Dynamics and Trends of National Food Reserve Agency Maize Price and Local Maize Market Price: Empirical Evidence from Sumbawanga Market

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Abstract

The general objective of this study is to analyse spatial maize price transmission and market integration in Tanzania with Rukwa Region as the case study. Thus, the study intended to assess dynamics and trends of National Food Reserve Agency maize price and local market maize price between Sumbawanga (the surplus market) and other selected deficit markets from 2008-2017. Monthly maize price data came from the National Bureau of Statistics and National Food Reserve Agency purchase books price records in Rukwa Region. The Vector Autoregressive (VAR) Model, granger causality and impulse response methods were used. Results indicated that National Food Reserve Agency's price granger caused local market maize price per ton and not otherwise. Impulse Response Functions indicated that the National Food Reserve price per ton had positive transitory and permanent impact on local maize market price per ton. The government should set enough money for more and timely National Food Reserve Agency grain reserves purchase; remove export bans; and improve communication, transport, marketing and storage facilities in surplus areas.

Key words: Dynamics, Trends, Impulse Response, Vector Autoregressive (VAR) Model.
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1.0 Introduction

1.1 Background

In sub-Saharan Africa and in the East Africa region in particular, maize is one of the staple food items. In Tanzania, maize is such an important crop inseparable from both politics and from food security (Maziku, 2015). It is produced as both a food and cash crop. The two maize face values require producers to have rational decision on how much produce should be for food and how much for sale to smoothen food consumption and income throughout the year. On their part, policy makers are traditionally faced with "food price dilemma" in maize marketing (Jayne, Mason, Burke, and Ariga, 2018). They are confronted with trade-offs between giving maize farmers' adequate price to incentivize production and marketing versus keeping food price relatively low to assure food security among net food buyers.

The importance of maize in food security and income generation makes the government regulate its availability and affordability through the National Food Reserve Agency (NFRA). The NFRA was established by the Executive Agency Act No.30 of 1999 and supported by the Agricultural Marketing Policy of 2008, which generally envisaged facilitating strategic marketing of agricultural products to ensure fair returns to all stakeholders based on competitive, efficient, and equitable marketing system. The NFRA replaced the then Strategic Grain Reserve (SGR) because of the perceived inefficiencies inherent in it. The new Agency came into effect on 1st July 2008 and was mandated to do operational functions including assuring access, enough, and affordable food during emergency and stabilize markets through purchase or selling (Pierre et al., 2018).

To execute its mandates, the agency owns branches or centres whose warehouses are strategically located in towns such as Sumbawanga, Makambako, Songea, Dodoma, Shinyanga, and Arusha (REPOA, 2018). NFRA business modal involves purchasing of crop products from local farmers termed as vendors and store them in their nearby warehouses. After purchases, the grain is stored for assuring enough food reserves for current and future uses, especially at times of food shortage or emergency. Apart from warehouse storages, NFRA sells crop products to referrals or institution so as to increase availability of food in the market (Pierre et al., 2018)

NFRA faces conflicting objectives of purchasing food grain at relatively high price to support domestic production and selling stored grain at reasonably low price to mitigate consumers' welfare loss at times of food emergency. The latter role is even more critical as many farmers, due to poverty, tend to sell their output immediately after harvesting for immediate cash needs. In this regard, maize markets in Tanzania are extensively subject to policy interventions, mostly banning exports, which tend to undermine private incentives and make price movements difficult to forecast. NFRA, as a key government actor in this market, has been intervening maize markets through setting price and distorting markets, creating disincentives to produce maize, or contributing to market uncertainty and price instability (Barreiro-Hurle, 2012; Stryker, 2015). Of course, government grain reserves are by nature distortionary where the private sector chooses not to fully participate or fails to achieve required outcome. Since market distortions are associated with efficiency losses, consensus is that government grain reserve activities should ideally be kept to a minimum (Murphy, 2009).

1.2 Objectives of the Study

This study, therefore, intended to assess the dynamics and trends of NFRA maize price and local maize market price from Rukwa market. This would help to understand the relative importance of the two prices in maize market and give a way forward on how best they should co-exist with minimum possible distortionary effects in surplus and deficit markets.

2.0 Literature Review

2.1 Theoretical Literature Review

Theoretically, NFRA purchases and sales operations in grain surplus producing regions in Tanzania intend to meet dual purpose, income generation for local market producers and food security across the country at times of food deficit. This creates two dependable domestic market channels in surplus producing areas, namely the NFRA markets and local surplus maize markets. The markets have different prices on maize purchase at times of surplus and deficit domestic production, climatic distress in neighbouring countries, or some regions in Tanzania. For maize producers and traders, NFRA market is an important institutional market working alongside surplus local market operations hence assuring predictable maize price along the crop's value chain.

In surplus domestic markets, however, NFRA price and local maize price affect local producers (net sellers) and local consumers (net buyers) differently depending on the relative dynamic strength of the two price series over time in the market. According to Mhlanga, Anaadumba and Ngaiza (2014), NFRA purchase price is set based on prevailing market prices, annual unit cost of production, and crop budget from statistical unit of the Ministry of Agriculture and Livestock Development plus a 5 per cent margin. From this fact, NFRA purchase price is theoretically expected to drag up the local maize market prices in surplus producing markets, while its sales price drags local surplus market price downwards, ceteris paribus.

To strike a balance, the government and policy makers have attempted to allow free local domestic maize market operations in conjunction with NFRA marketing and selling model. This is supported by the Agricultural Marketing Policy (AMP) of 2008. This policy aims at guiding operations of agricultural marketing systems, ensure coherence, profitability, and sustainability of activities to market participants. Similarly, the other policy task is to promote efficient marketing of agricultural products in domestic, regional, and international markets (United Republic of Tanzania [URT], 2008).

When NFRA price is set at relatively higher levels than its counterpart local market price, net sellers decide to use NFRA market channel and are more likely to gain over net buyers. Conversely, when the local maize market in surplus producing areas is higher than NFRA price; net sellers are more likely to sell in local marketing channel and are expected to gain over net buyers. The two parallel maize markets have different objectives: profit maximization for local market to incentivize producers and price stabilization for NFRA to safeguard net buyers. According to Maziku (2015), NFRA purchases maize from farmers at a fixed floor price above the market prices and sells the same at lower prices to mitigate abnormal price hike. Thus, assessment of dynamics and trends in NFRA prices and local market price in surplus market was motivated by presence of dynamic behaviours in NFRA purchase and sales price of maize over time. The assessment is critical for understanding effects of government policy regulation on spatial maize markets and along its value chain.

NFRA's operations and local domestic production dynamics are not the only factors influencing variability and trends in a domestic maize market price. Major grain staple food market price, like maize in most developing nations, has frequently faced varied restrictive trade policies. The policies range from tariff barriers, export bans, domestic support measures like subsidies, and market price support through strategic grain reserves, to mention, just a few (European Centre for Development Policy Management [ECDPM] and Economic and Social Research Foundation [ESRF], 2015). Export bans policies and strategic grain reserves are applied to ensure domestic food security (Davids,Schroeder and Meyer, 2012). However, their implementation in developing economies like Tanzania, react counterproductively, since customs capacity is not adequate due to extensive porous borders. Thus, their presence and use are likely to motivate informal cross-border export trade and further lead to dwindling revenue collection (Makame, n.d.; Sanogo, 2014).

Protectionist trade policies distort food prices and markets, hurting more vulnerable net buyers and sellers through policy or price variability (ECDPM and ESRF, 2015; Trevor-Wilson and Lewis, 2015; Diao and Kennedy, 2016; Makombe and Kropp, 2016). Recording their effects, Diao and Kennedy (2016) found that restrictive policies increase returns to non-agricultural capital and wage rate of skilled labour, hurting poor rural households' more than urban counterparts. Similarly, the study further shows that restrictive trade policies reduce income (wage rate) and employment opportunities for casual agricultural (lower skilled) labourers who, like smallholders, live close to the poverty line (Diao and Kennedy, 2016). Thus, government should use maize export ban policy with caution in order to balance the market.

2.2 Empirical Literature Review

Several studies have attempted to assess dynamic effects of National strategic grain reserves purchase and sales prices on their domestic local market in order to ascertain the extent of price pass through between them. Jayne et al. (2018) assessed the impacts of National Cereal and Produce Board (NCPB) procurement price on private maize price marketing channel in Kenya. Using monthly price data from January 1989 to 2004 and through reduced form Vector Autoregressive Model (VAR), the study found that NCPB stabilized maize market in Kenya, reduced maize price levels in the early 1990s and raised average maize price levels at around 20 per cent between 1995 and 2004. The net effect was income transferring from urban consumers and small scale household net buyers to small and large farmers who were net sellers of maize.

In Zambia, Zhou and Baylis (2019) investigated effects of stock holding policy on monthly maize prices from 2003 to 2008 in order to understand its ability to moderate price volatilities. The predicted sales and purchase targets data were collected from Zambia Food Reserve Agency (ZFRA) and were used as instrument variables to do away with the problem of endogeneity. Their empirical results showed that FRA activities stabilized retail prices in major district markets within the cropping year, its purchases raised local prices in surplus maize producers for nearly 5 per cent on average at harvesting times, whereas sales lowered consumers' prices in lean seasons up to about 7 per cent. Nevertheless, no evidence was found for FRA to reduce maize price volatilities over the period.

In a similar work, Mason and Myers (2013) studied the effects of food reserve agency on maize market price in Zambia based on monthly prices from July 1996 to December 2008 using Structural Vector Autoregressive (SVAR) model. The model was selected following complexity of maize value chain in the economy, few data availabilities on quantities stored and consumed, and prices along the value chain. Through simulation, empirical results revealed that FRA activities stabilized market prices throughout the time span and raised the mean prices between July 2003 and December 2008 by 17-19 per cent. Price raising effects by FRA policies action assisted surplus maize producers but negatively affected net buyers, the majority of whom were urban consumers and rural poor people.

Chapoto and Jayne (2009) examined effects of Food Reserve Agency activities (FRA) in Zambia on food security. The findings revealed that export bans were the main source of food price volatility. To iron out the crisis, the government intervention through FRA operations like trade volumes, export and import regulation would significantly regulate domestic price volatility. Accordingly, the study found that government intervention removed uncertainty, increased investment in maize value chain through production, transportation, storage and processing. This would improve trade and price stability and gains to all agents aligned along the maize value chain.

2.3 Conceptual Framework

For this study, it was hypothesized that holding constant annual unit production cost and annual budget allocated for NFRA maize purchase, the only input to affect NFRA maize market will be existing local maize market. At times of lower production in surplus producing areas of the country, it is more likely for NFRA to buy maize at relatively higher price than at times of bumper harvest as a way to hedge against food insecurity. Some local producers/sellers in surplus local market are expected to limit their supplies in a bid to wait for higher prices. In this case, NFRA maize monthly purchase price is likely to be influenced by existing local market prices.

Similarly, NFRA purchase price in surplus market is powerful enough to drag up or down local maize market prices, depending on alternating episodes of poor domestic production embedded with export bans and surplus production without export bans. With poor domestic food production, export bans are more likely to be instituted by the government to secure food security; this encourages informal cross-border trade, and silently drains domestic food supply and can put more pressure on NFRA price. In case of surplus domestic production, there is no pressure to institute export bans nor are there needs for informal cross-border trade; this reduces pressure on NFRA price to purchase food for reserve.

Alongside this, NFRA does not purchase the same amount of maize in every purchase season, and not all maize sent by farmers at buying centres are purchased (Haug and Hella, 2013). The main reason cited in literature, for example Maziku (2015), is that budget constrains purchase of all potential surplus from surplus producing regions of Tanzania. Similarly, according to NAFRA (2019), maize from farmers is procured mainly to meet the agency's obligation of responding to food shortage at emergency times. Budget allocation is also reflected in NFRA price announced for each purchase season. It is expected to be higher during poor production and lower in bumper harvests years.

The limited budget allocated for purchase of grain oscillates, depending on national state of domestic food production; it is raised in poor production years and lowered in bumper harvest years.

Other reasons for not purchasing in some seasons, according to NAFRA (2019), are inadequate space availability for storage, maize quality parameters, and the agency's ability to procure is less than 2 per cent of maize surplus produced in the country. As an aspect of NFRA maize purchase, space availability is expected to swing, depending on amount of previous purchases in warehouses; less previous purchases in warehouses would imply increase in current season's purchases and vice versa. Thus, annual production oscillations, space availability and budget constraints trigger dynamics and trends in maize price paths between NFRA maize market and local surplus market. The dynamics and trends of NFRA monthly maize purchase price and local market maize price are illustrated in Figure 1.

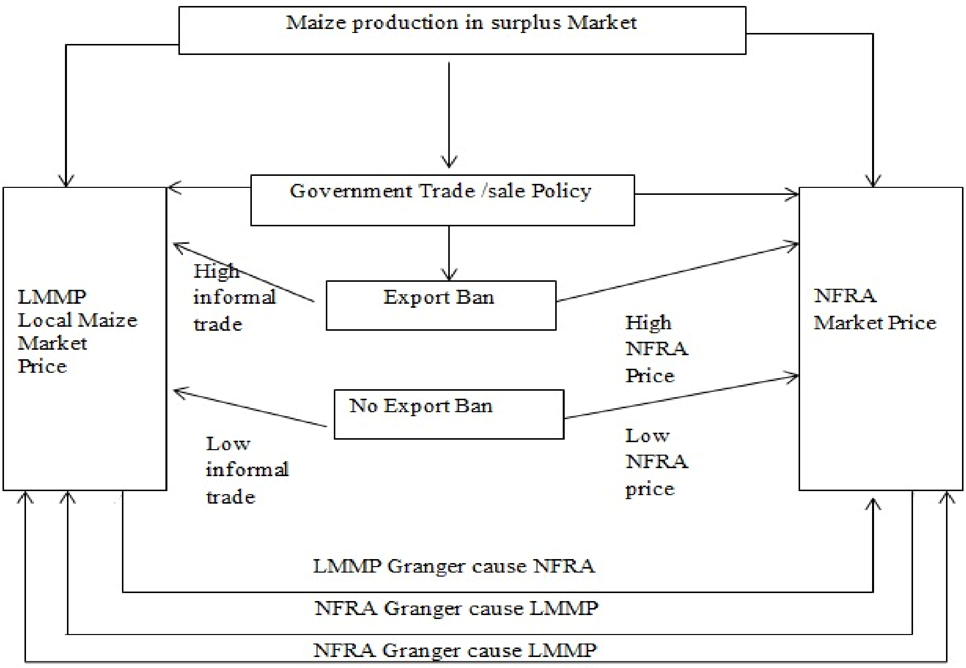

Figure 1: Conceptual Framework for Assessing Dynamics and Trends of NFRA monthly Maize Purchase Price and Local Market Maize Price
Source: Researchers' Own construction

3.0 Data and Methodology

3.1 Data

Data for assessing dynamics and trends of NFRA monthly maize purchase and local market price at Rukwa market were obtained from the National Bureau of Statistics (NBS). The choice of the Rukwa market was based on national level data availability. NFRA maize prices spanning from 2008 to 2017 were selected because officially NFRA started in 2008 replacing the then Strategic Grain Reserve (SGR) which was essentially meant for the role of price stabilization. Similarly, NFRA maize prices were obtained from seasonal purchase book records spanning from July to December each year from 2008 to 2017. Correspondingly, local market maize prices from July to December each year from 2008 to 2017 were obtained from NBS, and formed a sample size of 60-monthly time series observations. This study applied a series of statistical and econometric techniques to test the relationship between local market maize prices per ton and NFRA maize price per ton in Rukwa market. The two price series trends and dynamics were assessed to determine their co-integration, causality relationships and impulse responses analysis. Examination of the trends and dynamics of the price series was implemented through VAR model and co-integration assessment of NFRA maize price per ton and monthly local market maize price per ton.

3.2 Methodology

3.2.1 Co-Integration Modelling

Theoretically, the choice of co-integration modelling is due to the fact that most time series data are non-stationary in nature (Nelson and Plosser, 1982; Shrestha and Bhatta, 2018). Moreover, they have possibility of having spurious correlation between any two or more series due to either a coincidence or unknown third factor which can lead to misleading statistical conclusion if OLS is applied (Granger and Newbold, 1974). Also, Engle and Granger (1987) recommend co-integration approach as a remedy to spurious regression results, rather than de-trending which leads to loss of information.

$$NFRAPTON_{1t} = \alpha + \beta LMMPTONP_{2t} + \varepsilon \quad (3.1)$$

$$\varepsilon_t = NFRAPTON_{1t} - \alpha - \beta LMMPTON_{2t} \quad (3.2)$$

where, $NFRAPTON_{1t}$ is NFRA monthly maize price per ton in market 1 at time t and $LMMPTON_{2t}$ is average local monthly maize price per ton in market 2 at time t, ε_t is the error term, and α, β are constant parameters to be estimated. Co-integration exists when linear combination between series $NFRAPTON_{1t} - \alpha - \beta LMMPTON_{2t} I(0)$ is a stationary process even though each is individually non-stationary, a property termed co-integration relationship.

Through co-integration, short run and long run relationships between or among variables are accounted for. According to Nwoko et al. (2016), when non-stationary time series are co-integrated, we apply Vector Error-Correction Model (VECM) or restricted Vector Autoregressive (VAR) model to study their dynamic behaviours. Thus, in presence of co-integration we used restricted VAR or VECM to capture long run and short-run dynamics of NFRA maize purchase price and local market maize price per ton. Assessing how shocks in $NFRAPTON_{1t}$drag $LMMPTON_{2t}$ price away from and back to the long run equilibrium Vector Error Correction Model was used. If, however, $NFRAPTON_{1t}$ time series and $LMMPTON_{2t}$ were not co-integrated, only short run rather than long run dynamics were examined through un- restricted VAR model.

The descriptive statistics of monthly NFRA and local market maize purchase price per ton for the period of July to December in the year from 2008 to 2017 are presented in Table 1. The Table reveals that NFRA monthly price per ton ranged between TZS 300,000/= and TZS 620,000/=. Similarly, local market maize price recorded the minimum and maximum of TZS 187,416.00 and TZS 763,571.40 per ton respectively.

Table 1: Descriptive Statistics of NFRA Monthly Maize Purchase Price and Local Market Price at Rukwa Market for July-December from 2008-2017

Statistics	NFRAPTON	LMMPTON
Mean	434666.70	381449.70
Skewness	-0.30	0.89
Kurtosis	1.46	3.04
St. dev.	101510.70	144212.60
Min	300000.00	187416.00
Max	620000.00	763571.40

Source: Authors computation (2018)

In all price cases, NFRA's minimum purchase price was higher than minimum local market price, suggesting the fact that government does set this price using annual production costs, purchase season's budget, local market price and a 5 per cent margin. Contrarily, maximum local price exceeded NFRA maximum maize purchase price, suggesting that price in local market depended not only on the government decisions but also on market forces dynamics, the strength of which was controlled by relative scarcity of maize over time period.

The NFRA and local market average prices in TZS per ton recorded TZS 434,666.70 and TZS 381,449.70 respectively. The results signify that, for both price cases, NFRA price averages were above local maize market price; this was expected since Sumbawanga is a surplus market and government does set price at relatively higher price to incentivize producers after harvesting. Similarly, due to trade restrictions especially export bans; the market might have suffered price insulation effects in this local surplus market. Skewness value of -0.30 for NFRAPTON and 0.89 for LMMPTON maize price nearly mirrored a normal distribution of zero skewedness. The Kurtosis value for NFRA and local market price per ton were 1.46 and 3.04 respectively, indicating that, even if the two variables were normally distributed, the former was platykurtic in nature whereas the latter was mesokurtic.

Table 2: Correlation Matrix of NFRA Price per Ton (NFRAPTON) and Local Market Price per Ton (LMMPTON)

	NFRAPTON	LMMPTON
NFRAPTON	1.0000	
LMMPTON	0.6921	1.0000

Source: Author’s own computation (2018)

The correlation matrix in Table 3.2 indicates that local maize market price per ton LMMPTON was strongly positively related with the NFRA price per ton (NFRAPTON) by a correlation coefficient of 0.6921. The correlation matrix does not mean presence of causation; it only shows degree to which one variable of interests relates to another and is a sign of multi-collinearity problem. Generally, the variables in the correlation matrix indicated positive sign which means that the two variables were moving together.

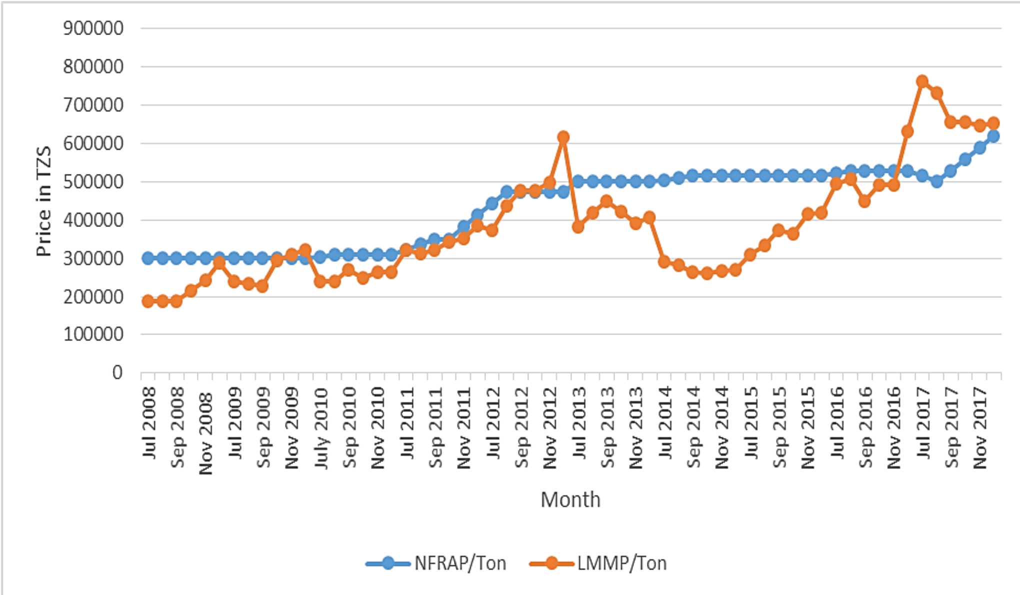

Figure 2: Trends and dynamics of monthly NFRAPTON and LMMPTON in Rukwa in TZS from July 2008 to Nov 2017
Source: Authors' Design

Generally, Figure 2 indicates moderate upward trends both in NFRA maize price and for local maize market price in Rukwa market from 2008-2017. Throughout the time span, NFRA price per ton exceeded local maize market per ton with exceptional episodes in September 2012 through December 2012 and November 2016 through November 2017. These were periods in the history of the country preceded by lower food production with some parts of the country having pockets of higher food deficits. The same period experienced highest levels of food deficit in neighbouring countries. Also, analysis in Table 2 was used to make pictorial validation of trend analysis of NFRAPTON and LMMPTON in Rukwa maize market.

Closer assessment of trends and dynamics of NFRAPTON and LMMPTON) indicates strong relationship between export bans periods and bans up-lifting periods. Institution of bans in the same period was in effect in January 2008, and was uplifted in October 2010 (Ahmed et al.,2012; Barreiro-Hurle, 2012; World Bank, 2009). According to Makombe and Kropp (2016), the government re-introduced maize export bans in May 2011.

Throughout the period, local maize market prices decreased below NFRA price per ton but fluctuated and showed some mild upward trend and instantaneously touching later price. Even with ban suppressing effects on local maize price, upward price closer to NFRA maize price per ton might have been caused by presence of informal trades which are pervasive with bans institution. Informal trade drain domestic maize supply creating excess demand amidst bans, raising local maize market price. Similarly, institution of government bans both in 2012 and June 2017 impacted (LMMPTON) negatively throwing it far below NFRA maize price per ton. This might have happened due to its insulating and suppressing effect on domestic economy's price. Bans up-lift periods were associated with strong upward pressure in local maize market in Rukwa region as indicated by such episodes as November 2012 and December 2016.

The trend results in Figure 2 were supported by USAID Tanzania Grain Report 2018 which found that between April 2017 and February 2018 maize price experienced downward trends. The report further found a 50 to 60 per cent price decline between April and November 2017 which was attributed to such factors as tight supplies, maize export bans and crop's poor performance of up to early 2017 which was worsened by dryness in the year.

Between July 2013 and December 2015, the LMMPTON saw low turn below that of NFRAPTON. However, immediately in the next purchase season of July 2016 and November 2016 LMMPTON became marginally below NFRAPTON due to market forces of demand tightening up in relation to supply. At similar dates, domestic and neighbouring countries food production did not perform well; thus in December 2017 local maize market price per ton (LMMPTON) in Rukwa market went up above NFRA price per ton (NFRAPTON), recording the highest level nearly in June and July after which it faced a decline trend.

3.2.2 Stationarity Tests

A time series data generating process is stationary if its value reverts to its long-run average value and properties of data series are not affected by the change in time only. If the same behaves otherwise, the time series is non-stationary in nature (Shrestha and Bhatta, 2018). Most time series data behave such that they are non-stationary in nature; statistical regression analysis with such variables leads to spurious regression results. Spurious regressions do yield inconsistent and inconclusive predictive power for the models. For similar reasons, it is suggested that agricultural time series need special treatment including stationarity/unit root test to avoid spurious results. Therefore, before using price data series for estimation and econometric analysis, formal tests for unit root are unavoidable. The study employed Augmented Dickey Fuller (ADF) test and Phillips-Peron (PP) to ascertain the stationarity of the NFRAPTON and LMMPTON variables. For ADF test, the null hypothesis for both tests was that the variables contain unit root. The decision criteria are rejecting the null hypothesis when test statistic is greater than the critical value at 5 per cent in absolute terms.

Table 3: Augmented Dickey Fuller Unit Root Test Results at Level

Variable	Z(t) statistic	1per cent CV	5per cent CV	10per cent CV	
NFRAPTON	-1.592	-3.750	-3.000	-2.630	I(1)
LMMPTON	-0.897	-3.648	-2.958	-2.612	I(1)

Source: Authors computation (2018)

In the results in Table 3, ADF unit root test shows that both variables, NFRATON and LMMPTON, were non-stationary at level. The general hypothesis that NFRA maize price per ton and local maize market price contained a unit root could not be rejected at 5 per cent level of significance. These results suggest that the two maize market price series were non-stationary at levels based on the ADF test. However, when the same were differenced, they became stationary i.e. I (0). This was supported by the results in Table 4 of differenced process; the Z-statistics in Table 4 exceeded a 5 per cent critical value/level of significance.

Table 3: Augmented Dickey Fuller Unit Root Test Results after First Difference

		Critical Values				
Variable	**Z(t) Statistic**	**1%**	**5%**	**10%**	**Decision**	
NFRAPTON	-3.173	-3.648	-2.958	-2.612	Stationary	I(0)
LMMPTON	-4.141	-3.648	-2.958	-2.612	Stationary	I(0)

Source: Authors computation (2018)

3.2.3 Co-Integration Tests

The decision to use VECM or VAR model to examine short run or long run relationship between NFRAPTON and LMMPTON requires co-integration test. Two stochastic processes, NFRAPTON and LMMPTON, were non-stationary at levels but stationary after differencing when their linear combinations were I (0). The phenomenon is termed as co-integration of the time series. The term implies that two stochastic processes are tied together by some economic attractors like market forces through arbitrage (Haldrup, 2003). Differently stated, any two sets of stochastic series are co-integrated where a linear combination of the series bears lower order of integration. For example, co-integration of I (1) NFRAPTON and LMMPTON individual stochastic process will exist where their linear combination is modelled as I (0). Where there exists co-integration, VECM model is applied to measure dynamics of the two variables in both short run and long run terms. If, however, there is no co-integration only unrestricted VAR model is used to measure only short run dynamics between the two variables.

Engle- Granger Co-Integration Test

Initially, the study applied Engle-Granger (1987) co-integration test for the two maize price series, NFRAPTON and LMMPTON. The choice of the two step co-integration procedure was based on the fact that originally Engle-Granger test was based on two stochastic price series that resemble our study. Co-integration through Engle-Granger measures whether the stochastic term ε_t contains unit-root by applying unit root tests such as Augmented Dickey-Fuller test (ADF). Once a unit root test is not evident, the error term ε_t in the price series is stationary, implying long run co-integration. More importantly, Engel-Granger Co-integration test procedure is simple to implement as it only requires a unit roots test of residuals, derived from Ordinary Least Squares (OLS) by using ADF. The results from Engle-Granger co-integration in Table 5 indicated no co-integrating equation between the two price series. This is supported by values of Z statistics from Table 5 which are less than 1 per cent, 5 per cent and 10 per cent critical values/levels of significance in absolute terms. Therefore, no long-run relationship between NFRAPTON and LMMPTON for the error terms was stationary at 5 per cent level. The no co-integration between the two series invited analysis of short run relationship between NFRPTON and LMMPTON using unrestricted vector autoregressive (VAR) model.

Table 4: Engle Granger Co-integration Test

					N (1st step) = 60 **N (test) = 50**	
	Test Statist	1% C V		5% CV	10% CV	
Z(t)	-1.135	-4.089		-3.442	-3.117	
Critical values from MacKinnon (1990, 2010)						
Engel-Granger 1st -step regression						
NFRAPTON	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]	
LMMPTON	0.4871884	0.0667105	7.30	0.000	0.353653	0.620724
_cons	248828.8	27176.19	9.16	0.000	194429.7	303227.8

Engel-Granger test regression						
D._egresid	Coef.	Std. Err	T	P>|t|	[95% Conf. Interval]	
_egresid L1.	-0.0480478	0.0423361	-1.13	0.262	-0.13313	0.037029

Source: Author's computations

An important point to note, however, is that despite its simplicity advantage, the Engle-Granger procedure is considered by some scholars as being defective in selecting which variable is dependent and which one is independent. Inappropriate choice of dependent and independent variables especially in finite samples causes misleading co-integration results (Michael, 2007; Mostafavi, 2012). Secondly, by applying a two-step estimation procedure, the Engle-Granger procedure generate residuals from OLS estimates and uses residuals to estimate regression of first-differenced residuals on lagged values; this sequentially designed approach may possibly introduce measurement errors from first step to the next. Thirdly, Engle-Granger co-integration test is applied in two equations, rather than in multivariate co-integration tests, and only a single co-integrating equation can be estimated (Bryant et al., 2006)

Johansen Maximum Likelihood Tests for Co-integration

Apart from using Engle and Granger (1987) integration test procedures, the current study used also full Maximum likelihood (ML) Co-integration test, popularly known as co-integration test procedures (Johansen and Juselius, 1990). Each method has strengths and weaknesses. Nevertheless, Johansen co-integration is regarded superior over the Engle-Granger co-integration approach. Haldrup (2002) noted that using the Engel-Granger integration test is not optimal since all price series are not jointly used as for Johansen co-integration test. The Johansen and Juselius (1990) method accommodates testing for multiple co-integrating vectors within a multivariate integration scenario. Since this test is carried out in a reduced form vector autoregressive (VAR) model, it avoids the endogeneity problem and, for that matter, test results remain invariable to the choice of the variable selected for normalization in the regression (Reddy, 2012).

Johansen co-integration test uses maximum likelihood to report presence or absence of co-integration by two main statistics: Trace statistics and maximum Eigenvalue statistics. As a general rule, when either trace or Maximum Eigenvalue statistics are less than critical values at a given level of significance the null hypothesis of no co-integration is accepted. From both trace and Max Eigenvalue statistics results, Tables 6 and Table 7 indicate that the two price series, NFRAPTON and LMMPTON, were not co-integrated. The results were the same as under Engle-Granger procedures under the previous section. The no co-integration outcome implied that NFRAPTON and LMMPTON had no long run stead state; only short run dynamics were estimated using unrestricted vector autoregressive model (VAR).

Table 5: Trace Values Statistics Johansen Co-integration Test

Maxi Rank	Parms	LL	Eigen value	Trace sta	5% critical	1% critical
0	12	-1278.8191		10.6453*	12.53	16.31
1	15	-1274.5253	0.14217	2.0578	3.84	6.51
2	16	-1273.4964	0.03608			

Source: Researcher's Own computations

Table 6: Maximum Eigen Value Statistics Johansen Co-integration Test

Maxi rank	Par	LL	Eigen v	Max st	5% CV	1% CV
0	12	-1278.8191		8.578*	12.53	16.31
1	15	-1274.5253	0.14217	2.0578	3.84	6.51
2	16	-1273.4964	0.03608			

Source: Researcher's Own computations

Fortunately, despite relative strengths and weaknesses in measuring co-integration between NFRAPTON and LMMPTON, both tests confirmed lack of co-integration between series. For this matter, short run dynamics through unrestricted VAR model rather than restricted VECM model was applied. To meet the intended objective, both Engle-Granger causality tests and impulse response functions were examined.

3.2.4 Granger Causality Tests

According to Granger (1969), Granger causality test examines if lagged values of one variable in a VAR model help to predict another variable. Verbeek (2012) states that a stochastic series is said to Granger cause another if the past values of the former help to predict the latter beyond information contained in the past values of the latter. In our study context, price series NFRAPTON is said to Granger cause LMMPTON if past values of NFRAPTON are helpful in predicting LMMPTON beyond information present in LMMPTON. Thus, Granger causality from NFRAPTON to LMMPTON exists if lagged values of NFRAPTON are statistically significant in an equation explaining LMMPTON. This study aimed at examining causality that existed in two VAR variable model of interest, NFRAPTON and LMMPTON. Results from the test are presented in Table 8.

Table 7: Granger Causality Test between NFRAPTON and LMMPTON

Equation	Excluded	chi2	df	Prob>Chi2
NFRAPTON	LMMPTON	0.60472	4	0.963
NFRAPTON	ALL	0.60472	4	0.963
LMMPTON	NFRAPTON	10.115	4	0.039
LMMPTON	ALL	10.115	4	0.039

Source: Author's own computation

Granger causality test was performed using Vector Auto-Regressive (VAR) approach. The null hypothesis states that the local market maize price per ton does not granger cause NFRA maize price per ton. The obtained p-value of 0.963 was not significant at 5 per cent level. We therefore could not reject the null hypothesis of no Granger causality running from local market maize price per ton (LMMPTON) to NFRAPTON. We therefore conclude that LMMPTON does not Granger cause NFRAPTON. These results are not consistent with those found by Doyle (2015). Doyle (2015) found that, when setting NFRA price, the government requires knowledge on market price, annual production costs, ministerial budget on grain purchase, and a 5 per cent profit market.

The contradictory results might have been caused by local market price and annual production costs heterogeneity. The past local market price in Rukwa might have been different from the average national wise maize market price used to set NFRAPTON by the government. Similarly, average national production cost are not necessarily uniform; for remote surplus market like Rukwa, inputs for maize production are relatively higher than other areas near ports with efficient means of transport. Thus, such cost differences might have existed between previous local production costs and previous national average production costs contained in setting NFRAPTON and might have contributed to no granger causality from LMMPTON to NFRPTON.

Regarding second scenario, the study tested causality moving from NFRAPTON to LMMPTON. The null hypothesis stated that NFRAPTON does not Granger cause LMMPTON. The p-value 0.039 obtained was smaller than the usual benchmark of 0.05, therefore indicating presence of causality running from NFRAPTON to LMMPTON. According to Verbeek (2012), this suggests that previous values of NFRAPTON are very important in predicting LMMPTON outside the information contained in LMMPTON alone. These results were expected as Doyle (2015) found that NFRAPTON formation depended on existing local market price, average annual production costs, annual government grain purchase budgets, and a 5 per cent margin imposed on local market price. NFRAPTON may possibly be higher than LMMPTON, making previous monthly price a necessary pre-determining factor for LMMPTON, especially in Rukwa the maize surplus market. The findings are supported by Figure 1which shows dynamics and trends for NFRAPTON and LMMPTON for the time spanning from 2008 to 2017. Such causal relationship revealed presence of uni-directional granger causality running from NFRAPTON to LMMPTON. However, economic theory under VAR support that, with bivariate VAR modelling, Granger causality results can be either uni-directional or bi-directional (Verbeek, 2012).

3.3 Analysis of Short-Run Dynamics between NFRAPTON and LMMPTON in Rukwa Using Vector Auto Regression Model

Absence of co-integration between NFRA maize price and local maize market price did not warrant application of Vector Error Correction model to measure long run relations between the two price series over the specified time period. The model used VAR instead to uncover and measure short-run dynamics of the two price series. Nwoko et al. (2016) found presence of co-integration between or among the variables entailing existence of long run equilibrium relationship, and a pre-requisite for using the VECM model approach. Nonetheless, formal test rejecting co-integration allows the application of VAR model estimation, implying that only short run dynamics were analysed between the variables of interest. Mitchell (2016) found that unknowing the actual long run data structure and estimating VAR model produce more accurate results than ignoring co-integration and estimating a VAR in levels. Thus, the two system VAR model between NFRA maize price series and local maize market prices were specified as follows:

$$NFRAPTON_t = \alpha + \sum_{i=1}^{k} \beta_{1i}\, NFRPTON_{t-i} + \sum_{j=1}^{k} \varphi_{1i}\, LMMPTON_{t-j} + u_{1t} \quad \dots \quad (3.3)$$

$$LMMPTON_t = \omega + \sum_{i=1}^{k} \beta_{2i}\, LMMPTON_{t-i} + \sum_{j=1}^{k} \varphi_{2i}\, NFRAPTON_{t-j} + u_{2t} \dots \quad (3.4)$$

Where $NFRAPTON_t$ the current NFRA maize price per ton is, $NFRPTON_{t-i}$ is the lagged NFRA maize price $LMMPTON_t$ is the current local maize market price, $LMMPTON_{t-i}$ is the lagged local maize market price, k is the number of lags while u_{1t} and u_{2t} are innovations which are individually identical and independently distributed, with zero mean, not auto correlated and uniform covariance matrix $E(\varepsilon_t' \varepsilon_t) = \Omega.$

When presented in matrix form VAR model the two system VAR model between NFRA maize price series and local maize market prices is also presented as below.

$NFRAPTON_t = \alpha + \beta_1 NFRPTON_{t-i} + \varphi_1 LMMPTON_{t-j} + u_{1t}$ …….. (3.5)

$LMMPTON_t = \omega + \beta_2 LMMPTON_{t-i} + \varphi_2 NFRAPTON_{t-j} + u_{2t}$ ……. (3.6)

$\begin{pmatrix} NFRAPTON_t \\ LMMPTON_t \end{pmatrix} = \begin{pmatrix} \alpha \\ \omega \end{pmatrix} + \begin{pmatrix} \beta_1 & \varphi_1 \\ \beta_2 & \varphi_2 \end{pmatrix} \begin{pmatrix} LMMPTON_{t-j} \\ NFRAPTON_{t-j} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$…….. (3.7)

Compactly stated equation (3.7) is written as

$Q_t = \vartheta + \Gamma Q_{t-1} + \varepsilon$ ………………………………………………… (3.8)

Where

$$Q_t = \begin{pmatrix} NFRAPTON_t \\ LMMPTON_t \end{pmatrix}, \vartheta = \begin{pmatrix} \alpha \\ \omega \end{pmatrix}, \Gamma = \begin{pmatrix} \beta_1 & \varphi_1 \\ \beta_2 & \varphi_2 \end{pmatrix}, Q_{t-1} = \begin{pmatrix} LMMPTON_{t-j} \\ NFRAPTON_{t-j} \end{pmatrix}$$

3.4 Lag Selection Criteria for NFRAPTON and LMMPTOM a VAR Model in Rukwa Region

Vector autoregressive (VAR) processes are often used in economics and other social sciences following their flexibility and simplicity nature when modelling short run dynamic behaviours of multivariate time series. The approach emanated out of Sim's critique who interrogated on traditional and standard simultaneous equations models. Sims (1980) advocated VAR models as alternatives for classical simultaneous models which were unable to capture the dynamics nature of one variable to other lagged variables in the system.

Using VAR modelling, the Granger causality between variables, forecasting, variance decomposition or impulse response examinations are realistic if the number of lags is optimally selected. Too many lags increase the error in the forecasts, while too few lags leave out relevant information. Various literature, like Akhter (2017), have demonstrated that VAR model results are highly sensitive to the number of lags selected and used for specific model usage. The number of lags for the study was, therefore, selected using different optimal lag selection criteria, likelihood ratio (LR), Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (HQIC), final predictor error (FPE) and Hannan-Quinn Information Criterion (HQIC).

When all criteria agree with asterisks, the selection is clear; getting conflicting results like in Table 8 necessitate selection criteria to be based on experience, knowledge, and theory. Ivanov and Kilian (2001) reported that in applying VAR models, AIC was more accurate with monthly data; HQIC did better with quarterly data for samples over 120 and SBIC works fine with any sample size for quarterly data (on VEC models). Moreover, Lütkepohl (2005) suggests that where multiple lags selection criteria exist, the option is choosing a lag order whose criteria values are minimized. Supporting that preposition, Kozlowski (2012) suggests that in case of disagreement among the criteria, AIC is opted for. Therefore, AIC criteria were used.

Table 8: Lag-Order Selection- Criteria

Sample: 2008m1 - 2017m12, but with gaps Number of observations = 60

lag	LL	LR	Df	P	FPE	AIC	HQIC	SBIC
0	-517				1.2E+20	51.9004	51.9198	52
1	-452.59	128.82	4	0	2.8E+17	45.8592	45.9175	46.1579
2	-443.44	18.314	4	0.001	1.7E+17	45.3435	45.4407	45.8414*
3	-437.96	10.96*	4	0.027	1.5e+17*	45.1956	45.3317*	45.8926
4	-433.73	8.4622	4	0.076	1.6E+17	45.19725*	45.3475	46.0687

Source: Author’s own computations

3.5 VAR Regression Results

Table 10 presents a two-system VAR Model variable NFRA maize price per ton and local maize market price per ton (LMMPTON). The VAR model results indicate short run dynamics between the variables under ceteris paribus effects since the parameters were obtained from OLS regression of VAR model in levels in the absence of auto correlated ε and uniform covariance matrix $E(\varepsilon_t'\varepsilon_t) = \Omega.$. Four numbers of lags were based on AIC criteria, depending on the nature of the data set.

Taking NFRATON equation it was found that the second and fourth lags of NFRATON had no significant effect of NFRATON. The second lag of NFRAPTON was not significantly affecting its current price though it was an immediate price, possibly because NFRAPTON did not change every month. It’s changed by the government depending existing market conditions. Contrarily, the first and third lags of NFRATON had positive and negative effects on NFRAPTON on average ceteris paribus at 1 per cent and 10 per cent levels of significance respectively. Relating local maize market price per ton (LMMPTON) with NFRA price per ton (NFRAPTON), all NFRAPTON lags had no effect on (LMMPTON).

From the local maize market price per ton equation (LMMPTON), the results showed that the first and fourth lags of NFRAPTON had no significant effect on (LMMPTON). Meanwhile, its first lag indicated positive effect on (LMMPTON) on average ceteris paribus at 1 per cent level of significance. The second and third lags of the same had significant negative effect on (LMMPTON) on average ceteris paribus at 10per cent level of significance. Local maize market price per ton equation indicated that (NFRAPTON) own first lag, third lag, and fourth lag had positive, negative, and positive effects on (LMMPTON) on average ceteris paribus at 1 per cent, 1 per cent, and 5 per cent respectively. Conversely, the second lag had significant effect on local maize market price per ton.

Intuitively, the VAR system of equations NFRAPTON had significant effect on LMMPTON at 10 per cent on average ceteris paribus. This was revealed by the p-values of 0.065 and 0.063 for the second and third lags of NFRAPTON on LMMPTON respectively. Additionally, given their significance level, NFRAPTON impacts on LMMPTON from the second and third lags seemed nearly symmetrical as represented by negative and positive coefficients of 3.60015 and 3.322603 respectively.

Table 9: VAR Regression between NFRAPTON and (LMMPTON) in Rukwa from 2008-2017

	Coefficient	Std. Err.	Z	P>z	[95% Conf.	Interval]
NFRAPTON						
NFRAPTON						
L1.	1.6485***	0.175832	9.38	0.000	1.303924	1.993173
L2.	0.0467	0.36492	0.13	0.898	-0.66855	0.761907
L3.	-0.5734*	0.334341	-1.72	0.086	-1.22873	0.081867
L4.	-0.1359	0.13406	-1.01	0.311	-0.39871	0.126795
LMMPTON						
L1.	0.019728	0.057811	0.34	0.733	-0.09358	0.133035
L2.	-0.01006	0.059685	-0.17	0.866	-0.12704	0.106924
L3.	0.015895	0.05913	0.27	0.788	-0.1	0.131788
L4.	-0.03561	0.052589	-0.68	0.498	-0.13868	0.067463
_cons	9208.721	6814.996	1.35	0.177	-4148.43	22565.87
LMMPTON						
NFRAPTON						
L1.	-0.27597	0.941493	-0.29	0.769	-2.12126	1.569325
L2.	-3.60015*	1.953967	-1.84	0.065	-7.42985	0.229556
L3.	3.322603*	1.790231	1.86	0.063	-0.18619	6.831392
L4.	0.490223	0.717824	0.68	0.495	-0.91669	1.897133
LMMPTON						
L1.	1.297953***	0.309547	4.19	0.000	0.691253	1.904654
L2.	0.242343	0.319583	0.76	0.448	-0.38403	0.868714
L3.	-0.95607***	0.316613	-3.02	0.003	-1.57662	-0.33552
L4.	0.669657**	0.281589	2.38	0.017	0.117753	1.22156
_cons	-25896.6	36490.91	-0.71	0.478	-97417.4	45624.3

Source: Author’s own computation

3.6 Post Estimation of Vector Autoregressive Diagnostic Test

After performing VAR model estimations, diagnostic tests were undertaken including normality test, autocorrelation test and stability test of the VAR system. The VAR model residual diagnostic tests are critically important violating them may lead to results not being dependable for estimation for variables dynamic behaviour analysis and forecasting. Serving as a reliable measure and forecasting instrument, VAR model residuals should obey OLS properties including normality, non-serial autocorrelation and stability. In Table 11, the results for Jacque Bera test for normality in (NFRATON) equation indicate a p-value lower than 5 per cent; thus, the null hypothesis was rejected, meaning that residuals from the equation were not normally distributed. For the second equation (LMMPTON), the results indicated that p-value was 0.7278 which exceeds 5 per cent, confirming that the null hypothesis of normality should not be rejected. Thus, residuals for the equations were normally distributed. However, the overall system of the two equations had residuals not following Gaussian normal distribution as the p-value was less than 5 per cent.

Table 10: Normality Test – Jacque Bera

EQUATION	chi2	df	Prob> Chi2
NFRAPTON	30.35	2	0.0000
LMMPTON	0.635	2	0.7278
ALL	30.986	4	0.0000

Source: Author's computation

Table 11: Stability Test

Eigen values	Modulus
.9524572 + .02117578i	0.952693
.9524572 - .02117578i	0.952693
.2354467 + .1408034i	0.274337
.2354467 - .1408034i	0.274337

Source: Author's own computation

Based on the results from two-way system VAR between NFRAPTON and LMMPTON, the absolute values of all Eigenvalue statistics were found within the unit circle which means the model satisfied the stability condition. Thus, the VAR model was stable and non-explosive in nature.

Table 12: Autocorrelation Test of Residuals in the VAR Model

Lags	chi2	df	Prob> Chi2
1	7.6484	4	0.10534
2	6.3262	4	0.17607

Source: Author's own computation

Regarding the results from Table 13, the null hypothesis of no autocorrelation could not be rejected because in both systems of the two VAR model the p-values exceeded 0.05. Thus, the two VAR system of equation behaved such that their innovations were not serially correlated. Impliedly, the results tell that the model was well specified and hence desirable for estimations and forecasting.

4.0 Empirical Results and Discussion

This section assesses the impact of innovation to changes in LMMPTON and NFRAPTON variables, and how each variable evolved over time and affected the other variable. Initially, the variables causal direction using Granger causality was presented and tested, followed by impulse response analysis. Vector Autoregressive model (VAR) in STATA Impulse Response Functions (IRF) are used to assess dynamics between NFRA price and local maize market price (LMMP) due to one-unit standard deviation in innovations in the VAR system. Table 10 indicates empirical test of causality between NFRAPTON and LMMPTON, based on vector auto regression modelling of the two price series. Secondly, direction of causation, size, and trajectory path of each variable which evolve due to innovation were assessed. In order to take informed trade and food price policy, the impulse response analysis was applied.

4.1 Impulse Response Functions (IRF)

One weakness embedded in Granger causality VAR analysis is the complexity in interpreting coefficients to assessing price transmission dynamics from one series to another (John, 2014). It has no power to express extent of price transmission from one price series set to another one; its only capable of telling existence or non–existence of price transmission. Ahmed and Singla (2017) noted that Granger causality affords only to capture direction of causality between one price series to the next one. It has no power whatsoever to track effects of stochastic shocks from different innovations on the future values of variables in the VAR system.

To assess causal interaction dynamics between NFRAPTON monthly purchase price and local maize market (LMMP) price in Rukwa region from 2008 to2017, bivariate VAR model was used. The VAR inherently generates IRFs; in VAR modelling current variables, the (NFRAPTON) or (LMMPTON) in the system are functions of own lagged variables, lags of other variables and their respective innovations. Thus, their relationships in the systems are not straight forwardly revealed from parametric matrices (Lütkepohl, 2005). The main reason is that all variables in the system are endogenously determined; an innovation or shock in one equation affects its own lagged variable and lags of other variables in other equations over a time horizon.

IRFs are more powerful than mere causality tests as they indicate dynamic interactions between variables in a vector autoregressive model. They indicate which impact of a shock an exogenous variable has upon endogenous variables over a span of time. Lütkepohl (2005) echoes that IRF traces impacts of shocks to systems of endogenous variables. Purposely, VAR models express evolutions of variables model in response to shocks in one or more variables; as such they are important in tracing transmission of shocks within the system of equations. They are thus useful proxies for informed economic policies assessment. Impulse response functions are capable of revealing dynamics behaviours both in bivariate granger causality and multivariate systems of variables from a unit standard deviation shock to the current as well as future prices in an integrated market over time.

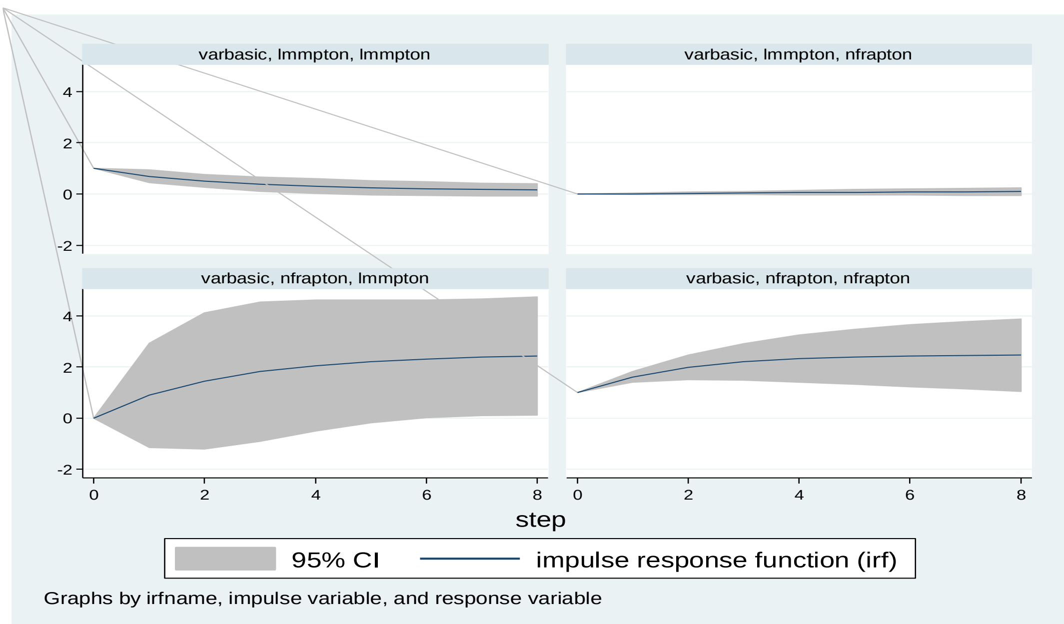

Figure 3: Impulse Response Functions Results
Source: Author's own computation

The combined graphical results of impulse response functions in Figure 3 show the dynamic price path behaviour of NFRA per ton and local market per ton in Rukwa region market over the study period. The graphs depict the effects of unanticipated shocks or innovations on NFRAPTON and LMMPTON, from u_{1t} and u_{2t}respectively.

From equations 3.5 and 3.6 a two-system VAR model was presented, and all the variables were endogenously determined as follows:

$NFRAPTON_t = \alpha + \beta_1 NFRPTON_{t-i} + \varphi_1 LMMPTON_{t-j} + u_{1t}$……….. (3.9)

$LMMPTON_t = \omega + \beta_2 LMMPTON_{t-i} + \varphi_2 NFRAPTON_{t-j} + u_{2t}$………. (3.10)

A shock from first equation on u_{1t} innovation firstly affects current $NFRAPTON_t$ through previous $NFRAPTON_t$ and $LMMPTON_t$ afterwards the effects are extended to current price in $LMMPTON_t$ in the second equation through its previous price. Similarly, a shock from second equation on u_{2t} innovation firstly affects the current $LMMPTON_t$ through previous $LMMPTON_t$ and $NFRATON_t$ after wards the effects are extended to current price in $NFRAPTON_t$ in the second equation through its previous price. Results revealed that any shock from innovations on the variable LMMPTON implies decreasing price path behaviour on own variable between the whole time period of the first eight months. For the impact of LMMPTON on NFRATON, a shock on the former causes a mild/slight increase in NFRAPTON over the whole observed time horizon of eight months. Thus, the impact of one standard deviation shock (innovation) in LMMPTON will bring about positive but gradual increase in NFRAPTON over the whole eight months' time horizon. This was expected; intuitively, when LMMPTON price channel increases, the government has to think on slight increase in NRFRA price to competitively purchase maize from farmers and other intermediaries in the maize value chain. Similarly, since LMMPTON is a component in setting NFRAPTON, the time taken by the government to plan, discuss and execute budget decisions to effect changes on NFRAPTON might be a source of gradual increase in NFRA price per ton.

There was sharp increase of LMMPTON in consequence of NAFRAPTON in short run period but constant in medium and long terms. The results were expected because higher NFRA price will increase supply of maize in the NFRA market channel; to motivate the same for local markets there should be a short run increased LMMTON. In a long run, however, there is no change in LMMPTON due to NFRAPTON because the latter is established as a function of current local price level, annual maize production costs and government budget;

the two cannot be readily adjusted to meet existing local market conditions. Also, even if market forces pull up local maize market price, NFRA price per ton would not abnormally increase since the agency would offer more of its previous reserve to regulate price in order to self-guard net buyers.

It is observed that in the first two months, one standard deviation shock/innovation in NFRAPTON initially impacted LMMPTON, making it increase at an increasing rate. Over the next last six months of time horizon there was constant LMMPTON price path in a long run; a one standard deviation shock on NFRA price per ton had both transitory and permanent positive impact on LMMPTON. The results were expected because, in principle, NFRA price is set at a relatively higher level than LMMPTON to motivate maize producers.

The results are congruent with results by Jayne et al. (2018) who found that NCPB marketing price strategy brought sustained increase in Kenya's maize local market price roughly by 20 per cent over the 1995 through 2004 span of time. Similar results were obtained by Paul et al. (2017) for onion market in India through vector error correction model impulse analysis. In price co-integration analyses of food crop markets in Ethiopia between wheat and teff through VECM, Gebremedhin et al. (2009) found similar results that most markets were co-integrated in both wheat and teff retail prices.

5.0 Conclusions and Policy Implications

This paper has empirically painted dynamics and trends in NFRA monthly maize purchase price and local maize market price in Tanzania spanning from 2008 and 2017 with data from Sumbawanga maize market in Rukwa region. Both static (causal directional) and dynamic (impulse responses) impacts were assessed to understand trends and dynamics between NFRA maize market and local market price channels. It is evident from Granger causality test that NFRA price per ton granger caused local maize market price per ton and not the other way round.

Furthermore, Impulse Response Function (IRF) analysis showed that a-one standard deviation shock/innovations on NFRA price per ton had both positive transitory and permanent impact on local maize market price per ton over an eight months' time horizon. With regard to the impact of LMMPTON on NFRATON, following a shock on the former causes a slightly moderate increase in NFRAPTON over the whole observed time horizon. Thus, impacts one standard deviation shock (innovation) on LMMPTON will bring about positive but gradual price path increase in NFRAPTON in the short- and long run. Importantly, NFRA price per ton and local maize price per ton at Sumbawanga market from 2008 through 2017 had an increasing trend. Over the time span, NFRAPTON was over and above LMMPTON, but exceptions were noticed, particularly at times of poor harvests, accompanied by export bans.

Based on the above findings and conclusions, various policy implications for developing countries like Tanzania which set price for annual strategic grain are derived. One of the policy options is for the government to increase domestic maize production by targeting subsidized inputs in surplus producing regions of the country. There should be increase in government budget on agriculture because it is an important component considered in setting NFRA price. The increased budget would allow timely strategic grain purchase at higher price when farmers face liquidity constraints; after the expected strategic grain purchase, the government should remove trade restrictions. This would promote free food market trade without fear of food insecurity, especially during episodes of poor harvest, coupled with export ban.

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