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The Risk Transfer among Exchange Rates, Energy Commodities, and Agricultural Commodity Prices in SADC Countries

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ABSTRACT

This paper investigates the risk transfer between exchange rates, energy commodities, and agricultural commodity prices in SADC nations from July 29, 2007, to December 18, 2022. The Time-varying parameter Vector Autoregression connectivity technique is specifically used. The total connectivity index for the specific network of energy commodities, currency rates, and agricultural commodities is 24.39%. The energy commodities index (crude oil and heating oil) and the ZAR were the largest shock transmitters, according to averaged dynamic connectedness. In contrast, two SADC currency markets (MWK and MZN), natural gas, and corn were net shock recipients. Furthermore, overall connection indices were shown to change dramatically with high sensitivity to crisis events, particularly the 2007/2008 crisis and the COVID-19 pandemic. As indicated by net directional connection, most energy commodities, as well as the Rand and the Pula, were persistent net transmitters over time. This is especially noteworthy given oil's direct impact on agricultural commodities. The findings of this paper are useful for policymakers who are attempting to maximize public benefit. Policymakers charged with developing policies for economically vulnerable segments of the population should use these findings to examine the potential impact of changes in energy prices on food and currency markets.

Keywords: TVP-VAR, SADC, Net Transmitters, Net Recipients
JEL Classifications: F31, G15, Q17, Q43

1. INTRODUCTION

After years of recording stable and low agricultural commodity prices, there have been noticeable swings in agricultural commodity prices since 2007 (Rezitis, 2015). A substantial body of research has identified a number of reasons why agricultural commodity prices fluctuate rapidly (Baffes, 2011; Wright, 2011; Irwin et al., 2009). A body of research claims that changes in the price of energy, especially crude oil, have an impact on other commodity markets (Ji and Fan 2012; Nazlioglu et al., 2013). Rezitis (2015) highlights the importance of this argument by asserting that fluctuations in energy and currency prices occur prior to fluctuations in the prices of agricultural commodities. Zhang and Joseph (2010) proposed that the frequency and volume of traded energy and agricultural commodity prices are influenced by the ongoing fluctuations in exchange rates. The Southern African Development Community (SADC) countries, according to Mishra and Kumar (2021: 28), heavily rely on commodity production, hence it is essential to investigate the possibilities of risk transfer between currency rates, energy prices, and agricultural commodity prices. According to Larisa (2015), commodity prices serve as a barometer for the global economy in addition to being a reliable indicator of the state of various country economies and domestic consumer pricing. As a shock to the commodity may be transmitted to the exchange rate, Sayed and Charteris (2022) state that volatility spillovers, which capture risk transmission, may also reflect the degree of connectedness between commodities and the exchange rate.

Adeleke and Awodumi (2022) argue that energy commodities are an integral input of the agricultural commodity production process. The literature has examined the connections between energy (particularly oil) and agricultural commodities (Nazlioglu and Soytas, 2012). The rise in the price of oil has been blamed for driving up the cost of agricultural products (Nazlioglu and Soytas, 2012). Therefore, a rise in oil prices could lead to an increase in the cost of agricultural products used as inputs in the production of alternative energy. Tiwari et al. (2022) argue that the oil market has an impact on agricultural product markets because the production of agricultural goods requires large amounts of oil for lighting, heating, food preparation on farms, transportation of inputs (labor, fertilizers, pesticides, etc.), tractors for clearing and cultivating land, and other vehicles.

Furthermore, Polat (2020: 405) emphasises this, stating that energy price shocks have a huge impact on the global economy through several avenues, including derivatives, commerce, and the stock market. Additionally, Wei et al. (2019) state that due to the same set of economic factors that affect both markets and inevitable cross-market arbitrage operations, the energy and agricultural markets may be interconnected. According to Wei et al. (2019), energy products like natural gas and oil are used in the production of agricultural goods. Consequently, the price of energy has a direct and indirect effect on the input and transportation costs of agricultural goods. In addition, Seghir et al. (2018: 71) contend that since the 2008 global food crisis and the subsequent rise in demand in the years 2010-2011, the agriculture commodities markets have been the primary focus and top priority of global concerns. Commodity prices for agriculture, which represent this priority, follow those for energy. Seghir et al. (2018) claim that prices for agricultural products increased between 2006 and 2008, and this increase was matched by an increase in energy prices globally. It also appears that exchange rates have an indirect impact on energy and agricultural commodity prices (Seghir et al., 2018).

Go et al. (2019: 455) believe that the estimation of commodity prices based on exchange rates is imperative for countries that import and export energy and agricultural commodities. Furthermore, Harri et al. (2009) reiterates by stating that currency markets are an imperative element of the traded energy and agricultural commodities as currency markets are anticipated to have a significant influence in the pricing of these commodities. Since speculative pressures on currency values frequently result in bubble-like patterns of volatility in the commodity markets, it is important to investigate how exchange rates might affect energy and agricultural commodity prices. Countries that import and export commodities frequently suffer significant losses because of changes in exchange rates (Go et al., 2019). As a result, when predicting the price of commodities, the exchange rate is frequently utilised as a proxy for macroeconomic factors.

According to Balcilar et al. (2016: 138), the main causes of rising agricultural commodity prices are the result of complex interactions between macroeconomic factors such as crude oil prices, exchange rates, rising food demand, sluggish growth in agricultural productivity, as well as national policy decisions. Changes in exchange rates affect the volume and frequency of the traded agricultural and energy commodities, and it is thus of utmost importance that the risk transfer among exchange rates, agricultural commodity and energy commodity prices is to be explored and investigated.

By means of quantitative research methodologies, this study intends to provide the most updated empirical evidence on the degree of risk transferred among exchange rates, energy commodity and agricultural commodity prices of selected SADC countries (Angola, Botswana, Malawi, Mozambique, and South Africa).

The risk transfer among exchange rates, energy commodities and agricultural commodity prices can be traced back to four economic channels, namely, energy demand and supply, expectations, terms of trade, and portfolio and wealth channel. Changes in the dollar exchange rate affect the prices paid to producers and consumers of oil, with the exception of the United States. These changes in prices affect the supply and demand for this energy commodity (Backus and Crucini, 2000). It's crucial to keep in mind that transactions pertaining to the demand channel are carried out in US dollars, which is the unit of currency used to display the price of an oil barrel (Qabhobho et al., 2023). Therefore, the demand for oil in countries that import it is determined by the price of a barrel after it is converted into the local currency. This pricing varies due to changes in the exchange rate. In particular, studies reveal a negative relationship between energy prices and exchange rates, which is explained by the dynamics of supply and demand in both markets. Furthermore, when considering changes in the oil supply, a drop in the value of the US dollar may result in a reduction in oil production and a rise in oil prices, helping oil-exporting nations like Angola to stabilize their export revenues. The demand for oil, however, may rise in importing countries like South Africa if the value of the US dollar declines since the cost of the commodity will decline relative to the local currency (Sun et al., 2021). Moreover, market volatility for agricultural and energy commodities can be adversely affected by crises, natural disasters, sudden changes in policy, or regime changes, according to Sun et al. (2021). Furuoka et al. (2023) argue that the Russian invasion of Ukraine has resulted in significant supply chain disruptions that have affected energy prices globally, ultimately impacting the volume of traded commodities. Shocks to energy prices thus affect agricultural commodities (Furuoka et al., 2023). Polat (2020) posits that significant geopolitical and financial events could have influenced commodity prices. The COVID-19 pandemic, for example, severely disrupted supply and demand, thereby driving up the price of energy commodities.

According to certain studies, there are two distinct ways that a shift in the price of oil could impact the exchange rate: The wealth effects and the terms of trade effects. The trading channel's parameters affect countries that produce and consume oil, albeit to differing degrees. In nations that export oil, positive terms of trade shock can trigger the "Dutch curse," which is typified by rising non-tradable prices and real currency appreciation. On the other hand, this effect should help the home country's real exchange rate appreciate if the non-tradable commodity remains a normal good (Tokarick, 2008). Prices rise as a result of increased demand for non-tradable goods brought on by higher earnings and wages in the primary sector. This increase then causes the real exchange rate to rise. Another important way that energy variations affect currency markets is through the wealth impact, which happens when an increase in oil prices transfers wealth from economies that import oil to those that export it. Due to portfolio imbalance, this affects the exchange rates of nations that import oil (Kilian and Park, 2009; Habib et al., 2016; Bodenstein et al., 2011; Qabhobho et al., 2023).

The empirical research conducted by Rezitis (2015), Burakov (2016), Balcilar and Bekun (2020), Dlamini (2019), Adeleke and Awodumi (2022), and others is closely related to the current study. Rezitis (2015) examines the dynamic relationship between oil prices, 24 agricultural commodities, and US dollar exchange rates between January 1980 and February 2010 using panel cointegration and causality analysis. The empirical findings provide compelling evidence for both the beneficial effects of a declining dollar on agricultural prices and the influence of oil prices on the pricing of agricultural commodities. The results of the panel causality analysis show that there are causal links between the price of oil and the price of agricultural products. Similarly, Burakov (2016) investigated the long- and short-term effects of changes in oil and currency rates on the prices of seven classes of agricultural products in Russia from 1999 to 2015 using the Granger Causality methodology. The results show that the impact of fluctuations in the price of oil and the value of the Russian ruble on agricultural prices is minimal.

Balcilar and Bekun (2019) examined the relationship between the price of oil, exchange rates, and agricultural commodities for the years 2006-2016 using the D-Y estimation technique. The empirical findings showed that weak spillover effects were seen among the variables under investigation, including rice, sorghum, price inflation, oil price, banana, cocoa, peanut, maize, soybean, and wheat—all of which are net transmitters of spillover. Adeleke and Awodumi (2022) used the D-Y technique to examine the relationship between the price of agricultural commodities and crude oil for the period spanning from January 1960 to August 2020. The findings demonstrated an asymmetric and bi-directional connectivity. Additionally, they discovered that crude oil is a net transmitter. Dlamini (2019) used the Toda-Yamamoto Granger causality test to examine the relationship between the price of crude oil and the Lilangeni-dollar exchange rate for the period of January 1st, 2005 to April 30th, 2018. Dlamini (2019) discovered a unidirectional causal relationship between the nominal exchange rate of Eswatini (SZL/USD) and the price of crude oil.

Unlike these papers, the current paper uses the time-varying parameters vector autoregression (TVP-VAR) model to address the limitations of the D-Y estimation technique. The rolling-window VAR based dynamic connectedness approach of Diebold and Yılmaz (2014) is essentially refined by the TVP-VAR based approach (Antonakakis et al., 2020; Korobilis and Yilmaz, 2018). This particular framework of analysis makes two key contributions possible. The first one has to do with using connectedness as a gauge for the coordination of market risk. To the best of our knowledge, no previous literature has looked into this particular angle in the case selected counties in SADC. The second contribution is related to the study of market risk coordination and employs an empirical method that improves upon common measurement flaws found in the standard rolling windows approach, including (i) the window length and forecast horizon being chosen arbitrarily, (ii) the inevitable inclusion of outliers distorting the data, and (iii) the loss of observations as we move across windows.

2. METHODOLOGY

2.1. Model Specification

To address the time-varying link between exchange rates, energy commodities, and agricultural commodities, TVP-VAR of Antonakakis et al. (2018) and Antonakakis et al. (2020) is utilised specially in this study. It builds on the work of Diebold and Yilmaz (2012) and Koop and Korobilis (2014) by reducing the burden of (i) losing valuable observations, (ii) arbitrary window size selection in most conditions, and (iii) sensitivity to outliers. The Bayesian information criterion (BIC)-specified TVP-VAR model of the lag length of order one is computed as follows:

$$y_t = B_t y_{t,1} + \varepsilon_t \,|\Omega_{t-1} \sim N(0, \Gamma_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1})\, v_t |\, \Omega_{t-1} \sim N(0, \rho_t) \tag{2}$$

Where y_t, y_{t-1} and ε_t are K×1 dimension vectors, but ε_t is of independently and identically distributed disturbance, and B_t and Γ_t denote K×K dimensional matrices. $vec(B_t)$ and v_t are $K^2 \times 1$ dimensional vectors while ρ_t is a $K^2 \times K^2$ dimensional matrix. Ω_{t-1} demonstrates all accessible information up to t–1. This model enables all B_t parameters and the series relationship to alter over time. It should also be noted that the variance-covariance matrices (Γ_t, ρ_t) fluctuate with time. Numerous studies have demonstrated that variance-covariance varies over time due to the varied nature of markets and their participants, as well as investment risk in the setting of financial markets.

Koop et al. (1996), Pesaran and Shin (1998), and Diebold and Yilmaz (2014) developed generalised impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) based on the time-varying coefficient and variance-covariance matrices retrieved from the TVP-VAR. As a result, the TVP-VAR must be translated into its vector moving average (VMA) representation using the Wold representation theorem, as shown below.

$$y_t = \Phi'\left(\Upsilon_t\left(Z_{t-2} + \xi_{t-1}\right) + \xi_t\right) \tag{3}$$

$$\xi_t = \Phi'(\Upsilon_t\left(Z_{t-3} + \xi_{t-2}\right) + \xi_{t-1}) + \xi_t) \tag{4}$$

$$\vdots \tag{5}$$

$$\Phi'(\Upsilon_t^{k-1} Z_{t-k-1} + \sum_{j=0}^{k} \Upsilon_t^{j} \xi_{t-j}) \tag{6}$$

Where y_t is an m × m dimensional matrix, ξ_t is an m × m dimensional vector, and Φ is an m × m dimensional matrix.

As k approaches ∞, taking the limit produces.

$$y_t = \lim_{k\to\infty} \Phi'\left(\Upsilon_t^{k-1} Z_{t-k-1} + \sum_{j=0}^{k} \Upsilon_t^{j} \xi_{t-j}\right) = \sum_{j=0}^{\infty} \Phi' \Upsilon_t^{j} \xi_{t-j}, \tag{7}$$

Following

$$y_t = \sum_{j=0}^{\infty} \Phi' \Upsilon_t^j \Phi \tau_{t-j} \; \Lambda_{jt} = \Phi' \Upsilon_t^j \Phi \quad (8)$$

$$y_t = \sum_{j=0}^{\infty} \Lambda_{jt} \tau_{t-j} \quad (9)$$

Where Λ_{jt} is an m × m dimensional matrix.

The GIRFs($\psi_{ij,t}^{g}(k)$) shows how all variables react to a shock in variable i. The differences between a K-step-ahead forecast where variable i is shocked and one where variable i is not shocked are computed due to the usage of a non-structural model. The discrepancy can be explained by a shock in variable i, which can be approximated using the formula.

$$GIRF_t\left(K, \iota_{i,t}, \mathrm{I}_{t-1}\right) = E(y_{t+k} | \tau_{i,t} = \iota_{i,t}, \mathrm{I}_{t-1}) - E(y_{t+k} | \mathrm{I}_{t-1}) \quad (10)$$

$$\psi_{ij,t}^{g}(k) = \sum_{ii,t}^{-\frac{1}{2}} \Lambda_{k,t} \sum_t \tau_{i,t} \sum_{ii,t}^{-\frac{1}{2}} \iota_{i,t} \qquad \sum \iota_{i,t} = \sum_{ii,t}^{\frac{1}{2}} \quad (11)$$

$$\psi_{i,t}^{g}(k) = \sum_{ii,t}^{-\frac{1}{2}} \Lambda_{k,t} \sum_t \tau_{i,t} \quad (12)$$

Where $\iota_{i,t}$ is the chosen vector, with one at the $\iota_{i,t}$ and zero anywhere else, and k is the anticipated period. After that, the $GFEVD(\tilde{\psi}_{ij,t}^{g}(k))$ is computed, which may be translated as the forecast error variance sharing one variable explained on others. After that, the variance shares are normalized so that each row equals one, showing that all the variables account for all of the variation in the variable produced by the I prediction error. This is performed by doing the following:

$$\tilde{\psi}_{ij,t}^{g}(k) = \sum_{t=1}^{k-1} \Psi_{ij,t}^{2,g} / \sum_{j=1}^{m} \sum_{t=1}^{k-1} \Psi_{ij,t}^{2,g} \quad (13)$$

With $\sum_{j=1}^{m} \tilde{\Psi}_{ij,t}^{g}(k) = 1$ and $\sum_{i,j=1}^{m} \grave{E}_{ij,t}^{g}(k) = m$

To begin, entire directional connectivity TO others is referred to as variable i transmitting its shock to all other variables j in the following manner:

$$C_{i \to j,t}^{g}(k) = \sum_{i,j=1}^{m} \tilde{\psi}_{ji,t}^{g}(k) \quad (14)$$

Additionally, determine the total directional interconnectedness FROM others, which is the shock variable i receives from variables j:

$$C_{i \leftarrow j,t}^{g}(k) = \sum_{j=1, i \neq j}^{m} \tilde{\psi}_{ij,t}^{g}(k) \quad (15)$$

The total directional connectedness TO others is subtracted from the total directional connectedness FROM others to calculate the NET total directional connectivity, which can be viewed as the influencing variable I has on the examined network. Greenwood-Nimmo, Nguyen, and Shin (2015) also compute the influence index (II) as follows:

$$C_{i,t}^{g} = C_{i \to j,t}^{g}(k) - C_{i \leftarrow j,t}^{g}(k) \quad (16)$$

$$II_{i,t} = \frac{C_{i \to j,t}^{g}(k) - C_{i \leftarrow j,t}^{g}(k)}{C_{i \to j,t}^{g}(k) + C_{i \leftarrow j,t}^{g}(k)} \quad (17)$$

$$AII_{i,t} = \left| II_{i,t} \right| \quad (18)$$

If a variable's NET total directional connection is positive, it means the network is more affected by the variable than the other way around. Network is driving variable i if the NET total directional connectedness is negative. The measure provided by the $II_{i,t}$ function is normalised between 1 and +1 and can be interpreted similarly. By computing the net pairwise directional connectedness (NPDC), pairwise impact index (PII), and its absolute version (APII), the NET total directional connectivity is further divided to study bidirectional relationships as:

$$NPDC_{\boldsymbol{ij}}(K) = \tilde{\psi}_{jit}(K) - \tilde{\psi}_{ijt}(K) \quad 19)$$

$$PII_{ij}(K) = \frac{NPDC_{\boldsymbol{ij}}(K)}{\tilde{\psi}_{jit}(K) + \tilde{\psi}_{ijt}(K)} \quad (20)$$

$$APII_{ij}(K) = \left| PII_{ij}(K) \right| \quad (21)$$

The PII_{ij} (K) standardises the $NPDC_{ij}$ (K) to be between −1 and +1. The NPDC identifies whether variable i is driving or being driven by variable j. A measure for determining market interconnection is the total connectedness index (TCI), as demonstrated.

$$C_t^{g}(k) = \frac{\sum_{i,j=1, i \neq j}^{m} \tilde{\psi}_{ij,t}^{g}(k)}{\sum_{i,j=1}^{m} \tilde{\psi}_{ij,t}^{g}(k)} = \frac{\sum_{i,j=1, i \neq j}^{m} \tilde{\psi}_{ij,t}^{g}(k)}{m} \quad (22)$$

The fundamental issue with this statistic is that it is difficult to define what exactly constitutes a high level of connectivity. The own variance shares are consistently greater than or equal to all cross-variance shares, according to Monte Carlo simulations. This suggests that the TCI is not at [0,1] but rather between $[0, \frac{m-1}{m}]$, making interpretation problematic. To enhance its interpretability, the TCI has to be significantly modified as:

$$C_t^{g}(k) = \left(\frac{m-1}{m}\right) \frac{\sum_{i,j=1, i \neq j}^{m} \tilde{\psi}_{ij,t}^{g}(k)}{m} \quad (23)$$

$$= \frac{\sum_{i,j=1, i \neq j}^{m} \tilde{\psi}_{ij,t}^{g}(k)}{m-1} \quad (24)$$

$$0 \leq C_t^{g}(k) \leq 1 \quad (25)$$

The pairwise connectedness index (PCI), a decomposed version of the TCI, assesses the degree of connectivity between two variables, i and j.

$$C_{ijt}^{g}(k) = 2 \frac{\tilde{\psi}_{ij,t}^{g}(k) + \tilde{\psi}_{ji,t}^{g}(k)}{\tilde{\psi}_{ii,t}^{g}(k) + \tilde{\psi}_{ij,t}^{g}(k) + \tilde{\psi}_{ji,t}^{g}(k) + \tilde{\psi}_{jj,t}^{g}(k)} \quad (26)$$

$$0 \leq C_t^{g}(k) \leq 1 \quad (27)$$

The degree of bilateral interconnectivity between variables *i* and *j* that is hidden by the TCI is represented by this measure, which has a range of [0,1]. The APII and PCI are used in this study to examine, respectively, the credibility assumptions of the asymmetric shock and financial assets. When the APII and PCI are small, variables i and j are more likely to be in the same OCA. Using bootstrapping, the average of each OCA metric and its confidence interval are determined.

2.2. Data Sources and Description

The study's chosen period, 2007-2022, encompasses economic shocks that affected currency, energy, and agricultural prices in SADC nations. Furthermore, the period exhibits the stable period before the economic shocks occurred, i.e., 2007 to show the variation in these market (s) prices. These shocks include the Covid-19 pandemic in 2020, the Global Financial Crisis (GFC) in 2007-2008, the emergency of biofuel production, and others (Balcilar and Bekun, 2020). The correlation between the world's currency, energy, and commodity markets has grown more complex because of these economic shocks.

This study employs an extended joint connectedness approach based on time-varying parameter vector autoregression (TVP-VAR) to characterize the connectedness of 2 agricultural commodities (wheat and corn), exchange rates, and energy prices (crude oil, natural gas, and heating oil) throughout the period of July 2007-December 2022. The employed model does not necessarily require validation from diagnostic techniques, however, because this study will be making use of a time series data, then a stationarity test is a must. This analysis is based on a weekly data set that includes the prices of two agricultural commodities from *investing.com*, as well as exchange rates and energy prices from *investing.com*.

3. RESULTS

3.1. Preliminary Statistics

Figure 1 demonstrates the graphs of exchange rates, energy commodities, and agricultural commodity prices and its returns for the four selected SADC countries. With respect to energy commodities, crude oil and heating oil prices exhibit a sluggish trend whereas natural gas demonstrates a downward moving trend. Crude oil, natural gas and heating oil exhibit a sharp decline in prices during the BREXIT in 2016 and COVID-19 in 2020 periods, however, the COVID-19 turmoil period seems to be more severe in relation to the BREXIT crisis period. Furthermore, amid the COVID-19 turmoil period, agricultural commodity prices have experienced a gradual decline. Therefore, it can be concluded that energy commodities are positively correlated to agricultural commodities during economic downturns.

On the other hand, all four selected SADC countries exchange rate exhibit an upward moving trend and that signifies depreciating currencies against the US dollar for the period at hand. All energy commodities, agricultural commodities and exchange rates returns exhibit volatility clustering with excess shocks in the COVID-19 turmoil period (except for wheat returns). Considering that both SADC currency markets and energy commodities are losing value simultaneously that implies investors can hedge or diversify by combing the assets from these two markets.

All agricultural and energy commodity markets (except for natural gas), as well as currency rates markets have positive means signifying a positive performance, wherein natural gas suggests a negative performance as presented in Table 1. All agricultural and energy commodity markets show negative skewness implying a negative performance. Contrary, all currency rates markets show positive skewness signifying a positive performance. All agricultural and energy commodity markets, as well as currency rates markets kurtosis values are above three, which signifies leptokurtic distributions. However, it is paramount to note an upward moving trend of exchange rate prices signifies the depreciation in domestic currency; therefore, positive means imply negative performance. According to the Jarque-Bera Statistics (JB) test, the time series is not evenly distributed as presented in JB Probability in Table 1. According to the accepted unit root tests, all data returns are stationary, as demonstrated by the Augmented Dickey Fuller (ADF).

3.2. Main Results

3.2.1. Averaged dynamic connectedness results

The results of the averaged dynamic connectedness are presented in Table 2. From Table 2 below, it is evident that for the specific network of agricultural commodities, exchange rates and energy commodities, the average value of the overall connectedness

Table 1: Descriptive statistics

Data	Mean	Median	SD	Skewness	Kurtosis	JBProbability	ADF
Agricultural commodity markets							
Wheat	0.090	0.061	4.698	−1.053	14.434	0.00	−28.681***
Corn	0.116	0.257	4.147	−0.400	6.086	0.00	−29.695***
Energy commodity markets							
Coil	0.046	0.4196	5.474	−0.632	9.081	0.00	−28.623***
Hoil	0.089	0.1048	4.555	−0.336	6.703	0.00	−29.918***
Ngas	−0.025	−0.077	7.0587	−0.169	4.1069	0.00	−31.222***
Currency rates markets							
EXRAOA	0.191	0.001	1.359	3.173	31.890	0.00	−17.478***
EXRZAR	0.104	−0.034	2.309	0.343	5.471	0.00	−31.748***
EXRMZN	0.108	0.000	1.857	2.634	55.892	0.00	−20.663***
EXRMWK	0.217	0.007	1.937	10.948	231.129	0.00	−14.316***
EXRBWP	0.106	0.000	1.471	1.035	10.539	0.00	−32.330***

Notes: Asterisks ***, **, * respectively denote 1%, 5%, and 10% levels of significance. ADF; Augmented dickey fuller, SD: Standard deviation.

Figure 1: Time series plots of prices and returns

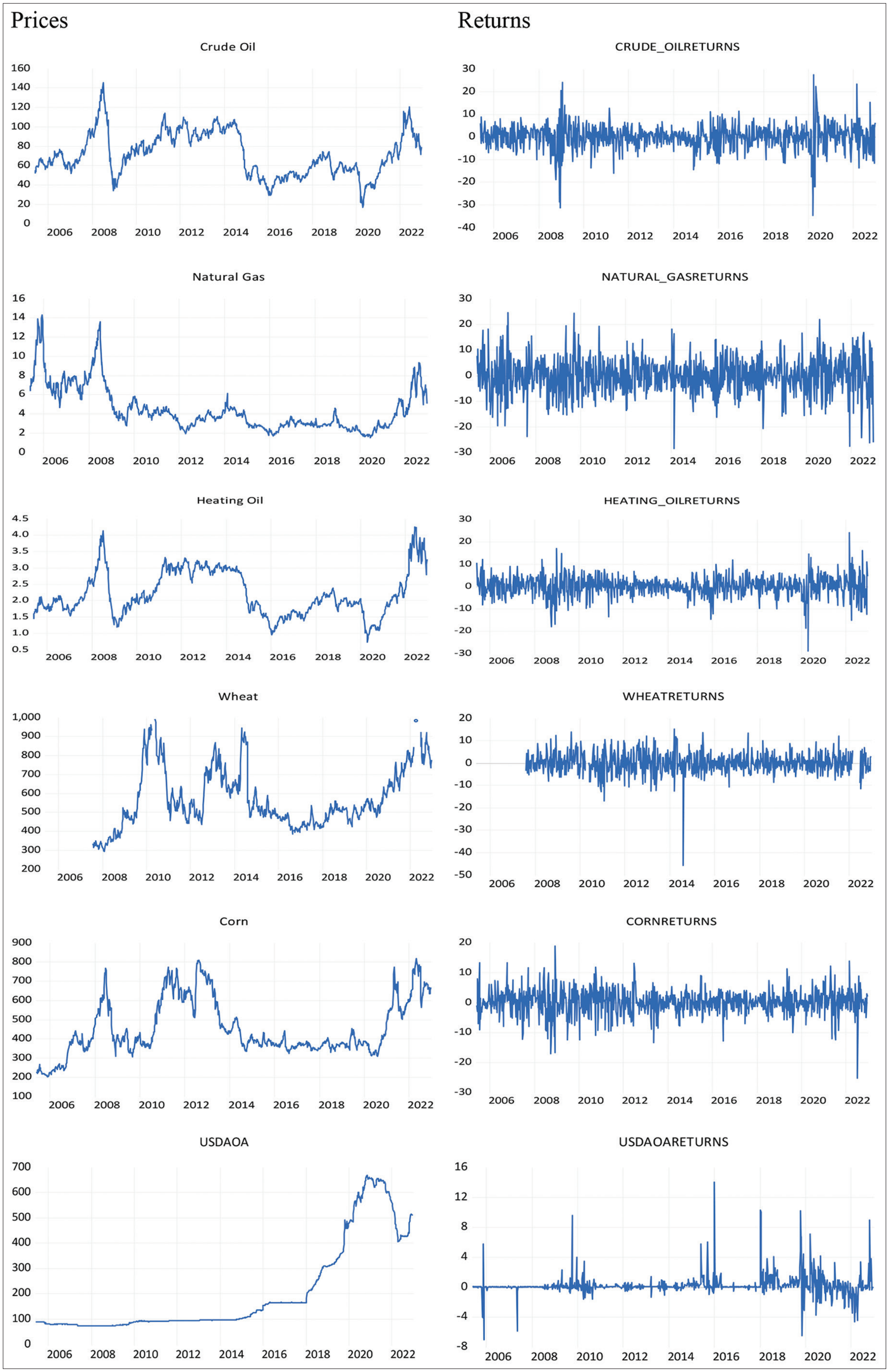


Figure 1: (*Continued*)

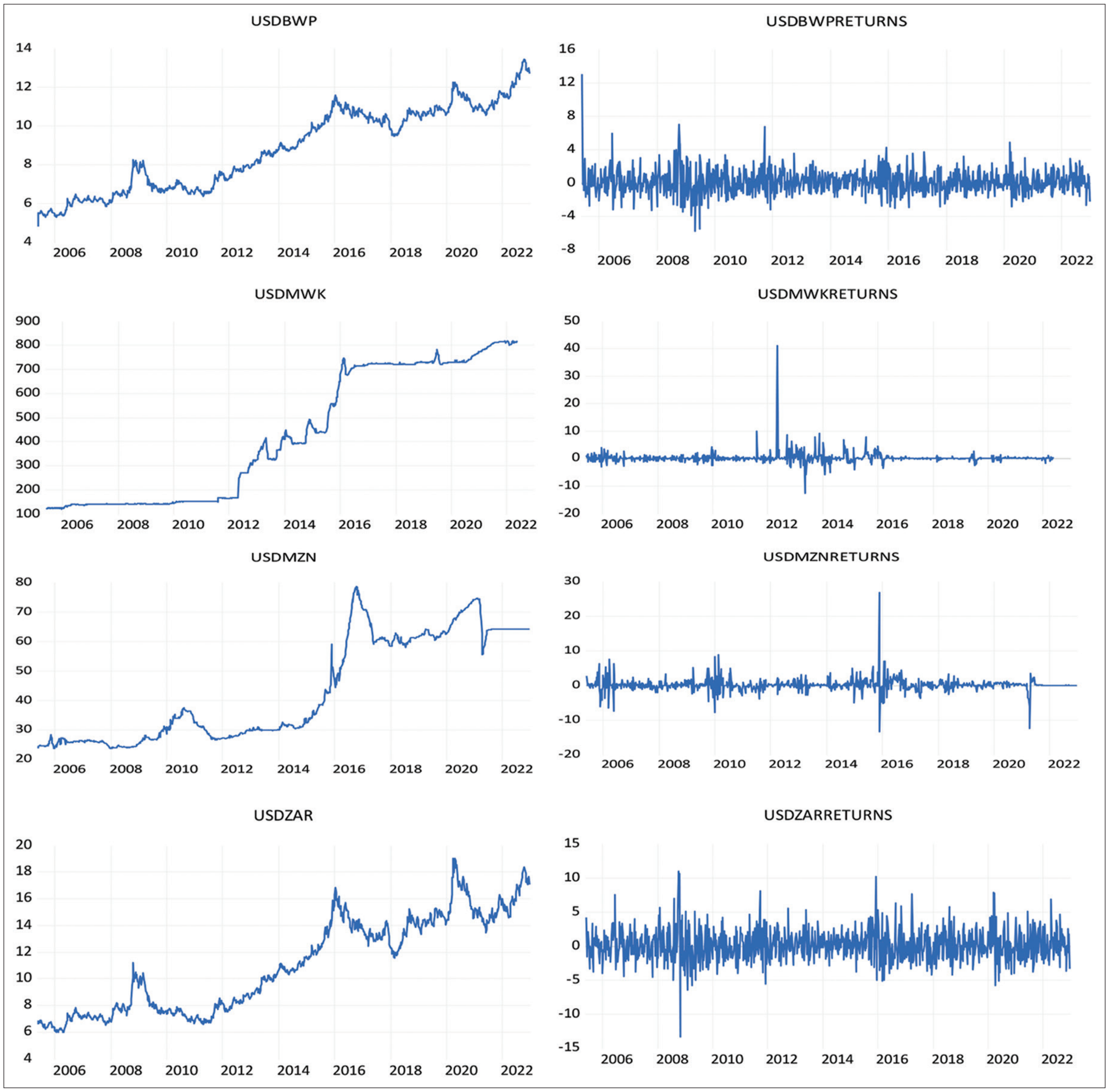


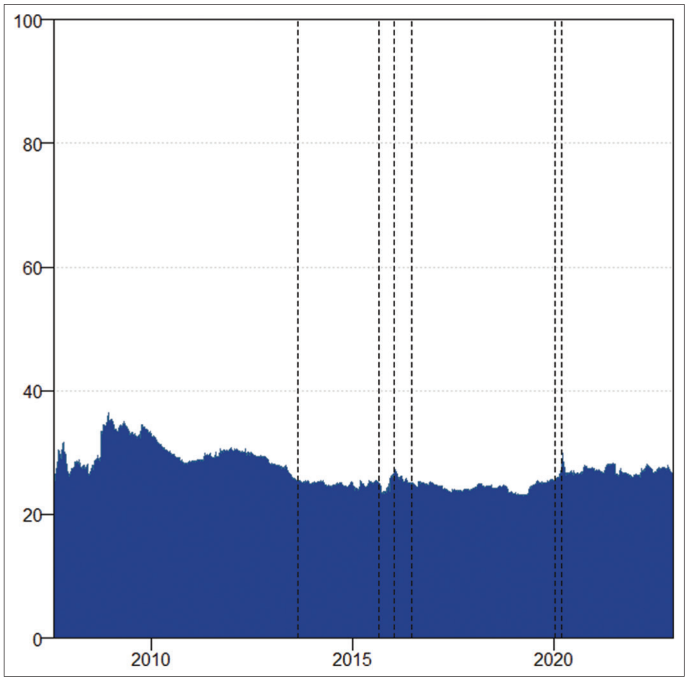
Table 2: Averaged dynamic connectedness

Variables	Crude	Ngas	Hoil	Wheat	Corn	AOA	BWP	MWK	MZN	ZAR	FROM others
Crude	53.11	2.86	38.51	0.16	0.63	0.39	1.28	0.99	0.35	1.71	46.89
Ngas	5.02	85.49	5.53	0.94	0.36	0.62	0.72	0.4	0.14	0.79	14.51
Hoil	38.74	2.77	51.62	0.17	0.64	0.6	2.13	0.51	0.19	2.63	48.38
Wheat	0.1	0.3	0.29	86.03	11.66	0.61	0.35	0.16	0.14	0.36	13.97
Corn	0.99	0.11	1.19	11.37	83.74	0.61	0.69	0.28	0.56	0.45	16.26
AOA	0.49	0.43	0.37	0.44	0.45	95.81	0.35	0.6	0.22	0.82	4.19
BWP	1.13	0.48	2.25	0.38	0.61	0.4	55.05	0.19	0.47	39.04	44.95
MWK	2.21	0.52	1.01	0.3	0.2	0.77	0.21	93.7	0.8	0.29	6.3
MZN	0.55	0.11	0.15	0.31	0.25	0.42	0.78	0.88	95.91	0.63	4.09
ZAR	1.27	0.34	2.54	0.1	0.29	0.56	38.8	0.23	0.19	55.68	44.32
TO others	50.51	7.91	51.85	14.17	15.09	4.97	45.32	4.25	3.06	46.73	243.87
Inc. own	103.62	93.4	103.47	100.2	98.83	100.79	100.37	97.95	98.98	102.4	TCI
NET	3.62	−6.6	3.47	0.2	−1.17	0.79	0.37	−2.05	−1.02	2.4	24.39
NPDC	3	8	4	4	7	2	4	7	6	0	

NPDC: Net pairwise directional connectedness

index is 24.39%. This signifies that 24.39% of the forecast error variance in this network of markets is because of cross-market innovations. As a result, idiosyncratic impacts are responsible for around 75.61% of the system's forecast error variance. Already existing literature suggests that agricultural commodities, energy commodities and exchange rates alter significantly with high

Figure 2: Dynamic total connectedness

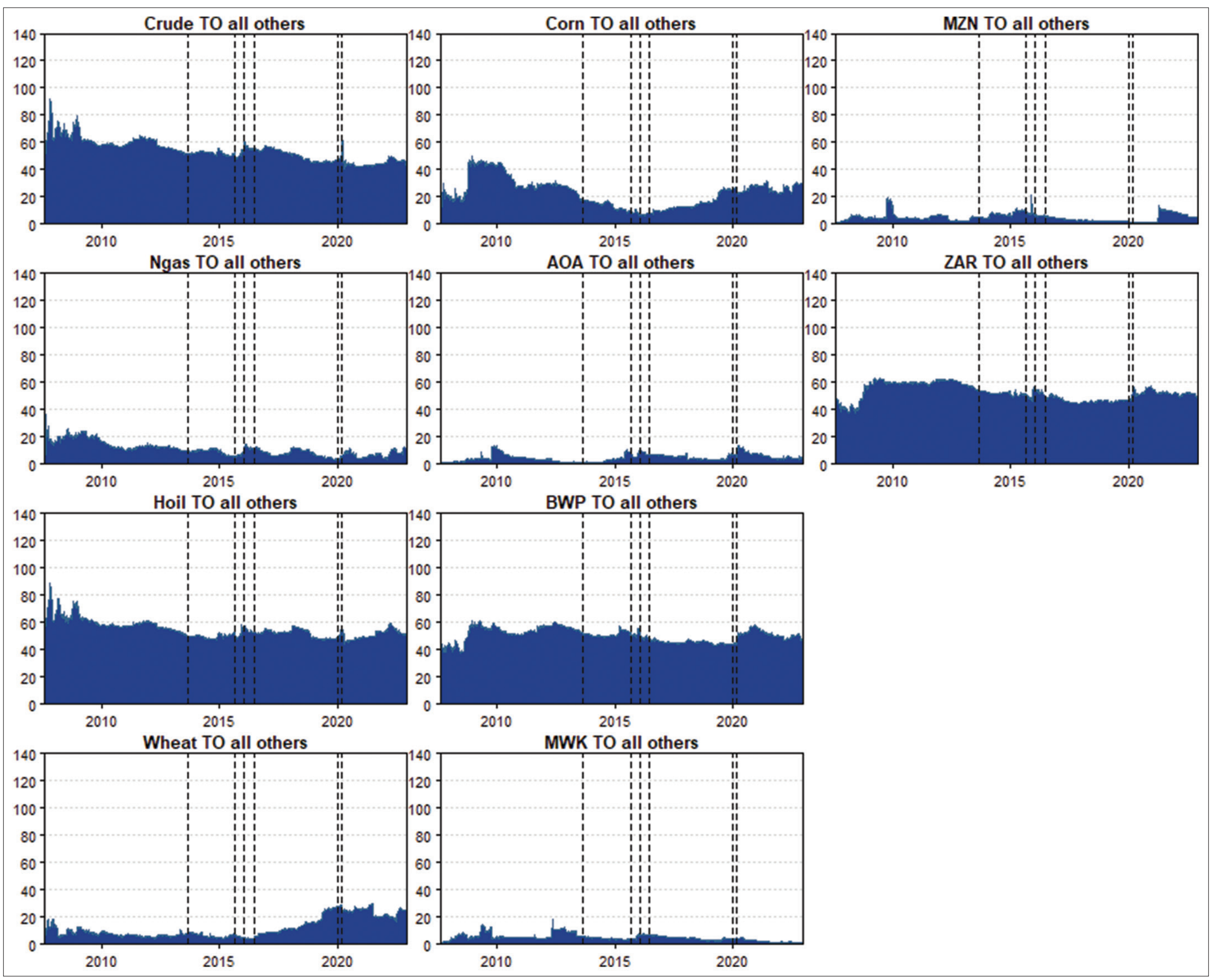


sensitivity to crisis situations, particularly the 2007/2008 crisis and the COVID-19 pandemic (Balcilar et al., 2016).

According to the averaged dynamic connectedness, the energy commodity index (crude oil and heating oil) and ZAR were the greatest shock transmitters (positive shocks). In contrast, two SADC currency markets (MWK and MZN), natural gas, and corn were net shock recipients (negative shocks). All negative recipients can serve as a good safe-haven and hedging for investments depending on the market condition. This study argues that the most energy commodities, as well as two currencies (Rand and the Pula) were persistent net transmitters over time, as shown by the net directional connectedness. This is especially significant given the direct influence oil on agricultural commodities.

The study's findings suggest that risk minimisation is feasible in a network of energy commodities, currency rates, and agricultural commodities. Considering this, the spillover connectivity does not imply a high degree of integration and are likely to increase investors' confidence. The spillover connection is also impacted by economic events with multiple shock recipients acting as other

Figure 3: Total directional connectedness to others



than realised volatility, safe-haven or to hedge (realised) risk transfer from too many shocks.

3.2.2. Dynamic total connectedness

It should be noted that average results are generally needed to summarize the underlying interdependence and are ineffective for helping to investigate the connections within a network of variables when taking important economic events into account. Consequently, an investigation of the dynamic technique is required. Qabhobho et al. (2023) argue that a dynamic technique is necessary for the analysis of the TCI's evolution and the presentation of how the importance of various variables within the network under study can change over time (for instance, from a net receiver to a net transmitter or vice versa).

The dynamic total connectedness results are displayed in Figure 2 below. The intertemporal evolution of the total connectivity index (TCI) is depicted in the figure below.

The study sample duration is observed to have a considerable impact on the total connectivity indices. Higher TCI values can be seen in the graph in 2007, 2008 and 2009 (amid the global financial crisis), 2015, stagnant TCI values are displayed (during the euro migrants' period), and 2020 slightly higher TCI values but less severe compared to 2007, 2008 and 2009 TCI values (during the COVID-19 pandemic), which indicate severe connectedness between the relevant financial time series.

The connection index reached its highest level in 2008/2009, slightly below the 40% mark and as low as 22%.

The below Figures 3 and 4 show the shock transmission from all other system variables to a single variable as well as the transmission from a single variable to all other underlying variables. The findings reveal that only crude oil, corn, ZAR, HOil and BWP are the greatest transmitters of shock and risk to other variables in the study, with crude oil particularly transmitting at peak just slightly below 100%. ZAR, HOil and BWP transmitting on average to other variables just slightly above 60%. MZN, Ngas, AOA, Wheat and MWK are the least transmitters of risk or shock to other variables, averaging around about 20% of directional connectedness to other variables.

Figure 4: Total directional connectedness from others

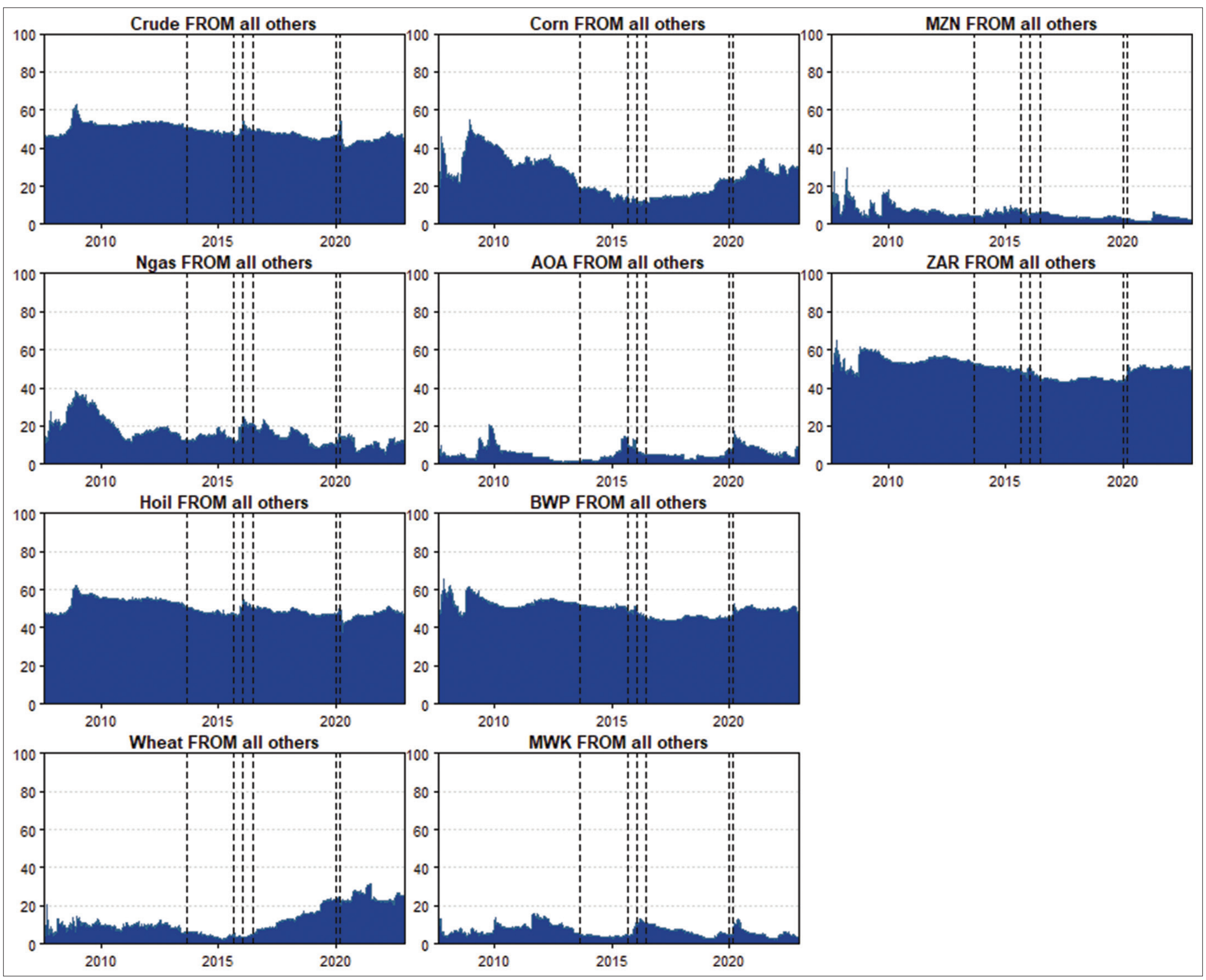
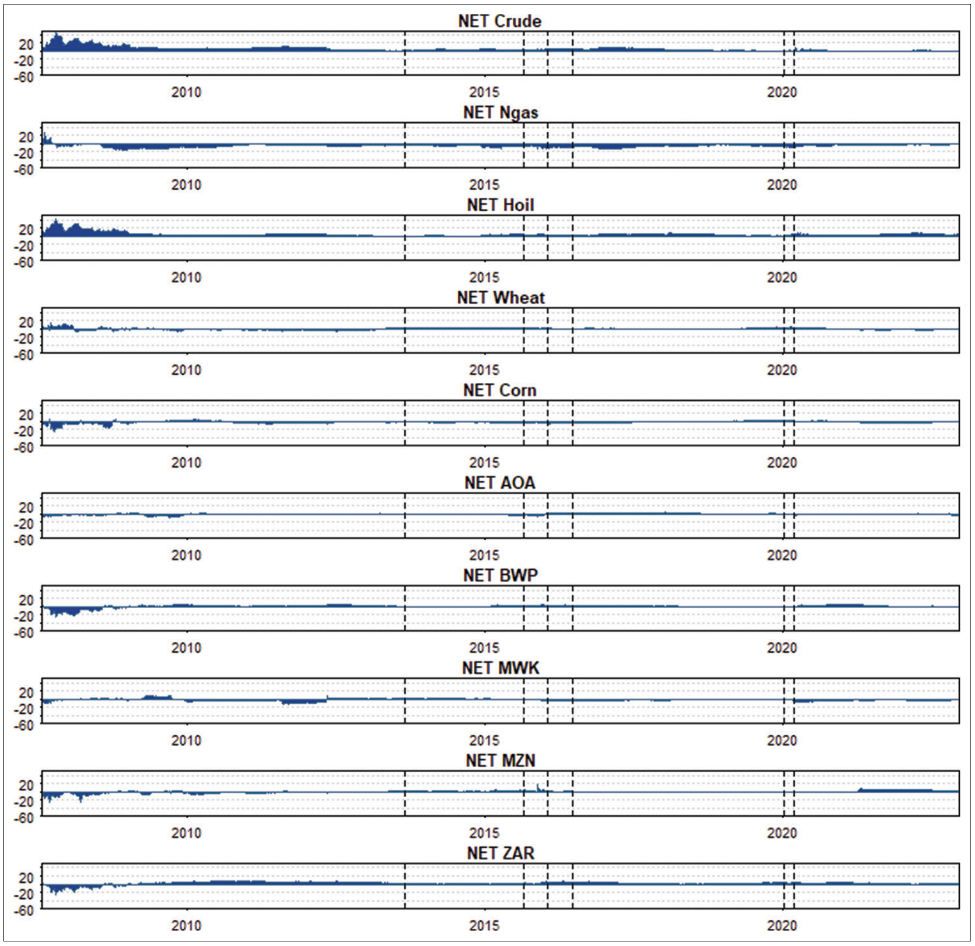


Figure 5: Net directional connectedness



On the other hand, the findings for the total directional connectedness from others reveal that MWK, MZN, Ngas, corn, AOA are net shock recipients.

3.2.3. Net total directional connectedness

This sub-section of this research paper examines the net connectedness findings in Figure 5 where variables are divided into net transmitting and net receiving roles. The dynamic framework in this section, in contrast to the categorisation the study delved into in section 5.2.1. above, may recognize the switch between the two functions (net transmitting and net receiving). This implies that every variable inside the network has the potential to change over time from being a net transmitter to a net receiver of shocks in the system. As already mentioned in the above sub sections that the negative represents the net receivers of shock and the positive represents the net transmitters of shocks.

Considering the net connectedness findings, Crude oil, HOil, ZAR, AOA, BWP are persistent net transmitters. On the other hand, Ngas, corn, MWK, and MZN are persistent net recipients of shocks. In detail, Crude oil, ZAR and HOil from the year 2007 has always been a net transmitter. Contrary, Ngas between 2007 and 2008 was a net transmitter and switched to a persistent net transmitter in the year 2009-2022. Wheat on the other hand started as a net transmitter in 2007, switched to be a net receiver up until 2014, became a net transmitter up until 2020 and lastly, a net receiver up until 2022. Corn has always been a net recipient of shocks. Conversely, AOA and BWP started as net receivers in 2007-2015 and switched to being a net transmitter.

4. CONCLUSION AND POLICY RECOMMENDATIONS

This study examined the risk transfer among exchange rates, energy commodities and agricultural commodity prices of the selected SADC countries. In this way, the specific objectives of the study were achieved by employing the TVP-VAR model. The model was able to identify the net transmitters and net recipients of risk and the results are in line with prior works of Sayed and Charteris (2022) on the connectedness and volatility spillover of energy commodities and agricultural commodity prices. This study argued that energy commodities play an integral role in the production process of agricultural commodities and suggested that there is a direct link between the two markets. Furthermore, the volume and frequency of these traded commodities are largely determined by the performance of the exchange rates.

Crude oil as anticipated was identified to be a net transmitter of risk to other variables such as corn as it has been established that crude oil affects the production process of agricultural commodities.

Practitioners, academics, and policymakers are all interested in the topic of volatility connectivity between asset classes. This is due to the increasing financialization of important commodities such as, energy, and agricultural products (Lu et al., 2019). In order to protect themselves from financial risk, investors are increasingly looking for assets that are uncorrelated with other investments. This is particularly important for portfolio managers who are always looking for safe-haven assets to lessen the increased risks brought on by exogenous shocks like COVID-19. As a result, the commodities market offers investors a range of tradeoffs across asset classes, allowing them to create portfolios that are highly diversified. As a result, mixing stocks and commodities in a portfolio may help to yield a better risk-return trade-off than focusing solely on stocks. The knowledge of volatility spillovers is important not only for investors, but also for regulators and policymakers, as fluctuating commodity prices can have a significant impact on financial markets and macroeconomic performance.

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