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Transmission of risks between energy and agricultural commodities: Frequency time-varying VAR, asymmetry and portfolio management[1]

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Abstract

This paper examines energy and agricultural commodities' short-run and long-run connectedness by using the Time-varying parameter vector autoregressions (TVP-VAR). It applies the frequency version of the TVP-VAR model, which is a modified version of the dynamic TVP-VAR model. The frequency decomposition definition also decomposes into short-run and long-run connectedness. We further the analysis by investigating the effect of asymmetry in returns on connectedness. It also examines how portfolio management strategies would lead to a maximization of profits with minimal risks. Empirical evidence indicates that only 32.52% and 31.38% of connectedness in oil and gas, respectively, are transmitted to agricultural commodities, which suggests their weak tendencies in influencing agricultural commodities; the total connectedness index hovers around 40-60% in the 2018-2019 period; however, it dropped below 40% in 2020-2021 when the COVID-19 pandemic contributed to

[1] The authors are grateful to Professor David Gabauer who makes available the R codes for all calculations in this paper at: https://gabauerdavid.github.io/ConnectednessApproach/

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disintegrate the connectedness between energy and agricultural commodities but increased further during the 2022 Russia-Ukraine saga. The findings also indicate that corn, wheat, and flour are net transmitters of risks to oil and natural gas in the long and short-run, and wheat-flour pairwise connectedness is the strongest in the connectedness. Asymmetry is also pronounced in the network of connectedness. Portfolio analyses indicate that investors require a low proportion of energy in a portfolio of energy-agricultural commodities to achieve an optimum profit. The findings will offer exciting insights into the connectedness of agricultural and energy commodities, particularly during periods of high price uncertainty.

Keywords:

Agricultural commodity; Asymmetry; Frequency TVP-VAR; Optimal weight; Risk

JEL Classification:

C22, N5, D8

1. Introduction

Since the outbreak of Covid-19, many countries, including the US, UK, and EU, have inevitably suffered from higher food and energy inflation as global supply chains have been disrupted. The rise in energy prices intensified this year (Figures 1 and 2) when Western countries imposed trade sanctions on energy inputs against Russia for its invasion of Ukraine last February. At the same time, Ukrainian agricultural shipments have been affected for months as the Russian military blocks transport routes by land and water. Russian President Vladimir Putin has called the 2022 Russian-Ukrainian war a "special military operation." Wartime production cuts have resulted in higher sales prices for food and energy than in the past, directly translating into the local inflation many countries are currently experiencing. Rising energy and food inflation, combined with high levels of uncertainty, could make it difficult for economies to weather the storm. Russia's cut in energy exports in retaliation for Western trade sanctions, although the latter aimed at cutting Russia's export earnings, has come at an unbearably high price for some Europe countries especially (Amaglobeli, Hanedar, Hong and Thevenot, 2022). Figure 3 shows that UK energy inflation took less than a year to rise from single digits in September 2021 to as high as 57.6% year-on-year in July 2022. Energy inflation in the Eurozone country Belgium recorded 69.2% year-on-year in October 2022 (Figure 4). While food inflation is not as high as energy, it does not appear to be less elastic (Figure 5). According to the World Bank's latest Commodity Market Outlook report, price shocks in world commodity markets will likely remain at record highs through the end of 2024. Although Asian countries do not participate in trade sanctions, lower energy exports and food shortages push up import prices and, in turn, local prices in the region.

In the future, given Russia's dominance in the share of world agricultural, fertilizer, and energy exports, as well as Ukraine's falling agricultural production, the world is expected to continue to face food and energy shortages for some time. Furthermore, there are no clear signs that the war will end anytime soon, which could mean that the world may continue to experience subsequent food and energy price increases.

Not only are food and energy inelastic inputs for output production, but more importantly, there are no viable substitutes for energy and agricultural inputs. No one can survive even a day without food and energy, which means that people still rely on food and energy for living, let alone rising prices. Moreover, transportation, where a vital input is an oil, is used to deliver goods, including food, to different locations. Due to these winding effects, food and energy prices are related in some way. As shown in Figure 6, both food and energy inflation always move in the same direction.

As Parker (2017) demonstrated, energy inflation is the most likely cause of outright price increases, followed by food, housing, and other goods. Rising energy prices have knock-on effects across various sectors of the economy. Not only do fluctuations in oil prices fluctuate transportation costs, but natural gas can also have broader economic impacts. Natural gas is not only a raw material for heating but also for fertilizer production. Given the tightening of global fertilizer exports after the Russian-Ukrainian war, higher gas prices will likely continue to drive up fertilizer costs, putting further pressure on food inflation.

Consequently, energy prices tend to have significant explanatory power for the upward trend in agricultural and food price volatility (Taghizadeh-Hesary, Rasoulinezhad and Yoshino, 2018). This implies that energy price shocks will likely trigger co-inflation in food, including agricultural inputs. Combined with prolonged periods of hot weather and drought, especially in Europe, the ensuing decline in agricultural production could exacerbate food shortages in the coming months.

The link between energy and food inflation is more pronounced in the second-round effect. This is because energy price shocks are likely to be passed on again and again to non-energy consumer prices, including food, as consumers continue to raise their inflation expectations along with the initial energy inflation (Battistini, Grapow, Hahn and Soudan, 2022).

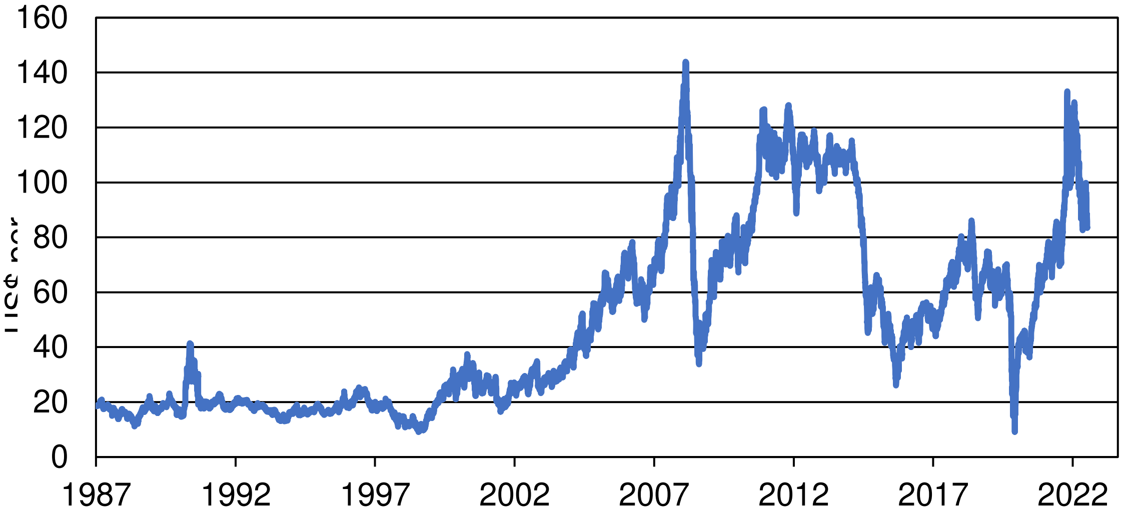

Figure 1. Crude oil prices: Brent - Europe (US$ per Barrel)

Source: Federal Reserve

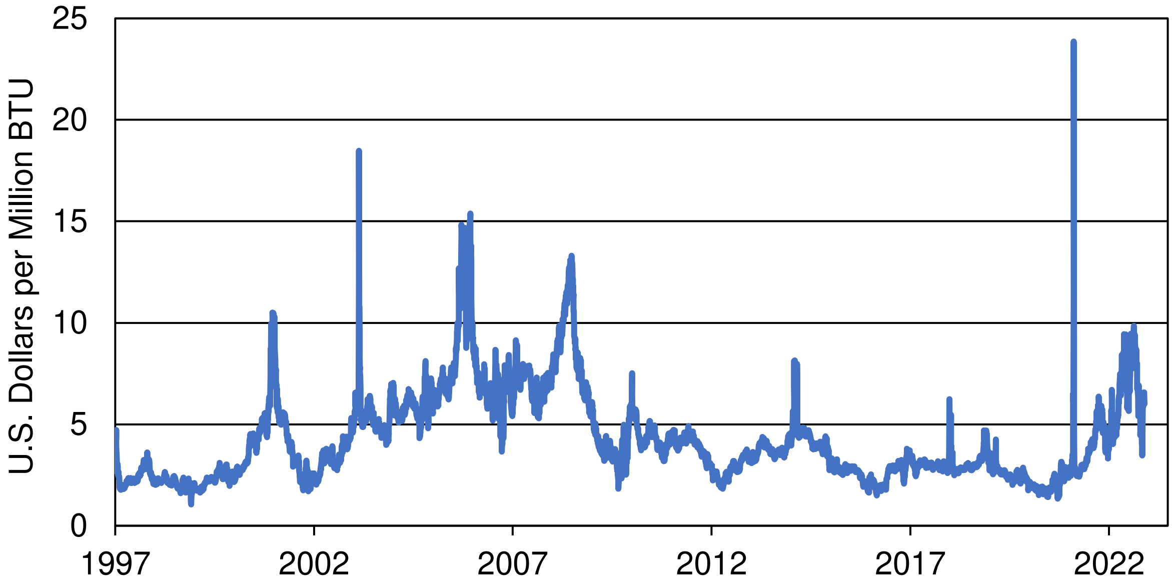

Figure 2. Henry Hub Natural Gas Spot Price

Source: Federal Reserve

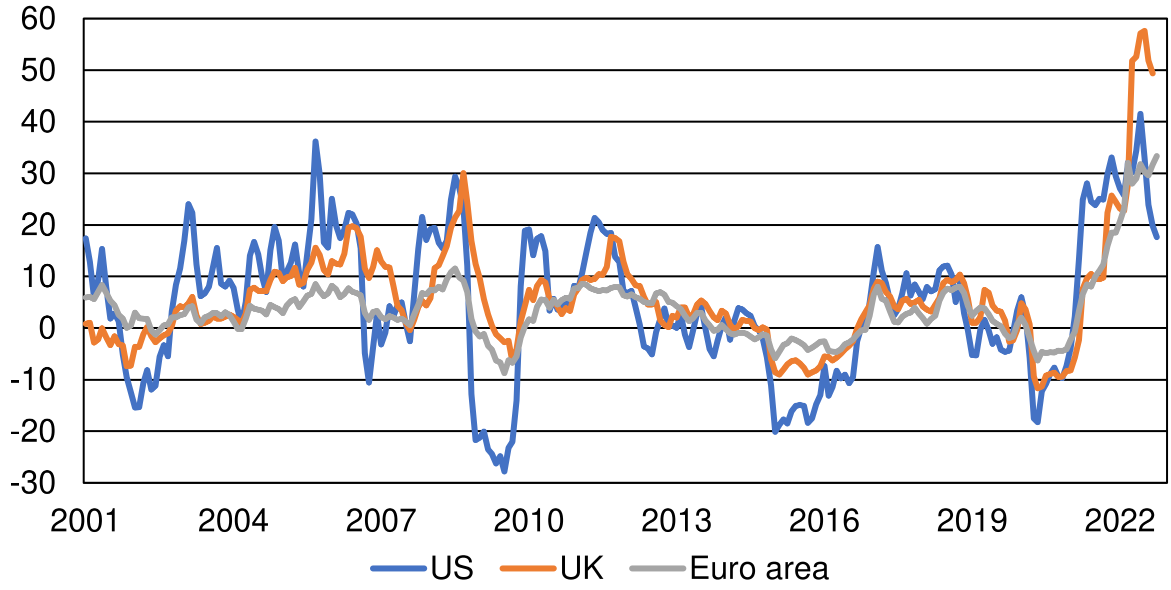

Figure 3. Energy inflation (%)

Source: Federal Reserve

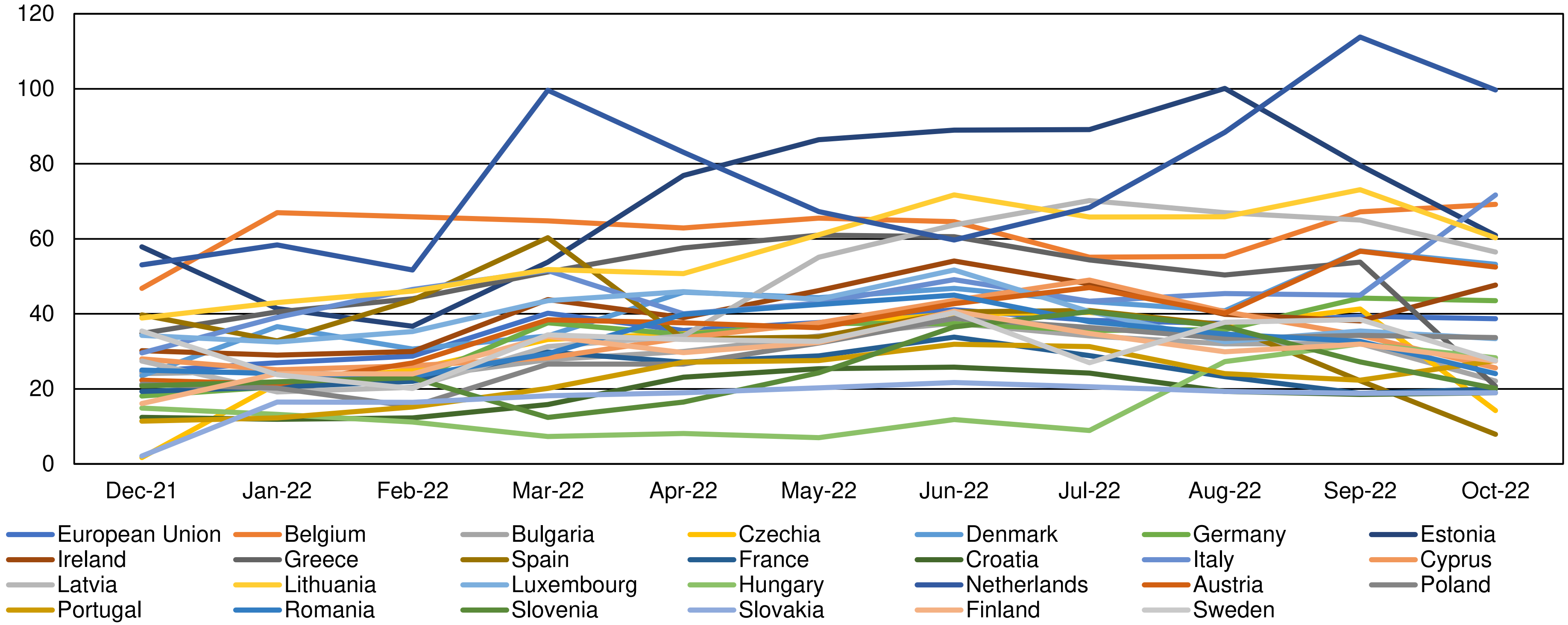

Figure 4. Energy inflation (%)

Source: Eurostat

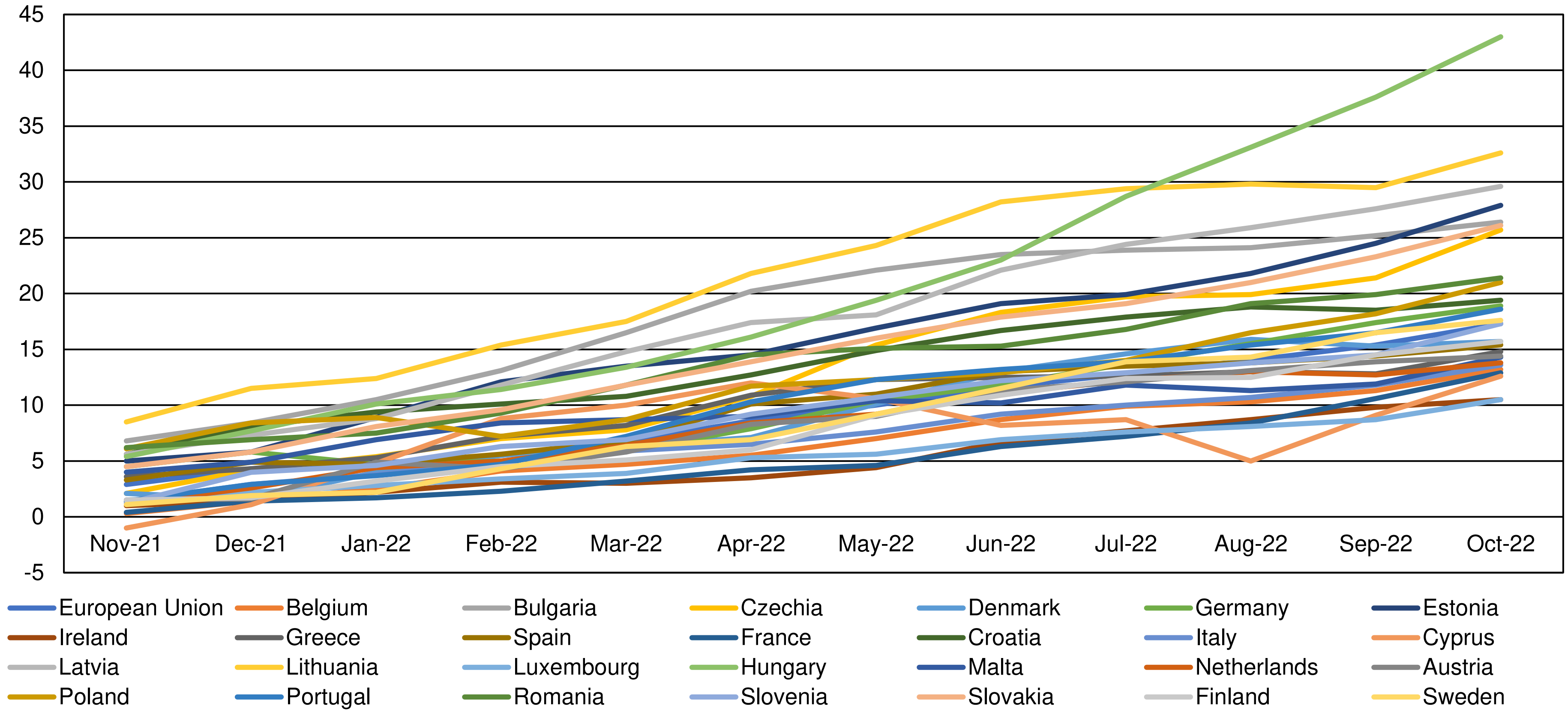

Figure 5. Food inflation (%)

Source: Eurostat

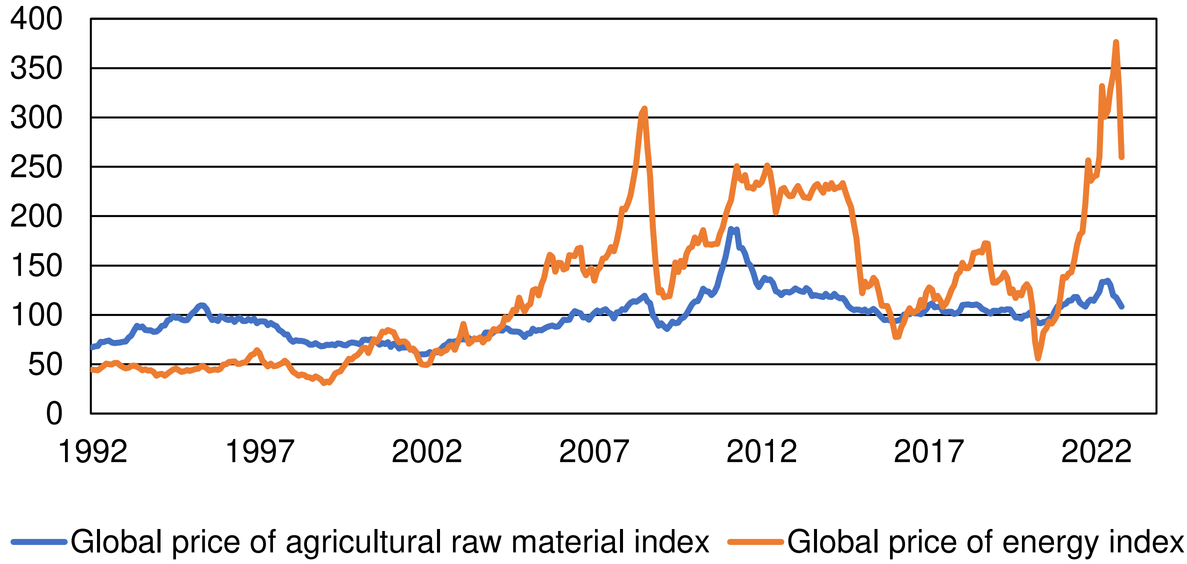

Figure 6. Global prices of agricultural raw materials and energy indices

Source: Federal Reserve

While energy price increases are likely to moderate faster than food price increases, the former could rise at any time and even quicker, which could have a longer-lasting effect on inflation for years. While oil prices have retreated in the last quarter of 2022, as global inflation data has shown, it is undeniable that general prices of goods and services have not and may not return to past levels. Subsequent increases in production costs and the cost of living, if not adequately compensated by wage increases, could destabilize the economic soundness of both developed and emerging markets. This enhances the contribution of the paper in examining the impact of inflation shocks on the future economy, which is one of the main concerns of current policymaking.

Global commodity and energy prices tend to be more correlated and integrated, especially during crises for instance the prominent recession next year (Adekoya et al., 2022a). As such, the interconnectedness of food and energy commodities to the world economy could further increase the likelihood of triggering the risk of a global recession through persistently high inflation. Against this background, this paper warrants further study to examine the dual price relationship between food and energy and its connected impact on economic development using a time-varying parametric vector autoregressive (TVP-VAR) model, capturing the time-varying nature of the underlying structure in an economy flexibly and robustly.

The energy-agricultural interdependency has been an econometric puzzle for decades due to different market uncertainty, oil crises, and geo-political crises that often affect market interlinkages within and outside borders. Diebold and Yilmaz (2009) hereafter DY, made a milestone contribution by introducing a new framework to measure the market return and volatility spillovers. The DY framework is prominent and widely used in investigating market interconnectivity regarding returns and volatility. The DY flamework is based on the Vector Autoregressive (VAR) model, and the Cholesky factor identification and the 200-week rolling windows are used to visualize the spillover effect. In Diebold and Yilmaz (2009), the interdependence of the global stock market during 1992-2007 is investigated, and findings showed a higher spillover effect between US, UK, and German stock markets in the Western countries and stock markets in Asian countries such as the Japanese, Korean and Taiwanese stocks. More importantly, the authors demonstrated that an economic crisis would produce volatility spillover but not return spillover.

Furthermore, Diebold and Yilmaz (2012) made an interesting methodical innovation to capture the directional spillover effect from a market to a particular market or another directional spillover effect to the market from a specific market. They used this new method to examine the volatility spillover between stock, bond, foreign exchange, and commodities markets between 1999 and 2010. They pointed out that there was a higher volatility spillover after the global financial crisis of 2007 and a more substantial volatility spillover effect from the stock market to the other three markets, namely bond, foreign exchange, and commodity markets.

There is numerous empirical research that is based on the DY connectedness methodology. For example, Awartani et al. (2013) used the directional spillover method to examine the spillover effect between the US and six stock markets in the Gulf Cooperation Council (GCC) member countries for the period of 2004-2012. They claimed that there was high volatility spillover from the US stock market to these GCC member countries' stock markets during the global financial crisis of 2008. Also, there is an increase in return spillover from the US stock market to these countries during the same period. Similarly, Awartani and Maghyereh (2013) also applied the directional spillover method to examine the spillover effect of oil price, stock return, and volatility in the GCC member countries for the period of 2006-2012. They claimed that there was an increase in total spillover of return and volatility from oil prices to the stock market in the GCC countries during the global financial crisis. Duncan and Kabundi (2013) examined the directional spillover effect between bonds, commodities, currencies, and the stock market in South Africa for the period of 1996-2010. They claimed that the commodities and stock markets are the primary sources of spillover effects among these four markets in the country.

Furthermore, Cronin (2014) examined the return and volatility spillover between money (i.e., M2 and monetary base and four different markets, namely stock, commodities, currencies, and bond markets in the United States for the period of 2000-2012. They claimed that there was an increase in total return spillover and volatility spillover during the global financial crisis of 2008. Interestingly, the spillover effect from the M2 to four different markets is much higher than that from the monetary base to these other markets. Zhang and Wang (2014) examined the directional spillover effects between three oil markets, Brent, West Texas, and Daqing (China), from 2001-2013. They pointed out an increase in the total return spillover during the global financial crisis of 2008. Maghyereh et al. (2016) examine the directional spillover effect between oil prices and the global stock market from 2008-2015. They claimed that the spillover effect could be bi-directional, meaning there is a spillover from oil prices to the stock market and *vice versa*. However, the spillover of oil price to the stock market would be more significant than the spillover from the stock market to the oil price. Zhang (2017) revisited the spillover effects between oil prices and six major stock markets, namely, New York, London, Frankfurt, Tokyo, Singapore, and Shanghai, for the period of 2000-2016. The researcher claimed that there is little spillover effect from oil prices to these stock markets, and there is a minor spillover from these stock markets to oil prices. The researcher also pointed out that there are increasingly essential spillover effects from the Shanghai stock exchange to other stock markets.

More recently, Antonakakis et al. (2018) examined the spillover effect between oil prices and 12 major oil and gas firms from 2001-2016. They claimed that oil price is not the net provider of the spillover effect but the receiver of the spillover effect. They also pointed out a rapid increase in the total volatility spillover effects during the global financial crisis of 2007. Ji et al. (2019) examined the asymmetric spillover effects between 6 key cryptocurrencies, namely, Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash, for 2015-2018. They claimed that two cryptocurrencies, namely Bitcoin and Litecoin, are two top providers of net return spillover effect, and three cryptocurrencies, namely Ethereum, Ripple, and Dash, are three top receivers of net return effect. More importantly, the asymmetric spillover effect method indicated that Ethereum and Ripple are the two leading receivers of the net negative return effect. Malik and Umar (2019) examined the spillover effects between the exchange rates of major oil exporting countries or importing countries and three different shocks, namely demand shock, supply shock, and risk shock, from 1991 to 2019. They claimed a strong spillover effect from demand shock and risked shock to the exchange rate of oil-importing or exporting countries.

However, supply shock has a weak spillover effect on their exchange rates. They also pointed out an increase in the total spillover effect after the end of the global financial crisis. Gong and Xu (2022) examined the spillover effects among five types of commodity markets, namely energy, precious metal, industrial metal, agriculture, and livestock products, from 2008 to 2020. They claimed three commodity markets, namely, energy, precious metal, and industrial metal, are net providers of spillover effects. By contrast, the remaining two commodity markets, namely, agriculture and livestock products, are net receivers of spillover effects. They also pointed out that there are bi-directional spillover effects in two commodity markets, namely, energy and agriculture. Mo et al. (2022) examined the spillover effects between three cryptocurrencies, namely Bitcoin, Litecoin, and Ethereum, and the commodity market for 2015-2021. They claimed that cryptocurrencies are the leading providers of spillover effects to commodity markets.

There are some benefits and limitations of previous studies on this topic. The main advantages of these studies are that researchers, most notably David Gabauer, have developed a systematic econometric analysis of the connectedness to examine the dynamic effect of spillover. They applied this novel approach to analyze the spillover effect in the financial markets. In other words, a limitation of these studies is that there is still a limited number of systematic and comprehensive empirical research to examine connectedness in different types of markets, such as the energy or commodities market. Therefore, the current study aims to fill the research gap in the empirical analysis. In other words, the novelty of the present study is to apply this new method to examine systematically and comprehensively the connectedness of energy and agricultural commodities.

The present paper, therefore, investigates the short-run and long-run connectedness of energy to agricultural commodities by employing the Frequency TVP-VAR model. The frequency version of the model by Chatziantoniou, Gabauer, and Gupta (2021) is an upgrade of the dynamic TVP-VAR model of Antonakakis et al. (2020a). The frequency decomposition definition in Barunik and Krehlik (2018) is applied in the dynamic TVP-VAR framework to decompose the connectedness measures into short-run and long-run, as given in Chatziantoniou et al. (2021). We further the analysis by investigating the effect of asymmetry in returns on the connectedness as in Adekoya et al. (2022a). Lastly, we consider portfolio management strategies, leading to maximized profits with minimized risks. In other words, the uniqueness of this study is primarily in the systematic application of the dynamic TVP-VAR framework for the short-run and long-run analysis of the connectedness between energy and agricultural commodities.

The results show total connectedness is time-varying, with the lowest energy agricultural commodities' connectedness observed during the 2020-2021 Coronavirus pandemic. It is also observed that there are occasions whereby more profound changes in the total connectedness in the long-run or short-run result in the loosening of connections of variables in the network, thus, giving opportunity for portfolio diversifications by investors. The results of net directional connectedness show that corn, wheat, and flour are net transmitters of risks to oil, natural gas, and other agricultural commodities in the network in the long and short run. At the level of pairwise directional connectedness, these agricultural commodities also posed a net transmitter of long-run and short-run risks to oil and natural gas except rice, while wheat-flour pairwise connectedness is the strongest, followed by corn-wheat, wheat-oats, corn-flour, and corn-oats in that order. The role of asymmetry is also found in the connectedness though this does not improve the total connectedness further. With the suggestive strategy at the end of the analysis, investors will learn how to combine assets appropriately in their portfolios, bearing in mind net transmitters of longer-term risks, and then adopt a proper long-term strategy.

The next part of this paper is structured as follows: Section 2 describes the time-varying parameter connectedness approach, which includes the frequency connectedness and relevant connectedness measures. Section 3 presents the data and some preliminary results, while section 4 gives the main findings. Section 5 then concludes the paper.

2. Methodology

Here, we describe the dynamic forecast error variance for the TVP-VAR approach. By using the VAR(p) process,

$$\Phi_t x_t = \Phi_{1t} x_{t-1} + \Phi_{2t} x_{t-2} + \cdots + \Phi_{pt} x_{t-p} + u_t \quad (1)$$

where x_t, x_{t-1}, …, x_{t-p} and u_t are vectors of dimensions $N \times 1$, and $u_t \sim N(0, \sum_t)$. The parameters Φ_{it}, $i = 1, \ldots, p$ are $N \times N$ time-varying variance-covariance matrix of time-varying VAR coefficients. With any vector of stationary time series process, x_t, the model in (1) can be re-written in TVP-VMA(∞) as $x_t = \Psi(B) u_t$ where $\Psi(B)$ is the matrix of moving average lag polynomial obtained from $\Phi(B) = [\Psi(B)]^{-1}$ and $\Phi(B) = [I_N - \Phi_{it} B - \cdots, \Phi_{pt} B^p]$ with I_N being an identity matrix. The $\Psi(B)$ includes an infinite number of lags which are approximated by $\Psi_{\mathrm{h}}(B)$ for $h = 1, \ldots, H$ horizons. The computation of generalized forecast error variance decomposition (GFEVD) is as in Pesaran and Shin (1998), even though the orthogonal version of GFEVD is used here. Thus, the GFEVD is the response of shocks from all variables j on a shock in variable i, given in terms of forecast error variance written as,

$$\tilde{\theta}_{jk,t}(H) = \frac{(\Sigma_t)_{kk}^{-1} \sum_{h=0}^{H} \left[(\Psi_h \Sigma_t)_{jkt}\right]^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi'_h)_{jj}} \tag{2}$$

where $\tilde{\theta}_{jk,t}(H)$ gives the total contribution of jth in terms of variance of forecast error, to the ith variable at forecast horizon H. The numerator of (2) gives the cumulate effects of the shock received by variable j from variables k, while at the denominator, the term gives the cumulative effect of the total shocks in the network of connectedness. By theory, the rows of (2) require normalization for them to sum to 1. Thus, (2) is normalized as,

$$\bar{\theta}_{jk,t}(H) = \frac{\tilde{\theta}_{jk,t}(H)}{\sum_{k=1}^{n} \tilde{\theta}_{jk,t}(H)} \tag{3}$$

where $\sum_{k=1}^{n} \bar{\theta}_{jk,t}(H) = 1$ and $\sum_{j,k=1}^{n} \bar{\theta}_{jk,t}(H) = n$.

3.1 Time-varying frequency connectedness models

By decomposing the forecast error variance for connectedness obtained in (2) into short-run and long-run, we obtain the frequency TVP-VAR total connectedness and its measures as subsequently obtained. The time-varying frequency connectedness is obtained by incorporating the VAR frequency connectedness of Barunik and Krehlik (2018) in the dynamic TVP-VAR described above. Thus, in the frequency domain, Chatziantoniou, Gabauer, and Gupta (2021) give the Fourier transformation of TVP-VMA(∞) in (1) as,

$$\begin{aligned} S_{x(\omega)} &= \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} \\ &= \Psi\left(e^{-i\omega h}\right) \Sigma_t \Psi'\left(e^{-i\omega h}\right) \end{aligned} \tag{4}$$

where $i = \sqrt{-1}$ and ω is a Fourier frequency. The frequency decomposition expression in (4) is then combined with the non-normalized GFEVD in (2) to give,

$$\tilde{\phi}_{jk,t}(\omega) = \frac{(\Sigma_t)_{kk}^{-1} \left|\sum_{h=0}^{H} \left(\Psi\left(\mathrm{e}^{-\mathrm{i}\omega\mathrm{h}}\right)\Sigma_t\right)_{jkt}\right|^2}{\sum_{h=0}^{H} \left(\Psi(\mathrm{e}^{-\mathrm{i}\omega\mathrm{h}})\Sigma_t \Psi'(\mathrm{e}^{-\mathrm{i}\omega\mathrm{h}})\right)_{jj}} \tag{5}$$

where $\tilde{\phi}_{ij,t}(\omega)$ is the part of the spectrum of the jth variable at a given frequency ω that is attributed to a shock in the kth variable. This is a within-frequency indicator as given in

Chatziantoniou, Gabauer, and Gupta (2021). The normalized version of this frequency GFEVD is,

$$\bar{\phi}_{jk,t}(\omega) = \frac{\tilde{\phi}_{jk,t}(\omega)}{\sum_{k=1}^{n} \tilde{\phi}_{jk,t}(\omega)} \qquad (6)$$

The frequency decomposition of connectedness, therefore, allows all frequencies to be aggregated within a specified range, $d = (a, b): a, b \in (-\pi, \pi), a < b$ as,

$$\bar{\phi}_{jk,t}(d) = \int_{a}^{b} \bar{\phi}_{jk,t}(\omega)\, d\omega \qquad (7)$$

Thus, frequency connectedness here provides the information about spillovers in a particular frequency range d.

3.2 Connectedness measures

Based on the frequency decomposed GFEVD in (6), the following relevant connectedness measures are obtained.

The average impact of a shock from a particular variable j to another set of variables k is the degree of network connectedness, and this is the average Total Connectedness Index, $TFCI_{jk}$ of j to any of k variables. This measures market risk as it gives the average amount of spillovers one variable j transmits to (receives from) another variable k. Thus, $TFCI_{jk}$ is computed by averaging the time-varying total connectedness in the network, $TFCI_t(d)$, obtained as,

$$TFCI_t(d) = n^{-1} \sum_{j=1}^{n} TO_{j,t}(d) = n^{-1} \sum_{j=1}^{n} FROM_{j,t}(d) \qquad (8)$$

where $TO_{j,t}(d)$ is the amount of a shock in a variable j which is transmitted to all other variables k . This is the total directional connectedness to others and is computed as,

$$TO_{j,t}(d) = \sum_{j=1, j \neq k}^{n} \bar{\phi}_{kj,t}(d) \qquad (9)$$

The $FROM_{j,t}(d)$ gives the amount of shocks in the variable j which is received from all other variables k in the network. This is the total directional connectedness received from others and it is given as,

$$FROM_{j,t}(d) = \sum_{j=1, j \neq k}^{n} \bar{\phi}_{jk,t}(d) \qquad (10)$$

The difference between $TO_{j,t}(d)$ and $FROM_{j,t}(d)$ is the directional connectedness, given by,

$$NET_{j,t}(d) = TO_{j,t}(d) - FROM_{j,t}(d) \qquad (11)$$

where, for $NET_{j,t}(d) > 0$, it implies the dominance of variable j on all other variables k in the network. Thus, variable j is the net transmitter of shocks in the network of the connectedness, and those variables k become the net receiver of shocks. If on the other way, $NET_{j,t}(d) < 0$, variable j becomes the net receiver of shocks and other variables k become net transmitters of shocks in the network. At the bilateral level where markets are paired instead, the net pairwise directional frequency connectedness (NPDFC) gives the bilateral transmission of risks between a particular variable j and a particular variable k. This measure is obtained from the net directional connectedness as,

$$NPDFC_{jk,t}(d) = NET_{j,t}(d) - NET_{k,t}(d) \tag{12}$$

where $NPDFC_{jk,t}(d) > 0$ implies that a particular variable j dominates a particular variable k in the connectedness, thus, shock from asset price j has a spillover effect on asset price k. Similarly, if $NPDFC_{jk,t}(d) < 0$, it implies the dominance of variable k on variable j. Thus, shocks from asset price k have a spillover effect on asset price j.

3. Data and Preliminaries

Oil prices and natural gas prices are used to proxy energy. Oil is traded in the Brent market, while natural gas is traded in the Henry Hub market. These are traded in a $/barrel and $/mm BTU, respectively. Three agricultural commodities: corn, wheat, and oats, are traded in a $/bushell, while flour and rice are traded in a $/cwt. The entire datasets are all of the daily prices, spanning 1 August 2017 to 21 August 2022, obtained from Data stream. Plots of price dynamics of those energies and agricultural commodities are given in Figure 7, where price increases are noticed, even though there were occasions of obvious bearish phases in all the commodity series. For example, the Brent market witnessed a sharp drop in price during the COVID-19 pandemic in 2020; rice and corn prices dropped significantly, too, during this period. Natural gas witnessed a sharp price drop towards the end of 2021, which had a corresponding effect on the prices of corn. The five agricultural commodities reached their peak prices in early 2022 before the Russian invasion of Ukraine, and the price fell for the remaining period of 6months to the end of the data analysis sample. The dynamics of the two energy sources (oil and gas) mimic the movement in those agricultural products, and there is a tendency for returns, and volatility would be spilled from energy to agricultural commodity markets. As displayed in the time plots, energy and agricultural commodity pricing dynamics corroborated with the recently observed UK and Eurozone energy inflations in the mid-2021 to 2022, just before the Russian production and transportation disruptions of agricultural commodities from Ukraine.

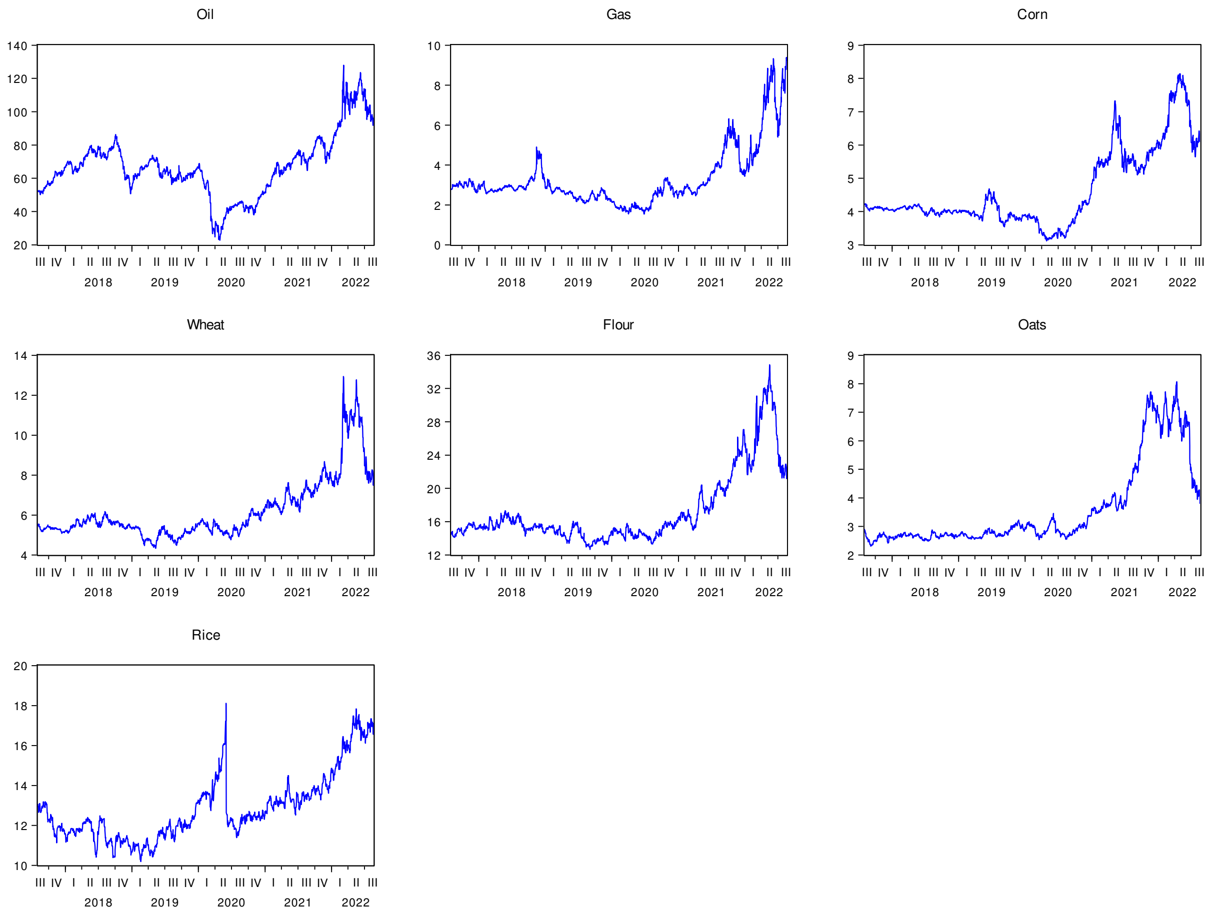

Figure 7: Plots of energy and agricultural commodity prices

We then concentrate on volatility as a measure of risks, proxied with absolute returns. We used percentage changes in prices to obtain the corresponding return series for each variable. The formula is given as, $y_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} * 100$ where P_{it} is the current price of a particular energy or agricultural commodity, and P_{it-1} is its previous day price, such that y_{it} is the return series, and the volatility proxy is based on absolute returns, $|y_{it}|$. Statistical properties of y_{it}, which are the returns, are then presented in the upper panel of Table 1. Some of the necessary conditions for such a volatility series are the asymmetry and non-normality in return variables. Mean returns are found to be positive while variances are higher than their corresponding mean. The lowest variance is found for flour with 2.01 implying the least volatile asset among all, while natural gas with 8.385 variable posed as the asset with the highest volatility. Skewness is significantly different from zero except for the case of flour. Oil, corn, oats, and rice indicated negative asymmetry in returns, while natural gas, wheat, and flour indicated asymmetry skewness in returns. Excess kurtosis estimates showed significant leptokurtosis in all the returns series and Jarque-Bera (JB) test statistics of normality against non-normality are decisively rejected in all cases. The ERS unit root test by Elliot et al. (1996) indicated rejection of unit root for no-unit root in all cases, as it is expected that returns should be stationary. The serial autocorrelation, Q test, and the ARCH/GARCH errors Q^2 tests are highly significant implying the possibility of investigating returns or volatility markets connectedness using TVP-VAR returns (or its transformed absolute values) (Fisher and Gallagher, 2012). In the lower panel of Table 1, results of Pearson moment correlations are given, where correlations are found to be significant between energy prices and agricultural commodities. All the statistics in Table 1, as well as the corelation estimates, support the applicability of the interrelationship of volatility among energy and agricultural commodities using an updated TVP-VAR approach of Chatziantoniou, Gabauer, and Gupta (2021).

Table 1: Descriptive Statistics

Descriptive statistics	Oil	Natural gas	Corn	Wheat	Flour	Oats	Rice
Mean	0.058	0.107	0.029	0.029	0.033	0.029	0.022
Variance	4.915	8.385	1.523	2.219	2.01	2.301	1.338
Skewness	-0.638***	0.380***	-0.529***	0.341***	0.015	-0.592***	-9.563***
Ex.Kurtosis	23.530***	7.352***	10.439***	5.355***	6.077***	6.542***	255.283***
JB	42710.8***	4202.2***	8468.1***	2241.6***	2840.2***	3400.0***	5040746.9***
ERS	-13.064***	-17.999***	-16.689***	-18.632***	-5.510***	-4.489***	-9.040***
Q(20)	21.867***	28.794***	25.648***	26.993***	11.578	26.901***	9.865
Q2(20)	241.301***	158.270***	235.706***	1013.250***	313.056***	67.826***	2.038
Pearson correlation	Oil	Natural gas	Corn	Wheat	Flour	Oats	Rice
Oil	1.000***	0.115***	0.205***	0.186***	0.131***	0.132***	0.066***
Natural gas	0.115***	1.000***	0.094***	0.067***	0.066***	0.064***	-0.003
Corn	0.205***	0.094***	1.000***	0.579***	0.476***	0.377***	0.118***
Wheat	0.186***	0.067***	0.579***	1.000***	0.752***	0.365***	0.153***
Flour	0.131***	0.066***	0.476***	0.752***	1.000***	0.321***	0.172***
Oats	0.132***	0.064***	0.377***	0.365***	0.321***	1.000***	0.091***
Rice	0.066***	-0.003	0.118***	0.153***	0.172***	0.091***	1.000***

4. Main Results

5.1 Frequency time-varying connectedness

We present the results of average frequency connectedness, where total connectedness is decomposed into log-run and short-run, with the impact of returns on the total connectedness assumed to be symmetric. The short-run connectedness renders the connectedness at a high-frequency band, i.e., five days. In contrast, the long-run connectedness renders the connectedness at a low-frequency band, i.e., six to 100 days, according to Barunik and Krehlik (2018). Table 2 presents the results of the average total connectedness (in the upper panel), short-run connectedness (middle panel), and long-run connectedness (lower panel). Thus, results represent the average connectedness for the entire sample and those of events that occurred at specific points in time, classified as long-term or short-term frequency events.

Table 2: Connectedness table (total connectedness, upper panel; connectedness at short-run, middle panel; and connectedness in the long-run, lower panel)

Total connectedness								
	Oil	Nat. gas	Corn	Wheat	Flour	Oats	Rice	From
Oil	62.55	7.24	6.75	6.46	5.75	6.07	5.18	37.45
Gas	7.68	65.06	5.5	5.56	5.49	7.13	3.58	34.94
Corn	5.2	5.08	49.66	16.61	11.39	8.16	3.9	50.34
Wheat	4.65	4.24	15.51	42.68	20.65	7.89	4.38	57.32
Flour	4.28	4.57	11.37	22.54	46.59	6.74	3.91	53.41
Oats	5.26	6.33	9.18	10.09	7.74	55.98	5.42	44.02
Rice	5.44	3.84	5.81	7.43	6.17	6.22	65.1	34.9
To	32.52	31.28	54.11	68.69	57.19	42.2	26.37	312.37
Inc.Own	95.07	96.34	103.77	111.38	103.78	98.18	91.47	TCI
Net	-4.93	-3.66	3.77	11.38	3.78	-1.82	-8.53	52.06
Short-run connectedness								
	Oil	Nat. gas	Corn	Wheat	Flour	Oats	Rice	From
Oil	46.01	4.5	3.84	4	3.61	3.8	3.41	23.15
Gas	4.73	47.22	3.3	3.92	3.91	4.88	2.51	23.24
Corn	2.75	2.63	33.17	10.62	7.56	5.28	2.55	31.4
Wheat	2.73	2.59	9.79	31.06	14.6	5.32	3.08	38.1
Flour	2.66	2.79	7.4	15.91	33.93	4.44	2.69	35.9
Oats	3.49	4.1	6.19	7.06	5.48	41.75	3.58	29.9
Rice	3.62	2.42	3.43	4.66	3.85	4.02	47.58	22.01
TO	19.97	19.03	33.94	46.17	39.02	27.75	17.82	203.7
Inc.Own	65.98	66.25	67.11	77.23	72.95	69.49	65.39	TCI
Net	-3.18	-4.21	2.55	8.07	3.12	-2.15	-4.19	33.95
Long-run connectedness								

	Oil	Nat. gas	Corn	Wheat	Flour	Oats	Rice	From
Oil	16.54	2.74	2.91	2.46	2.14	2.27	1.78	14.3
Gas	2.95	17.84	2.2	1.65	1.58	2.25	1.07	11.7
Corn	2.46	2.45	16.49	5.99	3.83	2.87	1.35	18.94
Wheat	1.93	1.65	5.72	11.63	6.04	2.57	1.3	19.22
Flour	1.62	1.78	3.97	6.63	12.66	2.3	1.22	17.51
Oats	1.78	2.23	2.98	3.03	2.26	14.24	1.84	14.12
Rice	1.82	1.41	2.39	2.77	2.32	2.19	17.52	12.89
TO	12.55	12.25	20.17	22.52	18.17	14.45	8.56	108.67
Inc.Own	29.09	30.09	36.66	34.15	30.83	28.69	26.08	TCI
Net	-1.75	0.55	1.23	3.31	0.66	0.34	-4.33	18.11

For example, from Table 2, in the case of the diagonal element for oil, 62.55% of connectedness (i.e., 46.01% in the short run and 16.54% in the long run) is attributed to shocks in terms of risks within the Brent oil market. In comparison, the remaining 37.45% is due to the interactions of other variables within the network. Since oil can hold significant forecast error variations, sending about 32.52% (which is less than 37.45% received from others) suggests its weak tendency to influence those five agricultural commodities. Looking at the interaction of wheat in the network, this commodity holds 42.68% of its innovations contributions, while the remaining is attributed to other markets. Out of this 57.32%, 6.46%, and 5.56% are attributed to oil and natural gas markets, respectively, and 16.61%, 22.54%, 10.09%, and 7.43% are attributed to corn, flour, oats, and rice, respectively. Thus, wheat transmits 68.69% of total forecast error variations to other markets but receives a lesser of 57.32%, making wheat a net transmitter of shocks in the network.

Similarly, in the short-run, wheat transmitted 46.17% variations, less than that transmitted for the total connectedness, and received 38.1%, which still makes it a net transmitter of shocks during the short-term frequency connectedness. At the level of total connectedness, corn, wheat, and flour are the net transmitters of shocks, while oil, natural gas, oats, and rice are net receivers of shocks. The three net transmitters (corn, wheat, and flour) are also the net transmitter during the short-run frequency connectedness, while natural gas and oats are marginally added to the list of net transmitters of shocks during the long-term frequency connectedness. The average Total Connectedness Index (TCI) is 52.06%, down to 33.95% for the short run and 18.11% for the long run. This implies that, for the overall connectedness, 52.06% of forecast error variance can be attributed to the connectedness network in terms of spillovers. In comparison, the remaining 47.94% is attributed to idiosyncratic shocks, i.e., the own shocks of each market. The fact that the TCI for long-run connectedness is less than that of short-run connectedness implies that connectedness in the energy-agricultural commodities network is generally driven by shocks transmitted in the short run.

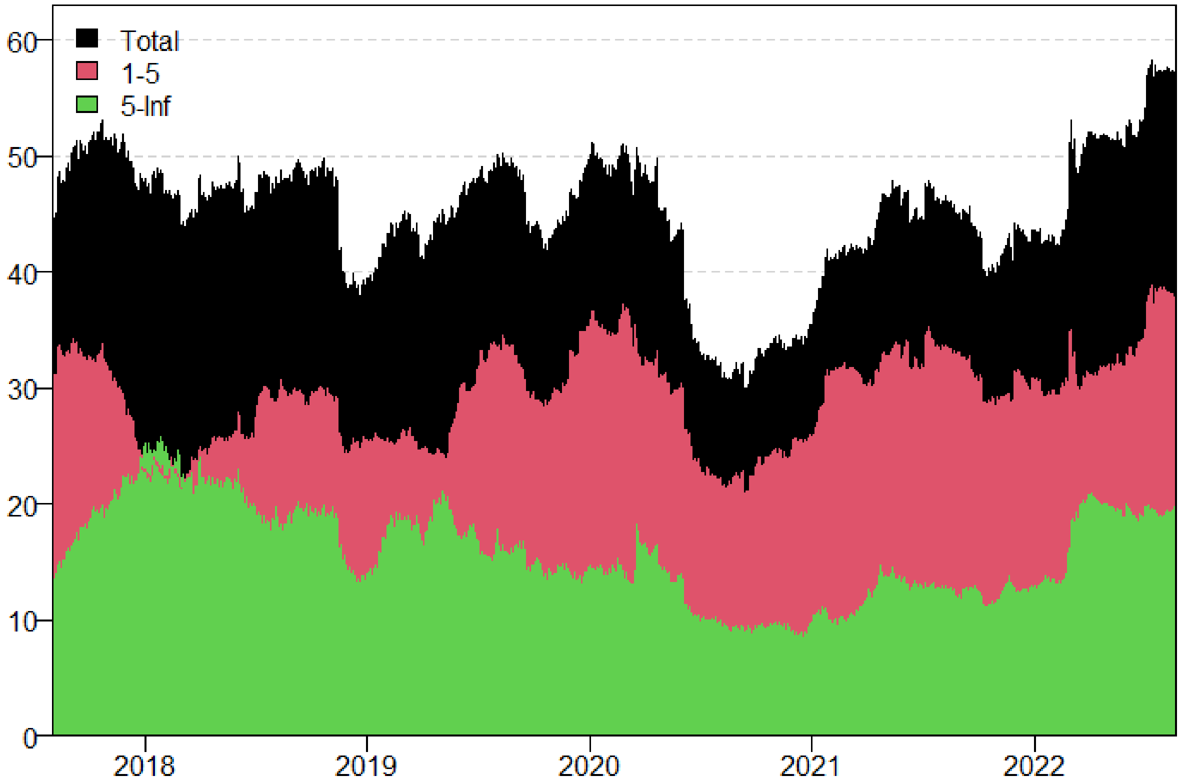

Figure 8: Total Frequency Connectedness

The connectedness explained above gives the average connectedness over time, while the time-varying total connectedness, the evolution of TCI over time, is shown in Figure 8. In the plots, the black-shaded area gives the total connectedness; the red-shaded area is the short-run connectedness, while the green-shaded area is the long-run connectedness. The total connectedness index hovers around 40-60%, excluding 2019 and late 2020 to 2021, when it dropped below 40% and 30%, respectively. 2020-2021 was the period of the COVID-19 pandemic when global financial and commodity markets disintegrated. The 2022 period reported the highest total connectedness of energy and agricultural commodities. By looking at the long-run frequency connectedness, this only dominated the short-run connectedness in 2018.

In this analysis, it is also important to note that using high frequency, such as daily data, implies fast information processing by respective markets in the network. Thus, risk transmission in the form of shocks occurs mainly in the short run, within a week. This also means that the reaction from past shocks, that is, those that occurred within 6-100 days need to be stronger to dominate the influence of short-term effects on the connectedness. The energy-agricultural commodity market interactions show the possibility of market integration in the short run (that is, the absence of significant market developments that affect the stability of the markets), with relatively less market integration in the long run (presence of turbulent market developments).

In sum, from Table 2 and Figure 8, agricultural commodities such as corn, wheat, and flour create more significant market disruptions in terms of volatility than natural gas and oil. These three transmit more volatility shocks to other commodities than they receive from other commodities in the network of connectedness. In addition, the ongoing Russia-Ukraine war further increased the connectedness of these three variables to energy and other agricultural commodities, as revealed in Figure 8 for the year 2022.

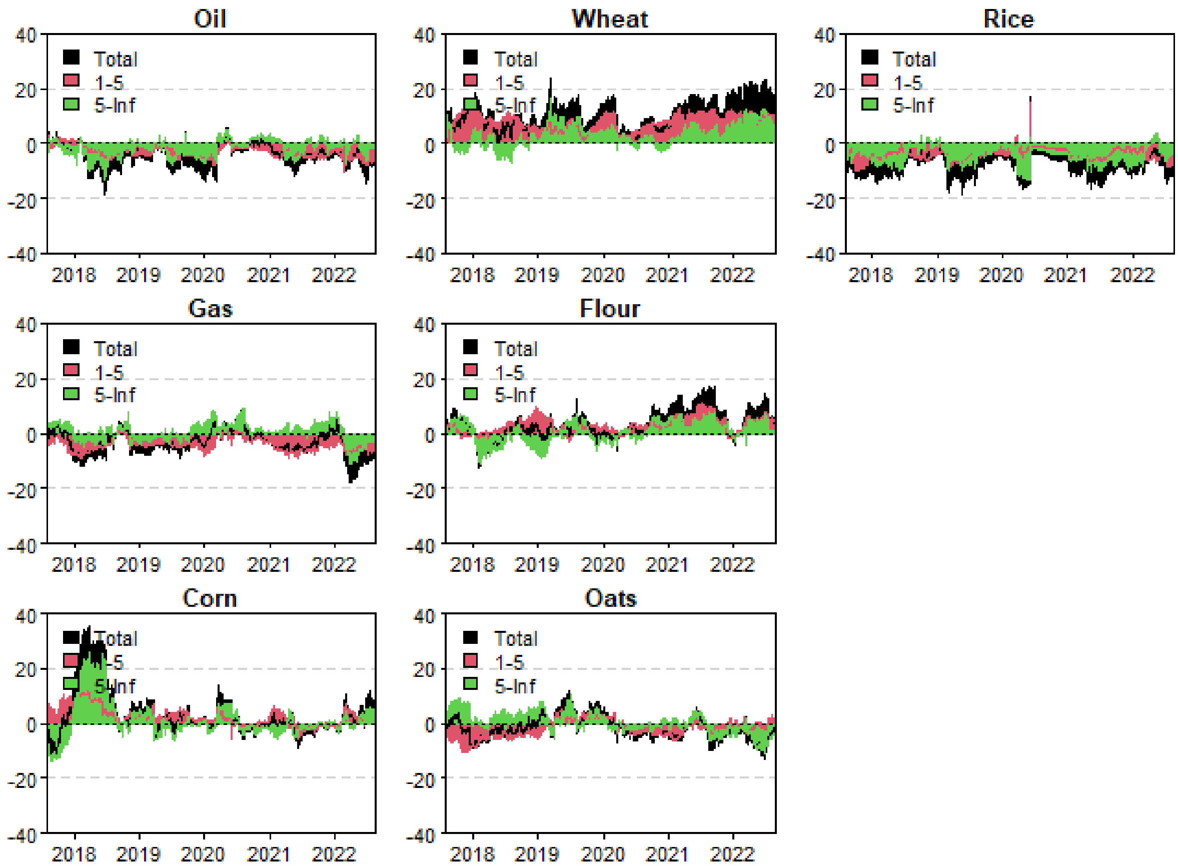

Figure 9: Net Total Directional Frequency Connectedness

To properly check each market for their contributions to short-term and long-term risks connectedness, that is, on the developments in the markets, we have plots in Figure 9 which give the net frequency connectedness of each market. The plots show that oil and rice are persistently the net receivers of volatility shocks in the network, except on sparing occasions within the sampled period. This corroborated the results obtained in the average long-run connectedness presented in the lower panel of Table 2 for the two variables. Wheat is the most vital net transmitter of shocks, as it is observed in the plots. During 2018-2019 in the wheat market, there were occasions where short-run connectedness (in red) dominated the total connectedness, and short-run also generally dominated the long run connectedness. In the remaining six markets, there are occasions where long run connectedness is seen dominating short run connectedness.

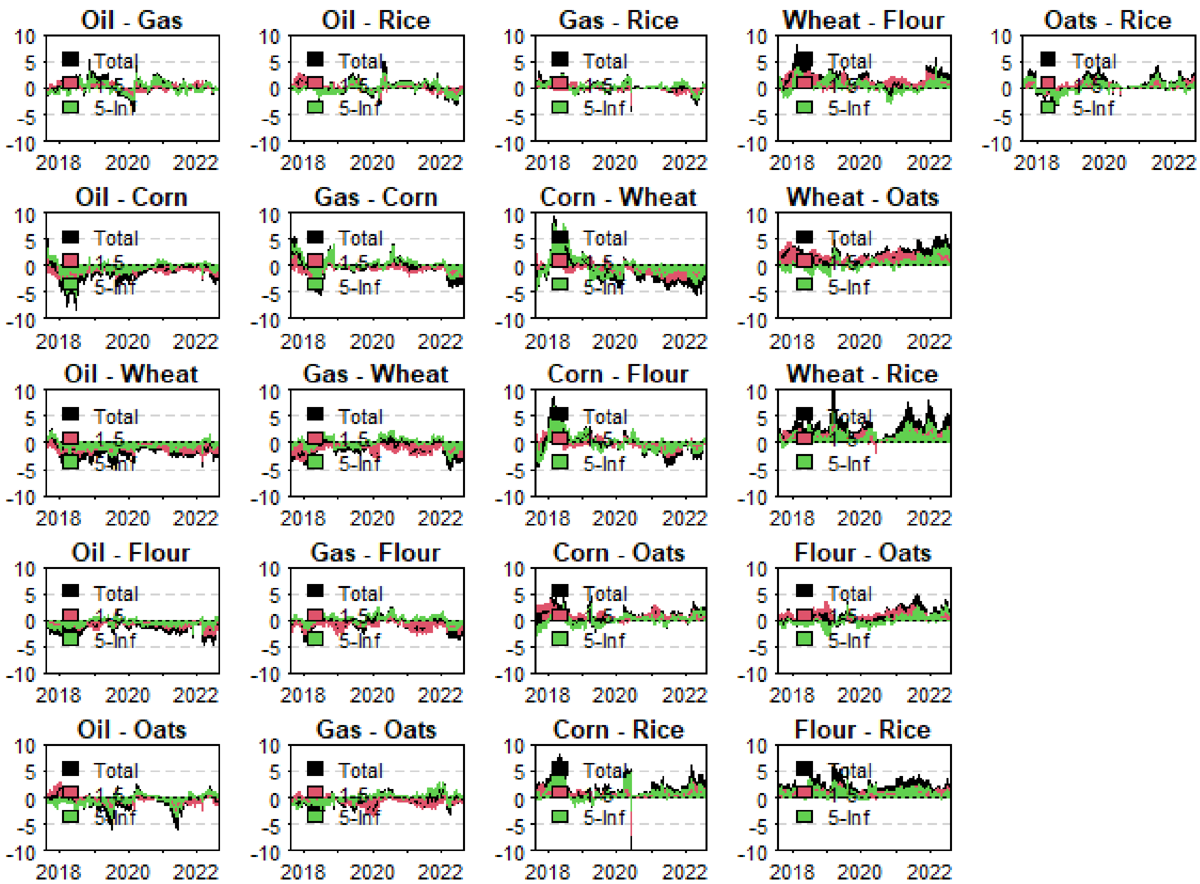

Figure 10: Net Pairwise Directional Frequency Connectedness

Further probing on the connectedness by using the net pairwise directional frequency connectedness in Figure 10 indicates that trading activities at corn, wheat, flour, and oats markets dominate the oil market, except in the case of oil-rice markets' pairs where this relationship is mixed throughout the sampled period. Recall that the dominance of a first market in the pair on the second market in the pair will indicate most parts or the entire plot on the positive side of the vertical axis, as inferred from equation (12). In contrast, in the case where the second market dominates the first market in the pair, the plot is found majorly on the negative side of the vertical axis, as in the case of corn, wheat, flour, and oats. It is also apparent to see that corn, wheat, flour, and oats dominate natural gas markets, as the plots are seen in the negative vertical axis side, while natural gas and rice markets neither dominate each other. Within agricultural commodities, wheat is seen to dominate all other food markets. Gabauer (2021) developed a Pairwise Connectedness Index (PCI) to measure the strength of pairwise connectedness, which scores the connectedness from 0 to 100. With the PCI, the short-run and long-run connectedness are more clearly observed.

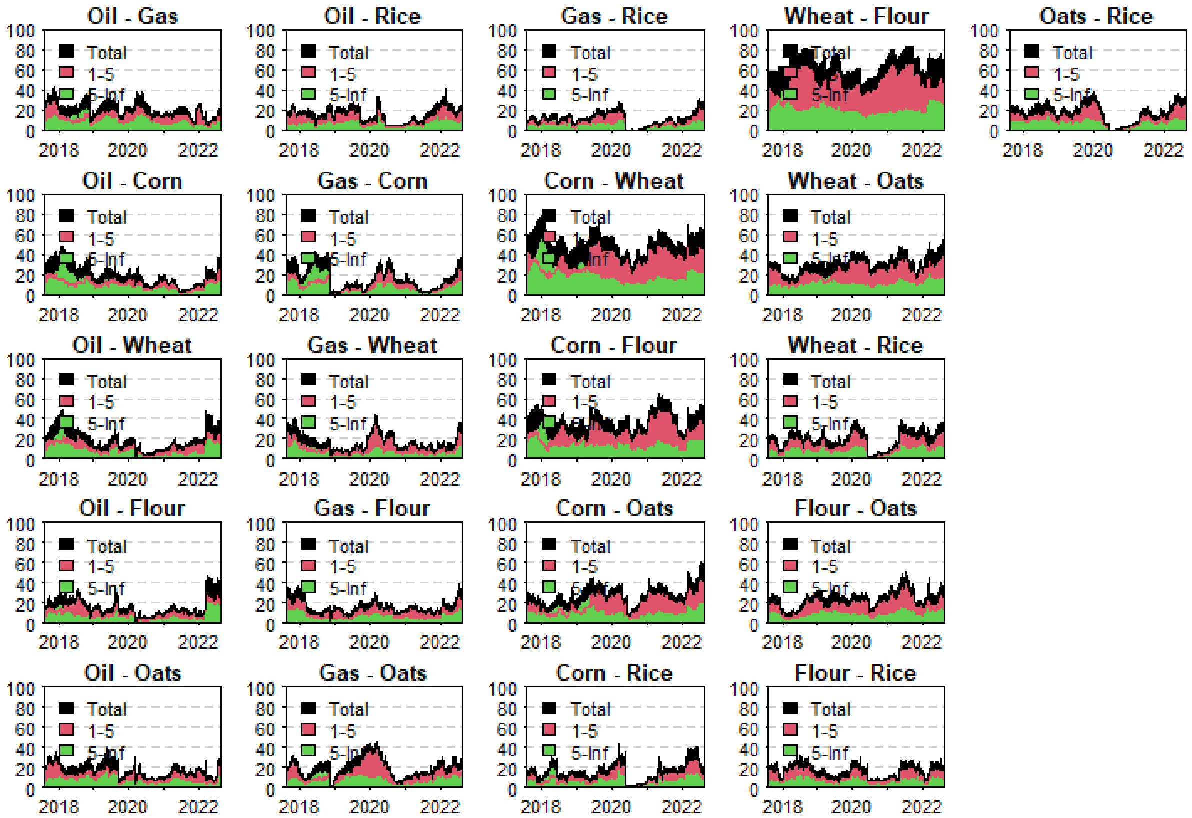

Figure 11: Pairwise Frequency Connectedness Index

In Figure 11, wheat flour PCI is the strongest implying the strong connection in the spillovers of risk between the markets. Next to this is corn-wheat and corn-flour PCIs. The strong pairwise connectedness for corn-wheat and corn-flour implies comparative market confidence in corn, wheat, and flour in the international commodity market. Energy-agricultural commodities' PCIs are generally weak over time in the network. It is observed that agricultural commodities dominated the energy markets, as these results agree with previous results obtained in the case of net pairwise connectedness.

5.2 Asymmetric connectedness

In order to investigate the possible influence of asymmetry on the network of connectedness, we disaggregated the returns, i.e. the percentage change in price indices into positive and negative returns by using the indicator,

$$S_t = \begin{cases} 0, & if \ y_t < 0 \\ 1, & if \ y_t \geq 0 \end{cases} \quad (13)$$

which obtains positive returns as $y_t^+ = S_t . y_t$ and negative returns as, $y_t^- = S_t . y_t$. Investigating asymmetry in the total connectedness of this form is first carried out by Adekoya et al. (2022a). The total connectedness in Table 3 has assumed an equal impact of returns of either sign on the network of connectedness. In Table 3, the results of average total connectedness for positive and negative returns are presented in the upper panel and lower panel of the table, respectively. Both results in the two panels are similar in the classification of markets into the main net-transmitter and net-receiver remain similar, as corn, wheat, and flour markets remain net-transmitters of volatility shocks to other markets (energy and other agricultural commodities). By looking at the coefficients of own-shocks in the main diagonals and spillover coefficients in off-diagonals, some disparities suggest the possibility of asymmetry in the connectedness. Estimates of TCI for positive returns connectedness is 42.01% while that of negative returns connectedness is 39.68%; thus, the difference in the two average values could warrant asymmetry in the network. Nevertheless, values reported in Table 3 are mere average values that may be biased, particularly when these measures' median and mean values do not overlap.

Table 3: Connectedness table (positive returns connectedness, upper panel; and negative returns connectedness, lower panel)

Positive returns connectedness								
	Oil	Nat. gas	Corn	Wheat	Flour	Oats	Rice	From
Oil	78.25	4.35	3.88	3.69	3.17	4.29	2.37	21.75
Gas	4.18	83.16	3.22	2.43	2.04	3.57	1.41	16.84
Corn	2.65	2.7	51.78	18.45	12.66	8.85	2.92	48.22
Wheat	2.11	1.39	17.17	44.95	24.56	7.32	2.5	55.05
Flour	1.95	1.32	12.54	26.22	49.01	6.24	2.72	50.99
Oats	3.38	2.77	10.88	9.94	7.9	62.38	2.75	37.62

Rice	2.4	2.06	4.87	4.4	4.44	3.42	78.41	21.59
TO	16.67	14.58	52.57	65.13	54.76	33.69	14.66	252.06
Inc.Own	94.92	97.73	104.35	110.08	103.78	96.07	93.07	TCI
Net	-5.08	-2.27	4.35	10.08	3.78	-3.93	-6.93	42.01
Negative returns connectedness								
	Oil	Nat. gas	Corn	Wheat	Flour	Oats	Rice	From
Oil	76.04	3.8	5.94	5.12	3.46	2.59	3.06	23.96
Gas	4.52	82.75	2.98	2.54	3.27	2.85	1.09	17.25
Corn	4.03	2.2	55.62	17.84	10.68	7.63	2	44.38
Wheat	3.19	1.63	15.47	47.15	23.02	6.92	2.62	52.85
Flour	2.21	2.12	9.97	25.06	52.07	5.73	2.84	47.93
Oats	2.31	2.69	8.66	9.48	7.46	66.91	2.48	33.09
Rice	2.73	1.18	2.88	4.39	4.5	2.92	81.4	18.6
TO	18.99	13.61	45.91	64.42	52.4	28.64	14.09	238.07
Inc.Own	95.03	96.37	101.52	111.57	104.47	95.55	95.5	TCI
Net	-4.97	-3.63	1.52	11.57	4.47	-4.45	-4.5	39.68

Plots of time-varying positive and negative returns connectedness are superimposed on total connectedness for clarity. The slight variation in the plot of total connectedness here in Figure 12 and that presented in Figure 8 is due to differences in time-domain and frequency-domain estimators. Since we are not comparing dynamic total and frequency total connectedness, this can be ignored. Concentrating on the asymmetry rendered by the positive and negative returns over time, the “green” lines give the path of the positive returns connectedness, while the “red” line shows the path of the negative return connectedness. We see in the plots that positive and negative returns increased the total connectedness over time more than the symmetric total connectedness (“black portion”). Also, a closer look shows that the “red” line, that is, the negative returns dominated the “green” line more. Even though, significant negative returns in form of the bear phase are expected to be short-lived compared to the bull phase (persistent high positive returns) according to the finding of Pagan and Sossounov (2003), Yaya et al. (2015) and Gil-Alana et al. (2016) but the current finding is exceptional due to recent uncertainties in the global markets, with high financial market integrations. Another explanation for the dominance of negative returns connectedness is that risk-averse investors react more to adverse shocks than positive ones since they target minimizing losses rather than maximizing gains (Dahlquist et al., 2017).

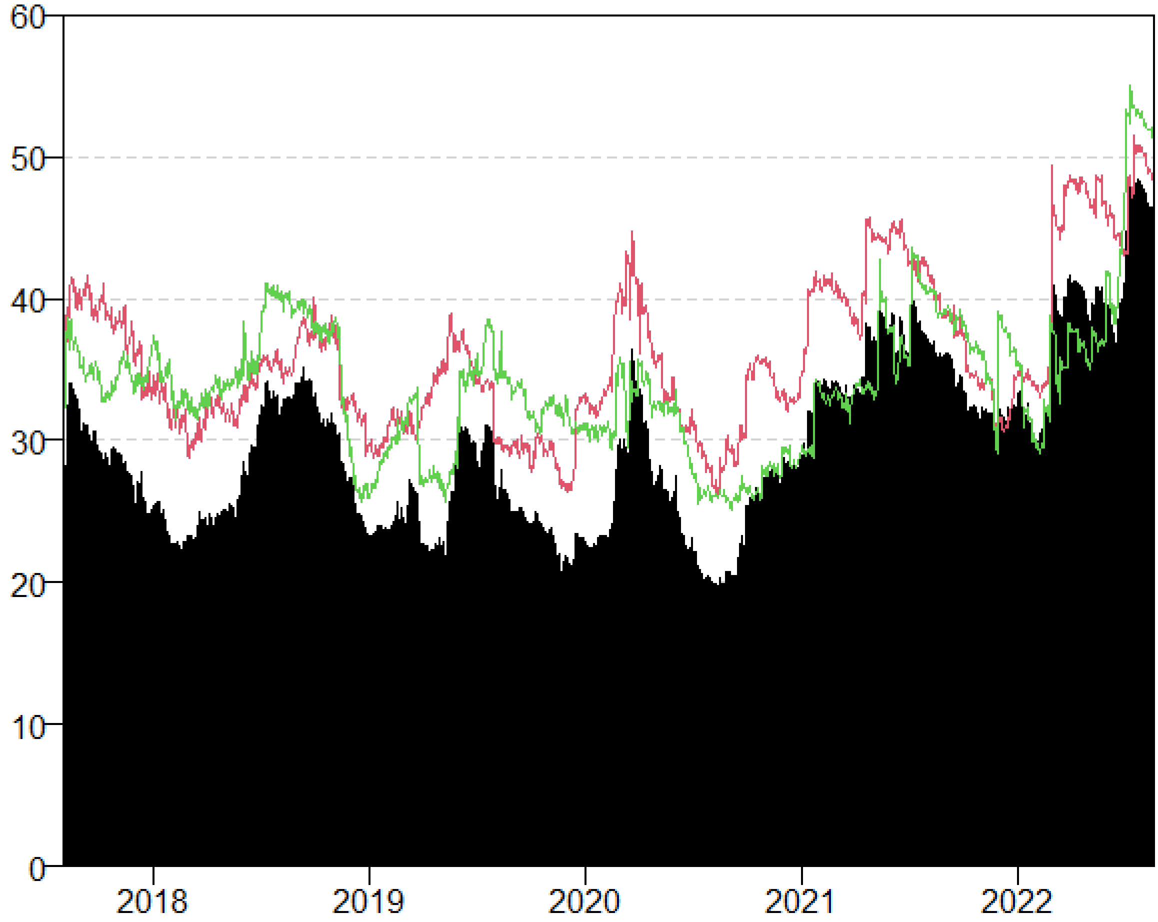

Figure 12: Dynamic Total Connectedness for asymmetry ("green": positive returns total connectedness; "red": negative returns total connectedness)

The results of net-total directional connectedness for asymmetry in Figure 13 show that asymmetry is well pronounced by each transmitter of shocks or receiver of shocks. In the pairwise connectedness plots and PCI in Figure 14 and Figure 15, respectively, asymmetry is also pronounced.

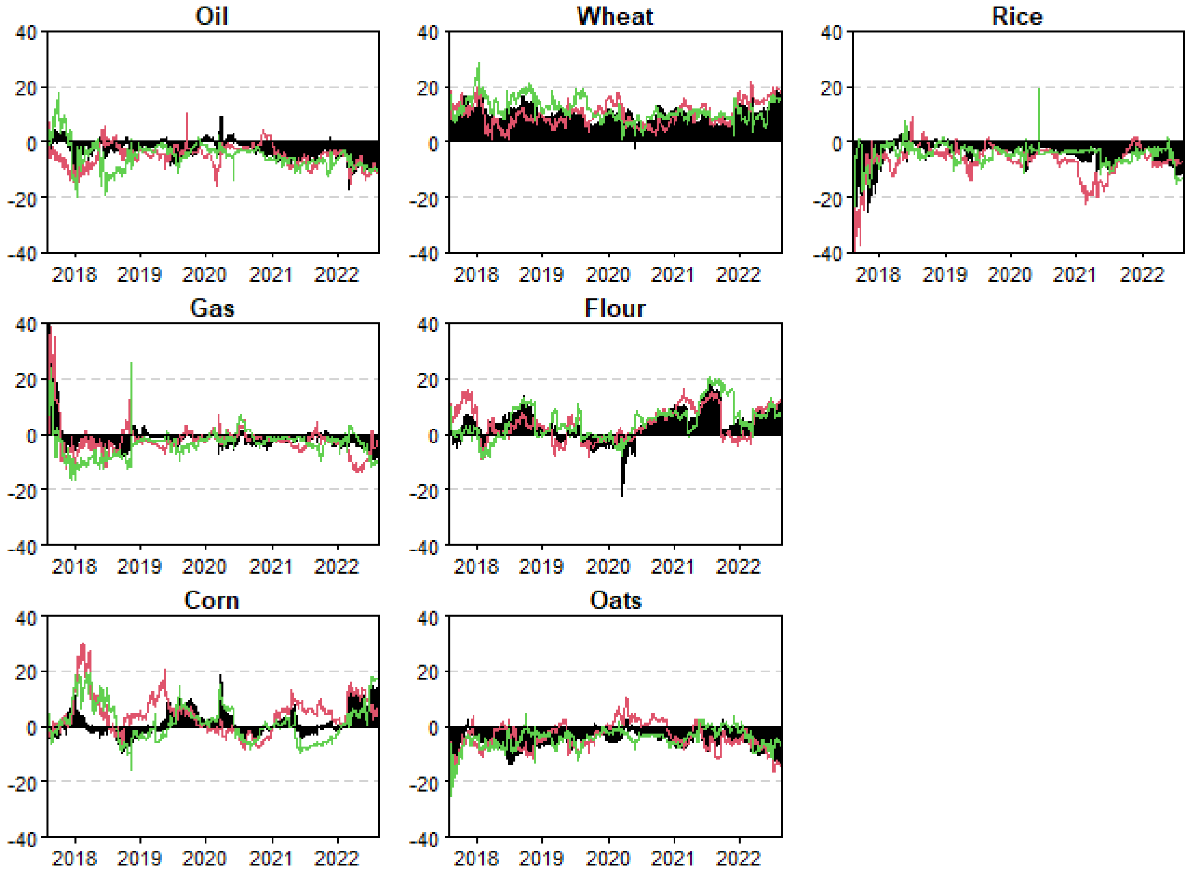

Figure 13: Net Total Directional Connectedness for asymmetry

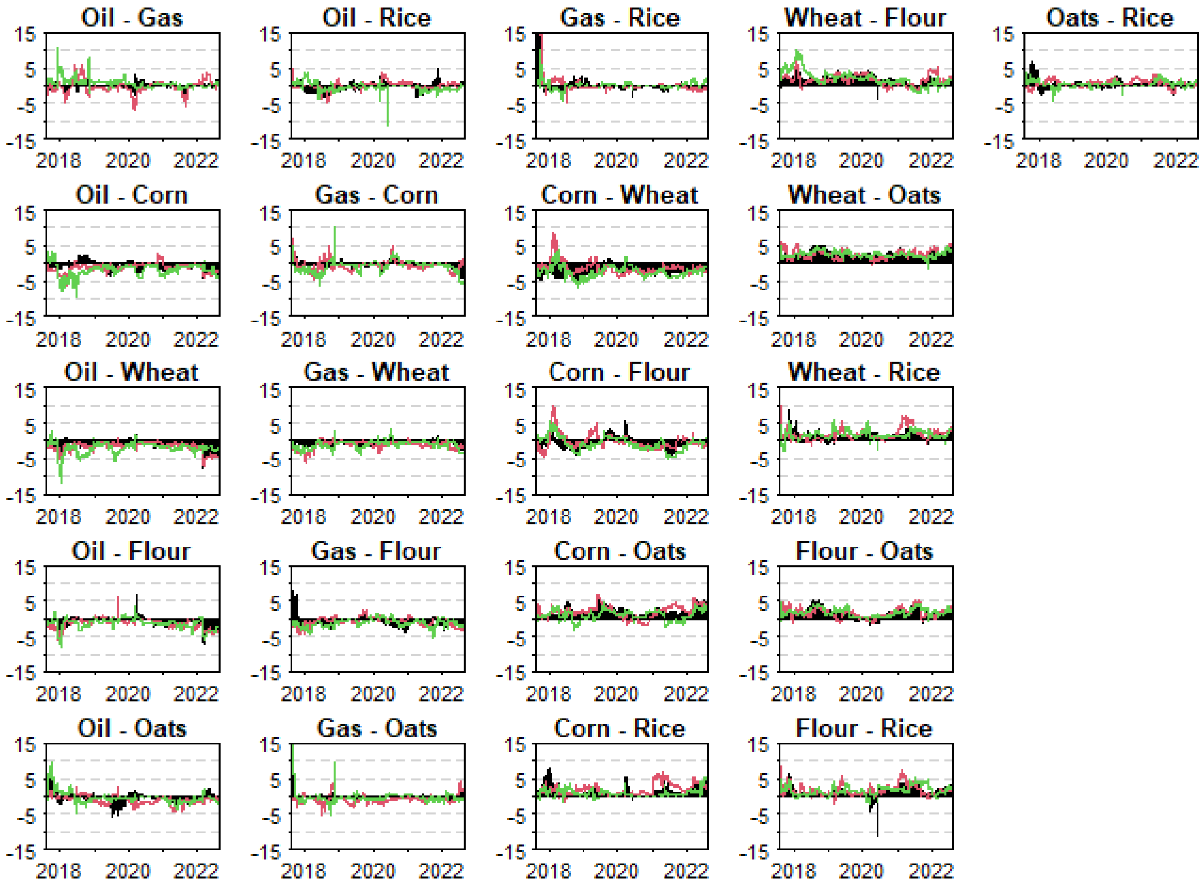

Figure 14: Net Pairwise Directional Connectedness for asymmetry

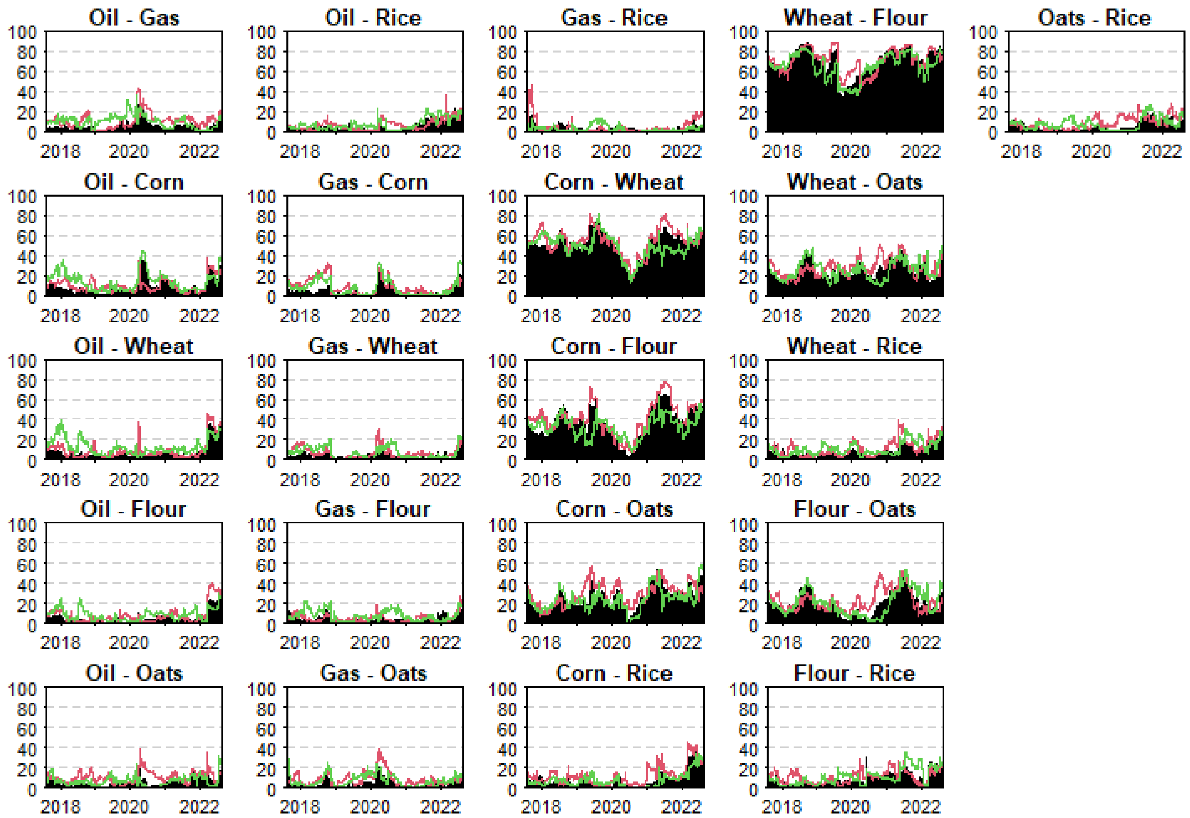

Figure 15: Pairwise Connectedness Index for asymmetry

5.3 Investment Strategies

This section of the paper presents the investment strategies necessary for portfolio managers to adopt to maximize their profits and minimize risks. The strategies rely on model estimates from the DCC-GARCH-t-Copula of Antonakakis, et al. (2020b). Kroner and Ng (1998) have proposed the dynamic portfolio weight strategy for maintaining current asset returns in the worst case or increasing them by minimizing risks encountered in each trading day, t. The dynamic measure uses estimates of variance-covariances in the multivariate GARCH model. The optimal portfolio weight formula, by Kroner and Ng (1998) is,

$$w_{jkt} = \frac{h_{jjt} - h_{jkt}}{h_{kkt} - 2h_{jkt} + h_{jjt}} \tag{14}$$

$$w_{ijt} = \begin{cases} 0, & if \ w_{ijt} < 0 \\ w_{ijt}, & if \ 0 \leq w_{ijt} \leq 1 \\ 1, & if \ w_{ijt} > 1 \end{cases}$$

where h_{jjt} and h_{kkt} are the conditional variance series from each of the asset's volatility models, and h_{jkt} is the corresponding covariance series at a time, t; w_{jjt} is the weight of asset j in a \$1 portfolio of the two assets (j, k) at time t, giving the proportional weight of the other asset k as $w_{jkt} = (1 - w_{jkt})$ provided they are traded in the same portfolio. In the case of the energy-agricultural commodities portfolio (en-ac), the above strategy implies that, in every \$1 portfolio worth of (en-ac), the weight of the energy asset to be traded with the agricultural commodity asset is $w_{en,ac,t}$ while the corresponding weight of agricultural commodity is $1 - w_{en,ac,t}$.

From the above strategy, the results obtained in Table 4 are presented with average optimal weights and their standard deviation. The hedging effectiveness is also given with its lower (5%) and upper quartile values (95%) probability of significance. The results show that hedging effectiveness can assist investors in minimizing risk and increasing profits, as the HE estimates are all significant at a 1% level. The highest hedging effectiveness exists for the oil-corn portfolio at 0.59 (its 95% upper quartile value), which corresponds to a mean value of 0.22 with a standard deviation of 0.16 by relying on the mean value of 0.22 implies that 22 cents of oil should be invested in a portfolio of oil-corn. In contrast, the remaining 78 cents should be invested in corn. Due to high turbulence in the oil market, as low as 0.00 cents (5% quartile value) is still expected to be invested in oil to balance the investment with 100 cents. The optimal weights obtained here are low, around 0.3, implying that oil and gas components (energies) are to be reduced for agricultural investments to achieve optimal profits by investors dealing with the portfolio of energy and agricultural commodities.

Table 4: Average optimal portfolio weights

	Mean	Std.Dev.	5%	95%	HE	p-value
Oil/Corn	0.22	0.16	0.00	0.59	0.78	0.00
Oil/Wheat	0.31	0.13	0.04	0.47	0.69	0.00
Oil/Flour	0.31	0.13	0.06	0.49	0.72	0.00
Oil/Oats	0.33	0.13	0.09	0.52	0.69	0.00
Oil/Rice	0.22	0.11	0.03	0.38	0.81	0.00
Gas/Corn	0.15	0.12	0.02	0.48	0.86	0.00
Gas/Wheat	0.21	0.10	0.08	0.40	0.79	0.00
Gas/Flour	0.21	0.10	0.09	0.41	0.81	0.00
Gas/Oats	0.22	0.09	0.09	0.37	0.78	0.00
Gas/Rice	0.17	0.12	0.03	0.40	0.89	0.00

Note, HE is the hedging effectiveness calculated based on the approach in Ederington (1979) and Antonakakis et al. (2020b).

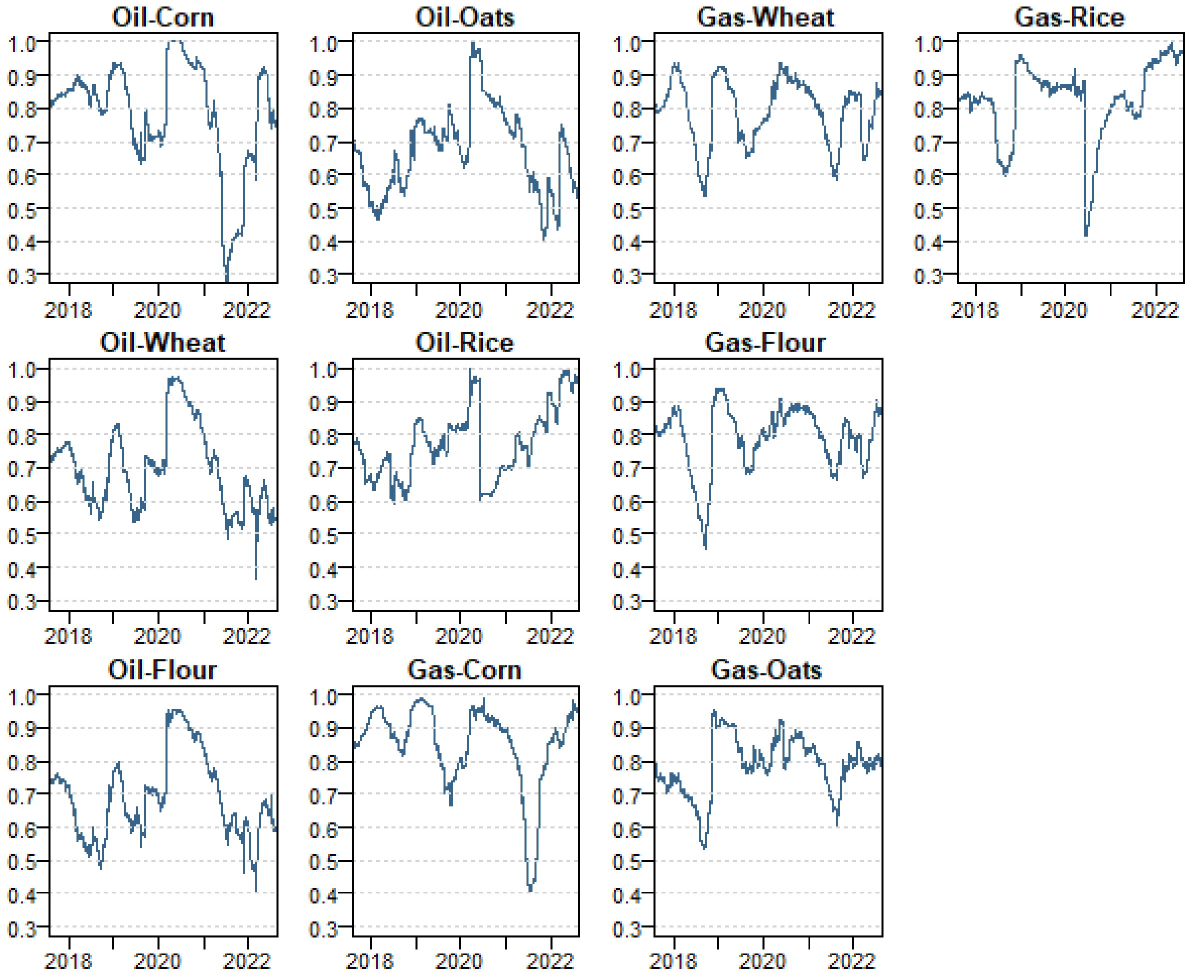

Figure 16: Dynamic optimal portfolio weights for energy - agricultural commodities portfolio

Figure 16 gives the time-variation of optimal portfolio weights as we observe fluctuations in the portfolio weights over time. This shows that energy-agricultural commodity markets have been affected by a series of market uncertainties. The last one was the period of COVID-19, which is clearly observed in the plot. In Figure 17, the corresponding expected returns based on the optimal portfolio weighting are given where returns are found to increase generally except with a fair little dip during the 2020-2021 crisis in some of the portfolios, and also in early 2022 as a result of the ongoing Russia-Ukraine war that affects energy supply and the production/transportation of agricultural commodities.

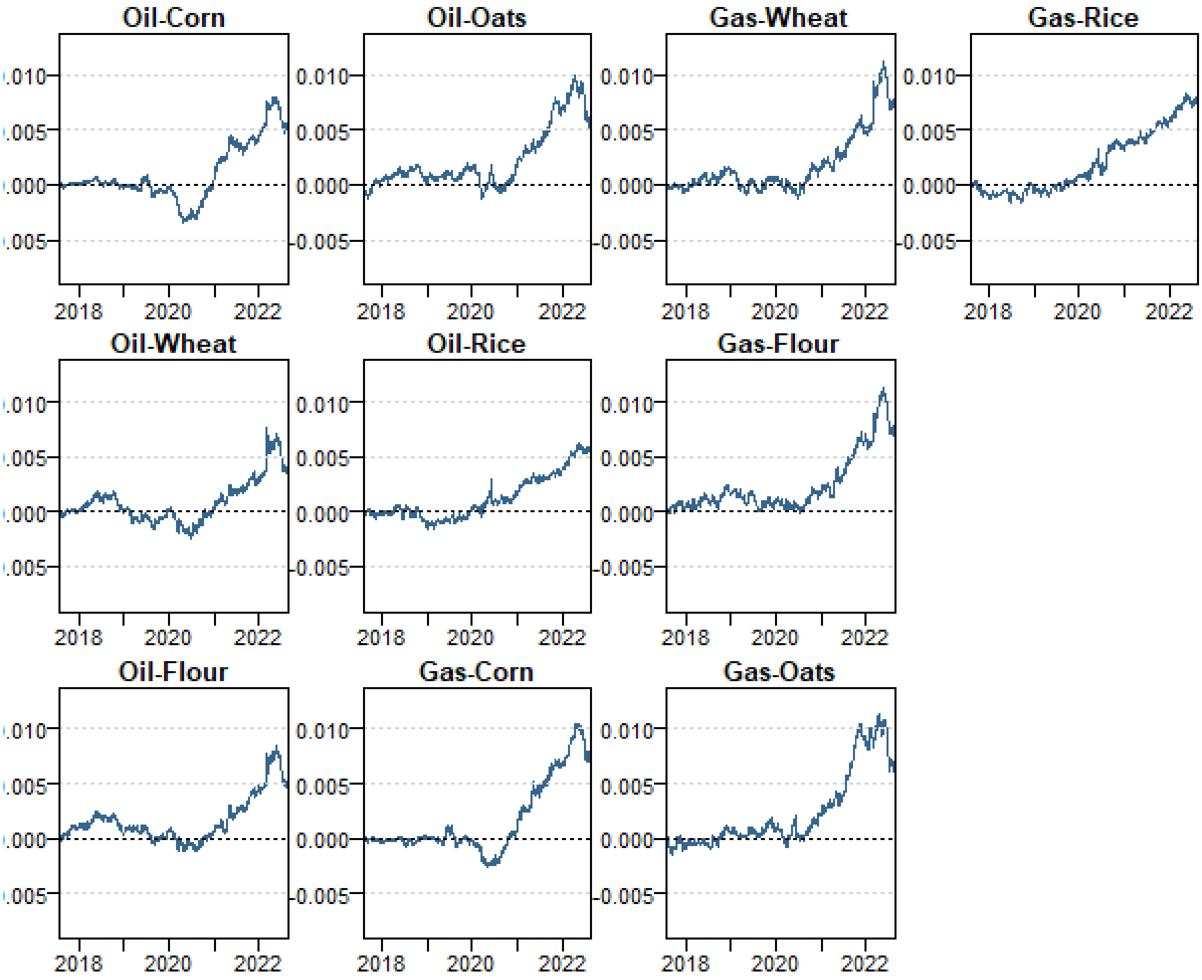

Figure 17: Cumulative portfolio return

The findings from the current study are generally in line with previous research on a similar topic. More specifically, the current study identified the strong connectedness between energy and agriculture commodities markets which confirmed those from similar studies, such as the stock-commodity market connectedness in the United States (Diebold & Yilmaz, 2012), the currency-commodity market connectedness in South Africa (Duncan & Kabundi, 2013), the bond-commodity market connectedness in the United States (Cronin, 2014). Interestingly, Gong and Xu (2022) pointed out that there are bi-directional spillover effects between the energy and agricultural market. The current study confirmed their studies and offered additional insights that wheat, rather than oil, could be considered the primary transmitter of spillover effects to other markets. Also, a lower proportion of energy is needed in a portfolio of energy-agricultural commodities by investors in order to achieve an optimum profit.

5. Conclusion

The paper investigates the connectedness of energy to agricultural commodities in the short-run and long-run by employing the frequency Time-Varying Parameter-VAR (TVP-VAR) model of Chatziantoniou et al. (2021). The frequency connectedness model is an upgrade to the dynamic TVP-VAR model of Antonakakis et al. (2020a), in which the total connectedness is not decomposed by time-frequency. The role of asymmetry in returns in connectedness is also investigated based on the approach detailed in Adekoya et al. (2022a). We further render appropriate portfolio management strategies that would guide portfolio managers during energy-agricultural commodities' trading activities.

Findings show that energy-agricultural commodities connectedness is time-varying, with the lowest connectedness found towards the third quarter of 2020, having recovered from the COVID-19 pandemic's effects, while the connectedness is increasing towards the end of 2020, that is, around 60%. Further analysis shows that corn, wheat, and flour are net transmitters of risks to oil, natural gas, and other agricultural commodities in the long and short-run networks. For pairwise directional connectedness, wheat-flour pairwise connectedness is the strongest, followed by corn-wheat, wheat-oats, corn-flour, and corn-oats, in that order. Asymmetry plays a significant role in connectedness, but this does not improve total connectedness further. Portfolio management strategies indicate a lower proportion of energy mix than the agricultural commodity in a portfolio of the two assets' class during trading to achieve an optimum profit.

The most critical policy implication on the connectedness of commodities is that the policymakers need to understand and pay due attention that there is an increasing trend in the spillover effects among agricultural and energy commodities in recent years. More importantly, among these commodities, policymakers need to understand that a net transmitter of risks is not energy commodities, such as oil or natural gas, but some agricultural commodities, such as corn, wheat, and floor. The policymaker also needs to pay due attention to the presence of asymmetry effects in the spillover effects in the connectedness of these commodities.

The main limitation of the current study is the limited usage of the dataset in empirical analysis. This study used the daily agricultural and energy commodities data from August 2017 to August 2022. The Russia-Ukraine war of 2022 is still ongoing, and the existing data could not fully capture the real impact of the war on the spillover effects on the commodity.

Regarding market selection, this study focuses on the energy and commodity market. However, other markets, such as currency or the stock market, may impact the commodities market.

In this sense, future research may need to use new and updated data, which would be used to examine the relationship of long memory cointegration to quantile connectedness of paired variables of energy to commodity in order to deduce if cointegration and connectedness are related, and further check if the strength of cointegration depends on bearish, bullish or normal market conditions (see Ajao et al., 2022; Gil-Alana & Yaya, 2014; Tiwari et al., 2022; Adekoya et al., 2022b). Researchers may also conduct similar research after the end of the Russia-Ukraine conflict. Alternatively, researchers may conduct similar research on the connectedness among currency, energy, and commodity markets. These further studies offer an exciting insight into the connectedness of agricultural and energy commodities.

References

Adekoya, O.B. and Oliyide, J. (2022). The hedging effectiveness of industrial metals against different oil shocks: evidence from the four newly developed oil shocks datasets. Resources Policy, 69, December 2020, 101831.

Adekoya, O. B., Akinseye, A. B., Antonakakis, N., Chatziantonviou, I., Gabauer, D. and Oliyide, J. (2022a). Crude oil and Islamic sectoral stocks: Asymmetric TVP-VAR connectedness and investment strategies. Resources policy https://doi.org/10.1016/j.resourpol.2022.102877

Adekoya, O.B., Oliyide, J. A., Yaya, O. S. and Al-Faryan, M. A. S. (2022b). Does oil connect differently with prominent assets during war? Evidence from intra-day data during the Russia Ukraine saga. Resources Policy, Volume 77, 102728.

Ajao, I. O., Olugbode, M. A., Olayinka, H. A., Yaya, O. S. and Shittu, O. I. (2022). Long Memory cointegration and Dynamic Connectedness of Volatility in US dollar Exchange rates, with FOREX portfolio investment strategy. SSRN paper.

Amaglobeli, D., Hanedar, E., Hong, G. H. and Thevenot, C. (2022). Fiscal policy for mitigating the social impact of high energy and food prices, IMF Note 2022/001, International Monetary Fund, Washington, DC.

Antonakakis, N., Gabauer, D., & Gupta, R. (2019). International monetary policy spillovers: evidence from a time-varying parameter vector autoregression. *International Review of Financial Analysis*, *65*, 101382.

Antonakakis, N., Chatziantoniou, I., and Gabauer, D. (2020a). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. Journal of Risk and Financial Management, 13(4):84.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., and de Gracia, F. P. (2020b). Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness. Energy

Economics, 91, 104762.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., and De Gracia, F. P. (2018). Oil volatility, oil and gas firms and portfolio diversification. Energy Economics, 70, 499-515.

Awartani, B., Maghyereh, A. I., and Al Shiab, M. (2013). Directional spillovers from the US and the Saudi market to equities in the Gulf Cooperation Council countries. Journal of International Financial Markets, Institutions and Money, 27, 224-242.

Awartani, B., and Maghyereh, A. I. (2013). Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council Countries. Energy Economics, 36, 28-42.

Awe, O. O., Akinlana, D. M., Yaya, O. S. and Aromolaran, O. (2018). Time Series Analysis of the Behaviour of Import and Export of Agricultural and Non-Agricultural Goods in West Africa: A Case Study of Nigeria. Agris-Online Papers in Economics and Informatics, 10(2): 15-22.

Baruník, J., and Krehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics, 16(2), 271-296.

Battistini, N., Grapow, H., Hahn, E. and Soudan, M. (2022). Wage share dynamics and second-round effects on inflation after energy price surges in the 1970s and today, ECB Economic Bulletin, Issue 5/2022, European Central Bank.

Chatziantoniou, I., Gabauer, D., and Gupta, R. (2021). Integration and Risk Transmission in the Market for Crude Oil: A Time-Varying Parameter Frequency Connectedness Approach (No. 202147).

Cronin, D. (2014). The interaction between money and asset markets: A spillover index approach. Journal of Macroeconomics, 39, 185-202.

Dahlquist, M., Farago, A., and Tedongap, R. (2017). Asymmetries and portfolio choice. Review of Financial Studies, 30(2): 667–702.

Diebold, F. X., and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. Economic Journal, 119(534), 158-171.

Diebold, F. X., and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting, 28(1), 57-66.

Duncan, A. S., and Kabundi, A. (2013). Domestic and foreign sources of volatility spillover to South African asset classes. Economic Modelling, 31, 566-573.

Ederington, L. H. (1979). The hedging performance of the new futures markets. The Journal of Finance, 34(1), 157-170.

Elliott, G., Rothenberg, T. J., and Stock, J. H. (1996). Efficient Tests For An Autoregressive Unit Root. Econometrica, 64(4): 813–836.

Fisher, T. J. and Gallagher, C. M. (2012). New Weighted Portmanteau Statistics for Time Series Goodness of Fit Testing. Journal of the American Statistical Association, 107 (498): 777–787.

Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the ERM I system. Journal of Multinational Financial Management, 60, 100680.

Gil-Alana, L. A. and Yaya, O. S. (2014). The Relationship between Oil Prices and the Nigerian Stock Market: An Analysis based on Fractional integration and cointegration. Energy Economics, 46: 328-333.

Gil-Alana, L. A., Gupta, R., Olubusoye, O. E. and Yaya, O. S. (2016). Time Series Analysis of Persistence in Crude Oil Price Volatility across Bull and Bear Regimes. Energy, 109: 29-37.

Gong, X., and Xu, J. (2022). Geopolitical risk and dynamic connectedness between commodity markets. Energy Economics, 110, 106028.

Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis, 63, 257-272.

Kroner, K. F. and Ng, V. K. (1998). Modelling Asymmetric Movements of Asset Prices. Review of Financial Studies 11(04), 817-844.

Kroner, K. F. and Sultan, J. (1993). Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures. Journal of Financial and Quantitative Analysis 28(04), 535-551.

Maghyereh, A. I., Awartani, B., and Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Economics, 57, 78-93.

Malik, F., & Umar, Z. (2019). Dynamic connectedness of oil price shocks and exchange rates. Energy Economics, 84, 104501.

Mo, B., Meng, J., and Zheng, L. (2022). Time and frequency dynamics of connectedness between cryptocurrencies and commodity markets. Resources Policy, 77, 102731.

Pagan, A. and Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. Journal of Applied Econometrics, 18, 23–46.

Parker, M. (2017). Global inflation: The role of food, housing and energy prices, ECB Working Paper, No. 2024, ISBN 978-92-899-2746-8, European Central Bank (ECB), Frankfurt a. M., https://doi.org/10.2866/243933.

Pesaran, H. H. and Shin, Y. (1998). Generalized Impulse Response Analysis In Linear Multivariate Models. Economics Letters, 58(1), 17–29.

Taghizadeh-Hesary, F., Rasoulinezhad, E. and Yoshino, N. (2018). Volatility linkages between energy and food prices: Case of selected Asian countries, ADBI Working Paper Series No. 829, Asian Development Bank Institute.

Tiwari, A. K, Abakah, E. J. A., Yaya O. S. and Appiah, K. O. (2022). Tail risk dependence, comovement and predictability between green bond and green stocks. Applied Economics. https://doi.org/10.1080/00036846.2022.2085869.

World Bank, Commodity Market Outlook October 2022 (2022) International Bank for Reconstruction and Development.

Yaya, O. S., Gil-Alana, L. A. and Shittu, O. I. (2015). Fractional Integration and Asymmetric Volatility in European, American and Asian Bull and Bear Markets: Application of High Frequency Stock Data. International Journal of Finance and Economics, 20(3): 276-290

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. Energy Economics, 62, 323-333.

Zhang, B. and Wang, P. (2014). Return and volatility spillovers between China and world oil markets. Economic Modelling, 42, 413-420.