Price and Volatility Spillover among Equity and Commodity Markets before and during COVID: Evidence from India

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ABSTRACT

The interactions among equity and commodity market prices and their volatility provide precious information to market participants. This paper explores such dynamic interrelations in India, especially whether relationships have undergone significant changes with the onset of the COVID-19 pandemic and the Russia-Ukraine war of 2022. Based on a daily dataset from January 2017 to May 2022, VAR-MGARCH models and dynamic correlations are estimated with prices of gold, equity and crude oil for spot and futures markets. Findings suggest that for all the markets for gold, crude oil and equity in spot and futures segments, there is evidence of significant persistence of volatility and spillover from own past shocks. Moreover, evidence of volatility spillover exists from one market to the other; evidences indicate bi-directional spillovers between markets, more so from the equity market to the crude oil and from crude oil to gold market. However, the most notable finding of the study is that the dynamic correlation between stock and crude oil markets has substantially increased during the COVID and WAR period both in spot and futures markets. This observation has certain resemblance with increased correlations of crude oil with gold and stock, observed during the global financial crisis.

Keywords: commodity prices; volatility spillover; dynamic relationship; multivariate GARCH; financial market

JEL Classification: G10, G11, F65

1 Introduction

During the last decade, there has been an enormous growth in financialization of commodity markets following a rise in commodity trading. Consequently, the commodity markets became highly interconnected. More recently, with the onset of the Coronavirus pandemic, uncertainty in financial markets further increased and triggered several episodes of significant downslide in stock markets. This resulted in increased volatility in stock returns across the markets and the investors moved away from equity markets to safe haven assets such as gold and commodity futures leading to a significant increase in investment in commodities (Bouri et al., 2020). Gold and energy markets have shown varying short and long term effects immediately after the outbreak of crisis. Crude oil prices declined sharply and crude oil futures recorded enormous losses due to the pandemic.

The interrelations among gold, equity and energy markets are of significant concern to global investors because on the one hand they play a major role in an economy, and on the other hand, in hedging against fluctuations in other markets the role of gold is vital as a safe haven. These three markets provide a diverse set of attractive investment opportunities and fluctuations in these markets can also potentially indicate early warning signals to the policy-makers about the economic stability. Moreover, when it comes to various macroeconomic risks, assets in these markets can act as a hedging instrument interchangeably against such risks (Gevorkyan, 2017). It was observed that correlation between equities and commodities has increased since early 2000 (Tang and Xiong 2012, Olson et al., 2014). Also, there is evidence that commodity price indexes can be predicted by stock price indexes (Chen et al., 2010).

Several factors may result in interlinkage among commodity and stock markets, e.g., commodities being tradable financial instruments, are important for financial markets. If there is an increase in the prices of commodities used as inputs in production, such as crude oil, there is a decline in firm profits (Lombardi & Ravazzolo, 2016) and this may adversely affect stock prices. Again, transmission of volatility from one market to the other may take place through several channels. For instance, as crude oil is used in production and supply of various commodities, oil price variations are likely to influence equity markets through its effect on corporate cash flows. Also, increase in oil prices raises inflation that leads to a rise in demand for gold and pushes its price up (Elgammal et al. 2021).

Recent phenomena such as COVID-19 and the Russia-Ukraine war, have introduced fresh uncertainties on global stock markets. Boungou and Yatie (2022), examine the impact of war on global stock market returns and find a negative stock market reaction; the impact was significantly greater for the countries that condemned the invasion compared to those that remained neutral, viz. China, India and South Africa. The effects of the ongoing conflict on financial markets are not to be ignored, at least for portfolio managers, investors and policy makers. Moreover, with the war, commodity markets have also received considerable attention in recent times, as the role of the countries in war in global commodity markets is important (Umar et al., 2022, Johannesson and Clowes, 2022). The war triggered fresh disruptions in global supply chain and adversely affected the sentiments of market participants. In particular, the war created the strong negative effects on markets of global crude oil and also adversely affected the links among these markets (Liadze et al. 2022). Since the response of different commodity markets to the war is heterogeneous due to different degrees of supply and demand shocks (Caporin et al., 2021; de Nicola et al., 2016), it is of considerable interest to examine the reciprocal relationships among different segments of commodity markets and the financial market, which is likely to have important implications to the policymakers and investors in various markets.

Along with spot prices, commodity futures market also deserves considerable attention in the context of interlinkage of commodities and financial markets. First, commodity futures exhibit high correlation with underlying commodity prices, and so these are linked to global supply and demand (Caporin et al., 2021). Second, commodity futures prices are often considered as the relevant indicator to policymakers to craft strategies and stabilize markets (Ahmadi et al., 2016; An et al., 2020). Third, commodity futures especially energy commodities are considered as safe havens to diversify risks from financial markets (Adams and Glück, 2015; Kang and Yoon, 2019). In order to withstand shocks brought by the Russia-Ukraine war, investors are observed to show interest in commodity assets.

In the Indian context, while some studies deal with finding out the interrelations among the gold, crude and stock prices, these studies hardly explore the volatility spillovers among these markets[1]. However, existing studies on India are quite dated. Moreover, the uncertainty created by COVID-19 led to a change in the dynamics of crude oil and gold prices, and resulted to aversion of risk (Gharib et al, 2020; Mensi et al. 2020).

Given this background it is pertinent to examine the interlinkages between commodity and financial markets and also within commodity markets in emerging markets especially in

[1]For example, Palamalai and Prakasam (2015) examine interrelations between stock price and gold price in India, while Jain and Biswal (2016) looks into the non-linear causality among oil price, gold prices, exchange rate and Sensex during the global financial crisis of 2008.

the context of COVID-19 and the conflict of Russia-Ukraine. As the evidences are mixed, country specific studies can provide important insights. This paper focuses on India and draws the motivation from the following factors. **First,** most of the recent studies on the effects of COVID-19 and the Russia-Ukraine war mostly focus on the developed countries with little attention to emerging market economies which may behave differently. **Second**, in recent literature on India, we hardly find any investigation of volatility spillover among commodity markets and stock market in the context of COVID-19 and Russia-Ukraine conflict; rather the studies mainly focus on the Global Financial Crisis[2]. **Third**, there is very limited evidence on the spillover effects in commodity futures markets in India.

This paper attempts to fill the gap by finding out the interrelations among commodity and financial markets in India in terms of the prices and their volatility in stock and commodity markets. More specifically, the interactions among stock, gold and crude oil markets are examined, for both pre and during COVID-19 period as well as for pre and post Russia-Ukraine war periods as it may have important implications for crude oil in spot as well as futures market. In particular, we investigate the volatility spillover among stock and commodity spot prices, and also futures prices. Based on a daily dataset from January 2017 to May 2022, VAR-MGARCH models are estimated for spot and futures markets separately. The results indicate that during the COVID period in the spot market, the stock returns and oil prices are found to be more connected and the negative relationship between gold and stock markets has weakened. Also, there is significant spillover of volatility between crude oil price and stock price. However, more recently significant changes are observed. While crude and gold prices are explained by stock returns during the pre-war period, such relationships do not exist during the more recent period, post-war. Moreover, gold-crude and crude-stock return correlations have significantly strengthened during war. The increased connectivity is more prominent in the futures market; for instance, during the pre-COVID times, no interlinkage among the three markets were observed, but during COVID, returns in both crude and gold market are influenced by returns in the stock market. Also, during COVID period, there is volatility spillover between stock and crude markets. In a nutshell, in the spot and futures market, the interlinkage in price and its volatility between crude oil and stock returns have become much stronger than before in the COVID period.

[2] For example, Jain and Biswal (2016), Maitra and Dawar (2019).

The paper is structured in the following manner: the next section provides an overview of the extant literature, especially in the emerging market context. Section 3 describes the data and methodology, followed by results and discussions in section 4. Section 5 concludes the paper.

2 Review of Literature on Emerging Markets

This section is further divided into three subsections: Subsection 2,1 presents the existing literature on interrelations and volatility spillover in emerging markets, followed by a brief account of the literature on impact of geo-political events on such interrelations in the next subsection, 2.2. subsection 2.3 presents a summary of the literature concerning India.

2.1 Linkage in Emerging Markets

A growing body of literature has emerged since last couple of decades on return transmission and volatility spillover between financial and commodity markets, particularly after global financial crisis (GFC), post pandemic and the most recent ongoing Russia-Ukraine conflict, following the massive spike in uncertainty in these markets. The effects of shocks on commodity market and volatility transmissions are heterogeneous due to the heterogeneity of supply/demand shocks, the degree of financialization, and other factors (Caporin et al., 2021; de Nicola et al., 2016). However, the risk spillovers between commodities and financial markets are observed to be the highest in the post crisis periods (Bahloul and Khemakhem, 2021; Daskalaki and Skiadopoulos, 2011) and this has happened in emerging markets, too.

Ahmed (2018) observes that in Qatar the mean and volatility transmission effects of prices run from natural gas to stock. He et al. (2020) observes that return transmissions run from crude oil to equity markets, but it is positive in China and negative in US. Bergmann et al. (2015) demonstrate that an increase in oil prices pushes up inflation which, in turn, raises price of gold. Kumar et al. (2012) observes that apart from interest rates, past oil prices and stock prices of high technology firms influence the variation in clean energy stock indexes. Awartani and Maghyereh (2013) find return and volatility spillover effects run from oil to stock market in the Gulf Cooperation Council (GCC) Countries during 2004-2012 and such spillover becomes more pronounced in post GFC in 2008. However, bi-directional spillovers between oil market and gold market in a number of emerging markets including GCC and BRICS are observed by Khalifa et al., (2014), Pandey and Vipul (2018), Ahmed (2018) and Liu et al. (2020). Ahmed and Huo (2021) apply VAR-BEKK-GARCH model with three variables and find the transmissions of shocks between stock market and oil prices to be bi-directional, and the volatility spillovers to be running from oil to gold in China. Tang and Xiong (2012) stated that as a result of the financialization process, futures prices of non-energy commodities became increasingly correlated with oil prices after 2004.

In the last decade, futures markets have received increased attention (Chen, 2015; Jiang et al., 2019; Kang and Yoon, 2019; Wen et al., 2021). Ji et al. (2020) suggests that during the outbreak of the COVID-19, oil commodity futures could not play an important role as a safe haven. Elgammal et al. (2021), based on data from January, 2015 to May 2020, observe that the relationships pertaining to transmission of return and volatility between commodity and financial markets have strengthened in post COVID-19 periods[3].

2.2 Geopolitical Factors and the linkage

Tirki and Maatoug (2021) observe that in US, correlations between equity and gold price increase during periods of extreme political events compared to peaceful periods. Li et al. (2021) examine the dynamic information spillover among gold, oil and BRICS geopolitical risks and find that spillovers of return and volatility are stronger in the short term than in long term. Also, China's geopolitical risks exert the greatest impact on gold, oil, and geopolitical risks in other countries. Maghyereh et al. (2021) explore hedging opportunities during 2004 to mid-2016 and find that GCC economies depend heavily on oil, when the political instability of the region creates more uncertainty. Hu et al (2020) find that crude oil volatilities are more influenced by macroeconomic variables as well as geopolitical risks, compared to futures in gold and soyabeans.

2.3 Linkage in Indian Market

In the Indian context, while some studies deal with the interrelations among gold, crude and stock prices, few others explore volatility spillovers among these markets. For example, Mishra, Swain, and Malhotra (2007) observe that there is bidirectional causality between equity and foreign exchange market while Adrangi et al. (2014) find a weak relationship between commodity and equity markets. Again, Shiva and Sethi (2015) observe one-way causality from gold prices to stock markets and exchange rates. Maitra and Dawar (2019) observe that during the post-crisis period, there is return spillover from equity markets to commodity markets and

[3]Further, spillover between energy and equity and gold markets are bidirectional, while that from gold to equity markets is unidirectional. For volatility spillover between gold and equity markets was bidirectional, while it was unidirectional between equity and energy and between energy and gold markets (from the first to the second market).

there is bi-directional volatility spillover between each of the pair of commodity, stock and foreign exchange markets in India. Also, spillover is larger from commodity indexes to stocks.

By estimating a wavelet based DCC-GARCH model, Chakrabarty et al (2015) find that volatility spillover responds to the changes in investment horizon. Palamalai and Prakasam (2015) do not find any evidence of long-run cointegrating relationship between stock price and gold price or any causality in the short run. Jain and Biswal (2016), in a DCC-GARCH framework, estimate the non-linear causality and observe that the correlations of crude price with stock market return, gold price and exchange rates were higher during the global financial crisis in 2008–2013 than the rest of the decade. Also, a fall in both crude prices and gold prices lead to a fall in Sensex, but a fall in Sensex causes gold prices to gain.

In a more recent study after COVID-19, Mukherjee and Bardhan (2022) and Mukherjee and Bardhan (2020), based on daily data from 2017 to 2020, estimate ARDL model to find out the long term movements of crude oil, gold spot prices and stock process and observe that during the pre-COVID times, stock return is influenced by gold and oil prices; but during the COVID period, volatility of gold and crude oil prices drives the stock returns. But, studies that have looked at both the return and the volatility spillover among commodity and financial markets in India, are very few. Sendhil et al. (2013) finds persistence of volatility in spot market while examining the efficiency of commodity futures of four agricultural commodities. There are studies that look at volatility spillovers between spot and futures prices in commodity market [Kumar et al. (2014), Gupta and Varma (2015), Malhotra and Sharma (2016)] and some of them find bidirectional volatility spillover between the two markets.

However, in this paper, we focus on the interactions among stock, gold and crude oil markets in India both during pre- and post-COVID periods, and also in pre and post Russia-Ukraine war. We explore the relationships in both spot and futures markets.

3 Data and Methodology

We examine the relationships between equity and commodity markets such as gold and oil, both spot and futures markets. For spot prices, the daily data on key stock indexes and the commodity derivatives market are taken. In the equity market, the benchmark stock index, Sensex of Bombay Stock Exchange (BSE) is considered and it is henceforth denoted as BSE. The returns are measured as log (P_t / P_{t-1}), and is denoted by RBSE. The data on commodity prices is collected from Multi Commodity Exchange of India Limited (MCX); among the commodities most actively traded in terms of value, crude oil and gold are the ones that rank among the top ten (Mukherjee and Bardhan, 2020). Daily per unit spot prices of gold and crude oil are taken. First difference of log of their price are denoted as DLPGOLD and DLPCRUDE, respectively.

For futures market, BSE Sensex Futures Index is taken from Asia Index website. This is excess return index and the return is denoted by RFBSE. For commodity futures of gold and oil, iCOMDEX indexes for gold and oil are taken from MCX. These also are excess return indexes, and are considered to be ideal for benchmarking and trading.[4] For gold and crude oil, the returns are denoted as RFGOLD and RFCRUDE. The data for spot prices is collected for the period of June 1, 2017 to May 31, 2022 leading to 1232 observations. For futures, the data spans from January 2, 2017 to June 30, 2022 resulting to 1360 observations. The sample period is chosen on a number of considerations: first, since the objective is to figure out whether the interrelations have changed during COVID-19 and Russia-Ukraine war, emphasis has been put on latest data, till middle of 2022. Second, unlike many existing papers, high frequency data, viz. daily data is taken and so very old data may not provide many insights on financial markets. From June 16, 2017, oil marketing companies was permitted by the Indian Government to decide the retail price of fuel, on the basis of international oil prices and exchange rate and. That is why we have considered data from 2017. Significant fluctuations in gold prices are observed during the same period. The spot prices and futures price indexes are presented in Figures 1 and 2, respectively. It is observed that while among spot prices, only gold prices exhibit some volatility during the sample period, among the futures indexes, except BSE, all others exhibit significant volatility during the period under study. Augmented Dickey-Fuller test is done for all the series and it is found that the returns of stocks and the first difference of log of prices of gold and crude (DLPGOLD and DLPCRUDE) are stationary.

The interrelations among the prices in the three markets are estimated by VAR-MGARCH model. To estimate volatility spillover, among the MGARCH models, diagonal BEKK model is estimated. The interrelations between the prices are obtained by estimation of VAR framework and variance decomposition, while the volatility spillover is explained by multiple GARCH and bi-variate conditional correlation estimated from the multivariate GARCH. This is done for pre and during COVID and pre and during war separately. The period prior to 31st January, 2020 is considered as pre-COVID period leading to 652 observations, and there are 579 observations during COVID. On the other hand, the period from February 25,

[4]It measures the returns accrued from investing in uncollateralized commodity futures or, in other words, the sum of the price return associated with an investment in commodity futures, and the roll return (see https://www.mcxindia.com/docs/default-source/market-data/mcx-icomdex/methodology-document-year-2021.pdf?sfvrsn=7039bd90_2)

2022 onwards is considered as the war period (leading to 63 observations), while the data prior to that is considered as pre-war period.

The VAR-MGARCH model for prices and their volatilities is estimated as simultaneous estimation of Vector Auto Regression (VAR) and multivariate GARCH (Engle and Kroner, 1995). While the VAR model provides insights about the interrelations among the prices of the stock and commodities (i.e., conditional mean), the covariance of residuals modelled by multivariate GARCH, depict the volatility spillover among the stock prices and gold and oil prices (i.e., conditional covariance matrix). Among the multivariate GARCH models, in this paper, diagonal BEKK model (DBEKK) is estimated[5]. Then, based on that, the conditional correlations are obtained.

The MGARCH model is briefly described here:

$$r_t = \mu_t + \varepsilon_t \qquad \text{…. (1)}$$

$$E\ (r_t|F_{t-1}) \equiv \mu_t = \theta_0 + \theta_1 r_{t-1} + \theta_2 r_{t-2} + \ldots\ldots\ldots\ldots\ldots + \theta_p r_{t-p} \qquad \text{…. (2)}$$

where r_t is a $k \times 1$ vector consisting of prices of the three markets; μ_t is its conditional mean. k denotes the number of prices taken, (k = 3 here, viz. stock, crude oil and gold). F_t denotes information at time t.

Also,

$$\varepsilon_t = H_t^{1/2}\, e_t \qquad \text{….. (3)}$$

$$E\left(\varepsilon_t \varepsilon_t^{'} \middle| F_{t-1}\right) \equiv\ H_t \qquad \text{… … … (4)}$$

$$e_t \sim N(0, I)\ \ and\ i.i.d. \qquad \text{……(5)}$$

where $\boldsymbol{H_t}$ is a k x k conditional covariance matrix.

In a BEKK model, the positiveness of $\mathbf{H}_t$'s is guaranteed by the following:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}{}' A' + BH_{t-1}B' \qquad \text{……..(6)}$$

where matrices **C**, **A, B** are of size $k \times k$. These are the matrices of parameters to be estimated. Here, CC' indicates a long term trend that influences the conditional covariance matrix, the estimated $\boldsymbol{H_t}$ with lag 1 ($\mathbf{H}_{t-1}$) depicts the GARCH term, and $\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'$ (i.e., one period lagged residuals) is the ARCH-term. The matrices represent the multivariate specification. In a

[5] Baba, Engle, Kraft and Kroner, 1990.

diagonal BEKK specification, which is a reduced form of full BEKK model[6], matrices A and B are diagonal. Here we apply diagonal BEKK model in the context of stock price and price of commodities such as gold and oil. We choose this model as the objective is not forecasting the prices, but rather to discover the interrelations. Several studies have advocated use of the BEKK model over DCC GARCH model for multiple reasons, in assessing volatility linkages in financial markets (e.g., Rastogi, 2021). As Huang et al. (2010) puts it, the goodness of fit is better than the DCC GARCH model; also, unlike the fixed conditional correlations in CCC GARCH, in BEKK they are dynamic (Katsiampa, 2019). Separate models are estimated for spot and futures prices for the same. The elements of A measure the effect of past shocks in own prices and that of B measures the effects of own past volatility on current volatility.

Apart from the VAR-MGARCH model, the variance decomposition is also examined to explain the interrelations. We estimate the interrelations with BSE and results of two such models with spot prices are presented in the next section, viz. results concerning spot prices for the pre- and the post-COVID period. Two more models for spot prices before and after the war are also estimated, but the results are reported in Appendix. Similarly, four other models are estimated to understand the interrelations for futures prices. The VAR model is chosen on the basis of Akaike information criteria with lags from 1 to 5. Lags beyond 5 are not considered as long history is not relevant in this context.

4 Results and Discussions

As mentioned in previous section, findings of only two VAR-DBEKK models are presented, viz. the estimations for spot prices and those for pre and during COVID. For the rest of the models, we present the dynamic correlation estimated from the VAR-DBEKK model. The model specifications and brief results are summarised in **Table 1**. It should be noted that except model 8 for futures prices during war, for all other cases, the coefficients of GARCH terms are significant implying high persistence of volatility. moreover, barring a couple of exceptions, ARCH terms are also significant indicating existence of volatility spillover from their own past values for all the three variables. For complete results of these models, see **Appendix 1-6**.

The estimation results for spot prices, pre- and post-COVID, are presented in **Tables 2 and 3**, respectively. Mean equations indicate that in the pre-COVID period, stock price returns

[6]The full BEKK specification has too many parameters and it becomes difficult to interpret them.

and crude prices are explained by gold prices, but during the COVID period such relationships cease to exist; only crude price is influenced by stock returns. However, from Panel B clearly indicates that almost all the ARCH and GARCH coefficients are significant at 1% level of significance implying strong volatility spillover from their own past values in each of the markets, as well as persistence of volatility in pre-COVID period. However, during the COVID period, though the same holds true for stock returns and crude, only the GARCH term is significant with gold prices.

The pattern of dynamic bivariate conditional correlations between the spot prices estimated from the models are presented in **Figures 3 and 4** for pre and during COVID period, respectively. It may be noted that the pattern has distinctly changed. In pre-COVID times, while the correlation between stock and crude oil and that between crude oil and gold remained negligible (around -0.2 to 0.2 with 0.04 on an average, and -0.2 to 0.3 with 0.1 on an average for most of the times, respectively), the correlation between stock and gold was negative and stronger (-0.2 to -0.4 most of the times, with -0.24 on an average). However, during COVID, correlations of gold with both stock and crude oil have weakened significantly (average correlation of -0.1 and -0.04). But the correlation between stock and crude oil has increased by a large amount, to 0.59 on an average, reaching 0.98 at times.

Figures 5 and 6 present the time-varying correlations between spot prices before and during the Russia-Ukraine war[7]. It is observed that during the pre-war period, the correlations of gold with stock and crude oil prices were zero for almost the entire sample period, while the correlation between stock return and crude oil has substantially increased towards the end of the pre-war period, from the range of -0.2 to +0.2 to the range of 0.4 to 0.6. From **Figure 6**, it is evident that during war, this correlation further increased at times, to 0.8; the average correlation has risen from 0.26 to 0.54. The correlation between gold and crude oil prices also recorded mild increase, to around 0.3. The results are in tune with the finding of Jain and Biswal (2016), that during the GFC too, the correlation of crude oil prices with stock prices and gold prices increased significantly compared to non-crisis period.

It may be concluded, from the conditional correlations and existence of strong spillover and persistence of volatility (depicted by significant ARCH and GARCH co-efficients), that volatility spillover exists from one market to the other. Similar pattern is also suggested by the results of variance decomposition of spot prices presented in **Table 4**. For each of the variables, it presents the amount of the forecast error variance, explained by exogenous shocks to the

[7]Results of estimated models for pre and during war, are presented in Appendix 1 and 2, respectively.

other variables. Forecast period considered here is 10 days. It is observed that for each of the three variables, their variance is explained mostly by the shocks from their own lagged values (95 to 100 per cent during pre-COVID period). Very little was explained by other two variables, e.g., only 4.6 (0.5) per cent of variation in gold prices (crude prices) by stock return (gold). However, during the COVID period, there has been significant changes, e.g., 4.6 per cent of variance in stock return is explained by crude prices, 2.2 per cent of variance of gold prices is now explained by stock return and 7.4 per cent of variation in crude prices is explained by stock returns. Similarly, during the pre-War period also, error variance for all three prices were mostly explained by their own past shocks (97 to 100 per cent). But, during the war period, the scenario has changed substantially. Though the stock return variance continues to be explained by its own past shocks, error variance of gold and crude oil is now significantly influenced by shocks from the other prices. For instance, 16 per cent of variance in crude prices is explained by shocks from stock returns and above 30 per cent (8 per cent) of error variance of gold is explained by shocks from crude oil (stock prices). The existence of volatility spillover between stock and the commodity markets during COVID and the war period resemble the observations of Maitra and Dawar (2019). However, the spillover is observed to be bidirectional and significantly higher compared to pre-COVID period.

When we look into the futures market returns, the dynamic correlations of the pre and during COVID are depicted by **Figures 7 and 8**[8]. In the pre-COVID period, the correlation between stock return and crude return is nearly zero, while that between stock and gold return is -0.2 on an average and between gold and crude is 0.2, on an average. But during the COVID period, all returns exhibit large volatilities for the entire period. While the correlation between gold and crude oil remains the same, the negative correlation between gold and stock return has declined to almost zero and the correlation between stock and crude oil return has strengthened and turned out to be positive and considerably high.

Similarly, in the pre-war period, there is significant volatility in the dynamic correlations of futures prices, but it is similar to that of pre-COVID period on an average, with more positive correlations (of around 0.4) between stock and crude oil towards the end of the period (**Figure 9**). However, as indicated in Table 1, during the war period, ARCH effects do not appear to be significant. GARCH terms have significant coefficients for crude oil and gold. Therefore, the possibility of volatility spillover in this period is much less, as indicated by

[8] For detailed results see Appendix 3 and 4.

Figure 10[9]. This indicates that the increased correlation of crude oil prices with stock prices during the COVID crisis gradually tends to be stabilized.

Figures 11 and 12 present a summary of the dynamic correlations from all these regressions in the form of Box-Whisker plots, separately for spot prices and futures prices, respectively. Quite obviously, the correlation between BSE and crude oil in spot as well as futures prices are not only higher than other correlations, their variations are also markedly higher. And the increase in the correlation during COVID and war is distinct.

5 Conclusion

This paper explores dynamic interrelations between financial and commodity markets in India, especially whether relationships have undergone significant changes with the onset of the COVID-19 pandemic and also the Russia-Ukraine war of 2022, another geo-political phenomenon. Based on a daily dataset from January, 2017 to May, 2022, joint VAR-MGARCH models are estimated with prices of equity, gold and crude oil in India for spot and futures prices separately. The results present some interesting insights.

In all the markets, spot and futures, evidence suggests significant persistence in volatility in gold, crude oil and stock prices and also, there is significant volatility spillover from their own past shocks. Some specific findings indicate the following: *first*, in the spot market, during the pre-COVID period, both stock return and change in the price of crude oil were influenced by gold, but during the COVID period, such relationships have changed and only crude price change is explained by stock returns. *Second*, for each of the three variables, their variance was influenced mostly by the shocks in their own lagged values (97 to 100 per cent) during pre-COVID period; but during the COVID period, considerable amount of variation in crude prices is influenced by shocks in stock prices. *Third*, evidence of volatility spillover indicates that it has increased during COVID as well as during the Russia-Ukraine conflict, especially in the case of crude oil and stock markets. The conditional correlation between stock and crude prices has increased significantly during COVID, from an average of 0.04 to 0.59. Stock-crude correlation has significantly strengthened during war, too, compared to pre-war period (0.54) with a similar increase in positive correlation between crude oil and gold (0.3), too. *Fourth*, in a similar fashion, in the futures market, linkage in volatility among the markets were very weak in the pre-COVID period, but during COVID, barring gold, positive conditional correlation between stock and crude markets has strengthened. *Fifth*,

[9]See also Appendix 5 and 6.

results from variance decomposition also point to the fact that volatility spillover is larger from the equity markets to the crude oil, and also from crude oil and equity to gold market, though evidence of bi-directional spillovers are also observed. *Sixth*, most importantly, similar to the increased correlation between oil and stock prices during the GFC period, during the COVID crisis also the correlations of crude oil with gold and stock have surged significantly. However, as the COVID crisis started to subside, such heightened correlation has started showing signs to stabilize.

It may be concluded that in the spot and futures market, the interlinkage in price and its volatility between crude oil and stock returns have got much stronger than before and the linkages with gold has become weaker in the COVID period. This positive and strong correlation has important policy implications for hedging and portfolio investments. In some cases, gold and crude oil correlations also have increased. This implies that the commodity spot and futures prices and the stock prices get more influenced by one another during a crisis. This will be helpful for investors and policymakers alike. However, it is yet to be seen whether the correlations come back to the original levels of the pre-crisis period in due course of time.

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APPENDIX

Appendix 1

Appendix 1: Spot Prices during Pre-War			
Panel 1 : Mean Equation Specification VAR(2)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
$RBSE_{t-1}$	0.036	0.162**	0.049*
p-value	**0.276**	**0.000**	**0.013**
$RBSE_{t-2}$	-0.005	0.080*	0.023
p-value	**0.890**	**0.044**	**0.209**
$DLPGOLD_{t-1}$	0.084*	0.040	0.104**
p-value	**0.013**	**0.286**	**0.000**
C	0.0008**	0.0013**	0.0005*
p-value	**0.001**	**0.000**	**0.039**
Adj. R-squared	**-0.01**	**0.02**	**0.01**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
RBSE	0.0000018**		
p-value	0		
DLPCRUDE	0.0000006**	0.0000002	
p-value	0.0057	0.074	
DLPGOLD	0.0000004**	0.0000001**	0.0000008*
p-value	0	0.0032	0.0113
	$\mathbf{A_{11}}$	$\mathbf{A_{22}}$	$\mathbf{A_{33}}$
A	0.325**	0.330**	-0.001
p-value	0	0	0.92
	$\mathbf{B_{11}}$	$\mathbf{B_{22}}$	$\mathbf{B_{33}}$
B	0.944**	0.954**	-0.999**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

Appendix 2

Appendix 2: Spot Prices during WAR			
Panel A : Mean Equation Specification VAR(1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
$RBSE_{t-1}$	0.085	-0.023	0.024
p-value	**0.527**	**0.884**	**0.789**
$DLPCRUDE_{t-1}$	-0.168	-0.104	-0.082
p-value	**0.248**	**0.542**	**0.319**
$DLPGOLD_{t-1}$	0.200	0.055	0.016
p-value	**0.423**	**0.855**	**0.911**
C	0.0002	0.0013	0.0001
p-value	**0.920**	**0.413**	**0.941**
Adj. R-squared	**-0.03**	**-0.03**	**-0.03**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
RBSE	0.0000040		
p-value	0.71		
DLPCRUDE	0.0000047	0.0000051	
p-value	0.11	0.68	
DLPGOLD	0.000001	0.0000005	0.0000001
p-value	0.32	0.71	0.76
	$\mathbf{A_{11}}$	$\mathbf{A_{22}}$	$\mathbf{A_{33}}$
A	0.13600	0.17100	0.03800
p-value	0.2	0.051	0.67
	$\mathbf{B_{11}}$	$\mathbf{B_{22}}$	$\mathbf{B_{33}}$
B	0.976**	0.969**	0.993**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

Appendix 3

Appendix 3: Futures Prices during Pre-COVID			
Panel 1 : Mean Equation Specification VAR(2)			
	RFBSE	**RFCRUDE**	**RFGOLD**
$RFBSE_{t-1}$	0.055	0.109	-0.005
p-value	**0.208**	**0.226**	**0.871**
$RFCRUDE_{t-1}$	-0.022	-0.022	0.010
p-value	**0.091**	**0.541**	**0.451**
$RFGOLD_{t-1}$	-0.079**	0.177	0.014
p-value	**0.028**	**0.150**	**0.736**
C	0.0008**	-0.0231	0.0151
p-value	**0.002**	**0.820**	**0.667**
Adj. R-squared	**0.005**	**-0.006**	**-0.007**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RFBSE	**RFCRUDE**	**RFGOLD**
RFBSE	.000003**		
p-value	0.002		
RFCRUDE	-.0000008**	0.0000001	
p-value	0.023	0.2425	
RFGOLD	-0.0000006**	0.0000001*	0.0000001*
p-value	0.0019	0.032	0.033
	A_{11}	**A_{22}**	**A_{33}**
A	0.307**	0.0008000	0.091**
p-value	0	0.97	0
	B_{11}	**B_{22}**	**B_{33}**
B	0.918**	1.000**	.995**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

Appendix 4

Appendix 4: Futures Prices during COVID

Panel 1 : Mean Equation Specification VAR(5)

	RFBSE	**RFCRUDE**	**RFGOLD**
$RFBSE_{t-1}$	0.065	0.246**	0.033
p-value	**0.160**	**0.001**	**0.235**
$RFBSE_{t-2}$	-0.0411	-0.182**	0.0189
p-value	**0.370**	**0.001**	**0.463**
$RFBSE_{t-3}$	-0.049	-0.050	-0.055*
p-value	**0.317**	**0.501**	**0.049**
$RFBSE_{t-4}$	0.0682	0.254**	0.0363
p-value	**0.135**	**0.000**	**0.275**
$RFCRUDE_{t-2}$	**-0.012**	**-0.095***	**0.010**
p-value	**0.398**	**0.039**	**0.375**
$RFGOLD_{t-1}$	0.0863	-0.1020	-0.0084
p-value	**0.084**	**0.185**	**0.852**
$RFGOLD_{t-2}$	**0.073***	**-0.071**	**0.004**
p-value	**0.049**	**0.261**	**0.927**
$RFGOLD_{t-3}$	0.0011	-0.1401	0.0258
p-value	**0.979**	**0.047**	**0.537**
C	**0.001***	**0.004****	**0.000**
p-value	**0.014**	**0.000**	**0.853**
Adj. R-squared	**-0.02**	**-0.050**	**0.016**

Panel 2: Variance-Covariance specification DBEKK (1,1)

	RFBSE	**RFCRUDE**	**RFGOLD**
RBSE	0.0000000		
p-value	0.78		
DLPCRUDE	0.0000000	0.0000000	
p-value	0.83	0.9	
DLPGOLD	0.000000	0.00000	0.00001*
p-value	0.59	0.81	0.028
	$\mathbf{A_{11}}$	$\mathbf{A_{22}}$	$\mathbf{A_{33}}$
A	0.343**	0.577**	0.189**
p-value	0	0	0.61
	$\mathbf{B_{11}}$	$\mathbf{B_{22}}$	$\mathbf{B_{33}}$
B	0.954**	0.882**	0.945**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

Appendix 5

Appendix 5: Futures Prices Pre-War			
Panel 1 : Mean Equation Specification VAR(5)			
	RFBSE	**RFCRUDE**	**RFGOLD**
$RFBSE_{t-1}$	0.061*	0.132*	0.004
p-value	**0.044**	**0.022**	**0.819**
$RFBSE_{t-4}$	0.001	0.192**	-0.011
p-value	**0.985**	**0.001**	**0.623**
$RFCRUDE_{t-4}$	**0.036****	**0.003**	**0.006**
p-value	**0.000**	**0.924**	**0.507**
$RFGOLD_{t-3}$	0.007	-0.108	-0.001
p-value	**0.795**	**0.087**	**0.980**
C	0.0008**	0.0009	0.0003
p-value	**0.000**	**0.139**	**0.206**
Adj. R-squared	**-0.006**	**0.00**	**0.002**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RFBSE	**RFCRUDE**	**RFGOLD**
RFBSE	0.0000001		
p-value	0.76		
RFCRUDE	0.0000003	0.000038**	
p-value	0.53	0	
RFGOLD	0.0000000	0.000001**	0.00000007*
p-value	0.54	0	0.022
	A_{11}	**A_{22}**	**A_{33}**
A	0.309**	0.419**	0.121**
p-value	0	0	0
	B_{11}	**B_{22}**	**B_{33}**
B	0.960**	0.878**	0.993**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

Appendix 6

Appendix 6: Futures Prices during WAR			
Panel 1 : Mean Equation Specification VAR(1)			
	RFBSE	**RFCRUDE**	**RFGOLD**
$RFBSE_{t-1}$	0.074	0.227	0.124
p-value	**0.639**	**0.365**	**0.121**
$RFCRUDE_{t-1}$	-0.021	0.071	0.009
p-value	**0.662**	**0.630**	**0.792**
$RFGOLD_{t-1}$	**-0.251**	**-0.794**	**-0.102**
p-value	**0.171**	**0.151**	**0.404**
C	-0.001	0.001	-0.0005
p-value	**0.560**	**0.772**	**0.607**
Adj. R-squared	**0.015**	**-0.045**	**-0.051**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RFBSE	**RFCRUDE**	**RFGOLD**
RFBSE	0.0000800		
p-value	0.156		
RFCRUDE	0.0000500	0.0000275	
p-value	0.053	0.146	
RFGOLD	-0.000001	0.00000	0.00002
p-value	0.758	0.758	0.88
	A_{11}	**A_{22}**	**A_{33}**
A	0.39500	0.04300	0.12500
p-value	0.079	0.805	0.30
	B_{11}	**B_{22}**	**B_{33}**
B	-0.477	0.969**	0.980**
p-value	0.27	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

TABLE 1: Summary of Models estimated for Spot and Future Prices						
Model	**Variables**	**Specification**	**Model Specification**	**Results (Effect of ARCH term in Eqn 6)**	**Results (Effect of GARCH term in Eqn 6)**	**Results shown**
1	RBSE, DLPCRUDE, DLPGOLD	Spot Prices, Pre-COVID	VAR (1)-DBEKK(1,1)	All significant*	All significant*	Table 2, Figure 3
2	RBSE, DLPCRUDE, DLPGOLD	Spot Prices, during COVID	VAR (5)-DBEKK(1,1)	All significant except gold	All significant	Table 3, Figure 4
3	RBSE, DLPCRUDE, DLPGOLD	Spot Prices, Pre-War	VAR (2)-DBEKK(1,1)	All significant except gold	All significant	Figure 5, Appendix 1
4	RBSE, DLPCRUDE, DLPGOLD	Spot Prices, during WAR	VAR (1)-DBEKK(1,1)	Crude oil significant	All significant	Figure 6, Appendix 2
5	RFBSE, RFCRUDE, RFGOLD	Future Prices, Pre-COVID	VAR (2)-DBEKK(1,1)	All significant except crude oil	All significant	Figure 7, Appendix 3
6	RFBSE, RFCRUDE, RFGOLD	Future Prices, during COVID	VAR (5)-DBEKK(1,1)	All significant	All significant	Figure 8, Appendix 4
7	RFBSE, RFCRUDE, RFGOLD	Future Prices, Pre-War	VAR (5)-DBEKK(1,1)	All significant	All significant	Figure 9, Appendix 5
8	RFBSE, RFCRUDE, RFGOLD	Future Prices, during WAR	VAR (1)-DBEKK(1,1)	None significant	Crude and gold significant	Figure 10, Appendix 6

Note: * significance at 1% level

Source: Authors' compilation

TABLE 2: Spot Prices during Pre-COVID period

Panel 1: Mean Equation Specification VAR(1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
$RBSE_{t-1}$	0.066	0.097	0.043
p-value	**0.121**	**0.299**	**0.161**
$DLPCRUDE_{t-1}$	0.004	-0.051	-0.003
p-value	**0.782**	**0.201**	**0.809**
$DLPGOLD_{t-1}$	-0.071*	0.440**	0.111**
p-value	**0.041**	**0.001**	**0.003**
C	0.0006**	0.0007	0.0004
p-value	**0.004**	**0.345**	**0.095**
Adj. R-squared	**0.000**	**0.02**	**0.01**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
RBSE	0.0000001		
p-value	0.0676		
DLPCRUDE	-0.0000001*	0.000000	
p-value	0.0348	0.1932	
DLPGOLD	-0.0000004**	0.0000005*	0.000001**
p-value	0.0022	0.0145	0.0007
	$\mathbf{A_{11}}$	$\mathbf{A_{22}}$	$\mathbf{A_{33}}$
A	0.294**	0.159**	0.175**
p-value	0	0	0
	$\mathbf{B_{11}}$	$\mathbf{B_{22}}$	$\mathbf{B_{33}}$
B	0.962**	0.988**	0.961**
p-value	0	0	0

Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

Source: Authors' computation

TABLE 3: Spot Prices during COVID			
Panel 1 : Mean Equation Specification VAR(5)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
$RBSE_{t-1}$	0.020	0.206**	0.044
p-value	**0.711**	**0.000**	**0.196**
$DLPCRUDE_{t-5}$	-0.047	0.104*	-0.004
p-value	**0.133**	**0.048**	**0.815**
$DLPGOLD_{t-2}$	0.084	0.032	0.040
p-value	**0.093**	**0.495**	**0.499**
C	0.002**	0.0017**	0.0002
p-value	**0.000**	**0.000**	**0.722**
Adj. R-squared	**0.009**	**0.020**	**0.002**

Panel 2: Variance-Covariance specification DBEKK (1,1)			
	RBSE	**DLPCRUDE**	**DLPGOLD**
RBSE	0.0000001		
p-value	0.29		
DLPCRUDE	0.0000001	0.0000001	
p-value	0.45	0.6192	
DLPGOLD	-0.000001	0.00000	0.00002
p-value	0.19	0.3273	0.42
	$\mathbf{A_{11}}$	$\mathbf{A_{22}}$	$\mathbf{A_{33}}$
A	0.421**	0.541**	0.02200
p-value	0	0	0.61
	$\mathbf{B_{11}}$	$\mathbf{B_{22}}$	$\mathbf{B_{33}}$
B	0.934**	0.905**	0.899**
p-value	0	0	0

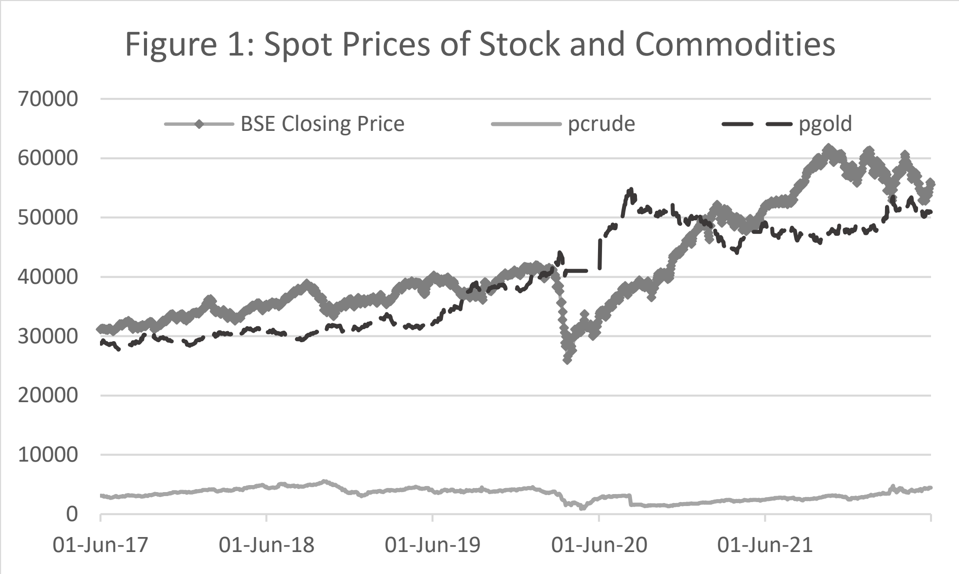
Note: Only the co-efficients that are significant in at least one equation are reported.

*significant at 5% los, **significant at 1% los

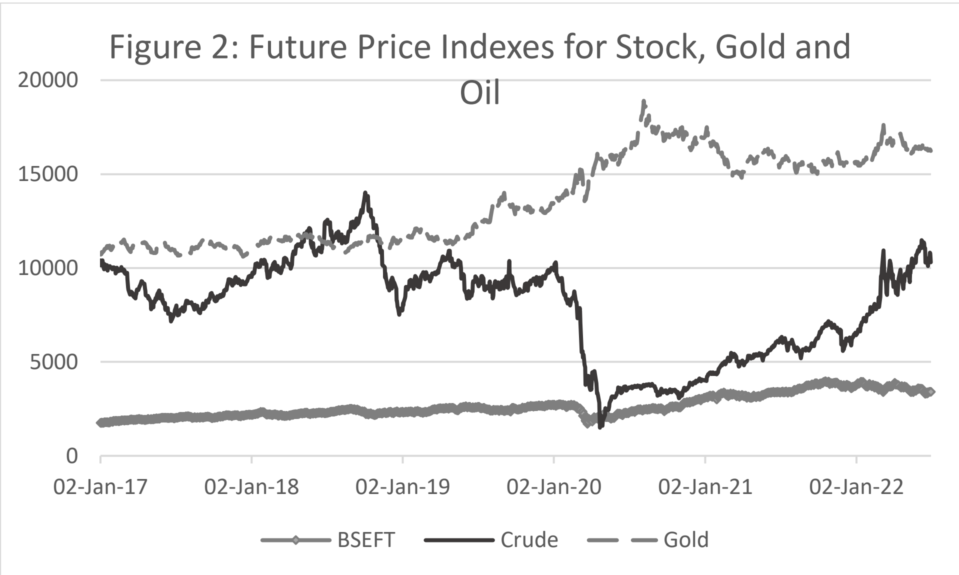
Source: Authors' computation

Table 4: Variance Decomposition of Spot Prices (Percent)						
	Pre-COVID			During COVID		
Explained by →	RBSE	DLPCRUDE	DLPGOLD	RBSE	DLPCRUDE	DLPGOLD
RBSE						
t=1	100.0	0.0	0.0	100.0	0.0	0.0
t=10	99.8	0.0	0.2	95.0	4.6	0.5
DLPCRUDE						
t=1	0.5	99.5	0.0	3.3	96.3	0.4
t=10	0.5	97.5	1.9	7.4	91.8	0.8
DLPGOLD						
t=1	4.6	0.1	95.3	0.4	0.0	99.6
t=10	4.8	0.2	95.0	2.2	0.3	97.5
	Pre-War			During War		
Explained by →	RBSE	DLPCRUDE	DLPGOLD	RBSE	DLPCRUDE	DLPGOLD
RBSE						
t=1	100.0	0.0	0.0	100.0	0.0	0.0
t=10	98.4	1.4	0.2	98.0	1.7	0.2
DLPCRUDE						
t=1	1.7	98.3	0.0	14.8	85.2	0.0
t=10	2.4	97.2	0.3	16.0	82.6	1.5
DLPGOLD						
t=1	0.5	0.3	99.2	7.0	30.6	62.4
t=10	1.0	0.4	98.6	8.0	30.8	61.1

Source: Authors' computation

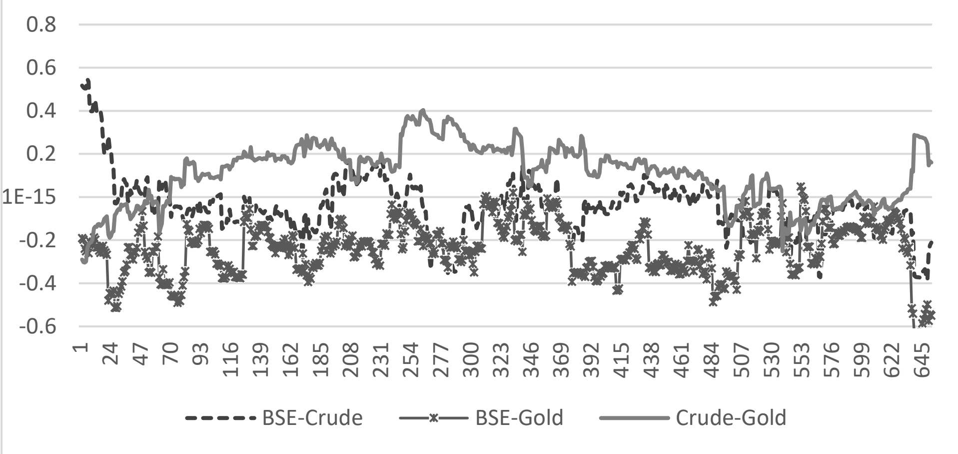


Source: BSE and MCX



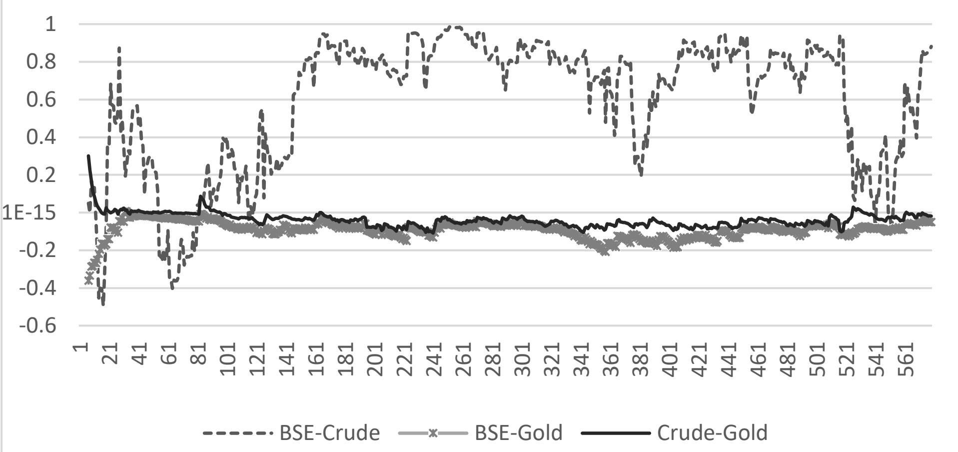
Source: BSE and MCX

Figure 3: Conditional Correlation for Spot Prices in Pre-COVID period

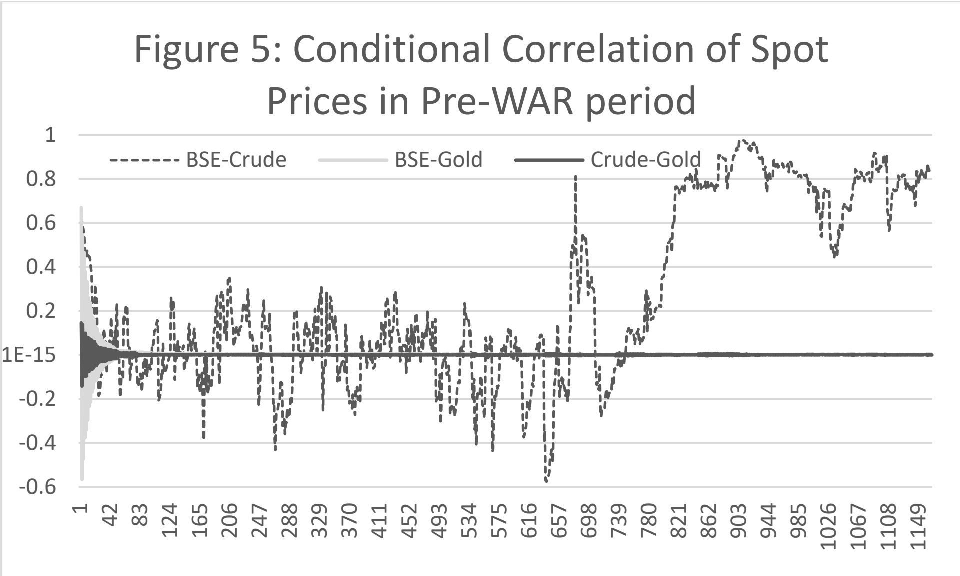


Source: Authors' computation

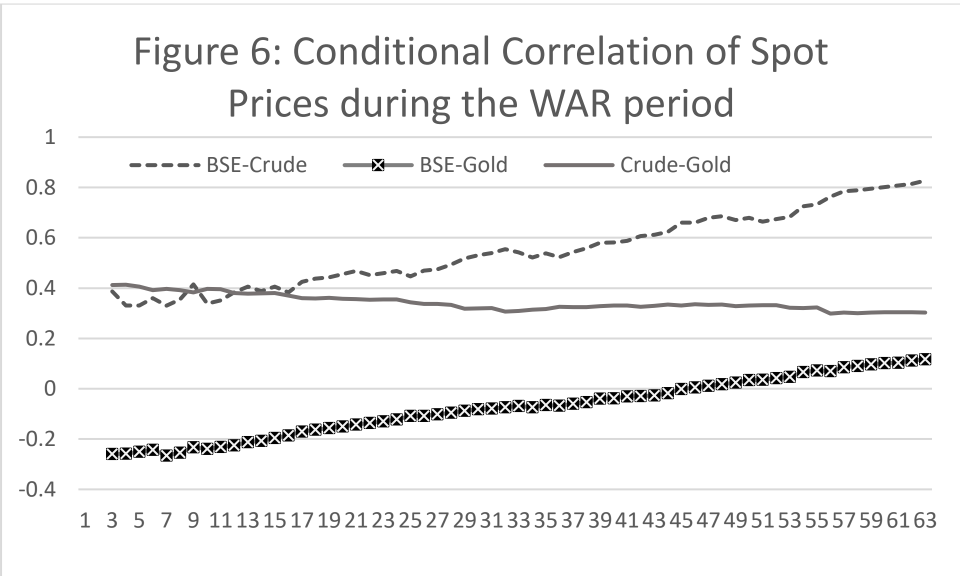
Figure 4: Conditional Correlation for SPot Prices during COVID period



Source: Authors' computation



Source: Authors' computation



Source: Authors' computation

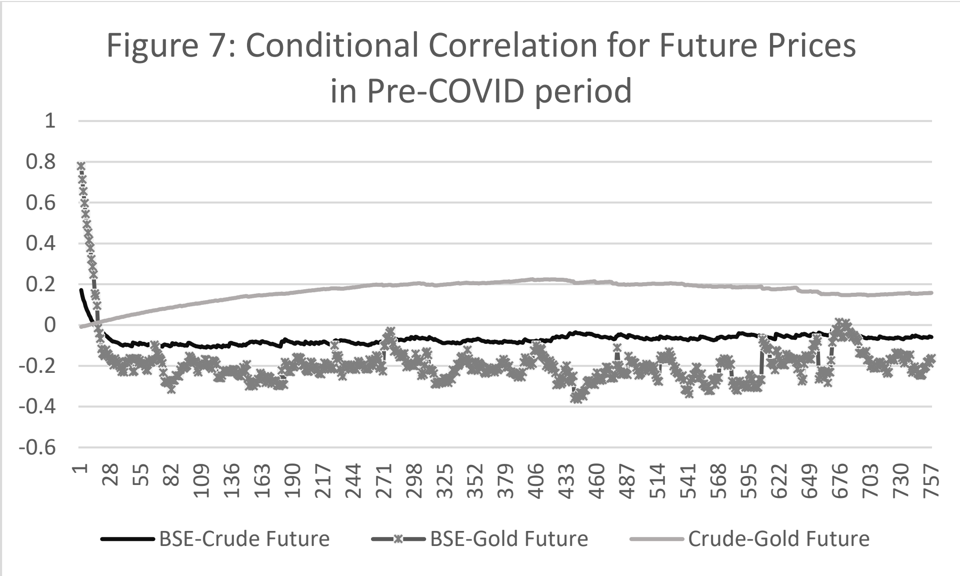


Figure 7: Conditional Correlation for Future Prices in Pre-COVID period

Source: Authors' computation

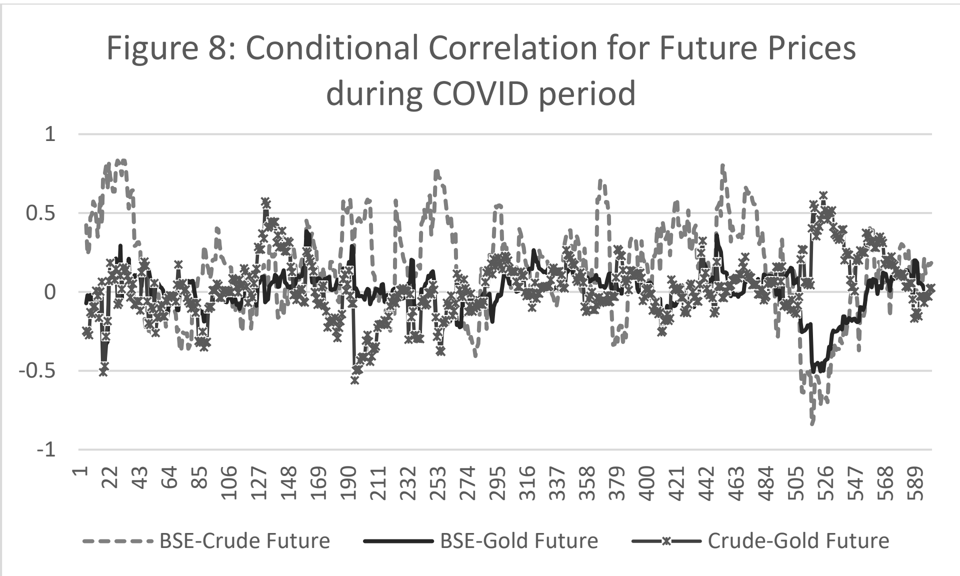
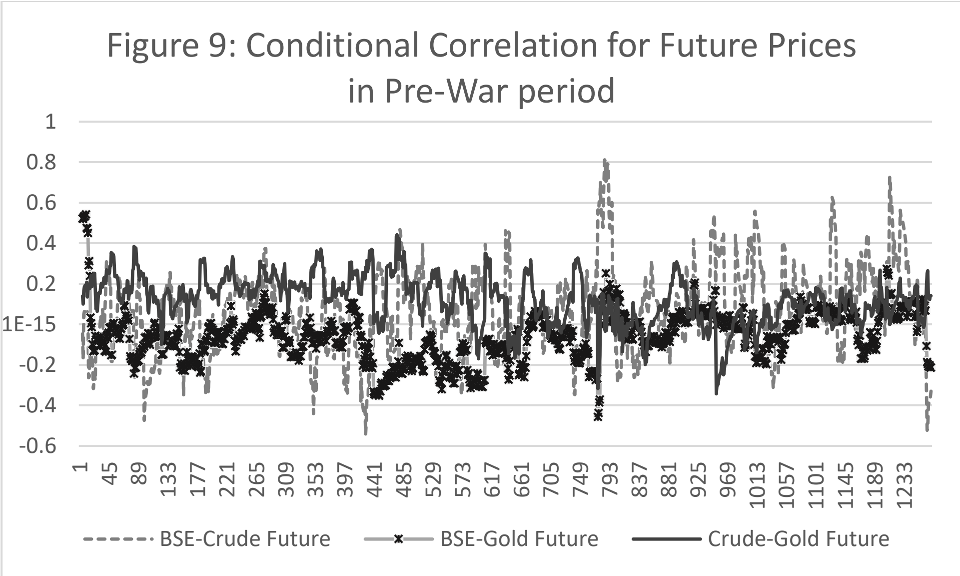
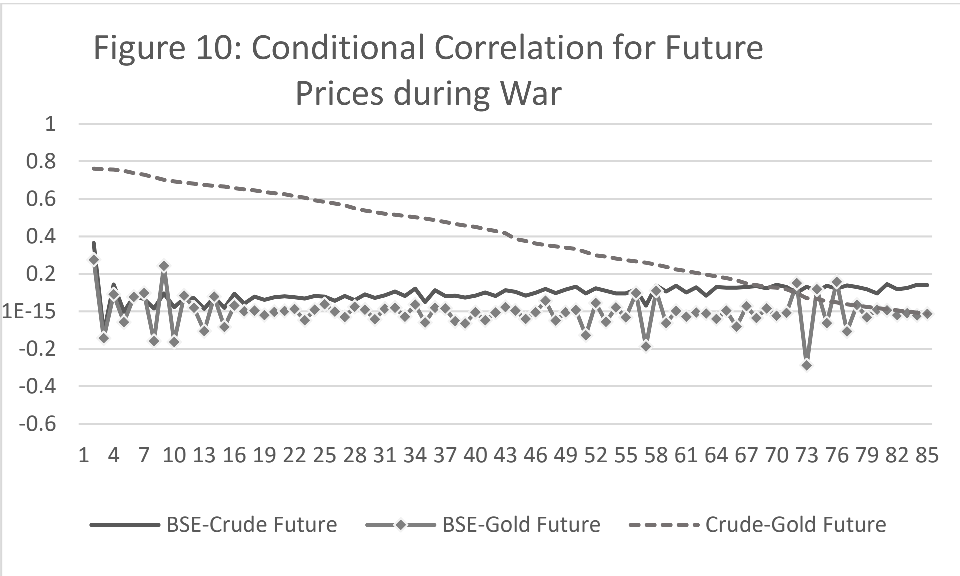


Figure 8: Conditional Correlation for Future Prices during COVID period

Source: Authors' computation

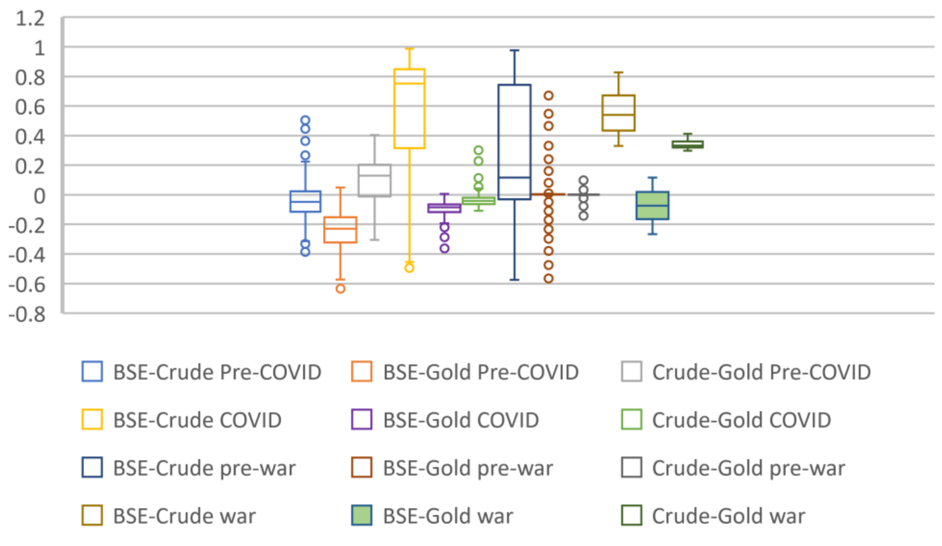


Source: Authors' computation



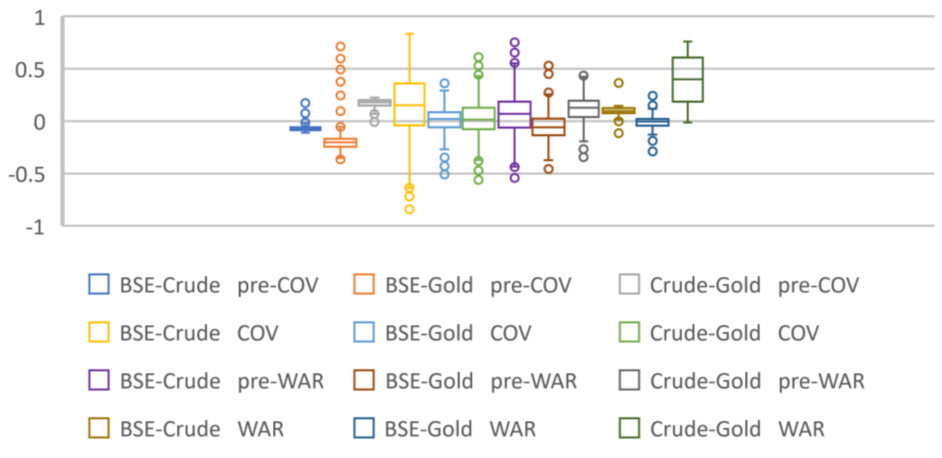
Source: Authors' computation

FIGURE 11: BOX-WHISKER PLOT OF DYNAMIC CORRELATIONS OF SPOT PRICES



Source: Authors' computation

FIGURE 12: BOX-WHISKER PLOT OF DYNAMIC CORRELATIONS BETWEEN FUTURES PRICES



Source: Authors' computation