Journal of Research in Economics and Finance Management
ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

EXPLORING DYNAMIC INTERRELATIONSHIP & VOLATILITY SPILLOVER BETWEEN OIL PRICES & STOCK MARKET RETURNS OF CHINA & PAKISTAN

Dr. Unbreen Arif
Assistant Professor
UE Business School
Division of Management & Administrative Sciences,
University of Education Lower Mall Campus, Lahore
unbreen.arif@ue.edu.pk

Dr. Israr Ahmed
Associate Professor
Faculty of Management Sciences
ILMA University
dr.israrahmed@ilmauniversity.edu.pk

Dr. Salman Khatani
Assistant Professor
Department of Business Administration
Iqra University

Bushra Hassan
PhD Scholar
Department of Computer Science
Manchester Metropolitan University, United Kingdom
22543412@stu.mmu.ac.uk

Abstract

The current study analyzes the dynamic interrelationship and volatility spillover impact between international crude oil prices and stock market returns of two economies, China and Pakistan, connected via the One Belt and One Road initiative as multiple projects are in process, and these two countries are in close strategic alliance through CPEC. The DCC-GARCH Model is used for the analysis of the daily data for the sample period of 10 years. The empirical results revealed that there exists a correlation between international oil prices and the SCI stock market returns and the KSE100 index. The findings also reported that the transmission of volatility has a significant impact both in the short term and long term on oil prices and stock market returns of the two countries. The study findings are useful for investors, traders, and fund managers to make decisions in bilateral arrangements between two countries to diversify and hedge their risk of portfolios.

Keywords: Machine Learning Models, Volatility Spillover, Stock Returns, Exchange Rate, Oil Prices.

Introduction

The volatility spillover is defined as the instability spillover from market to market. The shock transmission from one country's financial market to another is a phenomenon that is of special interest to investors and fund managers when making investment decisions and forecasting trends. After the financial Crisis of 2008, the

This work is licensed under a Creative Commons Attribution 4.0 International License.

financial market integration modelling and spillover impact gained the attention of investors and policymakers. As in the case of oil importing country, the volatility in the prices of oil will have an impact on foreign exchange, and the increase in demand for foreign exchange will have an impact on the trade balance of local & and foreign goods and ultimately on the cashflows of the companies and their returns. In the year 1990 (Engle et al.) gave the volatility spillover concept through two hypotheses: one is the "Heatwave hypothesis", and the second is the meteor Shower Hypothesis" In the first hypothesis, volatility is known as "volatility clustering", i.e. country-specific autocorrelation, while in the second hypothesis, volatility is called "volatility transmission" i.e. where the volatility is the result of its country spill over and the due to the other country market spill over (Bekaert, Ehrmann, Fratzscher, & Mehl, 2014).

Crude oil is an important commodity and vital to the performance of multiple sectors of an economy. Internationally, crude oil prices are dependent upon demand and supply, and the fluctuation in oil prices has a significant impact on the economy (Lin, Xiao, & Chai, 2023). The development of financial markets is also an indicator of economic health as they serve as a platform for fund seekers and fund providers. The development of the market is aligned with the development of business activities and the increased demand for energy resources to run businesses. So, the issue captures the interest of investors on whether fluctuations in international oil prices have a spillover impact on stock returns of financial markets. The volatility analysis serves as an opportunity and risk. The higher the volatility, the higher the probability of loss, but in the long term, it also serves as an opportunity for an investor to buy at lower and sell at higher, so the opportunity to gain exists. Most of the empirical investigations on the issue have emphasized developed markets only, while there exists a strong demand to explore the volatility impact of emerging economies due to their dependence on developed countries. This is of vital significance in the case of China & and Pakistan as they are interlinked with multiple projects initiated under CPEC.

The Dynamic Conditional Correlation GARCH (DCC-GARCH) model is a popular econometric model used to estimate the conditional correlation between two or more time series. The model is used to capture time-varying correlation in time series. The model consists of univariate GARCH for each time series, and the evolution of correlation concerning time is measured in a dynamic correlation model with an assumption that the individual time series conditional variances follow the GARCH process. In contrast, the conditional correlation between the series follows a separate process. The model provides an optimal estimation of risk and returns by capturing the time-varying correlation of assets and enables investors to benefit from efficient portfolios to get optimal returns. In 2002, to analyze the multivariate series, this model was introduced by (Engle R. , 2002). The DCC-GARCH Model is used to study interdependence in volatility in one variable on another. This model is driven by two parameters, α and β, and not only directly models variance & and covariance but also the flexibility, i.e. whether the variance relationship is of short-term persistence or long-term persistence. So, in order to measure the real impact of the volatility of one variable over another variable, the DCC GARCH Model is used.

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

Rationale

The study investigates the economic effects of the China-Pakistan Economic Corridor (CPEC), with a special emphasis on the relationship between regional connectivity and stock market return predictability between China and Pakistan. Considering the substantial fluctuations in exchange rates caused by intricate geopolitics and the fluctuations in oil prices impacting both countries as oil-importing states, the research aims to simulate and comprehend the transfer of this volatility to the stock markets of China (Shanghai Stock Market) and Pakistan (PSX). This analysis is important because both nations are engaged in CPEC-related strategic projects that could have an impact on their stock market performance and economic stability.

Problem Statement

The regional connectivity of countries under CPEC has reported uneven economic development, and also, due to the complex geopolitics, the exchange rate volatility is a significant issue (Geng & Guo, 2022). The current study objective is to investigate whether or not the regional connectivity of China and Pakistan shifted volatility spillover, which illustrates the predictability of PSX returns from the Shanghai Stock Market & vice versa. Moreover, since both countries are oil-importing countries, the volatility in oil prices has been observed over the past decades. So, there is a need to explore the volatility transmission of oil prices to stock returns of both economies. In the context of CPEC, where both countries have strategic alliances and multiple projects are in progress, the current study is an attempt to empirically investigate via modelling volatility transmission of the variables of oil Prices and stock market returns of both economies.

Research Questions

1. How does regional connectivity between China and Pakistan influence volatility spillover, and to what extent does this affect the predictability of PSX returns from the Shanghai Stock Market and vice versa?

2. What is the impact of oil price volatility on the stock returns of China and Pakistan?

3. Is the volatility spillover between China and Pakistan symmetric or asymmetric?

4. How does the volatility spillover effect vary over time, particularly in the short-term versus the long-term?

5. What distinct patterns of volatility spillover exist among oil-exporting countries connected through the strategic alliance of the Belt and Road Initiative (OBOR)?

6. Are there opportunities for hedging and portfolio diversification in the context of volatility spillover between China and Pakistan?

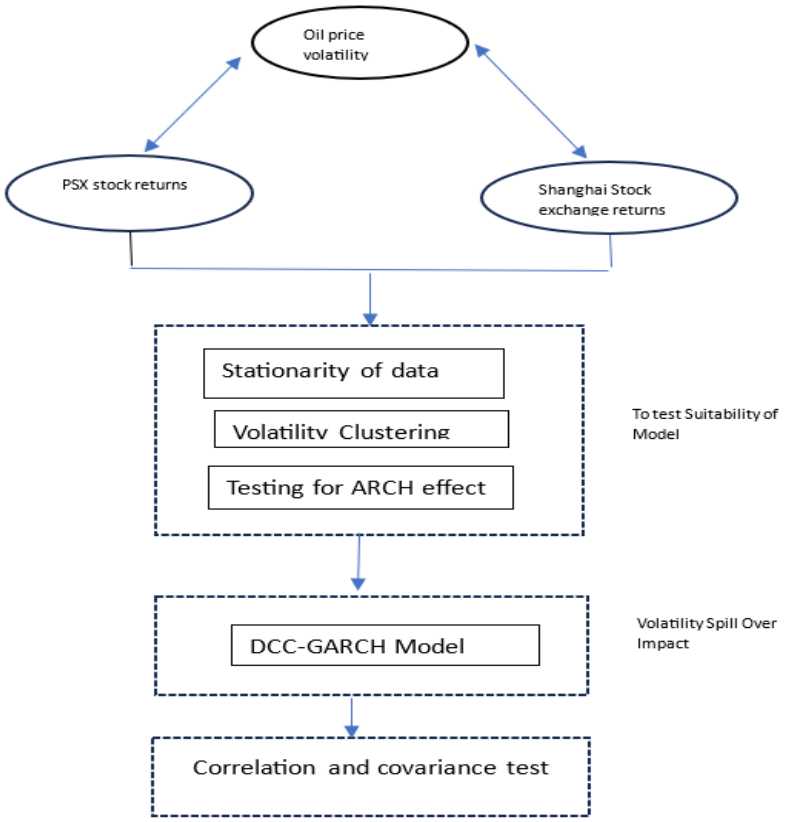
Research objectives

- To investigate whether or not the regional connectivity of China and Pakistan shifted volatility spillover, which illustrates the predictability of PSX returns from the Shanghai Stock Market & vice versa.
- To quantify the volatility spillover impact of oil prices and stock returns of China and Pakistan.
- To explore the spillover impact, whether symmetric or asymmetric.
- To investigate the time-varying effect of volatility spillover (short-term vs long-term)
- To explore the distinct patterns of oil exporting countries connected through the strategic alliance of OBOR.
- Identify whether hedging options and portfolio diversification opportunities exist in the context of volatility spillover between two countries.

Conceptual Framework

Volatility spillover is defined as a phenomenon where fluctuation or variation in one market has an impact on another market volatility, several factors both direct and indirect, contributes towards the spillover impact. have both direct and indirect To understand the complex link between oil prices, stock market returns and volatility spillovers is the main research challenge. It specifically attempts to look into whether there are major spillover effects between these two sectors and how changes in oil prices affect stock market performance. In the arbitrage pricing theory (APT), the stock returns are impacted by multiple factors (Gur, 1989) (Christian, 1991) the changes in oil prices have an impact on asset prices measured by the sensitivity of the APT model. The changes also influence the asset return information as the markets are efficient (Malkiel, 1989), and the asset prices reflect all the available information. So, from the perspective of the efficient market hypothesis (EMH), the changes or volatility of oil prices affect stock returns. China and Pakistan are emerging economies. Such economies are attributed to being highly volatile markets (Sabri, 2004), and both countries currently have a long history of relationships. They are strategically allied in multiple projects under CPEC (Hilali, 2019). Regional connectivity is analyzed with the network of interdependence and complex network theories of econometric models (Silva, Wihlem, & Tabak, 2023), as geopolitical events and financial Crises have an impact on multiple markets. The conceptual framework of volatility spillover impact constitutes multiple factors ranging from economic, behavioural and financial factors, which have time-varying effects analyzed through econometric models.

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024



Conceptual Framework: Author's work

Significance of the Study

The volatility spillover impact has gained significant importance. Crude oil is an important commodity and vital to the performance of multiple sectors of an economy to diversify, hedge and mitigate portfolio risk. The topic is of much interest to investors, policymakers and fund managers. China and Pakistan are major oil-importing countries, and currently, both countries are strategically interconnected under multiple CPEC projects. The current study filled the gap in the literature by analyzing the volatility spillover impact between oil prices and stock market returns. The findings of the study will provide insight to the investor's fund managers to streamline policies to hedge risk through an understanding of the ripple effect of oil prices on interconnected economies to diversify their portfolio of investments.

Limitations

The current study has analyzed the spillover impact of the Volatility of oil prices on stock market returns of the interconnected economies of China and Pakistan. At the same time, in further studies, other macroeconomic variables like foreign exchange rates may also be explored to test the volatility spillover impact of interconnected economies. The study was conducted to empirically investigate the volatility spillover impact of China and Pakistan's economic stock returns; under OBOR initiatives, more than 100 countries are interconnected. In the future, further

studies may be initiated to empirically investigate the volatility spillover impact of stock returns of OBOR member economies. Further, the machine learning models for the time series data may also be delayed in future studies.

In this context, the remaining sections of the paper are organized in a way that section 2 provides the empirical background and review of existing literature on dynamic spillover impact on stock and oil prices. In section 3, methodology and data will be explained. In sections 4 and 5, the empirical results of the study and conclusion and discussions are summarized.

Literature Review

After the global financial Crisis of 2008, the volatility spillover impact gained significant importance. The topic of diversifying hedges and mitigating portfolio risk is of much interest to investors, policymakers, and fund managers. The oil market, being the largest commodity market (Mensi, 2019), has shown a significant impact on the stock market over time and across frequencies. The oil exchange rate and stock market nexus have always remained a popular topic in multiple studies & exploring the volatility spillover effect. Many studies were initiated in the context of developed countries. The relationship between oil prices and the exchange rate was investigated by (Benhmad, 2012), who reported the findings that the linear and nonlinear causal relationship has varied over time between real oil prices & and real effective US Dollar Exchange rate. Another study of (Grobys, 2015) empirical results indicates that the volatility of the exchange rate of US Stock Market 03 trading partners, i.e. Canada, EU & Japan, is high in the preceding economic trouble phase. Using the copula approach to investigate the relationship between oil, gas, coal, and iron ore prices, Australian dollar and Chinese RMB exchange rate during the period 2010-2018, the findings reveal that the increase in prices of commodities is linked with the increase in AUD and decrease in Chinese RMB (Ma & Wang, 2019). Economic policy uncertainty causes volatility in exchange rates (Bartsch, 2019). The foreign exchange market is a contributor to the transmission of volatility, followed by the money market, while the stock market is the net recipient (Fasanya & Akinde, 2019). Volatility spillover is the result of financial events and market integration (He, 2001). The interconnectedness of the markets is due to the impact of events categorized as economic, political and financial events. A study was conducted in the prospect of 6 Asian countries. The efficient stock market returns truly reflect the occurrence of international and local/domestic events.

The emerging economies are attributed as highly volatile markets (Sabri, 2004), and very few studies are available that have explored the volatility transmission of oil prices, Exchange rates, & Stock returns, specifically in the context of China and Pakistan. The oil prices are very volatile and have an impact on the economy as well. The study results reported that in the case of oil-importing countries, the increase in oil prices caused foreign exchange depreciation in these countries and vice versa (Golub, 1983). another study reported while utilizing data from OPEC countries that a long-term relationship exists between oil prices and the exchange rates (Nibakht, 2010). The oil shocks have an impact on the economy, which ultimately has an impact on the country's competitiveness. The price volatility has an impact on the exchange rates of oil importing and exporting countries, but the

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

magnitude but no systematic pattern of impact of these shocks exists (Basher, Haug, & Sadorsky, 2016). The oil shocks are connected with the variation in the exchange rate of oil-dependent countries, and significant volatility impact exists between exchange rates (Farooq & Zaghum, 2019). The financial crisis has negatively impacted emerging market stock returns, as reported by the study (Al-Rjoub & Azzam, 2012). The nexus of volatility and exchange rate is explored by (Živkov, Gajić-Glamočlija, & Đurašković, 2022), who reported that bidirectional volatilities are present in selected countries and long-term spillover effects exist from exchange rate to Market returns. By employing the model of VAR-GARCH, the volatility spillover impact of oil prices, exchange rates, and stock returns of China and Russia were empirically investigated by (JAGHOUBI, 2021) and reported both markets are sensitive to their past returns. The empirical findings of a study conducted in Turkey using the EGARCH model to measure time-varying volatility between oil prices and stock returns reported a significant effect on stock returns (Cevik, Cevik, & Dibooglu, 2020).

Research Methodology

This study investigates the volatility transmission between oil prices, exchange rates, and stock market returns in China and Pakistan, a crucial area of interest following the 2008 global financial crisis. To analyze these relationships, the study employs the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, which is well-suited for capturing time-varying volatility in dynamic markets.

Daily data from the WTI Crude Oil Future Index, Shanghai Composite Index (SCI), KSE-100 Index, and foreign exchange rates are collected from 2010 to December 2021. The stationarity of the data is verified using the Augmented Dickey-Fuller (ADF) test, and the presence of volatility clustering is checked through the ARCH test, ensuring the data's suitability for GARCH modeling.

The DCC-GARCH model is implemented using R-Studio to analyze both short-term and long-term volatility spillovers. This model is chosen for its flexibility, accuracy, and widespread use in capturing volatility in financial markets, making it appropriate for addressing the study's research questions.

Econometric Method

The DCC-GARCH model can be defined as

Let Y_t Is (nx1) vector then Y_t~ DCC-GARCH if

$$Y_t = \mu_t + \varepsilon_t \quad (1)$$

$$\varepsilon_t = V_t^{\frac{1}{2}} \varepsilon_t$$

$$V_t = D_t \, C_t D_t$$

with

$$D_t = \begin{pmatrix} V_t^{\frac{1}{2}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & V_t^{\frac{1}{2}} \end{pmatrix}$$

Where

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \cdots & \rho_{3n,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \cdots & \rho_{n,n-1,t} & 1 \end{pmatrix}$$

And

$V_{i,t} = \alpha_{0i} + \sum_{q=1}^{Q_i} \alpha_{iq} \varepsilon_{i,t-q}^2 + + \sum_{p=1}^{P_i} \beta_{ip} V_{i,t-p}$

μ_t = nx1 vector of conditional expectation Y_t at time t.

ε_t = nx1 vector of conditional error of n.

V_t = conditional variance and covariance matrix of ε_t at time t.

D_t = diagonal matrix (nxn) of ε_t

C_t= nxn matrix of conditional correlation of ε_t at time t.

ε_t = (nx1) vector of errors. With properties E(ε_t) = 0 & E($\varepsilon_t \varepsilon_t'$)=$I_n$

C_t Elements are less than or equal to one, i.e. ($\rho_i \leq 1 \; \forall \; i$). Therefore C_t It can be split into two matrices.

$C_t = R_t^{*-1} R_t R_t^{*-1}$

Where,

$$R_t^* = \begin{pmatrix} \sqrt{r_{11}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{r_{nn,t}} \end{pmatrix}$$

$$R_t = \begin{pmatrix} r_{11,t} & \sqrt{r_{11,t} r_{22,t}} & \cdots & \sqrt{r_{11,t} r_{nn,t}} \\ \sqrt{r_{11,t} r_{22,t}} & r_{22,t} & \ddots & \sqrt{r_{22,t} r_{nn,t}} \\ \vdots & \vdots & \ddots & \vdots \\ \sqrt{r_{11,t} r_{nn,t}} & \sqrt{r_{22,t} r_{nn,t}} & \cdots & r_{nn,t} \end{pmatrix}$$

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

For DCC(p,r)

R_t = [1 - $\sum_{i=1}^{P} \alpha_{DCC,i} - \sum_{j=1}^{R} \beta_{DCC,j}]\bar{R} + \sum_{i=1}^{P} \alpha_{DCC,i(\varepsilon_{t-i}\varepsilon'_{t-i})} + \sum_{j=1}^{R} \beta_{DCC,j} R_{t-j}$

In Case of DCC (1,1)

R_t = (1-α_{DCC}-β_{DCC})$\bar{R}$ + $\alpha_{DCC,i(\varepsilon_{t-i}\varepsilon'_{t-i})}$+$\beta_{DCC,j} R_{t-1}$

C_t > 0 if & only if R_t> 0, so that V_t is positive, following conditions required to be satisfied

$\alpha_{DCC} \geq 0$

$\beta_{DCC} \geq 0$

$\alpha_{DCC} + \beta_{DCC} \leq 1$

The estimates of DCC and GARCH are obtained using the maximum likelihood method for the variable. $Y_t = \sqrt{V_t}\,\varepsilon_t$ likelihood function is

L(θ) = $\prod_{t=1}^{T} \frac{1}{\sqrt{(2\pi)^n / V_t}}$ exp(-$\frac{1}{2} Y_t^T V_t Y_t$)

Where θ = ($\emptyset, \omega$) are estimated parameters

$\emptyset$ = ($\alpha_0, \alpha_{1,i}, \ldots\ldots, \alpha_{p,i}, \beta_{1,i,}, \ldots\ldots \beta_{R,i}$); $\omega = (\alpha_{DCC}, \beta_{DCC})$

The log-likelihood may be written as:-

L= - $\frac{1}{2}\sum_{t=1}^{T}$(nlog (2$\pi$))+2log|$D_t$|+log|$D_t$| + log|$V_t$| + $X_t' D_t^{-1} D_t^{-1} C_t^{-1} Y_t$

L($\theta, \emptyset$) = $L_v(\theta)$ + $L_c(\theta, \emptyset)$

$L_v(\theta)$ = - $\frac{1}{2}\sum_{t=1}^{T}$(nlog (2$\pi$))+2log|$D_t$|+ $Y_t' D_t^{-1} D_t^{-1} C_t^{-1} Y_t$

$L_c(\theta, \emptyset)$ = $\frac{1}{2}\sum_{t=1}^{T}$(log |$C_t$| + $\varepsilon_t' C_t' \varepsilon_t - \varepsilon_t' \varepsilon_t$)

We estimate this model in two steps

Estimate conditional variance with univariate GARCH $L_v(\theta)$

Standardized residuals are used to estimate the parameters of the DCC matrix. $L_c(\theta, \emptyset)$.

As a result, which estimator obtained is $\emptyset^* = arg_{\emptyset} max L_c(\theta, \emptyset)$ with the condition that the likelihood estimator will converge & asymptomatically exhibit normality, i.e.$\sqrt{T}\left(\hat{\theta} - \theta_0\right) \rightarrow \aleph(0, V(\theta_0))$

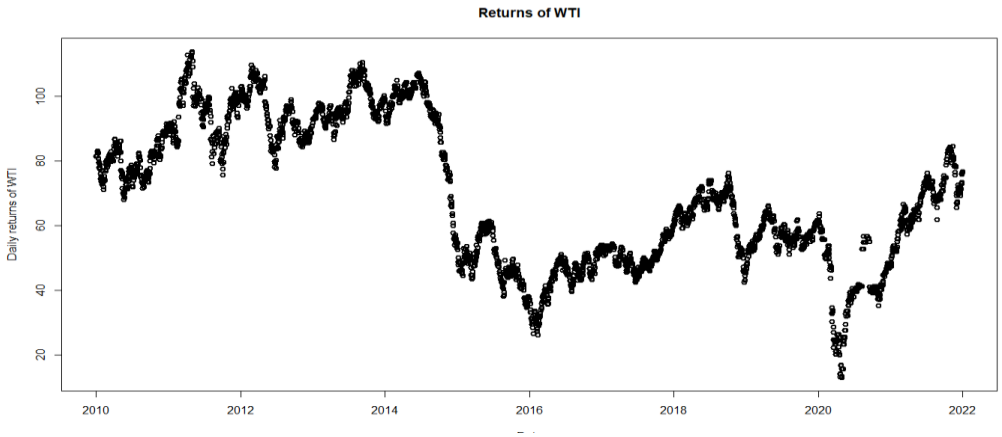
Data Analysis

The daily data of WTI Crude oil future index, SCI, KSE-100, & Foreign Exchange rates have been retrieved from PSX, Bloomberg & Yahoo finance for the period 2010 to December 2021 for analysis and to fit the DCC-GARCH model.

DCC-GARCH Model Appropriateness

The Dynamic conditional correlation Generalized autoregressive conditional heteroskedasticity (DCC-GARCH) econometric model to capture volatility in time series. The model is chosen to test the study problem because it allows the measurement of time-varying volatility over time since both the markets are dynamic and the commodity price is also very volatile. Hence, it is right to use the appropriate model to measure dynamic relationships. Other reasons are flexibility, computational efficiency and accuracy of measurements to capture the volatility of risk. This model is widely used in multiple studies (Engle, 2002; Yıldırım et al., 2022; Chen et al., 2020; Gomez-Gonzalez et al., 2019). The DCC-GARCH model is suitable for data and to address the research questions of the current study. The suitability of the GARCH model is determined by performing the following steps on the series of WTI Crude Oil future index, SCI index, and KSE 100 index, i.e. check the stationarity of the data through ADF test, determine the volatility clustering and the Arch Effect by performing ARCH test. The DCC-GARCH model was run on R-Studio to check the short-term and long-term spill spillover impact. Fig-A plots the returns of WTI, SCI, and KSE100, which indicates that the volatility of returns exists in time series data.

Figure 1A Log Returns of WTI, SCI & KSE100 Index



ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

Figure 1B Log Returns of WTI, SCI & KSE100 Index

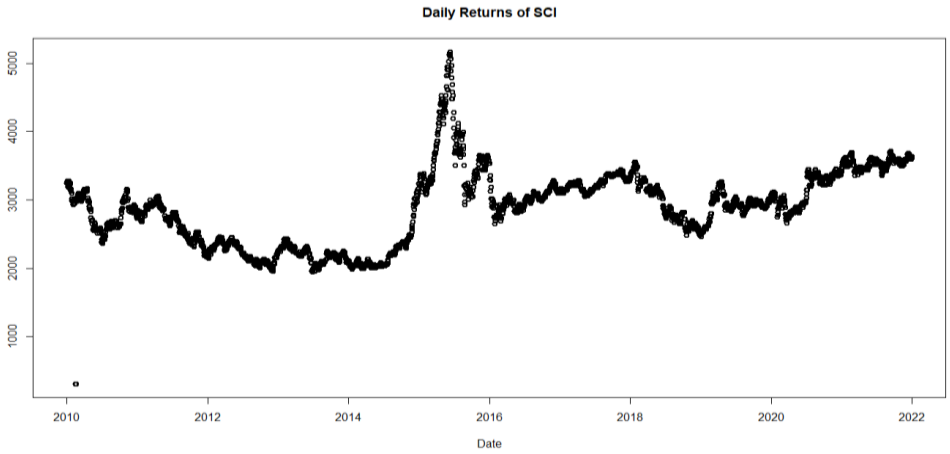
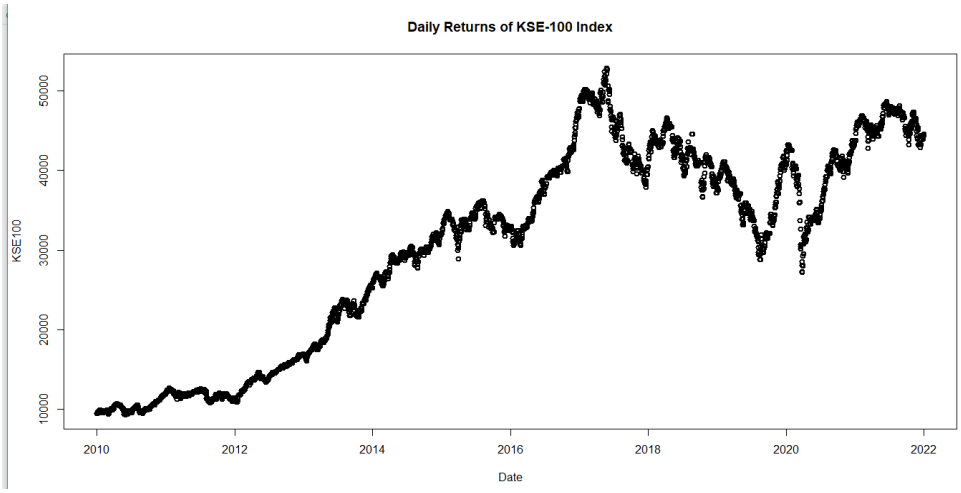


Figure 1C Log Returns of WTI, SCI & KSE100 Index



(Source: Author's calculation)

The visualization of the data indicates the volatility clustering as from the graph it is evident that large changes and the small changes follow the large changes are followed by small changes while passing all three tests makes the data qualified for the series suitability for the GARCH Model. Hence, as in the current study, there is a requirement to see the spillover effect, and given multivariate analysis, we fit the DCC-GARCH model.

Table 01: Descriptive Statistics			
Statistics	WTI	SCI	KSE100
Min.	-0.355	-2.281	-0.078
Q1	-0.008	-0.004	-0.003
Mean	-0.0001	0.00002	0.0003
Q3	0.009	0.005	0.004
Max	0.489	2.276	0.048
Kurtosis	68.981	1908.729	7.825
Skewness	0.072	-0.191	-0.849
Std Deviation	0.029	0.050	0.010

The description of the series indicates the presence of excess kurtosis and skewness, and the highest deviation of returns is indicated in SCI=0.054, with the highest kurtosis value followed by WTI = 0.0290. The descriptive exhibits the non-normality of the data being reported excess kurtosis and negative skewness. The linear regression analysis will not provide reliable results for the objective of the analysis. So, there is a need to test for the suitability of the GARCH model as in the current study. We want to predict the volatility of returns relation.

H_1: Spillover effect does not exist between SCI& KSE100

To test the hypothesis, first, we checked the Pre-conditions of DCC-GARCH

Table 02: Stationarity Check		
Return	ADF test	p-value
SCI	-22.75	0.01
KSE100	-14.756	0.01

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

Volatility Clustering

Figure 2A Volatility Clustering of Stock Market Returns

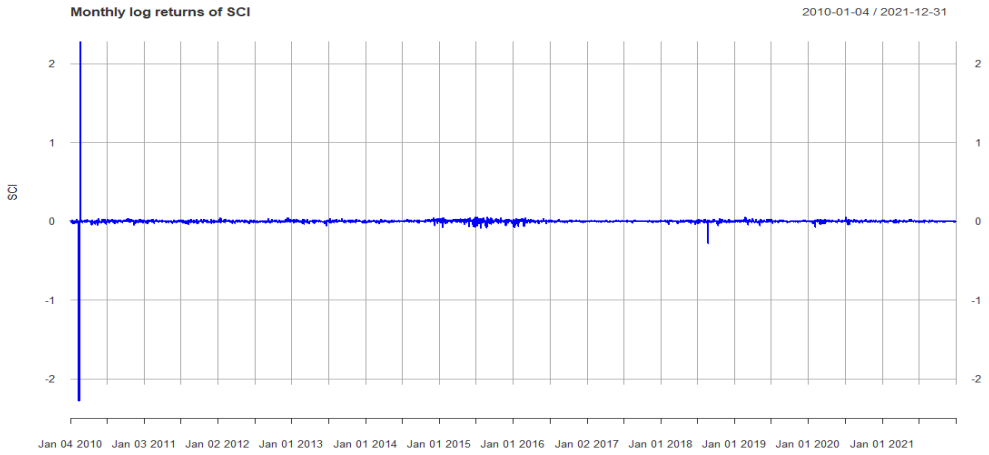
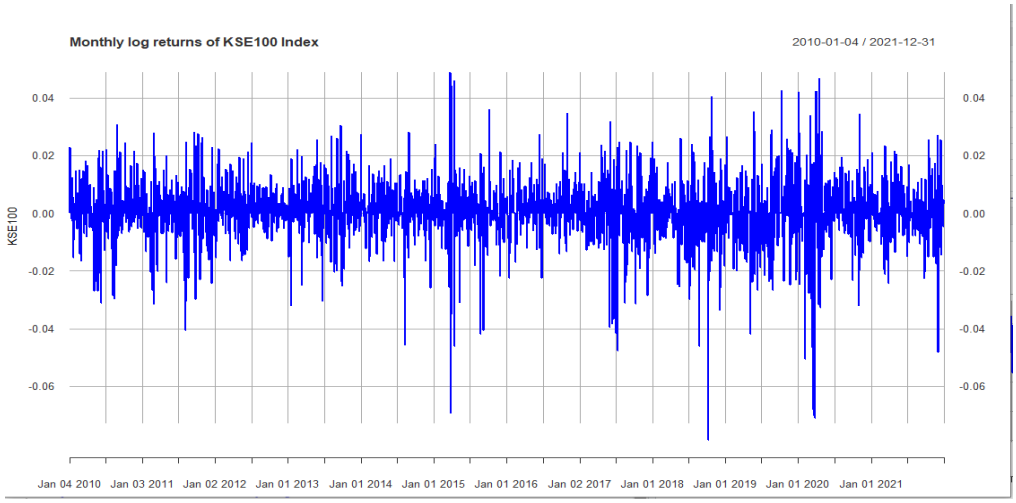


Figure 2B Volatility Clustering of Stock Market Returns



The graph of stock market returns indicates that the volatility of the returns exists in the case of PSX and SCI.

ARCH Effect

To test the ARCH effect, the null hypothesis is

Ho: There is no ARCH effect

Table 03: ARCH effect		
Index	Chi-squared	p-value
SCI	1447.9	0.000
KSE100	1229.9	0.000

Since the p<0.05, therefore, we reject Ho and conclude that the ARCH effect exists both in the case of SCI and KSE-100 index. Since all the conditions are satisfied to fit the DCC-GARCH Model

The fit of DCC-GARCH(1,1) optimal parameter estimates are presented in Table 04

Log likelihood15983.71 with 4359 number of observations.

Table 04: DCC-GARCH Model SCI and KSE 100 Index				
Parameters	Estimated Coef.	Std. Error	t-value	p-value
μ^{sci}	0.000067	0.003568	0.018	0.985
ω^{sci}	0.000003	0.001685	0.001	0.998
α_1^{sci}	0.053872	0.291333	0.184	0.853
β_1^{sci}	0.906084	8.357115	0.108	0.913
μ^{kse}	0.000677	0.000134	5.034	0.000
ω^{kse}	0.000003	0.000001	5.891	0.000
α_1^{kse}	0.049587	0.0006345	7.804	0.000
β_1^{kse}	0.915609	0.012751	71.804	0.000
$\mathrm{DCC}\alpha_1^{joint}$	0.108698	0.101695	1.068	0.285
$DCC\beta_1^{joint}$	0.754696	0.328412	2.298	0.021

Source: Author's calculation

At a 5% level of significance, the results indicate that there is no short-term spillover effect between the China Stock Market and Pakistan Stock Market as a $\mathrm{DCC}\alpha_1^{joint}$ = 0.108698 is insignificant as p>0.285132, but the long-term persistence

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

of the spill-over effect is there as DCC β1 = 0.754696 is significant at a 5% level of significance.

H1$_a$: spillover effect does not exist between the KSE100 index& and SCI

Table 05: Volatility Spillover Impact between KSE100 & SCI

Parameters	Estimated Coef.	Std. Error	t-value	p-value
μ^{kse}	0.000677	0.000134	5.034	0.000
ω^{kse}	0.000003	0.000001	5.899	0.000
α_1^{kse}	0.049587	0.006345	7.815	0.000
β_1^{kse}	0.915609	0.012751	71.805	0.000
μ^{sci}	0.000067	0.003568	0.018	0.985
ω^{sci}	0.000003	0.001685	0.001	0.998
α_1^{sci}	0.053872	0.291333	0.184	0.853
β_1^{sci}	0.906084	8.357115	0.108	0.913
DCCα_1^{joint}	0.108699	0.101853	1.067	0.285
$DCC\beta_1^{joint}$	0.754696	0.327473	2.304	0.021

Source: Author's calculation

Table 05 result indicates that the long-term spillover impact exists between the KSE100 index and SCI return since the p-value is significant at 5% as β of DCC measures the lingering/long-term effect of the shock impact of the conditional correlation, which is the persistence of the conditional correlation process.

Figure-3A Correlation SCI & KSE-100 Index

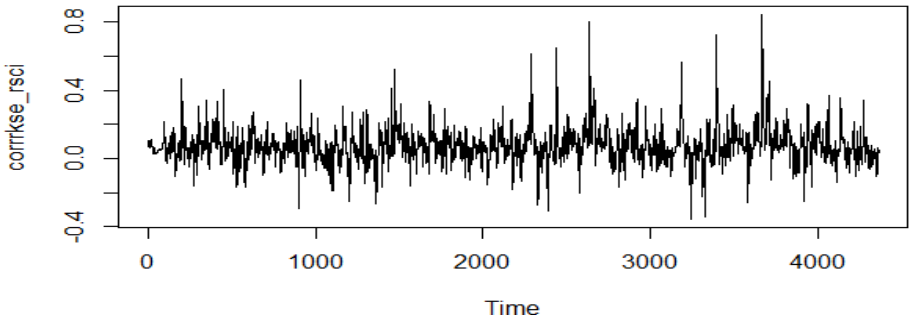
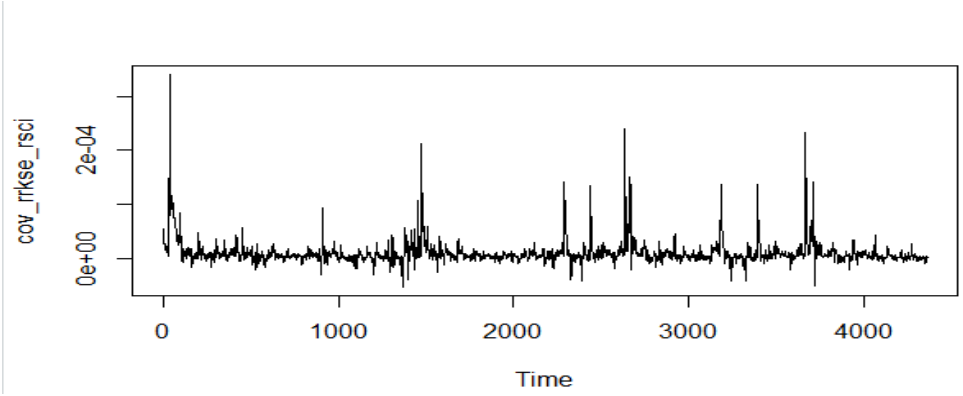
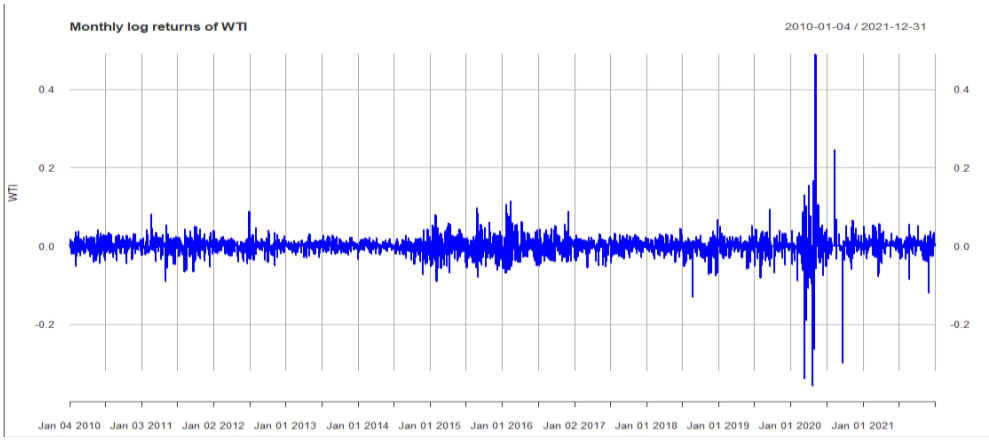


Figure-3B Covariance between SCI & KSE-100 Index



The sum of these two correlations will be less than one, which indicates that the conditional correlation in the model will not be constant over time.

Figure 04 Monthly Returns of WTI



The volatility of monthly log returns is evident as large changes and small changes follow large changes and small changes in returns.

H_2: Whether volatility spillover effect exists between oil prices and the stock market of Pakistan.

First, we test the conditions to check the appropriateness to fit DCC GARCH.

Table 06: Stationarity of data

Index	ADF test	p-value
WTI	-14.127	0.01

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

P value is significant at 5%, and the data is stationary.

The fit of DCC-GARCH(1,1) optimal parameter estimates are presented in Table 07

Log-likelihood 24495.83 with 4359 number of observations.

Table 07: DCC-GARCH Model of Oil Price and KSE-100 Index

Parameters	Estimated Coef	Std. Error	t-value	p-value
μ^{wti}	0.000251	0.000290	0.864	0.387
ω^{wti}	0.000002	0.000001	1.645	0.099
α_1^{wti}	0.036835	0.004797	7.679	0.000
β_1^{wti}	0.962165	0.003959	243.040	0.000
μ^{kse}	0.049587	0.000135	5.024	0.000
ω^{kse}	0.000003	0.000001	5.902	0.000
α_1^{kse}	0.049587	0.0006335	7.827	0.000
β_1^{kse}	0.915609	0.012739	71.874	0.000
$\mathrm{DCC}\alpha_1^{joint}$	0.001647	0.002223	0.740	0.458
$DCC\beta_1^{joint}$	0.958393	0.045426	21.098	0.000

The findings of the test indicate that the long-term volatility spillover impact exists between oil prices and the KSE 100 index return as the p-value is significant in case of the short term.

Figure 5A: Correlation between WTI and KSE-100 Index

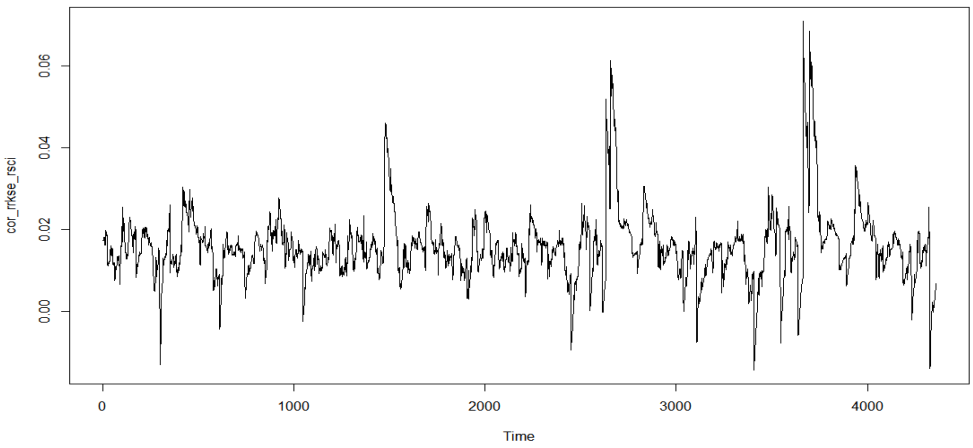
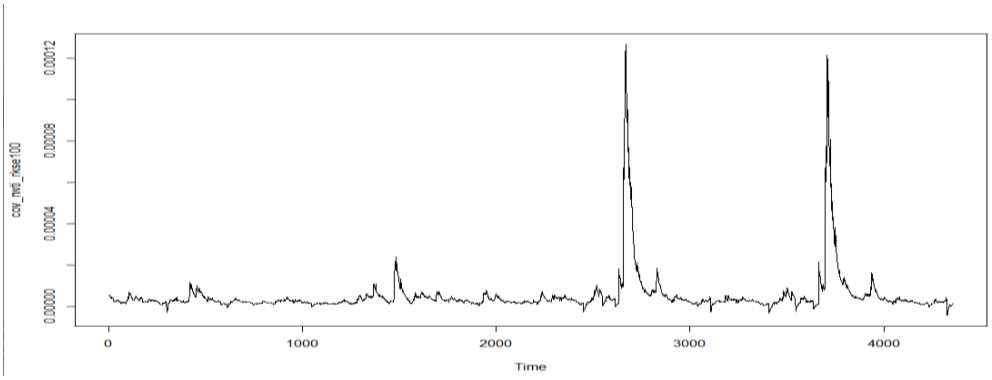


Figure 5B: Covariance between WTI and KSE-100 Index



H_3: Whether volatility spillover effect exists between oil prices and the stock market of China.

First, the conditions to fit DCC-GARCH models are tested

Table 08: Stationarity of data		
Index	ADF test	p-value
WTI	-14.127	0.01

Table 08 suggests that the WTI data has been tested for stationarity using the ADF test, with a highly negative test statistic (-14.127) and a low p-value (0.01), indicating strong evidence that the data is stationary.

Table 09: DCC GARCH Model WTI and SCI				
Parameters	Estimated Coef.	Std. Error	t-value	p-value
μ^{wti}	0.000251	0.000290	0.863	0.387
ω^{wti}	0.000002	0.000001	1.645	0.099
α_1^{wti}	0.036835	0.004796	7.680	0.000
β_1^{wti}	0.962165	0.003958	243.102	0.000
μ^{sci}	0.000067	0.003568	0.018	0.985
ω^{sci}	0.000003	0.001685	0.001	0.998
α_1^{sci}	0.053872	0.291333	0.184	0.853
β_1^{sci}	0.906084	8.357116	0.108	0.913
DCCα_1^{joint}	0.174679	0.142380	1.226	0.219
$DCC\beta_1^{joint}$	0.312909	1.046009	0.299	0.764

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

Both in the short term and long term, no evidence of volatility transmission is present between WTI and SCI as indicated DCC GARCH(1,1) optimal parameter estimates are presented in Table 09 with Log likelihood 12299.65.71 and 4359 number of observations.

Figure 7A: Correlation between WTI and SCI Index

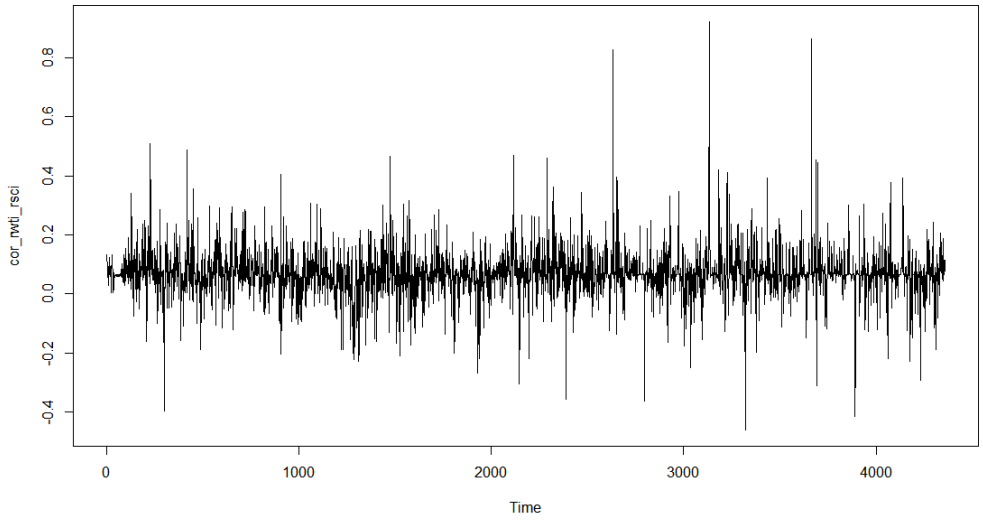
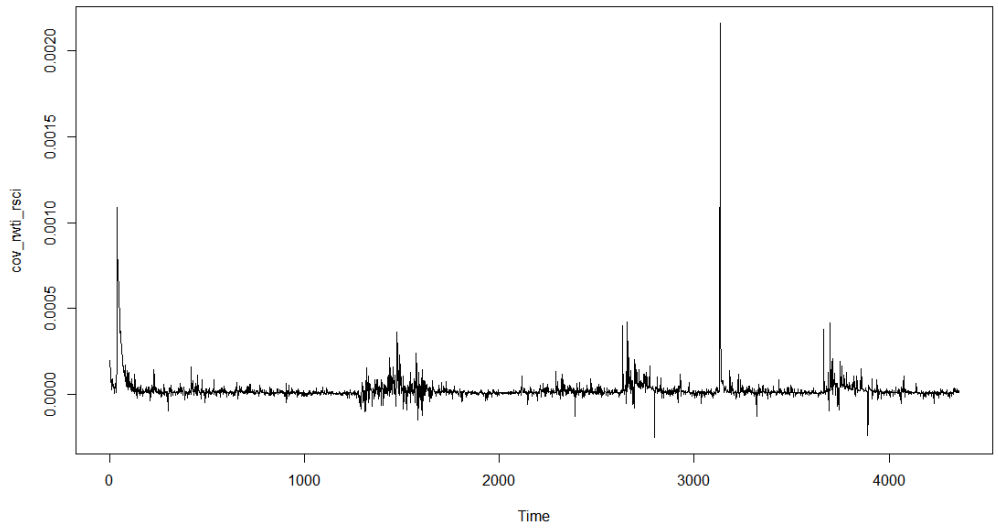


Figure 7B: Covariance between WTI and SCI Index



H_4: Volatility Spillover Impact of WTI on KSE100 Index and SCI

Table 10: DCC GARCH Model for WTI, KSE-100 index & SCI

Parameters	Estimated Coef	Std. Error	t-value	p-value
μ^{wti}	0.000251	0.000290	0.863	0.387
ω^{wti}	0.000002	0.000001	1.645	0.099
α_1^{wti}	0.036835	0.004796	7.680	0.000
β_1^{wti}	0.962165	0.003958	243.102	0.000
μ^{kse}	0.049587	0.000135	5.024	0.000
ω^{kse}	0.000003	0.000001	5.902	0.000
α_1^{kse}	0.049587	0.0006335	7.827	0.000
β_1^{kse}	0.915609	0.012739	71.874	0.000
μ^{sci}	0.000067	0.003568	0.018	0.985
ω^{sci}	0.000003	0.001685	0.001	0.998
α_1^{sci}	0.053872	0.291333	0.184	0.853
β_1^{sci}	0.906084	8.357116	0.108	0.913
$DCC\alpha_1^{joint}$	0.008771	0.523842	0.016	0.986
$DCC\beta_1^{joint}$	0.960169	2.589804	0.370	0.710

The fit of DCC-GARCH(1,1) with Log likelihood 26354.2 and 4359 number of observations optimal parameter estimates are presented in Table-VII. The findings of the result indicate that the highest coefficient of volatility is of wti as $\beta = 0.962165$, and the lowest is of sci. In contrast, the lowest value of p indicates the significant presence of volatility transmission between the selected market and the remaining market.

Conclusion and Implication

The result of the study indicates the presence of a spillover impact between oil prices and Stock market returns of two economies, China and Pakistan. The effect of volatility transmission is significant in the case of PSX's oil-to-stock market returns in the short term as well as in the long term compared to SCI. At the same time, the impact of the SCI spillover on the use-100 index is also reported as significant only in the long term, while in the short term, no volatility transmission was observed.

The empirical findings of the study have implications for investors, traders, and policymakers in making decisions to mitigate the risk of volatility transmission

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

in stock market returns and fluctuation in oil prices. Further study may be initiated to study the volatility transmission between oil prices, exchange rates and stock returns. Moreover, in future studies, the volatility spillover forecast can also be estimated by deploying machine learning models and comparing the results with the DCC-GARCH model.

Recommendations

Investors should diversify their portfolios and use dynamic hedging strategies to reduce the risks associated with volatility spillovers between oil prices, exchange rates, and the stock markets in China and Pakistan. Policymakers can stabilize exchange rates and mitigate the effects of global oil price fluctuations by implementing deliberate interventions. Improving financial integration between the two countries under CPEC may reduce market volatility. It is also advised that investors be made aware of the importance of making strategic investments during volatile times and that further research be done on the effects of volatility on other markets and industries.

References

Al-Rjoub, S. A., & Azzam, H. (2012). Financial crises, stock returns and volatility in an emerging stock market: the case of Jordan. *Journal of Economic Studies, 39*(2).

Bartsch, Z. (2019). Economic policy uncertainty and dollar-pound exchange rate return volatility. *Journal of International Money and Finance, 98*.

Basher, S. A., Haug, A. A., & Sadorsky, P. (2016). The impact of oil shocks on exchange rates: A Markov-switching approach. *Energy Economics, 54*, 1-23.

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and the Equity Market Contagion. *Journal of Finance, 69*(6), 2597-2649.

Benhmad, F. (2012). Modelling nonlinear Granger causality between the oil price and US dollar: A wavelet-based approach. *Economic Modeling, 29*(4), 1505-1514.

Cevik, N. K., Cevik, E. I., & Dibooglu, S. (2020). Oil Prices, Stock Market Returns and Volatility Spill Over Evidence from Turkey. *Journal of Policy Modeling, 42*(3), 597-614.

Chen, Y., Zheng, B., & Qu, F. (2020). Modelling the nexus of crude oil, new energy and rare earth in China: An asymmetric VAR-BEKK (DCC)-GARCH approach. *Resource Policy, 65*. doi:https://doi.org/10.1016/j.resourpol.2019.101545

Christian, G. S. (1991). On the arbitrage pricing theory. *Economic Theory*. doi:doi: 10.1007/BF01210561

Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of*

Business, Economics, Statistics, 20(3), 339-350. doi: 10.1198/073500102288618487

Engle, R. F., Ito, T., & Lin, W. (1990). Meteor Showers or Heatwaves? Hetroskeadastic intra Daily Volatility in the Foreign Exchange Market. *Econometrica, 58*(3), 525-542.

Farooq, M., & Zaghum, U. (2019). Dynamic Connectedness of Oil Price Shocks and Exchange Rates. *Energy Economics, 84*.

Fasanya, I. O., & Akinde, M. A. (2019). Volatility transmission in the Nigerian financial market. *The Journal of Finance and Data Science, 5*, 99-115.

Geng, X., & Guo, K. (2022). The spillover effect of VIX and oil prices on the exchange rate volatility among Belt and Road Countries. *The 8th International Conference on Information Technology and Quantitative Management.* www.sciencedirect.com.

Golub, S. (1983). Oil Prices and Exchange Rates. *Economic Journal, 93*(371), 576-593.

Gomez-Gonzalez, J. E., & Rojas-Espinosa, W. (2019). Detecting contagion in Asian exchange rate markets using asymmetric DCC-GARCH and R-vine copulas. *Economic Systems, 43*(3-4). doi:https://doi.org/10.1016/j.ecosys.2019.100717

Grobys, K. (2015). "Are volatility spillovers between currency and equity market driven by economic states? Evidence from the US economy. *Economic Letters, 127 (C)*, 72-75.

Gur, H. (1989). Arbitrage Pricing Theory. doi:doi: 10.1007/978-1-349-20213-3_5

He, L. T. (2001). Time Variation paths of international transmission of stock volatility-US vs Hongkong & South Korea. *Global Finance Journal*(12), 79-93.

Hilali, A. Z. (2019). China-Pakistan Economic Corridor and Dynamics of Regional Connectivity: Prospects and Challenges. *strategic studies, 39*(4).

JAGHOUBI, S. (2021). Modelling Volatility between Stock Returns, Oil Prices and Exchange Rates: Evidence from Russia and China. *Journal of Organizational Behavior Research, 6*(1), 220-232.

Lin, J., Xiao, H., & Chai, J. (2023). Dynamic effects and driving intermediations of oil price shocks on major economies. *Energy Economics, 124*.

Ma, Y., & Wang, J. (2019). Co-movement between oil, gas, coal, and iron ore prices, the Australian dollar, and the Chinese RMB exchange rates: A copula Approach. *Resources Policy, 63*.

ISSN (Print): 2959-099X ISSN (Online): 2959-1007
Volume 3, Issue 1, Page 73-95, June 30, 2024

Malkiel, B. (1989). *Efficient Market Hypothesis.* Palgrave Macmillan, London. doi:https://doi.org/10.1007/978-1-349-20213-3_13

Mensi, W. (2019). The global financial crisis and co-movements between oil prices and sector stock markets in Saudi Arabia: A VaR-based wavelet. *Borsa Istanbul Review*(19), 24-38.

Nibakht, L. (2010). Oil Prices and Exchange Rates: The Case of OPEC. *Business Intelligence Journal, 3*(1), 83-92.

R.Engle. (2002). Dynamic Conditional Correlation. *The Journal of Business Economics Statistics, 20*(3), 339-350.

Sabri, N. R. (2004). Stock Return Volatility and Market Crisis In Emerging Economies. *Review of Accounting & Finance, 3*(3), 59-83.

Silva, T. C., Wihlem, P. V., & Tabak, B. M. (2023). The effect of interconnectivity on stock returns during the Global Financial Crisis. *The Northern American Journal of Economics and Finance, 67*. doi:https://doi.org/10.1016/j.najef.2023.101940

Yıldırım, D. Ç., Esen, Ö., & Ertuğrul, H. M. (2022). Impact of the COVID-19 pandemic on return and risk transmission between oil and precious metals: Evidence from DCC-GARCH model. *Resource Policy, 79*. doi:https://doi.org/10.1016/j.resourpol.2022.102939

Živkov, D., Gajić-Glamočlija, M., & Đurašković, J. (2022). Volatility spillover analysis between stocks and exchange rate markets in short and long terms in East European and Eurasian countries. *International Journal of Emerging Markets*. doi:https://doi.org/10.1108/IJOEM-01-2021-0082