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Assessing the Impact of COVID-19 on Interactions among Stock, Gold and Oil Prices in India[♦]

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This paper attempts to explore the relationship between the stock prices and the prices of two mostly traded commodities in the derivatives market, viz. crude oil and gold in the Indian context. Based on the daily data during 2017-2020, the paper employs ARDL model in order to estimate the long-term relationships. It also finds out the impact of market disruptions following the recent COVID-19 pandemic, on this relationship in the context of Indian financial markets. The findings point to the fact that the stock returns and the commodity prices are closely linked with each other. Interestingly, our findings suggest that the pandemic has altered the relationship. In the pre-COVID period, there was no cointegration among the stock, gold and crude oil prices. However, during the pandemic, we find evidence of cointegrating relationships. The short run relationship also provides some interesting insights. In the pre-pandemic period, evidence points to a mutual impact on the two markets, e.g. past values of oil price and gold price influence the stock returns while returns on the stock market influences oil price volatility. However, during the COVID period, apart from crude oil prices, it is the volatility of gold prices that has emerged as the driver of the stock returns.

Keywords: Commodity market, ARDL, gold price, crude oil price, stock price, COVID-19
JEL Classification: G12, C22

1 Introduction

The interaction between commodity markets and financial markets has drawn a great deal of attention among economists, policy makers and investors alike

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during the last two decades. There is growing evidence that equity market and commodity markets are interconnected and that the correlations between commodities and equities have increased since the beginning of the decade of 2000 (Buyuksahin et al. 2008; Tang and Xiong 2012; Olson, Vivian, and Wohar, 2014). It is also argued that financial markets such as equity and bond markets offer useful information about the behaviour of commodity markets where stock price indices showed suggestive evidence of predictive ability for commodity price indices (Chen, Rogoff and Rossi, 2010). Gorton and Rouwenhorst (2006) argued that before 2000, commodity markets were largely segmented from outside the financial markets and each other. Prior to the early 2000s, in commodity markets, prices provided a risk premium for idiosyncratic commodity price risk and hardly showed evidence of co-movement with stocks and with each other. However, given the fact that there has been a sizeable increase in investment in commodity markets with significant flow of index investment in such markets, commodity markets and financial markets have become more integrated and less segmented (Tang and Xiong, 2012). Since index investors typically focus on strategic portfolio allocation between the commodity and other assets, such as stocks and bonds, they tend to trade in and out of all commodities in a given index at the same time. An estimate of the U.S. Commodity Futures Trading Commission (CFTC 2008) reveals that the estimated investment in commodity indices (and related instruments) increased from $15 billion dollars in 2003 to $200 billion in mid-2008. This particular feature indicates less segmentation between the two markets and suggests the possibility of spill-over effects from stock to commodity markets (Tang and Xiong, 2012; Rossi, 2012)[1].

Against this background, the motivations for this paper are drawn from a number of factors. First, commodities are traded in commodity markets both as a financial instrument and as raw materials used in the production of final commodities. In the recent past, investors consider commodity markets as financial assets (see for example, Mensi et al., 2013; Reboredo and Uddin, 2016; Vivian and Wohar, 2012). Commodity markets are also viewed as part of a portfolio diversification strategy, in order to diversify investment and also hedge against inflation (Arezki et al., 2014; Creti et al., 2013; Tadesse et al., 2014; Tang and Xiong, 2012). Increasing presence of investors in the commodity markets generate spillover effects from outside commodity markets into it. The volatility in individual commodities is partially driven by the increased return correlation

[1] In particular, country evidence showed that equity markets have some out-of-sample predictive ability for the global commodity price index since the mid 2000s (Rossi, 2012).

with oil, and that the indexed commodities experienced a higher increase in volatility. Second, commodity prices, in general, appear to be important given that these affect the general price level in the economy. For example, price of gold receives considerable attention of monetary authorities since the price of gold tends to increase as people switch from currency to gold as a hedge against expected inflation. Similarly, fluctuation in price of crude oil has been considered to have a significant impact on economic growth and several other macroeconomic variables such as inflation, investment, and output[2]. Third, commodity prices also play an important role in the financial market as these are used as tradable financial instruments. Market participants as well as policy makers focused on the dynamics of commodity price volatility because of its impact on economic growth and financial development (Cevik and Saadi Sedik, 2014). Increase in commodity prices, in general, follows from an increase in demand and expansion of economic activities (Kilian, 2009). With the increased cost of production following an increase in prices of commodities such as crude oil, gold and silver, used as inputs in the process of production, firm profits is also adversely affected. (Lombardi and Ravazzolo, 2016). This, in turn, is likely to adversely affect stock prices.

Fourth, there is a general agreement that the global pandemic, COVID-19, which started in Chinese city of Wuhan in December 2019, led to serious disruptions in global financial and economic systems that leads to reactions, not only from governments but also from businesses (Phan and Narayan, 2020). Global financial markets experienced severe adverse shocks following repercussions in commodity markets, particularly, fall in oil price. Two months after the onset of the COVID-19, global crude oil price significantly fell by around 30%, which is the largest slump since the Gulf war, after the unexpected decision of Saudi authorities to offer price discounts of \$6 to \$8 to their main customers in Europe, Asia, and the US (Sharif et al. 2020; Schneider and Domonoske, 2020)[3]. The financial markets have reacted with large drops, e.g. stock markets across the globe experienced significant downslide, as a consequence of the oil price war

[2]A rise in oil price leads to increase in energy bill for consumers and increased costs of production. Increasing oil prices are also indicative of reduction of its availability as a primary input in production following rising costs, thereby leading to a decrease in potential output. Rise in cost of production and a fall in growth of output and productivity, in turn, exert adverse impact on employment, inflation, profits and investment.

[3] The severe collapse in oil price in international markets seems to be the outcome of a fall in demand caused by the economic slowdown generated by COVID-19 pandemic and also failed negotiations between Russia and Organization of the Petroleum Exporting Countries (OPEC) to reduce daily barrel production.

and also the fears over the news of more infections and patient death, from countries of Italy, France and Spain. Salisu et al. (2020) observed that between the months of February and March 2020, when the virus spread quite rapidly and COVID-19 was declared a global pandemic by World Health Organization (WHO), most of the developed stock markets experienced severe downfall. While stock prices in US market fell by 32 percent, it declined by 27.9 percent in UK and 39.3 percent in Italy. Emerging market economies also had similar experiences with prices of stocks in the stock markets of Brazil, Russia and China falling by 40.5 percent, 24.2 percent and 10.1 percent respectively. Global stock markets also experienced significant volatility during January to May, 2020.

On the other hand, globally gold prices have experienced a relatively smaller decline with the outbreak of COVID-19, but this was followed by an upside trend commencing since the middle of March 2020 (Gharib et al. 2020). Evidently, the global uncertainty tied to this COVID-19 outbreak has significantly perturbed the price dynamics of crude oil and gold and created a risk-averse environment that has driven investors towards safe-haven assets such as gold (Mensi et al. 2020; Gharib et al, 2020). External shock also might lead to expectations of official gold purchases, leading to an increase in the expected future price of gold. As oil and gold are the most commonly traded commodities in the derivative markets, the entire market dynamics and the price movement of these two commodities are supposed to have important ramifications for the financial markets during the current pandemic of COVID-19.

Finally, we observe a vast body of literature that looks into the relationship between gold price, oil price and stock price (Bedoui et al., 2019; Ewing and Malik, 2013;Narayan et al.,2010; Soytas et al., 2009;Zhang and Wei, 2010). However, issues related to the economic impact of the Covid-19 pandemic in general, and the nexus between commodity markets and financial markets, in particular, are not much explored, specifically in the context of emerging market economies such as India. However, Indian markets are equally affected along with the rest of world since the outbreak of COVID-19 pandemic in January 2020. We come across couple of studies, in Indian context, that examine how COVID-19 pandemic impacted financial markets and their volatility. However, we hardly find any study that looks into the nexus between commodity derivatives markets and financial markets through their co-movements following the pandemic in Indian context.

The paper aims to assess the impact of COVID-19 pandemic on the interaction between commodity markets and stock markets in the Indian context. A scrutiny of the behaviour of the nexus between these two markets during the pandemic seems to be crucial from the point of view of both policy makers and investors. It seems to be relevant from investor's point of view, as well, who seeks to minimize their risks and eventually aims to maximize returns while diversifying their portfolio and hedging risks. In particular, we analyze the co-movement and causality of commodity prices and stock prices in Indian context. While the causality between commodity price fluctuations such as fluctuations of oil price and stock price relates to the financialization of the commodity markets, it happened to occur even before the outbreak of COVID-19.We hypothesise that the pandemic may produce a short-term economic impact on the commodity-financial market nexus through oil price-stock nexus or through gold price-stock nexus (Salisu et al. 2020; Wang et al., 2013; Salisu and Isah, 2017; Swaray & Salisu, 2018; and; Salisu et al., 2019; Gharib et al. 2020). For this purpose, we segregate our analysis into two periods of pre-COVID-19 and COVID-19 pandemic respectively and thereafter, we conduct a comparative analysis of the co-movement and causality of commodity prices and stock prices. It is hypothesized that the onset of the COVID-19 will have greater spillover effects on both commodity and financial markets and the response of the relevant agencies to the COVID-19 epidemic determines the behaviour of these spillovers in the long run. During crises, for example, the financial market volatility generally increases sharply and spills over across markets (Diebold and Yilmaz, 2012). Thus, analysing the probable shock spillovers since the emergence of COVID-19 will serve as 'early warning signs' regarding the severity and the consequences of the crisis. This information is particularly useful to investors who are more concerned about maximizing their returns even in the presence of risks. Moreover, it is of considerable interest to assess to which extent gold can act as a hedge, a safe haven and/or a diversifier against oil price movements during the period of COVID-19 outbreak.

This paper makes an attempt to analyse the above issues by estimating ARDL model on daily data in the recent past for the Indian financial market. The contribution of the paper lies not only in considering the impact of COVID-19 by comparing the relationship with pre-COVID period, but also to throw light on the linkage between Indian stock and commodity derivatives markets with the high frequency data in the recent past. Few existing studies on this in the Indian context are either dated or have not considered such kind of assessment of a crisis on the relationship.

Rest of the paper is organized as follows: Section 2 gives a brief overview of the state of Indian stock market as well as commodity markets. Section 3 presents a brief survey of literature. Section 4 presents data and methodology. Section 5 presents results and discussions. Section 6 concludes the paper.

2. Indian scenario

There has been a phenomenal growth and expansion of Indian stock market in terms of increase in size and volume of investment, with the introduction of financial sector reforms in the decade of 1990s. Therefore, perturbations in domestic macroeconomic factors as well as external factors are supposed to have significant effects on the movement of stock price and volatility of stock return in the stock market. This seems to be important from the point of view of both domestic as well as international investors and policy makers. Previous studies in Indian context reveal that Indian stock market is significantly influenced by movements in commodity markets by three important factors, i.e., international crude oil price, price of gold and exchange rates. Jain and Biswal (2016) explore the relationship between global prices of gold, crude oil, the USD-INR exchange rate, and the stock market in India. Findings reveal that fall in gold prices and crude oil prices lead to a fall in the value of stock index and these relationships appeared to be more pronounced in post global financial crisis period, 2008-2013. The findings of this study also consider gold as an asset class of investment among the investors. India is the major importer of both oil and gold in international markets. India was the fourth largest country in terms of its consumption of crude oil and petroleum products and also the fourth largest net importer after USA, China and Japan in 2015, (US Energy Information Administration, 2016)[4]. Since India is heavily dependent on imports of crude oil from international markets, to the extent of more than 80%, any significant change in price of crude oil is likely to exert an impact on inflation and hence the stock market (Ghosh and Kanjilal, 2016). Oil price effect gets transmitted to macroeconomic fundamentals, which, in turn, influences the liquidity in the financial market and stock prices. Consequently, market returns get affected through their effect on expected earnings (Jones et al., 2004).

On the supply side, increase in crude oil prices leads to an increase in production costs, thereby adversely affecting cash flow and hence stock prices (Kapusuzoglu, 2011). This happens because of adverse impact on profits of

[4]https://www.eia.gov/international/overview/country/IND.

firms. On the demand side, oil price increase may result in increase in inflation which may discourage investment in stock market due to the increase in interest in bond market (Ghosh and Kanjilal, 2016). Gold, on the other hand, is considered as a 'safe haven' to avoid risk in financial markets. Baur and McDermott (2010) found that gold appeared to be a strong "safe haven" during the 2008 global financial crisis for most of the developed stock markets in Europe and the US, but not for large emerging economies such as India.

3. Literature Survey

Baur and McDermott (2010), and Baur and Lucey (2010) show that gold serves as a hedge and a safe haven for the US, the UK, and the German stocks or bonds. Sadorsky (1999) studied the relation between oil prices and stock prices by using a VAR model that includes a short-term interest rate and industrial production and found that there is a relation between oil price and other variables. Chiou and Lee (2009) studied the West Texas Intermediate (WTI) daily oil prices on S&P 500 stock returns data from 1992 to 2006 using a model with oil price fluctuations. They found that fluctuations in oil prices have impact on stock returns. Choi and Hammoudeh (2010) studied the relation between commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index and found that commodity prices have affected portfolios in stock markets. Rossi (2012) explores whether the large fluctuations in commodity prices in the late 2000s can be attributed to less segmentation of commodity markets and finds evidence of out-of-sample predictive ability of the equity market in the middle of the decade of 2000s, implying a weak market segmentation and the possibility that shocks in equity markets might have spill-over effects on the commodity markets in that period. Bhunia (2013) studied the relationship of domestic gold price and stock price return, using Granger test and found evidence of the bidirectional causality between gold price and stock price return. Gokmenoglu and Fazlollahi (2015) used daily spot prices and S&P 500 index for gold and oil stock price in the context of US markets during January 2013 to November 2015 and investigated whether gold price, oil price, gold price volatility and oil price volatility exert impact on stock price index. Authors observe the presence of long-run equilibrium relationships and also reveal that stock price index converges to its long-run equilibrium level through adjustments via oil and gold market prices and their volatilities. Iscan (2015) studied the interactions between stock market and commodity prices in the context of Turkish markets during 2002-2014 and hardly found any evidence of the relations between two markets.

Bondia et al. (2016) investigated the long term relationship between stock prices of energy firms with oil prices in a multivariate framework. Using threshold cointegration tests, authors find evidence of the impact of oil price, interest rates, on energy stock prices.

As far as the recent literature on commodity markets-stock market nexus is concerned, we observe few studies which scrutinize the effects of COVID-19 pandemic. Sharif et al (2020) analyze the relationships among the recent spread of COVID-19, oil price volatility shock, the stock market, geopolitical risk and economic policy uncertainty in the US within a time-frequency framework using daily data;they unveil the unprecedented adverse impact of COVID-19 and oil price shocks on the stock market volatility along with other effects, in terms of perceived risks of US investors. Mensi et al. (2020) examine the impacts of COVID-19 on the multifractality of gold and oil prices based on upward and downward trends by applying the Asymmetric Multifractal Detrended Fluctuation Analysis (A-MF-DFA) approach to 15-minute interval intraday data. Findings reveal that gold and oil markets have been inefficient, particularly during the outbreak. Salisu et al. (2020) estimate the behaviour of oil-stock nexus during COVID-19 pandemic by applying panel Vector Autoregressive (pVAR) model and using daily data from a cross-section of 15 worst affected countries including India, due to COVID-19[5]. Findings suggest that both oil and stock markets may experience greater initial and prolonged impacts of own and cross shocks during the pandemic than the period before it. Gharib et al. (2020) examines the causal relationship between crude oil and gold spot prices to assess the impact of COVID-19, by using West Texas Light crude oil (WTI) and gold prices from January 4, 2010, to May 4, 2020. Findings reveal a bilateral contagion effect of bubbles in oil and gold markets during the recent COVID-19 outbreak. Mishra et al (2020) investigate the impact of COVID-19 on the Indian financial market and compare it with the outcomes of two recent structural changes of the Indian economy: demonetization and implementation of the Goods and Services Tax (GST). Using daily stock return, net foreign institutional investment, and exchange rate data from January 3, 2003 to April 20, 2020, the study finds negative stock returns for all the indices during the COVID19 outbreak, unlike during the post-demonetization and GST phases. Dev and Sengupta (2020) argued that exact magnitude of economic loss following COVID-19 cannot be predicted.

[5]Belgium, Brazil, Canada, China, France, Germany, India, Italy, Mexico, Netherlands, Russia, Spain, Turkey, UK and USA.

However, most of the existing studies discussed above focus on developed countries and also we find very few studies in the context of developing countries such as India that looks into the nexus between commodity markets and stock markets. This paper is expected to add to the existing literature on this issue.

4. Data and Methodology

4.1 Data

In order to investigate how the stock price is influenced by commodity prices and volatilities of commodity prices in the Indian context, and whether such relationship has changed during the COVID-19 pandemic, we take into account the daily data from the key stock markets of the country and the commodity derivatives market. For stock prices, two benchmark stock indices, viz. Sensex of Bombay Stock Exchange denoted henceforth as BSE and the Nifty 50 of National Stock Exchange denoted as NSE henceforth, are taken. BSE accounts for more than 50% of total turnover across all stock exchanges (Ghosh and Kanjilal, 2016). We consider S&P BSE SENSEX which is the free-float market-weighted stock market index of 30 well-established and financially sound companies listed on Bombay Stock Exchange. Stocks of the 30 constituent companies in S&P BSE SENSEX are the largest and most actively traded stocks and also representative of various industrial sectors of the Indian economy. Both are sourced from the respective websites of the stock exchanges. Daily closing prices of both the indices are taken in logarithmic form and denoted as LBSE and LNSE, respectively. Their returns (measured as the difference between the logarithm of price index on consecutive days, e.g. $LBSE_t – LBSE_{t-1}$), in turn, are denoted by RBSE and RNSE, respectively.

For commodity prices, the data is sourced from The Multi Commodity Exchange of India Limited (MCX), the commodity derivatives exchange, India’s first listed exchange that facilitates online trading of commodity derivatives transactions, thereby providing a platform for price discovery and risk management (https://www.mcxindia.com). In the previous sections, the linkage between stock market and commodities like gold and oil has been discussed. In MCX, gold and oil are among the top ten most actively traded commodities in terms of value. From MCX, per unit daily spot prices of crude oil and gold are taken[6]. Prices are taken in logarithmic form and denoted as LPCRUDE and LPGOLD, respectively.

[6] Unit of measurement of crude oil is one barrel (BBL). Spot price of gold is measured per 10 grams Per unit prices of crude oil and gold are expressed in rupees respectively (mcxindia.com). The average price of the two sessions are taken for both the variables.

In our empirical models, we also consider volatility of crude oil and gold. The 5-day Annualized Actual Volatility (AAV)[7] of oil price and gold price as provided by MCX are taken as measures of volatility. Here the daily closing prices of front month (spot month) futures contract are being used for the measurement of asset volatility and the volatilities are expressed in annualized terms[8].Since this is measured as the standard deviation of spot prices, it is taken in raw form and the volatilities are denoted as VOLCRUDE and VOLGOLD, respectively.Both stock exchanges (BSE and NSE) and commodity exchange (MCX) operate under the regulatory framework of Securities and Exchange Board of India (SEBI).

The daily data is taken from June 1, 2017 to August 10, 2020 leading to 783 observations. The sample is chosen on the basis of the following factors: first, since we are interested to figure out whether the relationship has changed during the COVID-19 pandemic, we have incorporated latest data available, till August, 2020. This period encompasses the periods of both pre-COVID-19 and post-COVID-19 in India. Second, for examining the relationships of financial variables, we have focused on high frequency data, viz. daily data. Third, we have taken the data from 2017, as from June 16, 2017, dynamic fuel pricing was implemented under which prices were to be revised every morning at 6 am. The Indian government has permitted oil marketing companies to determine the retail price of fuel based on the exchange rate and fluctuations in international oil prices[9].During the same period, gold prices also have recorded significant

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[7]This represents the weekly volatility trends in the underlying commodities. Annualized Actual Volatility (AAV) is measured as annualised standard deviation of the continuously compounded daily returns of the asset. The asset volatilities are expressed in annualized terms. The following formula is used to calculate the AAV.

$$AAV = 100 \times \sqrt{\left(\frac{252}{D}\right)\sum_{t=1}^{D}\left(\ln\frac{p_t}{p_{t-1}}\right)^2}$$

where, p_t and p_{t-1} are the closing prices of the underlying futures on day 't' and the business day prior to day 't'; D is the number of business days covered in the computation of respective historical volatility. The resultant volatility is expressed in percentage terms by multiplying with 100 (mcxindia.com).

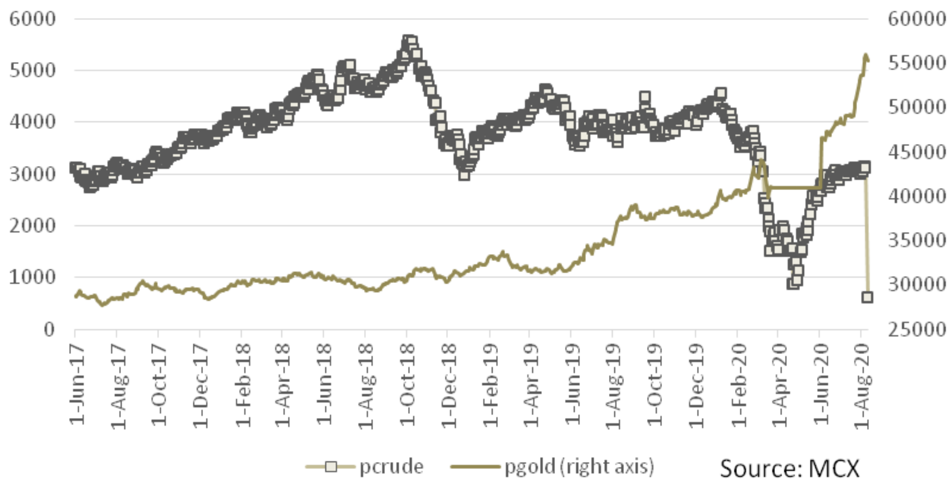
[8]Front month, also called 'near' or 'spot' month, refers to the nearest expiration date of a futures contract.

[9]Such a shift from administrative price mechanism (APM) to dynamic pricing was done to ensure that the can put into effect the benefit of the slightest change in international oil prices and thereby would prevent huge leaps in prices at the end of the fortnight. For details, see https://www.businesstoday.in/current/economy-politics/how-petrol-diesel-prices-are-fixed-why-they-change-every-day/story/281961.html#:~:text=As%20for%20the%20everyday%20change,and%2016th%20of%20every%20month.

fluctuations. Out of the total sample, the period from January 31, 2020 onwards has been considered as the period of COVID-19 pandemic as the first case of COVID-19 was reported on that date. Descriptive statistics for the entire sample is presented in Appendix Table 1.

Figures 1 and 2 present the movements of prices and the volatilities of prices of crude oil and gold. It is observed that crude oil price exhibits periods of fluctuations with changing trends, while gold price exhibits a rising trend with fluctuations. During the pandemic, crude oil price fell in March, but from the end of April it started moving up. On the contrary, gold price kept on moving up during the pandemic, possibly owing to its safe haven status. Both the prices record significant volatility, while the volatility of crude oil prices during the third week of April was extraordinary.

Figure 1: Spot Price of Crude Oil and Gold



Source: MCX

As far as the movement of stock prices during the period of COVID-19 is concerned, it is observed that on 2 March, the BSE SENSEX witnessed a flash crash (www.moneycontrol.com). On 9 March, BSE SENSEX closed 1,942 points lower at 35,635 while the NSE NIFTY 50 was down by 538 points to 10,451[10]. On 12th March, Indian stock markets suffered their worst crash since June 2017 after WHO's declaration of the outbreak as a pandemic. The BSE SENSEX

[10] https://economictimes.indiatimes.com/markets/stocks/news/monday-mayhem-may-mark-worst-day-for-sensex-5-factors-causing-this-crash/articleshow/74547106.cms.

dropped 8.18 per cent or 2,919 points which was its lowest in 23 months while the NIFTY dropped 9 per cent or 950 points[11]. The time plots of both LBSE and LNSE are presented in Figure 3 for the entire sample.

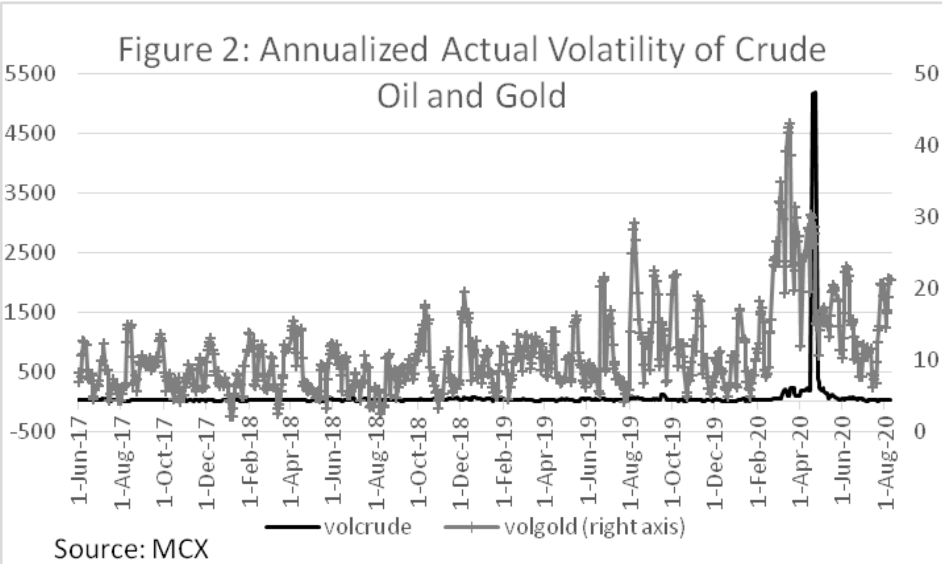


Figure 2: Annualized Actual Volatility of Crude Oil and Gold

Source: MCX

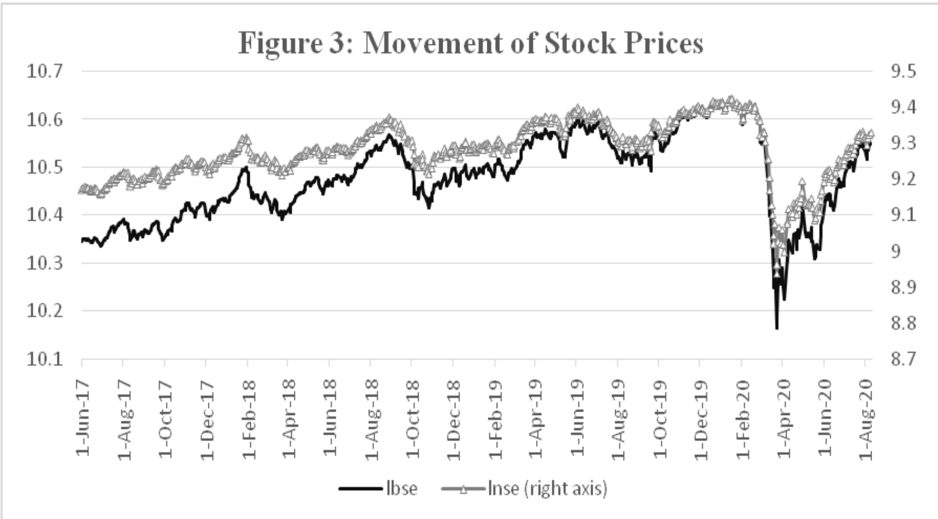


Figure 3: Movement of Stock Prices

Source: BSE and NSE

[11] https://www.ndtv.com/business/bse-sensex-today-live-market-news-sensex-ends-2919-points-lower-nifty-at-9590-amid-coronavirus-fear-2193751.

The stationarity of all the variables are tested by Augmented Dickey-Fuller unit root test and it was observed that LBSE, LNSE, LPCRUDE and LPGOLD were integrated of order 1, whereas VOLCRUDE and VOLGOLD are stationary at level. The correlation between the stock return and the price of gold, and that of stock return and price of crude oil are positive and moderately high (Table 1). Other volatilities are quite low.

TABLE 1: Correlation

	LNSE	LBSE	LPCRUDE	LPGOLD	VOLCRUDE	VOLGOLD
LNSE	1					
LBSE	0.99	1				
LPCRUDE	0.50	0.50	1			
LPGOLD	0.70	0.76	0.22	1		
VOLCRUDE	0.02	0.07	-0.04	0.15	1	
VOLGOLD	0.10	0.14	0.00	0.32	0.29	1

Source: Authors' computation

4.2 Methodology

The relationship that we would like to estimate is:

$$LBSE_t = \alpha + \beta_1 LPCRUDE_t + \beta_2 LPGOLD_t + \beta_3 VOLGOLD_t + \varepsilon_t \qquad (1)$$

$$LNSE_t = \alpha + \beta_1 LPCRUDE_t + \beta_2 LPGOLD_t + \beta_3 VOLCRUDE_t + \beta_4 VOLGOLD_t + \varepsilon_t \qquad (2)$$

Since the variables are integrated of different orders (0 and 1), the long term relationship may be estimated by applying Autoregressive Distributed Lag(ARDL) cointegration technique or bound test of cointegration (Pesaran and Shin 1999 and Pesaran et al. 2001). The ARDL(l,m,n,p,q) model in our context, is estimated in the following conditional ECM form:

$$\begin{aligned}\Delta LBSE_t = \beta_0 &+ \sum\nolimits_{i=1}^{l} \beta_i \Delta LBSE_{t-1} + \sum\nolimits_{j=0}^{m} \gamma_j \Delta LPCRUDE_{t-j} \\ &+ \sum\nolimits_{k=0}^{n} \delta_k \Delta LPGOLD_{t-k} + \sum\nolimits_{i=0}^{p} \alpha_i \Delta LVOLCRUDE_{t-1} \\ &+ \sum\nolimits_{j=0}^{q} \varphi_j \Delta VOLGOLD_{t-1} + \theta_0 LBSE_{t-1} + \theta_1 LPCRUDE_{t-1} \\ &+ \theta_2 LPGOLD_{t-1} + \theta_3 VOLCRUDE_{t-1} + \theta_4 VOLGOLD_{t-1} + \varepsilon_t\end{aligned} \qquad (3)$$

$$\begin{aligned}\Delta LNSE_t = \beta_0 &+ \sum_{i=1}^{l} \beta_i \Delta LNSE_{t-1} + \sum_{j=0}^{m} \gamma_j \Delta LPCRUDE_{t-j} \\ &+ \sum_{k=0}^{n} \delta_k \Delta LPGOLD_{t-k} + \sum_{i=0}^{p} \alpha_i \Delta LVOLCRUDE_{t-1} \\ &+ \sum_{j=0}^{q} \varphi_j \Delta VOLGOLD_{t-1} + \theta_0 LNSE_{t-1} + \theta_1 LPCRUDE_{t-1} \\ &+ \theta_2 LPGOLD_{t-1} + \theta_3 VOLCRUDE_{t-1} + \theta_4 VOLGOLD_{t-1} + \varepsilon_t \end{aligned} \quad (4)$$

Such models are widely applied to test for the presence of long-run relationship among economic variables. The bound test is performed by an F-test of the null hypothesis of no cointegration H_0: $\theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$, against the alternative hypothesis that H_0 is not true. A rejection of H_0 implies that we have a long run equilibrium relationship among the four variables. If long-run relationship is obtained from the bounds test, an error correction model (ECM) is estimated to examine the short-run dynamics of the relationship between the variables. If long term relationship is not there, we report the conditional ECM only.

ARDL optimal lag structure test, based on Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC) is applied to find out the optimum lags in ARDL (l, m, n, p, q) as an appropriate ARDL model. Since the objective is to find out whether the relationship has changed during a crisis like the COVID-19 pandemic, models are estimated separately for the pre-COVID and COVID period. For that, the sample is split into two – the period from June 1, 2017 to January 30, 2020 is considered as pre-COVID period (653 observations) and the rest of the sample is called the COVID period (130 observations).

We have also tested the relationship between the stock returns and the volatilities and levels of spot prices in the commodity futures market by pair wise Granger Causality test for up to 5 lags. The same is applied for both RBSE and RNSE and all other variables are taken in their stationary form. This causality test also is applied separately for pre-COVID and COVID periods. The results are presented in the next section.

5. Results

The ARDL bound tests are conducted for pre-COVID and COVID period for both BSE and NSE, with a specification of a model with restricted intercept and no trend. The results of the bound test are reported in Table 2[12]. From the Table it

[12]The model with unrestricted intercept and no trend was also estimated and the bound test results are similar.

is evident that during the pre-COVID period, there is no cointegration for both Sensex and Nifty with the commodity prices and their volatilities. But, during the post-COVID period, bound tests indicate that there is cointegration among the variables for both Sensex and Nifty and the error correction models are estimated for the COVID period. It should be noted that during the pre-COVID period, the long term relation suggests that only the price of gold is having a statistically significant and positive impact on Sensex and Nifty, viz. a 1% increase in price of gold leads to an increase in BSE by 0.72% and Nifty by 0.53%, respectively. It seems that investors invested in both gold and stock markets, in general. This probably speaks of the intent of diversification on the part of investors. This is also in synchronization with Jain and Biswal (2016). But in the COVID period, the relationship has changed. Gold price no longer influences the stock indices. Rather, the price of oil seems to affect the stock price indices positively. This again might be owing to the diversification motive. Moreover, with increase in last 5 day's volatility in crude oil prices, there has been a positive and significant increase in the stock prices. This is quite expected during a crisis as investors move away from crude oil owing to increased volatility to purchase stocks. But, interestingly, with more volatility in gold prices, stock price indices have declined. This is possibly due to the status of gold as safe haven and during an unprecedented crisis like a pandemic, investors did not shift to stock markets despite the volatility in gold prices. Moreover, it seems that with more fluctuations in gold prices, they reduced investment in stock markets to purchase other assets and/or gold. This observation is in conformity with few global evidence of gold price increase and decline of oil price and the corresponding decline of global stock market during January-March, 2020 (Gharib, 2020; World Economic Forum 2020).

Table 2: ARDL Long Run Parameter Estimation and Bounds Test

	Dependent Variable											
	LBSE (pre-COVID)			**LNSE (pre-COVID)**			**LBSE (COVID)**			**LNSE (COVID)**		
Regressors	Selected Model	Coefficient	Std. Error	Selected Model	Coefficient	Std. Error	Selected Model	Coefficient	Std. Error	Selected Model	Coefficient	Std. Error
Constant	(4,5,5,5,0)	3.04	3.30	(4,5,5,5,0)	3.90	2.56	(2,4,0,4,2)	8.40	1.79	(2,4,0,4,2)	7.02	1.77
LPCRUDE		0.01	0.23		-0.01	0.18		0.28***	0.06		0.28**	0.06
LPGOLD		0.72**	0.34		0.53**	0.25		-0.003	0.17		0.015	0.17
VOLCRUDE		0.003	0.003		0.002	0.003		0.00009***	0.00003		0.00008***	0.00003
VOLGOLD		-0.01	0.01		-0.01	0.01		-0.0095***	0.003		-0.0098***	0.003
Bound Test												
F Wald Test Statistic		1.31			1.35			5.12***			5.09***	
Source: Author's computation.												
Note: ***,**,* indicate p<0.01, p<0.05, p<0.10 respectively.												

The regressions are estimated taking cue from Table 2. Hence for the COVID period, the error correction models are reported to understand the short run dynamics. The results are presented in Table 3. It is observed that the sign of the error correction coefficient (denoted as ecm(-1)) in determination of LBSE and LNSE is negative (-0.16 and -0.15) and is statistically significant at 1% level of significance. This implies that BSE (NSE) converges to its long-run level by a speed of 16% (15%) daily, owing to contribution of oil and gold market prices and their volatilities. It is observed that some lags of independent variables have a significant short-run effect on the stock market return, viz. crude oil prices and the volatility of both crude and gold prices.

Table 3: ARDL Error Correction Representation for Pre-COVID and COVID Periods

	Dependent Variable			
	ΔLBSE (COVID)		**ΔLNSE (COVID)**	
	Model:(2,4,0,4,2)		Model:(2,4,0,4,2)	
Regressors	Coefficient	Std. Error	Coefficient	Std. Error
Δlbse(-1)	-0.20**	0.08		
Δlnse(-1)			-0.21**	0.08
Δlpcrude	0.01	0.01	0.01	0.01
Δlpcrude(-1)	-0.09***	0.03	-0.09***	0.03
Δlpcrude(-2)	0.03	0.03	0.03	0.03
Δlpcrude(-3)	0.04	0.03	0.04*	0.03
Δvolcrude	0.000001	0.000004	0.0000003	0.000004
Δvolcrude(-1)	-0.000008	0.000004	-0.000008**	0.000004
Δvolcrude(-2)	-0.000004	0.000004	-0.000003	0.000004
Δvolcrude(-3)	-0.00001***	0.000004	-0.00001***	0.000004
Δvolgold	0.001*	0.000520	0.0001*	0.000510
Δvolgold(-1)	0.001	0.001	0.001*	0.001
ecm(-1)	-0.16***	0.03	-0.15***	0.03

Source: Author's computation.

Note: ***,**,* indicate p<0.01, p<0.05, p<0.10 respectively.

The results of pairwise Granger causality test are presented in Table 4. Since the results for BSE and NSE are identical, results for BSE only are reported for pre-COVID and COVID period. During the pre-COVID period, we find evidence of one way causality from crude oil price to BSE return and from price of gold to BSE return. However, while the causality runs from BSE return to crude oil price volatility, for one lag there is evidence of causality from crude oil price volatility to BSE return, too. There is no causality between BSE return and gold price volatility. While comparing these observations with the causality of the variables during the COVID period, the causality from crude oil price to BSE return is still observed. However, other relationships have completely changed as was indicated in Tables 3 and 4. In this period, for each lag, there is evidence of one way causality from volatility in gold prices in the past 5 to 10 days (volatility being the AAV of last 5 days, the lag of 5 indicates the volatility of approximately 10 days) to BSE return. This largely corroborates to the findings in Tables 3 and 4.

TABLE 4 : Pairwise Granger Causality Test

	PRE-COVID PERIOD					*COVID PERIOD*				
Lag	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Null Hypothesis:	F-Statistic					F-Statistic				
ΔLPCRUDE does not Granger Cause RBSE	0.002	0.827	4.678***	4.38***	4.09***	1.13	2.75	2.85***	2.45	2.30**
RBSE does not Granger Cause ΔLPCRUDE	0.321	0.241	0.158	0.576	0.388	0.33	0.13	0.13	0.44	1.01
ΔLPGOLD does not Granger Cause RBSE	1.212	0.674	0.642	4.89***	5.72***	0.09	1.05	0.62	0.44	0.36
RBSE does not Granger Cause ΔLPGOLD	3.259	1.736	1.269	2.202	1.613	2.02	1.91	1.86	1.54	1.63
VOLCRUDE does not Granger Cause RBSE	2.568	1.380	1.028	2.058	3.41***	0.00	0.90	0.59	0.48	0.52
RBSE does not Granger Cause VOLCRUDE	11.82***	5.62***	4.18***	3.43***	3.51***	1.37	0.73	0.92	0.67	0.89
VOLGOLD does not Granger Cause RBSE	0.156	0.127	1.268	1.061	1.899	12.96***	7.09***	4.51***	3.44**	4.48***
RBSE does not Granger Cause VOLGOLD	3.619	2.037	1.412	1.023	0.795	0.06	1.20	0.91	0.75	1.75

Source: Author's computation.

Note: ***,** indicate $p<0.01$, $p<0.05$ respectively.

6. Conclusions

The paper focuses on finding out whether during the COVID-19 pandemic, the linkage between the stock market and the commodity derivatives market (gold and crude oil, in particular) has changed compared to the previous era in the Indian context. The paper is based on daily data on the prices of stocks and prices as well as volatilities of spot prices of gold and crude oil for the last 3 years in the Indian stock markets and the commodity derivatives market. Estimating the long run relationship among these variables by ARDL model and pairwise Granger causality tests, the paper provides a number of useful insights to the investors and policymakers alike.

First, it was observed that the relationship has changed during COVID-19 pandemic. For example, during the pre-pandemic period, stock prices are only positively influenced by contemporary gold prices and the long term trends of these variables are not related. However, during the pandemic, the relationship has changed and evidently, the stock price and prices as well as volatilities of prices of gold and crude oil exhibit a long term relationship. The long term relationship shows that the contemporary crude oil price and volatilities of both crude oil and gold are the drivers of stock prices during the COVID period. *Second*, given a shock in the long term relationship during the COVID period, short term adjustment takes place through the adjustments of the three variables, viz. crude oil price, volatility of crude oil price and that of gold price. *Third*, given a shock, BSE and NSE converge to their respective long-run level by a speed of daily adjustment of 16% and 15%, respectively. *Fourth*, the change in relationship is also evident from the change in causality among the variables. While the causality from oil price to stock returns remains the same during both the periods, BSE and NSE returns, in the pre-COVID period were caused by past values of gold price. But in the COVID period, there is strong evidence that the causality runs from the gold price volatility of past five to ten days to the stock returns. *Fifth*, the negative influence of gold price volatility on stock returns indicates the safe haven status of gold during the crisis. *Sixth*, the results clearly indicate that in the Indian financial market the stock returns and the commodity prices were closely linked with each other and there are evidence that point to a mutual impact on the two markets in the pre-COVID period, e.g. past values of oil price and gold price influence the stock returns, while returns on the stock market influences oil price volatility. But during the COVID period, through the influence of crude oil price and volatility of gold price on stock returns, the spillover effect seems to be running from commodity prices to the stock market and not the other way round.

The change in the relationship during COVID throws light on the behavior of the investors as a whole. However, the study may further be extended by incorporating some more commodities which are traded heavily, e.g. silver. The paper suffers from lack of data during the COVID period and a longer time after COVID may provide some more insights in future.

Appendix

Appendix Table 1: Descriptive Statistics

	LBSE	LNSE	LPCRUDE	LPGOLD	VOLCRUDE	VOLGOLD
Mean	10.5	9.3	8.2	10.4	68.6	10.8
Median	10.5	9.3	8.3	10.4	26.3	9.4
Maximum	10.6	9.4	8.6	10.9	5176.2	43.1
Minimum	10.2	8.9	6.4	10.2	3.5	2.0
Std. Dev.	0.1	0.1	0.3	0.2	411.1	5.9
Skewness	-0.2	-0.6	-2.2	1.1	12.2	1.9
Kurtosis	2.5	3.8	10.8	3.3	151.9	8.2
Jarque-Bera	13.0	77.2	2613.0	156.5	742542.6	1378.3
Probability	0.0	0.0	0.0	0.0	0.0	0.0
Observations	783	783	783	783	783	783

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