

Analysis of Effect of Dynamic Link Among Oil, Gold and Stock Markets of South Asian Economies During and After Covid-19

1. Shumaila Saleem, 2. Saima Kousar, 3. Shaistah Bashir

1. MPhil Scholar, Women University of Azad Jammu & Kashmir, Bagh, Azad Jammu
Kashmir

saleemshumaila800@gmail.com

2. PhD Scholar, Department of Economics, International Islamic University Islamabad,
Pakistan

saimakhan0986662@gmail.com

3. MPhil Scholar, Women University of Azad Jammu & Kashmir, Bagh, Azad Jammu
Kashmir

shaistabasir666@gmail.com

Abstract

This research study investigates the dynamic connectedness among gold, oil and selected South Asian Stock markets, during and after the COVID-19 pandemic. The study collected data of gold from World gold council oil data from West Texas intermediate and stock market from Yahoo finance on daily bases for time period 2020 to 2023. we adopted the recent DCC-GARCH CONNECTEDNESS approach proposed by Gabauer (2020) to conduct a time-varying analysis that investigates the dynamic connectedness among crude oil, gold and stock markets. Unlike traditional rolling-window analysis, the DCC-GARCH offers advantages in capturing time-varying transmission mechanisms without the loss of observations. Findings show stronger connectedness between oil, gold, and stock market indices during COVID-19 than after the COVID-19 pandemic. The findings highlight gold as a potential safe haven asset during economic slumps. This suggests that investors may consider allocating a portion of their portfolios to gold to hedge against market volatility and uncertainty. We also find that during

pandemic both gold and oil are receiver of shocks from the five stock markets whereas the oil and gold become net transmitter of shocks after pandemic subsidies. The empirical results show a moderate connectedness between gold, oil and south Asian stock markets which is helpful for investors and portfolio managers in the construction and reallocation of their portfolios under crises period. Policymakers to monitor and analyze volatility in oil and gold prices, and measures to address disruptions in oil demand and supply chains during pandemics. For instance, policymakers should be aware of the links between oil and gold and their effect on financial markets when preparing strategies to reduce connectedness between stock markets during pandemics and crises.

Key words: Oil, Gold, Stock, DCC GARCH, Connectedness, Volatility, COVID-19

1. Introduction

A marketplace where buyers and sellers exchange shares of publicly traded corporations is known as the stock market. To earn returns on their investments, investors can buy and sell ownership holdings in businesses, also called stocks or shares, through this platform. Because it facilitates capital formation, gives investors liquidity, and allows businesses to raise money for expansion and growth, the stock market is essential to the economy. Nowadays, stocks are traded electronically. Electronic networks help increase speed and lower transaction costs.

In addition to stocks, bonds, and mutual funds, investors can invest in the commodities market. Most investors prefer to invest in commodity markets, such as gold and oil. They have to take volatility into account while making financial selections. The rate at which prices fluctuate, whether they rise or fall, increases with volatility. Nonetheless, some investors are drawn to high-volatility investments because they offer high-return prospects that match the volatility; this type of investment is typically referred to as high-risk, high-return (Syahri and Robiyanto, 2020).

Gold, considered a safe-haven asset, typically sees increased demand during economic uncertainties or market turmoil (Balcilar, Gupta, and Wohar, 2016). Amidst the COVID-19 crisis, gold prices surged to record highs initially, reflecting investors' flight to safety. The price of gold tends to increase compared to the oil price decline during the COVID-19 pandemic. It means that the investors tend to shift their assets to gold commodity because it has low volatility and is considered the safest asset or safe haven (Kumar and Sahadudheen, 2015). Robiyanto, Wahyudi, and Pangestuti (2017); Robiyanto (2018) support the statement by mentioning

categorized gold as a safe haven in several countries. Also, Alali (2020) states that gold is considered a safe haven by seeing the price change of gold that tends to rise compared to stocks or other commodities during COVID-19.

During economic instability, the rise of gold prices and the attention of gold as a safe haven cause the equity prices to fall (Arfaoui and Ben Rejeb, 2017). However, as vaccine developments and economic recovery efforts progressed, gold prices moderated, albeit remaining elevated compared to pre-pandemic levels.

Oil, a critical commodity, plays a pivotal role in the global economy, with its prices influenced by supply-demand dynamics, geopolitical events, and macroeconomic conditions (Narayan and Sharma, 2011). The onset of the pandemic led to a historic collapse in oil prices due to a demand shock and price war between major oil-producing nations. Subsequent efforts to stabilize prices through production cuts and gradual demand recovery have contributed to oil price rebounds.

The twenty-first century has witnessed several pandemics, with the World Health Organization (WHO) designating the COVID-19 outbreak as an international disaster on January 30, 2020 (Sohrabi et al., 2020). COVID-19, one of the most significant health crises of this century, has affected billions of lives globally, causing palpable anxiety and widespread disruptions in economic activity (Jelilov et al., 2020; Razzaq et al., 2020).

South Asian stock markets, including those in India, Pakistan, Bangladesh, Sri Lanka, and Nepal, have been significantly impacted by both global and domestic factors during the COVID-19 crisis (Mohapatra and Sahu, 2021). Lockdown measures, supply chain disruptions, and economic slowdowns have heightened market volatility, with government interventions playing a crucial role in restoring stability and supporting economic recovery.

The COVID-19 pandemic has led to unprecedented disruptions across global financial markets, impacting the dynamics among various asset classes. Notably, gold, oil, and stock markets in South Asia have experienced substantial fluctuations due to uncertainties surrounding the pandemic's economic consequences and subsequent recovery efforts (Prabheesh et al., 2020).

The COVID-19 outbreak has caused significant disruptions in oil prices, impacting the financial and economic systems. The effectiveness of stock markets in oil-consuming nations is significantly influenced by oil prices, with fluctuations affecting manufacturing costs (Vidya

and Prabheesh, 2020). Lockdowns and decreased oil consumption due to the pandemic have led to a substantial drop in crude oil prices.

The linkages between stock markets and energy commodities have been extensively investigated to gain a better understanding of the attributes of investments and fluctuations in prices in energy markets (Batten et al., 2021; Lin and Su, 2020; Peng et al., 2021; Zhang et al., 2021). Some events, such as the Chinese stock market crash (CSC), European sovereign debt crisis (EDC), and global financial crisis (GFC), change the dynamics of the stock and commodity markets (Aromi and Clements, 2019; Wen et al., 2019, 2021b; Yousaf and Hassan, 2019). Recently, stock indices and energy prices have experienced a large shock due to COVID-19. For example, Sharif et al. (2020) find a significant relationship between United States stock markets and oil prices during the pandemic. In addition, COVID-19 has had a direct effect on business operations, essential services, and job security (Sharif et al., 2020).

Despite the extensive research on the impact of the COVID-19 pandemic on financial markets, there is a lack of comprehensive studies focusing specifically on the effects of the gold and oil markets on the South Asian stock market during and after the COVID-19. This research gap highlights the need for a detailed analysis of how the fluctuations in the gold and oil markets have influenced the stock market in the South Asian region, providing valuable insights for policymakers, investors, and researchers.

The choice to focus on South Asia is justified by the region's heavy dependence on petroleum imports, making these nations vulnerable to oil price fluctuations. With a quarter of the global population, South Asian economies are significantly affected by risks associated with oil imports. This investigation represents the first attempt to examine the dynamic connectedness of share returns, gold returns, and oil returns throughout and after the COVID-19 pandemic for selected South Asian nations. Furthermore, it seeks to apply the Dynamic Connectedness technique, which is underutilized in the context of South Asian countries, to estimate the connectedness of these markets.

1.1 Objectives

The present study was conducted to achieve the following objectives:

1. To explore the connectedness among gold, oil and selected stock market.
2. To investigate the volatility of selected South Asian Stock Market, oil and gold.

2. Literature Review

Nguyen (2023) discusses the effects of the volatility in six ASEAN emerging economies' stock indexes and West Texas Intermediate oil prices during the COVID-19 pandemic. The results reveal a beneficial transmission of volatility from crude oil prices to these developing equity markets, with co-movements becoming more pronounced during health emergencies, signaling the possibility of contagious effects. Kumar and Prabheesh (2023) further examine the changing interplay among epidemic-induced anxiety. Yen-ku et al. (2022) explore the affiliation between the dynamic prices of oil and gold and how these prices vary over time with the Chinese stock market. Their results suggest long-term harm to the Chinese exchange market due to rising oil and gold prices, with gold having a long-term positive effect and oil having a negative effect.

Siddiqui et al. (2022) investigate the link between stock returns and commodity. Ali et al. (2022) explore the nonlinear causation and spillover effects of oil price shocks on stock fluctuations. Ren, Chao (2022) study the links between gold prices, oil, and European equity markets using a trivariate VAR-BEKK-GARCH model, finding modest return ripples from the energy market to European capital markets and stronger shocks and volatility contagions from European stock markets to oil and gold markets. Finally, Chkili (2022) delves into the relationships among petroleum prices, gold prices, and Islamic capital exchange. Tabash et al. (2022) examine the interaction between Pakistan's currency rate, stock market index, and oil prices.

Mansi et al. (2022) examine the volatility spillovers before and during global health crises, Standard and poor 500 index, and oil as well as gold prices. Khan et al. (2022) explore the correlation between oil prices and Islamic and conventional indices of the Malaysian stock during COVID-19. Mishra et al. (2022) employ the unequal causation test to determine the fluctuations in the advert and coming prices of gold and oil, finding that both positive and negative shocks to oil prices Granger affect gold prices, and vice versa.

Farzana and Saqib (2021) investigated the interaction among financial markets and the price of oil in four specific countries using a non-linear autoregressive distributed lagged approach. They discovered a positive correspondence between stock indices and oil price, with responses to oil price variation being both positive and negative. Cobo-Reyes and Quirós (2005) examined the links between spikes in oil prices and corporate output, revealing detrimental effects on both dividends and industrial output, with a larger impact on dividends. The literature

review provides a comprehensive overview of studies investigating the relationships between various financial and commodity markets, particularly focusing on the effects during the COVID-19 pandemic. The research encompasses diverse methodologies and focuses on different regions, including Asian countries, ASEAN nations, Middle Eastern countries, and others.

3. Data And Research Methodology

In this research we empirically investigate the interaction among gold, oil market volatility in the daily closing prices of five South Asian stock exchange indexes, namely nifty-50, Kse100, Dse30, Colombo stock exchange and Nepal stock exchange. The research is divided into two periods: during and after the COVID-19 pandemic, to ensure a robust analysis and capture the dynamics effectively daily data will be utilized to examine the interaction among the studied markets. The first period spans from March 2020 to May 2021, coinciding with the rising trend of COVID-19 cases. There is no consensus in the data on the start date of the COVID-19 epidemic. Some studies have used 31 December 2019, the date of the first official COVID case in China Yousaf and Ali (2020), Just and Echaust (2020), while others have opted for 11 March 2020, the day the WHO declared COVID's global emergence, officially designating it as a pandemic Ajmi et al. (2021). In our study, we considered March 2020 as the start date of COVID-19, following Inacio et al. (2023), Dairi et al. (2021) and Yousaf (2021) and in line with the declaration by Johns Hopkins University regarding the virus' global release. The second period covers from June 2021 to March 2023. Data on world oil prices will be sourced from the United States Energy Information Administration (EIA), while stock index data will be obtained from Yahoo Finance and gold prices from the World Gold Council.

3.1 Data Source

Present data series depend on daily observation from 2020 to 2023. Daily data provides a higher frequency of observations, allowing for a more detailed analysis of the dynamic conditional correlations between assets. This higher frequency can help capture short-term fluctuations and volatility in the correlations, providing a more accurate assessment of the interconnectedness between stock markets, gold, and oil. Data will be sourced from the United States Energy Information Administration (crude oil data), Yahoo Finance (stock market data) and the World Gold Council (gold market data).

3.2 Research Methods

Many statistical techniques are use in study to check correctness of results. Unit root technique applies to check existence of stationary in the data (Agrawal 2010). ARCH heteroskedasticity technique is use in research to inquiry either ARCH effect is present or not in data (bhat 2015). We applied the DCC-GARCH-CONNECTEDNESS approach proposed by Gabauer (2020) which significantly improves Diebold and Yilmaz's (2012, 2014) original connectedness approach into two ways: (i) it does not rely on a rolling-window approach for time varying dynamics and (ii) it enables us to test whether the propagation mechanism is time-varying or not. Indeed, the DCC-test based on Engle and Sheppard (2001) evaluates whether spillovers vary over time.

3.2.1. Unit Root Test

The unit root technique was developed by economists Robert F. Engle and Clive W.J. Granger. This technique is commonly used in time series analysis to determine whether a series is stationary or non-stationary. The most popular unit root tests include the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Study examined whether stock return gold and oil return are organized of order zero, $I(0)$.

3.2.2. Auto Regressive Conditional Heteroskedasticity (ARCH)

Autoregressive Conditional Heteroskedasticity (ARCH) model was proposed by Engle (1982). ARCH used, if the variance of error term is related to the squared error in preceding term. Test is used to detect the presence of conditional heteroskedasticity in a time series data, which refers to the changing variance of the error term over time. The ARCH test helps in identifying whether there is volatility clustering in the data, where periods of high volatility tend to be followed by periods of high volatility, and vice versa.

3.2.3. Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity Connectedness Approach

Various research methods have developed to study transmission mechanism including the vector auto regressions (VAR) family of models, such as TVPVAR and PVAR. Notably, Diebold and Yilmaz (2009, 2012, 2014) dynamic connectedness approach, which decomposes forecast error variation has garnered considerable attention in the economic literature. The

investigation of volatility transmission occurs in two main steps. Firstly, a multivariate GARCH approach is utilized to gather time-varying volatility data, which serves as the foundation for a rolling-window VAR estimation procedure. However, the rolling window strategy has two significant drawbacks: the arbitrary selection of window size and the loss of observations, potentially leading to faulty conclusions.

Recent events in the global economy have reignited interest in understanding the mechanisms underlying the transnational spread of economic shocks. With the lingering effects of the Great Recession (2009) still being felt worldwide, the transmission of shocks among economic entities has become a matter of significant attention and concern. Given that the transmission mechanism serves as an early warning system, it is crucial for policymakers to investigate it thoroughly. Furthermore, these economic emergencies impact investors' emotional states, leading to changes in investment behavior and subsequent fluctuations in stock prices (Elgin, Basbug, and Yalaman, 2020).

To address these limitations and assess the overall connectivity among crude oil, gold and stock indexes of South Asian countries, we use dynamic conditional correlations volatility(DCC-GARCH) connectedness approaches developed by Gabauer (2020) as an alternative to the traditional connectedness approaches of Diebold and Yilmaz (2012, 2014) which is an extension framework for estimating the volatility transmission mechanism. This technique combines the connectedness approach of Diebold and Yilmaz with the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model. According to Gabauer (2020), this framework offers two main advantages: (i) it avoids the need for a rolling-window approach to capture time-varying dynamics, and (ii) it allows for testing whether the propagation mechanism is or is not time varying. These models are widely favored due to their ease of use, capacity to handle conditional heteroscedasticities, their flexibility in selecting different extensions, and the ability to conduct dynamic studies to analyze the time-varying relationships between variables over time. This model is particularly useful in studying the transmission of volatility and shocks between different markets, providing insights into how changes in one market can affect another.

In the context of the research described above, the DCC-GARCH connectedness methodology is employed to assess the overall connectivity between financial markets and commodity markets, specifically focusing on crude oil and gold. Here's how the DCC-GARCH connectedness model works and why it's suitable for this type of analysis:

The DCC-GARCH model allows for the estimation of time-varying conditional correlation coefficients between different assets. This means that it captures how the correlation between two assets changes over time, reflecting the dynamic nature of financial markets.

The GARCH component of the model is used to capture the volatility clustering and persistence commonly observed in financial time series data. It models the conditional variance of each asset's returns, allowing for the identification of periods of high and low volatility.

The term "dynamic" in DCC-GARCH refers to the ability of the model to capture changes in correlation and volatility over time. This is essential for understanding how shocks and events in one market can propagate to others, as correlations and volatility levels are not static but evolve with market conditions.

By using the DCC-GARCH connectedness model, we can assess the level of connectedness or interdependence between financial and commodity markets. This includes understanding how shocks and volatility in one market can transmit to another, providing insights into the overall stability and resilience of the global financial system.

This paper employs the DCC-GARCH connectedness approach proposed by Gabauer (2020). It is based on the volatility impulse response function (VIRF) that represents the impact of a shock in variable "i" on variable j's conditional volatilities. The VIRF can be written as

$$\psi = VIRF(J, \delta_{j,t}, F_{t-1}) = E(H_{t+j} \setminus \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(H_{t+j} \setminus \varepsilon_{j,t} = 0, F_{t-1})$$

(1)

Where $\square_{j,t}$ a selection is vector with a one at the j^{th} position and zero otherwise.

Conditional variance-covariance forecasting by using the DCC-GARCH model is at the core of VIRF and can be done by iteration in three steps.

First the GARCH (1,1) used to predict conditional volatility ($D_{t+h|F_t}$). The specific process as fellow:

$$E(h_{it,t+h} / F_t) = \varpi + \alpha \delta_{1,t}^2 + \beta h_{it,t} h = 1 \quad (2)$$

$$E(h_{it,t+h} / F_t) = \sum_{i=0}^{h-1} \varpi (\alpha + \beta)^i + (\alpha + \beta)^{h-1}$$

$$E(h_{it,t+h-1} / F_t) > 1 \quad (3)$$

As a second step $E(Q_{t+1} \setminus F_t)$ is forecasted

$$E(Q_{t+1} \setminus F_t) = (1 - a - b)\bar{Q} + au_t u_t' + bQ_t h = 1 \quad (4)$$

$$E(Q_{t+1} \setminus F_t) = (1 - a - b)\bar{Q} + aE(u_{t+h-1} u_{t+h-1}' \setminus F_t) + bE(Q_{t+h-1} \setminus F_t) h > 1 \quad (5)$$

where $E(u_{t+h-1} u_{t+h-1}' \setminus F_t) = E(Q_{t+h-1} \setminus F_t)$ allows to predict the dynamic conditional correlations as suggested by Engle and Shepard (2001).

In the third step, the dynamic conditional variance-covariance are predicted as

$$E(R_{t+h}, F_t) \approx \text{diag} \left[E(\sqrt{q_{ii} + h}), F_t, \dots, (\sqrt{q_{NN} + h}), F_t \right] \\ E(Q_{t+h}, F_t) \text{diag} \left[E(\sqrt{q_{ii} + h}), F_t, \dots, (\sqrt{q_{NN} + h}), F_t \right] \quad (6)$$

$$E(H_{t+h}, F_t) \approx E(D_{t+h}, F_t) E(R_{t+h}, F_t) E(D_{t+h}, F_t). \quad (7)$$

The generalized forecast error variance decomposition (GFEVD) is then computed using the VIRF and is interpreted as the variance share of one variable explains on others.

The normalized variance share is computed by

$$\phi_{ij,t}^g(j) = \frac{\sum_{t=1}^{j-1} \psi_{ij,t}^{2,g}}{\sum_{j=1}^N \sum_{t=1}^{j-1} \Psi_{ij,t}^{2,g}}$$

By employing the GFEVD, it is possible to construct the total connectedness index

(TCI) as follows:

$$C_t^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \Phi_{ij,t}^g(J)}{N}$$

The total connectedness presented in Eq. (9) allows finding the spillovers that variable "i" transmits to variables "j" (total directional connectedness), which are

calculated by:

$$C_{i \rightarrow j,t}^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \Phi_{ji,t}^g(j)}{\sum_{j=1}^N \Phi_{ji,t}^g(j)}$$

The total directional connectedness from others is computed by

$$C_{i \leftarrow j,t}^g(j) = \frac{\sum_{i,j=1, i \neq j}^N \Phi_{ji,t}^g(j)}{\sum_{j=1}^N \Phi_{ji,t}^g(j)}$$

The difference between the two previous measures allows computing the net total connectedness used to describe the influence of the variable "i" on the studied network,

which can be presented by

$$C_{i,t}^g = C_{i \rightarrow j,t}^g(J) - C_{i \leftarrow j,t}^g(J)$$

Finally, Gabauer (2020) defines the net pair wise directional connectedness

(NPDC) between variable "i" and variable "j" by

$$NPDC_{IJ} = \Phi_{ji,t}^g(J) - \Phi_{ij,t}^g(J)$$

3.3. Variables

There are three variables included in the present study. First one stock returns which is dependent variable stock return depends upon five South Asian stock markets namely national stock exchange of India, Pakistan stock exchange, Dhaka stock exchange of Bangladesh,

Colombo stock exchange of Sri Lanka and Nepal stock exchange. Second variable is gold market and third one is oil market. The collected daily observation from 2021 to 2023.

The econometric model is:

$$SM_t = \beta_0 + \beta_1(gr_t) + \beta_2(or_t) + u_t$$

SM Stock market (NSE, PSX, DSE, CSE, NEPSE)

3.4. Dependent Variable

Stock Market Returns (SM_t): The daily returns of selected South Asian stock market indices (e.g., NSE, PSX, DSE, CSE, NEPSE) during and after the COVID-19 pandemic. Where:

NSE: National Stock Exchange PSX: Pakistan Stock Exchange DSE: Dhaka Stock Exchange
CSE: Colombo Stock Exchange NEPSE: Nepal Stock Exchange Independent Variables

1. Gold Price (GP): The daily price of gold, representing the performance of the gold market during and after the COVID-19 pandemic.

2. Oil Price (OP): The daily price of crude oil, indicating the performance of the oil market during and after the COVID-19 pandemic.

4. Discussion & Data Analysis

4.1. Analysis Of Unit Root Test

This test is used to determine whether variables are stationary or not. If a variable is found to be non-stationary, it is further examined to determine if it possesses a unit root by calculating its first differences. A stationary series does not exhibit the property of a unit root. On the other hand, a non-stationary series poses challenges in regression analysis, as the results may not accurately represent the true relationship. Therefore, a significance level of 5% (0.05) was utilized for the Dickey-Fuller Augmented root-based test prior to conducting research and employing the GARCH test.

Analytical findings of the unit root technique are present in the form of table. These results explore the existence of stationary in variables as follow.

Table 1: Analysis of unit root test

Variable	At level		Decision	1 st difference		Decision
	ADF value	P value		ADF value	P value	
Crude oil return	0.9288	0.1829	Non Stationary	-20.42474	0.0000	Stationary
Gold return	0.8927	0.2331	Non Stationary	-17.73613	0.0000	Stationary
NSE	1.5315	0.9994	Non Stationary	-21.21179	0.0000	Stationary
PSX	1.4326	0.8934	Non Stationary	-21.60987	0.0000	Stationary
DSE	0.7132	0.6421	Non Stationary	-18.96079	0.0000	Stationary
CSE	1.2416	0.9566	Non stationary	-15.62811	0.0000	Stationary
NEPSE	1.0569	0.8933	Non	-21.29308	0.0000	Stationary
			<u>Stationary</u>			

To check the stationarity of the independent variables (gold and crude oil) unit root technique is used. The results explore that value of Augmented Dickey-Fuller is higher than the critical value at one percent level of significance and reject the null hypothesis. so stationary of gold and crude oil series is attended at level.

Stock market is dependent variable. To investigate the stationarity of stock market series used unit root test. Results show that value of Augmented Dickey-Fuller is higher than the critical value at one percent level of significance and null hypothesis is rejected. We find out volatility of all stock markets is stationary at level.

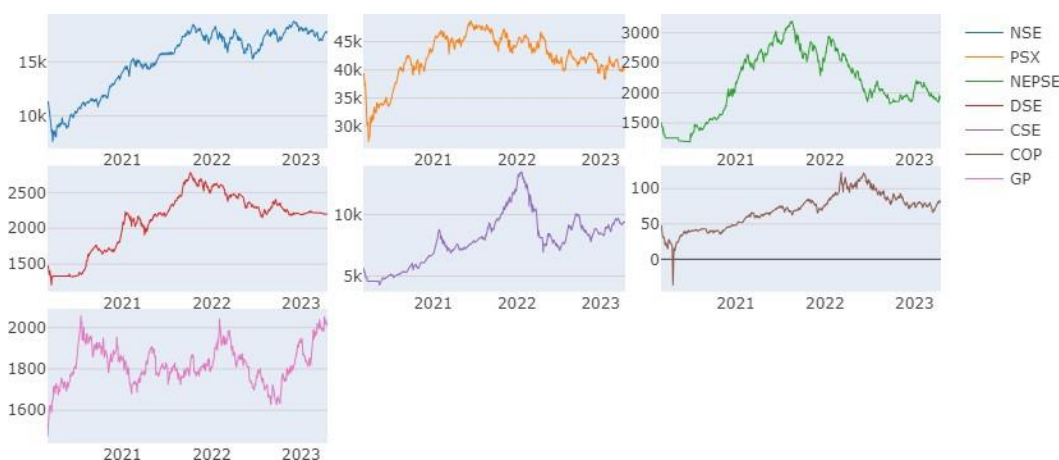
*Figure 1: Prices series evaluation*

Figure 1 Plots of five South Asian stock index price series. Note: The X-axis denote the time

line starting from first observation dated on 02-03-2023 to the last observation 19-04-2023. The total number of daily observations is 818.

Figure 4.1 shows volatility five south Asian stock markets oil and god prices from 2020 to 2021. Upon visual examination, the graphs clearly exhibit volatility with both upward and downward trends as well as irregular patterns that indicate the non-stationary of these time series. Consequently, all the series have been transformed into return.

4.2. Analysis of the Arch Model

The correctness of DCC-GARCH modeling is assessed by searching for ARCH effects in the series errors. We used the heteroskedasticity test to search for ARCH effects in the model.

Table 2: heteroskedasticity test

Series	F-statistic	Obs* R-squared	Prob.F(1,488)	Prob.Chi square(1)
NSE	17.10185	16.59053	0.0000	0.0000
CSE	149.9324	115.1640	0.0000	0.0000
DSE	22.81681	21.88698	0.0000	0.0000
NEPSE	2.746357	2.742180	0.0481	0.0000
PSX	1.287496	1.289371	0.0457	0.0000

Results show that our estimated value is less than level of significance. Both lags are significant. Our p value is 0.0000 which is less than 0.05%. Null hypothesis is rejected and accepted that there is an ARCH effect s exists in return. Heteroskedasticity exist in our model.

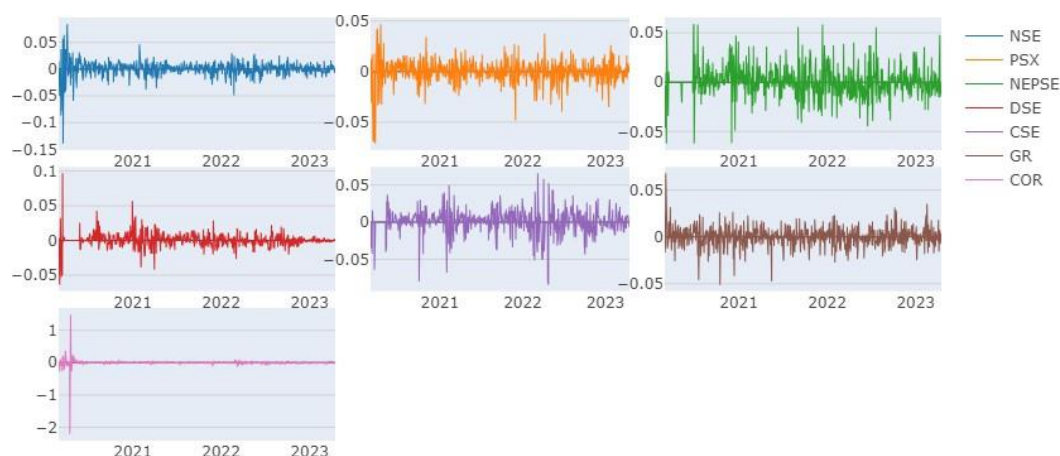


Figure 2: Return series

Figure 4.2 indicates that these series exhibit periods of small variations, followed by other periods where these variations become more pronounced. This suggests that volatility changes over time (Engle and Patton, 2001). Moreover, volatile periods tend to

persist before the market returns to a state of relative normalcy. These figures show that stocks and gold prices are volatile, and the fluctuations in these series can lead to substantial changes in price levels represent variation of return from 2020 to 2023 and there is volatility clustering exist in return series.

4.3. Descriptive Statistics of Return Series

The table below presents the descriptive statistics for the dataset under analysis. This summary includes key measures such as mean, median, mode, standard deviation, and range, which provide a comprehensive overview of the data's central tendency and variability. By examining these statistics, we can better understand the underlying patterns and trends within the data, facilitating informed decision-making and further analysis.

Table 3: Descriptive statistics of return series

	Mean	Standard	Skewness	Kurtosis	Jarque-Bera	ERS	Q(10)	Q ² (10)
NSE	0.009	0.72	4.700***	38.59***	5366.22***	-5.15***	34.132***	245.54***
PSX	0.008	0.70	2.949***	13.76***	7621.795***	-5.75***	206.18***	327.52***
NEPSE	0.01	0.71	1.779***	3.731***	903.803***	-9.39***	98.811***	80.410***
DSE	0.006	0.77	4.161***	30.784***	3474.38***	-7.47***	313.51***	132.60***
CSE	0.01	0.74	2.284***	7.435***	2588.990***	-6.28***	178.73***	147.76***
GOLD	0.007	0.64	2.407***	11.018***	4915.001***	-2.31***	10.95***	7.553
OIL	0.028	0.95	17.270** *	343.79***	4059.163***	-9.45***	289.59***	124.33***

Notes: i) *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

ii) Q

(10) and Q² (10) represent the outcomes of the Ljung-Box Q-test, assessing the absence of autocorrelation at a lag of 10, applied to both the return series and the squared return series, respectively.

In Table 4.3 we observe that the highest average return is attributed to crude oil 0.028 while the least profitable return is associated with NEPSE, with an average of 0.006.

The most volatile return is crude oil, whereas the least risky one is gold, with a standard

deviation of 0.95 and 0.64, respectively. The values of the Kurtosis statistic suggest a non-normal distribution and that all series exhibit a high probability of extreme points, as indicated by coefficients greater than 3. The Excess Kurtosis (Ex.Kurtosis) is positive. Regarding the Skewness coefficients a positive value is observed for all variables indicating that the distribution of these series is skewed to the right. However, the negative skewness indicating the presence of asymmetry in the left; that is, a negative shock has a more significant impact than a positive one. We also conducted three additional tests, namely, the ERS unit root test (Elliott et al., 1996), the Jarque-Bera normality test and an autocorrelation analysis. The results of the unit root test indicate the stationarity of the variables under investigation, and the Jarque-Bera test rejects the null hypothesis of normality. Furthermore, the autocorrelation analysis reveals that exchange rates and oil prices often exhibit a small correlation in their mean processes (the returns) but strong correlation in the square of the returns. In other words, there is a dependency in the squared return series that reveals the presence of an ARCH effect in the returns.

The literature has amply demonstrated the existence of autoregressive conditional heteroscedasticity (ARCH) in time series of asset returns. In other words, asset returns exhibit time-varying volatility (Maraqa and Bein, 2020; Yıldırım et al., 2022). Volatility clustering is defined as the process in which ‘big variations tend to be followed by big variations, or small variations tend to be followed by small variations’. This phenomenon of leptokurtosis in returns is strongly linked to the phenomenon of volatility clustering. Much research explains that asset returns are not independent and identically distributed random variables but tend to exhibit a fat-tailed distribution (Bala and Takimoto, 2017; Maraqa and Bein, 2020). This implies that asset returns are highly unpredictable, as extreme fluctuations are more likely to occur in fat tails. This characteristic of these tails implies that there is a probability of an extreme event for the markets, which suggests the presence of extreme values compared to the average and confirms that the DCC model is suitable for studying return correlations.

In summary, the return series exhibits issues related to residual non-normality, heteroscedasticity and extreme fluctuations in the fat tails. These findings further emphasize the relevance of the DCCGARCH-CONNECTEDNESS approach for exploring the dynamically changing interconnections between the oil, gold and stock markets.

4.4. Analysis Of Dcc-Garch Connectedness

Findings of dynamic conditional correlation generalize autoregressive conditional heteroskedasticity approach are explained in tabulation form (4.4 and 4.5) which show that connectedness exist or not and to which extent.

Table 4: Dynamic Connectedness between Oil and Studied Stock Markets

	NSE	PSX	NEPSE	DSE	CSE	COP	FROM
During COVID-19 period							
NSE	92.66	5.19	0.38	0.48	0.09	1.20	7.34
PSX	3.96	86.16	0.88	0.34	6.19	2.46	13.84
NEPSE	0.32	0.89	97.46	1.00	0.21	0.12	2.54
DSE	1.02	0.58	0.99	97.08	0.22	0.12	2.92
CSE	1.30	81.85	2.69	3.20	0.00	10.96	100.00
COP	3.04	18.91	0.31	0.67	8.92	68.16	33.84
TO	9.64	107.41	5.25	7.69	16.64	15.87	158.49
Inc.Own	102.30	193.57	102.71	102.76	15.64	83.03	TCI
NET	2.30	93.57	2.71	2.76	-84.36	-16.97	38.70
NPT	3.00	5.00	3.00	3.00	0.00	1.00	
After COVID-19 period							
nifty	94.70	0.33	0.01	0.04	1.99	2.94	5.30
kse	0.43	97.47	0.01	0.62	1.46	0.02	2.53
NEPSE	13.96	21.22	0.00	26.43	21.97	16.41	100.00
DSE	0.34	4.25	0.15	95.05	0.03	0.18	4.95
CSE	4.83	2.58	0.03	0.01	92.47	0.08	7.53
COP	5.65	0.03	0.01	0.04	0.06	94.21	6.79
TO	25.21	28.41	0.20	27.14	25.51	20.63	126.10
Inc.Own	119.91	125.87	0.20	122.19	117.98	113.84	TCI
NET	19.91	25.87	-99.80	22.19	17.98	13.84	30.22
NPT	5.00	4.00	0.00	1.00	2.00	3.00	

Table 5: Dynamic Connectedness between Gold and Studied Stock Markets

	NSE	PSX	NEPSE	DSE	CSE	GP	FROM
During COVID-19 period							
NSE	94.88	0.69	0.60	0.04	3.08	0.71	5.12
PSX	0.42	90.44	0.42	1.10	7.06	0.56	9.56

NEPSE	0.09	0.09	92.89	6.12	0.28	0.53	7.11
DSE	0.02	0.78	12.39	86.66	0.15	0.01	13.34
CSE	2.84	11.01	1.24	0.31	84.47	0.12	15.53
GP	16.64	20.86	59.29	0.37	2.83	0.00	100.00
TO	30.82	43.43	73.94	7.94	13.40	1.92	150.65
Inc.Own	114.90	123.87	166.84	94.60	97.87	1.92	TCI
NET	14.90	23.87	66.84	-5.40	-2.13	-98.08	33.83
NPT	1.00	3.00	5.00	4.00	2.00	0.00	
After COVID-19 period							
nifty	92.07	2.04	0.02	0.19	0.56	5.11	7.93
kse	1.24	86.59	0.01	0.14	0.28	11.74	13.41
NEPSE	0.04	0.03	12.12	0.32	0.08	87.41	87.88
DSE	0.24	0.44	0.18	83.24	0.15	15.75	16.76
CSE	0.38	0.34	0.02	0.09	93.60	5.58	6.40
Gp	0.54	1.60	2.97	1.64	0.79	92.47	7.53
TO	2.43	4.45	3.20	2.37	1.86	125.59	139.90
Inc.Own	94.51	91.03	15.32	85.61	95.46	218.06	TCI
NET	-5.49	-8.97	-84.68	-14.39	-4.54	118.06	27.67

Tables 4.4 and 4.5 illustrate the average dynamic connectedness measures among gold, oil, and the five studied stock markets during and after the COVID-19 pandemic. Table 4.4 shows that the total connectedness (TCI) between oil and the five stock markets increased during the COVID-19 pandemic, 38.70% against 30.22% in the Post-COVID-19 period.

Table 4.5 shows that the TCI between gold and the stock markets also increased during the COVID-19 pandemic (33.83% vs. 27.09% after the outbreak). The same results are shown by different researchers under COVID-19, such as for agricultural commodities (Umar et al., 2021) and stock markets (Zhang et al., 2021). These results reveal that information transmission increases during unstable periods like crises and wars. Results also prove that when uncertainty in a market increases, diversification provides fewer benefits (Yousaf and Hassan, 2019). Overall, the results indicate that the studied markets are moderately inter-connected and that the TCI among them increased during the pandemic period. In addition, our findings suggest that both oil and gold becomes the net receiver during the COVID-19 pandemic period while oil and gold acts as the net transmitter after pandemic which transfer to all studied stock market.

Moving to the 'TO' row, which illustrates the directional spillover effects, TO row of the table 4.4 and 4.5 gives the contribution of each series towards the system (all other variables combined except the selected one). During COVID-19 the stock indices of Nepal (NEPSE), Pakistan (KSE), and India (NIFTY) have the strongest effect on other variables with values of 73.94%, 43.63%, and 30.82%, respectively (meaning all other variables except NIFTY, KSE and NEPSE). Post COVID-19 all indices have little spillover in to the system where as the gold

is the largest average contributor of volatility spillovers to other markets with value 125.59%.

In table 4.4 during COVID-19 we find that the kse-100 is the largest average contributor of volatility spillovers to other markets (oil and stock markets). From the 'TO' row, we observe that the total directional connectedness TO others, which highlights the influence of oil price shocks on all stock indexes, is approximately 15.87% during COVID-19 and 20.63% for post COVID-19 period.

The last column of Table 4.5 shows the spillover received by each variable FROM the system. The gold market receives 100% spillover from all selected equity markets while the equity indices receive spillovers of between 5% to 15% during COVID-19. While after COVID-19 gold receives only 7.53%. In addition, the Nepal stock market is the largest recipient of volatility spillovers, with an average contribution of all other markets estimated at 87.88%. Similarly, volatility spillover from all stock indexes to the petrol market is around 33.84% and 6.79% during and after COVID-19 respectively. These TO and FROM values suggest that the connectedness between the oil and stock markets is moderate.

The net spillovers are presented in the last row of Table 4.4 and 4.5 which is useful to identify the net recipients and transmitters, explained by the net pair wise directional index. The stock indices India (NIFTY), Pakistan (KSE), Bangladesh (DSE) and Nepal (NEPSE) are net transmitters of spillover to other variables in the system while Sri Lanka (CSE), gold and oil are net recipients of spillover from other stock indices during COVID-

19. The equity index of Pakistan (KSE) transmits most spillover (93.53%) to the system, while the stock index of Sri Lanka (CSE) receives the most spillover (-84.36%) during COVID-19. After the pandemic period all stock indices are net recipients while gold is the net transmitter of spillover with a value of 118.06%. In the case of oil and stock indices only Nepal (NEPSE) is the net recipient with a value of -99.80% and oil and other stock indices are net transmitters of spillover ranging from 14% to 25%. The results of this study are in line with Zhang et al. (2021) who also find the highest volatility during COVID-19.

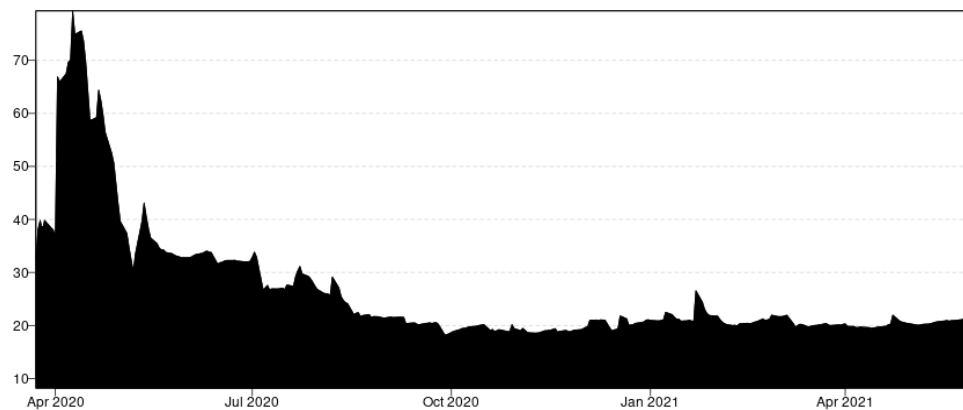


Figure 3 (a): Total connectedness index oil and stock markets during COVID-19

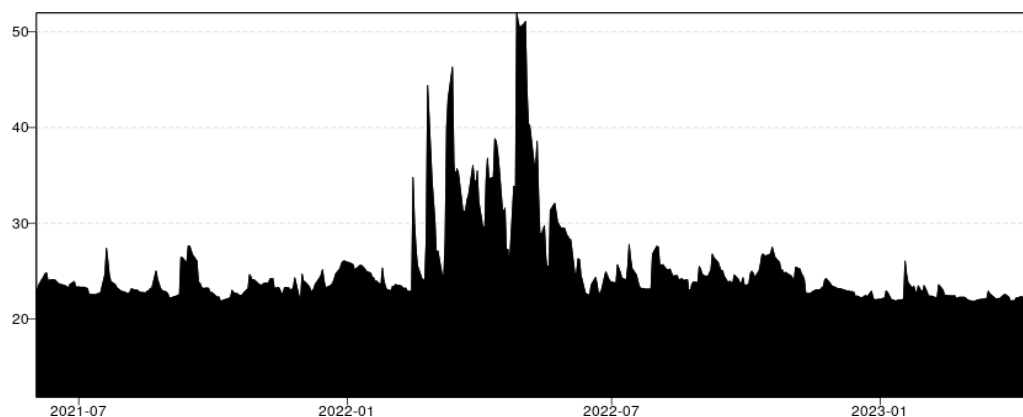


Figure 3 (b): Total connectedness index oil and stock markets after COVID-19

Figure 3(a) and 3(b) display the dynamic total connectedness (TCI). Regarding oil with these stock markets, the total connectedness index is approximately between 25 to 75% and after covid-19 from 25 to 53% approximately. Fig.3 shows that this index increased during the pandemic %. Fig.3 shows that this index increased during the pandemic, peaking at over 70% shortly after the pandemic was declared. Overall, our findings show that COVID-19 has influenced the connectedness level between the gold market and the studied stock markets and between the oil market and these markets, as well. This outcome is owed to the amplification of crisis effect transmission between them. These findings are consistent with the hypothesis of market contagion in the literature, suggesting that periods of financial crisis generate large return connectedness between commodities and stock markets.

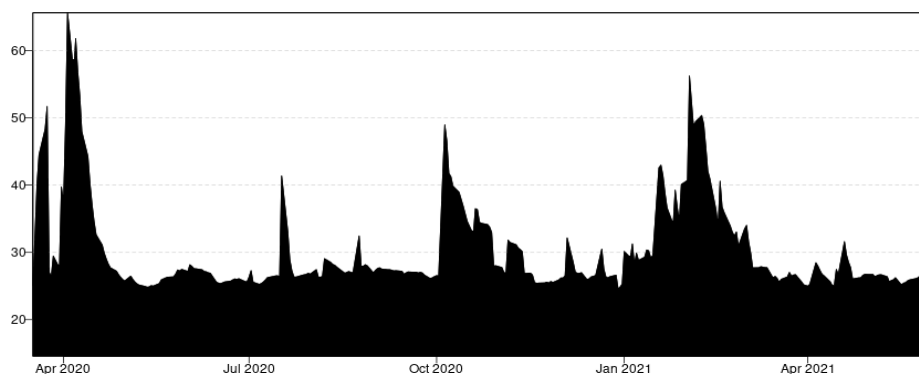


Figure 4 (a): Total connectedness index gold and stock markets during COVID-19

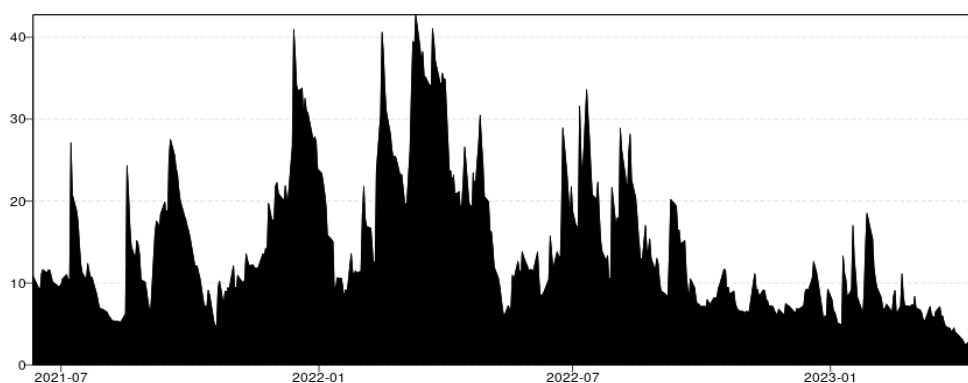


Figure 4 (b): Total connectedness index between gold and stock markets After COVID-19

Figure 4(a and b) indicates the TCI between gold and the five stock markets spanned approximately between 25 and 65% after the pandemic from 25 to 53% during it. Therefore, the TCI sharply increased instantly after COVID-19 was declared a pandemic by the World Health Organization (WHO), indicating this event significantly affected the connectedness between gold and the selected stock markets.

Comparing the spillover of these two periods, it is obvious that the highest rise in information transmission occurs during COVID-19, when the total connectedness increase 75%(oil and equity) and 55% (gold and equity markets).At the start of COVID-19, the information transmission increases to 75% then decreases gradually. Overall, these results show that the return and volatility spillover increase during turbulent periods such as financial crises and pandemics, because such incidents create uncertainty and panic among investors. This study supports the argument that when uncertainty in the market increases, diversification provides fewer benefits.

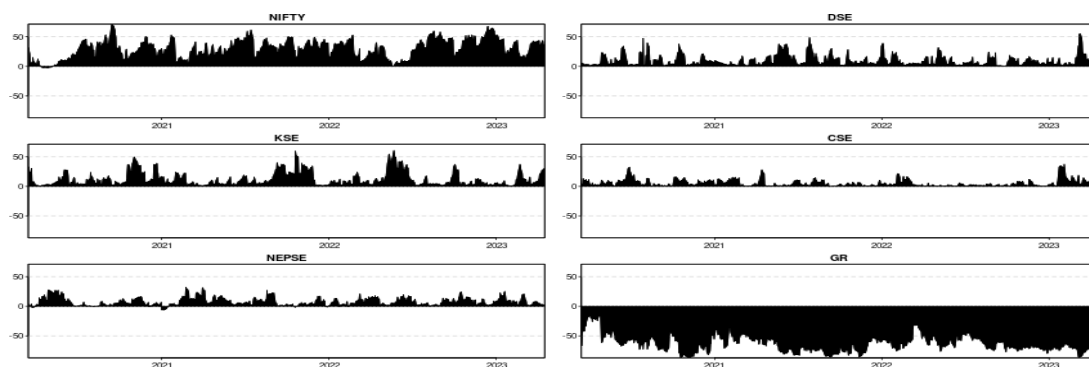


Figure 5: Net connectedness index for gold and the five stock markets

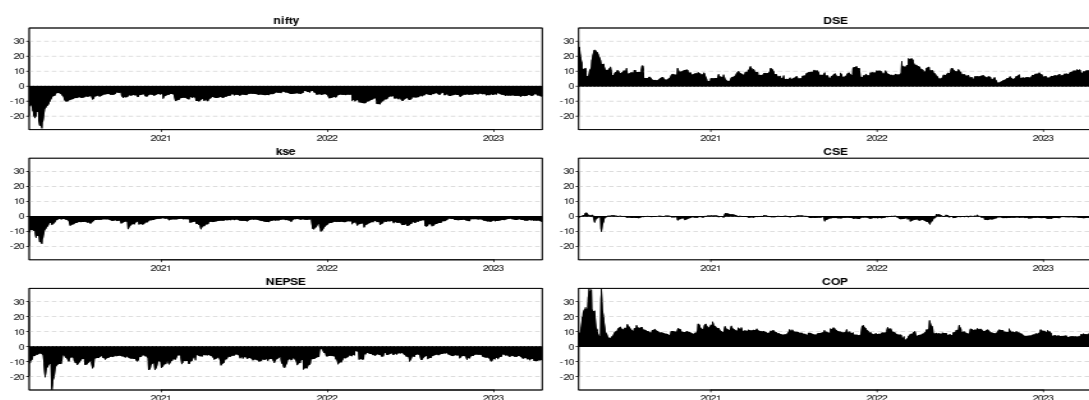


Figure 6: Net connectedness indexes for oil and the five stock markets

Figure 5 and 6 display the net total directional connectedness index over the compared periods. The main results emerging from these figures follow. First, the results highlight that the net connectedness of all studied markets peaked during the COVID-19 pandemic, in a behavior similar to the total connectedness index presented in the previous section. From these figures, it is evident that the net connectedness behavior has significantly changed during the pandemic compared to the post-COVID-19 period. Second, Fig. 5 shows that gold is a receiver of shocks from the five stock markets. Finally, similar behavior is found when considering the oil returns with the five stock markets. As shown in Figure. 6, oil exhibits a higher net connectedness index during the pandemic period. It remains a net transmitter of shock to all five selected stock markets during the entire pandemic period. The findings of the dynamic net connectedness replicate how stock markets react with oil and gold in periods of crisis. During the COVID-19 pandemic, the combination of stagnant production and high economic uncertainty generated increasing volatility in oil prices, making this strategic commodity the largest transmitter of shock to stock markets. Individual investors' pessimism boosts investment in gold, which is commonly viewed as a primary safe-haven asset, making this commodity the largest receiver of shock from stock markets.

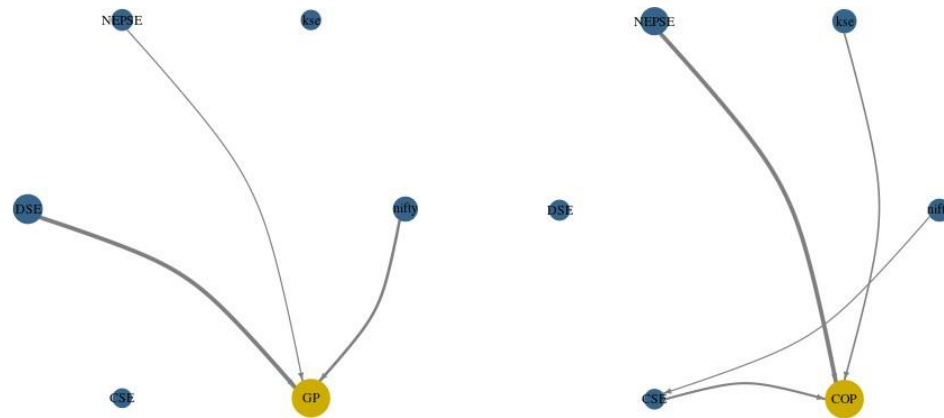


Figure 7: a Network plot during COVID-19

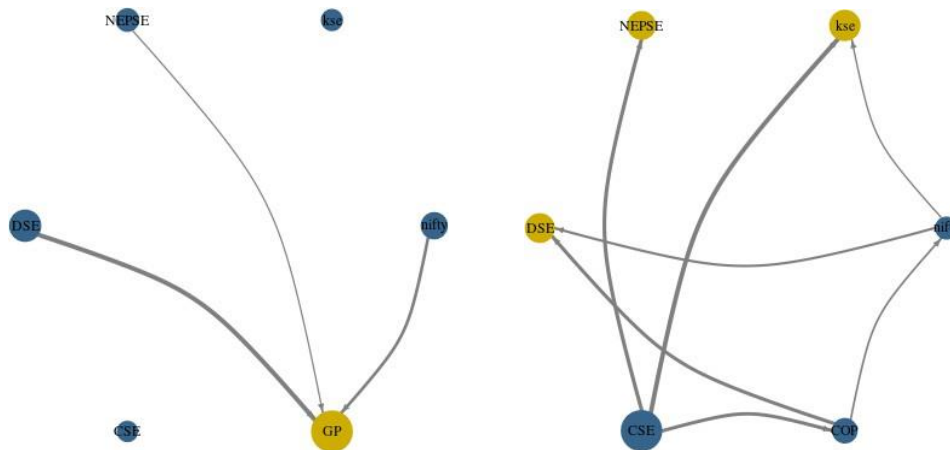


Figure 8: a Network plot after COVID-19

In the figures 7 and 8 the direction of connectedness is indicated by the arrows on each line. A yellow (blue) circle represents a variable that is a net receiver (net transmitter) of shocks. Figure 4.7 and 4.8 shows the direction of connectedness during COVID-19 both gold and oil became net receiver of shock from all stock markets and after normalcy of pandemic both oil and gold became net transmitter of shock to stock markets.

5. Conclusion and Policy Implication

5.1. Conclusion

The present study investigates dynamic connectedness oil gold and stock indices of emerging south Asian countries (India, Pakistan, Bangladesh, Sri Lanka and Nepal) during the sample period 2020 to 2023. The volatility spillovers are calculated using the DCC-GARCH connectedness approach proposed by Gabauer (2020). The static analysis of dynamic

connectedness shows that the total return connectedness index of the oil market and equity indices is 38.83% and gold and equity market is 33% a moderate integration. Which means that the markets transfer less risk to each other? These results are supported by Sharif et al. (2020) Benlagha et al (2021) and Zhang et al. (2021) who find similar results for developed stock markets. We also found that the COVID-19 pandemic increased the connectedness among oil, gold and the five selected stock markets. Our results also show that gold and oil is receiver of shock from the five stock markets during this outbreak and became transmitter of shock after the pandemic. These outcomes are associated with the hypothesis of market contagion, suggesting that the periods of financial distress induce large return connectedness in several asset markets.

The net volatility connectedness analysis shows that crude oil are net transmitters and most of the stock indices and gold are net recipients which supports the results of Abuzayed et al. (2021) who find the same for GCC stock markets. Therefore, the TCI sharply increased instantly after COVID-19 was declared a pandemic by the World Health Organization (WHO), indicating this event significantly affected the connectedness between oil and the selected stock markets.

Our dynamic analysis shows that commodities(oil and gold) are net recipient of risk during COVID-19, which contradict with the results of Benlagha and El Omari (2022) and Zhang et al. (2021) that commodities are net receivers of shocks before COVID-19 but become transmitters of shocks during COVID-19. Our results also contradict Mensi et al. (2021) who propose that during low volatility regimes, oil is a net receiver of shocks and, during high volatility regimes, a net transmitter of shocks, based on a study of United States and Chinese stock markets. Our findings imply that oil is a net transmitter of shocks during the overall period in emerging Asian stock markets.

The results imply that, during COVID-19, the south Asian financial markets are net transmitter of shocks instead Colombo stock exc, the study concludes that the highest spillover occurs during COVID-19 reducing the benefits of diversification. These findings follow the results of Jebabli et al. (2022) and Yousaf et al.(2022) who find the same for the relationship between the energy market (oil and natural gas) and stock markets.

The findings of the dynamic net connectedness replicate how stock markets react with oil and gold in periods of crisis. During the COVID-19 pandemic, the combination of stagnant

production and high economic uncertainty generated increasing volatility in oil prices, making this strategic commodity the largest transmitter of shock to stock markets. Individual investors' pessimism boosts investment in gold, which is commonly viewed as a primary safe-haven asset, making this commodity the largest receiver of shock from stock markets. As the COVID-19 pandemic, which has ruined the worldwide economic position, originated in China, there is more chance of transfer of this shock to other Asian stock markets, which may reduce the benefits of diversification. Therefore, investors and portfolio managers need to identify markets which can be used to diversify risk in a portfolio. As an alternative, investors and portfolio managers can add energy commodities and precious metal such as gold which are less interconnected to portfolios to diversify risk during COVID-19.

The study's findings demonstrate that, in contrast to oil, gold may be utilized for financing during a financial controversy such as the COVID-19 epidemic because a drop in oil demand can cause changes in oil prices. According to Hongsakulvasu and Liamukda (2020), the COVID-19 epidemic and the oil price battle caused an explosive dip in oil price. In light of COVID-19 plague practically every nation enacted a lockdown strategy, which decreased oil demand. The economy was forced to halt, particularly air and land traffic.

The conclusion suggest gold might serve precisely safe haven during an economic slump, and it is hoped that by examining each volatility, investors will be encouraged to add petroleum and gold instruments to their portfolios during times of crisis. Gold is either uncorrelated with any asset or has a negative correlation, making it a safe haven. The findings of this study may have significant policy ramifications for both stock investors and decision-makers. When formulating plans to lessen the interconnectedness of stock markets during pandemics, for instance, regulators should be cognizant connections amid precious metal and oil and their impact on financial markets.

5.2. Policy Implication

Based on the conclusions drawn from the research, several policy implications are suggested: Investors and portfolio managers could consider diversifying their portfolios by including both petroleum and gold instruments, especially during times of crisis such as the COVID-19 pandemic. The study suggests that while oil prices are susceptible to demand shocks, gold may serve as a safe haven during economic downturns.

Policymakers and regulators should take into account the dynamic associations between precious metals, oil prices, and stock markets when formulating risk management policies. Understanding the interconnections among these assets can help mitigate risks during pandemics and other crises.

The findings highlight gold as a potential safe haven asset during economic slumps. This suggests that investors may consider allocating a portion of their portfolios to gold to hedge against market volatility and uncertainty. Authorities should monitor and analyze the volatility of oil and gold prices, as well as their impact on financial markets, to ensure market stability during times of crisis.

This may involve implementing measures to prevent excessive volatility and mitigate potential negative spillover effects. Policymakers may need to consider implementing measures to address disruptions in oil demand and supply chains during pandemics. This could include strategies to support industries affected by reduced oil demand, as well as measures to promote alternative sources of energy.

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