



Impact of Petroleum Energy Price Volatility on Commodity Prices in Ghana

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ABSTRACT

The purpose of this article is to demonstrate the relationship between petroleum energy volatility and commodity prices in Ghana, which are indexed (energy grains, meat, and cooking oil), as well as to provide an empirical specification of the impact's direction. With reference to time series literature, the paper examined energy and commodity price connection models such as augmented dickey fuller, granger causality, co-integration, vector autoregressive and the vector error correction models used in estimating the association among petroleum energy volatility and the three selected commodity variables. The paper found that, there is a long run relationship between petroleum energy volatility and commodity prices in Ghana from 2011 to 2022. A single equation error correction model suggested that, petroleum energy shocks increase prices of grains, meat and cooking oil in both the short and long run. Impulse response function and variance decomposition conducted on the variables also suggested that there is both short and long run association between the variables.

Keywords: Petroleum Energy Price Volatility, Commodity Prices

JEL Classifications: C32, E31, O13

1. INTRODUCTION

Petroleum marketing agreements are generally made in dollars, petroleum energy prices are largely determined by the price of crude oil and the dollar exchange rate. Russia is the world's third largest oil exporter, and in response to the recent Russia-Ukraine crisis, several western countries, such as the United States and Canada, have opted to restrict imports from the Russia. It indicates that demand for oil from other producers has risen, resulting in higher prices (Finley and Krane, 2022). Most recently, crude oil prices have surpassed \$100 dollar per barrel for the first time since 2014 and as a result; members of the International Energy Agency have agreed to release 60 million barrels of crude from their stockpiles, including the world's largest oil producer, the United States. So far, this hasn't been enough to stop the steep price rises.

Fuel prices have reached all-time high across Africa. Fuel prices in Burkina Faso has increased by 8% within the first quarter of 2022 (Middendorf and Traoré, 2022). South Africa's national statistics institute believed fuel prices in December 2021 had raised by 40.5% compared to the previous year (Bell, 2020; Howe and Leiserowitz, 2013). It is possible that, Burundi is one of the African countries with high energy cost (Kpodar and Liu, 2022). Petrol prices in the Democratic Republic of the Congo have also increased by 3,000 Congolese francs, an equivalent of \$1.50, which is also a new high (Krishnan and Butt, 2022). Africans are being hit hard by rising fuel prices, which come at a time when the cost of basic consumables are also skyrocketing. Kenya's government has come under pressure to increase taxes on household products such as cooking gas, fuel, and food by 14%, food cost has nearly doubled in Togo and Ivory Coast as well (Mkalama, 2022).

In Ghana, the ex-pump price of gasoline and diesel has risen by an all-time high of 18.2% in March 16, 2022 (Acquah, 2022). According to the Ghana News Agency, several Oil Marketing Companies (OMCs) have increased their rates from GHS8.2/l to GHS9.7/l, a difference of GHS1.50/l. In this pricing window, the rate of increase is the largest since the beginning of the year. At the pumps on January 1, 2022, both gasoline and diesel were selling for an average of GHS6.30 a litre. Prior to March 1, 2022, the rate has risen to an average of GHS7.50/l, an increase of 8.6% over the preceding pricing period (Aygei & Tetteh, 2022). Fuel costs have risen by GHS3.40/l, or 53.9%, since the beginning of the year, according to the current rate of GHS9.70/l. The performance of the Cedi versus the US Dollar and the increase in Crude prices on the international market has been primarily blamed for the continuing rise in fuel costs at the pumps (Kojima, 2016). Some market analysts, including the Chamber of Petroleum Consumers (COPEC), predicted that the ex-pump price for petrol and diesel would cross GHS10/l if the rate of depreciation of the Cedi and the situation on the international market persisted before the start of the April 2022. The Institute for Energy Security (IES) revealed that the Cedi depreciated by 4.82% in the March 2022, first Pricing Window, closing at GHS7.17 to the Dollar, down from Gh6.85 to \$1 dollars in the previous window. In terms of the cost of fuel on the international market, the IES discovered that the price of the worldwide benchmark Brent Crude soared to 14-year highs during the evaluation period, averaging \$112.87 dollars per barrel, up 19.95% from the previous window's average price of \$94.10 dollars per barrel (Nyasapoh and Derkyi, 2022). There are currently twelve (12) taxes on petroleum goods, which account for 40% of the entire price increase. In a proposal to the Ministry of Energy, the National Petroleum Authority (NPA) proposed that the Special Petroleum Tax of 46p/l, the Energy Sector and Recovery Levy 14p/l, and the Sanitation Levy be reviewed 10p/l (Owulaku and Tetteh, 2022).

High commodity prices disproportionately affect the deprived as they spend over half of their income on buying consumable goods (Walby, 2013; Sovacool and Newell, 2022). According to Kollias and Tzeremes (2022) commodity price demonstrations are frequently triggered by high unemployment and increase in prices. Leonard et al. (2022) argue that if global commodity prices rise above a particular threshold, it could lead to social unrest, with other reasons as well. Other relevant research suggests that increased commodity prices are linked to conflict in poor nations when other drivers are taken into account, such as government actions (Mlambo, 2022; Hill and Johns, 2022). Despite the number of research papers on the subject matter, there is little literature linking the relation between petroleum energy volatility, and commodity prices in Ghana especially within the Corona Virus (COVID-19) and Russia-Ukraine crisis. Using vector error correction model (VECM), quarterly time series data of Commodity Prices were extracted from International Monetary Fund Database and United Nations International Trade Statistics Database, spanning a period of 2011-2022 to investigate the impact of petroleum energy volatility on commodity prices in Ghana.

2. LITERATURE REVIEW

Long-term economic swings in commodity prices have been recognized since the nineteenth century, most notably in the works

of (Shanahan, 2022; Runge, 2022; Lewis, 2022). However, none of these researches offered an explicit theory or model to explain the underlying dynamics of long-term commodity price movements. There is a growing body of knowledge about the relationship between petroleum price volatility and commodity prices. High energy prices have increased the expenses of producing agricultural goods that generate food, feed, energy, and fibre over the last few decades. According to economic theory, rising crude oil prices have a direct impact on agricultural prices by boosting input and transportation costs (Ranum and Garcia-Casal, 2014; Vastolo and Cutrignelli, 2022). A significant amount of empirical research on the nature of the relationship between petroleum and agricultural commodity prices, conducted using various approaches, reveals that there is an indirect correlation of varying scale between the prices (Nazlioglu and Soytaş, 2011; Jebabli and Teulon, 2014; Boubaker and Raza, 2017; Khalfaoui and Boubaker, 2015). When using a general equilibrium model with fully described macroeconomic linkages Esmaeili and Shokoohi (2011) discover a negative influence of petroleum prices on agriculture prices.

Sands et al. (2011) used the Food and Agricultural Policy Simulator, a multi commodity model of the United States agriculture sector, and Farm Level Partial Budget models to investigate the impact of rising energy prices on agriculture. Higher energy prices raise production costs and reduce net farm revenue, according to the researchers, with the size of the effect depending on area and commodity. Beckman et al. (2013) found that energy price shocks cause changes in production techniques that lower the usage of energy-intensive inputs, using data from the National Agricultural Statistics Service. They found that consumer reactions to rising energy prices differed by commodity and by the usage of energy-related inputs like fertilizer. One worry is that the merger of agriculture and energy markets may exacerbate the already turbulent agricultural market. Agricultural commodity prices have increased by 40% in 2021 and will continued to rise substantially within the first quarter of 2022 (Wegerif, 2022; Luderer and Madeddu, 2022). According to Forhad and Alam (2022) a major portion of increase in corn prices is due to increase in oil costs. Higher biofuel demand is responsible for 30% of the increase in grain prices, with corn prices increasing the most with a 39% increase in real prices (Hochman and Rajagopal, 2014). According to Ferrucci and Jimenez-Rodriguez (2010) oil price changes have the highest pass-through to food commodities and fertilizers among non-energy commodities. High energy prices, according to Garza et al. (2022) have increased the expenses of transportation and agricultural inputs such as fertilizer and pesticides, increasing the cost of agricultural output. According to Duarah et al. (2022) the developing ethanol market has integrated oil and maize prices to the point where the agricultural sector is now importing oil sector instability.

Giving to literature, crude oil has no direct impact on the pricing of other food groups. Awaworyi-Churchill et al. (2022) used data from copper, livestock, oil, corn, and gold collected between 2005 and 2018 and established a long-term link between crude oil and industrial metal markets, but they could not find any evidence of fuel-food links. (Saqib, 2022) use a co-integration test in conjunction with nonlinear Granger causality testing to establish

that, there is neither short- nor long-term price relationship between crude oil and food product prices. Philip et al. (2022) used a nonlinear autoregressive distributed lag model (NARDL) to examine the Malaysian instance. As a result of this research, no long-term association between the factors studied was discovered. However, he discovered that changes in the price of oil generate agricultural product price inflation in the short term.

2.1. Petroleum Sector in Ghana

Upstream, midstream, and downstream are the three main segments of the petroleum industry. The industry is classified into upstream and downstream subsectors for regulatory reasons in Ghana, which cover activities ranging from petroleum exploration and production to refining, storage, transportation, and marketing of petroleum products. Importation of crude oil and finished products, refining, storage, transportation (road, rail, lake, and ocean), marketing, and sale of petroleum products are all part of Ghana's Petroleum Downstream subsector (Hemachandiran, 2022; Bou-Hamdan, 2022; Hassani and Silva, 2018).

2.2. Liquefied Petroleum Gas

The recent discovery of significant indigenous associated and non-associated gas reserves in Ghana's fields has increased prospects for diversifying the economy by utilizing the gas resource endowments to generate power to support the country's industrialization efforts, as well as develop new industries such as commercial scale fertilizer production and a petro-chemical industry, both of which have significant job creation implications (Duruigbo, 2008; Ezenwinyinya, 1976). Inadequate infrastructure, gas monetization limits, and a lack of essential knowledge, on the other hand, continue to be important roadblocks to the establishment of a thriving and sustainable indigenous gas sector (Bhattacharyya, 2018).

3. METHODOLOGY

The study examined the impact of petroleum energy price volatility on commodity prices in Ghana from 2011 to 2022. The variables to be used for the analysis include energy, grains, meat and cooking oil extracted as time series data from the international monetary fund (IMF) commodity database. To be able to investigate the long and short term association of the variables, co-integration technique and Vector Error Correction Model are used alongside granger causality test, co-integration was expanded and formalized by (Granger, 1969), and further extended to variance decomposition. The first step in doing any estimating technique is to ensure that all variables are stationary or co-integrated. The procedures in this study are to test the unit root, then the co-integration test, and finally the Granger causality analysis based on VECM. Variables in time series are noted to be non-stationary. The problem of spurious regression will arise if this time series is directly regressed. To avoid spurious regression, Augmented Dickey-Fuller (ADF) unit root test is first performed to determine whether variables are stable. If the series is not stationary, it is necessary to check whether the variable is single co-integrated and use alternative processing to make it so. Co-integration test is run to examine long-term relationships between variables.

3.1. Vector Error Correction Model

If one or more co-integrating vectors are obtained for a collection of variables, a VECM (Vector Error Correction Model) is a good estimating technique since it accounts for both short run changes in variables and deviations from equilibrium. The choice of one lag for determining VECM is also suggested by lag length criterion (Chang and Fang, 2001). The coefficient of the error correction term is a critical parameter in the estimation of the VECM dynamic model (ect-1), which quantifies the rate at which energy price volatility returns to its equilibrium state. Under VECM, all variables are treated as endogenous (ΔY) and exogenous (ΔX) in order to establish the long, short run relationship and joint effect of variables. VECM is used with one co-integrating equation for the estimation ordered by each variable, and using OLS in the e-views environment. Individual coefficients of differentiated terms are used to capture short run effects, whereas the VECM variable coefficients contains information on whether previous values of variables affect current values of the variables under investigation. The size and statistical significance of the error correction term's coefficient measures each variable's tendency to return to equilibrium. A significant coefficient indicates that past equilibrium errors are important in affecting current results, and it captures the long-term impact (Adams and Fuss, 2010). Table 1 below shows the description of the variables and the measures used for the study.

3.2. Model Specification

Vector Autoregression (VAR) is differenced to obtain a Vector Error Correction Model (VECM) by losing a lag.

$$\Delta Y_t = r + \sum_{i=1}^{K-1} \Phi_i \Delta Y_{t-i} + \sum_{i=1}^{K-1} \eta_i \Delta X_{t-i} + \sum_{m=1}^{K-1} \delta_m \Delta R_{t-m} + \lambda ECT_{t-1} + \mu_t \quad (1)$$

ECT_{t-1} = the lagged ordinary least square residual obtained from the long-run co-integrating equation and expressed as follows:

$$Y_t = \alpha + \eta_t X_{t-1} - \omega_1 R_{t-1}$$

$ECT_{t-1} = (Y_t - \eta_t X_{t-1} - \omega_1 R_{t-1})$, the co-integrating equation. The Error Correction Term (ECT) explains the previous period's deviation from long-run equilibrium which influences short-run movement in the dependent variable.

Table 1: Definition of variables

SRL	Variable	Notation	Description
1.	Petroleum energy	Energy	Fuel price index, 2016=100, crude oil, Brent crude, natural gas, heating oil, gasoline, IMF database
2.	Grain	Grains	Kg per dollar (\$), corn, oats, rough rice, soybeans, wheat, IMF database
3.	Meat	Meat	Index 2016=100 in metric ton, Beef, sheep, chevon, chicken, fish, IMF database
4.	Cooking oil	Cookoil	Index, 2016=100, in metric tons, frytol, soybeans oil, palm oil, IMF database

Authors' compilation, 2022

λ = coefficient of the ECT is the speed of adjustment. It measures the speed at which y returns to equilibrium after changes in X and R .

$$\begin{aligned} \Delta \text{Energy}_{it} = & \sigma + \sum_{t-1}^{K-1} \beta_i \Delta \text{Energy}_{t-i} + \sum_{t-1}^{K-1} \phi_i \Delta \text{Grains}_{t-i} \\ & + \sum_{m-1}^{K-1} \phi_m \Delta \text{Meat}_{t-m} + \sum_{g-1}^{K-1} \beta_g \Delta \text{CookingOil}_{t-g} \\ & + \lambda_1 \text{ECT}_{t-1} + \mu_{it} \end{aligned} \quad (2)$$

$$\begin{aligned} \Delta \text{Grain}_{it} = & \theta + \sum_{t-1}^{K-1} \beta_i \Delta \text{Energy}_{t-i} + \sum_{t-1}^{K-1} \phi_i \Delta \text{Grains}_{t-i} \\ & + \sum_{m-1}^{K-1} \phi_m \Delta \text{Meat}_{t-m} + \sum_{g-1}^{K-1} \beta_g \Delta \text{CookingOil}_{t-g} \\ & + \lambda_1 \text{ECT}_{t-2} + \mu_{it} \end{aligned} \quad (3)$$

$$\begin{aligned} \Delta \text{Meat}_{it} = & \partial + \sum_{t-1}^{K-1} \beta_i \Delta \text{Energy}_{t-i} + \sum_{t-1}^{K-1} \phi_i \Delta \text{Grains}_{t-i} \\ & + \sum_{m-1}^{K-1} \phi_m \Delta \text{Meat}_{t-m} + \sum_{g-1}^{K-1} \beta_g \Delta \text{CookingOil}_{t-g} \\ & + \lambda_1 \text{ECT}_{t-1} + \mu_{it} \end{aligned} \quad (4)$$

$$\begin{aligned} \Delta \text{Cooking}_{it} = & \alpha + \sum_{t-1}^{K-1} \beta_i \Delta \text{Energy}_{t-i} + \sum_{t-1}^{K-1} \phi_i \Delta \text{Grains}_{t-i} \\ & + \sum_{m-1}^{K-1} \phi_m \Delta \text{Meat}_{t-m} + \sum_{g-1}^{K-1} \beta_g \Delta \text{CookingOil}_{t-g} \\ & + \lambda_1 \text{ECT}_{t-1} + \mu_{it} \end{aligned} \quad (5)$$

- i. $K-1$ = the lag length reduced by one (1).
- ii. $\beta_i, \phi_i, \phi_m, \beta_g$ = short-run dynamic coefficients of the model's adjustment long-run equilibrium
- iii. λ_i = speed of adjustment parameter with a negative sign
- iv. ECT_{t-1} = the error correction term is the lagged value of the residuals obtained from the co-integrating regression of the dependent variable on the regressors. Contains long-run information derived from the long-run co-integrating relationship.
- v. μ_{it} = the stochastic error terms often called impulse.

Table 1 below show the description of the various variables and their measure used by the researchers in the study.

4. RESULTS AND DISCUSSION

4.1. Stationarity Test

Stationary tests of Energy, Grains, Meat, and Cooking oil series are conducted using the widely known ADF (Augmented Dickey-Fuller) unit root test. The results of the tests are displayed in Table 2. The test findings in Table 2 revealed that the three sequences' level values are non-stationary, and that the energy, grains, meat, and cooking oil sequences are first-order difference stationary in Table 3. First-order difference is applied to the four sequences in order to reduce data volatility. Then, as shown in the table above, four new series are obtained: Energy, grains, meat, and cooking oil their values are <5% which signifies that the sequence are now stationary.

Table 2: Augmented dickey-fuller test statistic (At level)

Variable	t-statistic	Prob.*
Energy	0.723939	0.9918
Grain	0.558841	0.9874
Meat	0.781563	0.9929
Cooking oil	1.681558	0.9995

Authors' computation, 2022

Table 3: Augmented Dickey-Fuller test statistic (At first difference)

Variable	t-statistic	Prob.*
Energy	-5.715531	0.0000
Grains	-5.915380	0.0000
Meat	-4.861482	0.0000
Cooking oil	-5.873314	0.0000

Authors' computation, 2022

4.2. Vector Autogressive Model (VAR) Estimation

The VAR model's initial problem is determining Endogenous Lag Intervals. The higher the Lag Intervals for the Endogenous variables, the more accurately it can depict the model's dynamic character (Adelman and Adelman, 1959; Zhang and Peng, 2022). The ideal lag period for the VAR model can be determined using variety of ways. As indicated in Table 4, this paper used Akaike Information Criteria (AIC) to calculate Lag Intervals for Endogenous as part of a thorough consideration of selecting Lag Intervals for Endogenous. Table 4 shows that the ideal lag duration for the VAR is three (3), based on an evaluation of various lag lengths.

4.3. Tests for Co-Integration

The key to a successful cointegration test is choosing the right type of cointegration test and lag order. The Johansen and Juselius (1990) methods are commonly used to examine the co-integration relationship between variables in a VAR model. The selected sequences are linear trend terms, and the cointegration equation's test form is merely intercept. The Johansen cointegration test on energy, grains, meat and cooking oil as shown in Tables 5 and 6 reveal that test results indicates there are cointegrating equations in both the trace test and the maximum eigenvalues and therefore the null hypothesis of no cointegrating equation in the model is rejected. VECM modelling can be carried out further on the basis of the existence of cointegration relationships. Energy is positioned as the dependent variable in the model, in the long run; grains, meat, and cooking oil are all individually positively associated with energy prices in Ghana, on the average ceteris paribus. The coefficients are therefore statistically significant at 5% level.

4.4. Estimation and Analysis of the Vector Error Correction Model (VECM)

Grain, meat, cooking oil, and energy all exhibit long-run equilibrium relationships, but they are in disequilibrium in the short term, according to cointegration research. VECM can be used to express the short-term imbalance and dynamic structure. Because VAR has a lag order of three (3), VECM should have a lag order of two (2). As a result, econometric software is used to create the VECM model. There is no association between meat and energy prices in Ghana in the long run, as shown by the second cointegration equation, which contradicts the general economic

Table 4: Determination of optimal Lag length (P) for the model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-805.4109	NA	15544647	27.91072	28.05282	27.96607
1	-572.7064	425.2876	8851.642	20.43815	21.14865*	20.71490*
2	-553.5145	32.42769*	7995.919*	20.32808	21.60698	20.82624
3	-537.3386	25.10052	8115.066	20.32202*	22.16931	21.04158
4	-528.4142	12.61718	10778.80	20.56601	22.98170	21.50697

Authors' computation, 2022

scenario. As a result, the equation's findings are displayed in Table 7 above (6) when the first equation is interpreted as the cointegration equation of the VECM model.

The cointegration equation is:

$$\text{Energy}_{t-1} = -0.843422\text{grains}_{t-1} - 0.256880\text{meat}_{t-1} + 0.090085\text{cooking oil}_{t-1} + 1.409700.$$

The previous year's deviation from long run equilibrium is corrected in the current period at a speed of 56%. A percentage change in grains is associated with an 84% increase on energy on the average ceteris paribus in the short run. This means that, an increase in energy prices will result in an increase in the prices of maize, rice, wheat, sorghum among other food items within the grains bracket. Also, there is a negative association between meat and energy at a percentage of 25%. A percentage change in cooking oil will result in a positive association of 9.0% on the average, ceteris paribus.

Table 8 shows that the VEC model's R^2 fitting degree is >0.05 and the AIC and SC criterion values are low, indicating that the model estimation is reasonable. The VAR (3rd order) model is re-established after obtaining the lag order of 3. Figure 1 depicts a variety of test stationarities of the VAR model as well as the mod of AR characteristic root reciprocal of the VAR model, indicating that the mod of reciprocal of each characteristic root is in the circle. That is, a lag order of three is appropriate, and the developed VAR model has passed the stability test. To assess for the adequacy of the VECM model, Roots of characteristic of the Polynomial stability condition tests for Model stability, Breusch-Godfrey Serial Correlation LM Test, Breusch-Pagan-Godfrey of Heteroskedasticity test, and Jarque-Bera test for Normality tests were used. The Roots of Characteristic Polynomial stability condition (Figure 1) revealed that the VECM model satisfies stability conditions since all of the roots are contained within the unit circle. The results also failed to reject the null hypothesis of no serial autocorrelation for all lags in the Godfrey LM test, as well as the null hypothesis of no heteroskedasticity, implying that the residuals are homoscedastic, for the Breusch-Pagan-Godfrey of Heteroskedasticity test. As a result, the model does not have serial autocorrelation or heteroskedasticity. Finally, we investigated the world's normality, and the findings (Figure 2) from Histogram residual and Jarque-Bera test of normality show that the null hypothesis is rejected for all residuals, indicating that they are all normal.

4.5. Granger Causality Test

The cointegration test implies a long-term equilibrium link between the variables, but more testing is needed to determine

Table 5: Unrestricted cointegration rank test (trace)

Hypothesized	Eigenvalue	Trace	0.05	Prob.**
No. of CE (s)		Statistic	Critical value	
None*	0.386791	53.56644	47.85613	0.0132
At most 1	0.210963	25.20159	29.79707	0.1544
At most 2	0.104629	11.45898	15.49471	0.1848
At most 3*	0.083370	5.048975	3.841466	0.0246

Trace test indicates 1 cointegrating eqn (s) at the 0.05 level

*Denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) P values

Authors' computation, 2022

Table 6: Unrestricted cointegration rank test (maximum eigenvalue)

Hypothesized	Eigenvalue	Max-Eigen	0.05	Prob.**
No. of CE (s)		Statistic	Critical Value	
None*	0.386791	28.36485	27.58434	0.0397
At most 1	0.210963	13.74260	21.13162	0.3865
At most 2	0.104629	6.410009	14.26460	0.5612
At most 3*	0.083370	5.048975	3.841466	0.0246

Max-eigenvalue test indicates 1 cointegrating eqn (s) at the 0.05 level

*Denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) P values

Authors' computation, 2022

Table 7: Estimation of vector error correction model (VECM) and analysis

Cointegrating Eq:	Co-int Eq1
Energy (-1)	1.000000
Grains (-1)	-0.843422 (0.01763) [-47.8396]
Meat (-1)	-0.256880 (0.03924) [-6.54677]
Cookoil (-1)	0.090085 (0.06727) [1.33906]
C	1.409700

the causal relationship. If variable X is useful in predicting Y, for example, if the regression of Y is based on previous values of Y and past values of X are added, the explanatory ability of the regression can be considerably improved. Then X can be referred to as the Granger cause of Y; otherwise, it is referred to as the non-Granger cause. The null hypothesis, namely the existence of the Granger cause, must be rejected because the probability value is smaller than the significant level of 5%. From Table 9 above, energy does not granger cause cooking oil, grains and meat, however, cooking oil, and meat granger cause energy by 5% each. Grains does not also granger cause cooking oil, but cooking oil granger causes grains by 5% significant level. Meat granger causes grains by 5%

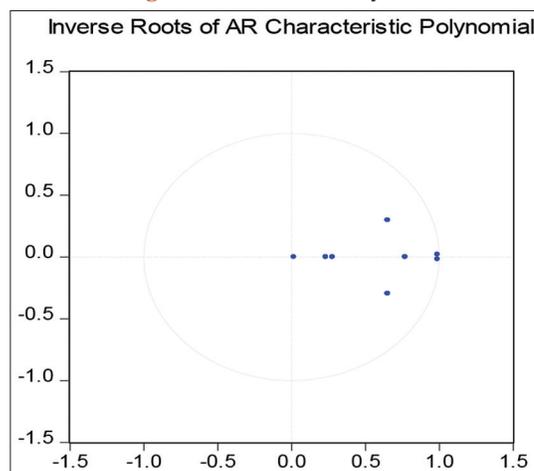
Table 8: VECM estimation results

Error correction:	D (ENERGY)	D (GRAINS)	D (MEAT)	D (COOKOIL)
CointEq1	-0.564609 (0.98435) [-0.57358]	-0.621798 (1.09852) [-0.56603]	0.780638 (0.45251) [1.72512]	0.262552 (0.51479) [0.51002]
D (ENERGY(-1))	2.310552 (2.71502) [0.85103]	2.448403 (3.02991) [0.80808]	-1.193736 (1.24810) [-0.95644]	-2.003869 (1.41987) [-1.41130]
D (ENERGY(-2))	-5.104973 (2.92076) [-1.74783]	-5.611596 (3.25951) [-1.72161]	-3.018063 (1.34268) [-2.24778]	-2.573728 (1.52747) [-1.68496]
D (GRAINS(-1))	-1.640290 (2.38661) [-0.68729]	-1.696614 (2.66341) [-0.63701]	1.053929 (1.09713) [0.96062]	1.813391 (1.24812) [1.45289]
D (GRAINS(-2))	4.275930 (2.55259) [1.67513]	4.700804 (2.84865) [1.65019]	2.593616 (1.17344) [2.21027]	2.257445 (1.33493) [1.69106]
D (MEAT(-1))	-1.016097 (0.63974) [-1.58831]	-1.198527 (0.71393) [-1.67876]	0.439454 (0.29409) [1.49429]	0.252684 (0.33456) [0.75527]
D (MEAT(-2))	0.573002 (0.68164) [0.84062]	0.705099 (0.76070) [0.92691]	0.182117 (0.31335) [0.58119]	0.348523 (0.35648) [0.97769]
D (COOKOIL(-1))	0.573781 (0.47397) [1.21058]	0.672043 (0.52894) [1.27054]	0.006554 (0.21789) [0.03008]	-0.023539 (0.24787) [-0.09496]
D (COOKOIL(-2))	0.239740 (0.45359) [0.52854]	0.214247 (0.50620) [0.42324]	0.184691 (0.20852) [0.88573]	-0.204317 (0.23722) [-0.86132]
C	1.552249 (0.82120) [1.89022]	1.616867 (0.91645) [1.76428]	0.873898 (0.37751) [2.31490]	0.811520 (0.42946) [1.88961]
R-squared	0.246900	0.247233	0.328975	0.149187
Akaike AIC	6.497278	6.716748	4.942935	5.200816
Schwarz SC	6.849403	7.068873	5.295060	5.552941

Table 9: Granger Causality Test

Null hypothesis:	Obs	F-statistic	Prob.
ENERGY does not granger cause COOKOIL	60	0.10236	0.9029
COOKOIL does not granger cause ENERGY		3.37739	0.0414
GRAINS does not granger cause COOKOIL	60	0.02038	0.9798
COOKOIL does not granger cause GRAINS		3.72302	0.0305
MEAT does not granger cause COOKOIL	60	3.27687	0.0452
COOKOIL does not granger cause MEAT		0.88493	0.4185
GRAINS does not granger cause ENERGY	60	2.72004	0.0747
ENERGY does not granger cause GRAINS		2.86048	0.0658
MEAT does not granger cause ENERGY	60	4.14444	0.0211
ENERGY does not granger cause MEAT		0.54044	0.5856
MEAT does not granger cause GRAINS	60	4.35179	0.0176
GRAINS does not granger cause MEAT		0.60181	0.5514

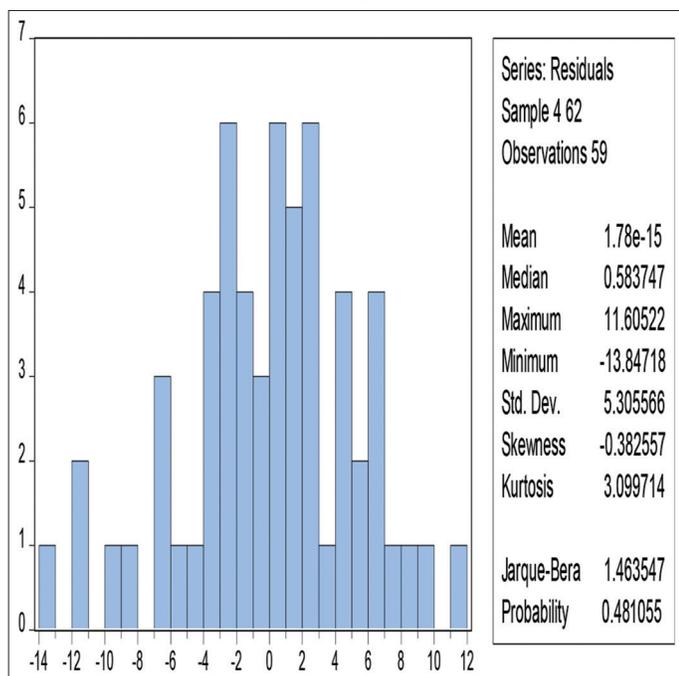
cent whereby grains do not granger cause meat.

Figure 1: Inverse Stability Test

4.6. Impulse Response Function and Variance Decomposition

Further analysis is carried out using the impulse response function and variance decomposition based on Vector Error Correction Model (VECM) to examine the dynamic effects of the model responding to various shocks, as well as how the effects are distributed across the four variables, and the findings for ten periods are produced. According to Granger test results, when standard deviation effects

Figure 2: Normality graph for VECM model



on energy are taken into account, the impacts of energy on grains, meat, and cooking oil are completely different. However, these swings are generally divergent, meaning that the effects of energy changes on grains, meat and cooking oil are long-lasting.

In Figure 3, a one standard deviation shock of energy has a positive impact on grains in the period of one (1) and two (2) periods. An increase in energy prices also saw an increase in grains from period one (1) through to period two (2). From the second period, the response gradually declines until period four (4) when it started appreciating in value.

Beyond the fifth (5th) period, energy rises above its steady state value and remained in the positive region. This means that, shocks in energy has short run and long run. In Figure 4, an innovation shock of energy impacted positively on meat to raise steady from period one (1) to two (2) and thereafter start to reduce from period two (2) to period three (3). Energy continued to rise from period two (2) to period six (6) and began declining from period six (6). Meat responded in the same trend, rising from period five (5) to period six (6). It can be concluded that, energy has a positive impact on meat in the short and long run. A one standard deviation shock to cooking oil initially increased the fluctuation on the graph from period one (1) to two (2) in Figure 5. As energy rises from period one through to period five (5) and then stayed positively steady in period six (6) at level, cooking oil declined from period two (2) to period three (3) and increase from period three (3) to period five (5), remained steady and began to slow down to period eight (8). Therefore, shocks to energy will have a symmetric impacts on cooking oil in the short and long runs.

4.7. Variance Decomposition

Variance decomposition analysis is frequently employed in the fields of economics and finance. The methodology entails breaking

Figure 3: Response of grains to energy

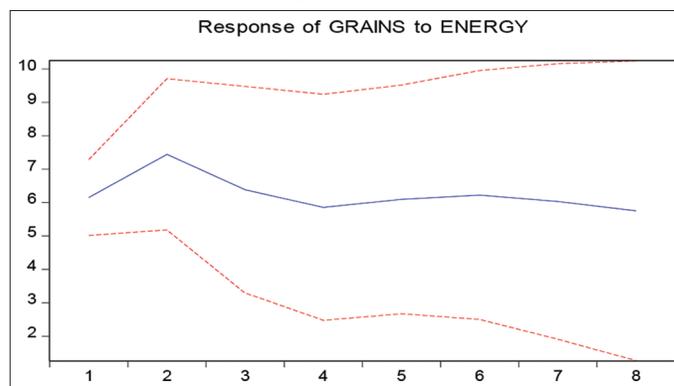


Figure 4: Response of meat to energy

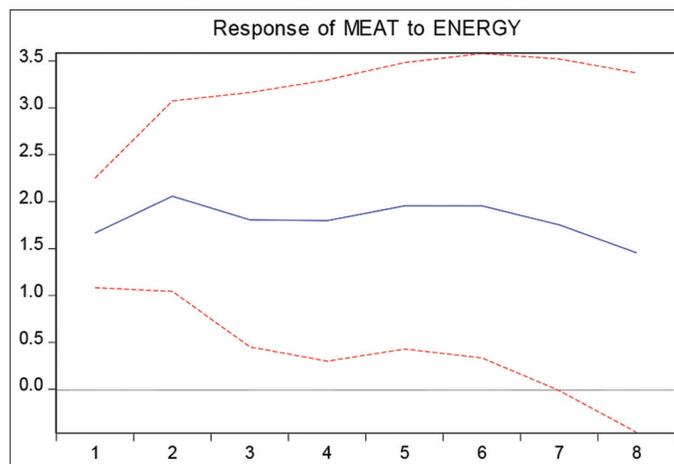
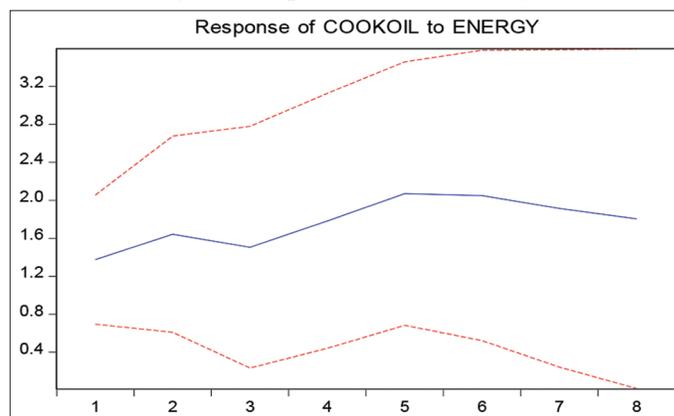


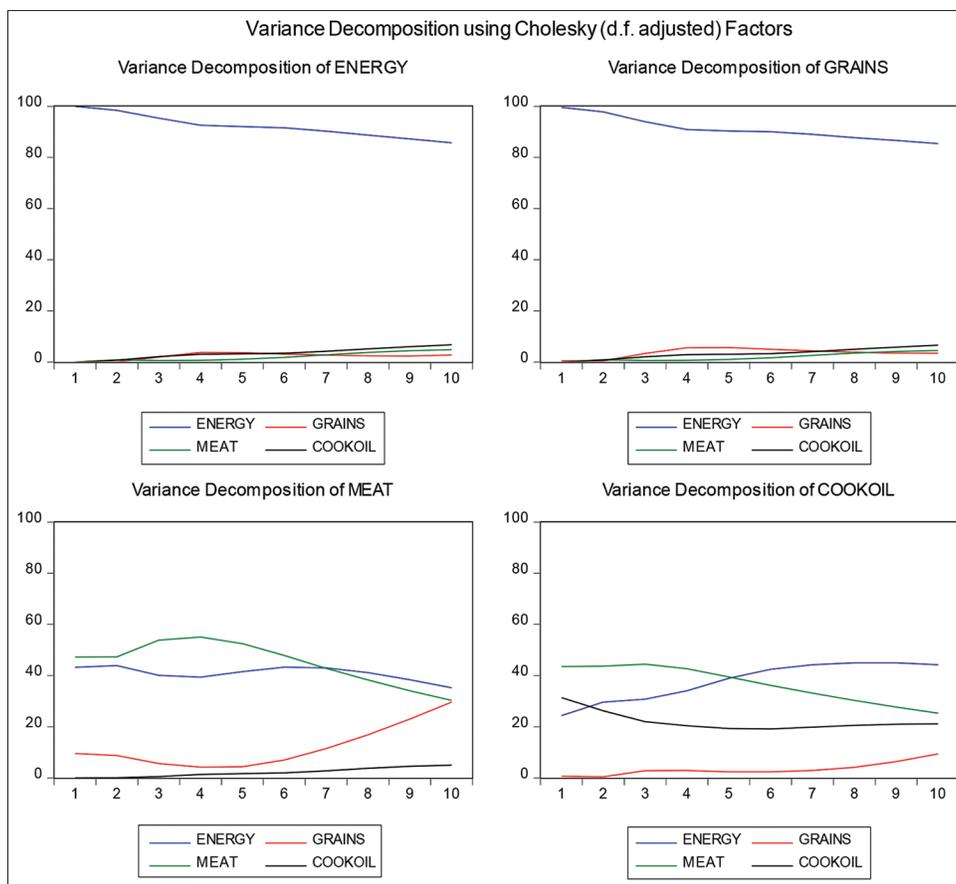
Figure 5: Response of cookoil to energy



down the total variance in an outcome variable. The methodology comprises determining which of a number of categories of factors has the greatest effect on a research outcome using quantitative analysis. The diagrams in figure six (6) explain the variance decomposition of the relationship between the dependent and independent variables.

4.8. Variance Decomposition of Energy

From Figure 6, shock to energy (own shock) accounts for 95.4% of the variation in energy in the short run, that is in third (3). In the short run, grain innovation can generate a 1.2% variation in energy fluctuation, meat a 0.6% shock in energy fluctuation, and

Figure 6: Variance decomposition using Cholesky (d.f. adjusted)

cooking oil a 2.1% variation in energy fluctuation. In the short run, the sum of all the factors' effects equals 100%. Shocks to energy, on the other hand, account for 85.7% of the variation in energy in the long run, a reduction of 10% from the short run; innovations in grains, on the other hand, accounted for 2.7% of the variation in energy in the long run, an increase of about 0.8% from the short run. In the long run, standard deviation shock to meat accounted for 4.8% variation in energy fluctuation.

4.9. Variance Decomposition of Grains

From Table 6, also, in the short run, shock to energy is 94%, and cause 3.4% fluctuation on grains. Impulse to grains can cause 3.4% fluctuation on grains (own shock), meat and cooking oil also account for 0.61% and 2.0% respectively on the volatility in grains. In the long run, energy accounts for about 85% volatility in grains whilst grains exhibit a 3.5% fluctuation on grains (own shock). Meat and cooking oil also accounts for 4.5% and 6.6% fluctuation in grains in the long run. From the analysis, energy contributed almost 13% higher in the short run to volatility in grains than in long run, grains accounted for almost the same amount in both the short and long run. Meat accounts for 0.6% in short run and 4.5% in the long run, cooking oil accounted for about 4.6% higher in the long run than in the short run.

4.10. Variance Decomposition of Meat

Energy in the short run accounted for an impulse response of 40.1% fluctuation in meat, grains also accounted for about 5.6%

whilst meat and cooking oil contributed to 53.8% and 0.5% respectively to the fluctuation of meat in the short run. In the short run, energy increased by 40.1% and declined by 35.2% in the long run; likewise, grains also declined by 5.6% in the short run and increased 29.6% in the long run. Meat had a decline in the long run accounting for about 30.3% fluctuation in meat. Cooking oil declined in the short run by 0.5% and increased by 4.9% in the long run.

4.11. Variance Decomposition of Cooking Oil

Finally, in the short run, impulse to energy of 30.7% accounts for the variation of the fluctuation in cooking oil. Grains, meat, cooking oil account for 2.8%, 44.4% and 21.9% respectively in the variation of the fluctuation in cooking oil. In long run, energy, grains, meat and cooking oil account for 44.2, 9.3, 25.3%, and 21.1% volatility in cooking oil. In the short run, energy declined by 30.7% and increased by 44.2% in the short run and increased by 9.3% in the long run. Meat also increased in the short run by 44.4% and declined by 25.3% in the long run. Innovation on cooking oil of 21.9% in the short run has reduced by 21.1% in the long run.

5. CONCLUSION AND POLICY IMPLICATIONS

On the basis of the VEC model, this paper established the impact of energy prices volatility on commodity price in Ghana, and investigated the causal links between the variables. The

findings show that, in both the short and long run, commodity price fluctuations are caused by energy prices whereas energy price fluctuations are not caused by commodity prices. There is granger causality between energy and some commodity items such as grains, meat and cooking oil. This is also demonstrated by the fact that the country's recent increase in commodity prices could be attributed to the unstable energy prices. The implications of the results show that, when global petroleum energy prices remain high, prices of food commodity items will continue to increase significantly as indicated in the VECM results. These rising energy prices also have direct impact on both the macro and micro economy with regards to inflation and exchange rates, which affect the financial position of the government and private sector investors. Also the relationship between energy prices and economic growth is affected due to fluctuation in economic patterns across the globe. The government will have to put in deliberate measures to reduce domestic energy taxes on petroleum products and improve upon its refinery plants since Ghana produces crude oil and has a number of oil fields currently in operation. New crude oil drilling techniques could also be adopted to extract more crude oil from the fields whilst enhancing energy conservation. Also, the impact of the Russia-Ukraine war has long-run effect on petroleum and commodity prices, and has direct influence on external debt and fiscal policy decisions for Ghana. It also significantly narrows the fiscal space and further erodes the current account balances of the government of Ghana in the long-term. There is an anticipated high cost of trade and inflation in the long-run if the standoff between Russia and Ukraine persist (Nezhyva and Mysiuk, 2022).

5.1. Limitation and Suggestions for Future Research

There is a direct relationship between petroleum prices, exchange rates, inflation, transportation fares and commodity prices, however, the study focused on the impact of petroleum energy price volatility on commodity prices in Ghana. Therefore, further studies on the impact of exchange rates on petroleum energy, and commodity prices, including transportation fares can be examined. Studies can also be conducted using weekly and monthly data to determine the frequency in which energy price fluctuations affect commodity prices.

REFERENCES

- Acquah, E. (2022), Ghana News Agency. Available from: <https://www.gna.org.gh/1.21434679> [Last accessed on 2022 Apr 18].
- Adams, Z., Fuss, R. (2010), Macroeconomic determinants of international housing markets. *Journal of Housing Economics*, 19(1), 38-50.
- Adelman, I., Adelman, F.L. (1959), The dynamic properties of the Klein-Goldberger model. *Journal of the Econometric Society*, 27(4), 596-625.
- Awaworyi-Churchill, S., Inekwe, J., Ivanovski, K., Smyth, R. (2022), Trends and correlations in commodity prices in the very long-run. *Energy Economics*, 108, 105933.
- Aygei, and Tetteh. (2022). Analysis of the effects of rainfall on production performance of a surface mine in Ghana. *Nigerian Journal of Technology*, 41(4), 760-766.
- Beckman, J., Borchers, A., Jones, C.A. (2013), Agriculture's supply and demand for energy and energy products. In: *Economic Information Bulletin*. Washington, DC: USDA-ERS. p.112
- Bell, B. (2020), US and UK labour markets before and during the Covid-19 crash. *National Institute Economic Review*, 252, R52-R69.
- Bhattacharyya, S.C. (2018), Mini-grids for the base of the pyramid market. A critical review. *Energies*, 11(4), 813.
- Boubaker, H., Raza, S. (2017), A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. *Energy Economics*, 64, 105-117.
- Bou-Hamdan, K.F. (2022), Applications of nanomaterials in the oil and gas industry. In: *Handbook of Research on Green Synthesis and Applications of Nanomaterials*. United States: IGI Global. p.173-198.
- Chang, T., Fang, W. (2001), Energy consumption, employment, output, and temporal causality: Evidence from Taiwan based on cointegration and error-correction modelling techniques. *Applied Economics*, 33(8), 1045-1056.
- Duarah, P., Haldar, D., Patel, A.K., Dong, C.D., Singhania, R.R., Purkait, M.K. (2022), A review on global perspectives of sustainable development in bioenergy generation. *Bioresource Technology*, 148, 126791.
- Duruigbo, E. (2008), The global energy challenge and nigeria's emergence as a major gas power. *Georgetown International Environmental Law Review*, 21, 395.
- Esmaili, A., Shokoohi, Z. (2011), Assessing the effect of oil price on world food prices. Application of principal component analysis. *Energy Policy*, 39(2), 1022-1025.
- Ezenwinyinya. (1976), *Economic Integration in West Africa*. United Kingdom: University of St. Andrews.
- Ferrucci, G., Jimenez-Rodriguez, R., Onorante, L. (2010), Food Price Pass-Through in the Euro Area. The Role of Asymmetries and Non-Linearities. Germany: European Central Bank. ECB Working Paper No. 1168.
- Finley, M., Krane, J. (2022), Reroute, Reduce or Replace? How the Oil Market Might Cope with a Loss of Russian Exports after the Invasion of Ukraine. Baker Institute for Public Policy. Rice University, Working Paper. Available from: <https://www.bakerinstitute>
- Forhad, A.R., Alam, R. (2022), Impact of oil demand and supply shocks on food-grain prices a Markov-switching approach. *Applied Economics*, 54(10), 1199-1211.
- Garza, M.G.G., Rodríguez, J.O., Palencia, E.P. (2022), The Effect of Energy Prices on Mexican Households' Consumption. Champaign: Springer. p.47-56.
- Granger. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Journal of the Econometric Society*, 424-438.
- Hassani, H., Silva, E.S. (2018), Big Data a big opportunity for the petroleum and petrochemical industry. *OPEC Energy Review*, 42(1), 74-89.
- Hemachandiran, A.S. (2022), Automation to find adulteration in downstream petroleum monitoring using machine learning. In: *Recent Advances in Manufacturing, Automation, Design and Energy Technologies*. Singapore: Springer Nature Singapore. p.415-423.
- Hill, S.E., Johns, P., Nakkash, R.T., Collin, J. (2022), From silos to policy coherence. Tobacco control, unhealthy commodity industries and the commercial determinants of health. *Tobacco Control*, 31(2), 322-327.
- Hochman, G., Rajagopal, D. (2014), Quantifying the causes of the global food commodity price crisis. *Biomass and Bioenergy*, 68, 106-114.
- Howe, P.D., Leiserowitz, A. (2013), Who remembers a hot summer or a cold winter? The asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the US. *Global Environmental Change*, 23(6), 1488-1500.
- Jebabli, I., Arouri, M., Teulon, F. (2014), On the effects of world stock market and oil price shocks on food prices: An empirical investigation based on TVP-VAR models with stochastic volatility. *Energy Economics*, 45, 66-98.
- Johansen, S., Juselius, K. (1990), Maximum likelihood estimation and

- inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, 52(2), 169-210.
- Khalifaoui, R., Boutahar, M., Boubaker, H. (2015), Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics*, 49, 540-549.
- Kojima, M. (2016), Fossil Fuel Subsidy and Pricing Policies: Recent Developing Country Experience. Washington, DC: World Bank. Policy Research Working Paper, 7531.
- Kollias, C., Tzeremes, P. (2022), The nexus between social unrest and economic growth in Middle East and Central Asia countries. *Review of Economics and Political Science*, 7(2), 74-86.
- Kpodar, K.R., Liu, B. (2022), The distributional implications of the impact of fuel price increases on inflation. *Energy Economics*, 108, 105909.
- Krishnan, R., Butt, B. (2022), "The gasoline of the future:" Points of continuity, energy materiality, and corporate marketing of electric vehicles among automakers and utilities. *Energy Research and Social Science*, 83, 102349.
- Leonard, A., Ahsan, A., Charbonnier, F., Hirmer, S. (2022), The resource curse in renewable energy: A framework for risk assessment. *Energy Strategy Reviews*, 41, 100841.
- Lewis, C.M. (2022), Capitalism, imperialism and the emergence of an industrialized global economy. In: *Evolutions of Capitalism: Historical Perspectives 1200–2000*. England: Bristol University Press. p.127.
- Luderer, G., Madeddu, S. (2022), Impact of declining renewable energy costs on electrification in low-emission scenarios. *Nature Energy*, 7(1), 32-42.
- Middendorf, B.J., Traoré, H., Middendorf, G., Jha, P.K., Yonli, D., Palé, P. (2022), Impacts of the COVID-19 pandemic on vegetable production systems and livelihoods: Smallholder farmer experiences in Burkina Faso. *Food and Energy Security*, 11(1), e337.
- Mlambo, C. (2022), Politics and the natural resource curse: Evidence from selected African states. *Cogent Social Sciences*, 8(1), 2035911.
- Nazlioglu, S., Soytaş, U. (2011), World oil prices and agricultural commodity prices: Evidence from an emerging market. *Energy Economics*, 33(3), 488-496.
- Nezhyva, M., Mysiuk, V. (2022), War in Ukraine challenges for the global economy Foreign trade. *Economics Finance Law*, 121(2), 16-25.
- Nyasapoh, M.A., Elorm, M.D., Derkyi, N.S.A. (2022), The role of renewable energies in sustainable development of Ghana. *Scientific African*, 16, e01199.
- Owulaku, A.K., Tetteh, A. (2022), The determinant of a five-stage downstream oil supply chain: An empirical study of Ghana. *Journal of Transport and Supply Chain Management*, 16, a609.
- Philip, L.D., Emir, F., Udemba, E.N. (2022), Investigating possibility of achieving sustainable development goals through renewable energy, technological innovation, and entrepreneur: A study of global best practice policies. *Environmental Science and Pollution Research International*, 29(40), 60302-60313.
- Ranum, P., Pena-Rosas, J.P., Garcia-Casal, M.N. (2014), Global maize production, utilization, and consumption. *Annals of the New York Academy of Sciences*, 1312(1), 105-112.
- Runge, C.F. (2022), Famine and free trade in the covid age: Lessons from the great Irish Famine. *Journal of World Trade*, 56(3), 453-470.
- Sands, R., Westcott, P., Price, J.M., Beckman, J., Leibtag, E., Lucier, G., McBride, W., McGranahan, D., Morehart, M., Roeger, E., Schaible, G., Wojan, T.R. (2011), Impacts of Higher Energy Prices on Agriculture and Rural Economies. *Economic Research Report* 1477-2017-4002.
- Saqib, N. (2022), Asymmetric linkages between renewable energy, technological innovation, and carbon-dioxide emission in developed economies non-linear ARDL analysis. *Environmental Science and Pollution Research*, 29(40), 60744-60758.
- Shanahan, M. (2022), An economic history of Australia. In: *Oxford Research Encyclopedia of Economics and Finance*. Oxford: Oxford University Press.
- Sovacool, B., Newell, P., Carley, S., Fanzo, J. (2022), Equity technological innovation and sustainable behaviour in a low-carbon future. *Nature Human Behaviour*, 6(3), 1-12.
- Vastolo, A., Calabrò, S., Cutrignelli, M.I. (2022), A review on the use of agro-industrial CO-products in animals' diets. *Italian Journal of Animal Science*, 21(1), 577-594.
- Walby, S. (2013), Finance versus democracy? Theorizing finance in society. *Work Employment and Society*, 27(3), 489-507.
- Wegerif, M. (2022), The impact of Covid-19 on black farmers in South Africa. *Agrekon*, 61(1), 52-66.
- Zhang, F., Peng, H. (2022), Influence of Tourism Economy on Air Quality-An Empirical Analysis Based on Panel Data of 102 Cities in China. *International Journal of Environmental Research and Public Health*, 19(7), 4393.