

Measuring Rice Price Volatility and Its Determinants in Tanzania: An Implication for Price Stabilization Policies

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Abstract

High price volatility in agricultural food markets has a greater impact not only on smallholder farmers but also can affect the incomes and purchasing power of a substantial proportion of the Tanzanian population and decrease food security, especially to the lower middle class. This study applies the ARCH-GARCH and the VAR/VECM models to examine the dynamics and factors influencing price volatility in the domestic rice market. The results of the price volatility analysis show that the volatility of rice prices tends to be low and persistent over the long run. This is supported by the estimation results of factors affecting price volatility, which showed that supply variables play an important role in the short and long run in influencing rice price volatility. The prices in the producing regions (large surplus areas) turned out to be more volatile than the prices in the main consuming regions (large deficit areas). This means that producers are exposed to a much higher price risk than consumers. Thus, a favorable marketing environment for traders and farmers, transparent trade policies, reliable market information, and organized market infrastructure are essential to reduce food price volatility which has a wider impact on economic growth.

Keywords

Price Volatility, Determinants, Rice Markets, ARCH-GARCH, Tanzania

1. Introduction

Market price volatility is often used as an indicator of market efficiency in the broadest sense (Foldvari & van Leeuwen, 2011). The volatility of food prices is of prime policy interest, as it can impact the prosperity of farmers, consumers, agribusiness, exporters, importers, and indirect effects on incomes and employment

in many other sectors (Headey, 2011; Worako et al., 2011; Ismail et al., 2017). One of the main problems of food price volatility in developing countries at the micro level is the variability and instability of incomes of both producers and consumers (Braun & von Tadesse, 2012). Excessive price fluctuations influence investment decisions in the agricultural sector by creating additional uncertainty for the producer (FAO et al., 2011). In addition, in economics, the price fluctuations over time are not always detrimental, especially when price fluctuations take place regularly and predictably following a certain trend or pattern (Timmer, 2011). However, price fluctuations become a problem when the change is huge, cannot be anticipated, and creates uncertainty about the future (i.e., increasing the risk of decision making for economic actors such as producers, consumers, and government).

Indeed, fluctuations in food prices make it difficult for the producer to predict in advance the exact level of these prices or to adjust the timing of the sale (Sirisupluxana & Bunyasiri, 2018). It also provides opportunities for traders to manipulate price information at the farm level (Seck et al., 2010). Moreover, poor consumers are more affected by price fluctuations as they have to reduce their food consumption or, in extreme cases, simply starve. In the worst case, price instability can lead to macroeconomic instability and social unrest (Timmer, 2004, 2011; Braun & von Tadesse, 2012). In short, extremely volatile prices increase the risks associated with production and sales and, ultimately, slow down economic growth especially in developing countries such as Tanzania. On the other hand, to manage food price volatility at the macro level, policymakers need to address its causes as the solutions to price volatility largely depend on the nature and type of causes (Ismail et al., 2017).

Due to improved rural infrastructures in some parts of Tanzania, more farmers are now depending on markets to sell their produce, while on the other hand, more and more urban consumers now depend on agricultural markets for their daily food needs (Baffes et al., 2017). However these food markets are characterized by high instability due to the wide range of prices (Achandi & Mujawamariya, 2016). Rice being one of the main staple foods in Tanzania, second after maize in production, and the most traded crop than any other food crop in Tanzania, its market is also exposed to the risks associated with price fluctuations (Ngailo et al., 2016). For example, most smallholder rice farmers are forced to sell immediately after harvest in order to pay for production inputs borrowed during the production season, or sell near the cropping season to meet capital needs for the next crop year thus becoming highly vulnerable to price fluctuations. On the other hand, the volatility of rice prices, which can lead to increased inflation, can also affect the incomes and purchasing power of a substantial proportion of the Tanzanian rice consumers and decrease food security, especially the lower middle class. The effects of rice price volatility on the food service markets can also have an impact on increasing unemployment (Putra et al., 2021).

Therefore, considering the importance of rice as the main staple food in Tan-

zania, it is necessary to know its price behavior, since the volatility of rice prices in such a country has a widespread impact on economic stability, social, political and economic resilience, which in turn can hinder economic growth. In addition to knowing how the trend or pattern of price volatility occurs, it is also necessary to know the factors that influence price volatility so that efforts can be made to anticipate. More knowledge on the trend and factors causing an increase in price volatility may allow the possible implementation of policies to reduce the volatility.

2. Material and Methods

2.1. Data Sources

The study is based on secondary data with periods ranging from January 2004 to December 2018. The data used to estimate price volatility are monthly rice prices at the wholesale markets obtained from the Tanzania Ministry of Industry and Trade. Data on factors influencing rice price volatility were obtained from the National Bureau of Statistics (NBS), Bank of Tanzania (BoT), Ministry of Agriculture (MoA), Energy and Water Utilities Regulatory Authority (EWURA), the Food and Agriculture Organization of the United Nations (FAO) and the World Bank (WB). The data included amount of paddy production, interest rates, fuel price as an indicator of transport costs (USD/liter), income per capita as an indicator of household consumption, the Consumer Price Index (CPI), and rainfall as a proxy of climate. The use of rainfall as a proxy of climate change is justified, especially in developing countries, where irrigation systems and agricultural mechanization have yet to be developed. In addition, being located a few degrees south of the equator, Tanzania enjoys a moderate tropical climate with seasons regulated by rainfall rather than temperature. Therefore, rainfall is the most frequently observed climatic element relative to temperature.

2.2. Methods

Volatility Estimation

There are several methods available to measure food price volatility, including; standard dispersion indicators (e.g., inter-quartile ratio (IQR), standard deviation (SD), moving standard deviation (MSD), etc.); alternatively, it is also possible to derive a volatility indicator from Autoregressive Conditional Heteroskedasticity and Generalized Autoregressive Conditional Heteroskedasticity (ARCH-GARCH), a stochastic volatility framework or nonparametric statistics based on high-frequency options data. This study focused on both, standard dispersion indicator-using MSD as well as the stochastic volatility framework-using ARCH-GARCH.

ARCH-GARCH Model

In order to calculate the extent of rice price volatility, the ARCH-GARCH analysis was performed. Autoregressive Conditional Heteroskedasticity (ARCH) models introduced by Engle (1982) and later generalized as GARCH by Bollerslev (1986) are specifically designed to predict conditional variances (CV).

The ARCH model assumes that the data variance over time is strongly influenced by the residual variance of the previous period. In comparison, the GARCH model assumes that the variance of the data over time depends not only on the residuals of the previous period but also on the variation of the previous period's residuals. Many authors such as [Jordaan \(2007\)](#) and [Safdar et al. \(2012\)](#), argue in favor of GARCH models on the grounds that they have the merit of taking into account both predictable and unpredictable components of the price process, being also able to capture various dynamic structures of conditional variance.

Before fitting the GARCH model, autoregressive integrated moving average (ARIMA) filtration was performed to identify the most suitable ARCH term, and then the GARCH model was fitted. The representation of GARCH(p, q) is given by:

$$Y_t = K + \delta_1 y_{t-1} + \dots + \delta_p y_{t-p} + \mu_t \quad (1)$$

Equation (1) is autoregressive process and the conditional variance equation is:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \quad (2)$$

where,

Y_t is the price of rice in the t^{th} period.

Y_{t-p} is the persistence of passed shocks on volatility.

y_t is variable of log rice price at time t .

p is the order of the GARCH term, and q is the order of the ARCH term.

ε_{t-i}^2 is the volatility of previous periods of time, measured with the aid of squared residuals.

β_i and α_i are estimated coefficient of order p and q respectively.

K and ω are constant variances.

The closer the sum ($\alpha + \beta$) is to 1 "one", it would indicate that the volatility shocks are quite persistent in the series. If the sum exceeds one, it indicates an explosive series with a tendency to move away from the mean value.

Approaches to analyzing time series data require that the economic variables be stationary. The stationarity of the rice price series was tested by applying the Augmented Dickey-Fuller (ADF) test. The ADF test is the unit root test in a time-series data that tests for an order of integration I (d), i.e., the number of times (d) the series needs to be differenced before transforming it into a stationary series ([Dickey & Fuller, 1979](#)). A time series is stationary if its parameters are independent of time, exhibiting constant mean and variance, and having autocorrelations that are invariant over time. Although many economic variables measured over time are non-stationary, their first difference is often stationary. Such variables are known as differenced-stationary or integrated of order one, I (1) ([Enders, 2015](#)).

The ADF test equation, having a random walk with drift and time trend, is specified as:

$$\Delta\gamma_t = \alpha + \beta_t + \delta\gamma_{t-1} + \sum_{i=1}^k \beta_i \Delta\gamma_{t-i} + \mu_t \quad (3)$$

where Δ denotes the number of differences required to make the γ_t variable stationary, α is the drift parameter, t is the time trend, and K is the number of lags required to whiten the residuals μ_t . The null hypothesis of the ADF tests is that the variable has a unit root ($\delta = 0$) with respect to the alternative of stationarity ($\delta < 0$). The optimum lag length is selected based on the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC).

2.3. Examining the Determinants of Volatility

VAR/VECM Model

Many factors can cause high food price volatility. To determine the most likely sources of rice price volatility, we model the relationship between the price of rice and a set of production and macroeconomic variables using a Vector Autoregression (VAR) model. The reduced form of this model can be written as follows (Sims, 1972):

$$X_t = \mu + \sum_{i=1}^p \Theta_i X_{t-i} + \varepsilon_t \quad (4)$$

where,

X_t = Vector of dependent variable ($n \times 1$).

μ = Vector of exogenous variables including constant (intercept) and trend ($n \times 1$).

p = Number of lag, or order for the VAR model.

ε_t = Vector of Error term ($n \times 1$).

Θ_i = Matrix of parameter, size $n \times n$ for each $i = 1, 2 \dots$

The corresponding Vector Error Correction Model (VECM), which is equivalent to the VAR equation, is written as follows:

$$\Delta X_t = \mu + \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + e_t \quad (5)$$

where Γ_i are parameter matrices, e_t is a vector of normally distributed random errors that are contemporaneously correlated, and ΠX_{t-1} is the error correction term, thus having a non-diagonal covariance matrix. If Π has a reduced rank, it can be decomposed as $\Pi = \alpha\beta$ with α and β being n by r matrices. The estimated coefficients measured the speed of adjustment of the considered series towards the long-run relations after an equilibrium shock. A standard F-test is then used to assess how one variable affects the prediction of the other.

3. Result and Discussion

3.1. Price Volatility in Tanzanian Rice Markets

3.1.1. Unit Root Tests and Order of Integration

Before commencing any time series analysis, it is necessary to identify the sta-

tionarity properties of the data series by testing for the presence of unit root. Unit root testing is essential in time series analysis to avoid deriving erroneous conclusions from a spurious regression. To address this, [Dickey and Fuller \(1979\)](#) proposed a test to detect the non-stationarity of series using the Augmented Dickey-Fuller test (ADF). [Table 1](#) depicts the results of unit root tests based on ADF statistics on levels and the first difference of the variables. The null hypothesis of the ADF tests is that the variable has a unit root (non-stationary). The results of unit root tests reveal that all series are I (1). Based on the information criterion (AIC and SBC), the optimal lag length is selected as two.

3.1.2. Unconditional Volatility in Rice Price Returns

The unconditional or historical volatility of rice price returns is measured by estimating the rolling twelve-month standard deviations of the price returns. Prices in major surplus and deficit markets (i.e., major producing regions—Mbeya, Morogoro, Shinyanga and Katavi (Mpanda); and consuming regions—Dar es Salaam, Lindi, Arusha and Dodoma) were analysed differently for comparison purposes. [Figure 1](#) and [Figure 2](#) illustrate the moving standard deviations of price returns in the major surplus and deficit markets. The results show that prices in the main producing regions are more volatile than prices in the main

Table 1. Unit root tests.

Market ¹	ADF ² Test statistics			
	Lag	Level (constant, no trend)	Lag	First difference (constant, no trend)
Dar es Salaam	3	-1.459 (0.89)	2	-11.641 (0.00)***
Mbeya	1	-1.569 (0.61)	0	-11.129 (0.00)***
Morogoro	1	-2.026 (0.37)	0	-9.908 (0.00)***
Shinyanga	1	-2.520 (0.95)	0	-10.894 (0.00)***
Mpanda	2	-1.966 (0.52)	1	-12.263 (0.00)***
Lindi	1	-1.464 (0.38)	0	-10.569 (0.00)***
Mtwara	1	-1.691 (0.29)	0	-8.811 (0.00)***
Dodoma	2	-1.688 (0.64)	1	-13.498 (0.00)***
Arusha	3	-1.313 (0.36)	2	-14.917 (0.00)***
Bukoba	1	-1.734 (0.41)	0	-12.479 (0.00)***
Songea	2	-1.162 (0.73)	1	-11.399 (0.00)***
Tanga	1	-1.546 (0.29)	0	-8.921 (0.00)***
Musoma	1	-1.978 (0.52)	0	-12.474 (0.00)***
Kigoma	2	-1.838 (0.35)	1	-10.593 (0.00)***

Notes: ***, **, * reject the null hypothesis at 1%, 5%, and 10% significance levels, respectively. Probability values in parenthesis. ¹All variables are nominal, ²ADF = Augmented Dickey-Fuller unit root test.

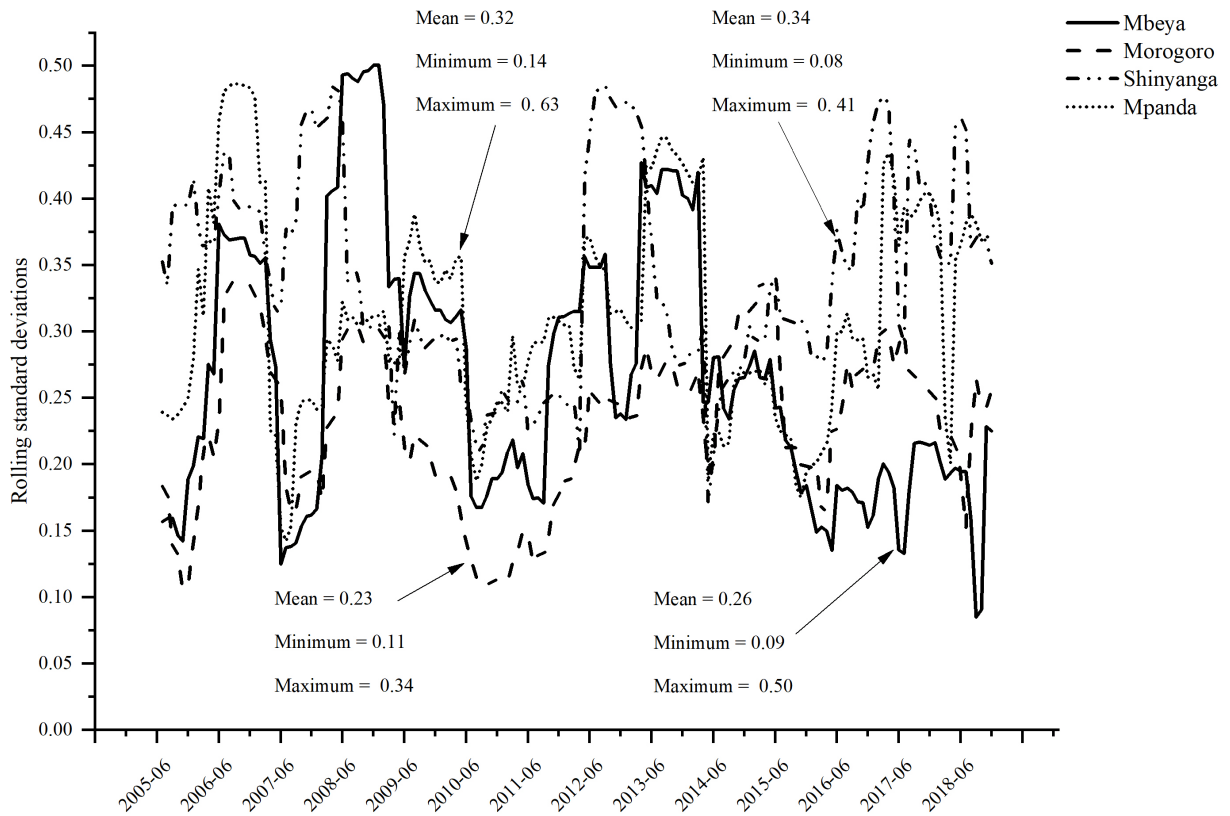


Figure 1. Unconditional volatility in producer markets (Major Surplus). Source: Authors' Estimation and Presentation.

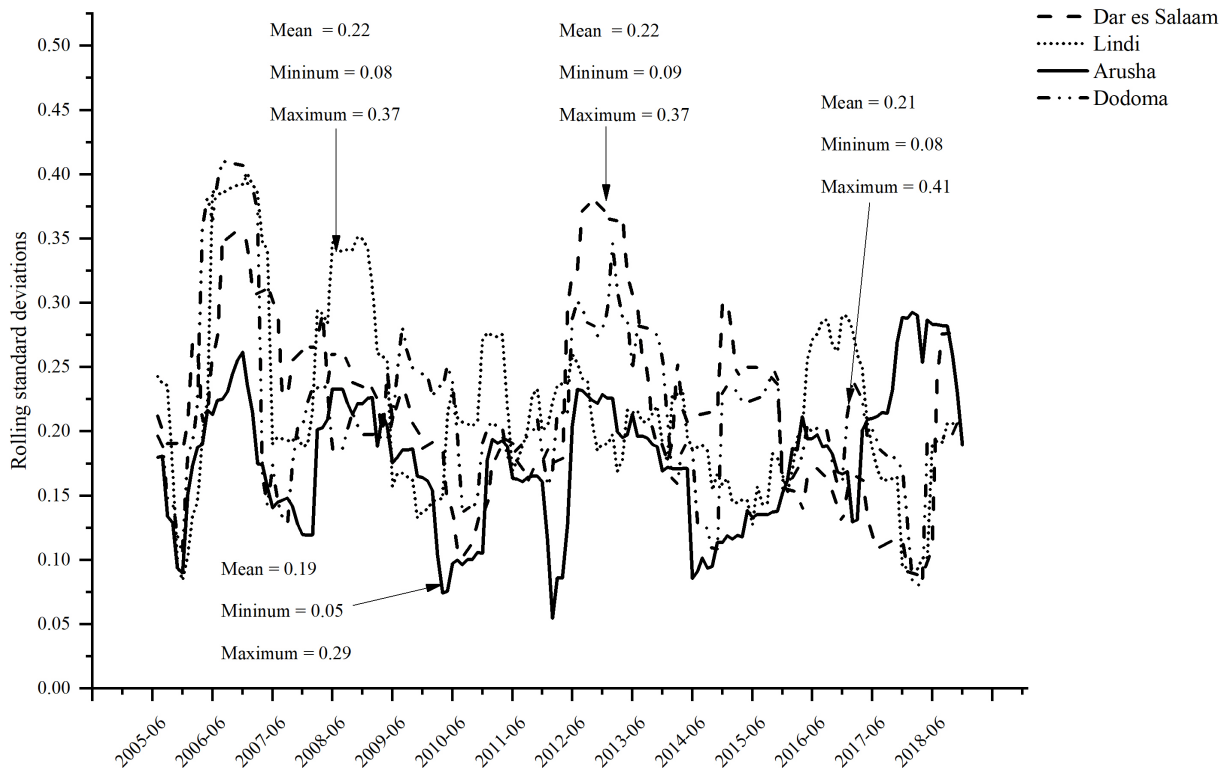


Figure 2. Unconditional volatility in consumer markets (Major Deficit). Source: Authors' Estimation and Presentation.

consuming regions. The average level of volatility of rice price returns in surplus markets is between 0.34 and 0.23, while those in deficit markets are between 0.22 and 0.19. One possible reason for the difference in the magnitude of volatility may be the price level and the lack of effective price risk management tools, especially at the producer level. In other words, the level of volatility to which producers are exposed is more unpredictable than that of consumers. Since their volatility level is unpredictable, it can be argued that consumers face less uncertainty than producers who face varying levels of volatility.

3.1.3. ARCH Effects and Volatility Clustering

The ARCH-GARCH model can be used to calculate the volatility if there is an ARCH effect on the residuals of the average equation of the rice price series. The ARCH effect tests aim to determine whether there is a heteroskedasticity problem in the price series of fourteen regional rice markets in Tanzania. The null hypothesis of the ARCH LM tests is that the residuals of the mean equations have no ARCH effect. The results in **Table 2** indicate that all the equations have heteroskedasticity problems (ARCH effect) at various lags. In other words, residuals experience periods of high and low volatility, which is called volatility clustering. The existence of heteroskedasticity (ARCH effects) in the residuals allows the standard GARCH models to be fitted to the price series (Safdar et al., 2012).

Table 2. The results of the ARCH LM test for rice price series¹.

Markets	Lag Order							
	Lag 2		Lag 4		Lag 6		Lag 8	
	Test Statistic	Pvalues	Test Statistic	Pvalues	Test Statistic	Pvalues	Test Statistic	Pvalues
Dar	15.086***	0.005	8.264***	0.003	4.567***	0.001	4.702***	0.003
Mbeya	10.071***	0.002	5.819***	0.005	2.512**	0.012	2.095*	0.068
Morogoro	13.319***	0.001	7.382***	0.006	2.335*	0.058	2.051*	0.062
Shinyanga	10.363***	0.008	5.812***	0.002	2.408**	0.023	2.284*	0.054
Mpanda	11.477***	0.006	6.057***	0.006	3.494***	0.004	2.506**	0.040
Dodoma	13.023***	0.004	7.521***	0.001	3.940***	0.001	2.752**	0.017
Arusha	17.823***	0.000	8.845***	0.000	4.339***	0.002	4.145***	0.001
Lindi	10.644***	0.003	5.298***	0.005	2.893**	0.029	2.654**	0.047
Mtwara	13.591***	0.000	7.229***	0.001	3.739***	0.006	2.508**	0.024
Bukoba	12.081***	0.001	6.599***	0.002	2.451**	0.048	1.641	0.139
Songea	7.706***	0.001	6.447***	0.000	4.230***	0.001	3.363***	0.002
Tanga	13.350***	0.008	7.690***	0.001	4.179***	0.002	2.778**	0.048
Musoma	10.834***	0.001	5.416***	0.005	3.691***	0.007	3.554***	0.002
Kigoma	10.062***	0.004	4.117***	0.009	2.688**	0.025	2.262*	0.073

Note: ***, **, * denotes significance levels of the ARCH and GARCH terms at 1%, 5%, and 10%. ¹Null hypothesis of no ARCH effect: reject the null hypothesis at probability < 5%.

3.1.4. The Results of ARCH-GARCH(1, 1) Models

Table 3 presents the results of the ARCH-GARCH(1, 1) model fitted to domestic rice price returns at different regional rice markets. The results show that apart from Dodoma and Mtwara rice markets, the estimated $\alpha + \beta$ coefficients in all other markets studied were closer to “one,” denoting the persistence of volatility in domestic rice markets. Dodoma had the lowest volatility persistence, meaning that prices took less time to stabilize. Dar es Salaam, Arusha, Lindi, Tanga, Songea, Morogoro, Shinyanga, Bukoba, and Mbeya markets had $\alpha + \beta$ coefficients close to one, indicating a prolonged period of uncertainty in rice markets after a shock that could affect both consumers and producers. On the other hand, Kigoma and Mpanda markets price returns recorded $\alpha + \beta$ coefficients greater than one, indicating an explosive series. This means that the prices in these markets tend to deviate from the mean value in times of price shocks. The statistical significance of the ARCH and GARCH terms indicates that the volatility of domestic rice prices during the previous period affects the current price volatility and that the current price variance depends on lagged price variances. The diagnostic tests attest to the adequacy of the adjusted ARCH-GARCH model. In other words, the model is free from the ARCH effect, the normalized residual squares are normally distributed, their squares are not autocorrelated, and there is no sign bias in the residuals.

Table 3. ARCH-GARCH analysis of rice prices for selected markets during 2004-2018¹.

Markets	Estimates of ARCH-term (α)		Estimates of GARCH-term (β)		$\alpha + \beta$	ARCH-LM test ² (<i>P</i> values)
Dar es Salaam	0.371	(0.007)***	0.591	(0.000)***	0.961	0.791
Mbeya	0.646	(0.001)***	0.304	(0.000)***	0.950	0.646
Morogoro	0.357	(0.042)**	0.569	(0.000)***	0.926	0.283
Shinyanga	0.264	(0.000)***	0.646	(0.000)***	0.909	0.408
Mpanda	1.070	(0.000)***	0.001	(0.988)	1.071	0.509
Dodoma	0.367	(0.004)***	0.158	(0.053)**	0.525	0.749
Arusha	0.648	(0.000)***	0.145	(0.032)**	0.793	0.788
Lindi	0.537	(0.001)***	0.361	(0.000)***	0.898	0.597
Mtwara	0.505	(0.001)***	0.195	(0.114)	0.700	0.731
Bukoba	0.424	(0.000)***	0.396	(0.000)***	0.820	0.253
Songea	0.276	(0.002)***	0.712	(0.000)***	0.988	0.628
Tanga	0.415	(0.005)***	0.522	(0.000)***	0.937	0.574
Kigoma	0.468	(0.000)***	0.548	(0.000)***	1.016	0.609

Note: ***, **, * denotes significance levels of the ARCH and GARCH terms at 1%, 5%, and 10%. Probability values in parenthesis, ¹Price in Tanzania shillings (“000”), ²Null hypothesis of no ARCH effect: reject the null hypothesis at probability < 5%.

Figure 3 illustrate the forecast of the conditional variance predicted from GARCH-fitted models of rice price returns in the producer (Mbeya) and consumer (Dar es Salaam) markets. A significant peak can be observed between 2008-2009 and 2011-2013. This could be due to the spikes in world food prices in 2007-2008 and 2010-2011, which caused volatility in international food prices. However, its effect was relatively small because Tanzania is not heavily dependent on rice imports. The remaining period shows a relatively lower level of volatility (intra-annual volatility), mainly due to seasonality and storage. Intra-annual volatility has a greater impact on farmers than on consumers as most farmers are often forced to sell at harvest time when prices are lowest due to over-marketing compared to household needs, due to liquidity constraints at harvest time and lack of storage capacity. However, studies have shown that intra-annual volatility can be beneficial for farmers if they can take advantage of rising intra-annual food prices to recoup their operations costs. This is the case of producers who can store products and market them in groups (collective marketing) (Ngare et al., 2014; Sirisupluxana & Bunyasiri, 2018).

3.2. The Main Determinants of Rice Price Volatility in Tanzania

Table 6 presents the empirical results of the Vector Error Correction Model (VECM) on factors affecting short and long-run rice price fluctuations. To run

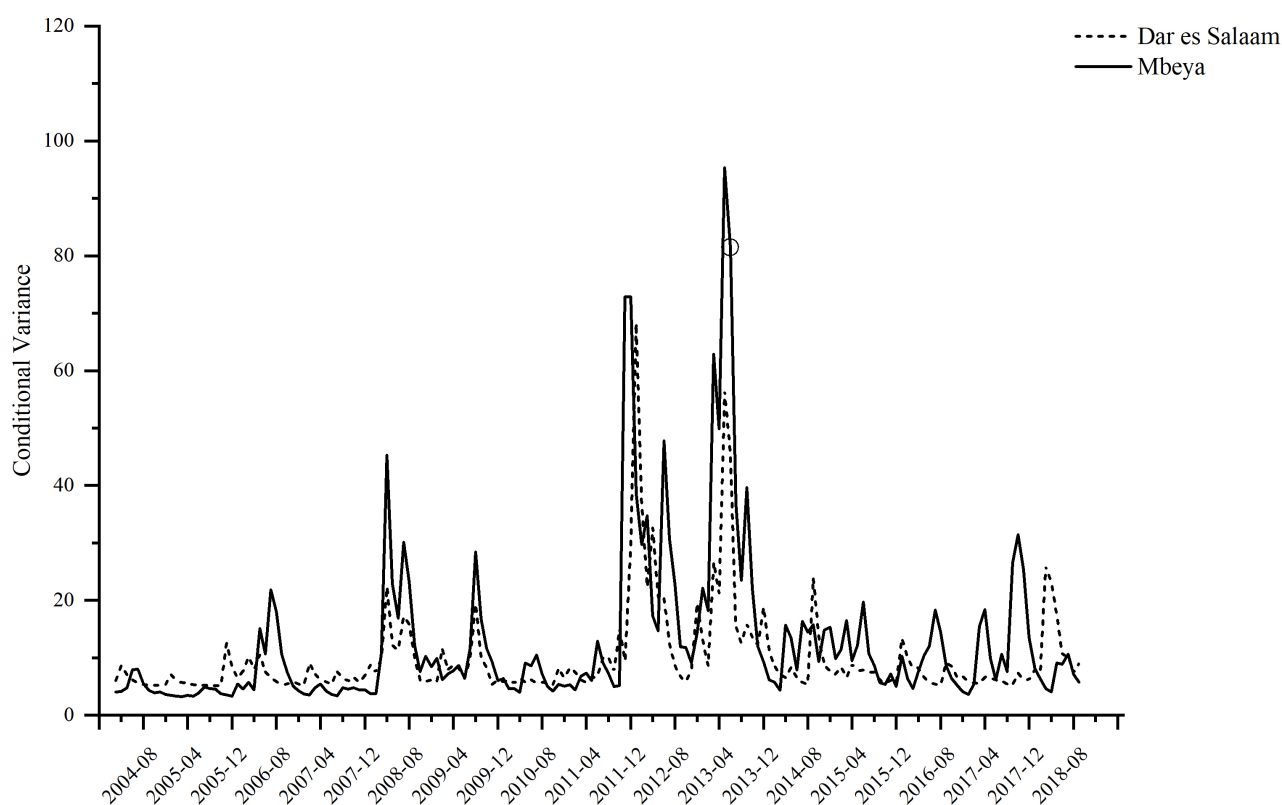


Figure 3. Fitted values of conditional variance of rice price returns during the Observed Period. Source: Authors' estimation and presentation.

the model, we first checked the series stationarity and cointegration (**Table 4** and **Table 5**). The results of the unit root test reported in **Table 4** found that all variables (past rice prices, rice production, changes in rainfall, household consumption, interest rates, per capita household income, and world oil prices) are integrated in the same order: I (1). Furthermore, the cointegration test results

Table 4. Unit root test for the volatility determinants¹.

Determinants ³	ADF ² Test statistics	
	Level (constant, no trend)	First difference (constant, no trend)
Domestic rice price	-1.5912	-11.2017***
Domestic rice production	-1.8456	-9.1993***
Rice consumption	-3.3684	-5.6148***
Exchange rate	-1.9415	-8.6634***
Fuel price	-1.6738	-7.4137***
Interest rates	-2.0451	-4.1535***
Per capita income	-4.5233	-9.8903***
Rainfall	-2.3053	-5.8192***
World rice price	-2.9803	-8.7141***
Rice import	-2.6631	-6.4279***
Consumer price index (CPI)	-1.7063	-7.6360***

Notes: ***, **, * reject the null hypothesis at 1%, 5%, and 10% significance levels, respectively. Probability values in parenthesis. ¹All variables are nominal, ²ADF = Augmented Dickey-Fuller unit root test, ³All variables are in natural logs.

Table 5. Johansen cointegration test results for volatility determinants.

Eigenvalue	Trace Test			Max-Eigen Test		
	Null	λ -trace	0.05 critical value	Null	λ -max	0.05 critical value
0.373	$r = 0$	324.777** (0.000)	239.235	$r = 0$	81.737** (0.001)	64.505
0.327	$r \leq 1$	243.040** (0.000)	197.371	$r = 1$	69.414** (0.003)	58.434
0.232	$r \leq 2$	173.626** (0.007)	159.529	$r = 2$	46.252 (0.185)	52.363
0.186	$r \leq 3$	127.374** (0.039)	125.615			
0.158	$r \leq 4$	91.320 (0.097)	95.754			

Note: ** denotes rejection of the hypothesis at the 0.05 level. The Critical Values are calculated using the approach in MacKinnon et al. (1999).

(Trace and Maximum Eigenvalues test statistics) in **Table 5** show that the null hypothesis of non-cointegration ($r = 0$) is rejected at a significance level of 5 per cent for all the variable. Therefore, it is possible to examine the long-run relation between the factors and price fluctuations.

In the long run, changes in world oil prices was found to have a significant positive influence with a coefficient of 0.642, which means that if the world oil price increases by 1 per cent, the volatility of rice price will increase by 0.64 per cent. This implies that the price of oil used as an indicator of production and distribution costs is an important factor in the formation of rice prices. Higher energy-related production costs would generally reduce agricultural production and lead to higher prices, while higher transport costs would also lead to high prices of agricultural products, so that food price volatility cannot be avoided (Nazlioglu et al., 2013).

Rice production also played an important role in influencing the volatility of rice price, with a negative coefficient value of 0.837. This indicates that if rice production increases by 1 per cent, rice price volatility will decrease by 0.84 per cent. The value of rice production elasticity is less than one, which means that rice production is inelastic in response to changes in the price volatility of rice. The high rice production translates into the availability of rice in the market. The excess supply of rice will lower rice price if the additional production is greater than the excess demand, so the volatility is relatively low. Rice production, which tends to be stable and self-sufficient, will make rice prices stable so that during the dry season, the government will not seek to import rice to keep rice prices stable. However, governments need to ensure that there is a good stock management system so that during the harvest season, the government can store the rice for use in the dry season. This will help manage the volatility of rice prices (**Table 6**).

The interest rate had an inverse relationship with the domestic rice price (i.e. a negative sign with a coefficient of 0.019). If the interest rate decreases by 1 per cent, rice price volatility will increase by 0.02 per cent. However, the volatility with respect to interest rates tends to be inelastic (observed to have the value of less than one). Basically, low interest rates push investors to invest their funds in physical rather than liquid form (Tangermann, 2011; Wright, 2011), such as investing in agriculture, while consumers no longer want to save but spend more. This investment leads to an increase in agricultural production; therefore, the price of agricultural products will increase on the supply side. The results are consistent with the findings of Sariannidis and Zafeiriou (2011), who found that lowering interest rates increase investment, which in the long run will increase the prices of output (including the price of food products).

Unlike the interest rate, household consumption was found to have a significant and positive effect on domestic rice price fluctuation, with a coefficient of 0.039. This means that if household consumption increased by 1 per cent, rice price volatility would also increase by 0.04 per cent. The increase in household

Table 6. VECM estimation results-short and long run.

Variable(s)	Short-run		
	Coefficient	t-statistic value	
Rice price (-1)	0.037	5.297	(0.000)***
Domestic rice production (-1)	-0.463	-3.695	(0.015)**
Rice consumption (-1)	0.016	1.273	(0.163)
Exchange rate (-1)	0.337	1.258	(0.341)
World oil price (-1)	0.478	-4.159	(0.003)***
Interest rates (-1)	-0.019	-2.430	(0.219)
Income per capita (-1)	0.058	2.115	(0.713)
Rainfall (-1)	-0.033	-2.304	(0.032)**
World rice price (-1)	0.384	1.373	(0.432)
Rice import (-1)	-0.019	-2.065	(0.189)
Consumer price index (CPI) (-1)	0.006	0.369	(0.535)
R ²	0.442		
R ² -Adjusted	0.421		
Variable(s)	Long-run		
	Coefficient	t-statistic value	
Rice price (-1)	0.015	4.193	(0.002)***
Domestic rice production	-0.837	-6.377	(0.001)***
World oil price	0.642	4.764	(0.000)***
Rice consumption	0.039	-2.651	(0.002)***
Exchange rate	0.422	3.103	(0.163)
Interest rates	-0.020	-2.725	(0.005)***
Income per capita	0.024	2.323	(0.001)***
Rainfall	-0.041	-2.168	(0.014)**
World rice price	0.224	2.944	(0.114)
Rice import	-0.097	-2.145	(0.230)
Consumer price index (CPI)	0.002	1.127	(0.519)
R ²	0.592		
R ² -Adjusted	0.576		

Note: ***, **, * denotes significance levels of the *t*-statistic values at 1%, 5%, and 10%. Probability values in parenthesis. Source: Authors' estimation results.

consumption is considered as an indicator of the increase in the households' standard of living, increased income, and increased purchasing power parity of households (Moratti & Natali, 2012; Khan & Morrissey, 2020), which can also be explained by the statistically significant value of household income per capita (0.024) observed in this study. Increasing per capita household income and rice

consumption would increase rice price and its fluctuations if excess demand exceeds supply.

The last variable that significantly affects the volatility of rice prices is the climatic variable, which is approximated by rainfall. The negative coefficient (0.041) means that if rainfall decreases by 1 per cent, the rice price volatility increases by 0.04 per cent. Rice in Tanzania is mainly produced by smallholder farmers who grow the majority of rice (74 per cent of the planted area) under rain-fed conditions, irrigated rice (20 per cent) and large-scale production (6 per cent). This means that the rice yield is highly dependent on the amount of rain and its variability. Therefore, the shortage of rainfall can negatively affect rice yields, reduce market supply and possibly increase rice prices. The results agree with Schmidhuber and Tubiello (2007), Lobell et al. (2011a, 2011b), Wood et al. (2014), and Pérez et al. (2016) who previously found that climate variability affects farmers' cropping decisions, crop yields, the stability of food supplies and the ability of people to access food at affordable prices.

Overall, the most influential factors on short and long-run rice price volatility are lagged rice price, domestic rice production, world oil price, and climate change. Additionally, the study noted that each variable has a different effect on volatility. This means that while some variables positively affect price fluctuations, others have a negative effect. For example, positive shocks to crude oil prices and financial markets increased food volatility, but production shocks reduced volatility. These results are consistent with most of the previous results available in the literature (see, for example, Gilbert & Morgan, 2010; Du et al., 2011; Mensi et al., 2013; Nazlioglu et al., 2013).

4. Conclusion and Policy Implications

This study analyzed the dynamics of price volatility in the Tanzanian rice markets and its determinants. The results from both the rolling standard deviation and GARCH(1, 1) revealed that the level of price volatility in rice markets changes over time. This means that producers and consumers are exposed to a substantially larger amount of price risk. As indicated by the conditional variation, the volatility of rice prices shows that, in general, the markets in the producing regions (large surplus areas) have experienced the highest volatility than the markets in the main consuming regions (large deficit areas). Furthermore, the magnitude of rice price volatility in most markets, measured by the GARCH model coefficients, indicates persistent volatility, which means that rice price volatility can persist for a long time after a shock and, therefore, may harm consumers and producers.

On the other hand, results revealed that the factors that significantly influence rice prices volatility in Tanzania are the price of the rice itself (past rice prices), rice production, climate change (rainfall), household consumption, interest rates, household income, and world oil prices. Among these factors, supply variables played a significant role in both the short and long run in influencing rice price

volatility. The shortage of rainfall can negatively affect rice yields, reduce market supply and possibly increase rice price, while high rice production would lower rice price if additional production exceeds excess demand. Interest rate is a common factor causing price volatility as it tends to affect investment in agriculture, while rice production and rice consumption are two interrelated factors. Furthermore, the price of oil used as an indicator of production and distribution costs is an important factor in the formation of rice prices. Higher energy-related production costs would generally reduce agricultural production and lead to higher prices, while higher transportation costs would also lead to high prices for agricultural products. These results confirm the continued need for government interventions to promote agricultural production and manage food prices in order to minimize price volatility. For example, policies aimed at improving infrastructure (transport, market, and irrigation), anticipating market behaviour, reducing or removing trade restrictions, facilitating price negotiations between public and private actors, and promoting regional integrations (the free movement of goods) will reduce the effects of price volatility and thus stabilize prices. The government also needs to improve its capacity to store food products in times of crisis or soaring prices.

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Declarations

Ethics Approval and Consent to Participate

- ✓ All the ethical procedure was followed during data collection, analysis, and presentation.

Availability of Data and Materials

- ✓ The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

- ✓ This work was carried out in collaboration with all authors. Author YJM designed the study, wrote the protocol, managed literature, performed the statistical analysis, and wrote the first draft of the manuscript. Author STST contributed to the data collection and analysis. Author PD verified the analytical methods and supervised precisely the whole work. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare that they have no competing interests.

References

- Achandi, E. L., & Mujawamariya, G. (2016). Market Participation by Smallholder Rice Farmers in Tanzania: A Double Hurdle Analysis. *Studies in Agricultural Economics*, *118*, 112-115.
- Baffes, J., Kshirsagar, V., & Mitchell, D. (2017). What Drives Local Food Prices? Evidence from the Tanzanian Maize Market. *The World Bank Economic Review*, *33*, 160-184.
- Bollerslev, T. (1986). Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*, 307-327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Braun, J., & von Tadesse, G. (2012). *Global Food Price Volatility and Spikes: An Overview of Costs, Causes, and Solutions*. ZEF-Discussion Papers on Development Policy No. 161.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, *74*, 427-431. <https://doi.org/10.1080/01621459.1979.10482531>
- Du, X., Yu, C. L., & Hayes, D. J. (2011). Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis. *Energy Economics*, *33*, 497-503. <https://doi.org/10.1016/j.eneco.2010.12.015>
- Enders, W. (2015). *Applied Econometric Time Series* (4th ed.). John Wiley & Sons.
- Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation. *Econometrica*, *50*, 987-1007. <https://doi.org/10.2307/1912773>
- FAO, OCED, IFAD, IFPRI, IMF, UNCTAD, WFP, World Bank, WTO, & UN-HLTF (2011). *Price Volatility in Food and Agricultural Markets: Policy Responses. Technical Report*. FAO and OECD in Collaboration with IFAD, IFPRI, IMF, UNCTAD, WFP, World Bank, WTO, and UN-HLTF on Global Food Security.
- Foldvari, P., & van Leeuwen, B. (2011). What Can Price Volatility Tell Us about Market Efficiency? Conditional Heteroscedasticity in Historical Commodity Price Series. *Cliometrica*, *5*, 165-186. <https://doi.org/10.1007/s11698-010-0055-y>
- Gilbert, C.L. & Morgan, C.W. (2010). Food Price Volatility. *Philosophical Transactions of the Royal Society B—Biological Sciences*, *365*, 3023-3034.
- Headey, D. D. (2011). Rethinking the Global Food Crisis: The Role of Trade Shocks. *Food Policy*, *36*, 136-146. <https://doi.org/10.1016/j.foodpol.2010.10.003>
- Ismail, A., Ihsan, H., Khan, S. A. & Jabeen, M. (2017). Price Volatility of Food and Agricultural Commodities: A Case Study of Pakistan. *Journal of Economic Cooperation and Development*, *38*, 77-120.
- Jordaan, H., Grové, B., Jooste, A., & Alemu, Z. G. (2007). Measuring the Price Volatility of Certain Field Crops in South Africa Using the ARCH/GARCH Approach. *Agrekon*, *46*, 306-322. <https://doi.org/10.1080/03031853.2007.9523774>
- Khan, R., & Morrissey, O. (2020). *Income Diversification and Household Welfare in Tanzania 2008-2013*. Research Report 20/4, Uongozi Institute & UNU-WIDER. <https://doi.org/10.35188/UNU-WIDER/2020/867-2>
- Lobell, D. B., Banziger, M., Magorokosho, C., & Vivek, B. (2011a). Nonlinear Heat Effects on African Maize as Evidenced by Historical Yield Trials. *Nature Climate Change*, *1*, 42-45. <https://doi.org/10.1038/nclimate1043>

- Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011b). Climate Trends and Global Crop Production since 1980. *Science*, *333*, 616-620.
- MacKinnon, J. G., Haug, A. A., & Michelis, L. (1999). Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. *Journal of Applied Econometrics*, *14*, 563-577.
[https://doi.org/10.1002/\(SICI\)1099-1255\(199909/10\)14:5%3C563::AID-JAE530%3E3.0.CO;2-R](https://doi.org/10.1002/(SICI)1099-1255(199909/10)14:5%3C563::AID-JAE530%3E3.0.CO;2-R)
- Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and Volatility Spillovers across Commodity and Stock Markets: Linking Energies, Food, and Gold. *Economic Modelling*, *32*, 15-22. <https://doi.org/10.1016/j.econmod.2013.01.023>
- Moratti, M., & L. Natali (2012). *Measuring Household Welfare: Short versus Long Consumption Modules*. Working Paper 2012-04, UNICEF Office of Research.
- Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility Spillover between Oil and Agricultural Commodity Markets. *Energy Economics*, *36*, 658-665.
<https://doi.org/10.1016/j.eneco.2012.11.009>
- Ngailo, J., Mwakasendo, J., Kisandu, D., & Tippe, D. (2016). Rice Farming in the Southern Highlands of Tanzania: Management Practices, Socio-Economic Roles, and Production Constraints. *European Journal of Research in Social Sciences*, *4*, 2056-5429.
- Ngare, I., Simtowe, F., & Massingue, J. (2014). Analysis of Price Volatility and Implications for Price Stabilization Policies in Mozambique. *European Journal of Business and Management*, *6*, 160-173.
- Pérez, I., Janssen, M. A., & Anderies, J. M. (2016). Food Security in the Face of Climate Change: Adaptive Capacity of Small-Scale Social-Ecological Systems to Environmental Variability. *Global Environmental Change*, *40*, 82-91.
<https://doi.org/10.1016/j.gloenvcha.2016.07.005>
- Putra, A. W., Supriatna, J., Koestoer, R. H., & Soesilo, T. E. B. (2021). Differences in Local Rice Price Volatility, Climate, and Macroeconomic Determinants in the Indonesian Market. *Sustainability*, *13*, Article No. 4465. <https://doi.org/10.3390/su13084465>
- Safdar, H., Maqsood, S., & Ullah, S. (2012). Impact of Agriculture Volatility on Economic Growth: A Case Study of Pakistan. *Journal of Asian Development Studies*, *1*, 24-34.
- Sariannidis, N., & Zafeiriou, E. (2011). The Spillover Effect of Financial Factors on the Inferior Rice Market. *Journal of Food, Agriculture and Environment*, *9*, 336-341.
- Schmidhuber, J., & Tubiello, F. N. (2007). Global Food Security under Climate Change. *Proceedings of the National Academy of Sciences of the United States of America*, *104*, 19703-19708.
- Seck, P. A., Tollens, E., Wopereis, M. C., Diagne, A., & Bamba, I. (2010). Rising Trends and Variability of Rice Prices: Threats and Opportunities for Sub-Saharan Africa. *Food Policy*, *35*, 403-411. <https://doi.org/10.1016/j.foodpol.2010.05.003>
- Sims, C. (1972). Money, Income and Causality. *American Economic Review*, *62*, 540-552.
- Sirisupluxana, P., & Bunyasiri, I. N. (2018). Risk Assessment and Risk Management Decisions: A Case Study of Thai Rice Farmers. *The Business & Management Review*, *9*, 200-207.
- Tangermann, S. (2011). *Policy Solutions to Agricultural Market Volatility: A Synthesis*. Issue Paper No.33, International Centre for Trade and Sustainable Development.
- Timmer, C. P. (2004). *Food Security in Indonesia: Current Challenges and the Long Run Outlook*. Working Paper No. 48, Center for Global Development.
- Timmer, C. P. (2011). *Managing Price Volatility: Approaches at the Global, National, and*

Household Levels. Stanford Symposium Series on Global Food Policy and Food Security in the 21st Century. The Center on Food Security and the Environment.

Wood, S. A., Jina, A. S., Jain, M., Kristjanson, P., & DeFries, R. S. (2014). Smallholder Farmer Cropping Decisions Related to Climate Variability across Multiple Regions. *Global Environmental Change, 25*, 163-172.

<https://doi.org/10.1016/j.gloenvcha.2013.12.011>

Worako, T. K., Jordaan, H., & van Schalkwyk, H. D. (2011). Investigating Volatility in Coffee Prices along the Ethiopian Coffee Value Chain. *Agrecon, 50*, 90-108.

<https://doi.org/10.1080/03031853.2011.617865>

Wright, B. D. (2011). The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy, 33*, 32-58. <https://doi.org/10.1093/aep/ppo033>