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Spatial price transmission between white maize grain markets in Mozambique and Malawi

Helder Zavale* and Rafael da Cruz Macamo

Department of Agricultural Economics and Development, Faculty of Agronomy and Forestry Engineering, Eduardo Mondlane University, Maputo, Mozambique.

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The objective of this study was to measure white maize grain price transmission among markets in Mozambique and Malawi. Our analysis included two major deficit markets (Maputo in Southern Mozambique and Blantyre in Southern Malawi) and two major surplus markets (Chimoio in Central Mozambique and Nampula in Northern Mozambique). We used monthly wholesale white maize grain prices covering the period 2000 through 2016 to test for and quantify the magnitude of short- and long-run price transmission. To do so, we employed a combination of methodological approaches: Johansen cointegration test, Granger causality test and error correction model (ECM). Our findings revealed that Chimoio market has joint long-run relationship with Maputo, Nampula and Blantyre markets. All three Mozambique market pairs (Maputo and Chimoio; Maputo and Nampula; and Chimoio and Nampula) exhibited bidirectional causality in the long run. However, price changes in Maputo, Chimoio and Nampula are transmitted to Blantyre, but not the reverse. In the short run, only two Mozambique market pairs (Maputo and Chimoio, and Chimoio and Nampula) show bidirectional causality. Blantyre appeared to not exhibit short-run causality with Maputo, Chimoio nor Nampula.

Key words: Market integration, white maize grain, causality, price transmission

INTRODUCTION

Maize is among the most important commodities in terms of production and consumption in both Malawi and Mozambique. Data from the nationally representative Integrated Household Survey (IHS), administrated by the Malawi National Statistics Office (NSO) in 2016, administrated by the Malawi National Statistics Office (NSO), show that 70.8% of the 3.8 million households grew maize in the 2015/2016 agricultural season in Malawi. Similarly, data from the nationally representative Integrated Agricultural Survey (IAI), conducted by Mozambique Ministry of Agriculture and Food Security (MASA) in 2015, conducted by the Mozambique Ministry of Agriculture and Food Security (MASA), indicate that 67.2% of the about 4.0 million households grew the crop in the 2014/2015 agricultural season in Mozambique. These two nationally representative surveys also reveal that the shares of the total cultivated area accounted for by maize in each country averaged 56.2% in Malawi and

*Corresponding author. Email: hzavale@gmail.com.

33.2% in Mozambique. On the other hand, sizeable proportions of households consume maize in both countries: 98.2% in Malawi computed from data from IHS in 2016 and 74.0% in Mozambique computed from the nationally representative National Budget Survey (IOF) administrated by Mozambique National Institute of Statistics (INE) in 2015. During the period between 2003 and 2013, data from FAOSTAT indicate that maize contributes on average to 50.7% of the total daily caloric intake in Malawi and to 21.7% in Mozambique. This makes maize rank undoubtedly first in Malawi and second only to cassava (with 29.3%) in Mozambique in terms of contribution to total daily caloric intake. FAOSTAT data also reveal that maize consumption per capita is higher in Malawi than in Mozambique (132 versus 56 Kg per capita).

Malawi is on aggregate a maize grain surplus country, whereas Mozambique is on aggregate a white maize grain deficit country. Between 2005 and 2015, data from United State Department of Agriculture (USDA), Foreign Agriculture Service (FAS) indicate that white maize grain production is greater than maize consumption on average by about 170 thousand metric tons (MT) in Malawi, while maize production is smaller than maize consumption on average by about 100 thousand MT in Mozambique. However, whether white maize grain production outweighs maize consumption varies across regions within both Malawi and Mozambique. According to Cirera and Arndt (2008) and Myers (2013), Southern Malawi and Southern Mozambique are white maize grain deficit regions; whereas Central Malawi and Northern and Central Mozambique are white maize grain surplus regions. Moreover, Northern Malawi is a white maize grain surplus region in some years and deficit in others depending on weather patterns. These authors also document that white maize grain surpluses generated in Northern and Central Mozambique flow to Southern Mozambique and Southern Malawi.

White maize grain supply flows from Mozambique to Malawi and vice-versa, although Mozambique is a net exporter of white maize grain to Malawi. This bidirectional flow of white maize grain between Mozambique and Malawi depends to a large extent on seasonality and the relatively small difference between white maize grain production and consumption within each country. Between 2010 and 2015, data from Famine Early Warming Systems Network (FEWS NET) reveal that Mozambique exported a total of 125,000 MT of white maize grain to Malawi through informal channels; while Malawi exported a total of 97.7 thousand MT of white maize grain to Mozambique; suggesting that Mozambique is a net export of white maize grain to Malawi. During the same period, informal white maize grain export from Mozambique to Malawi outweighed that from Malawi to Mozambique in 5 out of 6 years, with an annual average of 15.9 thousand MT. Furthermore, data from FEWS NET show that Malawi accounted for 82.6% of the total white maize grain exported from Mozambique between 2010 and 2015; making Malawi rank first, followed by Zambia and Zimbabwe with shares of 16.2 and 1.2%, respectively, of Mozambique white maize grain exports. This suggests that markets in Malawi are more important in contributing to price determination in Mozambique than those in Zambia and Zimbabwe.

Two major existing studies have investigated price transmission among white maize grain markets in Mozambique. First, Tostao and Brorsen (2005) measured spatial arbitrage efficiency in white maize grain markets in Mozambique. Their findings showed that price spreads between white maize grain markets in Northern and Southern Mozambique generally fell below transport costs during the period between July 1994 and Abril 2001; suggesting that it was not profitable to ship white maize grain from surplus markets in Northern Mozambique to deficit markets in Southern Mozambique. This finding was mainly associated with poor roads connecting Northern to Southern Mozambique coupled with the lack of a bridge over the Zambezi River and traders' limited access to capital. Prior to August 2009, there was no bridge over the Zambezi River; which created a natural barrier to trade – especially for low-value commodities like white maize grain – by physically isolating markets in Northern Mozambique from those in Central and Southern Mozambique. A modern bridge was built over the Zambezi River in August 2009, facilitating trade between Northern and Southern regions.[1]

Second, Cirera and Arndt (2008) assessed the impact of road rehabilitation on spatial maize market efficiency in Mozambique between February 1992 and June 2005 and found that road rehabilitation increased spatial market efficiency but not as robust as one would expect due to substantial fuel prices increases after the road-rehabilitation period. The lack of a bridge over the Zambezi River could also explain this not robust impact of road rehabilitation especially between maize markets in Northern and Southern Mozambique.

Both of the above-mentioned studies assessed maize market efficiency prior to the construction of the bridge over the Zambezi River. We are not aware of a study that investigated white maize grain market efficiency in Mozambique after the construction of the bridge by also measuring whether the bridge contributed to white maize grain market efficiency. This study aims at filling this knowledge gap. Furthermore, unlike the studies by Tostao and Brorsen (2005); and Cirera and Arndt (2008), this study also attempts to take into account spatial market efficiency between white maize grain markets in Mozambique and those in Southern Malawi. The main

[1] The bridge was named after Armando Emilio Guebuza who was Mozambique's president between 2005 and 2015 and inaugurated the bridge.

Table 1. Maize production and sales in the 2014/2015 agricultural season.

Item	Region			Total
	Northern	Central	Southern	
% maize growers	73.3	83.6	45.9	67.2
Maize production (thousand MT)	441.2	445.0	114.4	1,000.6
Share of production (%)	44.1	44.5	11.4	100.0
Sales (thousand MT)	83.6	53.3	2.9	139.7
Share of sales (%)	59.8	38.1	2.1	100.0
Share of production sold (%)	18.9	12.0	2.5	14.0

Source: Authors' calculation using data from IAI 2015

objective of this study was to measure white maize grain price transmission among markets in Mozambique and Malawi.

MAIZE PRODUCTION AND MARKETING IN MOZAMBIQUE

Maize is among the main staple and cash crop in Mozambique. The crop is grown during the rainy season spanning October through March, harvested between March and July, and commercialized between July and September. White maize grain production and sales are concentrated in Central and Northern Mozambique where farmers cultivating small plots dominate. Farmers cultivating less than 1.5 ha accounted for 93.5% of the total number of maize growers in the 2014/2015 agricultural season. Table 1 summarizes maize production and sales in the 2014/2015 agricultural season. This table shows that maize is grown by 67.2% of smallholder farmers in Mozambique. Central Mozambique with 83.6% and Northern Mozambique with 73.3% are undoubtedly the regions with the largest shares of maize grower; followed by Southern Mozambique with 45.9%. This is to a large extent because Central and Northern Mozambique are endowed with way more favorable biophysical conditions for growing maize compared to Southern Mozambique. Table 1 also illustrates that Central (44.5%) and Northern (44.1%) regions accounted together for 88.6% of the total white maize grain production in the 2014/2015 agricultural season. Northern Mozambique, accounting for 59.8%, ranks undoubtedly first in terms contribution to the total white maize grain sales in the 2014/2015 agricultural season; followed by Central Mozambique with share of 38.1% and Southern Mozambique with a share of only 2.5%.

Table 1 reveals that a small share of total white maize grain production is sold (less than 15%), but the share varies across regions; ranging from 18.9% in the Northern region to 12.0% in the Central region to only 2.5% in the Southern region. The proportion of maize growers who sold their production follows a pattern similar to that of share of white maize grain production sold, including the magnitude. These findings suggest that a considerable share of white maize grain production goes to own consumption. Moreover, data from IAI (2015) show among maize growers, 16.6% of smallholder farmers sold their maize production in the 2014/2015 agricultural season; Northern Mozambique with 21.1% stands out as the region with the largest share of smallholder farmers who sold their maize production, followed by Central Mozambique with 17.7% and Southern Mozambique with 3.1%.

In addition to shipments to Southern Mozambique, white maize grain surplus generated in Northern and Central Mozambique is traded across the border especially to Southern Malawi. Figure 1 shows monthly average white maize grain export to and import from Mozambique over the period 2010 through 2015. This figure illustrates that white maize grain export to Malawi outweighs white maize grain imports from Malawi between March and July; while the opposite is true between November and February. This is consistent with seasonal pattern of white maize grain production in Mozambique: The harvesting season for white maize grain runs from March to July, while the lean season runs from November to February. Seasonal white maize grain index is also consistent with both this finding and harvest pattern as Seasonal white maize grain price index is below annual average white maize grain price between March and September (reaching seasonal lowest) and above it between November and February (reaching seasonal peak).

South Africa is another important channel through which white maize grain is sourced to meet deficit Southern Mozambique's requirements. Between 2010 and 2015, Mozambique imported 454.5 thousand MT of white maize grain from South Africa; making Mozambique the fourth most important destination of the South African

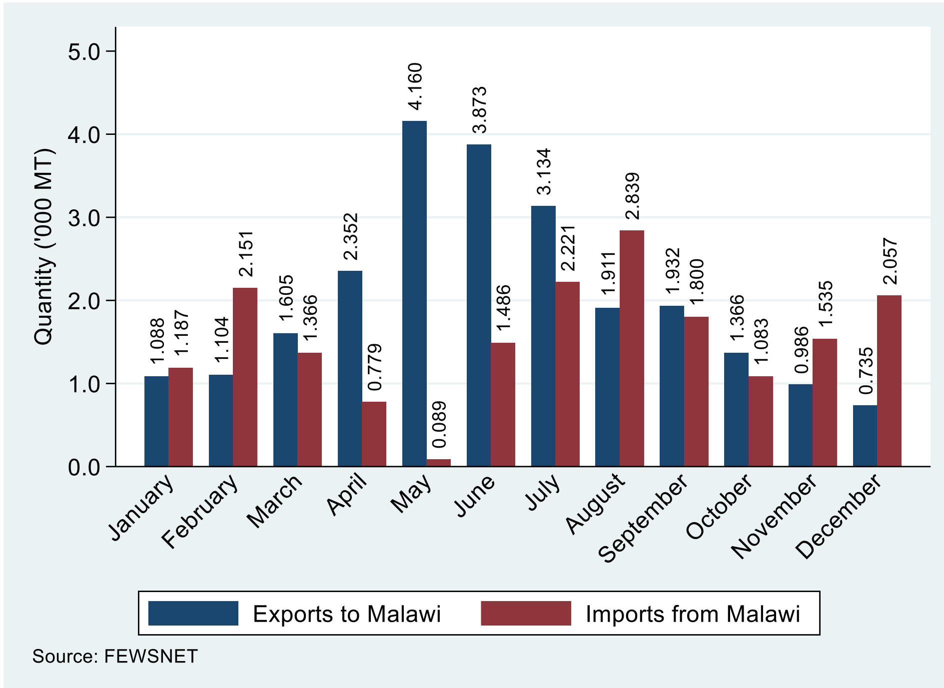

Figure 1. White maize grain export from and import to Mozambique from 2010 to 2015.

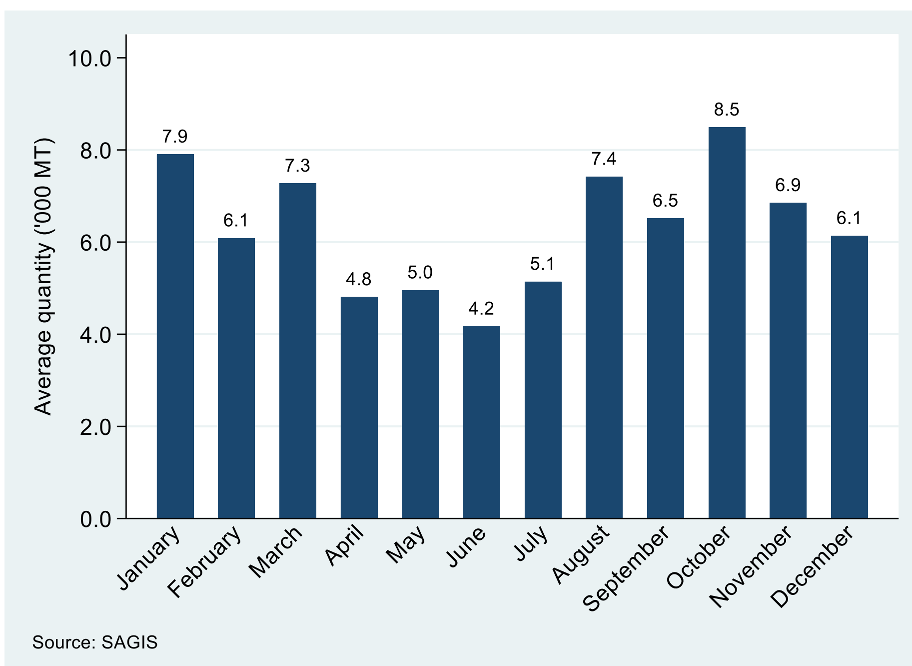

Figure 2. White maize grain imported from South Africa between 2010 and 2015.

white maize grain export to the African continent in terms of the total volume imported; following Botswana with 958.5 thousand MT, Lesotho with 629.2 thousand MT, and Namibia with 528.3 thousand MT. Figure 2 summarizes monthly average white maize grain import from South Africa during the period 2010 through 2015.

This figure shows that average quantity of white maize grain imported from South Africa is lowest between April and July and largest between October and March; consistent with seasonal pattern of white maize grain production in Mozambique. Anecdotal evidence reveals that the sizable share of white maize grain imported from South Africa is taken up by large-scale maize meal processors in Maputo; while white maize grain sourced from Central and Northern Mozambique is purchased by consumers who hand pound it or take it to small-scale hammer millers. This suggests that South African white maize grain goes through different market channels compared with white maize grain coming from Central and Northern Mozambique.

In addition to availability of white maize grain, road conditions connecting white maize grain markets affects the flow of white maize grain from surplus to deficit markets. This is because transport costs are among the key impediments to smallholder farmers' input and output market participation. Data from National Road Administration (ANE) illustrate that Mozambique had 30.5 thousand kilometers of classified roads in 2017; of which 74.2% were classified as unpaved and the remaining as paved. Northern Mozambique with 38.1% and Central Mozambique with 36.3% are the regions accounting for the largest share of the total extension of unpaved roads in the country. Data from ANE show that of the 30.7 thousand kilometers of the total classified road in 2013, 48.2% are classified as being in bad conditions.[2] As in the case of unpaved roads, the largest share of the total extension of roads in bad conditions are accounted for by Central Mozambique (39.9%) and Northern Mozambique (35.9%). This sizable share of poor road infrastructure especially in Central and Northern regions – which are maize surplus regions – limits maize trade between surplus and deficit regions, as also highlighted by Tostao and Brorsen (2005), and Cirera and Arndt (2008).

Maritime transport could be an alternative to road transport given that Mozambique is endowed with about 2.4 thousand kilometers of coastline linking Southern to Central to Northern Mozambique and with three largest ports (one in each region).[3] However, extremely low vessel availability and frequency lead to prohibitively high ocean transport costs (vessel rental price). This coupled with low volumes of white maize grain trade make maritime transport inefficient and out of reach for small-scale maize traders who are the majority. Railway transport could be another alternative to move white maize grain from surplus to deficit markets. Mozambique has three main railway systems namely Maputo railway corridor connecting Maputo port to Swaziland and South Africa, Beira railway corridor connecting Beira with Malawi and Zimbabwe, and Nacala corridor connecting Nacala port to Malawi. No railway connects Southern to Central to Northern Mozambique regardless of existing small railway networks scattered through the country. This makes railway transport very inefficient for white maize grain traders except those trading white maize grain between South Africa and Mozambique in the Southern region and those trading between Mozambique and Malawi in certain parts of the Central and Northern Mozambique.

METHODOLOGICAL APPROACH

Conceptual framework

Prices, trade volumes or both are used to describe spatial market relationships between spatially separated markets; however, neither on its own can inform us whether actual trading behavior are efficient. Spatial market integration means transfer of Walrasian excess demand between geographically distinct markets manifested in three ways: physical flow of commodity between markets or transmission of price signals or both. Price transmission – one of forms in which market integration is manifested – occurs when a price change in one market leads to a price change in another market (Barrett and Li, 2002; Kabbiri et al., 2016). This suggests that price signals are not transmitted from a deficit market to a surplus market when the two markets are not spatially integrated.

Market integration could also be vertical rather than spatial. Vertical market integration occurs when price signals are transmitted between distinct marketing channels for a given commodity. We consider price transmission for white maize grain across spatially separated markets. Let p_t^i denote white maize grain price in market i at time t, r_t^{ij} represent transaction costs – such as transport cost, negotiation, etc. – of spatial arbitrage associated with the physical movement of white maize grain between markets i and j at time t, and q_t^{ij} denote white maize grain trade flow from market i to market j at time t. Following Barrett (2001), and Negassa and Myers (2007), competitive spatial equilibrium can be specified as follows:

$$p_t^i - p_t^j \begin{cases} \le r_t^{ji} & \text{if } q_t^{ji} = 0 \\ = r_t^{ji} & \text{if } q_t^{ji} \in \left[0, q_t^{ji*}\right] \\ \ge r_t^{ji} & \text{if } q_t^{ji} = q_t^{ji*} \end{cases} \tag{1}$$

Equation (1) suggests that we could have three possible equilibrium regimes. The first regime occurs when the price differential between two spatially separated markets is smaller or equal to the transaction costs associated with the movement of white maize grain between

[2] ANE categorizes classified roads into four groups in terms of road conditions: Good, fair, bad and very bad. We grouped roads in very bad and bad conditions, according to ANE classification, into one category referred to as "bad condition". For classification in terms of road conditions, we used data for 2013 because this is latest year for which ANE classification is available.

[3] The main ports in Mozambique include Maputo in Southern Mozambique with a cargo capacity of 2.5 million MT per year, Beira in Central Mozambique with a cargo capacity of 2.3 million MT per year and Nacala in Northern Mozambique with a cargo capacity of 2.4 million MT per year. These three main ports account for about 95% of the total tonnage of commodities handled in all ports.

the two markets (the first weak inequality in Equation 1 above), implying that no white maize grain trade between the two markets occurs because no profitable arbitrage opportunities exist between the two markets. However, if trade between the two markets occurs under this regime, then traders make losses. In the second regime the price spread between the two geographically distinct markets is equal to the transaction costs (the strict equality in Equation (1) above), implying that the volume of white maize grain trade between the two markets will lie between zero and some trade flow ceiling $\left(q_t^{ji*}\right)$ if the ceiling exists. Under the second regime, the two markets are said to be in a competitive spatial equilibrium assumed under the law of one price (LOP).

This equilibrium condition suggests that competitive spatial equilibrium could occur with or without physical transfer of white maize grain between the two geographically separated markets because when transaction costs between two markets are fully exhausted, traders are indifferent between trading and not trading. If two markets are in the competitive spatial equilibrium, perfect price transmission occurs when a price change in one market stemming from local supply or demand shocks results in an identical price change in the other market.

The third regime occurs when the price spread between two spatially distinct markets is greater than or equal to the transaction costs (the last weak inequality in Equation (1) above), implying that the white maize grain trade between the two markets will be equal to some trade flow ceiling. Under this regime, the markets are not efficient regardless of whether white maize grain trade between the two markets occurs. Conditions that could lead to this regime include restrictions on the volume that could be traded between two geographically separated markets, government price support, licensing requirements, among others.

Empirical strategy

Our empirical strategy could be grouped into three categories. First, we perform unit root tests to assess whether white maize grain price series for each market is stationary as a crucial initial step for the following steps. This is because we should use stationary white maize grain price series in the following steps to avoid spurious regression. Second, we tested cointegration and direction of causality to assess whether current and lagged white maize grain prices for a given market help to predict future white maize grain price for another market. Third, we measured degree of market integration and price transmission between white maize grain markets.

Unit root test

Following Gujarati (2003), the augmented Dickey-Fuller (ADF) unit root test is specified as follows:

$$\Delta p_t^i = \beta_1 + \beta_2 T + \delta p_{t-1}^i + \sum_{s=1}^{m} \alpha_s \Delta p_{t-s}^i + \varepsilon_t^i \tag{2}$$

where p_t^i denotes white maize grain price in market i at time t; p_{t-1}^i represents lagged white maize grain price in market i; Δp_{t-s}^i is the price difference where $\Delta p_t^i = p_t^i - p_{t-1}^i$, $\Delta p_{t-1}^i = p_{t-1}^i - p_{t-2}^i$ and so on; T denotes time trend; ε_t^i is the independently and identically distributed error term; and β_1, β_2, δ and α_s are unknown parameters to be estimated. A white maize grain price series for market is nonstationary (or has a unit root) if $\delta = 0$; if we reject this null hypothesis (against the alternative hypothesis that δ is less than zero) then the white maize grain price series is stationary. If a white maize grain price series is nonstationary, we differentiate it until it becomes stationary based on the ADF test. The number of times (d) a white maize grain price series has to be differenced to become stationary gives the order of integration of the price series denoted as $I\left(d\right)$. As a robustness check, we also tested for stationarity using Phillips-Perron (PP) unit root test. Unlike the parametric ADF test that adds lagged difference terms to deal with serial autocorrelation in the error term, PP test is a nonparametric approach that takes care of serial autocorrelation without adding lagged difference terms.

Cointegration test

For spatially separated markets with white maize grain price series that are integrated of the same order using the appropriate unit root test, we investigated whether those price series are cointegrated, implying that they exhibit a long-run relationship and interdependence. Absence of cointegration among geographically separated markets suggests that those markets are segmented. Two price series that are integrated of the same order are said to be cointegrated if their linear combination is stationary. Consider the following long-run relationship between white maize grain prices in two geographically separated markets i and j:

$$p_t^i = \gamma_0 + \gamma_1 p_t^j + \nu_t \tag{3}$$

where p_t^i denotes white maize grain price in market i at time t; parameter γ_0 captures the price differential between the two markets (such as transportation cost, quality differences, processing costs, sales tax, etc.); γ_1 denotes the cointegrating parameter, and ν_t is the random error term. According to Engle and Granger (1987), if the two white maize grain price series have the same order of integration, testing for cointegration is equivalent to testing whether ν_t is stationary using the ADF test after estimating Equation (3) by ordinary least square (OLS). This approach implies pairwise testing of the long-run cointegrating relationship. However, long-run relationship between prices could happen for more than two markets jointly. Hence, we also employed the Johansen approach to test for cointegration. Enders and Siklos (2001) argued that unlike the Engle and Granger approach, the Johansen approach allows for more than one cointegrating relationships and is more robust to the choice of the dependent variable.

Following Johansen (1988, 1991), cointegration can be tested from the following specification

$$\Delta \mathbf{p}_t = \boldsymbol{\pi} \mathbf{p}_{t-1} + \mathbf{v}_t \tag{4}$$

where Δ denotes the first difference operator; $\mathbf{p}_t$ is a $n \times 1$ vector of white maize grain price series all integrated of the same order; $\mathbf{p}_{t-1}$ is a $n\times1$ vector of lagged white maize grain price series; $\boldsymbol{\pi}$ is a $n\times n$ matrix of unknown parameters to be estimated; and $\mathbf{v}_t$ is a $n\times1$ vector of normally distributed error terms. Johansen approach consists in estimating matrix $\boldsymbol{\pi}$, determining its rank, and making use of the trace Eigen value and maximum Eigen value statistics given, respectively, by

$$\lambda_{trace}\left(r\right)=-T\sum_{i=r+1}^{n}\ln\left(1-\lambda_i\right) \quad (5)$$

$$\lambda_{\max}\left(r,r+1\right)=-T\ln\left(1-\lambda_{r+1}\right) \quad (6)$$

where λ_i denotes the estimated values of the characteristics roots obtained from the estimated matrix $\boldsymbol{\pi}$; n denotes the number of price series for which we would like to test for cointegration; r is the rank of matrix $\boldsymbol{\pi}$ and represents the number of cointegrating vectors; and T represents the number of observations.

Granger causality test

For stationary price series for two geographically separated markets, we performed Granger causality test to assess whether white maize grain price changes in market i affect white maize grain price changes in market j and vice-versa. This provides an indication of the extent of integration between two geographically separated markets. For two markets with white maize grain price series that are integrated of the same order, say $I\left(d\right)$, the model to test for Granger causality is specified as follows:

$$p_t^i=\alpha^i+\tau^iT+\sum_{s=1}^{a}\eta_s^ip_{t-s}^i+\sum_{r=1}^{q}\varphi_r^ip_{t-r}^j+u_t^i \quad (7)$$

$$p_t^j=\alpha^j+\tau^jT+\sum_{r=1}^{q}\varphi_r^jp_{t-r}^j+\sum_{s=1}^{a}\eta_s^jp_{t-s}^i+u_t^j \quad (8)$$

where p_t^i denotes white maize grain price in market i at time t; p_{t-s}^i represents lagged white maize grain price in market i; T is the unit-step (monthly) time trend; u_t^i is the independently and identically distributed error term for market i where u_t^i and u_t^j are assumed to be uncorrelated; α, τ, η, and φ are unknown parameters to be estimated; and a and q denote the number of lagged white maize grain prices to be included in the regression specification. We used several statistical tests to select the number of lags. These statistical tests for selection of number of lags include Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike's Information Criterion (AIC), Hannan and Quinn Information Criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC).

Two directions of causality are possible: Unidirectional where white maize grain price changes in market i affects white maize grain price change in market j and not the reverse, and bidirectional where white maize grain price changes are transmitted in both ways between markets i and j. Using Equations (7) and (8), three hypotheses of causality could be tested:

a) Unidirectional causality: white maize grain prices in market j Granger cause white maize grain prices in market i if at least one of the coefficients φ_1^i to φ_q^i in Equation (7) are statistical different from zero and all coefficients η_1^j to η_a^j in Equation (8) are not statistically different from zero; and similarly, white maize grain prices in market i Granger cause white maize grain prices in market j if at least one of the coefficients η_1^j to η_a^j in Equation (8) are statistically different from zero and all coefficients φ_1^i to φ_q^i in Equation (7) are not statistical different from zero;
b) Bidirectional causality: white maize grain prices in markets i and j Granger cause one another if at least one of the coefficients φ_1^i to φ_q^i in Equation (7) and at least one of the coefficients η_1^j to η_a^j in Equation (8) are statistically significant;
c) Independence: markets i and j are independent if all coefficients φ_1^i to φ_q^i in Equation (7) and all coefficients η_1^j to η_a^j in Equation (8) are not statistically different from zero.

Vector auto-regression (VAR)

To assess adjustment process in both short-run and long-run responsiveness to price changes between spatially separated markets which usually reflects arbitrage and market efficiency, we used vector autoregression (VAR) technique to examine endogenous and dynamic structural relationship between white maize grain price series for markets in Mozambique and Malawi. VAR technique is widely used in the literature for this purpose. For instance, Pierre and Kaminski (2019) employed VAR framework to analyze maize market integration and price transmission among global and local markets in twenty-seven Sub-Saharan Africa (SSA) countries; while Gitau and Meyer (2019) investigated spatial price transmission under different policy regimes in maize markets in Kenya, also using the VAR approach. In our application, the reduced-form VAR of the dynamic structural relationship between white maize grain price series can be specified as follows

$$\mathbf{p}_t=\sum_{k=1}^{q}\mathbf{\Phi}_k\mathbf{p}_{t-k}+\mathbf{\Gamma}\mathbf{X}_t+\boldsymbol{\varepsilon}_t \quad (9)$$

where $\mathbf{p}_t$ is a $n\times1$ vector of stationary white maize grain price series; $\mathbf{p}_{t-k}$ is a $n\times1$ vector of lagged white maize grain price series; $\mathbf{X}_t$ is a $m\times1$ vector of exogenous variables including the intercept; $\mathbf{\Phi}_k$ and $\mathbf{\Gamma}$ are matrices of unknown parameters to be estimated; and $\boldsymbol{\varepsilon}_t$ is a $n\times1$ vector of independently and normally distributed error terms with zero mean and variance $\mathbf{\Omega}$.

We estimated a system with four equations (white maize grain price series from three markets in Mozambique plus another one from Malawi). For the sake of exposition, easy of understanding and simplicity, considering only two markets and adding an exogenous variable to the system of equations, the structural relationship between white maize grain prices can be written as

$$p_t^i = \alpha_0^i + \sum_{k=1}^{q} \alpha_k^i p_{t-k}^i + \sum_{k=1}^{q} \beta_k^i p_{t-k}^j + \gamma^i DB_t + \varepsilon_t^i \quad (10)$$

$$p_t^j = \alpha_0^j + \sum_{k=1}^{n} \alpha_k^j p_{t-k}^i + \sum_{k=1}^{n} \beta_k^j p_{t-k}^j + \gamma^j DB_t + \varepsilon_t^j \quad (11)$$

where DB_t is an exogenous dummy variable equal to one starting in August 2009 onward and zero otherwise (before August 2009). This dummy variable capture whether construction of the bridge over the Zambezi River had an impact on long-run white maize grain price relationship. As discussed before, absence of the bridge over the Zambezi River created a natural barrier to trade especially between Northern and Southern Mozambique and between Northern and Central Mozambique.

Error correction model (ECM)

For cointegrated white maize grain series, we can describe their short-run dynamics consistent with their long-run relationship through an error correction model (ECM) representation. It has also been widely shown in the literature that every stationary VAR can be expressed as an ECM representation and that VAR and ECM are observationally equivalent (Engle and Granger, 1987; Gujarati, 2003). One of the advantages of ECM over VAR is that ECM allows direct estimation of the short-run and long-run relationships, making their interpretation easier. For the VAR represented in Equation (9), the corresponding ECM can be specified as

$$\Delta \mathbf{p}_t = \mathbf{\Pi} \mathbf{p}_{t-1} + \sum_{k=1}^{q-1} \mathbf{\Lambda}_k \Delta \mathbf{p}_{t-k} + \mathbf{\Gamma X}_t + \boldsymbol{\varepsilon}_t \quad (12)$$

where Δ denotes the first difference operator, $\mathbf{\Pi} = \sum_{j=1}^{q} \mathbf{\Phi}_j - \mathbf{I}_n$, and $\mathbf{\Lambda}_k = -\sum_{j=k+1}^{q} \mathbf{\Phi}_j$. The VAR representation is called cointegrated of rank r (where $0 < r < n$) if matrix $\mathbf{\Pi}$ has rank r and thus can be decomposed as $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ with $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ being of dimension $n \times r$ and of rank r. The matrix $\boldsymbol{\beta}$ is called cointegration matrix, while matrix $\boldsymbol{\alpha}$ is called loading matrix. We tested for short-run and long-run relationships among markets using estimates from the ECM.

Data

This study focuses on two countries, namely Mozambique and Malawi. For both countries, the study employed white maize grain price series covering the period from January 2000 through December 2016. We gathered monthly white maize grain prices at wholesale levels from the Market Information Systems from both Mozambique Ministry of Agriculture and Food Security (MASA) and the Malawi Ministry of Agriculture, Irrigation and Water Development (MOAIWD). Our VAR specification consisted of price series from four markets: Three markets from Mozambique (Maputo, Chimoio and Nampula) and one from Malawi (Blantyre). Chimoio in Central Mozambique and Nampula in Northern Mozambique are key white maize grain surplus markets in Mozambique; while Maputo in Southern Mozambique and Blantyre in Southern Malawi are main white maize grain deficit markets being the capital cities in the respective countries and consequently major consumption hubs. Price series in two markets included in our VAR specifications had missing observations for certain months: Two missing observations for Nampula market and one for Chimoio market. We used annual average price for the corresponding year and market to fill in these missing observations.

We averaged weakly white maize grain prices measured in domestic currencies – Mozambican Metical (MZN) for Mozambique and Malawian Kwacha (MWK) for Malawi – per kilogram (Kg) to obtain monthly white maize grain prices. We then calculated monthly white maize grain prices measured in United States Dollars (USD) per kg by dividing monthly white maize grain prices measured in domestic currencies by the corresponding monthly exchange rates. These price conversions were made because our VAR specification comprised of white maize grain prices from markets from both countries; and also, to allow price comparisons among markets in both countries. For consistency, monthly exchange rates employed in the price conversions from domestic currencies to US Dollars were obtained from the International Monetary Fund (IMF)'s International Financial Statistics.

RESULTS

Descriptive statistics

Table 2 summarizes descriptive statistics for white maize grain prices in the four markets included in our VAR specifications. This table shows that between January 2000 and December 2016, the white maize grain prices averaged 0.33 USD/kg in Maputo, 0.26 USD/kg in Blantyre, 0.24 USD/kg in Nampula and 0.23 USD/kg in Chimoio. This price pattern (higher prices in Maputo, followed by Blantyre, Nampula and Chimoio) is observed in every single year between 2000 and 2016 and is consistent with the marketing positions for those four markets: Relatively higher white maize grain prices are registered in the deficit markets of Maputo and Blantyre and relatively lower prices in surplus markets of Chimoio and Nampula.[4]

With these price differentials, price signals could potentially be transmitted between any two geographically separated markets. These price differentials could create profitable arbitrage opportunities for traders to move white maize grain from surplus markets (Chimoio and Nampula) to deficit markets (Maputo and Blantyre) if the price differentials cover at the least the transaction costs associated with the movement of white maize grain between any two physically separated markets. We

[4] We tested whether the price differentials were statistically significant for all possible market pairs and the findings revealed that the price differentials are indeed statistically significant at one-percent significance level for all market pairs except one that was significant at 10 percent significance level.

Table 2. Descriptive statistics for white maize grain prices (USD/kg).

Market	Observations	Mean	Standard Deviation	Minimum	Maximum
Maputo	204	0.33	0.12	0.11	0.72
Chimoio	204	0.23	0.10	0.06	0.57
Nampula	204	0.24	0.11	0.06	0.50
Blantyre	204	0.26	0.12	0.08	0.66

Table 3. Augmented Dickey-Fuller and Phillips-Perron unit root tests.

Parameter	H_o: Unit root		H_o: Unit root	
	H_1: Stationary process		H_1: Stationary process with trend	
	p-value for Z(t)		p-value for Z(t)	
	Dickey-Fuller	Phillips-Perron	Dickey-Fuller	Phillips-Perron
		Level		
White maize grain price in Maputo	0.4183	0.0388	0.0608	0.0000
White maize grain price in Chimoio	0.0947	0.0285	0.0024	0.0006
White maize grain price in Nampula	0.1198	0.0239	0.0090	0.0006
White maize grain price in Blantyre	0.0018	0.0025	0.0065	0.0059
		First difference		
White maize grain price in Maputo	0.0000	0.0000	0.0000	0.0000
White maize grain price in Chimoio	0.0000	0.0000	0.0000	0.0000
White maize grain price in Nampula	0.0000	0.0000	0.0000	0.0000
White maize grain price in Blantyre	0.0000	0.0000	0.0000	0.0000

investigate with more details whether spatial price transmission occurs among two markets in the successive parts of this paper, starting with the next where stationarity is tested.

During the period between January 2000 and December 2016, price variability, measured by the coefficient of variation which is given by the ratio of the standard deviation to the mean, is relatively higher in deficit markets (Chimoio with 0.44 and Nampula with 0.44) than in surplus market (Maputo with 0.35), with the exception of Blantyre market (0.45). This higher variability in deficit markets in Mozambique could be associated with higher dependence on seasonality of production coupled with almost nonexistence storage conditions in deficit markets compared with surplus markets.

Stationarity

Cointegration test, Granger causality, and VAR models require that price series included in the model be stationary. To determine whether each white maize grain price series is stationary in the time series sense, we tested for unit roots using Augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests. For the ADF test, we chose the optimal lag lengths based on five statistical tests, namely Likelihood Ratio (LR); Final Prediction Error (FPE), Akaike's Information Criterion (AIC), Hannan and Quinn Information Criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC). These statistical tests suggested that the optimal lag lengths would be: Six for Maputo, Chimoio and Nampula markets and seven for Blantyre market.

Table 3 summarizes the results of ADF and PP unit root tests. This table suggests that based on both ADF and PP tests at five-percent significance level, the price series for all four markets do not have unit roots with a deterministic time trend included in the specification. However, without a deterministic time trend included, we found mixed results depending on whether we consider ADF or PP tests. Given that it is more sensible to include a deterministic time trend in this context, we consider that all price series are stationary in levels.

Cointegration

We tested for cointegration using the Johansen cointegration test. This cointegration test is based on the number of lags on the underlying VAR specification.

Table 4. Johansen cointegration test for Mozambique and Malawi markets.

Maximum rank	Eigenvalue	Statistic	Critical value 5%	Critical value 1%
		Trace test		
0		72.88	47.21	54.46
1	0.147	41.63	29.68	35.65
2	0.112	18.28	15.41	20.04
3	0.077	2.67	3.76	6.65
4	0.014			
		Max test		
0		31.25	27.07	32.24
1	0.147	23.35	20.97	25.52
2	0.112	15.61	14.07	18.63
3	0.077	2.67	3.76	6.65
4	0.014			

Hence, prior to testing for cointegration, we determined the optimal lag length for the underlying VAR specification using five statistical tests, namely LR, FPE, AIC, HQIC, and SBIC. The LR test selected a VAR with specification with eight lags, while the FPE and AIC tests indicated that three lags are required. On the contrary, the HQIC and SBIC tests selected specifications with two and one lags, respectively. Given these inconsistent findings regarding the optimal lag length, we employed the Lagrange multiplier (LM) test to verify whether residuals from each suggested VAR specification (VAR with one, two, three and eight lags) exhibited serial autocorrelation. Findings from the LM test revealed evidence of serial autocorrelation for residuals from the VAR specifications with three, two and one lags; while the VAR specification with eight lags did not exhibit serial autocorrelation. Hence, we chose the VAR specification with eight lags for our analysis and this specification was also employed to test for cointegration.

Table 4 summarizes the results of the Johansen cointegration test for the set of four markets included in our analysis. This table shows that the null hypothesis of no cointegration between white maize grain prices in Mozambique and Malawi is rejected at one percent significance level for the Trace test and at five percent significance level for the max test. The table also illustrates that the null hypothesis of having two cointegration relationships is reject for both trace and max tests at five percent significance level. However, no evidence exists to reject the null hypothesis for three cointegration relationships at one percent significance level for both the trace and max tests. These findings suggest that there exist three cointegration relationships which can be interpreted as the presence of long-run cointegrating relationships among white maize grain prices in Mozambique and Malawi markets. Furthermore, these findings demonstrate that white maize grain markets in Mozambique and Malawi are linked, implying that estimation of ECM for Mozambique and Malawi is important to test for the evidence of price transmission among markets in Mozambique and Malawi.

This presence of long-run cointegration relationships is consistent with findings presented earlier in this paper and showing the presence of trade of white maize grain between Mozambique and Malawi (Figure 1). As discussed earlier, white maize grain flow from Mozambique to Malawi and vice-versa throughout the year. White maize grain export to Malawi outweighs white maize grain imports from Malawi between March and July; while the opposite is true between November and February. This is consistent with seasonal pattern of white maize grain production in Mozambique: The harvesting season for white maize grain runs from March to July, while the lean season runs from November to February.

Granger causality

We tested for short-run causality among markets for white maize grain in Mozambique and Malawi using Granger causality test. Table 5 summarizes results of the Granger causality test. This table suggests that white maize grain prices in Chimoio Granger cause white maize grain prices in Maputo, implying that prices in Chimoio help improve forecasting of prices in Maputo. This table also reveals that prices in Maputo Granger cause prices in Chimoio. Hence, Maputo and Chimoio markets have bi-directional Granger causality. Moreover, bi-directional Granger causality was also found between Chimoio and Nampula markets. White maize grain prices in Maputo market provide further information to forecast

Table 5. Granger causality test for white maize grain prices in Mozambique and Malawi.

Null hypothesis	Chi-squared	p-value
Chimoio does not Granger cause Maputo	22.76	0.0040
Nampula does not Granger cause Maputo	12.31	0.1380
Blantyre does not Granger cause Maputo	6.90	0.5470
Maputo does not Granger cause Chimoio	28.66	0.0000
Nampula does not Granger cause Chimoio	34.33	0.0000
Blantyre does not Granger cause Chimoio	10.00	0.2650
Maputo does not Granger cause Nampula	15.48	0.0500
Chimoio does not Granger cause Nampula	15.41	0.0520
Blantyre does not Granger cause Nampula	7.49	0.4850
Maputo does not Granger cause Blantyre	13.84	0.0860
Chimoio does not Granger cause Blantyre	8.21	0.4130
Nampula does not Granger cause Blantyre	10.08	0.2600

Table 6. Long-run white maize grain price causality in Mozambique and Malawi.

Market	Maputo	Chimoio	Nampula	Blantyre	Constant	Cointegrating term
Maputo	1.000	-2.178(0.0000)	0.696(0.0080)	0.187(0.1450)	-0.037	0.039(0.5480)
Chimoio	-0.459(0.0000)	1.000	-0.319(0.0080)	-0.086(0.1430)	0.017	-0.543(0.0000)
Nampula	1.438(0.0010)	-3.132(0.0000)	1.000	0.270	-0.053	0.045(0.2240)
Blantyre	5.334(0.0010)	-11.618(0.0000)	3.710(0.0090)	1.000	-0.196	0.001(0.9360)

p-values are in parentheses.

white maize grain prices in Nampula in the Granger causality test, but not vice-versa. This suggests unidirectional Granger causality between prices in Maputo and Nampula markets.

Table 5 shows that white maize grain prices in Blantyre market do not Granger cause white maize grain prices in Maputo, Chimoio and Nampula markets; however, white maize grain prices in Maputo market do help forecasting of white maize grain prices in Blantyre markets, suggesting unidirectional Granger causality between Maputo and Blantyre markets.[5] These findings demonstrate some extent of integration among geographically separated markets for white maize grain in Mozambique and Malawi and are consistent with the findings for the Johansen cointegration test. This reinforces that white maize grain markets in Mozambique and Malawi are linked, opening the way for estimating ECM for Mozambique and Malawi to evaluate short-run (and long-run) price transmission among markets in Mozambique and Malawi.

Short- and long- run price relationships

Since white maize grain prices in Mozambique and Malawi are co-integrated, we estimated an ECM model. Johansen cointegration test presented earlier suggests that presence of three long-run cointegration relationships among markets for white maize grain in Mozambique and Malawi. For sake of parsimony and simplicity, we considered only one cointegrating term in the estimation of ECM model. Table 6 summarizes results from the ECM model testing for long-run price transmission among markets in Mozambique and Malawi. This table illustrates that only Chimoio market have joint long run price transmission with Maputo, Nampula and Blantyre markets because the coefficient for the error correction term is negative and statistically significant at one percent level for only Chimoio market. This is expected because Chimoio, located in Central Mozambique, is among the largest surplus markets in Mozambique supplying white maize grain to markets in Southern Mozambique (including Maputo market) and Southern Malawi (including Blantyre market). Table 6 suggests that Chimoio market

[5] Findings from the Granger causality test revealed that white maize grain prices in Chimoio, Nampula and Blantyre markets combined Granger cause white maize grain prices in Maputo markets and that white maize grain prices in Maputo, Nampula and Blantyre markets combined provide information to help forecast white maize prices in Chimoio market. We found similar results for Nampula market. These findings are available from the authors upon request.

Table 7. Short-run white maize grain price causality in Mozambique and Malawi.

Null hypothesis	Chi-square	p-value
No causality from Chimoio to Maputo	17.20	0.0161
No causality from Nampula to Maputo	3.08	0.8771
No causality from Blantyre to Maputo	5.17	0.6390
No causality from Maputo to Chimoio	32.45	0.0000
No causality from Nampula to Chimoio	20.36	0.0048
No causality from Blantyre to Chimoio	7.88	0.3429
No causality from Maputo to Nampula	12.67	0.0850
No causality from Chimoio to Nampula	13.89	0.0532
No causality from Blantyre to Nampula	5.03	0.6558
No causality from Maputo to Blantyre	9.98	0.1899
No causality from Chimoio to Blantyre	7.81	0.3500
No causality from Nampula to Blantyre	5.91	0.5502

has the speed of convergence towards the long run equilibrium of 54.3%. This indicates that a sizable long-run price spreads (45.7%) exist among Chimoio, Maputo, Nampula and Blantyre markets.

As suggested by the law of one price (LOP), price spread for the same commodity in geographically separated markets is related with transaction costs associated with the movement of the commodity among those markets. The sizable long-run price spread is consistent with empirical evidence (Tostao and Brorsen, 2005; Cirera and Arndt, 2008) suggesting that sizable transaction costs exist in Mozambique. As mentioned earlier, 48.2% of classified roads in Mozambique are in bad conditions; and Central Mozambique with 39.9% and Northern Mozambique with 35.9% are the regions that account for the largest share of the total classified roads in bad conditions in Mozambique. This sizable share of roads in bad conditions constrains profitable arbitrage opportunities to trade white maize grain among markets in Mozambique.

Although the findings suggest that Chimoio market exhibited joint long-run causality with Maputo, Nampula and Blantyre markets, Table 6 shows that pairwise long run price transmission exists among all four markets (Maputo, Chimoio, Nampula and Blantyre). This table illustrates that in the long run, changes in the white maize grain prices in Chimoio has a positive impact, while those in Nampula has a negative impact, on the white maize grain prices in Maputo, as the coefficients for Chimoio and Nampula are statistically significant at one percent level. This suggests that Chimoio and Nampula have asymmetric effects on Maputo in the long run. Similarly, our findings suggest that in the long run at one percent significance level, changes in the white maize grain prices in Maputo have positive impact on those in Chimoio and negative impact on those in Nampula. At one percent significance level, changes in prices in Chimoio have positive long-run impact on those in Nampula and vice-versa. These findings imply that the long run causality between white maize grain prices is bidirectional among markets in Mozambique.

Table 6 also shows that change in white maize grain prices in Blantyre have no long-run impact on white maize grain prices in Maputo, Chimoio and Nampula. On the contrary, in the long run, price changes in Maputo and Nampula have negative impact while price changes in Chimoio have positive impact on price changes in Blantyre. This suggests that the direction of long run causality goes from markets in Mozambique to those in Malawi and not vice-versa.

Table 7 summarizes short-run causality based on findings from the ECM model. Findings presented in Table 7 are consistent with those presented in Table 5 for the Granger causality test. Table 7 shows white maize grain prices in Maputo and Chimoio have bi-directional short-run causality at one percent significance level. Similar pattern is revealed for the short-run causality of white maize grain prices in Chimoio and Nampula. Table 7 illustrates that changes in white maize grain prices in Maputo have a significant influence on white maize grain prices in Nampula at ten percent significance level, but not the reverse. This table also shows that changes in white maize grain prices in Blantyre do not have a significant short-run effect on white maize grain prices in Maputo, Chimoio and Nampula; neither do the findings suggest significant short-run causality from Maputo, Chimoio and Nampula to Blantyre.

Conclusion

Our findings show that markets for white maize grain in Mozambique and Malawi exhibit both short- and long-run relationships. These findings are supported by both

Granger causality test and ECM test for price transmission. The results of this study revealed that Chimoio is the only market that showed joint long-run relationship with Maputo, Nampula and Blantyre markets. Our findings revealed that several market pairs have bidirectional long run causality: Maputo and Chimoio; Maputo and Nampula; and Chimoio and Nampula. On the contrary, our findings indicate unidirectional causality from Maputo, Chimoio and Nampula to Blantyre in the long run. In the short-run, only two market pairs in Mozambique (Maputo and Chimoio, and Chimoio and Nampula) exhibited short-run causality; while we found unidirectional causality between Maputo and Nampula going from Maputo to Nampula. Findings from ECM showed that Blantyre does not have short-run causality with Maputo, Chimoio and Nampula.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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