dependent variable is expressed as a function of its lagged values, the current and lagged values of the exogenous variables (Abuhabel & Olanrewaju, 2020; Katrakilidis & Trachanas, 2012).

$$\Delta LnUGA_t = \alpha_i + \sum_{i=1}^{p}\theta_i\Delta LnUGA_{t-i} + \sum_{i=0}^{q}\beta_{1i}\Delta LnTZA_{t-i} + \sum_{i=0}^{q}\beta_{2i}\Delta LnKEN_{t-i} + \lambda_{1i}LnUGA_{t-1} + \lambda_{2i}LnTZA_{t-1} + \lambda_{3i}LnKEN_{t-1} + u_{1t} \quad \text{...................... (4)}$$

$$\Delta LnTZA_t = \alpha_{ii} + \sum_{i=1}^{p}\theta_{ii}\Delta LnTZA_{t-i} + \sum_{i=0}^{q}\beta_{1ii}\Delta LnUGA_{t-i} + \sum_{i=0}^{q}\beta_{2ii}\Delta LnKEN_{t-i} + \lambda_{1ii}LnTZA_{t-1} + \lambda_{2ii}LnUGA_{t-1} + \lambda_{3ii}LnKEN_{t-1} + u_{2t} \quad \text{........................ (5)}$$

$$\Delta LnKEN_t = \alpha_{iii} + \sum_{i=1}^{p}\theta_{iii}\Delta LnKEN_{t-i} + \sum_{i=0}^{q}\beta_{1iii}\Delta LnUGA_{t-i} + \sum_{i=0}^{q}\beta_{2iii}\Delta LnTZA_{t-i} + \lambda_{1iii}LnKEN_{t-1} + \lambda_{2iii}LnUGA_{t-1} + \lambda_{3iii}LnTZA_{t-1} + u_{3t} \quad \text{........................ (6)}$$

Where Δ represents the first difference, α is the term of the constant, θ and β are the short-run parameters, λ represents long-run parameters, u_t is the error term, and p and q lags are used for dependent and exogenous variables, respectively. In this study, the appropriate values for the optimum lags, p, and q were determined using the Akaike information criteria (AIC).

The ARDL models in equations 4, 5, and 6 were used to formulate the NARDL models used in this study. The NARDL models incorporate the asymmetric effects of changes in wholesale maize prices unlike the ARDL models which assume that all the exogenous variables affect the dependent variable symmetrically (Kamaruddin *et al.*, 2021). In the NARDL model, the movement of the variables is decomposed into their negative and positive sums (Bahmani-Oskooee & Fariditavana, 2016) as expressed in equations 7, 8, and 9.

$$LnUGA_t = \beta_1^{+}LnTZA_t^{+} + \beta_2^{-}LnTZA_t^{-} + \beta_3^{+}LnKEN_t^{+} + \beta_4^{-}LnKEN_t^{-} + u_{1t} \quad \text{.................. (7)}$$

$$LnTZA_t = \beta_{1i}^{+}LnUGA_t^{+} + \beta_{2i}^{-}LnUGA_t^{-} + \beta_{3i}^{+}LnKEN_t^{+} + \beta_{4i}^{-}LnKEN_t^{-} + u_{2t} \quad \text{................. (8)}$$

$$LnKEN_t = \beta_{1ii}^{+}LnUGA_t^{+} + \beta_{2ii}^{-}LnUGA_t^{-} + \beta_{3ii}^{+}LnTZA_t^{+} + \beta_{4ii}^{-}LnTZA_t^{-} + u_{3t} \quad \text{................. (9)}$$

Where, β^{+} and β^{-} are the associated long-run parameters, $LnUGA_t^{+}$, $LnUGA_t^{-}$, $LnTZA_t^{+}$, $LnTZA_t^{-}$, $LnKEN_t^{+}$, and $LnKEN_t^{-}$ are the partial sum process of positive and negative changes in $LnUGA_t$, $LnTZA_t$, and $LnKEN_t$, which are decomposed as:

$$LnUGA_t = LnUGA_0 + LnUGA_t^{+} + LnUGA_t^{-} \quad \text{....... (10)}$$

$LnTZA_t = LnTZA_0 + LnTZA_t^+ + LnTZA_t^-$ ……….. (11)

$LnKEN_t = LnKEN_0 + LnKEN_t^+ + LnKEN_t^-$……… (12)

$LnUGA_t^+ = \sum_{j=1}^{t} \Delta LnUGA_j^+ = \sum_{j=1}^{t} \max(\Delta LnUGA_j, 0)$; $LnUGA_t^- = \sum_{j=1}^{t} \Delta LnUGA_j^- = \sum_{j=1}^{t} \min(\Delta LnUGA_j, 0)$ …………… (13)

$LnTZA_t^+ = \sum_{j=1}^{t} \Delta LnTZA_j^+ = \sum_{j=1}^{t} \max(\Delta LnTZA_j, 0)$; $LnTZA_t^- = \sum_{j=1}^{t} \Delta LnTZA_j^- = \sum_{j=1}^{t} \min(\Delta LnTZA_j, 0)$ ……………... (14)

$LnKEN_t^+ = \sum_{j=1}^{t} \Delta LnKEN_j^+ = \sum_{j=1}^{t} \max(\Delta LnKEN_j, 0)$; $LnKEN_t^- = \sum_{j=1}^{t} \Delta LnKEN_j^- = \sum_{j=1}^{t} \min(\Delta LnKEN_j, 0)$ ……….…….. (15)

By associating equations 7, 8, and 9 to the ARDL models in equations 4, 5, and 6, the following asymmetric error correction models (AECM) are obtained;

$\Delta LnUGA_t = \alpha_1 + \rho_1 LnUGA_{t-1} + \beta_1^+ LnTZA_{t-1}^+ + \beta_2^- LnTZA_{t-1}^- + \beta_3^+ LnKEN_{t-1}^+ + \beta_4^- LnKEN_{t-1}^- + \sum_{j=1}^{p-1} \varphi_j \Delta LnUGA_{t-j} + \sum_{j=0}^{q} (\pi_j^+ \Delta LnTZA_{t-j}^+ + \pi_j^- \Delta LnTZA_{t-j}^-) + \sum_{j=0}^{q} (\pi_j^+ \Delta LnKEN_{t-j}^+ + \pi_j^- \Delta LnKEN_{t-j}^-) + e_{1t}$ …………… (16)

$\Delta LnTZA_t = \alpha_2 + \rho_2 LnTZA_{t-1} + \beta_{1i}^+ LnUGA_{t-1}^+ + \beta_{2i}^- LnUGA_{t-1}^- + \beta_{3i}^+ LnKEN_{t-1}^+ + \beta_{4i}^- LnKEN_{t-1}^- + \sum_{m=1}^{p-1} \varphi_m \Delta LnTZA_{t-m} + \sum_{m=0}^{q} (\pi_m^+ \Delta LnUGA_{t-m}^+ + \pi_m^- \Delta LnUGA_{t-m}^-) + \sum_{m=0}^{q} (\pi_m^+ \Delta LnKEN_{t-m}^+ + \pi_m^- \Delta LnKEN_{t-m}^-) + e_{2t}$ …………… (17)

$\Delta LnKEN_t = \alpha_3 + \rho_3 LnKEN_{t-1} + \beta_{1ii}^+ LnUGA_{t-1}^+ + \beta_{2ii}^- LnUGA_{t-1}^- + \beta_{3ii}^+ LnTZA_{t-1}^+ + \beta_{4ii}^- LnTZA_{t-1}^- + \sum_{n=1}^{p-1} \varphi_n \Delta LnKEN_{t-n} + \sum_{n=0}^{q} (\pi_n^+ \Delta LnUGA_{t-n}^+ + \pi_n^- \Delta LnUGA_{t-n}^-) + \sum_{n=0}^{q} (\pi_n^+ \Delta LnTZA_{t-n}^+ + \pi_n^- \Delta LnTZA_{t-n}^-) + e_{3t}$ …………… (18)

Where $-\frac{\beta^+}{\rho}$ and $-\frac{\beta^-}{\rho}$ are the associated asymmetric long-run parameters, $\sum_{j=0}^{q} \pi_j^+$, $\sum_{j=0}^{q} \pi_j^-$, $\sum_{m=0}^{q} \pi_m^+$, $\sum_{m=0}^{q} \pi_m^-$, $\sum_{n=0}^{q} \pi_n^+$, and $\sum_{n=0}^{q} \pi_n^-$ are the associated short-run parameters.

Models 16, 17, and 18 are estimated by the standard Ordinary Least Squares method (OLS), followed by testing for the presence of a long-run relationship between the variables $LnUGA_t$, $LnTZA_t$, $LnKEN_t$, $LnUGA_t^+$, $LnUGA_t^-$, $LnTZA_t^+$, $LnTZA_t^-$, $LnKEN_t^+$, $LnKEN_t^-$ using the bounds cointegration test. The null hypotheses (H_0) of the bounds test are, $\rho_1 = \beta_1^+ = \beta_2^- = \beta_3^+ = \beta_4^- = 0$ for equation 16, $\rho_2 = \beta_{1i}^+ = \beta_{2i}^- = \beta_{3i}^+ = \beta_{4i}^- = 0$ for equation 17, and $\rho_3 = \beta_{1ii}^+ = \beta_{2ii}^- = \beta_{3ii}^+ = \beta_{4ii}^- = 0$ for equation 18, implying no long-run relationship. The alternative hypotheses (H_1) can be expressed as $\rho_1 \neq \beta_1^+ \neq \beta_2^- \neq \beta_3^+ \neq \beta_4^- \neq 0$ for equation 16, $\rho_2 \neq \beta_{1i}^+ \neq \beta_{2i}^- \neq \beta_{3i}^+ \neq \beta_{4i}^- \neq 0$ for equation 17, and $\rho_3 \neq \beta_{1ii}^+ \neq \beta_{2ii}^- \neq \beta_{3ii}^+ \neq \beta_{4ii}^- \neq 0$ for equation 18. This implies the existence of a long-run relationship among wholesale maize prices in Tanzania, Kenya, and Uganda. H_0 is rejected if the computed F-statistic is higher than the upper critical value and, if the F-statistic is below the lower critical value, then the null hypothesis cannot be rejected. The result is inconclusive if the computed F-statistic falls within the upper and lower bound values (Abuhabel & Olanrewaju, 2020; Keho, 2021).

Long-run and short-run symmetries are then examined using the Wald test. Long-run symmetry takes the forms $\beta = \beta^+ = \beta^-$, while short-run symmetry can take one of the following forms:

$\pi_j^+, \pi_m^+, \pi_n^+ = \pi_j^-, \pi_m^-, \pi_n^-$ (19) for all j,m,n = 1,…,q or

$\sum_{j=0}^{q} \pi_j^+, \sum_{m=0}^{q} \pi_m^+, \sum_{n=0}^{q} \pi_n^+ = \sum_{j=0}^{q} \pi_j^-, \sum_{m=0}^{q} \pi_m^-, \sum_{n=0}^{q} \pi_n^-$ ………………….. (20)

And finally, the asymmetric ARDL models 16, 17, and 18 are used to derive the asymmetric cumulative dynamic multiplier effects of a unit change in x_t^+ and x_t^- on y_t: Here x and y denote LnUGA, LnTZA, and LnKEN in their respective models. $m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^+}$, $m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^-}$, h = 0,1,2,… As $h \rightarrow \infty$, then $m_h^+ \rightarrow \beta^+$ and $m_h^- \rightarrow \beta^-$, which are the asymmetric long-run parameters.

Diagnostic Tests

The estimated models were tested for serial correlation and normality of the errors using the Breusch-Godfrey Serial Correlation Lagrange multiplier (LM) Test and Jarque-Bera (JB) normality tests, respectively. The Breusch-Pagan-Godfrey and ARCH heteroscedasticity tests were also performed to test for heteroscedasticity. The Ramsey RESET test was performed to test for correct model specifications. Finally, the cumulative sum of recursive residuals (CUSUM) was used to test for the stability of the models.

RESULTS AND DISCUSSION

Tables 1 and 2 present the results of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Elliott-Rothenberg-Stock DF-GLS unit root tests and the Augmented Dickey-Fuller and Phillips-Perron unit root tests with a structural break. Results from the five tests reveal that wholesale maize prices in Tanzania, Kenya, and Uganda for the period under study are I(1). It can thus be concluded that none of the variables under study is I(2). Therefore, they fulfill the primary condition of the ARDL model, which states that the series examined must be I(0), I(1)) or mutually cointegrated.

Table 1: ADF, PP, and DF-GLS unit root tests

Variables	Augmented Dickey-Fuller test		Phillips-Perron test		Elliott-Rothenberg-Stock DF-GLS test	
	Constant T-Stat. [Prob.]	Constant and trend T-Stat. [Prob.]	Constant T-Stat. [Prob.]	Constant and trend T-Stat. [Prob.]	Constant T-Stat. [Prob.]	Constant and trend T-Stat. [Prob.]
LnUGA	-2.5459 [0.1084]	-2.6114 [0.2765]	-2.5091 [0.1166]	-2.5783 [0.2911]	-1.0845 [0.2814]	-2.2758** [0.0255]
LnTZA	-2.3276 [0.1658]	-2.2590 [0.4512]	-2.6434* [0.0881]	-2.6543 [0.2580]	-0.9560 [0.3421]	-2.0202** [0.0468]
LnKEN	-1.8404 [0.3590]	-2.1835 [0.4927]	-1.4985 [0.5300]	-1.8556 [0.6693]	-1.3629 [0.1763]	-2.3155** [0.0229]
ΔLnUGA	-8.2626*** [0.0000]	-8.2163*** [0.0000]	-8.1889*** [0.0000]	-8.1330*** [0.0000]	-8.2881*** [0.0000]	-8.3056*** [0.0000]
ΔLnTZA	-4.8073*** [0.0001]	-4.7821*** [0.0011]	-8.1685*** [0.0000]	-8.1234*** [0.0000]	-4.8104*** [0.0000]	-4.8080 [0.0000]***
ΔLnKEN	-6.6790*** [0.0000]	-6.6825*** [0.0000]	-6.6556*** [0.0000]	-6.6938*** [0.0000]	-6.7049*** [0.0000]	-6.6564*** [0.0000]

Note: Δ denotes the first difference operator, ***, **, and * denote rejection of the null hypothesis of unit root at the 1%, 5%, and 10% levels, respectively. The optimal lag structure of the ADF and DF-GLS tests was selected based on the AIC, while the optimal bandwidth of the PP test was selected based on the Newey-West Bartlett kernel method.

Table 2: ADF and PP unit root tests with one structural break

Variables	Augmented Dickey-Fuller test		Phillips-Perron test	
	T-Stat. [Prob.]	Break Date	T-Stat.	Break Date
LnUGA	-3.6055 [0.6259]	2017M04	-3.1824	2017M05
LnTZA	-2.9850 [0.9158]	2020M10	-2.9842	2017M12
LnKEN	-3.7875 [0.5081]	2018M05	-3.7711	2020M06
ΔLnUGA	-8.6168* [< 0.01]	2015M08	-9.0068*	2018M07
ΔLnTZA	-8.8980* [< 0.01]	2020M03	-8.7973*	2020M03
ΔLnKEN	-7.1397* [< 0.01]	2019M04	-7.3717*	2020M06

Note: Δ denotes the first difference operator, critical values for the PP test are -6.32, -5.59, and -5.29 at the 1%, 5%, and 10% levels, respectively, * denotes rejection of the null hypothesis of unit root at the 1% level.

The results of the bounds test for nonlinear cointegration presented in Table 3 show that the F-statistic in all models is greater than the upper critical bound at all significance levels for models 2 and 3, and at the 5% level of significance for model 1. This suggests that the variables are cointegrated, i.e., there is a non-linear long-run relationship among the wholesale maize prices of Tanzania, Kenya, and Uganda.

Table 3: Bounds test for nonlinear cointegration

Significance		10%	5%	2.5%	1%
Asymptotic critical values	LCB I(0)	2.2	2.56	2.88	3.29
	UCB I(1)	3.09	3.49	3.87	4.37
F-statistics	Model 1: UGA	4.1648			
	Model 2: TZA	6.0432			
	Model 3: KEN	11.3756			

Table 4 presents the long-run estimates of the specified models. For model 1 (UGA), the positive and negative components of wholesale maize prices in Tanzania have the expected signs but are statistically not significant, which suggests that changes in wholesale maize prices in Tanzania do not influence price changes in Uganda. Similarly, the positive and negative components of wholesale maize prices in Kenya have the expected signs. However, the positive component of wholesale maize prices in Kenya is highly significant at the 1% level of significance, while its negative component is statistically significant at the 5% level of significance. The estimate of the long-run coefficient $LnKEN^{+}$ equals 0.8943 while that of the coefficient $LnKEN^{-}$ equals 0.7363. These suggest that a 1% increase (decrease) in the wholesale price of maize in Kenya leads to a 0.8943% (0.7363%) increase (decrease) in the wholesale maize prices in Uganda. The long-run positive shocks in the wholesale prices of maize in Kenya are transmitted to the wholesale prices in Uganda with greater intensity compared to negative ones. Specifically, the transmission elasticity of positive price shocks in Kenya to those in Uganda is 15.8 percentage points higher than that of negative price shocks.

The dynamic multipliers presented in Figure 3 and 4 enable tracing out the evolution of a price at a given market following a shock to a price at another market thus, providing a picture of the path to the new equilibrium (Fousekis *et al.*, 2016). In Figure 3, it can be observed that the effect of a decrease in wholesale prices in Tanzania is larger than that of the increase in prices in both the short and long run. The equilibrium correction in response to both increases and decreases in wholesale prices in Tanzania is achieved after nearly 4 months. In Figure 4, it can be observed that the effect of a decrease in wholesale prices in Kenya is larger than that of an increase in prices in the short run. However, in the long run, the effect of an increase in wholesale prices in Kenya is larger than that of a decrease in prices. The equilibrium correction in response to both increases and decreases in wholesale prices in Kenya is achieved after nearly 5 months.

For model 2 (TZA), the positive and negative components of wholesale maize prices in Uganda are statistically not significant, which suggests that changes in wholesale maize prices in Uganda do not influence price changes in Tanzania. On the other hand, the positive and negative components of wholesale maize prices in Kenya have the expected signs and are highly significant at the 1% level of significance. The estimate of the long-run coefficient $LnKEN^{+}$ equals 0.6079 while that of the coefficient $LnKEN^{-}$ equals 1.1752. These suggest that a 1% increase (decrease) in the wholesale price of maize in Kenya leads to a 0.6079% (1.1752%) increase (decrease) in the wholesale maize prices in Tanzania. These findings corroborate well with the findings in Baffes, Kshirsagar, and Mitchell (2019)'s study about the drivers of local food prices in Tanzania. In this study, the authors reported that price movements in Kenya (Nairobi) influenced Tanzanian maize price movements in the long run. It can be noted that the long-run negative shocks in the wholesale prices of maize in Kenya are transmitted to the wholesale prices in Tanzania with greater intensity compared to the positive ones. Specifically, the transmission elasticity of negative price shocks in Kenya to those in Tanzania is 56.73 percentage points higher than that of the positive price shocks. The dynamic multipliers presented in Figure 7 also show that the effect of a decrease in wholesale prices in Kenya is larger than that of the increase in prices in both the short and long run.

For model 3 (KEN), the positive and negative components of wholesale maize prices in Uganda and Tanzania have the expected signs. However, significance is only realized for the positive and negative components of prices in Uganda and the positive component of prices in Tanzania, moreover at the 1% level of significance. The negative component of prices in Tanzania is not statistically significant, which suggests that decreases in wholesale maize prices in Tanzania do not influence prices in Kenya. The estimate of the long-run coefficient $LnUGA^{+}$ equals 0.5652 while that of the coefficient $LnUGA^{-}$ equals 0.6487. These suggest that a 1% increase (decrease) in the wholesale price of maize in Uganda leads to a 0.5652% (0.6487%) increase (decrease) in the wholesale maize prices in Kenya. It can also be noted that the long-run negative shocks in the wholesale prices of maize in Uganda are transmitted to the wholesale prices in Kenya with greater intensity compared to the positive ones. Specifically, the transmission elasticity of negative price shocks in Uganda to those in Kenya is 8.35 percentage points higher than that of the positive price shocks. The estimate of the long-run coefficient $LnTZA^{+}$ equals 0.3635, which suggests that a 1% increase in the wholesale price of maize in Tanzania leads to a 0.3635% increase in the wholesale maize prices in Kenya. It is worth mentioning that the long-run positive shocks in the wholesale prices of maize in Tanzania are transmitted to the wholesale prices in Kenya with greater intensity compared to the negative ones. This is supported by the fact that the positive component of prices in Tanzania is highly significant at the 1% level of significance, while the negative component is not statistically significant.

The dynamic multipliers presented in Figure 9 also show that wholesale maize prices in Kenya respond to increases and decreases in prices in Uganda at different rates in both the short and long run. In the short run, the effect of an increase in wholesale prices in Uganda is larger than that of a decrease in prices. However, the long-run effect of a decrease in wholesale prices in Uganda is larger than that of the increase in prices. The equilibrium correction in response to both increases and decreases in wholesale prices in Uganda is achieved after nearly 6 months. In Figure 10, it can also be observed that wholesale maize prices in Kenya respond to increases and decreases in prices in Tanzania at different rates in both the short and long run. In the short run (the first 3 months), the effect of negative shocks on wholesale prices in Tanzania is larger than that of the positive shocks. However, in the long run, the effect of positive shocks on wholesale prices in Tanzania is larger than that of negative shocks. The equilibrium correction in response to both positive and negative shocks to wholesale prices in Tanzania is achieved after nearly 7 months. The behavior of the dynamic multipliers of the three models provides additional evidence for short and long-run asymmetry.

The lack of a statistically significant relationship between wholesale maize prices in Uganda and Tanzania could be a possible indicator of the lack of integration between maize markets in Uganda and those in Tanzania. This is consistent with the fact that maize exports and imports between the two countries are lower compared to their trade with Kenya. On the contrary, the results reveal that Kenya and Uganda, Kenya and Tanzania are well integrated with high rates of price transmission. This is consistent with results reported by Ihle, Cramon-Taubadel, and Zorya (2011) in their study about the integration of staple food markets in Sub-Saharan Africa. The above results further indicate that maize prices in Kenya significantly influence maize prices in both Uganda and Tanzania, moreover with greater intensity compared to the effect of maize prices in both countries on prices in Kenya. This highlights the economic role of Kenyan markets in influencing maize prices in the East African region. This is also consistent with the fact that Kenya is a major importer of maize from both Uganda and Tanzania, thus being able to influence maize prices in both countries.

Table 4: Estimated long-run coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Model 1: UGA				
$LnTZA^+$	0.0904	0.2218	0.4075	0.6847
$LnTZA^-$	0.2122	0.2594	0.8178	0.4158
$LnKEN^+$	0.8943	0.2768	3.2305	0.0018
$LnKEN^-$	0.7363	0.3171	2.3223	0.0227
C	6.5423	0.1043	62.7193	0.0000
Model 2: TZA				
$LnUGA^+$	0.1445	0.1397	1.0337	0.3046
$LnUGA^-$	-0.0798	0.1594	-0.5007	0.6180
$LnKEN^+$	0.6079	0.1899	3.2013	0.0020
$LnKEN^-$	1.1752	0.2480	4.7387	0.0000
C	6.2030	0.0970	63.9685	0.0000
Model 3: KEN				
$LnUGA^+$	0.5652	0.0780	7.0674	0.0000
$LnUGA^-$	0.6487	0.0778	8.3400	0.0000
$LnTZA^+$	0.3635	0.0925	3.9311	0.0002
$LnTZA^-$	0.1589	0.0997	1.5926	0.1156
C	2.9748	0.0477	62.3363	0.0000

The coefficients of the lagged error correction term (ECT) in the three models presented in Table 5 are very significant even at a 1% level of significance and have negative signs as required. This provides additional evidence of the presence of a long-run relationship among the variables in all models. The coefficient of the ECT signifies the proportion of the long-term imbalance of the dependent variable that is corrected in each short-run period (I. Ozturk & Acaravci, 2010; Rahman & Kashem, 2017). This value was calculated as -0.4346 for model 1, -0.4705 for model 2, and -0.4343 for model 3. This implies that it takes approximately 2.3 months (1/0.4346), 2.13 months (1/0.4705), and 2.3 months (1/0.4343) to eliminate the disequilibria in models 1, 2, and 3, respectively.

Table 5: Estimates from the Error Correction Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Model 1: UGA				
$\Delta LnUGA(-1)$	0.2274	0.0988	2.3018	0.0239
$\Delta LnKEN^-$	1.7221	0.4152	4.1473	0.0001
ECT(-1)	-0.4346	0.0844	-5.1472	0.0000
Model 2: TZA				
$\Delta LnTZA(-1)$	0.3258	0.0957	3.4035	0.0011
$\Delta LnTZA(-2)$	0.2282	0.0975	2.3400	0.0219
$\Delta LnTZA(-3)$	0.3563	0.1021	3.4898	0.0008
$\Delta LnKEN^-$	0.9967	0.2746	3.6292	0.0005
$\Delta LnKEN^-(-1)$	-0.2914	0.3002	-0.9704	0.3349
$\Delta LnKEN^-(-2)$	-0.4633	0.3007	-1.5411	0.1275
$\Delta LnKEN^-(-3)$	-0.7096	0.2873	-2.4696	0.0158
ECT(-1)	-0.4705	0.0756	-6.2191	0.0000
Model 3: KEN				
$\Delta LnKEN(-1)$	0.2126	0.0773	2.7488	0.0075
$\Delta LnUGA^-$	0.0698	0.0574	1.2170	0.2275
$\Delta LnUGA^-(-1)$	-0.1718	0.0678	-2.5334	0.0134
$\Delta LnTZA^+$	0.0447	0.0788	0.5676	0.5720
$\Delta LnTZA^+(-1)$	-0.1996	0.0862	-2.3160	0.0234

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\Delta LnTZA^{-}$	0.2131	0.0826	2.5784	0.0119
$\Delta LnTZA^{-}(-1)$	-0.0244	0.0904	-0.2702	0.7878
$\Delta LnTZA^{-}(-2)$	-0.1800	0.0827	-2.1757	0.0328
$\Delta LnTZA^{-}(-3)$	-0.1442	0.0783	-1.8428	0.0694
ECT(-1)	-0.4343	0.0509	-8.5398	0.0000

The diagnostic tests presented in Table 6 indicate that the estimated models pass all the diagnostic tests. The results suggest the absence of serial correlation and heteroscedasticity as pointed out by LM, Breusch-Pagan-Godfrey, and ARCH test results. The normal distribution and correct model specification of the models are evident from the outcomes of Jarque-Bera (JB) normality, and Ramsey RESET tests, respectively. The CUSUM tests presented in Figures 2, 5, and 8 show that the CUSUM in all models is within critical bounds, which signifies the constancy of the parameters and stability of the models.

Table 6: Diagnostic tests

Models	UGA	TZA	KEN
Durbin-Watson stat	1.9433	2.0699	1.9795
Jarque-Bera	16.1950 (0.0003)	0.9554 (0.6202)	0.4374 (0.8036)
Breusch-Godfrey Serial Correlation LM Test	0.1770 (0.8381)	2.4592 (0.0531)	0.0994 (0.9823)
Heteroscedasticity Test: Breusch-Pagan-Godfrey	0.0816 (0.9991)	1.3178 (0.2266)	1.6509 (0.0858)
Heteroscedasticity Test: ARCH	0.1580 (0.8541)	0.7436 (0.5652)	0.6279 (0.6440)
Ramsey RESET Test	0.0869 (0.7689)	0.3715 (0.5440)	1.2716 (0.2632)

Note: Figures in brackets are probabilities, values for LM, Het, and Ramsey tests are F-statistics

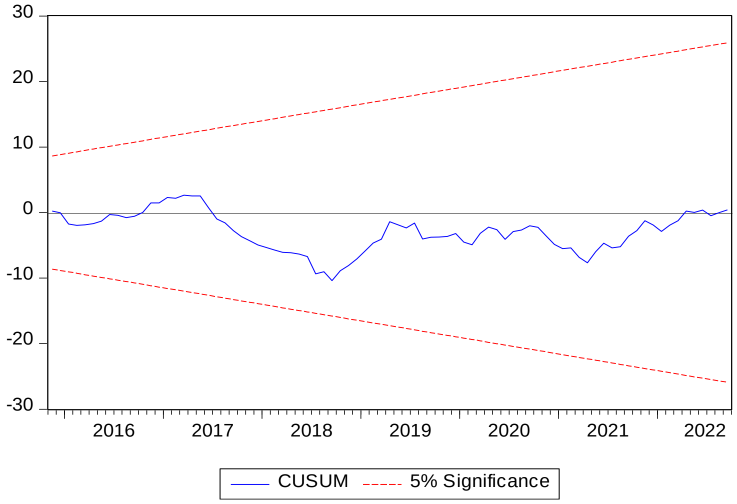

Figure 2: CUSUM for model 1 (UGA)

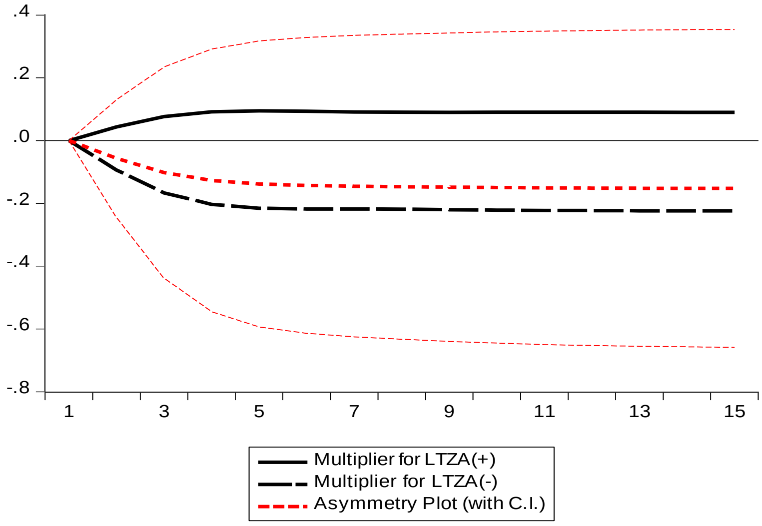

Figure 3: Dynamic Multipliers for model 1 (UGA). Tanzania to Uganda

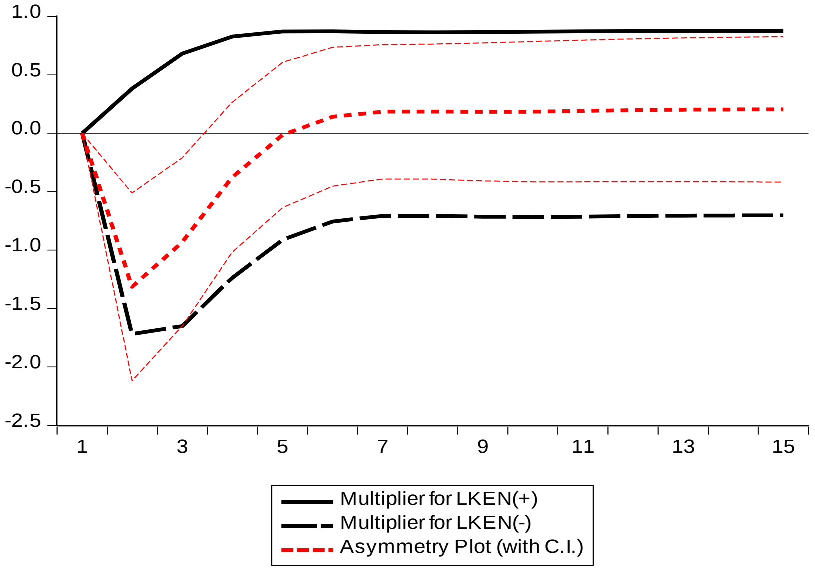

Figure 4: Dynamic Multipliers for model 1 (UGA). Kenya to Uganda

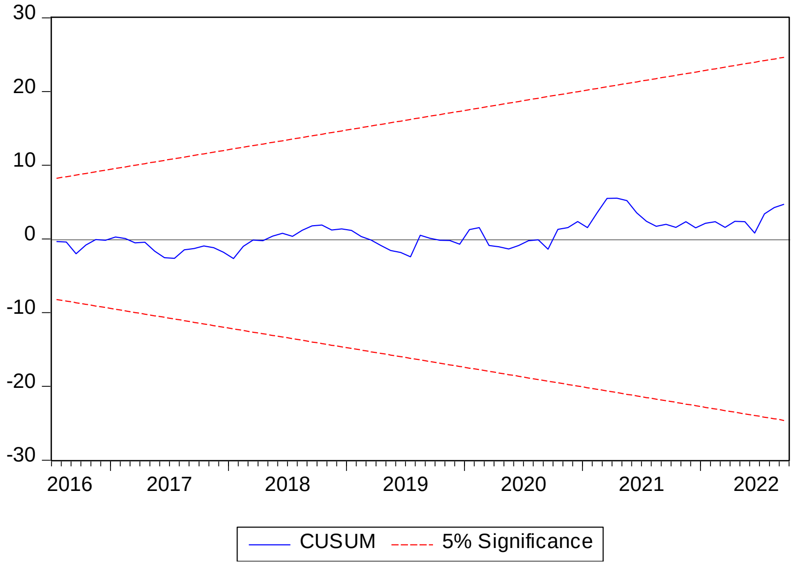

Figure 5: CUSUM for model 2 (TZA)

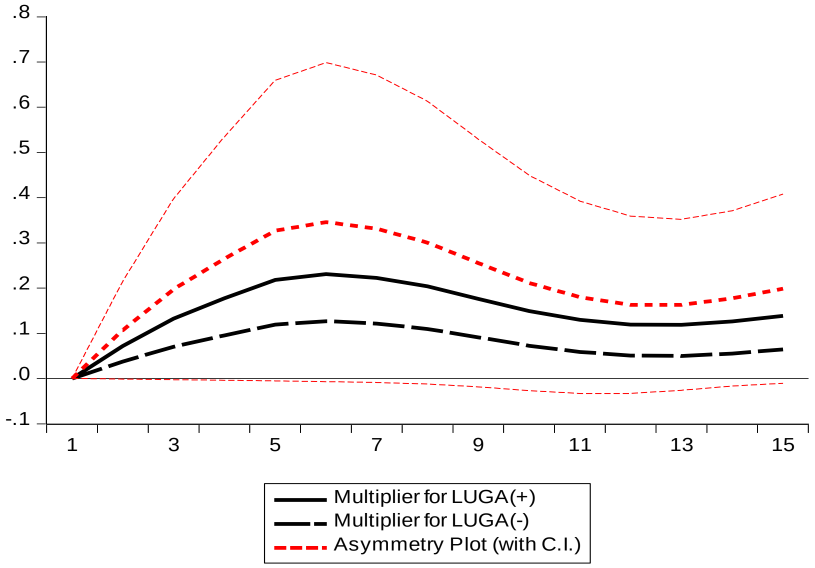

Figure 6: Dynamic Multipliers for model 2 (TZA). Uganda to Tanzania

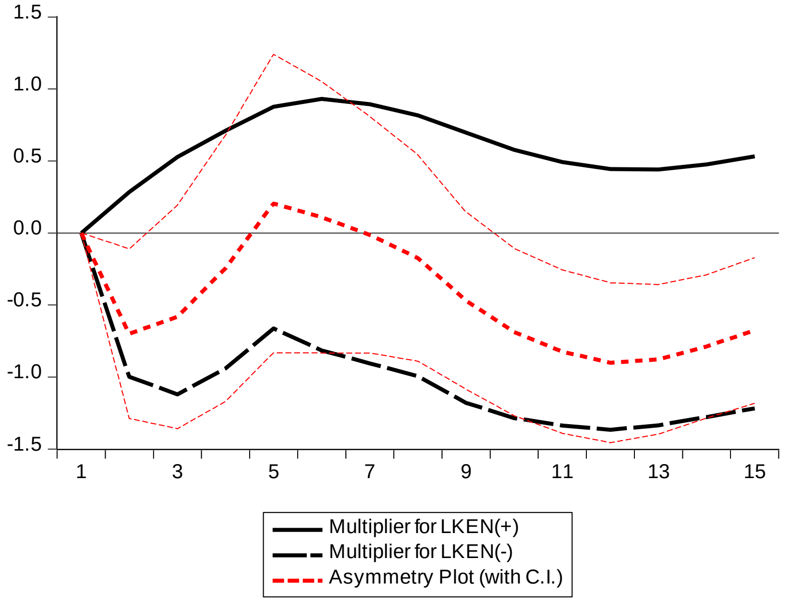

Figure 7: Dynamic Multipliers for model 2 (TZA). Kenya to Tanzania

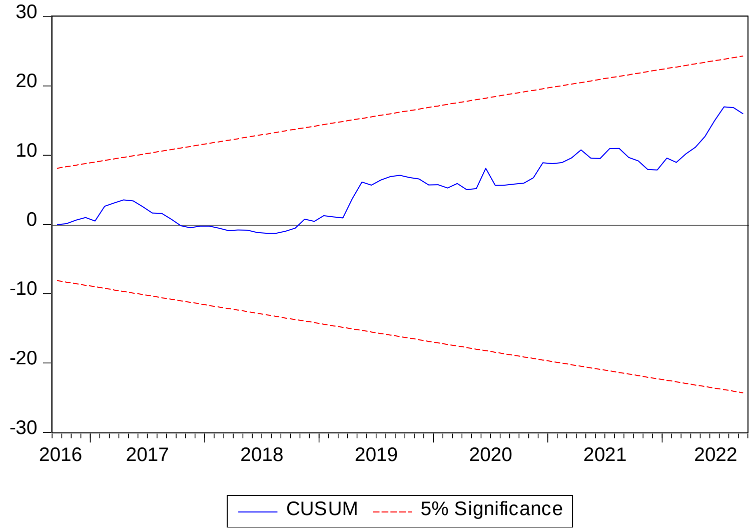

Figure 8: CUSUM for model 3 (KEN)

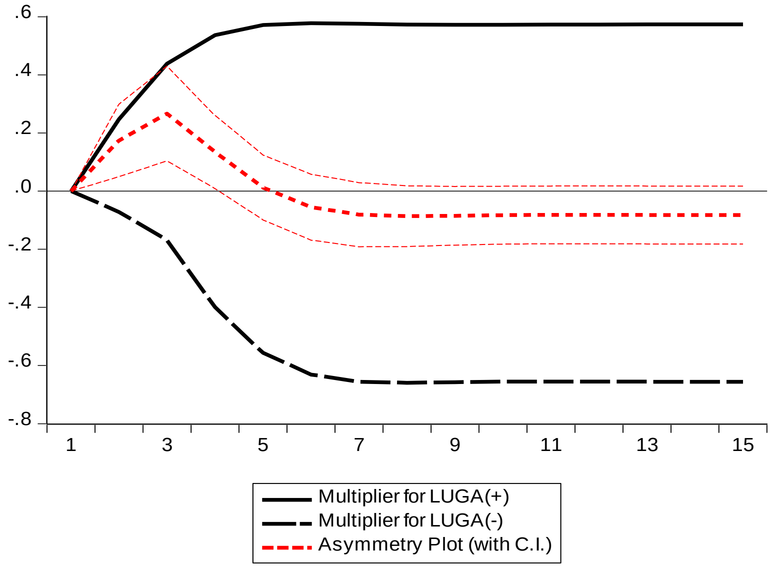

Figure 9: Dynamic Multipliers for model 3 (KEN). Uganda to Kenya

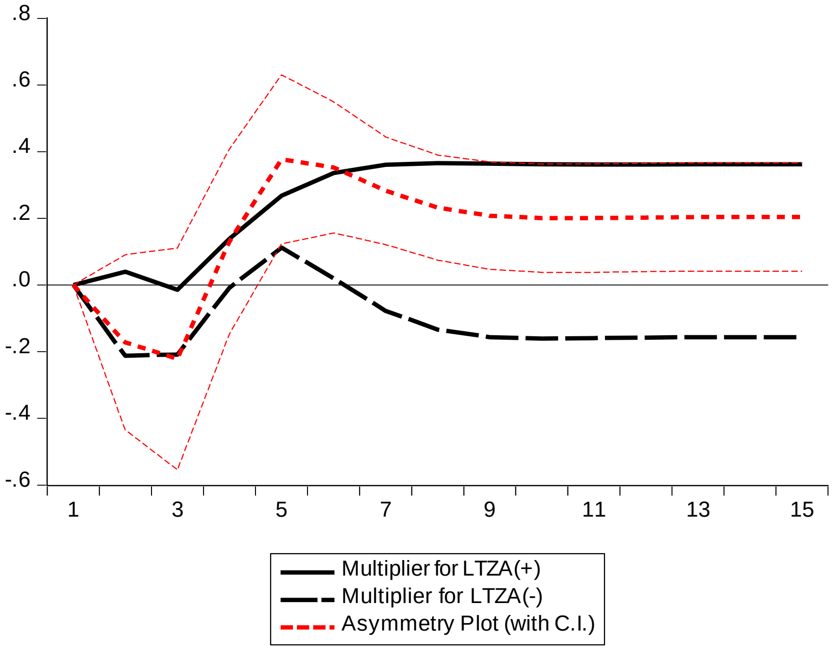

Figure 10: Dynamic Multipliers for model 3 (KEN). Tanzania to Kenya

CONCLUSION

This study employs the Nonlinear ARDL model to investigate the spatial price transmission of wholesale maize grain prices among East African Community (EAC) countries Tanzania, Kenya, and Uganda. The bounds test reveals the presence of a non-linear long-run relationship among wholesale maize prices in the three countries. Empirical results together with the behavior of the dynamic multipliers of the three models used in this study provide evidence for short and long-run asymmetry among the wholesale maize prices. Furthermore, the empirical results indicate that there is no statistically significant relationship between wholesale maize prices in Uganda and those in Tanzania. On the other hand, there is a statistically significant relationship between wholesale maize prices in Kenya and those in Uganda and Tanzania. According to the results, a 1% increase (decrease) in the wholesale price of maize in Kenya leads to a 0.8943% (0.7363%) increase (decrease) in the wholesale maize prices in Uganda. In addition, a 1% increase (decrease) in the wholesale price of maize in Kenya leads to a 0.6079% (1.1752%) increase (decrease) in the wholesale maize prices in Tanzania. On the other hand, a 1% increase (decrease) in the wholesale price of maize in Uganda leads to a 0.5652% (0.6487%) increase (decrease) in the wholesale maize prices in Kenya, while a 1% increase in the wholesale price of maize in Tanzania leads to a 0.3635% increase in the wholesale maize prices in Kenya.

It is clear from the results that the long-run positive shocks in the wholesale prices of maize in Kenya are transmitted to the wholesale prices in Uganda with greater intensity compared to negative ones. On the contrary, long-run negative shocks in the wholesale prices of maize in Uganda are transmitted to the wholesale prices in Kenya with greater intensity compared to the positive ones. Similarly, the long-run negative shocks in the wholesale prices of maize in Kenya are transmitted to the wholesale prices in Tanzania with greater intensity compared to the positive ones. While the long-run positive shocks in the wholesale prices of maize in Tanzania are transmitted to the wholesale prices in Kenya with greater intensity compared to the negative ones. These findings contribute to a better understanding of the extent to which shocks in wholesale maize prices are transmitted from one market (country) to the other among the East African Community countries under study. Such information is important in measuring the degree to which these markets function efficiently thus enhancing the realization of objectives such as developing the food supply value chain, improving the functioning of these markets, facilitating the integration of these markets, and stabilizing domestic maize prices.

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