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Volatility Impact of COVID–19 on Macro-Economic Indicators in India

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Abstract

Covid-19 (C-19) has resulted in economic and financial meltdowns across the world. The countermeasures to tackle the virus created economic loss for people from every stratum. Macroeconomic indices like unemployment, inflation, and GDP growth rates were severely hit. This study estimates the C-19's volatility impact on four macroeconomic variables (gold prices, interest rate, crude oil prices, and exchange rate in the Indian economy. The paper uses daily time series data of the macroeconomic variables and cases of C-19 in India for the period from 5th January 2020 to 4th April 2022. The volatility impact of COVID-19 is measured using Bi-Variate GARCH models. The GARCH models (BEKK-GARCH [BG] and DCC-GARCH [DG]) provide robust results. The result finds the existence of both short and long-term C-19's volatility impact on all variables, although in different degrees. This paper is original since it considers the impact of these four variables altogether and the study contributes to the literature by capturing the volatility spillover effects of these four variables using BEKK-GARCH and DCC-GARCH. This paper significantly delivers key implications to policymakers to critically treat C-19 for economic stability while making policies.

Key words: Covid-19, Macro-Economic, India, BEKK-GARCH, DCC-GARCH

JEL Code: C32, O11, O50, E66

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1. Introduction

An unexpected rebirth of the SARS virus in December 2019 (named 2019-nCov/SARS-COV2/Covid–19) through a new strain dared the man-made order in the world, creating uncertainty across all spheres of life (Bchetnia et al., 2020; Wu et al., 2020). The unpredictable and cataclysmic C-19 followed a sinusoidal trend for both the number of confirmed cases and deaths. Around January 2021(during the deadlier second wave), peak daily death rates touched nearly 15,000+ (World Health Organization, 2022). To counter the magnitude and multifaceted nature of the virus, national and international governing bodies developed several strategic multi-pronged approaches, including vaccination, lockdowns, use of masks, and restrictions, etc. counter measures (Kumar et al., 2020; Li and Mutchler, 2020). Consequently, macroeconomic indicators (GDP growth, unemployment, inflation, industrial production, household consumption, etc.) took a deep plunge worldwide; calling for policy prescriptions to ensure stability. This intrigued researchers to estimate this pandemic's impact on various economic, social, and financial parameters and produce plausible policy frameworks (Shahzad et al., 2021; Del et al., 2021).

The ripple effect created by the pandemic disrupted worldwide economic and trade activities (Zeren and Hizarci, 2020). Nationwide counter measures (like domestic lockdowns and travel restrictions) along with restrictive cargo movement adversely affected the foreign trade velocity (Chang et al., 2020; Jomo and Chowdhury, 2020; Gunay, 2020; Au Yong and Laing, 2021; Biswas et al., 2022). Stock and financial markets tumbled (Yousfi et al., 2021; Louhichi et al., 2021; Amar et al., 2021), calling for the central banks to intervene with monetary policy instruments (Wei and Han, 2021; Rubbaniy et al., 2021; Rebucci et al., 2021; Liu et al., 2020). As a result of the cascading effect, currency markets were affected as well (Andreou et al., 2013; Sui and Sun, 2016; Tsagkanos and Siriopoulos, 2013). The excessive fall in demand for crude oil created an excess supply scenario, leading to a shortage in storage spaces (Wilson, 2020). Consequently, crude oil prices fell, even touching negative at one point (Salisu et al., 2020; Albulescu, 2020; Izzeldin et al., 2021).

Investors seek safer investment opportunities during tumultuous times. Gold is one such avenue of investment with high intrinsic value, high liquidity, and historically proven performance against instability (Ciner et al., 2013; Baur and Lucey, 2010; Bouri et al., 2020; Baur and McDermott, 2016; MoneyControl, 2022; Reboredo, 2013a, 2013b). Fluctuations in other markets (oil, foreign exchange) caused gold prices to rise steeply during Covid–19 (Gautam et al., 2022). Conversely, the three other variables (oil prices, foreign exchange markets, and interest rates) witnessed a sharp decline (Li et al., 2021). Covid–19 differed from its predecessors in scale and nature, creating exogenous shocks on both demand and supply. It majorly affected the economies which were already underperforming before the pandemic hit. Most developing countries were the worst hit with massive capital outflows (OECD, 2020).

Apart from the growth parameters, gold prices, crude-oil prices, foreign exchange rates, and interest rates were severely affected by the pandemic. The onus to stabilize any economy (low and stable inflation) lies with the central banks. In response to the pandemic, the objective was to maintain credit flow, support liquidity, mitigate stress in currency and bond markets (IMF, 2022). Counter policies were quickly prescribed to mitigate the falling macroeconomic indicators. However, macroeconomic recovery requires both short and long-term objectives (Hoshi and Kashyap, 2004).

Volatility in the general sense measures the risk of any asset through the price-changing rate over a time-period. Higher volatility is usually associated with riskier financial asset prices (Xiao and Aydemir, 2007). Studies by Baek (2019), and Baker et al. (2020), successfully links C–19 impacts and financial market-volatility (stock market-volatility) citing governmental curtailing measures as a root cause. Rigorous initiatives of the government in some countries resulted in higher market volatility in those countries (Zaremba et al., 2020). It becomes imperative to analyze the volatility effects of such a large-scale pandemic on the economy vis-à-vis its macro-economic components. Volatility spillovers are best measured using Engle's Generalised Autoregressive Conditional Heteroscedasticity [GARCH] models (Engle, 1982) and Bollerslev's Autoregressive Conditional Heteroscedasticity [ARCH] models (Bollerslev, 1986). Rath (2023) also examines the relationship between volatility in asset return (i.e. banking, gsec, equity, money and forex stock) and macroeconomic indicators (i.e. Foreign portfolio investment, GDP, Market capitalization to GDP ratio Inflation and US Treasury Yield) in India. Bhosale et al (2023) also examine the impact of Corona virus on the prices of gold, crude oil prices and exchange rate for the period of November 2019 to April 2021 using Johansem Cointegration test and find there is no cointegration between all three variables.

Most of the papers pertaining to Covid–19 have used one or two components to understand the volatility spillover effects. Through this paper, we elaborate on the number of variables (to four) and penetrate the respective markets to gain better insights on the subject. This paper focusses on studying the volatility spillover effects of Covid–19 on four macro-economic factors; crude oil prices (COP), interest rates (INTR), gold prices (GOLD) and exchange rates (EXR) in respect to the Indian context. The originality of this paper is that this study uses other macroeconomic indicators (i.e gold prices, interest rate, exchange rate and crude oil prices) that was not used in previously as four variables altogether and the study contributes to the literature by capturing the volatility spillover effects of these four variables using BEKK-GARCH and DCC-GARCH. We use Bi-variate BG model by Engle and Kroner (1995) and DG model by Engle (2002). These two methods will provide a robust understanding of the interdependencies of the spillovers among the different markets. Investors can utilize the knowledge from this paper to detect the susceptible international shocks and thereby diversify their investments to different asset and commodities.

The paper also reviews existing literature in section 2 and provides a detailed explanation of the collected data and the methodology applied in section 3.

Explanation regarding empirical results covers section 4. Discussions and Conclusion form the final sections of the paper.

2. Literature Review

Volatility spillovers from one market to the other have always fascinated researchers. Typically, papers use one or two markets simultaneously to measure the degree of spillovers. This paper covers this gap by extending the number of variables vis-à-vis markets. We introduce four different macro-economic variables (gold prices, interest rates, exchange earnings and crude oil prices) to observe the C-19's volatility-effects on them. Simultaneously, we use two models of GARCH to ensure robustness. This allows us insights on the degree of spillovers to different markets. Through this portion, we review some of the papers which have previously delved in this concept.

2.1 Volatility and gold prices

Yousef and Shehadeh (2020), use GJR-GARCH models to test the C-19 volatility effects on gold spot-prices. The study concluded a positive connection between the two; increasing Covid–19 cases were found to positively impact gold prices. This was due to excessive demand for gold due to instability in other economic and financial markets. Selvan and Raj (2022), uses historical gold spot prices of Multi Commodity Exchange (MCX) to analyse gold price volatility impact pre and during Covid–19. The paper uses E-GARCH (Nelson, 1991) to measure price volatility on daily data from June 2017 to June 2021. The authors found a negative relationship between bad news and volatility of gold returns i.e., an increase in Covid–19 cases make gold returns more volatile. The paper found a volatility clustering effect and presence of asymmetric-volatility in gold prices due to the spread of Covid–19. Arfaoui and Yousaf (2022), uses asymmetric BEKK-GARCH model to examine volatility spillovers across stock indexes, gold, bitcoin, and oil markets during the pandemic C–19. The study found oil markets to be major receiver of volatility spillovers and gold was found to exhibit strong resilience against the pandemic. Rastogi et al., (2021) conduct a study to find the volatility effect on price of gold and crude oil market on the interest rate of India. The outcome of this study reveals that there is no association between the changes in the prices of gold and crude oil on the interest rate.

Mahajan and Mahajan (2021), use GARCH models (both symmetric and asymmetric), ARMA and Granger test to study the dynamics of stock market and gold during C–19 period. The paper tracks NIFTY Index and Gold prices from January to May of 2020 (the period during lockdown) to understand the impact of the latter on the former. The paper found a substantial negative effect of gold on the returns of NIFTY and concluded the importance of Gold as a trustable instrument of investment during periods of uncertainty.

H1: Volatility effect transmits from Covid-19 to gold prices.

2.2 Volatility and stock return

The stock market's performance is often equated to a country's financial health (Ratanapakorn and Sharma, 2007). Previously, papers have extensively analyzed the connection between different macro-economic determinants and the stock markets' volatility (mostly in USA and other advanced countries) (Ajayi and Mougoué, 1996; Bulmash and Trivoli, 1991; Campbell and Shiller, 1987; Chaudhuri and Smiles, 2004; Fama and French, 1989; Chen et al., 1986; Fama, 1981, 1990; Cheung and Ng, 1998; Humpe and Macmillan, 2009; Kim, 2003; Mukherjee and Naka, 1995; Nieh and Lee, 2001).

Volatility spillovers of financial markets are best measured using GARCH models (Setiawan et al., 2021). Chaudhary et al. (2020) employed GARCH analysis to determine returns and volatility of stock-market indices of the top ten economies (as per GDP) during Covid–19. Using market-indices' returns on daily basis for January 2019 – June 2020, the paper finds daily mean returns of all market indices to be negative, maintaining the presence of high volatility during the studied period. Also, the exogenous regressor (COVID–19 variable) for all market indices was found to be positive and significant. Kusumahadi and Permana (2021) studies stock return volatility across 15 countries in the world to know the pandemic's impact. The paper uses T-GARCH (Zakoian, 1994) on daily data of 18 months (January 2019- June 2020) and succeeds in identifying consistent structural changes and a positive relation between C–19 and return volatilities. The paper asserts an existing inverse connection of exchange rates to stock returns for all nations excluding the United Kingdom.

Hsing (2011) uses the GARCH model to explain how macro-economic factors influence the Bulgarian stock-market index (SOFIX). The paper concluded a positive relation between SOFIX and macro-economic variables (like the M2/GDP-ratio, real GDP, and index of the U.S. stock market). However, a negative relation was found between government deficit to BGN/USD exchange rate, GDP, expected inflation-rate, interest rate (domestic real), and government bond yield of euro-area and the SOFIX.

Babar et al . (2023) conducted a study on volatility spillover and returns between agricultural commodities and the stock market evident the effect of Covied 19 and the Russian-Ukraine war. The result shows that there is weak relationship between agricultural commodities and return from the stock market.

H2: Volatility effect transmits from COVID-19 to interest rate.

2.3 Volatility and oil prices

Rizvi and Itani (2021), compare three events in the last two decades (SARS–02, Financial Crisis–08, and Covid–19) to understand whether these events induce volatility fluctuations in the oil market. The study uses asymmetric GJR-GARCH

(Glosten et al., 1993) and symmetric GARCH on price returns and price spread of oil. The low probability and high severity of C–19 resembled a 'black swan' incident on the skewness and kurtosis basis. The paper concludes presence of high degree of asymmetry and volatility clustering (GARCH effect) during C–19 as compared to the previous events.

Bourghelle et al. (2021), used the duration of C–19 period to study the volatilities of the oil shocks. The paper uses VAR model to understand the effects of oil shocks on "West Texas Intermediate (WTI)" crude-oil price volatility. The paper concludes that uncertainty on investors part and pandemic-induced oil shocks create greater price volatility. Devpura and Narayan, (2020), examined the hourly changes in the price of oil due to rise in Covid19 cases and death rate. The study finds that on daily basis 8% to 22% volatility in oil prices.

H3: Volatility effect transmits from Covid-19 to crude oil prices.

2.4 Volatility and exchange rates

Banerjee et al. (2020) uses foreign exchange rates and stock market performances as variables to explore causal relations and growth rates to observe the C–19 pandemic impact. The study uses VAR model to understand the potential trend of the variables. Contrary to popular belief (that rising cases of C–19 is indirectly proportional to growth, currency, and stock markets; all three fell with rise in cases), the VAR results concluded that rise in cases did not affect exchange rates and stock markets, split across different time periods. Singh et al. (2021), use G7 nations to study the effect of partial and complete wavelet coherence on certain variables (exchange rates, stock-market-return, count of C-19 cases, and temperature) to analyze the time-varying patterns. Benzid and Chebbi (2020), study the impact of C-19 on the exchange rate volatility and find that there is positive association between rise in cases and death rate and USD exchange prices. Rai and Garg (2022), analyze the effect of C-19 in BRICS Nation on dynamics correlation and volatility spillover between exchange rates and stock prices. The study finds that there is a negative and significant relationship between stock price and exchanges rates. Sreenu (2023) conducted a study on the Indian stock market using the ARDL and GARCH models. The study investigates the long- and short-term impact of exchange rate volatility and inflation on the Indian stock market indices. The study results evident that there is a positive and significant association in long term but a negative association in short term.

H4: Volatility effect transmits from COVID-19 to exchange rate.

The review of existing literature clearly asserts the need for a paper that considers the different markets (variables) simultaneously to better understand the volatility spillover effects of Covid–19.

3. Methodology

3.1 Data

This research utilizes the daily time series data (from 5th January 2020 to 4th April 2022) of the macroeconomic factors Crude oil prices (COP), Gold prices (GOLD), Exchange rates (EXR), and Interest rates (INTR) and Covid–19 cases in India. Exchange rate is considered on USD to INR. The interest rate is the yield (interest rate on a one-year Indian bond). The diurnal new cases of COVID–19 form another data point. Additionally, in line with Sardar and Sharma (2022), this research analyses the daily percentage change of natural log values of the sample variables ((lnPt-lnPt-1) /lnPt-1 where Pt represents value at time t and Pt-1 is value at day before). The macroeconomic data and COVID–19 data are retrieved from the official website of NSE (National Stock Exchange) and Bloomberg database. Table 1 presents the variables list taken for the study.

Table 1. Variable description

Name	**Description**
COP	Logarithmic value of WTI Crude Oil Spot Price
Gold	Logarithmic value of Gold Spot Price
INTR	Logarithmic 5-year bond yield (India)
EXR	USD/INR Currency Spot Price
COV	Logarithmic value Covid-19 cases in India

Note: Describe the variable used in this study.

Source: The author(s)'

3.2 Methodology

This study applies multivariate-GARCH models for timeseries analysis to test the volatility transmission from one variable to another. A stepwise strategy is followed to get consistent analysis. First, the statistical summary (descriptive statistics) of timeseries variables used in the investigation is examined (see Table 2). The Jarque-Bera (JB) test (Jarque & Bera, 1987) is applied to check the normality. The monitoring of stationarity of the sample data is done by the Phillip-Perron (PP)-test (Phillips and Perron, 1988) and ADF ('Augmented-Dickey-Fuller')-test (Dickey and Fuller, 1981). The Arch effects observe volatility clustering, and it is tested by the ARCH test. To indicate the goodness of model

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fitness, 'Akaike-information-criterion' (AIC) or log likelihood are seen in the analysis. Finally, two very comparable multivariate GARCH (Bi-variate DCC-GARCH and BEKK-GARCH) models are applied to investigate the volatility effects transmitting from one market to another. The two are employed for confirming the results robustness.

3.2.1 Multivariate GARCH Model

Multivariate GARCH models explore the transmission of volatility effects between the multiple markets (from one market to another) (Bauwens et al., 2006a; Rastogi and Kanoujiya, 2022). This study mainly deploys the bi-variate BEKK-GARCH (1, 1) model to investigate the volatility-transmission from Covid–19 to macroeconomic factors. The DCC-GARCH (1,1) is also employed to check the robustness of results. As BEKK-GARCH keeps the definiteness of variance-covariance matrix (Bauwens et al., 2006b; Siddiqui and Khan, 2000). Therefore, it is consistent with smaller samples as well. For the results robustness check, the DCC-GARCH is also a good choice because this reveals similar attributes of the BEKK-GARCH outcomes. The DCC-GARCH needs lesser parameters for estimation of volatilities accurately (Bauwens et al., 2006c; Engle, 2002; Rastogi and Kanoujiya, 2022).

3.2.2 BEKK-GARCH (1, 1) Model

Engle and Kroner (1995) theorised the BG model (Rastogi & Kanoujiya, 2022). It is also found to be consistent with smaller observation and gives accurate estimates for volatility effects transmission between markets. It exhibits both short-term volatility (shock effects) and long-term price volatility effects. The BEKK-GARCH is developed as:

The variance-covariance matrix is represented by Ht as: which

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \text{ For i=1,2} \qquad \text{Eq.1}$$

a) The Ht represents the variance of error-term in BEKK
b)

$$H_t = C_0' C_0 + \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} + \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$$ (1, 1), is specified as:

$$H_t = D_0' D_0 + E_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' E_{11} + F_{11}' H_{t-1} F_{11} \qquad \text{Eq.2}$$

c) Where D_0 is N×N matrix (upper triangular), and E and F are N×N parameter matrix. The bi-variate BEKK (1,1) model is implemented using following equation:

$$H_t = C_0'C_0 + \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} + \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix} \quad \text{Eq.3}$$

e_{ij}, and f_{ij} are the elements of parameter matrix E and F, respectively. These elements indicate the shock effects (short term volatility) and long-term price volatility spillover effects, e_{ij} is for shock effects and f_{ij} for long-term effects. e_{ij}, and f_{ij} show volatility effects in same market if i = j; else they indicate volatility effects transmission from one market to another (cross-market). The equation (Eq.3) also leads to arrive at following conditional variance and co-variance equations.

$$h_{11,t} = c_1 + e_{11}^2\varepsilon_{1,t-1}^2 + 2e_{11}e_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + e_{21}^2\varepsilon_{2,t-1}^2 + f_{11}^2 h_{11,t-1} + 2f_{12}f_{21}h_{12,t-1} + f_{21}^2 h_{22,t-1}$$
Eq.4

$$h_{22,t} = c_3 + e_{12}^2\varepsilon_{1,t-1}^2 + 2e_{12}e_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + e_{22}^2\varepsilon_{2,t-1}^2 + f_{12}^2 h_{11,t-1} + 2f_{12}f_{22}h_{12,t-1} + f_{22}^2 h_{22,t-1}$$
Eq.5

$$h_{12,t} = c_2 + e_{11}e_{12}\varepsilon_{1,t-1}^2 + (e_{21}e_{12} + e_{11}e_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + e_{21}e_{22}\varepsilon_{2,t-1}^2 + f_{11}f_{12}h_{11,t-1}^2 + (f_{21}f_{12} + f_{11}f_{22})h_{12,t-1} + f_{21}f_{22}\,h_{22,t-1}^2$$
Eq.6

3.2.3 DCC-GARCH (1, 1) Model

This study also deploys the DCC-GARCH model for robustness check of results. It is also very compelling multivariate GARCH model to estimate the volatility connection (both short-term and long-term) of timeseries variables (Engle, 2002; Rastogi and Kanoujiya, 2022). This model has further advancement by breaking down expressing-variance and mean estimation of the variables.

$$d_t = \mu_t + \omega d_{t-1} + r_t \quad \text{Eq.7}$$

Where, d_t vector presents the residuals of returns. Symbols μ_t and r_t are vectors representing the conditional-mean and residuals, respectively. The variance equation is further constructed as:

$$k_t = c + xe_{t-1}^2 + yk_{t-1} \quad \text{Eq.8}$$

where, kt is conditional-covariance at time t, while c is constant-term in the Eq. 8. The ARCH effect (x) is for the short-term shock transmission to conditional-variance between the variables, while GARCH effect (y) is for the long-run volatility spillover to the conditional-variance between the variables.

4. Empirical Results

The timeseries analysis is done by RATS 9.0 software. Table 3 portrays the descriptive statistics of the timeseries data. The mean value of Covid–19 daily changes is 12.599 in sample period. The daily changes in crude price and gold price have mean value -0.795 and 0.160, respectively. Exchange rate and interest rate have mean values 0.012 and -0. 084, respectively.

Table 2. Correlation Matrix

	5th Jan 2011 to 4th 2022				
	COV	**COP**	**GOLD**	**EXR**	**INTR**
COV	1.000				
COP	-0.016	1.000			
GOLD	0.074	0.024	1.000		
EXR	0.058	-0.137*	0.149*	1.000	
INTR	0.072	0.052	0.004	0.076	1.000

Note: Correlation-coefficients between Crude, Gold, INTR, and EXR. * is significance-level at 5%.

Source: The author(s)' calculation

The Jarque-Bera test shows significant values at 1% for all variables hence, it rejects null of normality in data. The ARCH (LM) test confirms the ARCH effect in the timeseries data of all variables hence, GARCH models can be performed consistently. The unit root test i.e., ADF test and the PP test by showing significant values confirm the stationarity of data required for the analysis. The multicollinearity issue does not exist as no significant correlation has a value more than 0.800 (Table 2).

Table 3. Descriptive Statistics

	5th Jan 2020 to 4th April 2022				
	COV	**COP**	**Gold**	**EXR**	**INTR**
Mean	12.599	-0.795	0.106	0.012	-0.084
Maximum	93.333	53.086	4.580	0.608	10.388
Minimum	-89.911	-301.966	-5.870	-1.944	-6.065
Standard Deviation	89.669	17.365	1.141	0.389	1.196
Skewness	9.622	-13.905	-0.375	-0.027	1.132
Kurtosis	93.647	234.076	3.743	2.960	17.958
Jarque-Bera	148.627***	90.326**	235.33***	141.02***	531.81***
Observations	400	400	400	400	400
ARCH (LM) Test	30.900***	239.503***	83.313***	80.336**	28.396***
Unit Root Tests					
Augmented Dickey–Fuller	-5.908***	-7.705***	-7.801***	-6.513***	-8.383***
Phillips–Perron	-398.33***	-262.78***	-353.99***	-428.96***	-440.55***

Note: ***, **, * are indication for the 1%, 5% and 10% significance-level, respectively. Unit-Root-Test is employed to observe constraint and trend. ARCH test shows serial-correlation of the heteroskedasticity in the time-series data at lag 1.

Source: The author(s) calculation

4.1 Bivariate-GARCH Estimation

The study employs the bi-variate BG model to explore the short-term and long-term volatility effects of corona on the economy of India considering macroeconomic indicators (oil price [COP], gold price [GOLD], interest rate [INTR] and exchange rate [EXR]). Table B. 4 and B. 5 present the results of BG and DG Models' estimations. The Akaike Information Criterion (AIC) or Loglikelihood is to indicate the good fit model (lower (or higher) the AIC value (or Loglikelihood) better the model good fit).

The study mainly considers the following parameters in BEKK-GARCH: E (i, j) for ARCH effects to check short-term volatility and F (i, j) for GARCH effects to check long-term effects from market i to market j. Parameter D (i, j) is constant-term (Engle and Kroner, 1995; Lee and Yoder, 2007). In DCC-GARCH, $JDCCA_1$ is looked for joint ARCH term to observe short-term volatility effect. The long-term volatility effect is observed by $JDCCB_1$ for joint GARCH term.

Table 4. Bivariate BEKK GARCH (1,1) Estimation (Covid and Macroeconomic Indicators)

	COV (1) COP (2)	COV (1) GOLD (2)	COV (1) EXR (2)	COV (1) INTR (2)
Variance Equation:				
D_{11}	89.669*	34.593*	84.286*	89.669**
D_{21}	-0.287	0.017	0.025	-0.086
D_{22}	17.363*	0.276*	0.126***	1.193
E_{11}	0.100**	0.000*	0.000*	0.100**
E_{12}	0.020*	-0.500***	-0.500*	0.020
E_{21}	0.020	-0.000	-0.000	0.020
E_{22}	0.100	0.390*	0.407*	0.100
F_{11}	0.900*	0.927*	0.341*	0.900**
F_{12}	0.010	-0.500*	0.500*	0.010
F_{21}	0.051	0.000	-0.000	0.051
F_{22}	0.900*	0.890*	0.853*	0.900**
Model Diagnostics:				
AIC	-4614.399	-2944.256	-2521.817	-4522.54

Note: AIC is for Akaike-Information-Criterion. ***, **, * are indication for the significance level at 10%, 5% and 1% respectively.

Source: The author(s)' calculation

In Table 4, the BEKK-GARCH estimates are presented. The E12 coefficients of the pairs covid & crude oil, covid & gold, and covid & exchange are found significant. The covid & crude oil exhibits the positive (0.020). E12 coefficient indicating that covid has significant and positive shock effect (short-term volatility effect) on crude oil price. The pairs of covid & gold and covid & exchange rate have negative (-0.500 each). E12 coefficient showing covid has a negative short-term volatility effect on gold and exchange rate. The covid & interest rate pair has insignificant E12 coefficient hence, no show effect is found from covid to interest rate.

Moreover, in Table 4, F12 coefficient of covid & gold is significant and negative with value -0.500 indicating covid also has long-term volatility effect on gold prices. The covid and exchange rate pair exhibits the significant and positive F12 coefficient with value 0.500. F12 coefficients for covid & crude oil and covid & interest rate are insignificant hence, no significant long-term volatility effect exists.

Table 5: Bivariate DCC GARCH (1,1) Estimation (Covid and Macro-economic Indicators)

	COV (1) COP (2)	**COV (1) GOLD (2)**	**COV (1) EXR (2)**	**COV (1) INTR (2)**
Optimal Parameters:				
$\mu(1)$	0.327**	0.327**	0.327**	0.327**
$\omega(1)$	0.218**	0.218**	0.218**	0.218**
$\alpha_1(1)$	0.166*	0.166*	0.166*	0.166*
$\beta_1(1)$	0.832*	0.832*	0.832*	0.832*
$\mu(2)$	-0.003	0.079***	-0.010	-0.040
$\omega(2)$	1.024*	0.076**	0.016**	0.108**
$\alpha_1(2)$	0.456*	0.1536*	0.165**	0.298
$\beta_1(2)$	0.542*	0.795*	0.727*	0.700*
$JDCCA_1$	0.017*	0.000	0.006	0.016
$JDCCB_1$	0.982*	0.944***	0.993*	0.983*
Model Diagnostics:				
AIC	191.10	188.78	186.72	189.00
Log Likelihood	-95.52	-94.36	-93.33	-94.47

Note: AIC is for Akaike-Information-Criterion. ***, **, * are indication for 10%, 5% and 1% significance-level, respectively.

Source: The author(s)' calculation

4.2 Robustness Check

Table 5 demonstrates the DCC-GARCH estimates. $JDCCA_1$ coefficient (ARCH effect) is found significant and positive only for covid and crude oil price. Hence, here the shock effect from covid to crude oil price exist. However, for rest of the pairs (covid & gold, covid & exchange rate, and covid & interest rate), the $JDCCA_1$ coefficients are insignificant.

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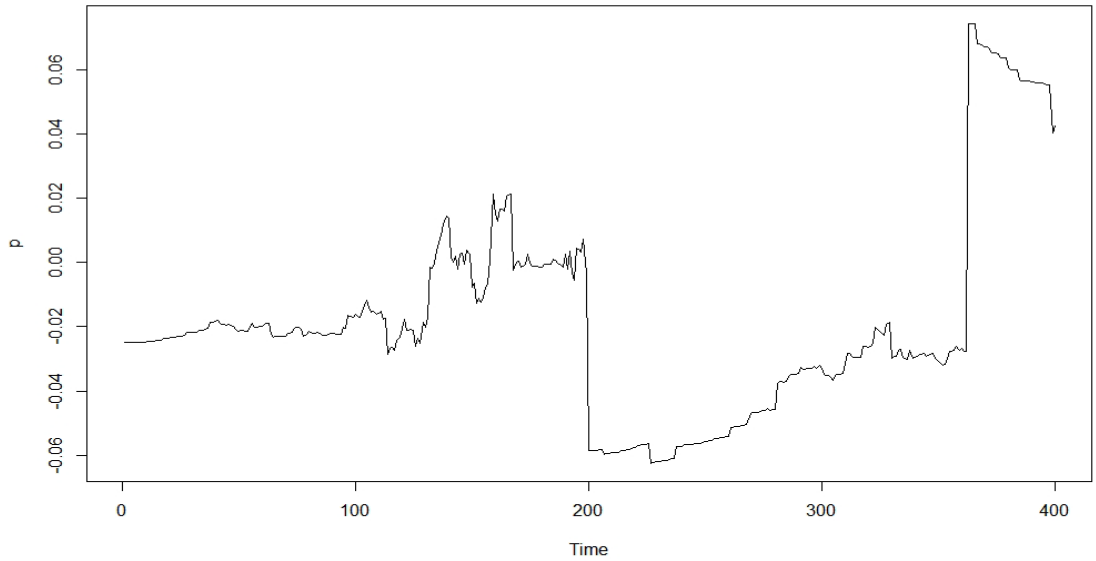
The $JDCCB_1$ coefficient for all the pairs is significant indicating covid has a long-term volatility impact on crude oil, gold, exchange rate, and interest. The sum of $JDCCA_1$ and $JDCCB_1$ is less than equal to one hence, the validity of DCC-GARCH is ensured for the analysis. The figure 1, 2, 3 and 4 portray the conditional correlation over the time between the pairs covid & crude oil price, covid & gold, covid & exchange rate, and covid & interest rate, respectively and represented as 'p' in figures.

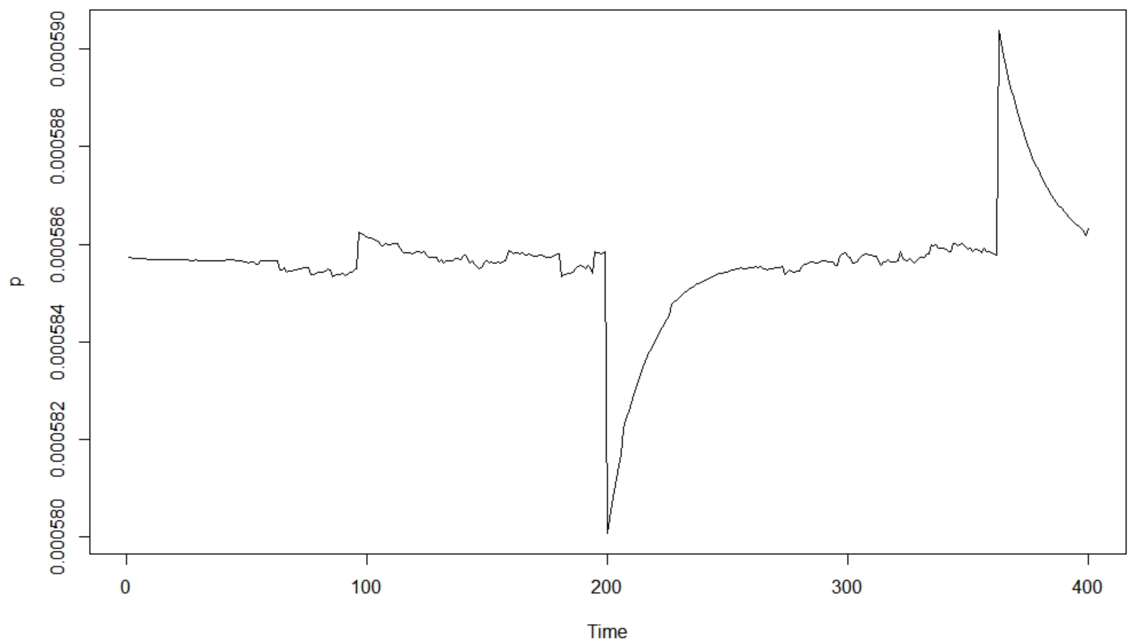
Two different M-GARCH models (DG and BG models) are used on the sample timeseries in this study to ensure that the results are robust. In Table 4 and 5, both the models show similar outcome that Covid–19 has volatility effects on macroeconomic determinants in India (short-term or long-term or both). Therefore, the similarities in findings from both models ensure robustness of the results.

Figure 1. Conditional Correlation between Covid & Crude Oil Price



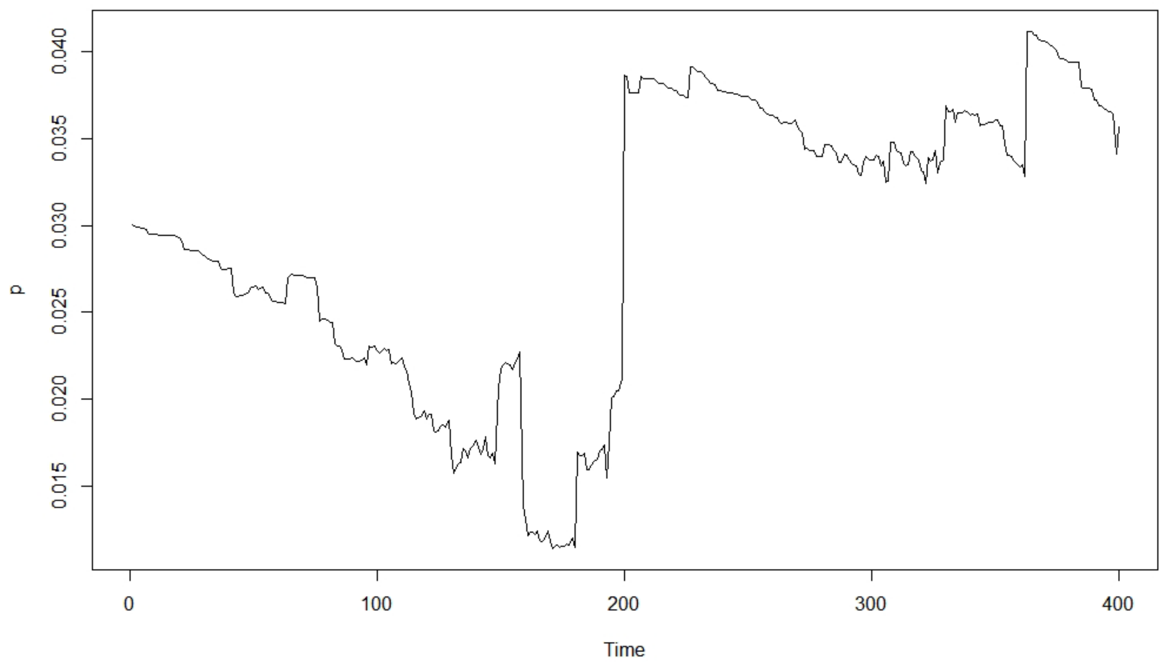
Source: The author(s)' estimate

Figure 2. Conditional Correlation between Covid & Gold



Source: The author(s)' estimate

Figure 3. Conditional Correlation between Covid & Exchange rate



Source: The author(s)' estimate

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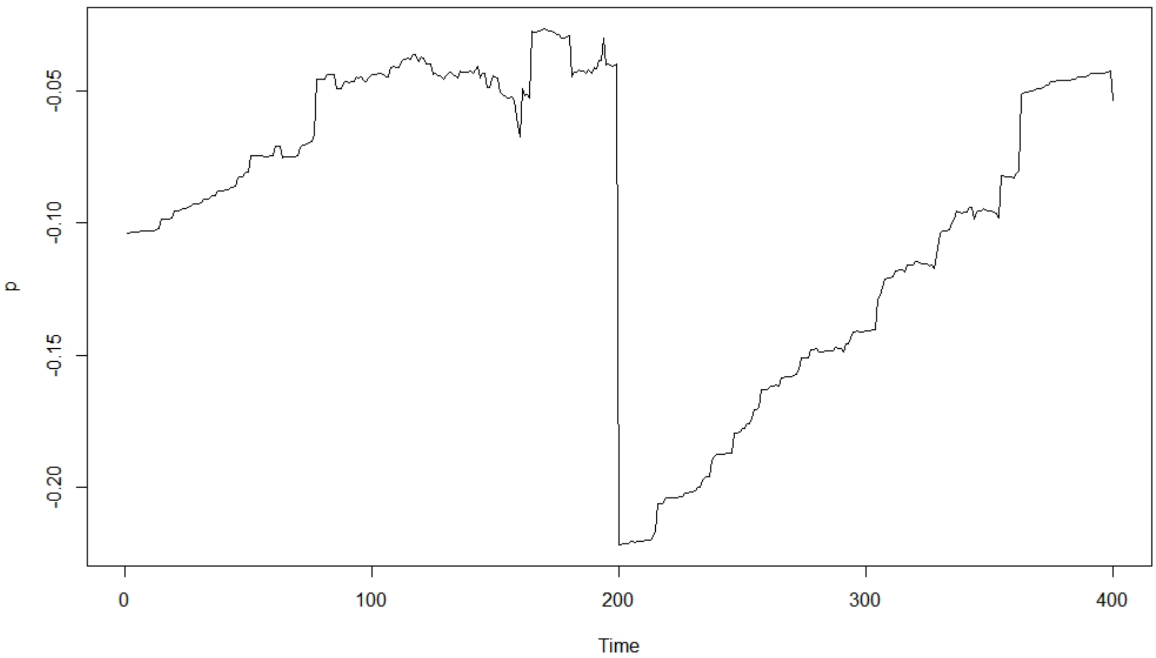
Figure 4. Conditional Correlation between Covid & Interest rate



Source: The author(s)'

5. Discussion

This paper successfully defends the four hypotheses vis-à-vis a positive volatility effect of Covid–19 on all four variables: crude-oil price, gold-price, interest-rates and exchange-rates in India. Both the BEKK-GARCH and DCC-GARCH models provide robust results to support the same findings All earlier works confirm the presence of volatility spillovers from Covid–19 (Chaudhary et al., 2020; Kusumahadi and Permana, 2021; Mahajan and Mahajan, 2021; Selvan and Raj, 2022; Yousef and Shehadeh, 2020) but this paper uses different markets (oil-prices, gold-prices, exchange-rates and interest-rates) to expand the results. Results often vary when compared over different time horizons. Through this paper, we explore the complexities in relationship between the said variables both in the short and long- term.

Our study improves the works of Rizvi and Itani (2021) and Bourghelle et al. (2021) by introducing both short- and long-term results and different markets (gold, interest and exchange rates). The short-term volatility effects of Covid–19 is found positive only for crude oil prices but stands negative for gold and exchange rates. However, the long-term volatility effects of Covid–19 are quite dominant on gold prices. Similar results from both BEKK-GARCH and DCC-GARCH confirm it.

This paper successfully differentiates in methodology from the existing scope of work. We carefully construct the relationship between C–19 and all four macro-economic variables. Thereafter, we analyse the volatility spillovers from C–19 to them in both short and long-term. This provides sufficient base and evidence to make this paper stand out from the rest of the work.

6. Conclusion

Without any historical benchmark other than assumed death rates, it becomes difficult to estimate the brutality of any pandemic. C–19 was the first pandemic of the 21st century, a time when we have numerous indices and instruments to measure the intensity of the damages. The scientific progresses across different spheres have managed to provide solutions to deal with the persisting problems. Despite heavy downfall in the economic projections during C–19, institutions were careful to prescribe solutions that controlled the fluctuations with remarkable precision.

Prices of oil, gold, exchange rates and interest rates often act as economic indicators (Arfaoui and Ben Rejeb, 2017). The price dynamics of these act as important macro-economic indicators to investors. These indicators share common characteristics and are correlated with each other (Chkili et al., 2014; Vivian and Wohar, 2012). The price fluctuations in these variables provide an indication towards future market movements in the global economy. The simultaneous use of multiple variables from different markets helps to provide a solid foundation for future works relating to India. These also serve as important arguments from an investment or managerial decision-making point of view.

Our results are expected to be guiding investors and policymakers to make better asset allocation and management during a pandemic. This paper clearly concludes the short and long-term volatility implications of C–19 based on four macro-economic variables (gold-prices, interest-rate, crude-oil-prices, and exchange-rate) in the Indian economy. This research can be extended by examining the dynamics, direction, and volatility transmission of C–19 or other events on a larger number of important macro-economic indicators**.**

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