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The nexus between fuel and food prices: A time series regression with Newey-West standard errors

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ABSTRACT

This study examines the relationship between diesel prices and the prices of three staple food crops (maize, beans, and rice) using a time-series regression approach with Newey–West standard errors. It tests the common assumption that rising diesel costs increase agricultural production and transportation expenses, thereby driving up food prices. This study draws on cost-push inflation theory, agricultural household production theory, and time-series econometric theory. Using monthly time series data, the study applies unit root tests, Granger causality analysis, and Newey-West regression estimation to assess both dynamic and simultaneous relationships. The unit root tests confirm that all variables are stationary at levels, making them suitable for time series analysis. Granger causality results reveal heterogeneous transmission effects between diesel and food prices. Diesel prices Granger-cause rice and beans prices at the 5% significance level, while no causal effect is found on maize prices. In addition, there are interdependencies among food crops, with evidence of causality running from beans to maize and from maize to rice, indicating partial price transmission within agricultural markets. However, no reverse causality from food crops to diesel prices is observed, supporting the exogeneity of diesel prices in the system. The Newey-West regression results further show a statistically significant positive relationship between diesel prices and all three food crop prices. These findings highlight the critical role of fuel costs in driving food price inflation through production and transportation channels, although the magnitude of impact varies across commodities. The study concludes that energy price shocks are an important determinant of food price dynamics in Tanzania, with implications for both agricultural and macroeconomic policy coordination. Coordinated energy–agriculture policy integration is essential for enhancing food price stability and protecting consumers from external price shocks.

Keywords: Beans, Fuel, Maize, Newey-West Regression, Rice

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I. INTRODUCTION

The relationship between fuel and food prices is well-documented in the literature. This is evidenced by the works of Bashir et al. (2025); Ivanova & Dospatliev (2023); Kirikkaleli & Darbaz (2021); Zingbagba et al. (2020); Baumeister & Kilian (2014); Zhang et al. (2010); Gilbert & Morgan (2010) and Abbott et al. (2008), to mention a few. The Economic theory generally predicts a positive relationship between fuel prices and food prices, arguing that higher fuel costs raise the cost of agricultural production and distribution through increased expenses for machinery operation, fertilizer production, irrigation, and transportation. As fuel serves as a key complementary input in farming, rising fuel prices shift the supply curve upward, leading to higher food prices through cost-push inflation. Additionally, in markets where agricultural commodities are used for biofuels, higher fuel prices can increase demand for crops such as maize or any other staple food, further pushing food prices up. These mechanisms suggest that fuel price shocks can transmit into food markets through production costs, transportation costs, and biofuel demand channels (Zhang et al., 2010; Campiche et al., 2007; Baffes, 2007).

According to Abbott et al. (2008), food price levels are the result of complex interactions among multiple factors, including crude oil prices, exchange rates, growing demand for food and slowing growth in agricultural productivity, as well as the agricultural, energy and trade policy choices made by nations of the world. It is thus not fuel prices that would explain precisely the changes in food prices, but as Abbot et al. (2008) put it, other variables must be considered for the complete explanation. In their study, Bashir et al. (2025) found that fuel prices can have a positive or negative influence on food prices; for example, oil prices caused the price of beans to increase, while showing a negative impact on the price of rice. Taghizadeh-Hesary et al. (2020) conducted a study in Malaysia and revealed that the price of petrol does not have any effect on food prices. Further revealed that the price of diesel was found to be detrimental to the economy as it can trigger inflation in the long run. However, in the short run, the prices of petrol and diesel do not affect food prices. This means that it is not always possible to have a positive relationship between fuel and food prices, although they make economic sense.

Literature on the relationship between fuel and food prices in Tanzania is limited, which prompted the need to document the same. The originality of the paper spans the type of data used, coupled with the choice of the methodology for its analysis, which, to the best of my knowledge, has not been done before. This study has used monthly time series data for maize, beans and rice prices along with the price for diesel for the period 2004 to 2025. Time series data are common for such analysis (Taghizadeh-Hesary et al., 2020; Baumeister & Kilian, 2014) because time series data almost always show autocorrelation (especially economic series) and data fluctuations, allowing for time series methodologies to prepare the data well for analysis. This study builds on the time series regression with Newey- West standard errors, never been used before in the Tanzanian context.

Using time series regression with Newey–West standard errors is particularly relevant for analyzing the relationship between diesel prices and the prices of maize, beans, and rice because it allows valid statistical inference even when the error terms exhibit both autocorrelation and heteroscedasticity, conditions that are very common in fuel and agricultural price data. According to Newey and West (1987), the estimator was designed purposely to correct these issues without requiring the specification of the exact structure of dependence in the residuals and thereby ensuring consistent standard errors under weak assumptions. Unlike standard Ordinary Least Squares (OLS) regression, which produces unreliable standard errors when heteroscedasticity or autocorrelation is present, the Heteroscedasticity and Autocorrelation Consistent (HAC) estimators, such as Newey–West, provide robustness against these violations (Wooldridge, 2013). As argued by Stock and Watson (2019), this makes the approach especially useful when analyzing commodity price data, which often contains structural shocks, seasonality, and persistence over time. The Newey–West method allows for a simple regression structure while still ensuring valid statistical inference as opposed to other time-series methods such as ARIMA or VAR models, which require assumptions that are more restrictive or multiple endogenous variables. In practice, the Newey–West estimator offers a flexible and practical way to obtain consistent standard errors in economic time series, making it well-suited for fuel and food price analysis where unpredictability and serial correlation are unavoidable (Baum, 2006).

1.1 Research Objective

The objective of the study was to examine the relationship between diesel prices and the average prices of three staple food crops (maize, beans, and rice) using a time-series regression approach with Newey–West standard errors.

II. THEORETICAL REVIEW

2.1 Introduction

The relationship between fuel prices and food prices is grounded in several complementary economic theories that explain cost transmission, market linkages, and price dynamics in agricultural systems. This study draws on cost-push inflation theory, agricultural household production theory, and time-series econometric theory to justify both the conceptual linkage and the empirical methodology.

2.2 Cost –Push Inflation Theory

The primary theoretical basis for this study is the cost-push inflation theory, which posits that increases in input costs, such as energy, lead to higher production costs and, consequently, higher output prices. Diesel fuel is a critical input in agricultural production, powering machinery, irrigation systems, and transportation networks. According to Blanchard and Johnson (2013) an increase in diesel prices raises the marginal cost of production and distribution, which is then passed on to consumers in the form of higher food prices. In developing economies like Tanzania, where agriculture is highly dependent on fuel-intensive transport systems and has limited infrastructure efficiency, this pass-through effect can be particularly strong. Empirical studies have consistently shown that energy price shocks significantly influence food price inflation through both direct (production) and indirect (transportation and marketing) channels (Baffes, 2007; Headey & Fan, 2008).

2.3 Agricultural Household and Market Integration Theory

In old literature of Singh et al. (1986), the agricultural household model suggests that farm households act both as producers and consumers, making them sensitive to price changes in both inputs and outputs. Rising diesel prices increase input costs, reducing profitability unless output prices adjust upward. This creates upward pressure on food prices in equilibrium. Additionally, market integration theory explains how price signals are transmitted across markets and commodities. The observed causality among maize, beans, and rice prices aligns with the notion of spatial and cross-commodity price transmission, where shocks in one market propagate to others due to substitution effects, shared input costs, and trade linkages (Fackler & Goodwin, 2001). This supports the empirical finding of interdependencies among food crops.

2.4 Energy–Food Price Nexus

The energy–food price nexus literature provides a broader framework linking fuel markets with agricultural commodity prices. Energy is a key input not only in production but also in fertilizer manufacturing and post-harvest logistics. As argued by Baffes (2007), a significant proportion of food price variation can be explained by energy price fluctuations. Similarly, Headey and Fan (2008) argue that global food crises have often been accompanied by rising fuel costs, reinforcing the structural linkage between these sectors.

2.5 Time-Series Econometric Theory

From a methodological standpoint, this study is grounded in time-series econometrics, particularly the analysis of dynamic relationships among economic variables. The use of unit root tests follows the principle that non-stationary data can lead to spurious regression results (Engle & Granger, 1987). By confirming stationarity at levels, the study ensures that standard regression techniques can be validly applied. The application of Granger causality, developed by Clive Granger (1969), provides a statistical framework for identifying predictive relationships between variables. It does not imply true causation but rather temporal precedence and information content, making it suitable for analyzing directional linkages between diesel and food prices.

2.6 Newey–West Estimation and Robust Inference

The use of the Newey–West estimator, introduced by Whitney Newey and Kenneth West (1987), is theoretically justified in the presence of heteroskedasticity and autocorrelation in time-series data. Economic time series, especially monthly price data, often exhibit serial correlation and non-constant variance, which violate classical Ordinary Least Squares (OLS) assumptions.

The Newey–West estimator corrects the standard errors without altering coefficient estimates, ensuring consistent and reliable inference. This makes it particularly appropriate for this study, where residual autocorrelation may persist even after ensuring stationarity.

In summary of the appropriateness of the theoretical underpinnings, diesel price act as exogeneous cost drive in the food supply chain while food prices respond to diesel price changes through cost transmission mechanisms. The interdependencies among food crops arise from market integration and substitution effects whereby the relationships are dynamic and time- dependent, requiring appropriate econometric techniques for valid inference. Ultimately, this integrated framework supports both the empirical strategy and the interpretation of results, linking theoretical expectations with observed statistical relationships.

2.7 Empirical Model

The theoretical framework outlined above implies that diesel prices influence food prices through cost transmission mechanisms, while interdependencies among food crops arise from market integration. To operationalize these relationships, the study specifies an empirical model grounded in time-series econometrics.

2.7.1 Model Specifications

Following the cost-push inflation framework, food prices are modeled as a function of diesel prices:

$$foodprice_t = \propto + \beta dieselprice_t + \varepsilon_t$$

Where:

$\beta > 0$ is expected based on production and cost-push theory

ε_t may exhibit autocorrelation, justifying Newey–West correction

The inclusion of separate equations for maize, beans, and rice follows the argument in Barrett (2001) that agricultural markets are commodity-specific and may respond differently to shocks.

To reflect commodity-specific dynamics, the model is estimated separately for maize, beans, and rice prices:

$$\omega_{i,t} = \alpha_i + \beta_i diesel_t + \varepsilon_{i,t};\ \ i = (maize, beans, rice)$$

Where:

$\omega_{i,t} =$ price of food crop i at time t

$diesel_t =$ diesel price at time t

$\beta_i =$pass-through effect of diesel prices

$\varepsilon_{i,t} =$ error term

A positive β_i is expected, consistent with cost-push inflation theory (Blanchard & Johnson, 2013).

2.8 Dynamic relationships and Granger causality

To capture the dynamic interactions suggested by market integration theory, the study applies the Granger causality framework developed by Clive Granger. The general form of the test is:

$$Y_t = \sum_{k=1}^{p} \alpha_k Y_{t-k} + \sum_{k=1}^{p} \gamma_k X_{t-k} + u_t$$

Whereby;

Y_t = dependent variable (e.g food price)
X_t = independent variable (such as diesel price)
p = lag length

If the coefficients γ_k are jointly significant, diesel prices are said to Granger-cause food prices.

This framework aligns with the theoretical expectation that price transmission is time-dependent, not instantaneous, due to adjustment costs, storage, and market frictions (Fackler & Goodwin, 2001).

2.9 Stationarity and Unit Root testing

Time-series econometric theory requires that variables be stationary to avoid spurious regression results (Engle & Granger, 1987). The study therefore applies unit root tests (e.g., ADF test) to verify that:

$$Var\ (X_t) = constant\ over\ time$$

Since all variables are found to be stationary at levels, the model can be estimated using standard regression techniques without differencing, preserving long-run information.

III. METHODOLOGY

3.1 Data Types and Sources

The study used secondary data from the Bank of Tanzania website available at https://www.bot.go.tz/Publications/Filter/13. These are time series monthly data from February 2004 to December, 2025. Price data for maize, beans, and rice are per 1000 kg; these are the common staple foods in Tanzania, and the price of diesel is per litre. The prices are in Tanzanian shillings (TZS), and there were no missing data. The first difference was done to address the non-stationarity problem. This is a common method in time series analysis, as in many cases, the time series data are not stationary.

3.2 Time Series Tests

The null hypothesis in this statistical test is that the sample data are normally distributed and have the same characteristics as the population. According to Ivanova and Dospatriev (2023), violating these assumptions results in an analysis that can be misleading or very erroneous.

3.2.1 Augmented Dickey-Fuller test

This is a unit-root stationarity test that tests the null hypothesis that a unit root exists in the time series data. It states that, H_0: A unit root exists in a time series data against the alternative that no unit root exists or data are stationary, and is denoted theoretically as H_1. The statistic of ADF that has been used is a negative value (less than zero). According to Greene (1997), the more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. It implies that, if H_0, is adopted, then apply the first difference and test the null hypothesis against the alternative. Then, the equation with the lag values added has the form:

$$\delta Y_t = \alpha + \beta t + \rho Y_{t-1} + \sum_{i=1}^{k} \gamma_i \delta Y_{t-i} + \varepsilon_t \ldots\ldots \quad (1)$$

Where δ represents the difference operator, $\delta Y_t = Y_t - Y_{t-1}$; $\delta Y_{t-1} = Y_{t-1} - Y_{t-2}$, α represents the constant, β represents the coefficient on time trend t, and ρ represents the number of lags, and ε_t stands for the noise error term (Ivanova & Dospatriev, 2023). The number of lags added to the model is empirically defined by: Akaike information criterion (AIC), defined by the following equation (Akaike, 1974; Burnham & Anderson, 2002).

$$AIC = 2k - 2\ln(\tilde{L}) \ldots\ldots \quad (2)$$

Where k represents the number of estimated parameters (plus the intercept), $\tilde{L}$, represents the maximized value of the likelihood function. The Bayesian information criterion (BIC), also known as the Schwarz information criterion

(SIC) or the Schwarz–Bayesian information criterion (SBIC), is defined by the following equation (Ivanova & Dospatriev, 2023; Claeskens & Hjort, 2008; Wit et al., 2012):

$$BIC = kln(n) - 2\ln(\tilde{L}) \qquad (3)$$

Where k represents the number of estimated parameters, $\tilde{L}$ represents the maximized value of the likelihood function, and n represents the number of observations.

3.2.2 Granger Causality Test

The assessment of causal – effect relationship among variables is important in time series analysis. If one variable can be predicted by another variable, then the Granger test may reveal the causal- effect relationship between the two variables. The test statistic to test the null hypothesis that one variable does not Granger-cause another variable and the alternative hypothesis that one variable does Granger-cause another variable is given as;

$$F = \frac{(RSS_R - RSS_{UR})/_{m}}{RSS_R/_{(n-k)}} \sim F_{(m,n-k)}$$

Where:

RSS_R =Restricted residual sum of squares
RSS_{UR} =Unrestricted residual sum of squares
m =Number of lagged terms
k =number of parameters estimated in the unrestricted regression
$F_{(m,n-k)}$ = F- distribution with m and $n-k$ degrees of freedom

3.3 Newey – West regression with standard errors

A time-series regression with Newey–West standard errors is theoretically grounded in the heteroscedasticity and autocorrelation consistent (HAC) estimator introduced by Newey and West (1987). The method adjusts standard errors to remain consistent even when the error terms exhibit serial correlation and non-constant variance, conditions that frequently arise in economic time series. Although OLS coefficient estimates remain unbiased under these violations, their standard errors become unreliable; the Newey–West estimator corrects this problem by providing asymptotically valid inference without altering the underlying regression specification.

Time series regression relies on the classical linear regression model (CLRM), which assumes that the error terms are independently and identically distributed $(i.i.d.)$, with no autocorrelation and no heteroskedasticity. However, in real-world time-series data, especially economic and financial data, like ours, these assumptions are often violated, especially when data do not meet the autocorrelation and heteroscedasticity properties. Although these violations do not bias the estimated coefficients (β), they render the standard errors inconsistent, resulting in misleading t-statistics, unreliable confidence intervals, and invalid hypothesis testing. As a remedy to this, Newey and West (1987) developed a Heteroscedasticity and Autocorrelation Consistent (HAC) covariance estimator. This estimator adjusts the standard errors so they remain consistent even when both heteroscedasticity and autocorrelation are present. The Newey – West modifies the $Var(\hat{\beta}) = \sigma^2(X'X)^{-1}$ by estimating the variance–covariance matrix of β using a HAC estimator that remains valid under weaker assumptions. In ordinary regressions, OLS estimators remain unbiased and consistent if the regressors are exogenous, but the traditional variance estimator $Var(\hat{\beta}) = \sigma^2(X'X)^{-1}$ becomes no longer valid.

The Newey–West estimator is based on the large-sample (asymptotic) theory of OLS. It provides a consistent estimate of the true covariance matrix even when:

i. Errors are heteroskedastic
ii. Errors are autocorrelated up to a certain lag

The estimator takes the form:

$$\widehat{Var_{NW}}(\hat{\beta}) = (X'X)^{-1}\left(\textstyle\sum_{k=-L}^{L} w_k\tau_k\right)(X'X)^{-1} \qquad (4)$$

Where τ_k is the estimated auto covariance at lag k; w_k shows weights that decrease as lag increases (Bartlett kernel); and L is the chosen maximum lag length. This weighting structure ensures the covariance estimate remains positive semi-definite and consistent.

IV. FINDINGS & DISCUSSION

4.1 Descriptive statistics for the variables

Table 1 presents the descriptive statistics for the variables diesel price, maize, beans, and rice prices. The descriptive statistics help in giving the general descriptions of the variables to be used for the inferential statistics.

Table 1

Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Maize	263	51550.87	24180.01	13400	119484.3
Rice	263	145020.2	61047.41	44663	300067.5
Beans	263	148515	69126.26	32007	298649.7
DieselTZSL~e	263	2025.301	640.6147	745.4693	3525.935

The mean prices are 51,550 TZS (USD 21), 145,020 (59.7 USD), and 148,515 (58.5 USD) for maize, rice, and beans, respectively, while for diesel per litre was 2025.301 (0.82 USD); all these average prices are for a month.

4.2 Time series line plots

The plots are used to show how each variable changes over time and whether trends move together. Due to the hypothetical relationship between fuel prices and food prices, it is imperative to plot them separately, and this gives an early sense of correlations and trends. Each crop is plotted independently, all three crops together, and the fuel price with all three crops in one plot. The idea is to compare before further analysis. Figure 1 presents these graphs.

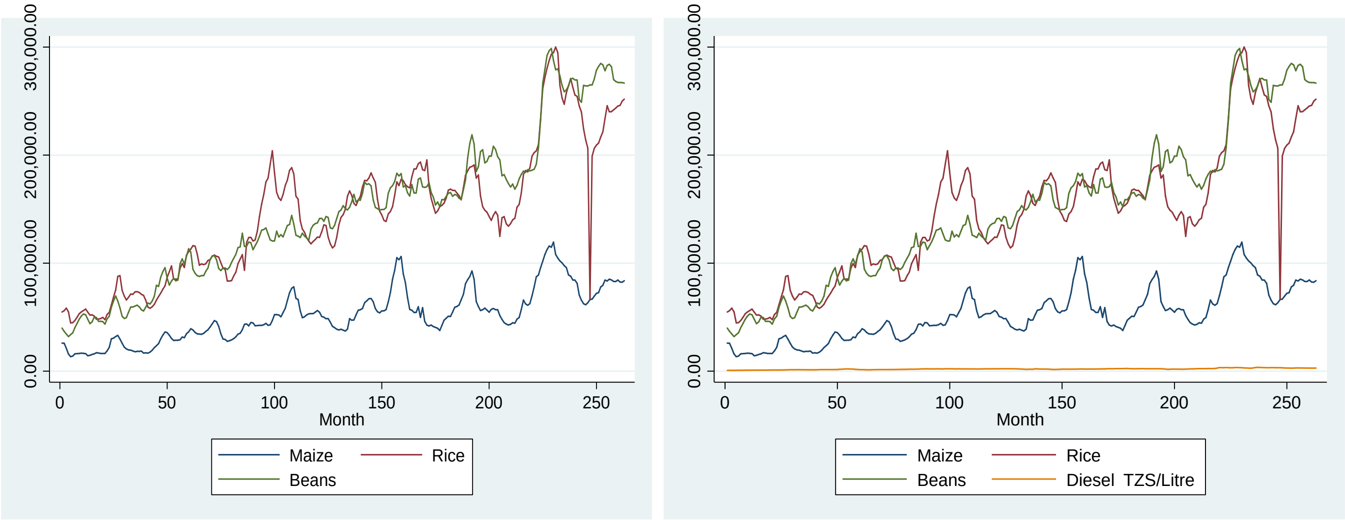
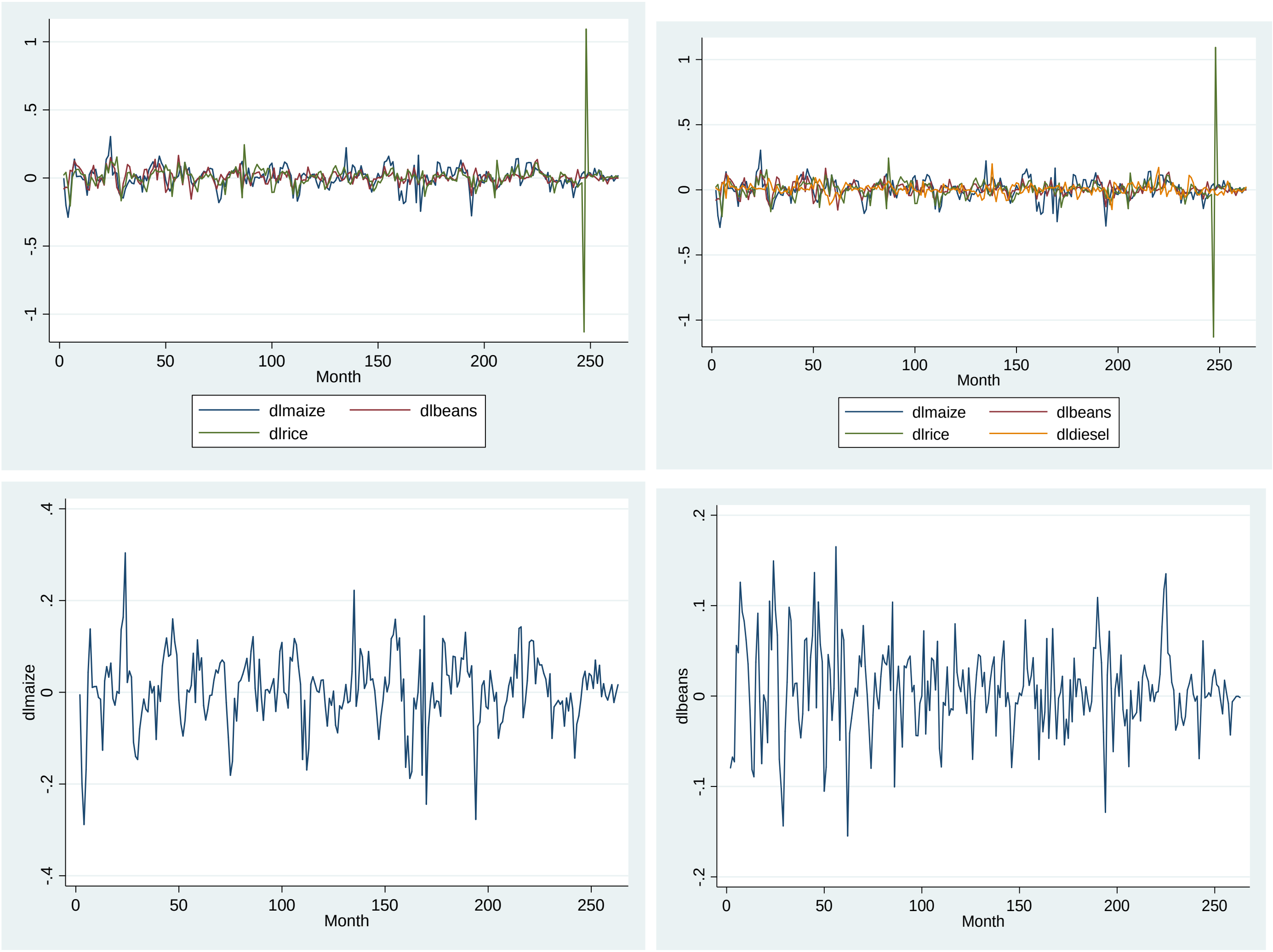


Figure 1
Time Series Plots for All the Variables in a Model before Differencing

After revealing that the series are not stationary, we performed first differencing to bring the data into stationarity; similar results were also realized for the log variables, as shown in the plots in Figure 2 below.



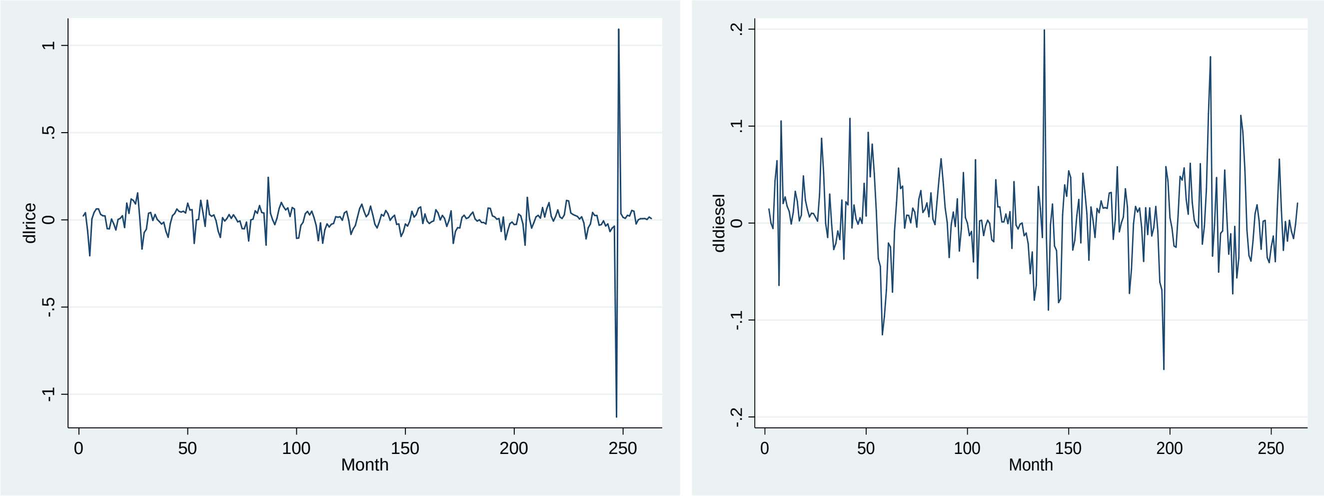


Figure 2
Stationery Time Series Plots for All the Variables after Differencing

Figure 3 shows the strength and direction of the relationship between diesel price and each crop price in a much more feasible way.

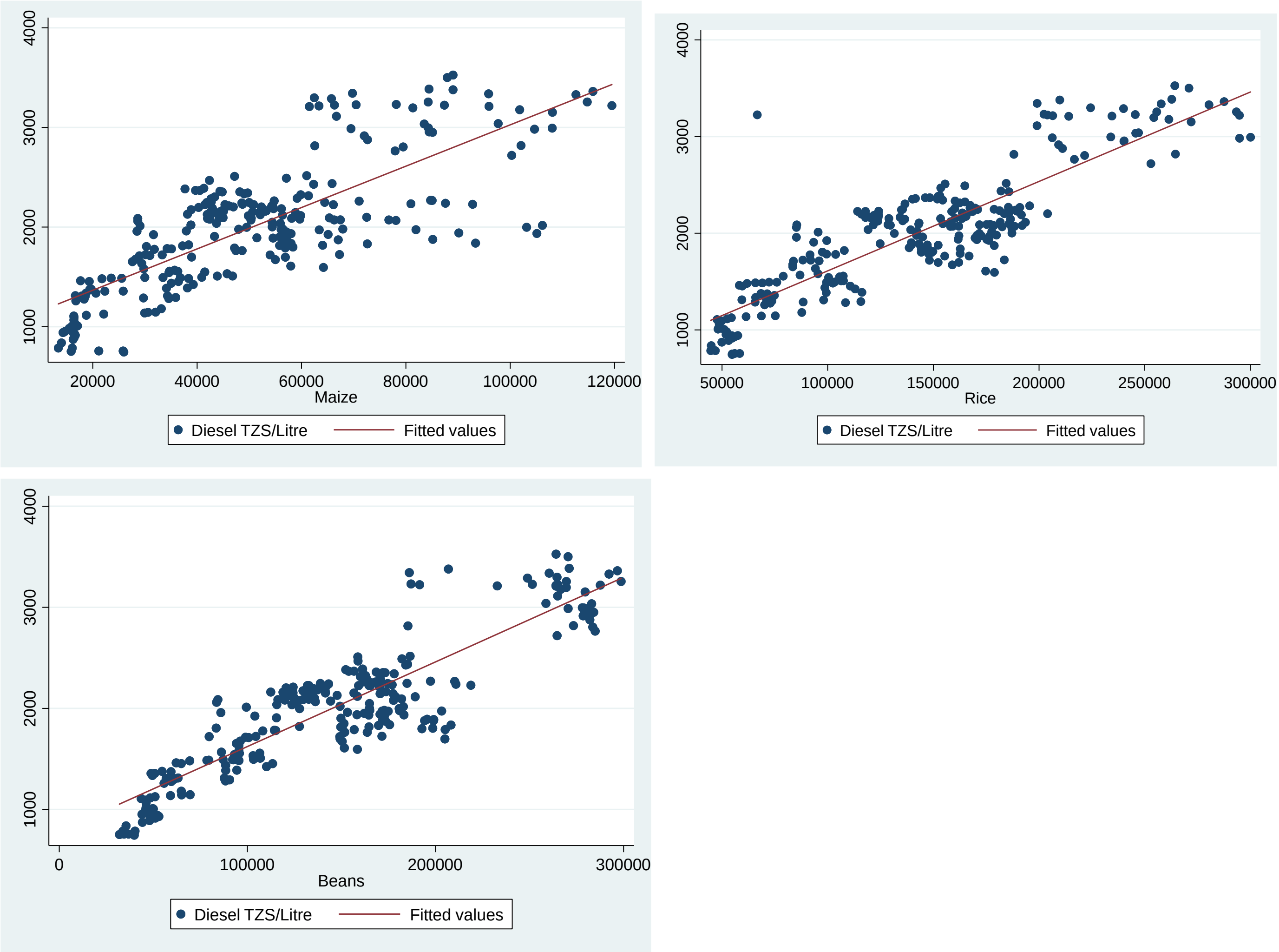


Figure 3
Scatter Plots (Relationship between Diesel and Each Crop Price) Autocorrelation Checks

Table 2

Results for the Correlograms

corrgram DieselTZSLitre, lag(4)				**-1**	**0 1 -1**	**0 1**
LAG	**AC**	**PAC**	**Q**	$Prob > Q$	**[Autocorrelation]**	**[Part Autocor]**
1	0.9795	0.9865	255.23	0.0000	|-------	|-----
2	0.9541	-0.2974	493.44	0.0000	|-------	--|
3	0.9282	0.0750	729.27	0.0000	|-------	|
4	0.9021	-0.0148	948.24	0.0000	|-------	|
corrgram Maize, lag(4)				**-1**	**0 1 -1**	**0 1**
LAG	**AC**	**PAC**	**Q**	$Prob > Q$	**[Autocorrelation]**	**[Part Autocor]**
1	0.9791	0.9858	255.01	0.0000	|-------	|-----
2	0.9449	-0.4501	493.44	0.0000	|-------	---|
3	0.8987	-0.2370	709.96	0.0000	|-------	-|
4	0.8477	0.1038	903.32	0.0000	|------	|
corrgram Rice, lag(4)				**-1**	**0 1 -1**	**0 1**
LAG	**AC**	**PAC**	**Q**	$Prob > Q$	**[Autocorrelation]**	**[Part Autocor]**
1	0.9632	0.9746	246.78	0.0000	|-------	|-----
2	0.9372	0.1893	481.32	0.0000	|-------	|-
3	0.9091	-0.0187	702.86	0.0000	|-------	|
4	0.8787	-0.0584	910.65	0.0000	|------	|
corrgram Beans, lag(4)				**-1**	**0 1 -1**	**0 1**
LAG	**AC**	**PAC**	**Q**	$Prob > Q$	**[Autocorrelation]**	**[Part Autocor]**
1	0.9853	0.9965	258.24	0.0000	|-------	|-----
2	0.9671	-0.3492	507.97	0.0000	|-------	--|
3	0.9480	0.0612	748.86	0.0000	|-------	|
4	0.9286	0.0080	980.9	0.0000	|-------	|

From the given correlograms in Table 2, it is evident that spikes are higher at lag 1, indicating that autocorrelation exists. This confirms that the Newey–West is needed in analyzing this relationship. The correlogram results for diesel and all food prices (maize, rice, and beans) reveal very high and slowly decaying autocorrelation coefficients, with first-lag values exceeding 0.96 and remaining above 0.84 even at lag 4, alongside statistically significant Ljung–Box Q-statistics (p = 0.000). This indicates strong persistence and serial dependence in all series, suggesting that price movements are not random but instead follow a gradual adjustment process over time. This reflects the nature of commodity and fuel markets, where price changes are transmitted slowly due to adjustment costs, market frictions, storage behaviour, and expectations, causing current prices to depend heavily on past values. Such persistence is typical of price series influenced by inflationary trends and supply chain dynamics, particularly in developing economies, such as Tanzania. While these features point to likely non-stationarity, they also justify proceeding with further time-series analysis, as they suggest the existence of meaningful dynamic and potentially long-run relationships between diesel and food prices.

Heteroscedasticity checks: This uses a plot of fitted values against the residuals. The prominent question has been whether the model captures the true diesel price pattern well or whether the structures are left in the residuals. From Figure 4, we reveal that the residuals are randomly scattered around zero with no pattern or curvature. This means that there are no missing nonlinear terms, no omitted variables, and autocorrelation has been handled fully. Hence, the model explains diesel price reasonably well using prices of maize, beans, and rice as used in the model.

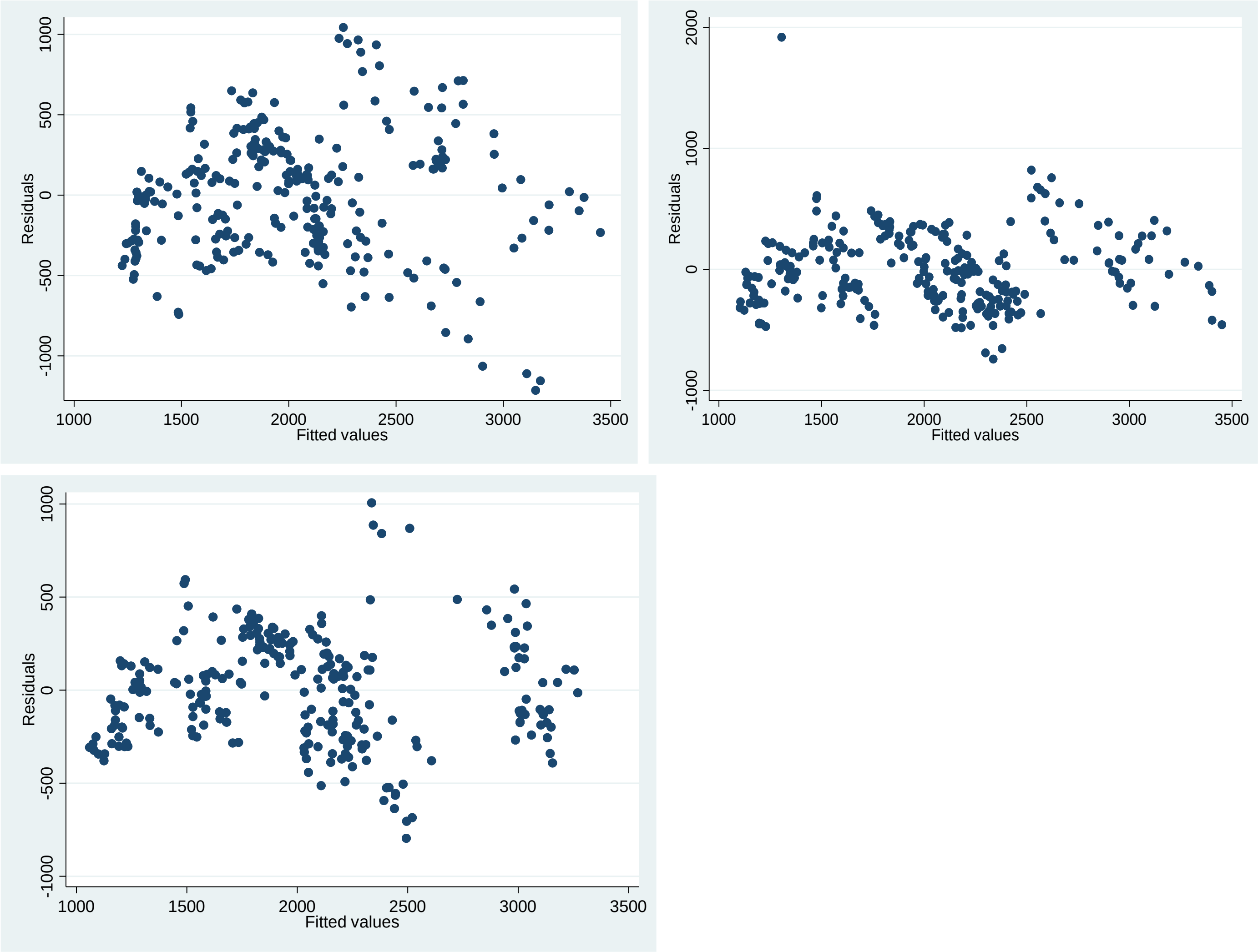


Figure 4
Plot of Fitted Values versus Residuals

The Dickey-Fuller test for stationarity was performed, and the null hypothesis is "There is a unit root". At both the first test, the levels were non–stationary, while after first differencing, all the levels were stationary. This necessitated the use of Newey-West, as it works fine even if levels are non-stationary, as long as the results obtained are carefully interpreted.

Table 3
Dickey-Fuller Test for the Unit Root

	Variable	Test statistic	1% critical value	5% critical value	10% critical value	MacKinnon's approximate p-value of $Z(t)$
Before differencing	diesel_price	-1.600	-3.459	-2.880	-2.570	0.4836
	maize_price	-1.306				0.6264
	rice_price	-1.769				0.3961
	beans_price	-0.606				0.8695
After differencing	diesel_price	-11.987	-3.459	-2.880	-2.570	0.0000
	maize_price	-9.703				
	rice_price	-21.287				
	beans_price	-11.272				

After first differencing, the results in Table 3 show that the null hypothesis "Unit root exists" is rejected at 5% level of significance, and thus all the data series are now stationary to allow for a proper time series analysis. Further, the Granger causality tests in Table 4 emphasizes on the correlation between fuel and food prices to also allows proceeding with the Newey-West regression results, as shown in Table 5 for the detailed relationship between food prices and fuel price (diesel price).

Table 4
Granger Causality Wald Test Results

Equation	Excluded	chi2	df	Prob > chi2
Maize	Rice	4.9301	4	0.295
Maize	Beans	19.416	4	0.001
Maize	DieselTZSLitre	1.2806	4	0.865
Maize	ALL	39.423	12	0.000
Rice	Maize	18.237	4	0.001
Rice	Beans	3.8755	4	0.423
Rice	DieselTZSLitre	11.037	4	0.026
Rice	ALL	56.168	12	0.000
Beans	Maize	4.1937	4	0.380
Beans	Rice	9.4521	4	0.051
Beans	DieselTZSLitre	23.17	4	0.000
Beans	ALL	34.821	12	0.001
DieselTZSLitre	Maize	2.2199	4	0.695
DieselTZSLitre	Rice	2.3033	4	0.680
DieselTZSLitre	Beans	2.2127	4	0.697
DieselTZSLitre	ALL	8.064	12	0.780

The Granger causality results indicate heterogeneous transmission effects between diesel prices and food crop prices. Specifically, diesel prices Granger-cause both rice and beans prices at the 5% significance level, suggesting that diesel is an important predictor of price movements in these two markets. However, no evidence is found that diesel prices Granger-cause maize prices, implying that maize prices are relatively insulated from diesel price dynamics within the model. Among the food crops, there are also notable interdependencies: bean prices Granger-cause maize prices, while maize prices Granger-cause rice prices, indicating a degree of cross-market price transmission among staple crops. In contrast, rice does not Granger-cause maize, and maize does not Granger-cause beans, suggesting asymmetry in these relationships. Importantly, none of the food crop prices Granger-cause diesel prices, supporting the treatment of diesel as an exogenous driver within the system. Overall, the results suggest that diesel price shocks are transmitted selectively across food markets, with stronger effects observed in rice and beans, while maize appears less responsive, and food markets exhibit partial but not uniform interlinkages. This is consistent with Kirikkaleli and Darbaz (2021), who found that fuel prices can have a positive or negative influence on food prices; for example, oil prices caused the price of beans to increase, while showing a negative impact on the price of rice. Tables 5, 6, and 7 show the estimated coefficient results by the Newey- West standard errors using levels of each crop to the diesel prices.

Table 5
Estimated Coefficients by the Newey-West standard errors for Maize and Diesel prices

Regression with Newey-West standard errors **Maximum lag: 4**				**Number of obs = 263** **F(1, 261) = 195.30** $\boldsymbol{Prob > F} = \mathbf{0.0000}$		
lmaize	Coef.	Newey- West Std. Err.	t	$P > \|t\|$	[95% $Conf. Interval$]	
ldiesel	1.271795	.0910052	13.97	0.000	1.092597	1.450992
_cons	1.114719	.6953176	1.60	0.110	-.254427	2.483865

Table 6
Estimated Coefficients by the Newey-West standard errors for Rice and Diesel Prices

Regression with Newey-West standard errors **Maximum lag: 4**				**Number of obs = 263** **F(1, 261) = 322.79** $\boldsymbol{Prob > F} = \mathbf{0.0000}$		
lrice	Coef.	Newey- West Std. Err.	t	$P > \|t\|$	[95% $Conf. Interval$]	
ldiesel	1.21917	.067858	17.97	0.000	1.085551	1.352789
_cons	2.568292	.5166873	4.97	0.000	1.550885	3.585698

Table 7

Estimated Coefficients by the Newey-West Standard Errors for Beans and Diesel prices

Regression with Newey-West standard errors **Maximum lag: 4**				**Number of obs = 263**		
				F(1, 261) = 666.08		
				$Prob > F$ = 0.0000		
lrice	Coef.	Newey- West Std. Err.	t	$P > \lvert t \rvert$	[95% $Conf.Interval$]	
ldiesel	1.437485	.055698	25.81	0.000	1.32781	1.547159
_cons	.9153781	.4250746	2.15	0.032	.0783659	1.75239

The results in Tables 5, 6 and 7 show that at 5% level of significance, the price of fuel affects all three food crops (maize, beans and rice) significantly. This is consistent with Bashir et al. (2025); Ivanova and Dospatliev (2023), as well as Zingbagba et al. (2020), in that there is a relationship between fuel price and food crop prices. All the coefficients are positive, indicating a positive relationship between fuel price and food crop prices. Since the data used were transformed into logarithmic form, the interpretation follows that a unit increase in diesel price per litre leads to a 1.3 per cent, 1.2 percent and 1.4 per cent increase in maize price, rice price and beans price, respectively.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The empirical results provide consistent evidence on the relationship between diesel prices and food crop prices in Tanzania. First, the unit root tests confirm that all series are stationary at the 5% level of significance, implying that the data are suitable for time series estimation and inference. Second, the Granger causality results reveal a heterogeneous pattern of price transmission between diesel and food commodities. Diesel prices are found to Granger-cause rice and beans prices at the 5% significance level, indicating that diesel serves as a leading indicator for price movements in these markets. However, no statistically significant causal effect is detected from diesel to maize prices, suggesting that maize is relatively less sensitive to fuel price dynamics. The results further show interdependencies among food crops, where beans Granger-cause maize prices and maize Granger-causes rice prices, while no reverse causality is observed from food crops to diesel prices. This supports the assumption of diesel as an exogenous driver in the system. Finally, the Newey-West regression results confirm a robust and statistically significant positive relationship between diesel prices and all three food crop prices. These findings suggest that fuel price shocks are strongly transmitted into food markets through production and transportation cost channels, although the magnitude of transmission varies across crops. Overall, the study concludes that diesel prices play a critical role in shaping food price dynamics in Tanzania, with differential effects across commodities and evidence of both direct and indirect price linkages within the food market system.

5.2 Recommendations

The findings of this study have several important policy implications for food price stability and energy-agriculture linkages in Tanzania. First, the evidence that diesel prices significantly influence food crop prices, particularly rice and beans, implies that fuel price shocks are an important driver of food inflation. This suggests that macroeconomic and energy policies cannot be designed in isolation from agricultural markets. Stabilization mechanisms for fuel prices, such as strategic fuel reserves, smoothing taxes, or targeted subsidies during periods of global oil price volatility, may help reduce downstream pressure on food prices. Second, the heterogeneous impact across crops indicates that maize is less responsive to diesel price changes compared to rice and beans. This suggests that policy interventions should be crop-specific rather than uniform. For example, transport-intensive and market-dependent crops like rice and beans may require targeted support in logistics and input supply chains to reduce vulnerability to fuel price shocks.

Third, the presence of interdependencies among food crops implies that shocks in one market can propagate to others. Strengthening regional and national food market integration, improving market information systems, and reducing transaction costs could help dampen price transmission effects and improve market efficiency. Finally, since diesel is found to be exogenous to food prices, policies aimed at improving energy efficiency in agriculture and transportation, such as promoting fuel-efficient transport systems, rural infrastructure development, and alternative energy sources, could reduce the sensitivity of food prices to fuel shocks. Overall, coordinated energy–agriculture policy integration is essential for enhancing food price stability and protecting consumers from external price shocks.

Declaration of Interest

The author declares that he has no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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