Dynamic Linkages of Energy Commodities with Bullion and Metal Market: Evidence of Portfolio Hedging

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ABSTRACT

This paper examines the dynamic linkages of volatility of energy commodities with bullion and the metal market. The proxies of energy commodities are crude oil and natural gas; bullion markets are Gold, silver and platinum and metal markets are copper and zinc. We collect daily data extending from March 18, 2010, to January 15, 2021, a period for about 12 years and employ Granger causality, Dynamic Conditional Correlation (DCC), Diebold Yilmaz (2012), Baruník & Křehlík (2018), and Network analysis for the purpose of examining spillover effect in the data considered. It is observed that there are short-run dynamic spillovers from energy (crude oil) to metal (copper) while long-run linkage is witnessed among all the constituent series. Further, Baruník & Křehlík (2018) test reveals that the total connectedness of the seven data series under study are found to be higher in frequency 2 (6 days to 15 days) than in the short run and long run. Referring to the network analysis, negative correlations are found between each pair of indices considered, i.e., Gold, silver, platinum, zinc, copper with crude oil while positive correlation is witnessed between Gold and silver. In addition, we determine portfolio hedge ratios and portfolio weights for the investors and portfolio managers. It is found that the Crude /Zinc pair had the most expensive optimal hedge ratio, while Crude/Gold had the least expensive hedging.

KEYWORDS

Dynamic Linkages, Energy Commodity, Bullion Market, Metal Market, Portfolio Hedging

JEL Classification: C12; C32; G15

INTRODUCTION

Theoretically, investors were well aware of the portfolio optimization strategies in volatile markets, using less correlated equities. However, the correlations varied with time, and the optimization task became increasingly complex. Consequently, a pearl of collective wisdom was established on understanding the time-varying interdependencies of markets. This paved the way for studying volatility spillover and it has been argued that the spillover is crucial as they represent the arrival of information (Cheung and Ng, 1996). Investment theory advocates the optimal estimation of correlations among price returns to devise an optimal hedging strategy (Engle, 2002).

It is essential to characterize the volatility mechanism to fully understand the information transmission process (Ross 1989; Kyle 1985). As the information flow is neither complete nor instantaneous, lead-lag relationships exist without any opportunity for arbitration, and thus spillovers arise (Dean *et al*., 2010). Kang *et al*. (2017) described the phenomenon of spillover as "the only large

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shock increases the correlation of returns not just of the own asset but also other assets". Investors have been driven to look for alternative avenues to diversify risk to exploit diversification benefits and optimal hedging strategies completely. This led to the emergence of commodities as a hedging tool. Commodity markets and their products are important constituents of the real economy. The fundamental motivation behind the use of commodities to hedge is relatively easy to understand. One, the fluctuation cycle for commodities is relatively different from the equity markets (Roll, 2013). Secondly, the macro-economic factors that exhibit higher correlation to equity prices may or may not affect commodity prices similarly (Gorton and Rouwenhorst, 2006). Additionally, with the increasing financialization of commodities, several varied instruments are now available that offer a higher yield along with a benefit of diversification (Aloui *et al*., 2011; Yoon *et al.,* 2019). Ever since the financialization of commodities has happened, there has been an innate need to understand cross-market interdependencies.

Commodity futures prices have exhibited high volatility in the last decade and exhibited dwindling trends (Mandaci *et al.,* 2020). Also in the last few years, the commodity markets have faced the brunt of political uncertainty and economic turmoil leading investors and policymakers to study the linkages both at the macro and micro levels. Post the financialization of commodities, portfolio managers have been trusting the precious metal market futures, specifically to hedge the risk of stocks. In this connection, Gold is assumed as a safe asset (Jaffe, 1989; Chua *et al*., 1990; Aggarwal and Lucey, 2007; Arouri *et al.,* 2015; Yaya *et al.,* 2016). In addition to Gold, there was growing evidence of using precious metals such as silver, platinum, and palladium as their role in effectively hedging risk is crucial. Conover *et al.* (2009) highlight that a 25% allocation of equity into precious metals markets significantly reduces the risk and increases the overall portfolio's performance. The attention to cross-asset interdependencies, especially within the energy commodities market, have been studied during the Global Financial Crisis in particular (Alizadeh and Tamvakis, 2016; Baruník *et al*., 2015;).

Energy markets exhibit cross-asset interdependencies. For instance, Zhang and Wei (2010) show a strong unidirectional causality from oil to Gold. Martínez and Torró (2015) find that the natural gas portfolio has a higher hedging effectiveness when seasonal factors are considered. Mandacı *et al*. (2020) also signal towards highest hedging efficacy of natural gas. In response, several literatures have attempted to explain the volatility spillovers, dynamic linkages and risk transmission between natural gas and other markets such as crude oil, stocks. Some of notable studies are (Susmel & Thompson, 1997; Nick & Thoenes, 2014; Van Goor & Scholtens, 2014; Ergen & Rizvanoghlu, 2016; Zhang *et. al.* 2018; Wang and Wang (2019); Egging & Holz, 2016; Lin *et al*., 2019). It has been studied earlier that energy markets are driven more by commodity sector shocks than by equity or general financial shocks (Aromi and Clements, 2019). The volume of trade in this market is also significantly increasing daily. Commodity markets have now become a preferred source of alternative investment classes compared to traditional bond and stock market investments (Ciner, 2011). Notional amounts outstanding for commodity contracts stood at 2114 billion US dollars in 2021. In contrast, Gold alone stood at 834 billion US dollars against other precious metals held at 8 billion US dollars in 2021. Commodity futures have given the investors to diversify portfolio risk and are considered profitable investment alternatives (Chong and Miffre, 2010). It is a strategy of the investors to add commodity futures to optimize asset allocation and reduce downside risk.

Several multivariate GARCH techniques have been employed to study spillovers and thereby calculate optimal weights and hedging ratios (Sadorsky, 2014; Aboura and Chevellier, 2015). However, there is a limitation with these models, as they fail to capture the direction of spillovers across several assets. Direction of spillover provides useful information to the policy makers so that they can make structural changes, if required. Thus, our study makes use of dynamic conditional correlation (DCC), Diebold Yilmaz (2012), Baruník & Křehlík (2018) and network analysis of the series under study. The benefits of these techniques lie in their ability to measure the magnitude of return and spillovers among several commodity markets, which assists in better asset allocation.

Additionally, the linkages demonstrated by using Diebold Yilmaz (2009, 2012) are more robust and not sensitive to outliers (Liu and Gong, 2020). This paper finally examines the optimal portfolio and estimates portfolio weights for hedging in the commodity futures portfolio. The depiction of optimal asset portfolios will give global investors and portfolio managers several optimal strategies. In addition to the previous literature, the paper also offers optimal portfolio weights along with hedge ratios for the investors based on DCC-GARCH estimated covariates.

This paper aims to examine the dynamic linkages of volatility of energy commodities with the bullion and metal market. In addition, we determine the portfolio weight for the hedged portfolios for the investors and portfolio managers who will keep an eye on constituent markets. Based on the daily observations of these markets from March 18, 2010, to January 15, 2021, we use Granger causality, dynamic conditional correlation (DCC), Diebold Yilmaz (2012), Baruník & Křehlík (2018) and network analysis for the purpose of analysis of data. Empirical results show that the constituent series have fewer dynamic linkages in the short run than long run. To validate the result of this test Baruník & Křehlík (2018) test reveals the total connectedness in the same direction as DCC. Next, network analysis shows that there is negative correlation in more series than positive correlation.

At last, the results of portfolio hedge indicate that the Crude /Zinc pair is more expensive than the other pairs and the Crude/Gold has the least hedging ratio. This paper contributes many folds to the existing studies: first, it examines the dynamic linkages of energy commodities to the bullion and metal market which a very few academicians conducted. Second, we use DCC GARCH, Diebold Yilmaz (2012) and Baruník & Křehlík (2018) tests to validate these dynamic linkages clearly so that portfolio managers and investors can diversify their investments based on their intentions. Third, network analysis has been used to know the overall connectedness and magnitude of association among the constituent series. Fourth, we compute portfolio hedging and weight of each series in the total portfolio to decide how much of one market should be in a long position and how much should be in a short position.

The paper is organized as follows. In section 2, a brief review of the literature is conducted to identify the existing literature gaps and highlight the present study's specific objectives. Section 3 presents the econometric models. Section 4 provides the data and preliminary analysis. Section 5 provides the empirical results, followed by concluding observation in Section 6.

REVIEW OF LITERATURE

Ever since the financial markets have developed, investors have been looking for investment avenues and linkages among them. Knowledge of correlation between various asset classes helps investors to design their portfolios. Assets that do not co-move, act as good picks to have a diversified portfolio. On the contrary, if the portfolio consists of highly correlated assets, then a fall would lead to southward movement in the other (Rajwani & Kumar, 2019). Previous studies indicate the correlation between the assets changes due to passage of time and turbulence in the markets and their spillover effect (Longin & Solnik, 1995, 2001; Chiang *et al*., 2007; Markwat *et al*., 2009; Sensoy 2015). Unlike equity and bond market, energy and metals are viewed as safer investment opportunities especially during turbulent times (Abanomey and Mathur, 2001; Georgiev, 2001; Hillier *et al*., 2006; Gorton and Rouwenhorst, 2006; Chong & Miffre, 2010; Büyükşahin *et al*., 2009; Belousova and Dorfleitner, 2012, Yaya *et al.* 2016, Akbar *et al.*, 2019). As a clean fossil energy, natural gas has extreme strategic significance (Li *et al* ,2019).

Another reason investors move to commodities during periods of shock is that equity and commodities generally have a low correlation. This is because commodities are tangible assets; hence, they are viewed as safer options against the equity. On examining the relationship between three precious metals, namely, Gold, silver and platinum with S&P 500 and EAFE, low correlations have been found among the series suggesting that the precious metals have the potential of diversification and hedging capability; especially during the period of extreme volatility in the markets (Hiller *et al*., 2006). By using the copula approach for tail dependence and conditional value-at-risk (CoVaR), Uddin *et al.* (2020) examined US stock markets and precious metals (Gold, silver, platinum) and oil. The results show that Gold has a weak connection with the US stock market and can be used to diversify equity portfolios. US stock market influences oil and silver and in turn gets influenced by silver and platinum. Tiwari et al. (2019) examined the dependence between Gold and stocks in seven emerging countries using cross-quantilogram introduced and quantile-on-quantile regression. For the whole sample, the study found a weak positive dependence in all the quantiles of Gold and stock returns across all the countries selected during mild market conditions. Albulescu *et at*. (2020) examined the dependencies among energy, agriculture and metal commodities markets using copula-based local Kendall's tau approach and documented that commodities markets' co-movements increase in extreme situations, while a stronger dependence was found between energy and other commodities markets at lower tails. Kumar *et al.* (2020), using a pair-vine-copulas approach, examined the conditional multivariate dependence of 13 major commodity markets and provided evidence of dependencies among commodities that change in a complex manner and that there exist fatter tails in the distributions of returns. Tiwari *et al*. (2020a) examine the dependence structure and dynamics between Gold and oil prices using time-varying Markov switching copula models and documented the evidence of time-varying Markov tail dependence structure and dynamics between Gold and oil and that Gold is a good hedge for oil returns, and for short- and medium-term investors. Still, it cannot protect long-term investors against losses arising from increasing oil prices. Tiwari *et a*l. (2020b) examined the lead-lag relationship between the price indices of energy fuels and each of food, industrial inputs, agriculture raw materials, metals and beverages in the time-frequency domain. They documented that the agricultural sector is the most affected by shocks from the other markets. Tiwari *et al*. (2021) examined the frequency domain connectedness among the return's series of crude oil, stock market index and four metal prices and found that titanium, platinum, Gold and silver are the net contributors to volatility, while steel, crude oil, stock prices, and palladium are net receivers of volatility. Khalfaoui *et al*. (2021) examined the connectedness between the oil market and the Gold, silver, platinum, palladium and copper using the wavelet coherence and quantile cross-spectral analyses and found Gold and platinum are highly connected with oil and they influence oil prices, especially during global markets' turmoil. Further, the factors affecting the prices of commodities are different from that of equity. Hence, during the shocks, portfolio diversification can be done by adding commodities and energy futures.

Long and short-term relationships between commodities, especially metals and energy have been an area of interest for researchers. Under metals, Gold holds a special place under metals as it qualifies as an asset with a store of value and can be put to various uses. It has been observed that Gold is considered to be a safe haven, especially during turbulent times like the Global Financial Crisis (Bildirici & Turkmen, 2015). The authors have further examined various factors that lead to changes in the long-term relationship between precious metals and oil prices during periods of distress. Change in the structure of the oil sector, refining and redistribution of oil, lag in production, change in the behaviour and trend of macroeconomic variables might lead to structural breaks, thus distorting the relationship between oil and precious metals (Bildirici & Turkmen 2015).

Because of increased integration, financial markets are more correlated than ever, resulting in the emergence of spillover (Forbes & Rigobon, 2002). It is evident from the rise of spillover studies in the recent past, largely driven by the need to optimize asset allocations spanning key economies.

As unprecedented market volatility, varying trade flows, and globally shrinking demand has surfaced lately, the presence of these spillovers in a volatile situation can be alarming. Additionally, these discrete volatility changes may also lead to the emergence of novel information (Ross, 1989). Various research has been conducted to derive the relationship between energy and precious metals and other metals. The studies have exhibited mixed results. By examining the daily data of oil and precious metals and by employing Diebold and Yilmaz 2012, 2014; based on the time-varying parameter vector autoregressive (TVP-VAR) model, the moderate connectedness between the series was found. It was further observed that due to the passage of time, there was a change in volatilities especially during the housing bubble of 2007-08 (Mandaci *et al.*, 2020). By employing Baruník & Kley (2015) methodology for 20 years ending 31st July 2020, on a sample of energy, precious and industrial use metals; the presence of low to moderate level integration was found between the said sample commodities (Rehman & Vo, 2021). Volatility spillover between metals from 2006 to 2012 was examined using the multivariate heterogeneous autoregressive (HAR) model. This period covered the pre and post GFC period and further indicated the future price volatility (Todorova *et al.*, 2014). By employing a VAR BEKK GARCH model, Vardar *et al.*, 2018 have examined the volatility spillover from developed and emerging economies to commodity spot prices of crude oil, natural gas, platinum, silver, and Gold. The study is done over a time frame of 11 years covering the pre-global financial crisis-era to post-crisis era. Using the Diebold and Yilmaz (2009) methodology, weak integration was found among the four main precious metals (Batten *et al.*, 2015). By employing the spillover index of Diebold and Yilmaz (2012), bi-directional return and volatility spillover was found among S&P 500, crude oil, and Gold over 22 years ending August 2018 (Balcilar *et al.*, 2019). Looking at the results of the spillover effect from metals to each other, it was found that the yellow metal, Gold contribute to shocks in other countries whereas silver, copper, and zinc are the least contributors (Al-Yahyaee *et al.,* 2020).

We thus observe that some studies have already been done in the area of dynamic connectedness between the various metals or price shocks from the oil market to metals. The current paper contributes to the body of knowledge in the following ways. First, the paper attempts to examine the dynamic connectedness between crude oil, natural gas, and metals like Gold, silver, platinum, copper, and zinc. The paper adds to the body of empirical studies done previously by Ciner *et al.* (2013), Aboura and Chevallier (2014), and Batten *et al.* (2015), Kumar et al. (2020), Tiwari et al. (2020a,b), Khalfaoui *et al.* (2021), Tiwari at al. (2021). Very few studies have considered oil and natural gas together to study the dynamic connectedness between energy and metals. Second, the model suggested by Diebold and Yilmaz (2012) and Baruník & Křehlík (2018) is being used to examine the dynamic spillovers from energy to various metals. The method has been applied to examine the spillover during tranquil times as well as one year of the crisis period, i.e., COVID- 19. Thus, this study is an extension of previous studies done in this area of research. Previous studies have emphasized the impact of the Global Financial Crisis (GFC) on stocks, bonds, energy, and metals. However, this study emphasizes the impact of COVID-19 on energy prices and metals. Thirdly, after understanding the dynamic connectedness between energy and metals during a crisis period, the paper has worked on calculating optimal portfolio weight to reduce the risk of different asset classes. Additionally, we calculate the hedge ratios to plan the strategy for hedging risk during periods of crisis.

ECONOMETRIC MODELS

This paper attempts to unravel the dynamic linkages of volatility of energy commodities with bullion and metal market. Investors and portfolio managers park the investment amount based on volatility condition of the market (Ashok *et al.,* 2022). Volatility in one market can be the cause of another market hence, we employ Granger causality to check the cause and effect between these two markets, but it does not depict the dynamic linkages of considered markets in short and long time. For it, dynamic conditional correlation is employed which investigates the dynamic linkages or spillover from one variable to another, both in short and long run (Yadav & Pandey, 2020). However, this model does not depict the magnitude of volatility spillover among variables. To overcome this problem, Diebold and Yilmaz (2012) method is used. To get further insights on which frequency spillover is highest, we used Baruník & Křehlík (2018) proposed approach which helps us understand which asset class is net receiver/contributor of the volatility at which frequency. And finally, portfolio analysis is conducted to provide investors insights into hedging effectiveness. These models are briefly explained as below.

GRANGER CAUSALITY

Granger and Ding (1969) causality is a model which is employed to check the cause and effect among variables. It shows the direction in form of univariate, bidirectional and none (Yadav & Pandey, 2020). The causal connection determined by two basic principles in this model: (a) the cause occurs before the consequence and (b) the cause contains unique information. Granger causality asserts that the information is relevant to the prediction of the respective variables y and x which is constrained of these variables. Granger causality involves estimating pairs of regressions which are depicted as below:

$$y_t = \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-j} + \mu_{1t} \tag{1}$$

$$x_t = \sum_{i=1}^{n} \gamma_i x_{t-i} + \delta_i y_{t-j} + \mu_{2t} \tag{2}$$

$where$ μ_{1t} and μ_{2t} are uncorrelated.

Unidirectional Causality is indicated from x to y if the value of the estimated coefficients on the lags of x is different from zero statistically as a group,

i.e., $\alpha_i \neq 0.$

To test the hypothesis F test is used which is presented as follows:

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

This model is applied when the time series is stationary. If the series is non-stationary, it has to be converted into stationary series.

DYNAMIC CONDITIONAL CORRELATION

In an empirical analysis, DCC GARCH model pioneered by Engle (2002) is used to examine the presence of spillover between series. As the procedure adjusts the values of volatility, DCC-GARCH does not possess volatility bias. So, it constantly keeps adjusting the value of the correlation as volatility varies with time. Therefore, estimates of DCC-GARCH are far more superior estimates of correlation (Cho & Parhizgari, 2008).

The multivariate DCC GARCH model can be depicted as:

$$\varepsilon_{i,t} = z_{i,t}\sqrt{h_{i,t}} \tag{3}$$

$$h_{i,t} = \omega_{i0} + \sum_{j=1}^{2} \alpha_{ij}\varepsilon_{j,t-1}^{2} + \sum_{j=1}^{2} \beta_{ij} h_{j,t-1} \tag{4}$$

Here, $z_{i,t}$ is the residual series that has been standardized, and $h_{i,t}$ is the conditional variance,

$$H_t = D_t P_t D_t \tag{5}$$

and H_t is the 2 x 2 conditional covariance matrix, P_t depicts the conditional correlation matrix and Dt represents the diagonal matrix which also includes time-varying standard deviations,

$$D_t = diag\left(\sqrt{h_{11}}, \sqrt{h_{22}}\right) \tag{6}$$

and

$$P_t = diag\left((Q_t)^{\frac{-1}{2}}\right) Q_t \, diag\left((Q_t)^{\frac{-1}{2}}\right) \tag{7}$$

where Q_t is a (2 x 2) symmetric positive definite matrix, $Q_t = \left(q_t^{ij}\right)$, and is given as:

$$Q_t = (1 - \theta_1 - \theta_2)Q_{t-1} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} \tag{8}$$

where $Q_t$is a (2 x 2) matrix of the unconditional correlation of standardized residuals. θ_1 and θ_2 are non-negative scalars and it is assumed that $\theta_1 + \theta_2 < 1$. The estimates of correlation are given as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{9}$$

In this model, the diagonal bivariate GARCH model is based on the assumption that there is no dynamic conditional correlation between asset returns. In other words, DCC between a series of asset returns is zero, i.e., $\rho_{i,j,t} = 0$ for all *i* and *j*. On the other hand, the constant conditional correlation considers $P_{i,j} = \rho_{i,j}$ and $P_t = P$.

DIEBOLD YILMAZ METHODOLOGY: FREQUENCY CONNECTEDNESS

This methodology brings a novel framework to study the financial time series connectedness. The model is a multivariate time series model given by Diebold-Yilmaz (2012). We follow Le *et al.* (2021) to estimate the time domain spillover through DY (2012) methodology. The first model suggested by DY is a variance decomposition model into a VAR (Vector Autoregression Model). It computes the forecast error variance decomposition (FEVD) from a generalized vector autoregression to test the presence of connectedness. The model begins with the estimation of M variable, VAR(p) system which is mathematically presented as follows:

$$y_t = c + M_1 y_1 + M_2 y_2 + \ldots\ldots\ldots\ldots M_p y_{t-p} + u_t \tag{10}$$

$where, y_t$ is the vector of K*1 vector of variables at time t, c is the constant and m represents the coefficients of K * K dimensions matrix. VAR is used to estimate the degree to which one variable contributes to the other in explaining the variation.

A forecast of the mean square error of variances is depicted as follows:

$$MSE|y_{i,t} \cdot (H)| = \sum_{j=0}^{H-1} \cdot \sum_{k=0}^{k} (e_i' \Theta_j e_k)^2 \tag{11}$$

where, e_i' represents the ith column of I_K and $\Theta_j = \phi_P,\ P$ is the lower triangular matrix. P is estimated considering Koop *et al.* (1996) and Pesaran and Shin (1998) studies.

Additionally, $\phi = JA^{j}J'$, $J = |I_{k,}0, \dots ..,0)$. The estimation of k is done by using the following,

$$\theta_{ik,H} - \sum_{j=0}^{H-1}(e_i'\Theta_j e_k)^2 \,/\, MSE\,|y_{i,t}(H)| \tag{12}$$

Total connectedness from Diebold Yilmaz (2012) in the system is measured by abridging all the elements in $\theta(H)$ from 1 to K.

$$TC_H = \frac{1}{K}\sum_{ij=1}^{K}\theta_{ij}^{H}(i \neq j) \tag{13}$$

The above equation ensures the estimated coefficients range between 0 and 1 by omitting the diagonal elements. This is one of the most important measures which examines the variations in system components initiated by other variables. Intuitively, if the value is zero, the system's components are independent and no spillover effect is exhibited. A value closer to 1 implies greater connectedness. Diebold and Yilmaz test robustness of the results (2012) proposed generalized decomposition which may be expressed as follows.

$$\theta_{iK,H}^{g} = \sigma_{ii}^{-1}\sum_{j=0}^{H-1}(e_i'\emptyset_j \textstyle\sum_u^k e_k)^2 \,/MSE(y_{i,t}(H)). \tag{14}$$

Next, we measure the connectedness in frequency following Baruník & Křehlík (BK) (2018), In financial markets, investors enter with either long term or short-term time horizon preferences. To help investors to decide which time horizon to choose, BK (2018) test is suitable. In this model generalised causation spectrum over frequencies can be estimated by Σ.

$$\big(f(\omega)\big)_{j'k} = \frac{\sigma_{kk}^{-1}\left|\left((\psi(e^{-l\omega})\Sigma)_{j,k}\right)\right|^2}{(\psi(e^{-i\omega})\Sigma\psi'(e^{+i\omega})_{jj}} \qquad (\omega)\epsilon(-\pi,\pi) \tag{15}$$

where $\psi\big(e^{-i\omega}\big) = \Sigma_h e^{-i\omega h}\psi_h$ denotes the Fourier transformations of impulse response function of ψ and $\big(f(\omega)\big)_{j'k}$.

This depicts the part of the spectrum of the j-th variable possessing frequency ω as a consequence of shock in the kth variable.

The frequency band is set to: d= (a, b): a b ϵ = $(-\pi,\pi)$, a < b. The scaled down version under frequency band d = d= (a, b): a b ϵ = $(-\pi,\pi)$, a < b of generalized variance decomposition is given by:

$$(\Theta_d)_{j,k} = (\Theta_d)_{j,k}/\sum_k^j(\Theta_\infty)_{j,k.} \tag{16}$$

The within connectedness is formulated under frequency band d as below:

$$WC_d^F = C_d^W \Sigma \frac{\Theta_d}{\Theta_\infty} \tag{17}$$

Finally, following Kroner and Sultan (1993) we estimate hedge ratios from the computed covariances from DCC GARCH model. Symbolically, it is shown as follows:

$$\beta_{jit} = h_{ijt} / h_{iit} ,$$

In this, $h_{ijt}$and h_{iit}indicatethe conditional covariance of I and j and the conditional variance of I respectively. Further, we follow Kroner and Ng (1998) to calculate optimal portfolio weight using the conditional covariances estimated from DCC-GARCH.

$$w_{jit} = \frac{h_{iit} - h_{ijt}}{h_{ijt} - 2h_{ijt} + h_{iit}} \tag{18}$$

DATA AND PRELIMINARY ANALYSIS

Data employed in this study are log-returns of daily closing market indices for energy commodities (Crude oil, Natural Gas), bullion markets (Gold, Silver) and metal markets (Platinum, Copper and Zinc). The period of analysis covers from March 18, 2010, to January 15, 2021. The data have been compiled from BLOOMBERG. There were a few data points where observations were missing due to holidays etc., therefore we remove those sets of observations for other markets as well (Hamao *et al*., 1990; Tabachnick and Fidell, 2007; Kundu and Sarkar, 2016). Further, we check the pattern of the data employing descriptive statistics.

Table 1 provides descriptive statistics of the daily returns of constituent series considered in this study. All the markets exhibit zero or near-zero mean daily returns. The difference between the minimum and maximum returns shows the range or volatility in daily returns. Crude oil and Natural Gas show highest negative mean returns followed by Copper and Zinc. Crude oil depicts the maximum range of daily returns, followed by Natural Gas, Silver, Platinum, Zinc; Copper and Gold show the least range. The highest variance is shown by Crude oil, slightly less by Natural Gas while Gold shows the lowest. This means that the highest variance indices have shown the highest variation in daily returns and the lowest mean returns, which are crude oil and NG. The constituent markets exhibit significant positive skewness except for Gold and Silver. However, the level of positive skewness is not high. Significant excess kurtosis is being depicted by all the markets, except Natural Gas, Copper, and Zinc where the kurtosis is around 3; thus, demonstrating leptokurtosis in the distribution of returns of most of the indices. The JB test is a test of normality. Large values of the JB test indicate that errors are not normally distributed. All the indices have large and positive values; hence we reject the null hypothesis of normality at 1% level of significance.

Table 1. Descriptive Statistics

	Crude	NG	Gold	Silver	Copper	Platinum	Zinc
Mean	*-0.016*	*-0.016*	*0.018*	*0.013*	*-0.012*	*0.006*	*-0.007*
Minimum	*-0.28221*	*-0.180545*	*-0.09821*	*-0.195457*	*-0.062492*	*-0.099238*	*-0.097666*
Maximum	*0.319634*	*0.197984*	*0.05778*	*0.077257*	*0.083276*	*0.127995*	*0.087675*
Variance	*8.392*	*8.759*	*1.068*	*3.838*	*1.972*	*1.75*	*2.503*
Skewness	*-3.084 ******	*0.257 ******	*-0.645 ******	*-1.023 ******	*0.204 ******	*0.554 ******	*0.169 ******
Kurtosis	*89.185 ******	*3.949 ******	*6.810 ******	*8.046 ******	*2.340 ******	*10.622 ******	*2.241 ******
JB	*899764.450 ******	*1785.529 ******	*5408.277 ******	*7759.026 ******	*635.227 ******	*12839.730 ******	*578.272 ******
ERS	*-11.027 ******	*-12.076 ******	*-5.438 ******	*-7.945 ******	*-18.585 ******	*-15.189 ******	*-6.927 ******
ZA	*-16.709 ******	*-16.844 ******	*-16.595 ******	*-15.677 ******	*-15.513 ******	*-17.278 ******	*-16.306 ******
KPSS	*0.04032*	*0.02524*	*0.157383*	*0.130769*	*0.191028*	*0.155071*	*0.062372*
ADF	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***
PP	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***	*0.0100 ***
Q(20)	*112.608 ******	*14.535*	*13.228*	*18.685 ***	*21.448 ******	*25.329 ******	*18.995 ***
Q2(20)	*584.546 ******	*310.377 ******	*158.321 ******	*263.080 ******	*427.824 ******	*798.015 ******	*243.215 ******
ARCH-LM(10)	*428.7 ******	*179.7 ******	*103.0 ******	*164.2 ******	*225.2 ******	*566.5 ******	*130.5 ******
No. of Observations	*2702*	*2702*	*2702*	*2702*	*2702*	*2702*	*2702*

Source: Author's Calculations
*** is at 1% level of significance; ** is at 5% level of significance; * is at 10% level of significance

Referring the table for Augmented Dickey-Fuller (ADF), it is found that each series is stationary which is confirmed by the PP and KPSS test. The insignificant values of KPSS test show that the series are stationary. To apply the dynamic conditional correlation (DCC), the series must have the presence of the ARCH effect. For the same, the ARCH LM test is applied and found there is the presence of the ARCH effect. Hence, it is observed that volatility is autocorrelated, which means that today's volatility depends on past volatility (Orskaug, 2009). It confirms the volatility clustering and mean-reversion process.

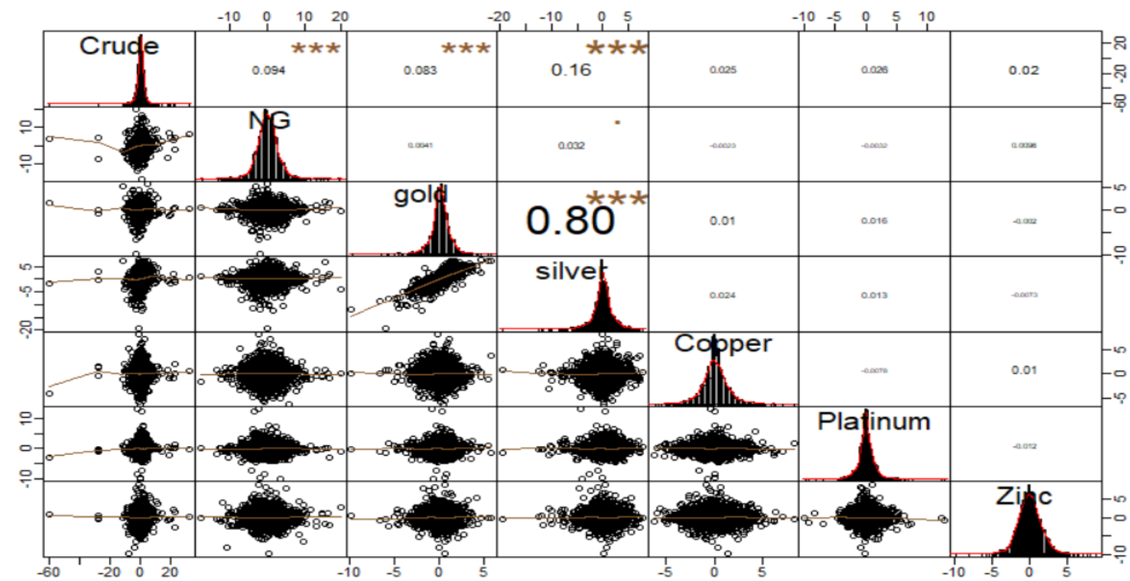


Figure 1. Plots of the Distribution and the Pairwise Correlations Between Energy and Metal Indices

Fig. 1 exhibits a plot of data in pairwise correlations form. Highest correlation, 0.80 has been found between Gold and Silver indices, which seems quite natural as both belong to the same sector of precious metal. Following Gold and silver correlation, positive correlation was found between Crude and NG, Crude and Gold, Crude and Silver pairs. Few other pairs too have positive correlation, but that is too negligible. Negative correlation has been found in NG- Copper, NG- Platinum, Gold- Zinc, Silver-Zinc, Platinum- Copper and Platinum-Zinc pairs.

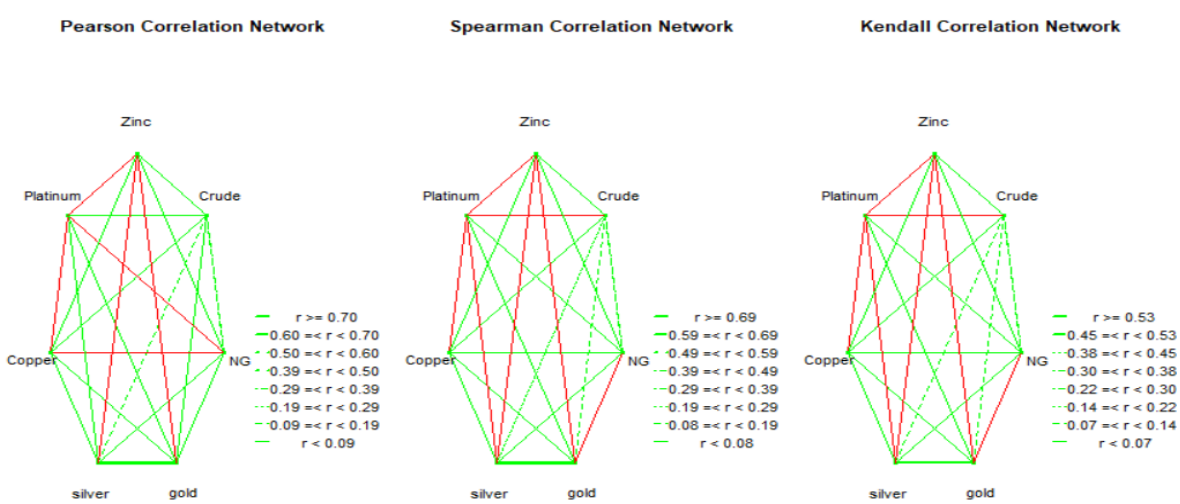


Figure 2. Plot of Network Analysis

Fig. 2 depicts the network analysis of pairwise correlations between the variables in the sample. If the line between a pair is red, it depicts negative correlations and if it is green, it depicts a positive correlation. The variables may be placed as clusters if the correlation value among them is high. Further, the distance/proximity between two variables depicts the overall magnitude of the correlation between the two variables. In Fig. 2, it is quite evident that clustering is absent. Negative correlations are found between zinc and Gold, silver, platinum with gold silver and platinum with crude oil. All three correlation networks show similar correlation structures among chosen commodities. The thickness of the network lines depicts the strength of the correlation. Clearly evident from the results, Gold and silver exhibit highest positive correlations with a correlation coefficient varying between 0.70 to 0.53.

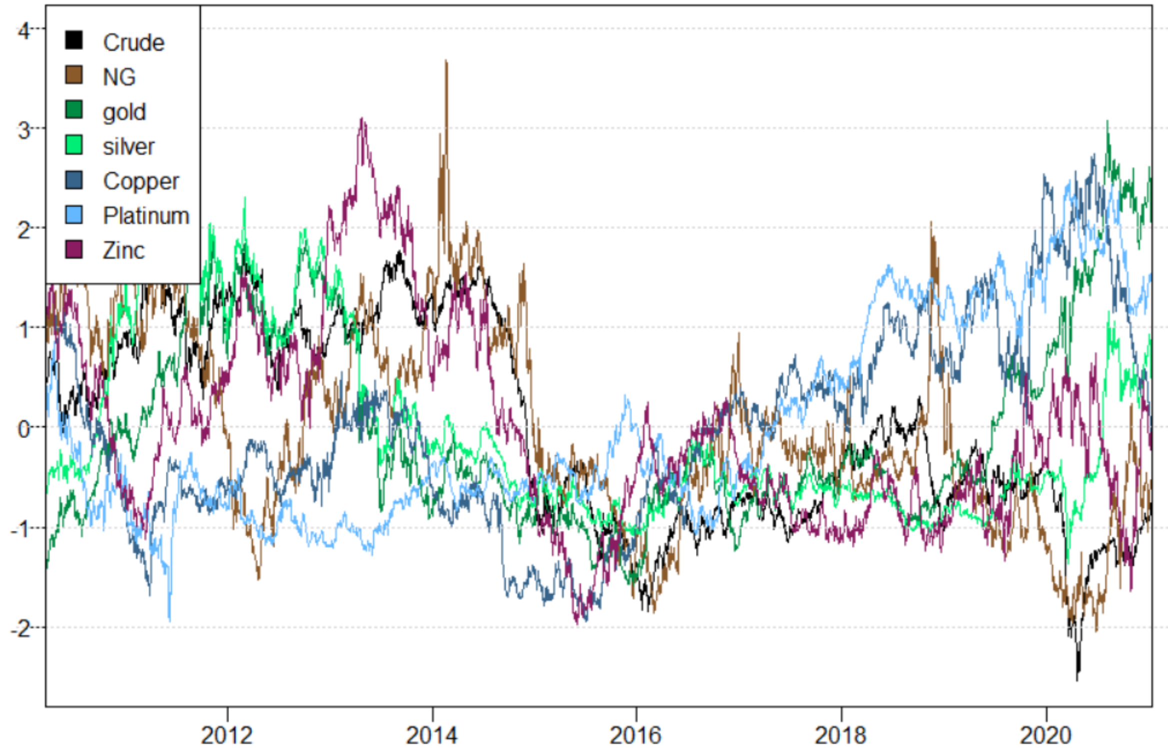


Figure 3. Plot of Log Return Series of All Indices Under Study

The plot of each index's log return series shows the returns' volatility. The graph shows that the indices were quite volatile until about 2014, which shows that the market sentiments kept changing possibly due to the fading impact of the Global Financial Crisis of 2008. The market picked up momentum by 2018 and we can see through the graph that 2019 and 2020 also witnessed extreme fluctuations in the log returns.

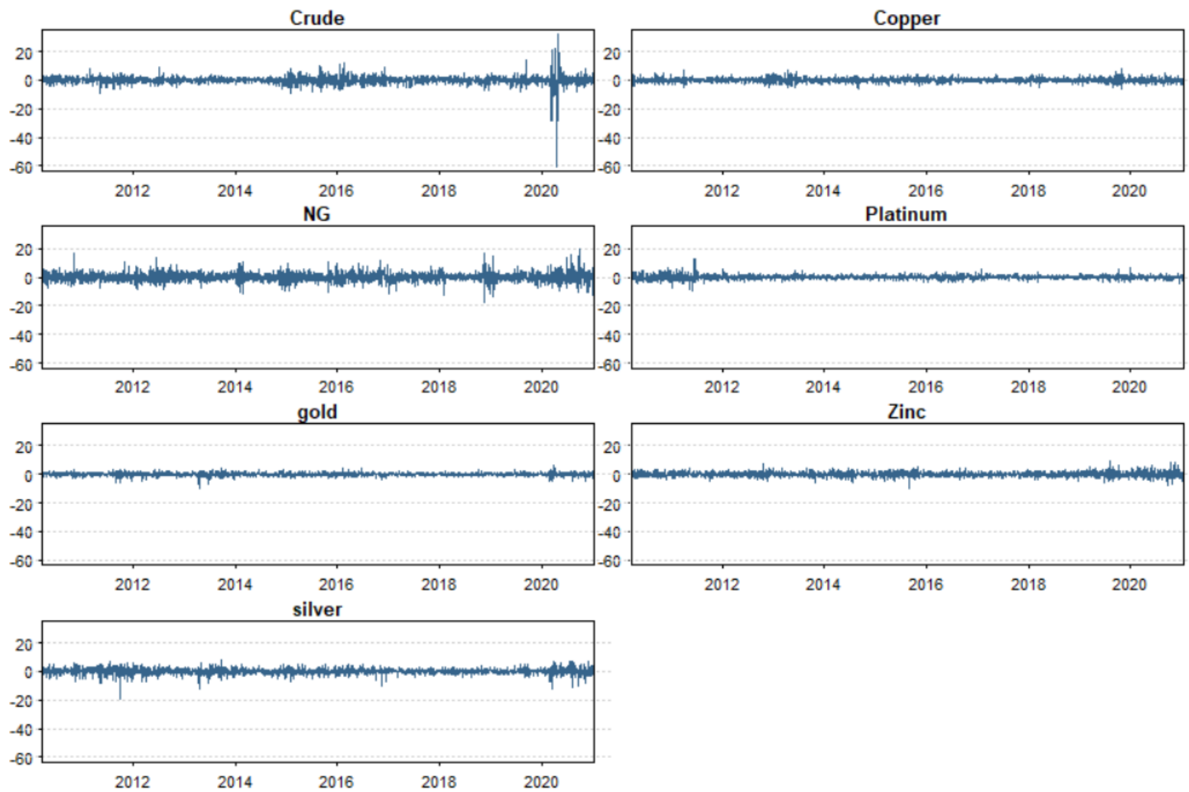


Figure 4. Individual Plot of Log Return Series of All Indices Under Study

The individual graph plots show that Crude and NG indices show the highest number of fluctuations amongst the indices under study, followed by Silver.

EMPIRICAL RESULTS

GRANGER CAUSALITY

Table 2 furnishes the results of the Granger causality test. The test named after the British econometrician Sir Clive Granger examines the causal relationship between two variables. Using the F- statistic and Student's t- statistic, it verifies whether statistically significant values of variable Y can be predicted using values of the variable X. Let us first examine the results of causality from crude oil towards various metals and vice versa. Since the p-value is statistically significant at a 1% level of significance, we reject the null hypothesis that crude oil does not Granger cause the yellow precious metal. This means that by using crude oil prices, we can predict the future values of Gold. On the other hand, the reverse is not true for the crude oil and gold pair, i.e., by using gold prices, we will not be able to significantly predict the future crude oil prices. Thus, there is a unidirectional relationship between crude oil and Gold. The bi-directional causality between the two is suggested by examining the p-values of the crude oil and silver pair. This means that crude oil significantly granger causes silver and vice-versa. For all rest of the metals, i.e., copper, platinum, and zinc; we examine insignificant causal relationships between crude oil and each metal pair.

While appraising the results of Granger causality between Natural Gas and all the bullion and metal market respectively, the null hypothesis was rejected of "no causality" from the yellow precious metal, silver, and copper to Natural Gas at a 5% level of significance. However, the null of "no causality" was accepted for causality from platinum and Zinc to Natural Gas. On the other hand, while verifying the results from Natural Gas (NG) to each metal, it was found that NG has unidirectional causality towards platinum at a 5% level of significance.

Table 2. Result of Granger Causality from Crude oil and Natural Gas to Various Metals

Null Hypothesis	F-value	Probability
Crude Oil does not Granger cause Gold.	*3.2259*	*0.0065******
Gold does not Granger cause Crude Oil.	*1.9805*	*0.0784*
Natural Gas does not Granger cause Gold.	*0.3218*	*0.9001*
Gold does not Granger cause Natural Gas.	*2.4006*	*0.03502* **
Crude Oil does not Granger cause Silver.	*3.2498*	*0.0062* ***
Silver does not Granger cause Crude Oil.	*3.5826*	*0.0031* ***
Natural Gas does not Granger cause Silver.	*0.8247*	*0.5319*
Silver does not Granger cause Natural Gas.	*2.5334*	*0.02695* **
Crude Oil does not Granger cause Copper.	*0.4183*	*0.8363*
Copper does not Granger cause Crude Oil.	*0.8974*	*0.4818*
Natural Gas does not Granger cause Copper.	*0.9263*	*0.4627*
Copper does not Granger cause Natural Gas.	*2.7495*	*0.01749* **
Crude Oil does not Granger cause Platinum.	*0.3723*	*0.8679*
Platinum does not Granger cause Crude Oil.	*1.6432*	*0.1451*
Natural Gas does not Granger cause Platinum.	*2.3295*	*0.04024* **
Platinum does not Granger cause Natural Gas.	*0.7814*	*0.563*
Crude Oil does not Granger cause Zinc.	*0.6995*	*0.6238*
Zinc does not Granger cause Crude Oil.	*0.7855*	*0.5600*
Natural Gas does not Granger cause Zinc	*1.737*	*0.1227*
Zinc does not Granger cause Natural Gas.	*0.3009*	*0.9125*

Source: Author's Calculations
*** is at 1% level of significance; ** is at 5% level of significance; * is at 10% level of significance

DYNAMIC CONDITIONAL CORRELATION FROM ENERGY COMMODITIES TO BULLION AND METAL MARKETS

To examine the spillover effect or dynamic linkages from energy commodities to bullion and metal markets, we apply dynamic conditional correlation (DCC). Table 3(a) depicts the spillover from crude oil to bullion and metal market while table 3(b) provides spillover from natural gas to bullion and metal market. The terminologies like Mu, omega, alpha1, and beta1 are overall mean, constant, ARCH coefficient, and GARCH coefficient respectively. Referring to table 3(a), we observe that alpha1 and beta1 of each constituent series are positive and significant which signifies that these energy commodities, bullion, and metal markets capture the new information or news and there is the presence of volatility persistence. To confirm the stationarity and time decay of volatility persistence, the sum of alpha1 and beta 1 is computed (Yadav & Pandey,2020). The sum of alpha1 and beta1 of each series is less than 1, confirming stationarity. Considering the joint dcca1 and dccb1, they are the measures of spillover in the short run and long run respectively. The coefficient of dcca1 is significant for Gold, silver, and copper while the dccb1 of each series is significant. We observe that there is short-run volatility spillover from crude oil to Gold, silver, and copper while long-run spillover is witnessed in all the series. As regards spillover from natural gas to bullion and metal markets shown in table 4(b), the alpha1 and beta1 of individual series is significant and their sum is also less than1. Further, we notice that there is volatility spillover from natural gas to bullion and metal market in the long run as the dccb1 is significant for all the series while there is an absence of volatility spillover in the short run (dcca1 is insignificant). Based on the results, it is found that there is a possibility of diversification opportunities in the short run from natural gas to each constituent series of bullion and metal market and crude oil to the metal market (platinum and zinc only).

Based on dynamic conditional correlation output, its graphical representation is shown in figure 2. These figures depict the dynamic correlation estimates from crude oil and natural gas to return on Gold, silver, copper, platinum, and zinc. This helps us to understand how the conditional correlations have varied over time.

Table 3(a). Result of Dynamic Conditional Correlation GARCH (DCC) from Crude Oil to Bullion and Metal Market

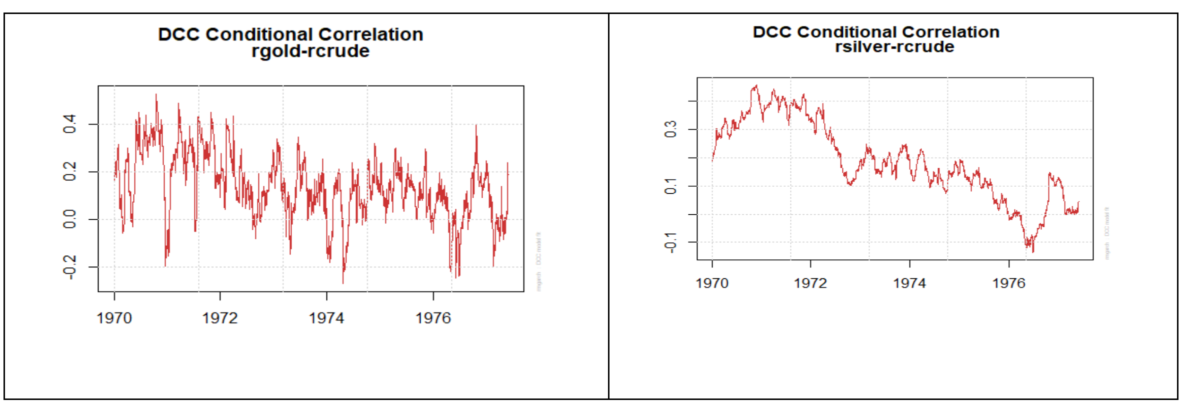
	Gold	Silver	Copper	Platinum	Zinc
MU	0.0003	0.0003	0.0003	0.0003	0.0003
Omega	0.0000	0.0000	0.0000	0.0000	0.0000
Alpha1	0.1152***	0.1152***	0.1152***	0.1152***	0.1152***
Beta1	0.8711***	0.8711***	0.8711***	0.8711***	0.8711***
Joint DCCA 1	0.0304***	0.0070**	0.0669***	0.0170	0.0000
Joint DCCB 1	0.9449***	0.9917***	0.1036	0.7842***	0.9099***

Source: Author’s Calculations

Table 3(b). Result of Dynamic Conditional Correlation GARCH (DCC) from Natural Gas (NG) to Bullion and Metal Market

	Gold	Silver	Copper	Platinum	Zinc
MU	0.0001	0.0001	0.0001	0.0001	0.0001
Omega	0.0000	0.0000	0.0000	0.0000	0.0000
Alpha1	0.0796*	0.0796**	0.0796**	0.0796**	0.0796**
Beta1	0.9080***	0.9080***	0.9080***	0.9080***	0.9080***
Joint DCCA 1	0.0103	0.0126	0.0000	0.0012	0.0012
Joint DCCB 1	0.9494***	0.8798***	0.9204***	0.9092***	0.9092***

Source: Author’s Calculations
*** is at 1% level of significance; ** is at 5% level of significance; * is at 10% level of significance



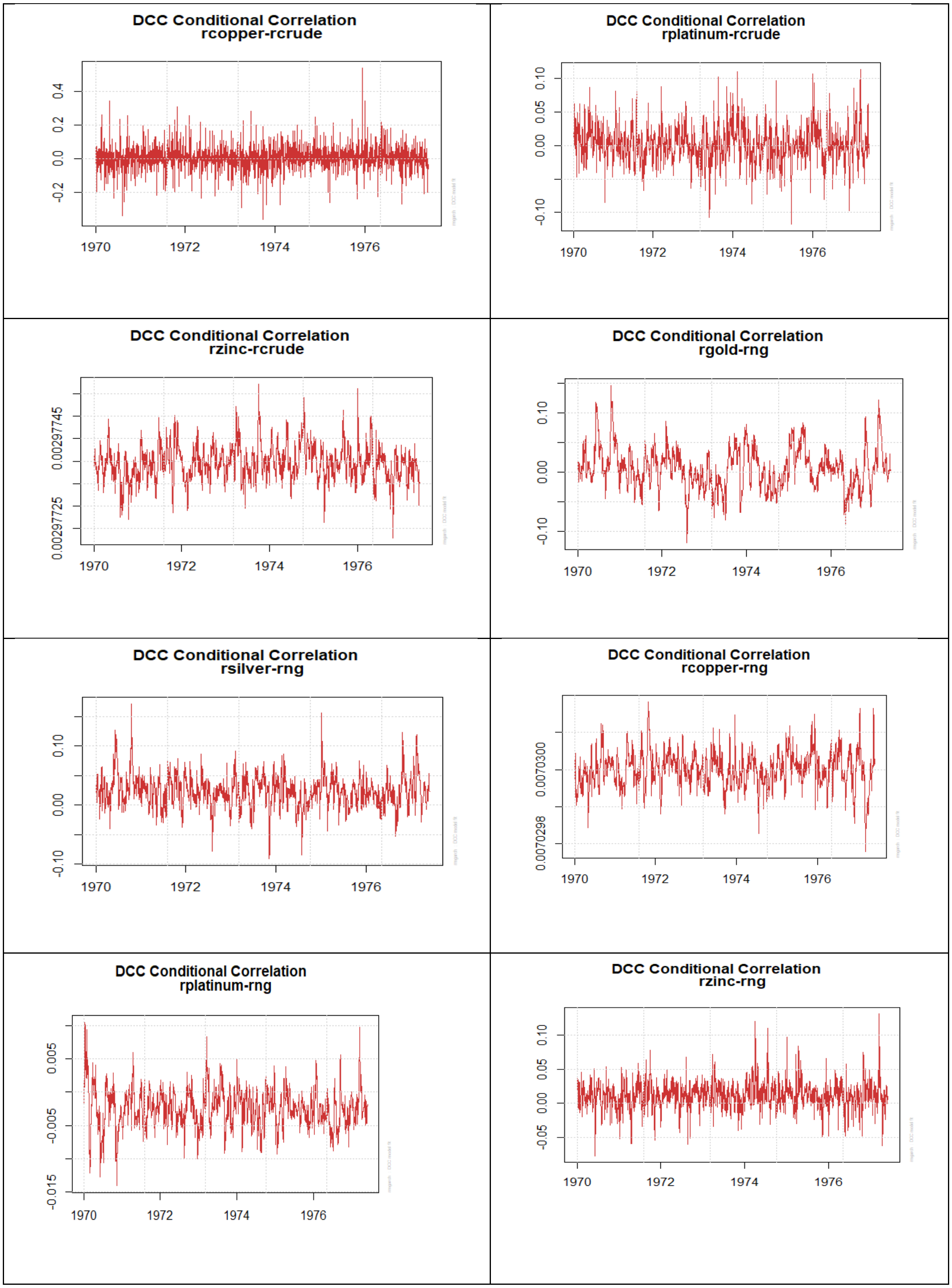


Figure 5. Graphical Presentation of DCC from Crude Oil and Natural Gas to Various Bullion and Metal Markets

APPLICATION OF DIEBOLD-YILMAZ (2012) AMONG ENERGY, BULLION, AND METAL MARKETS

We used lag 1 (determined by AIC, HQ, SC and FPE) for VAR modelling for application of DY and BK proposed spillover approaches while for dynamic analysis 200 days were used for rolling window. Table 4 shows the result derived from Diebold-Yilmaz (2012) of dynamic linkages among energy, bullion, and metal markets. Diagonal and off-diagonal elements of the matrix represent within the market and cross-market dynamic linkages. "From" the dynamic linkage indicates the dynamic linkages obtained from other markets, whereas "To" indicates the dynamic linkages contributed to other markets considered in this study. As regards the result of "From" dynamic linkages, we observe that silver has the highest return dynamic linkages (5.75%) from other markets followed by Gold. Further, silver is found the most contributing series for dynamic linkage (14.49) within the sample followed by zinc (14.34). Gross dynamic linkage is computed by adding the "FROM" and "TO" dynamic linkages which is an indicator of market openness Mittal *et. al* (2019).

Table 4. Result of Diebold and Yilmaz (2012) Model

	Crude	NG	Gold	Silver	Copper	Platinum	Zinc	FROM
Crude	*95.24*	*0.75*	*0.67*	*2.61*	*0.3*	*0.1*	*0.31*	*0.68*
NG	*1.01*	*98.24*	*0.12*	*0.33*	*0*	*0.01*	*0.28*	*0.25*
Gold	*0.45*	*0.01*	*60.55*	*38.93*	*0.02*	*0.02*	*0.02*	*5.64*
Silver	*1.66*	*0.08*	*38.42*	*59.74*	*0.03*	*0.01*	*0.05*	*5.75*
Copper	*0.08*	*0.04*	*0.09*	*0.08*	*99.49*	*0.05*	*0.16*	*0.07*
Platinum	*0.08*	*0*	*0.03*	*0.02*	*0.03*	*99.83*	*0.02*	*0.02*
Zinc	*0.05*	*0.01*	*0.05*	*0.02*	*0.06*	*0.05*	*99.75*	*0.04*
TO	*0.48*	*0.13*	*5.63*	*6*	*0.07*	*0.03*	*0.12*	***TCI = 12.45***
Net	*-0.20403*	*-0.12321*	*-0.00912*	*0.247381*	*-0.00713*	*0.010355*	*0.085748*	

Source: Author’s Own Presentation

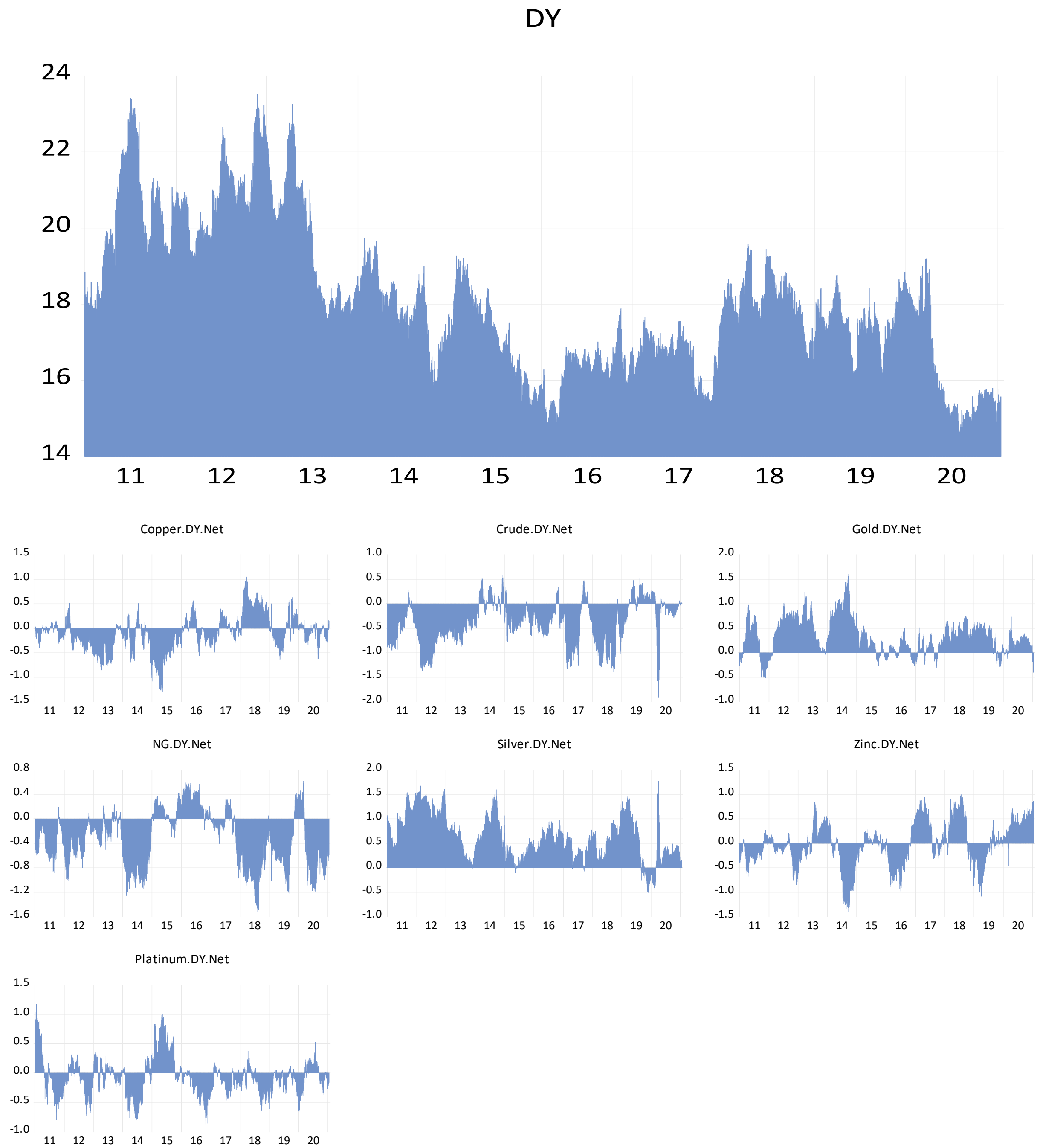


Figure 6. Plot of DY

EVIDENCE OF BARUNÍK & KŘEHLÍK (2018) TEST

Table 5 shows the BK (2018) test of spillover containing the volatility contribution of return on crude, natural gas (NG), Gold, silver, copper, platinum and zinc. It provides the magnitude and direction of the spillover "from" and "to" of the various markets examined in this study. We report the contribution of volatility from frequency 1 (1 day to 6 days) to frequency 3 (15 days to infinity). In frequency 1, it is observed that silver has the highest spillover (4.83%) derived from other series followed by Gold (4.73%) while platinum receives the least spillover (0.02%). Surprisingly, silver is the largest contributor to the spillover followed by the Gold. As regards frequency 2 (6 days to 15 days) and frequency 3 (15 days to infinity), it follows the frequency 1 in form of maximum and least spillover "from" and "to" of the markets. From the Baruník & Křehlík (2018) frequency connectedness, the total connectedness of the seven series is found to be higher in frequency 2 (6 days to 15 days) than in the short run and long run. In this table, positive net spillover value signifies that the respective market is assumed as a spillover contributor while a negative spillover value shows the net receiver which receives spillover from other constituent markets. In the short run, crude, natural gas (NG) and copper are net receivers while Gold, silver, platinum and zinc are net receivers. In frequency 2, crude, platinum and Gold are the net receivers and rest are net spillover contributors. Further, in the long run (frequency 3 - 15 days to infinity), the contributors net receivers are the same as frequency 2.

Table 5. Baruník & Křehlík (2018) Spillover Result

Freq1. The Spillover Table for Band: 3.14 to 0.52 that Roughly Corresponds to 1 Day to 6 Days

	Crude	NG	Gold	Silver	Copper	Platinum	Zinc	FROM_ABS
Crude	*80.81*	*0.6*	*0.55*	*2.09*	*0.23*	*0.1*	*0.29*	*0.55*
NG	*0.97*	*82.88*	*0.1*	*0.24*	*0*	*0.01*	*0.26*	*0.23*
Gold	*0.35*	*0*	*50.88*	*32.67*	*0.02*	*0.01*	*0.02*	*4.73*
Silver	*1.31*	*0.06*	*32.39*	*50.27*	*0.03*	*0.01*	*0.04*	*4.83*
Copper	*0.06*	*0.03*	*0.07*	*0.06*	*85.07*	*0.04*	*0.15*	*0.06*
Platinum	*0.06*	*0*	*0.02*	*0.01*	*0.02*	*82.1*	*0.02*	*0.02*
Zinc	*0.04*	*0.01*	*0.04*	*0.02*	*0.05*	*0.05*	*83.65*	*0.03*
TO_ABS	*0.4*	*0.1*	*4.74*	*5.01*	*0.05*	*0.03*	*0.11*	*10.44*
TO_WTH	*0.47*	*0.12*	*5.64*	*5.96*	*0.06*	*0.04*	*0.13*	
NET	*-0.1517*	*-0.1249*	*0.0143*	*0.17875*	*-0.00961*	*0.0114*	*0.08161*	

Freq2. The Spillover Table for Band: 0.52 to 0.21 that Roughly Corresponds to 6 Days to 15 Days

	Crude	NG	Gold	Silver	Copper	Platinum	Zinc	FROM_ ABS	FROM_ WTH
Crude	*8.51*	*0.09*	*0.07*	*0.31*	*0.05*	*0*	*0.01*	*0.08*	*0.81*
NG	*0.02*	*9.05*	*0.01*	*0.06*	*0*	*0*	*0.02*	*0.02*	*0.17*
Gold	*0.06*	*0*	*5.69*	*3.69*	*0*	*0*	*0*	*0.54*	*5.72*
Silver	*0.21*	*0.01*	*3.55*	*5.58*	*0*	*0*	*0.01*	*0.54*	*5.78*
Copper	*0.01*	*0*	*0.01*	*0.01*	*8.51*	*0.01*	*0.01*	*0.01*	*0.08*
Platinum	*0.01*	*0*	*0*	*0*	*0*	*10.41*	*0*	*0*	*0.03*
Zinc	*0.01*	*0*	*0*	*0*	*0.01*	*0*	*9.49*	*0*	*0.04*
TO_ABS	*0.05*	*0.02*	*0.52*	*0.58*	*0.01*	*0*	*0.01*	*1.18*	
TO_WTH	*0.48*	*0.17*	*5.58*	*6.21*	*0.1*	*0.02*	*0.07*		*12.63*
NET	*-0.03059*	*0.000734*	*-0.01346*	*0.03997*	*0.001417*	*-0.00061*	*0.00255*		

Freq3. The Spillover Table for Band: 0.21 to 0.00 that Roughly Corresponds to 15 Days to Infinite Days.

	Crude	NG	Gold	Silver	Copper	Platinum	Zinc	FROM_ABS
Crude	5.92	0.07	0.05	0.22	0.03	0	0.01	0.05
NG	0.01	6.31	0.01	0.04	0	0	0.01	0.01
Gold	0.04	0	3.97	2.57	0	0	0	0.37
Silver	0.15	0.01	2.48	3.89	0	0	0.01	0.38
Copper	0.01	0	0.01	0.01	5.91	0.01	0	0.01
Platinum	0.01	0	0	0	0	7.32	0	0
Zinc	0.01	0	0	0	0.01	0	6.62	0
TO_ABS	0.03	0.01	0.36	0.41	0.01	0	0	0.83
TO_WTH	0.49	0.18	5.58	6.22	0.1	0.02	0.06	
NET	-0.02172	0.000955	-0.00998	0.02865	0.001063	-0.00052	0.00155	

Source: Author's Own Presentation

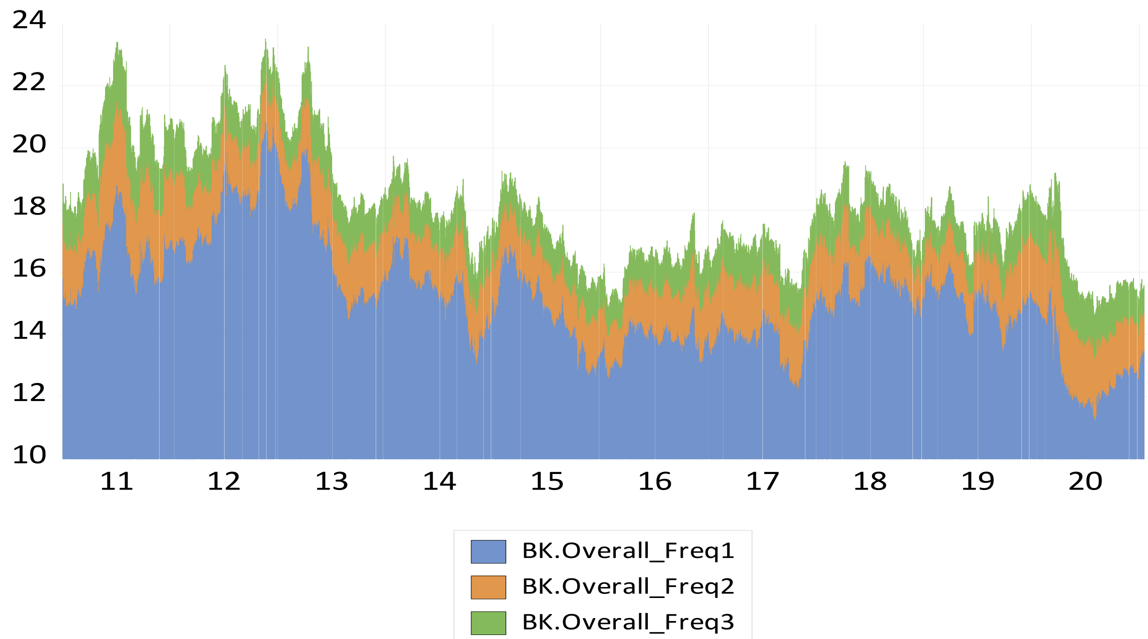


Figure 7. Plot of Baruník & Křehlík (2018) Test

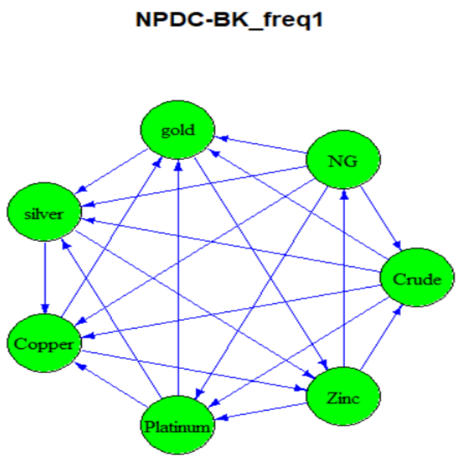
After estimating the results of the DY test in Table 5, a network analysis was done. Using DY (2012,2014) the interconnectedness between the variables is plotted. Further, results of pairwise net spillovers using network analysis are computed at several frequencies. The direction of the arrows in the network analysis depicts positive net directional connectedness from one variable to another. It is quite evident from the figure that the returns on Gold play a significant lead role in total connectedness. Both Gold and silver are net receivers of volatility both from base metals as well as energy markets. Results show that crude oil and natural gas are both volatile net transmitters. This result fixes our evidence into the importance of energy markets as it strongly affects commodity markets in both time and frequency domain. It is also evident that crude oil plays a leading role in total connectedness and Gold receives more than it transmits while crude among energy markets transmits more than it receives. Overall, results further indicate Gold and major commodities are net receivers while crude oil is a net shock transmitter. We also carried out robustness/sensitivity analysis and reported results in Appendix of the paper. We used Gamba-Santamaria *et al.* (2017) proposed approach for robustness analysis. These authors have extended the framework of Diebold and Yilmaz (2012) and constructed volatility spillover indexes using a DCC-GARCH framework to model the multivariate relationships of volatility among assets.

Additionally, we use lag 2 to 6 and forecast horizon 5 to 10 for the sensitivity of the Diebold and Yilmaz (2012) based results. We found that spillover based on DCC-GARCH provide very close approximation of results derived from the approach proposed by Diebold and Yilmaz (2012) while Diebold and Yilmaz (2012) results are found results were not sensitive to the different forecast horizon chosen. Furthermore, results were found to be a bit sensitive with respect to different lag-lengths. Still, all criterion of lag-selection (i.e., AIC, BIC, HQ and FPE) had suggested one lag to be used. Therefore, we can argue that overall results are robust to the different method and forecast horizon.

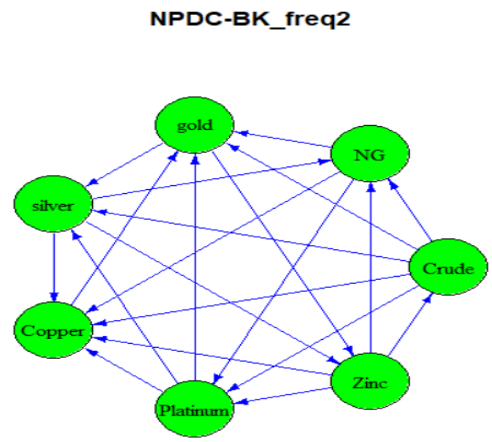
PORTFOLIO WEIGHT AND OPTIMAL HEDGE RATIO

After examining the dynamic linkages, we report the portfolio weight and optimal hedge ratio result based on the conditional variance and covariance in table 5. This is calculated using the DCC-GARCH. Similarly, the temporal covariance matrix manages the risk creating an optimal portfolio. The basic purpose of calculating optimal portfolio weight is to reduce the risk in selecting the constituent markets. Additionally, we calculate the hedge ratios to plan the strategy for hedging. We should create a portfolio containing energy commodities, bullion, and metal markets to decrease the risks without reducing an expected return. We report that a portfolio investor manages the exposure to energy commodity movements by investing their funds in bullion and metal markets. We employ Kroner and Ng (1998) and Kroner and Sultan (1993) to build portfolio weight and hedging. The mean (average) of the hedge ratio represents that an investor can consider a short or long position in the energy commodity, bullion, and metal market. The descriptive statistics of the portfolio weights and hedge ratio of energy commodity, bullion, and metal markets are shown in table 5. Crude oil and natural gas are the proxies of energy commodities. Therefore, two different portfolio weights and hedging of Crude oil and natural gas are shown separately. Considering the first portfolio weight of crude oil, we observe that Crude and Gold have the least average portfolio weight (0.1385) while Crude and Silver have the highest portfolio weight (0.7835) respectively. Low weight (0.1385) indicates that 13.85% must be invested in Crude while the rest of the portions 86.15% (1-Wjit) will be invested in Gold. Similarly, a high portfolio weight (0.7835) signifies that 78.35% must be invested in Crude, and the remainder 21.65% will be invested in Silver. The second portfolio weight is calculated based on the natural gas, bullion, and metal markets. As regards it, Natural Gas and Copper have the lowest portfolio weight (0.1847) and Natural Gas and Silver have the highest portfolio weight (0.6513). The lowest weight 0.1847 represents that 18.47% will be invested in Natural Gas and the remainder of the 65.13% will be invested in copper. Next, a high portfolio weight (0.6513) indicates that 65.13% must be invested in natural gas while 34.87% will be invested in Silver.

(a) Plot of BK frequency 1



(b) Plot of BK frequency 2



(c) Plot of BK frequency 3

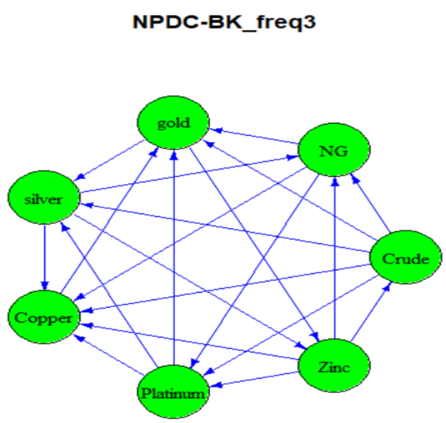


Figure 7. Network Connectedness

Further, we apply Kroner and Sultan (1993) to calculate the hedge ratio to reduce the portfolio risk (energy commodity, bullion, and metal market) shown in table 5. We include the proportion to take a long position of $1 in energy commodities to hedge a short position in the bullion and metal market. A long position refers to a situation where one has to buy, and a short position signifies the sell. As the proxies of energy commodities are crude oil and natural gas, two different portfolio hedging have been computed. The first is between crude oil and constituent markets where the most expensive optimal hedge ratio is witnessed of Crude /Zinc pair (0.3190) while the least expensive hedging pair is of Crude/Gold (0.0378). The optimal hedge ratio of Crude/Zinc indicates that a $1 long position in Crude will be hedged shorting an investment of 31.90 cents to reduce the risk. Similarly, the optimal hedge ratio between Crude/Gold indicates that a $1 long position in Crude must be hedged holding an investment of 3.78 cents in Gold. The present study corroborates with the investigations of Zhang *et. al.* 2018 and Lau *et al*. (2017).

Table 5(a). Result of Portfolio Weight and Hedge Ratio

Market		Mean	Std. Dev.	Min	Max
Crude	*NG*	*0.64*	*0.19*	*0.02*	*0.98*
Crude	*Gold*	*0.18*	*0.13*	*0*	*0.73*
Crude	*Silver*	*0.44*	*0.21*	*0*	*0.94*
Crude	*Copper*	*0.33*	*0.17*	*0*	*0.82*
Crude	*Platinum*	*0.28*	*0.16*	*0*	*0.81*
Crude	*Zinc*	*0.38*	*0.16*	*0.01*	*0.78*
NG	*Gold*	*0.13*	*0.08*	*0.01*	*0.58*
NG	*Silver*	*0.31*	*0.14*	*0.02*	*0.89*
NG	*Copper*	*0.21*	*0.11*	*0.03*	*0.62*
NG	*Platinum*	*0.18*	*0.12*	*0.01*	*0.75*
NG	*Zinc*	*0.25*	*0.11*	*0.02*	*0.6*
Gold	*Silver*	*1*	*0.01*	*0.74*	*1*
Gold	*Copper*	*0.64*	*0.14*	*0.18*	*0.96*
Gold	*Platinum*	*0.58*	*0.15*	*0.13*	*0.97*
Gold	*Zinc*	*0.69*	*0.13*	*0.22*	*0.9*
Silver	*Copper*	*0.37*	*0.16*	*0.04*	*0.87*
Silver	*Platinum*	*0.32*	*0.13*	*0.04*	*0.74*
Silver	*Zinc*	*0.43*	*0.15*	*0.05*	*0.83*
Copper	*Platinum*	*0.44*	*0.16*	*0.11*	*0.94*
Copper	*Zinc*	*0.56*	*0.11*	*0.17*	*0.88*
Platinum	*Zinc*	*0.61*	*0.17*	*0.09*	*0.9*

Source: Author's Own Presentation

Table 5(b). Result of Optimal Hedge Ratio

Crude Oil, Bullion, and Metal Market			Return on Natural Gas, Bullion, and Metal Market		
Series	**Mean**	**St Dev**	**Series**	**Mean**	**St Dev**
Crude Oil/Gold	*0.1385*	*0.0671*	*Natural Gas/Gold*	*0.2524*	*0.1039*
Crude Oil/Silver	*0.7835*	*0.1567*	*Natural Gas/Silver*	*0.6513*	*0.2830*
Crude Oil/Copper	*0.2356*	*0.1341*	*Natural Gas/Copper*	*0.1847*	*0.0810*
Crude Oil/Copper	*0.2674*	*0.0921*	*Natural Gas/Copper*	*0.3193*	*0.1216*
Crude Oil/Platinum	*0.5147*	*0.3724*	*Natural Gas/Platinum*	*0.4871*	*0.2771*
Crude Oil/Zinc	*0.2870*	*0.1563*	*Natural Gas/Zinc*	*0.4110*	*0.0975*
Crude Oil/Gold	*0.0378*	*0.0051*	*Natural Gas/Gold*	*0.1920*	*0.0153*
Crude Oil/Silver	*0.1674*	*0.0782*	*Natural Gas/Silver*	*0.0923*	*0.0403*
Crude Oil/Copper	*0.2812*	*0.1152*	*Natural Gas/Copper*	*0.1701*	*0.0923*
Crude Oil/Copper	*0.1711*	*0.0919*	*Natural Gas/Copper*	*0.1820*	*0.1195*
Crude Oil/Platinum	*0.0400*	*0.0283*	*Natural Gas/Platinum*	*0.0905*	*0.0501*
Crude Oil/Zinc	*0.3190*	*0.1166*	*Natural Gas/Zinc*	*0.2465*	*0.1333*

Source: Author's Own Presentation

CONCLUSION AND POLICY IMPLICATION

Energy markets are known to exhibit cross-asset interdependencies. It has been studied earlier that energy markets are driven more by commodity sector shocks than by any equity or general financial shocks. Portfolio investors constantly need information regarding the interconnectedness of the markets which has important implications for holding an extremely well-diversified portfolio. Therefore, this study provides motivation to examine the dynamic linkages of energy commodities with bullion and the metal market. It will be important for investors in terms of the suitability of different commodities regarding different investment periods and dynamic market conditions of bullion and metal market.

This paper examines the dynamic linkages and frequency-connectedness among commodity markets (precious metal/ base metals and energy) during the past decade and suggests optimal solutions for efficient risk diversification. The study incorporates highly liquid bullion markets (silver, Gold), base metals (Zinc and Copper) and major energy commodities (crude oil, natural gas) as the commodity asset classes. We analyse the time-varying conditional correlations using the DCC-GARCH, Diebold & Yilmaz (2012, 2014) and Baruník & Křehlík (2018). It further attempts to help to build an optimal portfolio using hedge ratios computed from covariances estimated from DCC-GARCH using a large data set spanning from March 18, 2010, to January 15, 2021.

The empirical analysis of dynamic interconnectedness concludes that, among the bullion i.e., silver and gold markets, exhibit a high degree of openness. Based on the dynamic interconnectedness approach, results indicate a low degree of connectedness from other markets except for Gold and Silver which have high return linkages from other markets as well as to another market. Silver has the highest return dynamic linkages (5.75%) from other markets followed by Gold. Gross Linkages which indicate the degree of openness of the markets also indicate high openness of Gold and Silver. Our results are consistent with recent studies (P. Evrim Mandaci *et al*., 2020). Bullion metals are extremely price sensitive and exhibit high volatility which may, in turn, cause an effect on the price movement of commodity markets as well as other asset markets as a whole (Gokmenoglu and Fazlollahi, 2015). The pairwise volatility spillover are low among the energy assets and the pairwise volatility spillover between the precious metals, Gold, and silver are relatively higher than base metals Finally the study concludes with calculating optimal portfolio weight to reduce the risk in selecting the constituent markets. Three portfolios were created; first, Gold and crude oil were used, indicating crude oil to have the least weight. Second Crude oil and silver, where high investment should be in crude oil and less in silver. Thirdly, in the case of the alternative energy commodity that is natural gas, the weight of natural gas received a higher weight than silver. The optimal hedge ratio of Crude/Zinc indicates that a $1 long position in Crude will be hedged shorting an investment of 31.90 cents to reduce the risk. Similarly, the optimal hedge ratio between Crude/Gold indicates that a $1 long position in Crude must be hedged holding an investment of 3.78 cents in Gold.

The result of this study has three different implications. First, the DCC result indicates that there are short-run dynamic linkages from energy (crude oil) to metal (copper) while the long-run linkage is witnessed among all the constituent series. Hence, investors can hold crude oil and copper in their portfolio for the long run to mitigate the risk while the rest of stocks can be held for a short run. Second, we observe that silver has the highest return dynamic linkages (5.75%) from other markets followed by Gold. Further, silver is found the most contributing series for dynamic linkage (14.49) within the sample followed by zinc (14.34). It signifies that silver is considered as one of the most affected investment alternatives due to which the risk cannot be mitigated more by holding it in the portfolio. Third, network analysis indicates that negative correlations are found between zinc, Gold, silver, platinum, Gold, silver and platinum with crude oil while positive correlation is witnessed between Gold and silver, therefore, investors and portfolio managers should include these investment alternatives.

The findings of this study are subject to limitations which furnishes the scope for further research. In the future, a study can be done applying wavelet analysis to examine the co-movement among energy, bullion and metal markets. It can be also done by applying various cointegration tests to check the possible portfolio diversification opportunity and short run dynamic adjustment.

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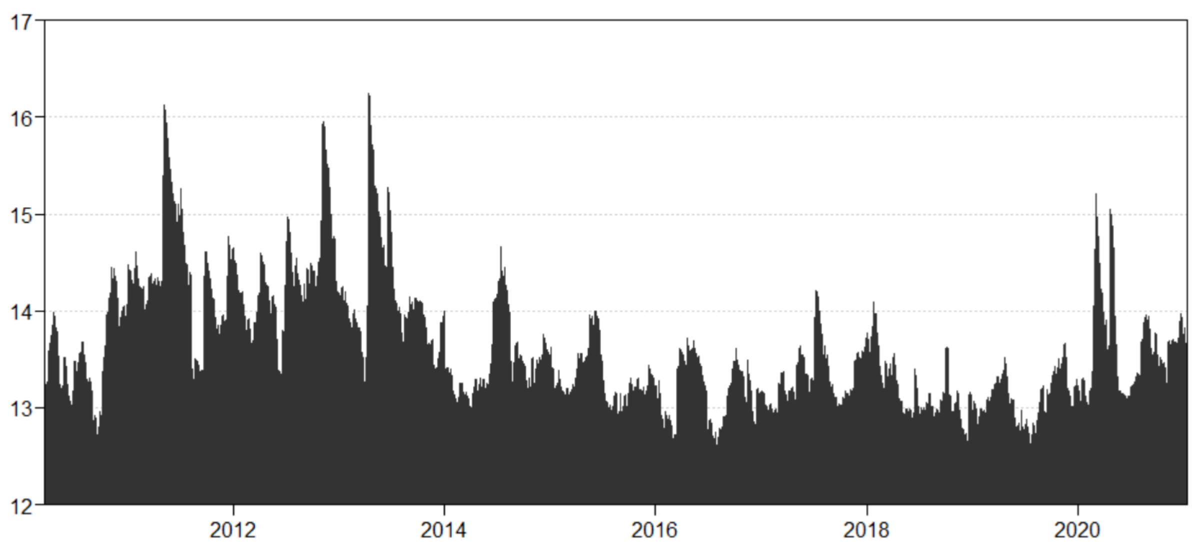
APPENDIX

SENSITIVITY/ ROBUSTNESS ANALYSIS

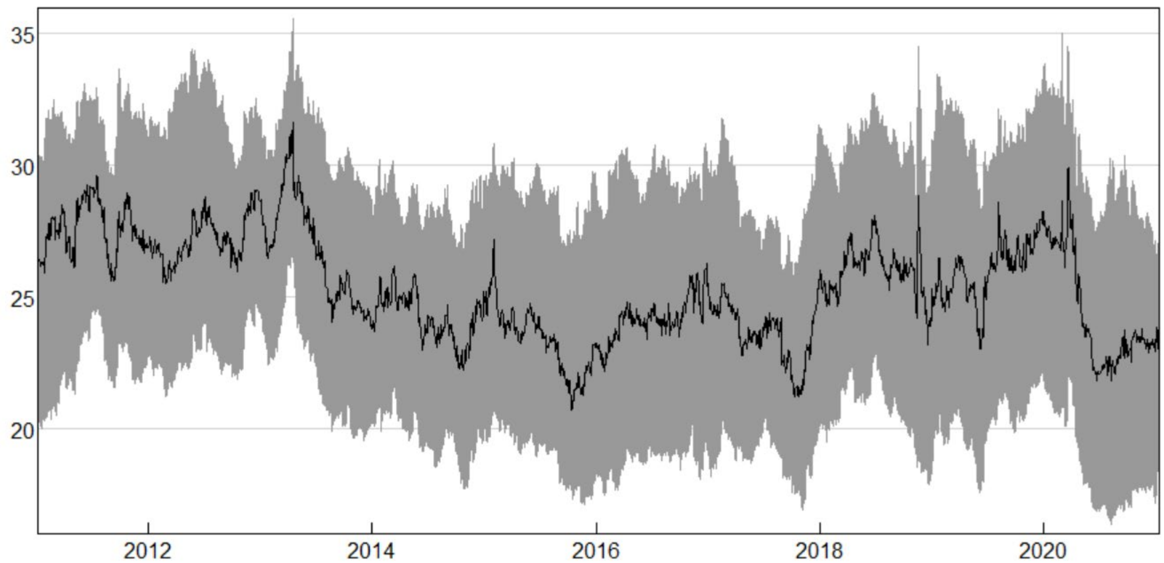
DCC-based spillover based on Gamba-Santamaria et al. (2017)

	Crude	NG	gold	silver	Copper	Platinum	Zinc	FROM others
Crude	91.82	1.16	1.92	3.66	0.67	0.13	0.65	8.18
NG	1.39	97.47	0.22	0.41	0.05	0.06	0.4	2.53
Gold	1.25	0.05	59.27	39.27	0.08	0.03	0.06	40.73
Silver	2.33	0.1	38.81	58.56	0.07	0.03	0.09	41.44
Copper	0.14	0.08	0.18	0.15	99.06	0.12	0.27	0.94
Platinum	0.08	0.05	0.05	0.05	0.11	99.59	0.07	0.41
Zinc	0.09	0.09	0.12	0.07	0.15	0.12	99.37	0.63
TO Others	5.29	1.52	41.31	43.61	1.12	0.48	1.54	94.87
Inc. Own	97.1	98.99	100.57	102.18	100.17	100.07	100.91	TCI=
NET	-2.9	-1.01	0.57	2.18	0.17	0.07	0.91	13.55



Gamba-Santamaria, S., Gomez-Gonzalez, J.E., Hurtado-Guarin, J.L. And Melo-Velandia, L.F. (2017). Stock Market Volatility Spillovers: Evidence for Latin America. Finance Research Letters, 20: 207-216

DY spillover sensitivity with respect to lags (2 to 6)



DY spillover sensitivity with respect to forecast horizon (5 to 10)