Financial Contagion Between Crude Oil, Gold, and Equity Sectors in India During COVID

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Abstract

Purpose : This study examined the financial contagion between crude oil and gold prices with the equity prices of different sectors in the Indian equity market during the recent COVID crisis.

Design/Methodology/Approach : Dynamic conditional correlation (DCC) GARCH model was employed to analyze the behavior of time-varying conditional correlation during the time of COVID-19. For examining the financial contagion, regression analysis was performed on the dynamic conditional correlation and the conditional volatilities of the different markets.

Findings : The DCC model showed a sharp increase in correlations between markets during the COVID-19 wave. It also suggested the presence of financial contagion between the crude oil and gold markets and the different equity sectors. It also indicated that the COVID-19 effect on the conditional correlation between gold and equity sectors was temporary. In contrast, it increased the correlation between crude oil and the equity sectors.

Practical Implications : The findings of this study have implications for portfolio diversification methods because higher correlations lower the benefits of diversification.

Originality : This study examined the financial contagion during COVID-19 from crude oil and gold to equity sectors. Not all sectors react in the same way to changes in the prices of these commodities, and some may witness less impact compared to others during the crisis period, which makes it interesting for the study.

Keywords : COVID-19, DCC GARCH, financial contagion, Indian equity markets, crude oil, gold

JEL Classification Codes : C32, G11,G14

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During the latter part of 2019, a contagious disease was identified in China, termed Coronavirus infectious disease 2019 (COVID-19). It spread quickly to the entire world, and as of April 2022, it had already infected close to 500 million people across the globe[1]. The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020. COVID-19 hugely impacted the world economy. Many countries imposed restrictions on public movement, including air travel, and placed localized lockdowns. Some countries, including India, chose to go for a total lockdown. On March 24, 2020, the Government of India ordered a 21-day nationwide lockdown. The Nifty 50, the leading benchmark of India's National Stock Exchange (NSE), lost close

[1] Worldometer Coronavirus statistics.

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to 40% of its value from the peak of January 2020 to March 2020 (Varma et al., 2021). The demand for energy-related products was at an all-time low due to the closure of business and industrial activities. Crude oil prices fell to their historical prices during the peak COVID period and turned negative for the first time in history (Gharib, Mefteh-Wali, Serret, & Ben Jabeur, 2021). The world economy is still reeling under the pressure of the Coronavirus pandemic. In its economic outlook update for January 2022, the IMF reported that global growth is expected to be 4.4%, down from 5.9% in 2021. This uncertainty in the financial markets leads investors toward assets considered a safe haven during a crisis, such as gold (Baur & McDermott, 2010). Gold prices were on an upward trend due to this increase in investors' interest during the early stage of COVID-19. Therefore, it is worthwhile to examine the impact of gold and crude oil prices on the stock market during periods of uncertainties such as COVID-19. Many researchers have analyzed the effects of COVID-19 on the financial sectors. Their research shows that the financial markets reacted sharply to the COVID-19 pandemic; there was an increase in volatility which resulted in the erosion of investors' wealth (Ali et al., 2020; Albulescu, 2021; Zhang et al., 2020).

This study contributes to the existing literature by examining the impact of crude oil and gold prices on the Indian stock sectors, especially during COVID-19. The analysis is more critical for a country like India because both commodities play an essential role in the growth of the Indian economy. India meets most of its crude oil demand through imports. It is the third-largest importer of crude oil. An increase or decrease in crude oil prices indirectly affects the input cost of production. On the other hand, India is the fifth largest importer of gold. Moreover, not all sectors react the same way to changes in the prices of these commodities. Sectors such as technology and clean energy stocks may witness less impact than auto and manufacturing stocks. Thus, it is important to study how the volatilities from these commodities transmit to the different sectors of Indian equity markets. Following Ahmad et al. (2013), Chiang et al. (2007), and Min and Hwang (2012), we also examine the financial contagion between the markets.

Literature Review

The volatility spillover between the stock market, gold, and crude oil has been extensively examined in the research (Awartani et al., 2016; Bouri et al., 2017; Debasish, 2012; Joshi & Dutta, 2011; Kang et al., 2017; Kumar & Khanna, 2018; Kumar et al., 2022; Maghyereh et al., 2017; Mensi et al., 2013, 2017; Mishra, 2019; Pandey & Vipul, 2018; Perumandla & Kurisetti, 2018; Raza et al., 2016; Roy & Roy, 2017; Seth & Sidhu, 2021; Siddiqui & Roy, 2019; Singh & Kaur, 2015; Thuraisamy et al., 2013). Huang et al. (1996) investigated the relation between oil price returns and stock returns. The findings indicated that, except for oil company stocks, there was no correlation between oil price returns and stock price returns. Malik and Ewing (2009) examined the transmission between oil prices and US equity sector returns. The results supported the volatility transmission between the oil prices and the equity sector returns. Sadorsky (2012) used a multivariate GARCH model to investigate correlations between the prices of oil, clean energy companies, and technology companies. The results showed a stronger correlation between clean energy companies and technology prices than with oil companies.

After the onset of COVID-19, many researchers analyzed the impact of the pandemic on the financial markets (Albulescu, 2021; Anh & Gan, 2021; Au Yong & Laing, 2021; Gharib, Mefteh-Wali, & Jabeur, 2021; Heinlein et al., 2021; Liu et al., 2022; Mazur et al., 2021; Narayan et al., 2020; Rahman et al., 2021; Sakurai & Kurosaki, 2020; Salisu et al., 2021; Scherf et al., 2022; Uddin et al., 2021; Zaremba et al., 2021; Zhang et al., 2020). Ali et al. (2020) examined the effect of COVID-19 on the global stock markets. The results suggested that while the Chinese market stabilized, the global stock markets went into a downtrend during the spread of the coronavirus. Baek et al. (2020) studied the impact of the coronavirus on the US stock market at the industry level. The results showed that COVID-19 news significantly affected the stock market, and the negative information was more impactful. Also, total and idiosyncratic risks also rose across the industries during the period. Adekoya et al. (2021) analyzed the hedging efficiency of gold against the crude oil and stock markets. The results supported the hedging efficiency of gold during the COVID-19 period. Akhtaruzzaman et al. (2021) re-examined gold's hedging and safe haven properties during COVID. The data were analyzed during different phases of the coronavirus pandemic. The results suggested that gold lost its role as a safe haven during the second phase, and the hedging cost increased in the second phase.

Dutta et al. (2021) examined the dynamic relationship between climate bonds and other asset classes during stress. The correlation between climate bonds and the other markets is time-varying, increasing significantly during COVID-19. It was negatively correlated with the stock market; whereas, it was positively related with gold. Also, the hedging efficiency of climate bonds reduced significantly during COVID-19. Mensi et al. (2021) examined the spillover between the stock markets, crude oil, and gold futures using Markov switching vector autoregressive model. The study suggested that the spillover increased from commodity to stock markets during COVID-19. Zeinedini et al. (2022) studied the impact of gold and crude oil prices on the Iranian stock market during COVID-19. The study found no significant relationship between gold price movements and the Iranian stock market movements. However, crude oil prices and the Iranian stock exchange had a significant inverse relationship.

Data

Daily data have been employed for this study from April 1, 2014 – December 31, 2021. The Indian companies follow a financial year that starts on April 1 and ends on March 31. Also, December 31, 2021, was taken as the end date because COVID-19 was declining in India at the time of writing this article. The data from the National Stock Exchange (NSE) is employed for the study. The study has taken NSE 500 index as a representative of the Indian stock market. It represents 500 companies listed on the NSE and roughly 96% of the overall market capitalization. Indices of main sectors such as banking, FMCG, auto, pharma, and infrastructure are used for the sector study. The spot prices of crude oil and gold are from India's Multi Commodity Exchange (MCX). All the data were sourced from the Datastream database. The date for which the price of any time series was missing is removed from the data.

Methodology

The volatility in financial markets is often found to be clustered and auto-correlated. The generalized autoregressive conditional heteroscedasticity (GARCH) models introduced by Bollerslev (1986) are extensively used in the literature to model the volatility of a single asset. And to model the joint behavior, the multivariate GARCH model is used. This study also uses the dynamic conditional correlation (DCC) GARCH model to examine the joint behavior of crude oil and gold returns with the stock market return.

DCC - GARCH Model

Engle (2002) proposed the DCC-GARCH model. The main idea behind the DCC - GARCH model is to estimate the conditional variances and correlation, and then, using these two, the conditional covariance is estimated. It involves two steps. The first step estimates the conditional variance using a univariate GARCH model. The residuals from the univariate GARCH model estimate the conditional correlation between the time series.

The return series follows the form of :

$$r_t = \mu_{it} + \beta_1 r_{t-1} + \beta_2 r^j_{t-1} + \varepsilon_t \qquad (1)$$

where, r_t are the NSE 500/sector indices and $\varepsilon_t | \xi_{t-1} \sim N(0, H_t)$, where ξ_{t-1} is the information set at time t–1. r_{t-1} is the lagged return of the NSE 500/sector indices to account for the autocorrelation present in the financial time series. r^j_{t-1} is the lagged return from crude oil/gold to account for the impact of these commodities on the stock market.

The conditional variance matrix can be written in terms of the conditional variances and the conditional correlation between the series. We can write the conditional variance as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{2}$$

where, D_t is the diagonal matrix of the conditional variances and R_t is the time-varying conditional correlation matrix.

$$D_t = diag(h_t) = \begin{pmatrix} h_{11t} 0 \\ 0 h_{22t} \end{pmatrix} \text{ and} \tag{3}$$

$$h_{it} = \omega_{i0} + \omega_{i1} \epsilon^2_{it-1} + \omega_{i2} h_{it-1} \tag{4}$$

From equation (4), the standardized residuals are obtained. These standardized residuals are then used to estimate the time-varying conditional correlation matrix R_t using DCC (1, 1). The dynamic conditional matrix is given by:

$$R_t = diag(Q_t)^{-1/2} Q_t \, diag(Q_t)^{-1/2} \tag{5}$$

where, Q_t is specified by the DCC (1, 1) model in matrix form as:

$$Q_t = (1 - a - b)\overline{Q} + a\mu_{t-1} \mu^T_{t-1} + bQ_{t-1} \tag{6}$$

Here, μ_{t-1} are the standardized residuals obtained from the univariate GARCH model, and $\overline{Q}$ is the unconditional variance-covariance matrix of the standardized residuals. *'a'* and *'b'* are the non-negative estimated parameters satisfying the condition of $a + b < 1$.

Conditional Correlation and Financial Contagion

After estimating the pair-wise time-varying conditional correlation, we examine the financial contagion effect of crude oil and gold on the Indian stock markets. Following Chong et al. (2009), Ahmad et al. (2013), Ahmad et al. (2014), and Roy and Roy (2017), the conditional correlation is regressed on the conditional volatilities using the following equation:

$$\rho_{ijt} = \alpha + \theta_1 h_{it} + \theta_2 h_{jt} + \eta_t \tag{7}$$

where, ρ_{ijt} is the time-varying conditional correlation between the crude oil/gold returns and NSE 500 index/sector index returns. h_{it} is the NSE 500 index/sector index returns volatility, and h_{jt} is the crude oil/gold return volatility. A significant and positive θ_i obtained from the regression model would suggest that the conditional correlation rises with the rise in volatility and supports the financial contagion. However, a negative θ_i would indicate that the conditional correlation falls when the volatility increases in equity markets, which helps investors in diversification strategies.

To examine the effect of COVID-19 on the conditional correlations, we follow Chiang et al. (2007), Min and Hwang (2012), and Ahmad et al. (2013). A COVID-19 dummy variable is used to examine the time series behavior of conditional correlations. The model is given as follows:

$$\rho_{ijt} = \alpha_1 + \sum_{k=1}^{p} \Phi_k \rho_{ijt-k} + \psi Dummy_{Covid} + \epsilon_{ijt} \tag{8}$$

where, ρ_{ijt} is the conditional correlation between the crude oil/gold returns and the stock market returns. $Dummy_{Covid}$ is a dummy variable that takes the value of 1 during COVID-19 and zeroes otherwise. Since the conditional correlations exhibit heteroscedastic behavior, the conditional variance of the equation (8) is assumed to follow a GARCH (1, 1) specification, and it is given as:

$$h_{ijt} = \omega_0 + \omega_1 \epsilon^2_{ijt-1} + \omega_2 h_{ijt-1} + \psi_1 Dummy_{Covid} \quad (9)$$

The significance of the dummy variable exhibits structural changes in the mean and/or variance shift of the correlation due to the external shocks during COVID-19. If the coefficient of the dummy variable is significant, it implies structural changes in the correlation's mean and/or variance due to external shocks during the crisis period.

Analysis and Results

Table 1 presents the descriptive statistics of the sample. To analyze the impact of COVID-19 on the return of assets, the sample is divided into two sub-samples: pre-COVID and COVID periods. The period before January 31, 2020, is considered the pre-COVID period, while the period after January 31, 2020, is taken as the COVID period because the first case of COVID-19 was identified in India on January 31, 2020. Panel A is for the entire sample; whereas, Panels B and C are pre-COVID and COVID periods, respectively. The entire sample statistics

Table 1. *Descriptive Statistics*

Panel A: Full Sample							
	Gold	**Crude Oil**	**Nifty 500**	**Bank Nifty**	**Infra**	**Auto**	**FMCG**
Mean	0.03	(0.00)	0.06	0.05	0.03	0.03	0.04
Min	(4.88)	(56.84)	(13.71)	(18.31)	(12.84)	(14.91)	(11.20)
Max	4.40	34.70	7.41	10.00	7.24	9.90	7.99
Std. Dev	0.74	3.27	1.08	1.52	1.28	1.44	1.11
Skewness	0.12	(2.17)	(1.72)	(1.02)	(0.71)	(0.55)	(0.57)
Kurtosis	4.06	66.27	21.05	16.49	9.56	11.12	12.15
Jarque–Bera (JB)	1,309.38	349,545.39	36,041.83	21,889.09	7,398.04	9,893.31	11,810.00
Ljung–Box(LB)	13.53	88.09	71.99	38.69	42.71	18.29	34.90
Observations	1,902	1,902	1,902	1,902	1,902	1,902	1,902
Panel B: Pre-COVID Period							
	Gold	**Crude Oil**	**Nifty 500**	**Bank Nifty**	**Infra**	**Auto**	**FMCG**
Mean	0.03	(0.03)	0.04	0.06	0.01	0.02	0.04
Min	(2.93)	(10.61)	(6.95)	(7.15)	(7.34)	(7.53)	(6.97)
Max	4.40	14.54	5.16	7.98	7.24	9.44	5.24
Std. Dev	0.68	2.40	0.88	1.18	1.16	1.23	1.01
Skewness	0.32	0.28	(0.45)	0.25	(0.04)	0.08	(0.40)
Kurtosis	2.81	3.53	4.22	3.51	3.23	4.37	4.51
Jarque–Bera (JB)	492.88	760.73	1,108.76	745.72	619.39	1,134.71	1,246.65
Ljung–Box(LB)	13.53	88.09	71.99	38.69	42.71	18.29	34.90
Observations	1427	1427	1427	1427	1427	1427	1427

Panel C: During COVID Period

	Gold	Crude Oil	Nifty 500	Bank Nifty	Infra	Auto	FMCG
Mean	0.03	0.09	0.09	0.03	0.09	0.06	0.04
Min	(4.88)	(56.84)	(13.71)	(18.31)	(12.84)	(14.91)	(11.20)
Max	4.24	34.70	7.41	10.00	6.93	9.90	7.99
Std. Dev	0.90	5.04	1.53	2.25	1.59	1.95	1.34
Skewness	(0.16)	(2.50)	(2.20)	(1.35)	(1.48)	(0.98)	(0.76)
Kurtosis	4.45	45.53	18.71	11.81	13.11	10.76	17.78
Jarque–Bera (JB)	393.58	41,521.16	7,316.32	2,904.05	3,576.72	2,368.98	6,302.03
Ljung–Box(LB)	13.53	88.09	71.99	38.69	42.71	18.29	34.90
Observations	475	475	475	475	475	475	475

show that the highest average return is for the Nifty 500 index, and the lowest is for crude oil. Crude oil is also the most volatile asset; whereas, gold is the least volatile. The rest of the securities are negatively skewed except for gold, suggesting a higher downside risk. Also, the excess kurtosis indicates that the returns series are not normal, which can be confirmed by the significant Jarque - Bera (JB) statistics. The Ljung-Box Q statistic test suggests the presence of autocorrelation in the return series. Comparing the descriptive statistics between the COVID and non-COVID periods indicates that the COVID period is highly volatile. For example, the kurtosis for all the securities is very high during COVID. Also, the minimum and maximum values for all the statistics are during the COVID period for all the securities.

It can also be inferred that the stock and the commodity markets have recovered as the average returns from all the securities are higher than their average return before the COVID period. The commodities, banking, and auto sectors show positive skewness before the COVID period, but during COVID, only gold returns retain this property.

DCC - GARCH Analysis

Table 2 presents the results of the DCC - GARCH model for gold returns, while Table 3 presents the results of

Table 2. ***DCC - GARCH Gold with Equity Sector Returns***

	Return Equations			Variance Equation		
	μ	**β1**	**β2**	**ω0**	**ω1**	**ω2**
Gold	0.020	.060***		.035***	.089***	.851***
	1.518	**2.625**		**3.341**	**4.961**	**26.276**
Nifty 500	.081***	.059***	(0.022)	.031***	.044***	.928***
	4.871	**7.879**	**(0.828)**	**8.184**	**12.602**	**155.873**
Bank Nifty	.103***	.028**	(0.058)	.039***	.053***	.931***
	4.400	**2.268**	**(1.559)**	**5.505**	**11.082**	**140.071**
Pharma	0.041	.050***	0.069	.082***	.042***	.912***
	1.542	**2.723**	**1.781**	**3.126**	**4.784**	**42.432**
Infra	.058***	.042***	(0.064)	.047***	.041***	.929***
	2.692	**3.435**	**(1.951)**	**5.079**	**8.858**	**102.475**

Auto	.066***	.048***	(0.049)	.046***	.054***	.925***
	2.731	**3.422**	**(1.353)**	**4.845**	**9.350**	**107.481**
FMCG	.048**	0.025	0.002	.040***	.052***	.918***
	2.326	**1.437**	**0.065**	**4.649**	**8.216**	**83.874**
		Multivariate DCC Equation				
		Coefficient	***t*-value**			
		a .013***	**7.833**			
		b .960***	**156.284**			

Notes. μ is the intercept, β1 is the first-order auto-regressive term of the mean equation, β2 is the lagged-return from gold. The numbers in bold represent the *t*-value. *** implies significance at 1% level, ** implies significance at 5%.

Table 3. ***DCC - GARCH Crude Oil Returns with Equity Sectors Returns***

		Return Equations		Variance Equation		
	μ	**β1**	**β2**	**ω0**	**ω1**	**ω2**
Gold	0.0658	–.059**		.124***	.122***	.874***
	1.2350	**(2.4086)**		**4.166**	**10.003**	**81.683**
Nifty 500	.083***	.056***	(0.0015)	.032***	.044***	.927***
	8.0215	**16.8673**	**(0.2005)**	**7.191**	**11.149**	**132.206**
Bank Nifty	.099***	.032***	0.0063	.039***	.052***	.931***
	5.7735	**3.5555**	**0.5982**	**5.116**	**9.836**	**124.415**
Pharma	0.0471	.044**	0.0132	.079***	.043***	.913***
	1.9160	**2.3378**	**1.3520**	**3.119**	**4.621**	**42.555**
Infra	.060***	.039***	0.0018	.048***	.043***	.927***
	3.6990	**3.6798**	**0.2050**	**4.605**	**8.119**	**90.298**
Auto	.067***	.043***	(0.0027)	.047***	.055***	.923***
	3.6321	**3.4042**	**(0.2567)**	**5.331**	**9.061**	**108.811**
FMCG	.050***	0.0238	(0.0116)	.042***	.053***	.915***
	2.8013	**1.3432**	**(1.3879)**	**3.967**	**7.143**	**68.715**
		Multivariate DCC Equation				
		Coefficient	***t*-value**			
		a .015***	**7.0349**			
		b .956***	**121.0525**			

Notes. μ is the intercept, β1 is the first-order auto-regressive term of the mean equation, β2 is the lagged –return from gold. The numbers in bold represent the *t*-value. *** implies significance at 1% level, ** implies significance at 5%.

crude oil returns with the stock and sector indices returns. The return equation consists of a constant term and a lagged one-day return. The AR(1) term in the return equation (1) is positive and significant for all the stock markets, suggesting that the past returns of the equity market significantly affect their present returns. The lagged returns of gold/crude oil are also included in the return equation to check if the past returns of gold/crude oil impact the equity returns. The results indicate that crude oil and gold returns do not affect equity returns.

For the variance equation, all the parameters are positive and significant for the overall equity market and sectors. The sum of the parameters ω_0 and ω_1 is less than one, which satisfies the stability condition of the univariate GARCH model. For all the equity sectors and the overall market, $\omega_0 + \omega_1$ is close to one, suggesting the persistence of volatility, that is, the shocks in the markets take longer to die down. Also, both the DCC parameters are positive and significant, and their sum is less than one, which satisfies the stability condition of the model. The significance of the DCC parameters suggests that the correlation is time-varying.

Financial Contagion

Correlation plays an essential role in examining the financial contagion and interdependence between the

Table 4. ***Linear Regression on Conditional Correlation***

	β_1	β_2	Adj. R^2
Gold			
Nifty 500	–.052***	.013***	0.0160
	(3.6578)	**2.7915**	
Bank Nifty	–.080***	.008***	0.0516
	(6.1005)	**3.2020**	
Pharma	–.030***	.046***	0.0297
	(3.0757)	**7.0162**	
Infra	–.038***	(0.0105)	0.0295
	(2.7814)	**(1.9464)**	
Auto	–.059***	.015***	0.0287
	(4.5162)	**4.9127**	
FMCG	–.004***	0.0047	0.0008
	(0.3541)	**1.0262**	
Crude Oil			
Nifty 500	–.008***	.093***	0.1788
	(4.7429)	**9.7745**	
Bank Nifty	–.005***	.032***	0.0594
	(3.0810)	**5.0351**	
Pharma	.008***	.048***	0.2896
	8.6037	**6.3420**	
Infra	–.001***	.080***	0.2235
	(0.4213)	**7.7979**	
Auto	0.0005	.038***	0.1100
	0.2525	**3.9325**	
FMCG	–.007***	.115***	0.2879
	(6.2966)	**13.0152**	

Notes. β1 is the gold/crude oil return volatility, β2 is the equity return volatility of different sectors. The numbers in bold represent the *t*-value. *** implies significance at 1% level, ** implies significance at 5%.

markets. In literature, a significant increase in the correlation between the markets during the crisis is called financial contagion. On the other hand, a continuous high correlation is defined as interdependence. The presence of financial contagion can be conferred by estimating equation (7). A significant and positive θ_i would suggest that the conditional correlation between the crude oil/gold and the equity markets rise with the increase in volatility.

The results are presented in Table 4. The upper table shows the regression of the correlation between the gold and equity market returns and their respective volatilities. The coefficients of the gold volatility are negative for all the equity sectors and the overall market. It suggests that the conditional correlation between these markets and the gold market decreases with increased gold volatility. However, the coefficient of the equity sector returns and the overall market returns are positive and significant. The coefficient is not significant only for the FMCG sector. It indicates that whenever there is an increase in the volatility in equity returns, the correlation between these markets and gold increases, supporting financial contagion. One of the reasons for the increase in the conditional correlation is that the investors, during the crisis when the volatilities are high, may move to gold which is regarded as a safe haven. The lower table represents the regression of the correlation between crude oil returns and equity market returns with their respective volatilities. The coefficients for crude oil volatility are negative for all the equity sectors and the overall market except for pharma and auto. On the other hand, the coefficient for the volatility of the equity sector returns and the overall market returns are positive and significant, implying the presence of financial contagion.

Conditional Correlation During the Time of Crisis

Figure 1 shows the conditional correlation between the equity sector returns and gold returns, and Figure 2 shows its conditional correlation with crude oil returns. The correlation of equity returns with gold returns is negative for all the sectors. In contrast, it is close to zero for crude oil, which suggests that these commodities can help in portfolio diversification. During the first COVID wave, there was a sudden increase in the conditional correlation, and for both commodities, it became positive. It reverts to its pre-COVID level after the first COVID wave. It is, therefore, essential to check for any structural change in the conditional correlation due to COVID.

Equations (8) and (9) are estimated to analyze the impact of COVID-19 on conditional correlations. The results of the estimation are presented in Table 5. A significant estimate of the parameter would indicate that the external

Figure 1. ***DCC Between Gold Returns and Equity Sector Returns***

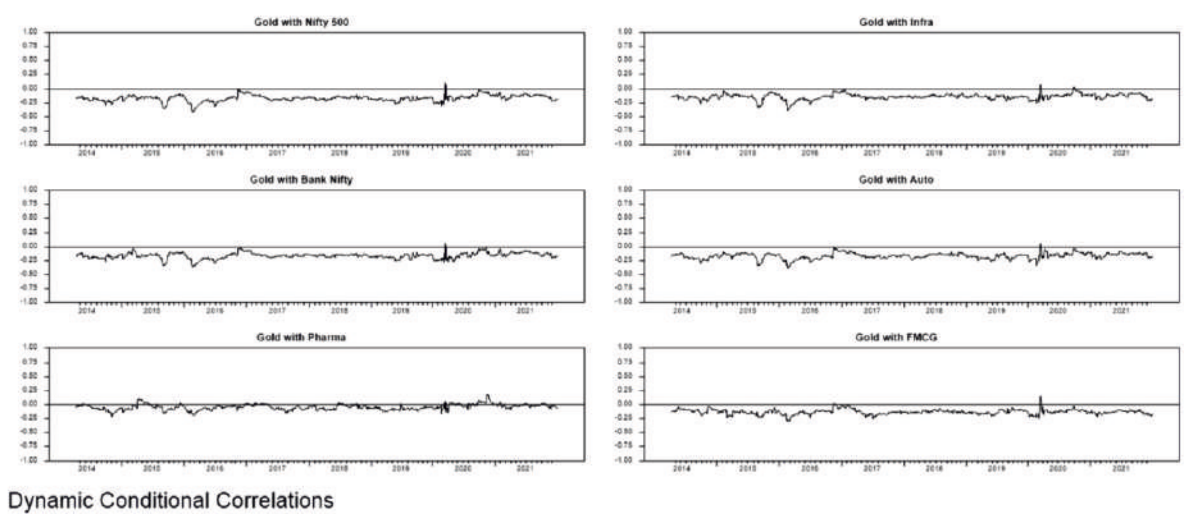

Figure 2. ***DCC Between Crude Oil Returns and Equity Sector Returns***

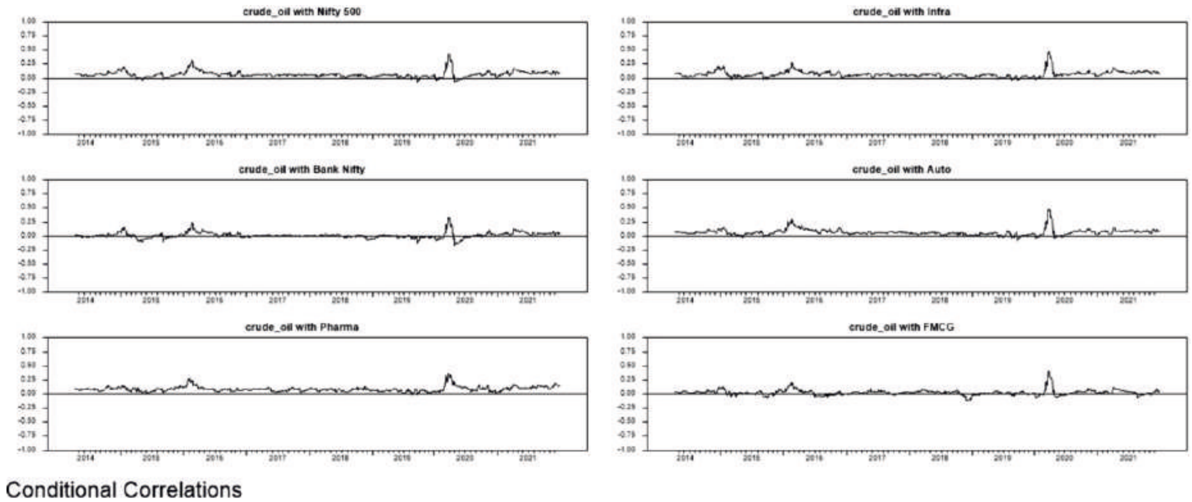

Table 5. ***Change in DCC During the COVID Period***

	Mean Equation			Variance Equation			
	α1	ρ*t*–1	Covid Dummy	ω	ω	ω	Covid Dummy
Gold							
Nifty 500	–.005***	.972***	.001**	.000***	.194***	.677***	.000**
	(5.19300)	**183.79610**	**2.14690**	**6.52420**	**7.07710**	**17.75370**	**(1.82230)**
Bank Nifty	–.007***	.959***	0.00080	.000***	.134***	.816***	.000**
	(6.23920)	**152.47500**	**1.23400**	**5.98950**	**7.44660**	**42.17900**	**2.39710**
Pharma	–.002***	.965***	0.00122	.000***	.225***	.679***	.000***
	(3.63628)	**154.79900**	**1.71792**	**8.12129**	**5.32776**	**22.87235**	**2.76165**
Infra	–.005***	.967***	0.00077	.000***	.134***	.706***	(0.00000)
	(4.85623)	**142.98465**	**1.25894**	**4.53946**	**5.66091**	**13.88871**	**(1.05484)**
Auto	–.005***	.969***	0.00094	.000***	.162***	.687***	.000***
	(5.35644)	**172.38796**	**1.28236**	**6.26215**	**5.99849**	**16.73172**	**3.94450**
FMCG	–.006***	.956***	0.00007	.000***	.120***	.773***	.000***
	(5.83558)	**129.30404**	**0.12681**	**4.17175**	**5.64170**	**17.56094**	**(3.68086)**
Crude Oil							
Nifty 500	.002***	.965***	.001***	.000***	.123***	.876***	0.000000
	4.178320	**143.036070**	**2.705530**	**7.005500**	**9.505550**	**98.777700**	**0.707220**
Bank Nifty	0.000094	.965***	.001***	.000***	.113***	.881***	.000***
	0.470420	**134.530700**	**2.706310**	**5.418700**	**9.320550**	**86.929240**	**3.062930**
Pharma	.003***	.954***	.001**	.000***	.109***	.808***	0.000003
	5.296910	**128.989240**	**2.347540**	**6.150250**	**6.296640**	**33.850300**	**1.569920**
Infra	.006***	.894***	0.002008	.000***	.824***	.317***	0.000004

	15.789720	**196.224230**	**3.517060**	**9.618910**	**6.690060**	**5.809720**	**0.895540**
Auto	.002***	.964***	.001***	.000***	.151***	.863***	0.000001
	3.806550	**133.238830**	**2.698870**	**5.911200**	**8.936840**	**75.110020**	**1.502120**
FMCG	.001***	.944***	0.000563	.000***	.108***	.884***	0.000001
	4.335620	**118.863390**	**1.220680**	**6.078860**	**8.963560**	**99.763450**	**1.046140**

Notes. Numbers in bold represent the *t*-value. *** implies significance at 1% level, ** implies significance at 5%.

shock caused structural changes in the mean/variance of the correlation coefficients in the COVID-19 period. The regression equation is estimated using a GARCH (1, 1) model. The COVID-19 dummy variable for the gold correlation is positive for all the sectors but only significant for the Nifty 500, indicating no difference between the conditional correlation before and after the COVID-19 crisis. It also suggests that the COVID-19 effect on the conditional correlation between gold and the different sectors is temporary. The estimates of the dummy variable in the variance equation are significant for Bank Nifty, Pharma, Auto, and FMCG sectors. It suggests that during the crisis period, the changes in the conditional correlation may take some time to diminish.

The coefficients from the regression of the correlation coefficient between crude oil and the equity market are all positive and significant except for the FMCG sectors. This result contrasts with the result obtained from the gold and equity correlation. One reason that may be attributed to this is that during COVID-19, the Indian government announced a nationwide lockdown, drastically reducing crude oil demand. It also suggests that the crude oil and equity market investors shared the same set of behaviors that resulted in a higher correlation. This also supports the herding behavior hypothesis discussed by Chiang et al. (2007). The estimates of the dummy variable in the variance equation are positive but insignificant for all the markets except the Bank Nifty.

Conclusion and Implications

This paper investigates the financial contagion effect of crude oil and gold on the Indian stock market and its different sectors. To examine the financial contagion, dynamical conditional correlations are estimated between the overall equity market/ equity sector returns and crude oil/gold returns. The estimated correlation suggests a sudden increase in the correlation during COVID, which returned to its average level over the period. Linear regression is estimated between the conditional correlations, equity volatilities, and crude oil/gold returns to check the presence of financial contagion. The results suggest the presence of financial contagion between the crude oil/gold market and the stock markets, meaning high volatility in the equity market increases the correlation between these commodities and the equity market. The high correlation between the equity markets and gold can be attributed to the fact that investors regard gold as a safe haven. So, during market turmoil, investors move their investments toward safe investments such as gold.

On the other hand, the demand for crude oil during COVID-19 reached the lowest level. As a result, it also showed a high correlation during the increased volatility in equity markets. To examine the impact of COVID-19 on the conditional correlation, a regression equation is estimated between the correlation and its lagged value and the COVID-19 dummy. The results suggest that the COVID-19 effect on the conditional correlation between gold and the different sectors is temporary. On the other hand, it impacts the conditional correlation between crude oil and stock market returns, which supports the hypothesis of the herding behavior of investors in these markets. It also suggests that the crude oil and equity market investors share the same set of behaviors that result in a higher correlation during COVID-19.

This study's results impact portfolio diversification strategies as an increase in correlation reduces the diversification benefit. Financial contagion highlights the importance of effective risk management, diversification, and liquidity management in the financial industry. Managers should proactively identify and manage the risks associated with contagion to minimize its impact on their firms and the wider financial system.

Limitations of the Study and Scope for Future Research

Some possible limitations of this study could be improved in future research. Firstly, the research focuses only on the COVID-19 event in the Indian market for analysis. The time period and the specific events chosen for analysis can also impact the results. Secondly, the research only identifies the existence of contagion but does not further establish the causes of such contagion. In future research, a multi-country analysis can be done for different time periods and events to assess the impact of financial contagion on the financial markets.

Author's Contribution

Dr. Vikas Pandey is the sole author of this paper. He conceived the idea and developed qualitative and quantitative designs to undertake the empirical study. Dr. Vikas Pandey extracted research papers with high repute, filtered these based on keywords, and generated concepts and codes relevant to the study design. The numerical computations were done by Dr. Vikas Pandey using RATS software. Dr. Vikas Pandey wrote the final manuscript.

Conflict of Interest

The author certifies that he has no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

Adekoya, O. B., Oliyide, J. A., & Oduyemi, G. O. (2021). How COVID-19 upturns the hedging potentials of gold against oil and stock markets risks: Nonlinear evidences through threshold regression and markov-regime switching models. *Resources Policy, 70*, 101926. https://doi.org/10.1016/j.resourpol.2020.101926

Ahmad, W., Bhanumurthy, N. R., & Sehgal, S. (2014). The Eurozone crisis and its contagion effects on the European stock markets. *Studies in Economics and Finance, 31*(3), 325–352. https://doi.org/10.1108/SEF-01-2014-0001

Ahmad, W., Sehgal, S., & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling, 33*, 209–225. https://doi.org/10.1016/j.econmod.2013.04.009

Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., & Sensoy, A. (2021). Is gold a hedge or a safe-haven asset in the COVID–19 crisis? *Economic Modelling, 102*, 105588. https://doi.org/10.1016/j.econmod.2021.105588

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters, 38*, 101699. https://doi.org/10.1016/j.frl.2020.101699

Ali, M., Alam, N., & Rizvi, S. A. (2020). Coronavirus (COVID-19) — An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance, 27*, 100341. https://doi.org/10.1016/j.jbef.2020.100341

Anh, D. L., & Gan, C. (2021). The impact of the COVID-19 lockdown on stock market performance: Evidence from Vietnam. *Journal of Economic Studies, 48*(4), 836–851. https://doi.org/10.1108/JES-06-2020-0312

Au Yong, H. H., & Laing, E. (2021). Stock market reaction to COVID-19: Evidence from U.S. firms' international exposure. *International Review of Financial Analysis, 76*, 101656. https://doi.org/10.1016/j.irfa.2020.101656

Awartani, B., Aktham, M., & Cherif, G. (2016). The connectedness between crude oil and financial markets: Evidence from implied volatility indices. *Journal of Commodity Markets, 4*(1), 56–69. https://doi.org/10.1016/j.jcomm.2016.11.002

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters, 37*, 101748. https://doi.org/10.1016/j.frl.2020.101748

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance, 34*(8), 1886–1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bouri, E., Jain, A., Biswal, P. C., & Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy, 52*, 201–206. https://doi.org/10.1016/j.resourpol.2017.03.003

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance, 26*(7), 1206–1228. https://doi.org/10.1016/j.jimonfin.2007.06.005

Chong, J., Miffre, J., & Stevenson, S. (2009). Conditional correlations and real estate investment trusts. *Journal of Real Estate Portfolio Management, 15*(2), 173–184. https://doi.org/10.1080/10835547.2009.12089840

Debasish, S. S. (2012). Analysis of lead-lag estimates between spot and futures market for selected companies in Indian scenario. *Abhigyan, 30*(1), 10–22.

Dutta, A., Bouri, E., & Noor, M. H. (2021). Climate bond, stock, gold, and oil markets: Dynamic correlations and hedging analyses during the COVID-19 outbreak. *Resources Policy, 74*, 102265. https://doi.org/10.1016/j.resourpol.2021.102265

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Gharib, C., Mefteh-Wali, S., & Jabeur, S. B. (2021). The bubble contagion effect of COVID-19 outbreak: Evidence from crude oil and gold markets. *Finance Research Letters, 38*, 101703. https://doi.org/10.1016/j.frl.2020.101703

Gharib, C., Mefteh-Wali, S., Serret, V., & Ben Jabeur, S. (2021). Impact of COVID-19 pandemic on crude oil prices: Evidence from Econophysics approach. *Resources Policy, 74*, 102392. https://doi.org/10.1016/j.resourpol.2021.102392

Heinlein, R., Legrenzi, G. D., & Mahadeo, S. M. (2021). Crude oil and stock markets in the COVID-19 crisis: Evidence from oil exporters and importers. *The Quarterly Review of Economics and Finance, 82*, 223–229. https://doi.org/10.1016/j.qref.2021.09.007

Huang, R. D., Masulis, R. W., & Stoll, H. R. (1996). Energy shocks and financial markets. *The Journal of Futures Markets, 16*(1), 1–27. https://doi.org/10.1002/(SICI)1096-9934(199602)16:1<1::AID-FUT1>3.0.CO;2-Q

Joshi, H., & Dutta, V. (2011). Does foreign market listing results into greater foreign institutional ownership and better market co-integration: Evidence from Indian companies listed on New York stock exchange. *Abhigyan, 29*(1), 1–9.

Kang, S. H., McIver, R., & Yoon, S.-M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics, 62*, 19–32. https://doi.org/10.1016/j.eneco.2016.12.011

Kumar, A., & Khanna, S. (2018). GARCH - BEKK approach to volatility behavior and spillover: Evidence from India, China, Hong Kong, and Japan. *Indian Journal of Finance, 12*(4), 7–19. https://doi.org/10.17010/ijf/2018/v12i4/122791

Kumar, A., Khanna, S., Dhingra, S., & Sinha, N. (2022). Financial contagion in European equity markets: Evidence from the US subprime and the Eurozone crises. *Indian Journal of Finance, 16*(8), 8–28. https://doi.org/10.17010/ijf/2022/v16i8/171372

Liu, Y., Wei, Y., Wang, Q., & Liu, Y. (2022). International stock market risk contagion during the COVID-19 pandemic. *Finance Research Letters, 45*, 102145. https://doi.org/10.1016/j.frl.2021.102145

Maghyereh, A. I., Awartani, B., & Tziogkidis, P. (2017). Volatility spillovers and cross-hedging between gold, oil and equities: Evidence from the gulf cooperation council countries. *Energy Economics, 68*, 440–453. https://doi.org/10.1016/j.eneco.2017.10.025

Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis, 18*(3), 95–100. https://doi.org/10.1016/j.irfa.2009.03.003

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters, 38*, 101690. https://doi.org/10.1016/j.frl.2020.101690

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling, 32*, 15–22. https://doi.org/10.1016/j.econmod.2013.01.023

Mensi, W., Hammoudeh, S., Al-Jarrah, I. M., Sensoy, A., & Kang, S. H. (2017). Dynamic risk spillovers between gold, oil prices and conventional, sustainability and Islamic equity aggregates and sectors with portfolio implications. *Energy Economics, 67*, 454–475. https://doi.org/10.1016/j.eneco.2017.08.031

Mensi, W., Reboredo, J. C., & Ugolini, A. (2021). Price-switching spillovers between gold, oil, and stock markets: Evidence from the USA and China during the COVID-19 pandemic. *Resources Policy, 73*, 102217. https://doi.org/10.1016/j.resourpol.2021.102217

Min, H.-G., & Hwang, Y.-S. (2012). Dynamic correlation analysis of US financial crisis and contagion: Evidence from four OECD countries. *Applied Financial Economics, 22*(24), 2063–2074. https://doi.org/10.1080/09603107.2012.698161

Mishra, A. (2019). Foreign exchange, gold, and real estate markets in India: An analysis of return volatility and transmission. *Indian Journal of Finance, 13*(7), 50–64. https://doi.org/10.17010/ijf/2019/v13i7/145535

Narayan, P. K., Devpura, N., & Wang, H. (2020). Japanese currency and stock market—What happened during the COVID-19 pandemic? *Economic Analysis and Policy, 68*, 191–198. https://doi.org/10.1016/j.eap.2020.09.014

Pandey, V., & Vipul, V. (2018). Volatility spillover from crude oil and gold to BRICS equity markets. *Journal of Economic Studies, 45*(2), 426–440. https://doi.org/10.1108/JES-01-2017-0025

Perumandla, S., & Kurisetti, P. (2018). Time-varying correlations, causality, and volatility linkages of Indian commodity and equity markets: Evidence from DCC - GARCH. *Indian Journal of Finance, 12*(9), 21–40. https://doi.org/10.17010/ijf/2018/v12i9/131558

Rahman, M. L., Amin, A., & Al Mamun, M. A. (2021). The COVID-19 outbreak and stock market reactions: Evidence from Australia. *Finance Research Letters, 38*, 101832. https://doi.org/10.1016/j.frl.2020.101832

Raza, N., Shahzad, S. J., Tiwari, A. K., & Shahbaz, M. (2016). Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. *Resources Policy, 49*, 290–301. https://doi.org/10.1016/j.resourpol.2016.06.011

Roy, R. P., & Roy, S. S. (2017). Financial contagion and volatility spillover: An exploration into Indian commodity derivative market. *Economic Modelling, 67*, 368–380. https://doi.org/10.1016/j.econmod.2017.02.019

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics, 34*(1), 248–255. https://doi.org/10.1016/j.eneco.2011.03.006

Sakurai, Y., & Kurosaki, T. (2020). How has the relationship between oil and the US stock market changed after the Covid-19 crisis? *Finance Research Letters, 37*, 101773. https://doi.org/10.1016/j.frl.2020.101773

Salisu, A. A., Vo, X. V., & Lawal, A. (2021). Hedging oil price risk with gold during COVID-19 pandemic. *Resources Policy, 70*, 101897. https://doi.org/10.1016/j.resourpol.2020.101897

Scherf, M., Matschke, X., & Rieger, M. O. (2022). Stock market reactions to COVID-19 lockdown: A global analysis. *Finance Research Letters, 45*, 102245. https://doi.org/10.1016/j.frl.2021.102245

Seth, N., & Sidhu, A. (2021). Price discovery and volatility spillover for Indian energy futures market in the pre- and post-crisis periods. *Indian Journal of Finance, 15*(8), 24–39. https://doi.org/10.17010/ijf/2021/v15i8/165816

Siddiqui, S., & Roy, P. (2019). Do Brent crude oil, Nifty 50 and USD/INR exchange rate walk together? An ARDL-bounds testing approach. *Abhigyan, 37*(3), 33–43.

Singh, A., & Kaur, P. (2015). Modelling dynamic volatility spillovers from the U.S. to the BRIC countries' stock markets during the subprime crisis. *Indian Journal of Finance, 9*(8),45–55. https://doi.org/10.17010/ijf/2015/v9i8/74562

Thuraisamy, K. S., Sharma, S. S., & Ali Ahmed, H. J. (2013). The relationship between Asian equity and commodity futures markets. *Journal of Asian Economics, 28*, 67–75. https://doi.org/10.1016/j.asieco.2013.04.003

Uddin, M., Chowdhury, A., Anderson, K., & Chaudhuri, K. (2021). The effect of COVID – 19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty? *Journal of Business Research, 128*, 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061

Varma, Y., Venkataramani, R., Kayal, P., & Maiti, M. (2021). Short-term impact of COVID-19 on Indian stock market. *Journal of Risk and Financial Management, 14*(11), 558. https://doi.org/10.3390/jrfm14110558

Zaremba, A., Aharon, D. Y., Demir, E., Kizys, R., & Zawadka, D. (2021). COVID-19, government policy responses, and stock market liquidity around the world: A note. *Research in International Business and Finance, 56*, 101359. https://doi.org/10.1016/j.ribaf.2020.101359

Zeinedini, S., Karimi, M. S., & Khanzadi, A. (2022). Impact of global oil and gold prices on the Iran stock market returns during the Covid-19 pandemic using the quantile regression approach. *Resources Policy, 76*, 102602. https://doi.org/10.1016/j.resourpol.2022.102602

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

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