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RESEARCH PAPER

From Wells to Wallets: Tracing Volatility Spillover from Crude Oil to South Asian Stock Markets

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ABSTRACT

The association between stock and oil prices is essential because these are subjected to economic changes. The changing economic and political conditions create shocks in the economy that bring Instability in the oil market that spills over to developing nations 'stock markets. The study has used the daily data to study the spillover from crude oil to the stock markets of South Asia. The Markov-Switching and DCC-GARCH approaches have been used in this study. The results found the positive impact of crude oil prices on the stock markets and reflect that high price volatility in the crude oil market brings positive spillover and shocks in the South Asian stock markets. Furthermore, the DCC-GARCH model found the decay in the persistence of volatility over time. Further, they explored that there does not exist volatility spillover from the crude oil to the stock markets of Nepal, Bhutan, and Sri Lanka in the short run. However, the volatility spillover in the long run exists for all the stock markets except the Colombo Stock Exchange. This shows an opportunity for the investors for portfolio diversification in Nepal, Bhutan, and Sri Lanka because these are independent of the instabilities in the crude oil market. Overall, the study provides valuable insight for policymakers and investors on spillover from oil to stock markets, risk management, and its diversification approaches in the stock markets of South Asia.

KEYWORDS DCC-GARCH Model, Markov-Switching Approach, Spillover, Volatility

Introduction

A Because of this improved trade, fast processing of information, and advancement in information technology, the transmission of returns and volatilities has amplified in the world's financial markets. The portfolio and finance managers must comprehend the association and its strength among these business markets (Maghyereh et al., 2017). Moreover, the relationship among the financial marketplaces is examined by finding the mean and volatility spillover across them because it is crucial for designing the optimal portfolio and smart hedging strategies (Sahabuddin et al., 2023; Wang et al., 2023).

Spillovers can be defined as the variations in one asset's price that change the other asset's price. Spillovers have gained importance in the financial industry due to their importance in designing portfolios, establishing regulations, and risk management strategies. The history of financial markets is filled with global economic crises that stress the importance of recognizing the actual reason for these crises. Globalization, capital movement, internationalization, and massive investments have made the markets mutually dependent (Mishra et al., 2007). Diagnosing the volatility spillover among the markets is essential for stock valuation across and within the markets for hedging and trading approaches. Investors are interested in the phenomenon of volatility spillover because they need to monitor and evaluate the stock market price changes to diversify their portfolios to get the maximum returns (Jung & Maderitsch, 2014; Kocaarslan et al., 2017). Globalization and economic interdependence have stressed the importance of conducting empirical research to explore the patterns of volatility spillover in the financial markets (Jarungkitkul & Sukcharoensin, 2016).

The fractal market hypothesis argues that the stock market prices show fractal properties because their sharp uncertainties in the market can lead to market crises. Secondly, the meteor shower effect explains that the changes in a market can spill over to marketplaces, endures in that market, and keeps producing volatility in geographically distant markets, which open many hours later (Susmel & Engle, 1994). When the big financial markets of the world face any disaster, its effect can disturb the other international markets, which have strong integration with it, and vice versa. The spillover effect occurs when the event in one country has a ripple effect on the following country's economy. The global integration of the stock markets does create opportunities for international investors that enable them for portfolio diversification. However, it also brings challenges for them. Hence, the study of spillover and integration among the stock and crude oil markets is crucial. Investing in the least integrated financial markets will help them reduce their risk and maximize their profits.

Stock markets are closely connected to oil prices and financial activities, and it is a commonly accepted phenomenon affecting stock returns (Tchatoka, 2019; Yadav, 2023; Phoong, 2023). The relationship among stock and oil markets is important because of its vibrant nature. The financial crisis of 2008, the oil price downfall in 2014, the Brexit referendum in 2016, the European Debt crisis, COVID-19, and the Paris Climate Agreements are considered the main reasons that have affected oil prices in the previous twenty years (Bachmann et al., 2013; Caggiano et al., 2017; Nagarakatte & Natchimuthu, 2022). The war in Ukraine will affect developing nations through the different trade and investment channels, which include the commodity prices of food and energy, supply chains, logistic networks, and foreign direct investment (Ruta, 2022). International events affect the oil markets because increased oil prices decline stock returns (Aruna & Acharya, 2020; Kilian & Park, 2009). This will increase South Asian stock market volatility because investors are unwilling to invest in a country with risky returns (Shear et al., 2020). Therefore, it becomes mandatory for international portfolio managers to adjust the allocation of their assets between the different financial markets based on this spillover. It also calls for the attention of policymakers to take sound actions for the stable working of their monetary and commodity markets throughout the crisis. The main issue for international portfolio managers is how much allocations of assets need to be changed to diversify their portfolios during the crisis period. Consequently, a study must explore the dynamic link among the stock and crude oil markets.

The particular objective of this study is to explore the volatility spillover from crude oil markets to the South Asian stock markets, which include the stock markets of Pakistan, Afghanistan, Maldives, India, Bangladesh, Sri Lanka, Bhutan, and Nepal. Any increase in oil prices due to national events like Russia or Ukraine results in decreased expected growth rates and increased inflation worldwide. This, in turn, decreases the growth and reduces the expected earnings of the companies (Aruna & Rajesh, 2020). Overall, it shows a dampening impact on the companies 'stock prices. Therefore, the study will check the influence of international oil markets on stock prices. Investigating the degree of dependence and dynamic spillover among the stock and crude oil markets is necessary for finding the opportunities for diversification in South Asian stock markets. The rapid upsurge in the stock market volatility on account of the international crises is the primary motivation of this study. Firstly, it shows the effect of different crisis that has taken place in the last two decades and that influence the association between the crude oil and stock markets. Secondly, the study has made use of the non-parametric approach for checking the spillover from the crude oil market by applying the Markov regime-switching model, while the existing literature has made use of the parametric models (Kilian & Park, 2009; Lv et al., 2020; Phan et al., 2015; Ready, 2018). The adverse changes in the relationship between stock and oil markets prevail due to the changing conditions of the international market (Ren et al., 2022). Moreover, the study has also used the non-parametric model of DCC-GARCH, which studies the underlying relationship between stock and oil markets and how their relationship varies over time. Finally, studies have shown that spillover in stock markets stems from the international crude oil markets (Wang et al., 2023). The study of the spillover is beneficial for investors because their diversification decisions are based on their spillover relations among different markets. This study has several benefits because investors can invest in countries that are weak in relation. Consequently, it will help optimize their portfolios' results by diversifying their risk. Therefore, portfolio managers and investors can benefit from this study by investing their funds in frontier markets with a weak correlation with internationally developed markets. Thus, the concept of spillover is crucial in finance literature.

The study has been organized into the following sections. The literature in the second section has been reviewed, exploring the nexus between stock and crude oil markets. The methodology is explained in the third section, while results discussed in the fourth and fifth chapter concludes the study.

Literature Review

Different empirical studies have explored the mean and volatility spillover between countries' stock and oil markets using different methodologies and assumptions. For instance, Lin et al. (2019) examined the contagion among the London Gold, crude oil, Stoxx 600 Index, and the Shanghai Composite Index of China (Lin et al., 2019). They used the linear, non-linear Granger Causality, GARCH models, Wavelet analysis, and decomposition tests. They found unidirectional contagion from the commodity markets to the stock markets of Europe and China during the irregular period, while the stock market of Europe produced volatility in the Crude oil market throughout the irregular epochs. On the contrary, a bidirectional risk contagion exists among China and Europe's oil and stock markets during the crisis. Naeem et al. (2020) studied the BRICS economies' gold, oil, and emerging stock markets at different frequencies (Naeem et al., 2022). They found a lower tail dependency among the stock markets of BRICS economies and gold markets after the effect of the financial crisis of 2008. They have also found that gold is a perfect diversifying asset, while the oil market serves as the hedging asset for the investors of the BRICS economies. The findings of Naeem et al. were inconsistent with those of Junttila et al. (2018), who concluded that gold is preferred for hedging instead of oil in hedging against the risk from the USA markets.

Singhal et al. (2019) investigated the stock markets of Mexico and found the mean and volatility spillover from across Mexico's gold, oil, stock, and exchange markets (Singhal et al., 2019). They have reported significant results and came with the findings that oil prices have a constructive effect on the stock markets of Mexico. They validate the discoveries of Tursoy and Faisal (2018), who studied Turkey's oil, gold, and stock prices. They found that these markets are strongly cointegrated, and the prices of gold negatively affect Turkey's stock prices (Tursoy & Faisal, 2018). Volatility spills over exist China's and the USA's oil and international stock markets (Xu et al., 2019). The Stock market crash in China and financial crisis have affected the economic structures of the whole world and its financial markets.

Enwereuzoh et al. (2021) tested the association among crude oil supply, demand, stock markets, and price shocks in Africa using the Smooth transition regression and VAR models. They have concluded that shocks in the oil demand have an insignificant influence on the stock prices of African economies. They have also found that the oil supply shocks have a low impact on the returns of African stock markets (Enwereuzoh et al., 2021). Moreover, the study also revealed that positive shocks have less ability to affect stock returns than negative shocks. Adekoya et al. (2021) employed threshold regression along with the regime-switching models of Markov to study the hedging effectiveness of gold concerning the price movements in the oil and markets through the pandemic of COVID-19 (Adekoya et al., 2021). The findings showed a significant and dynamic relationship among these markets. They have also found that oil and gold hedge the stock markets during this pandemic, and the yellow metal is a better hedging instrument than oil during the pandemic of COVID-19.

Vo and Hung (2021) examined the US stock, gold, and oil markets to explore the returns and volatility spillover. They found a significant diffusion of returns in these markets during the crisis of COVID-19 (Hung & Vo, 2021). On the other hand, Zeinedini et al. (2022) found a negative correlation between oil and the stock markets of Iran. They have also found an insignificant dependency among the same region's stock and gold markets (Zeinedini et al., 2022). Zhao & Wang (2020) examined the impact of the uncertainty in the monetary and economic policy in China and the USA on the commodities of gold, oil, and the stock markets. They have found that these uncertainties heterogeneously affect the gold-stock and oil-stock pairs (Gao et al., 2021). Mensi & Kang (2022) investigated the spillover of volatility among the oil, gold, and stock markets of the United States of America before and after the health crisis by employing the FIAPARCH-DCC model on the daily data. They have found a significant and positive association among the S&P500 and oil markets, while a negative correlation exists between gold and the S&P500 (Mensi et al., 2022). They have also found that this relationship gets more substantial during COVID-19, and gold has a higher capacity than oil for optimizing the gains of portfolios by diversifying their investments during the pandemic of COVID-19. Moreover, they found that oil had more hedging efficiency than gold during all the sub-periods.

As mentioned earlier, all the studies have studied the volatility spillover in the world's developed markets. However, this phenomenon has yet to be explored for the developing markets. This study attempts to check the impact of the oil markets on the stock markets of South Asian countries. Based on this literature, the following hypothesis has been developed:

H_1: The volatility spillover from crude oil to the stock markets of South Asia.

H_0: The volatility does not spillover from crude oil to the stock markets of South Asia.

The nexus among the stock and Oil market

According to Kilian & Park (2009), the theoretical link between the oil and returns of the stock markets can be explained with the help of different channels (Kilian & Park, 2009). However, the most recommended one is the financial channel. The main idea of this channel is based on the cash flow discounting method. As per the model, the stock's actual value is the sum of its present values of all of its future cash flows. This channel describes that higher oil prices upsurge the companies' production costs and inflation in the economies. This results in increased interest and discount rates in the economy. These low expected corporate earnings and high discount rates lower the prices of the stocks in the markets.

The consumers are the other channel for explaining the theoretical link among the oil and stock markets. This channel describes that when the prices of oil upsurge in the global markets, it also inflates the oil prices at the domestic level. Consumers start spending more on oil and gasoline, and little money has been left to spend on other commodities. Consequently, the aggregate demand of the consumer fell due to the decreased demand and sales of the companies. This results in declining corporate earnings and, ultimately, the country's stock prices.

According to Hamilton (1983), oil is a strong and influential commodity affecting the country's economy and other financial markets. The increased oil prices in the international oil markets can both increase and decrease the cash flows of the companies and their related discount factors (Hamilton, 1983). The discount factors of the firms are related to macroeconomic factors, such as inflation, monetary policy, oil prices, and interest rates.

The corporate earnings decreased because of two reasons. Firstly, because of the increased cost of Production due to the expensive input for the companies, and secondly, due to the decline in the firm's sales due to the decreased demand of the consumers. These decreased corporate earnings ultimately affect the stock prices of the economy. Local and international investors try to adjust their portfolios to make them resistant to political and global health crises (Bouri et al., 2017). Therefore, the means and volatility spillover from international oil prices to the stock markets is crucial for international investors. Several crises have been studied in the literature for their impact on developed markets. However, insight is mandatory for the reaction of the South Asian stock markets to the fluctuations in worldwide oil prices.

Material and Methods

The study has employed the following models:

The Markov-Switching Model

Ordinary Least square Regression is a statistical technique for checking the association among the variables under the study. However, due to the integration of the financial markets, irregular patterns, seasonal changes, and linear trends in the data affect the findings of the study and lack accuracy and precision (Phoong et al., 2019). To address these issues, a new framework called the Markov-Switching model has been devised, which is beneficial as the data used for this study contains the different financial, geopolitical, natural, and economic events that can disturb the association between stock and crude oil markets.

The study has used the Markov-switching regression model to address the non-linear nexus of oil and the stock market. This technique has the benefit over the conventional techniques because it addresses the non-linear nature of the time series data. The switching regression helps find non-linearity and asymmetry in the financial data of the markets. The model is also helpful whenever adjustments are driven mainly by exogenous actions (Basher & Sadorsky, 2006). Consequently, the technique helps study the volatility spillover from crude oil to stock markets. The model without switching has been estimated as follows:

$$Y_t = \alpha X_t + \in_1, \in_1 \sim i, i, d. N(0, \sigma^2)$$

In the above model, x is a 1 × m exogenous variable and the values of the coefficient of the autonomous variable of the crude oil market. The evolution of the variable S_t depends upon the values of $S_{t-1}, S_{t-2}, and\ S_{t-n}$. The whole process is discrete; therefore, S_t is entitled as the nth-order Markov-switching process, and it has the probabilities for its transitions that have been estimated below:

$$\text{P}\ (S_t = 1 \int S_{t-1} = 1) = p = \frac{Exp\ (p_o)}{1 + Exp\ (p_o)}$$

$$\text{P}\ (S_t = 1 \int S_{t-1} = 1) = q = \frac{Exp\ (q_o)}{1 + Exp\ (q_o)}$$

Where $p_{0\ and}\ q_{t0}$ are the unrestricted factors, the probabilities of transition for the bivariate Markov-switching model are then restated P $(S_t = 1 \int S_{t-1} = 1) = i, i, j = 0, 1.$ The estimation of transition probability provides information about the probable duration for two different regimes that the Markov-Switching Model has developed. The Markov-switching regression model assumes two different models of Regression for each Regime. The unobservable variables $R_t\ and\ X_t$ are the condition means y_t of in regimes m(m = 1,2) for the bivariate model with two regimes, and it is expressed as follows:

$$y_t\ (m) = \infty_m X_t' + R_t \beta$$

Where are β, and ∞_m are the vectors of the coefficients.

DCC-GARCH Model

For estimating the spillover from the oil market to the stock markets of South Asia, the DCC-GARCH model has been used, which was proposed by Engle. The model enables estimating the correlations in the volatilities that are dynamic in nature. This further helps devise the optimal diversification alternatives for the investors and portfolio managers. The model is based on the two stages. In the first stage, the GARCH parameters have been estimated. On the other hand, conditional correlations have been estimated in the second stage that reflecting the association between the oil and stock markets. The subsequent equation can estimate the model:

$$r_t = \mu_t + \in_t, \text{ where } \in_t \int F_{t-1} \sim N(0, H_t)$$

$$H_t = D_t R_t D_t, D_t = diag\sqrt{H_{iit}} \ldots\ldots \sqrt{H_{NNt}}$$

In the above model, $r_t, \mu_t,$ and $\in_t$ are the N $\times 1$ vectors, demonstrating the financial data of crude oil and stock markets, conditional mean, and error term analyzed by this study. Let F_{t-1} represent the information set that is available up to t-1. Additionally, H_t is the conditional variance-covariance matrix that is dynamic in nature, and D_t represents the diagonal matrix of the square root of conditional variance. Lastly, h_{iit} is the univariate GARCH model, along with R_t, representing the matrix that consists of the conditional correlation that keeps changing with time.

The study has used the daily data of South Asia's crude oil and stock markets. The stock markets include Maldives, Pakistan, Sri Lanka, Afghanistan, Nepal, Bhutan, and Bangladesh stock exchanges. The country of Afghanistan was later skipped from the study due to the unavailability of its stock data because it needs its stock exchange. The study has chosen the countries because they have commonalities and share almost the same economic problems and political and global health crises. The study has used the daily data because the high-frequency data helps estimate the volatility, jumps, and transformation of the information in market noise (Liu et al., 2021). According to the research of the United States Institute of Peace (USIP), China and the USA are the most significant trading partners in the world, and they see the South Asian regions as necessary because of their advancing population and strategic geography (USIP, 2020).

Results and Discussion

The study has used the daily data of stock and crude oil markets. The oil prices have been gathered from the EIA (Energy Information Administration). The spot prices of oil are taken as the benchmark for the pricing of crude oil internationally. On the contrary, the stock data of all the exchanges have been gathered from their respective websites. The used variables for this study are listed in Table 1, along with their acronyms.

Table 1
Data Description

Variables	Acronyms
Karachi Stock Exchange	KSE-100
The National Stock Exchange of India Limited	Nifty-50
Nepal Stock Exchange	NEPSE
Dhaka Stock Exchange	DSEX
Maldives Stock Exchange Index	MASIX
The Royal Securities Exchange of Bhutan Limited (RSEBL)	BSI
Colombo Stock Exchange	CSE-All Share
Crude oil Prices	EIA

Descriptive Statistics

Table 2 summarizes the results of descriptive statistics of the returns series of stock and oil markets. The results show that the average returns of NEPSE stock markets have the highest value of 0.000728, while crude oil markets have the lowest mean return of 0.000205. The table also shows that the Maldives Stock Exchange Index (MASIX) has a maximum value of returns of 0.614748, while the crude oil market has the lowest possible minimum returns of -0.643699. The values of the standard deviations show the volatility of that market, and results demonstrate that the crude oil market's returns have the highest value of standard deviation of 0.027646, which makes it riskier, while the Royal Securities Exchange of Bhutan Limited (BSI) is having least amount of standard deviation of 0.005200. Moreover, the values of Skewness help in understanding the nature of data distribution. The lowest value of Skewness -2.187724 is for the returns of the oil prices, and it further illustrates that these negative returns are pulling down the mean returns. Moreover, the Maldives Stock Exchange Index (MASIX) has a maximum value of skewness of 6.102631, which makes it positive or right-skewed. Then, the Kurtosis value is larger than three for all the market returns, making the returns leptokurtic with shaper peaks and fatter tails. The high value of Kurtosis tends to produce extreme returns in the market that can also be positive and negative. Moreover, Jarque-Bera's values are also significant for the returns of all the series and endorse that these returns distributions are not normal.

Preliminary Analysis

The daily prices of all the markets have been taken, and results show that the prices fluctuate and have high volatility. Daily prices' main advantage is that they can be easily converted to their returns series by taking their natural logarithms. For analysis purposes, using the methodology of (Phoong et al., 2023) to convert the price series into their returns series. It has calculated the difference between the two consecutive values by using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

The price movements of the stock and crude oil markets of South Asia are shown in Figure 1. The graphs of the price series show that there exists volatility and trends in them. The period of high volatility is trailed by high volatility and vice versa. From this, we can infer that the data is not stationary.

Return Movements of Prices

Figure 2 shows the plotted returns movements of the prices of stock and oil markets. The returns have been calculated by taking the logarithm of their respective prices. The graphs show that the prices' return movement fluctuates with time, and these fluctuations are consistent over time. The returns also show that Volatility clustering dominates in low and high-volatility regimes. It is also evident from the graphs that some of the stock markets have the same movement patterns as that of oil prices. This points out the existence of volatility in these markets.

Table 2
Descriptive Statistics

	ROP	RKSE100	RNIFTY50	RNEPSE	RDSEX	RMASIX	RBSI	RCSE
Mean	0.000205	0.000604	0.000439	0.000728	0.000223	0.000361	0.000386	0.000522
Median	0.000729	0.000863	0.000878	0.000000	0.000438	0.000000	0.000000	0.000210
Maximum	0.412023	0.085071	0.163343	0.082905	0.097984	0.614748	0.061516	0.182881
Minimum	-0.643699	-0.077414	-0.152303	-0.162390	-0.090517	-0.244172	-0.021974	-0.138931
Std. Dev.	0.027646	0.013225	0.014598	0.016937	0.010101	0.026102	0.005200	0.011797
Skewness	-2.187724	-0.299017	-0.594888	-0.632218	-0.203294	6.102631	3.052297	0.015679
Kurtosis	76.83172	7.062742	14.52930	13.19011	17.52514	147.0192	34.39969	28.46350
Jarque-Bera	1290755.	3979.088	31127.76	6031.878	16909.20	3337257.	32913.15	148778.6
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.161716	3.418530	2.442566	0.999900	0.429363	1.385110	0.297890	2.877370
Sum Sq. Dev.	4.327513	0.990317	1.184779	0.393590	0.196011	2.611456	0.020849	0.766258

Unit Root Test

The ADF (Augmented Dicky Fuller) and Phillip-Perron tests have been used for checking the stationarity level of series and results have been reported in Table 3. The results show that all the price series are non-stationary at their level, and these get stationary after differencing them at the first level. Hence, the study can discard the null hypothesis of stationary series at their level. This suggests that all of these series have a unit root, and their first difference should be used for further analysis to avoid spurious regressions.

Table 3
Unit Root Test

	Augmented dicky Fuller Test		Phillips-Perron Test	
	At Level	1st difference	At Level	1st difference
Oil Prices	-2.204023 (0.4867)	-73.24746 (0.0001)	-2.213094 (0.4816)	-73.22438 (0.0001)
KSE-100	-2.290850 (0.4383)	-66.85219 (0.0000)	-2.379139 (0.3905)	-67.23381 (0.0000)
NIFTY-50	-1.367530 (0.8703)	-72.84815 (0.0000)	-1.428690 (0.8527)	-72.84814 (0.0000)
NEPSE	-1.944770 (0.6302)	-17.74329 (0.0000)	-1.791986 (0.7084)	-34.27323 (0.0000)
DSEX	-1.608200 (0.4782)	-18.36499 (0.0000)	-1.558398 (0.5038)	-41.32477 (0.0000)
MASIX	-2.118733 (0.5346)	-62.55131 (0.0000)	-2.064393 (0.5650)	-62.56268 (0.0000)
BSI	-0.183291 (0.9933)	-17.34174 (0.0000)	-0.867967 (0.9575)	-28.96248 (0.0000)

CSE-All Share	-3.371212 (0.0554)	-11.30339 (0.0000)	-2.978903 (0.1382)	-62.64702 (0.0000)

Heteroscedasticity and ARCH-LM Test

To apply the ARCH/GARCH model, we need to check for the autocorrelation and heteroscedasticity of the returns series. This family is used for analysis when the variance of the error term is serially associated with its lagged prices, and there exists serial autocorrelation in the series, and results have been reported in Table 4. For checking these two conditions, firstly, the heteroscedasticity has been checked, and it shows significant results at a 5% level for all the returns series except the returns of The Royal Securities Exchange of Bhutan Limited (BSI), which were significant at a 10% level. Secondly, for checking the ARCH effects in the data, the ARCH-LM Test has been used. The results reject the null hypothesis of no autocorrelation in the favor of alternate hypothesis that confirms the ARCH effect's existence in the series. After fulfilling both conditions, the volatility spillover has been checked with the help of Markov-& DCC-GARCH approaches.

Table 4
Heteroscedasticity & ARCH-LM Test

		Heteroscedasticity	ARCH-LM
Oil Prices	F-Statistics	733.3579	1.901880
	P-value	0.0000	0.0906
KSE-100	F-Statistics	407.9319	2.712131
	P-value	0.0000	0.0996
NIFTY-50	F-Statistics	250.7401	3.498413
	P-value	0.0000	0.0037
NEPSE	F-Statistics	159.9088	2.310969
	P-value	0.0000	0.0420
DSEX	F-Statistics	11.05881	5.454523
	P-value	0.0009	0.0001
MASIX	F-Statistics	1.566210	0.674734
	P-value	0.2108	0.6426
BSI	F-Statistics	3.309424	8.141818
	P-value	0.0693	0.0000
CSE-All Share	F-Statistics	192.7449	6.297404
	P-value	0.0000	0.0000

Volatility Spillover among Oil and South Asian Stock Markets

The Markov Switching Model has been employed for investigating the volatility spillover from crude oil to the stock markets, and its results are presented in Table 5. Previous research has suggested the model using the same model (Brunner, 1992; Neftci, 1984). The value of standard deviation shows the magnitude of volatility for each Regime. The higher value standard deviation's coefficient is considered the Regime with higher volatility, while the lower standard deviation's coefficient is considered the Regime with lower volatility. The first Regime has a "low price fluctuation," while the second Regime has a "high fluctuation in prices ."For the first Regime, the influence of the oil market on the stock markets of the National Stock Exchange of India Limited (NIFTY-50) and Nepal Stock Exchange (NEPSE) is positive and significant at a 5% level. On the contrary, this effect on the stock prices from the oil prices is significant at a 5% level and has negative value for the Royal Securities Exchange of Bhutan Limited (BSI) and Colombo Stock Exchange (CSE-All Share). In contrast, its impact is insignificant for the remaining stock markets.

For Regime 2, this study has found a significant and positive impact at 5% and 10% levels of oil prices on all the South Asian stock markets except the Nepal Stock

Exchange (NEPSE). The positive influence of crude oil markets on the stock markets reflects that high price volatility in international oil markets is generating spillover and positive tremors in the stock markets. Moreover, the transition of these shocks from the crude oil market is more significant during the volatile conditions of the same market. These outcomes are consistent with the studies that find an unstable association between oil and stock (Balcilar et al., 2015; Lee & Chiou, 2011).

Moreover, the regression coefficients have lower values of standard errors in the second Regime than in the first Regime for most of the stock markets. The standard error is the measure of variability. The low values of standard error bring more accuracy to the model estimates. The value of standard errors of the first Regime is greater than that of the second Regime, and both values are almost close to zero. This shows that the statistics have no random error, the data is adequate, and its predicted value is near its real value.

Table 5
Bi-Variate Markov Switching Model

Stock Markets	Regimes	Variable	Coefficient	St. Error	Z-Statistics	Probability
KSE-100	Regime 1	ROP	0.051573	0.039381	1.309585	0.1903
	Regime 2	ROP	0.012882	0.007141	1.804047	0.0712
NIFTY-50	Regime 1	ROP	0.051558	0.006950	7.418804	0.0000
	Regime 2	ROP	0.096068	0.020108	4.777586	0.0000
NEPSE	Regime 1	ROP	0.598046	0.042717	14.00031	0.0000
	Regime 2	ROP	-0.023146	0.013659	-1.694522	0.0902
DSEX	Regime 1	ROP	-0.012738	0.007776	-1.638051	0.1014
	Regime 2	ROP	0.408237	0.023499	17.37234	0.0000
MASIX	Regime 1	ROP	0.001235	0.010431	0.118408	0.9057
	Regime 2	ROP	0.658133	0.023135	28.44713	0.0000
BSI	Regime 1	ROP	-2.268685	0.195458	-11.60703	0.0000
	Regime 2	ROP	0.010640	0.003625	2.934697	0.0033
CSE-All Share	Regime 1	ROP	-2.302981	0.083655	-27.52939	0.0000
	Regime 2	ROP	0.042512	0.005966	7.126291	0.0000

Transition Probabilities and Expected Durations from Markov Switching Model

The study has reported the estimates of probabilities for transition along with the forecasted duration in each Regime in Table 6. The probabilities for the transition from the first Regime to the second Regime (P_{12}) are lower than the transition probabilities from the second to first Regime(P_{21}). From this, the first Regime is stable compared to the second Regime, and the transition process from the first Regime to the second Regime is comparatively slow. Furthermore, the expected durations of the second Regime are large for the National Stock Exchange of India Limited (NIFTY-50), Dhaka Stock Exchange (DSEX), and Maldives Stock Exchange (MASIX). However, the anticipated period in the second Regime is highest for the Bhutan Stock Index (BSI) and lowest for the Maldives Stock Exchange (MASIX). Additionally, the one-step ahead Regime switching probabilities for all the stock markets are shown in Figure 1.

Table 6
Transition Probabilities and Expected Durations

Stock Markets	Transition Probabilities				Expected Duration	
	P_{11}	P_{12}	P_{21}	P_{22}	DU_1	DU_2
KSE-100	0.433522	0.566478	0.021326	0.978674	1.765294	46.89045
NIFTY-50	0.985446	0.014554	0.739130	0.260870	68.70865	1.352942
NEPSE	0.214293	0.785707	0.023186	0.976814	1.272739	43.13029
DSEX	0.991554	0.008446	0.670633	0.329367	118.3982	1.491128
MASIX	0.987306	0.012694	0.979131	0.020869	78.77636	1.021313
BSI	9.62E-05	0.006463	0.999904	0.993537	1.000096	154.7354

CSE-All Share	0.182767	0.817233	0.007759	0.992241	1.223641	128.8814

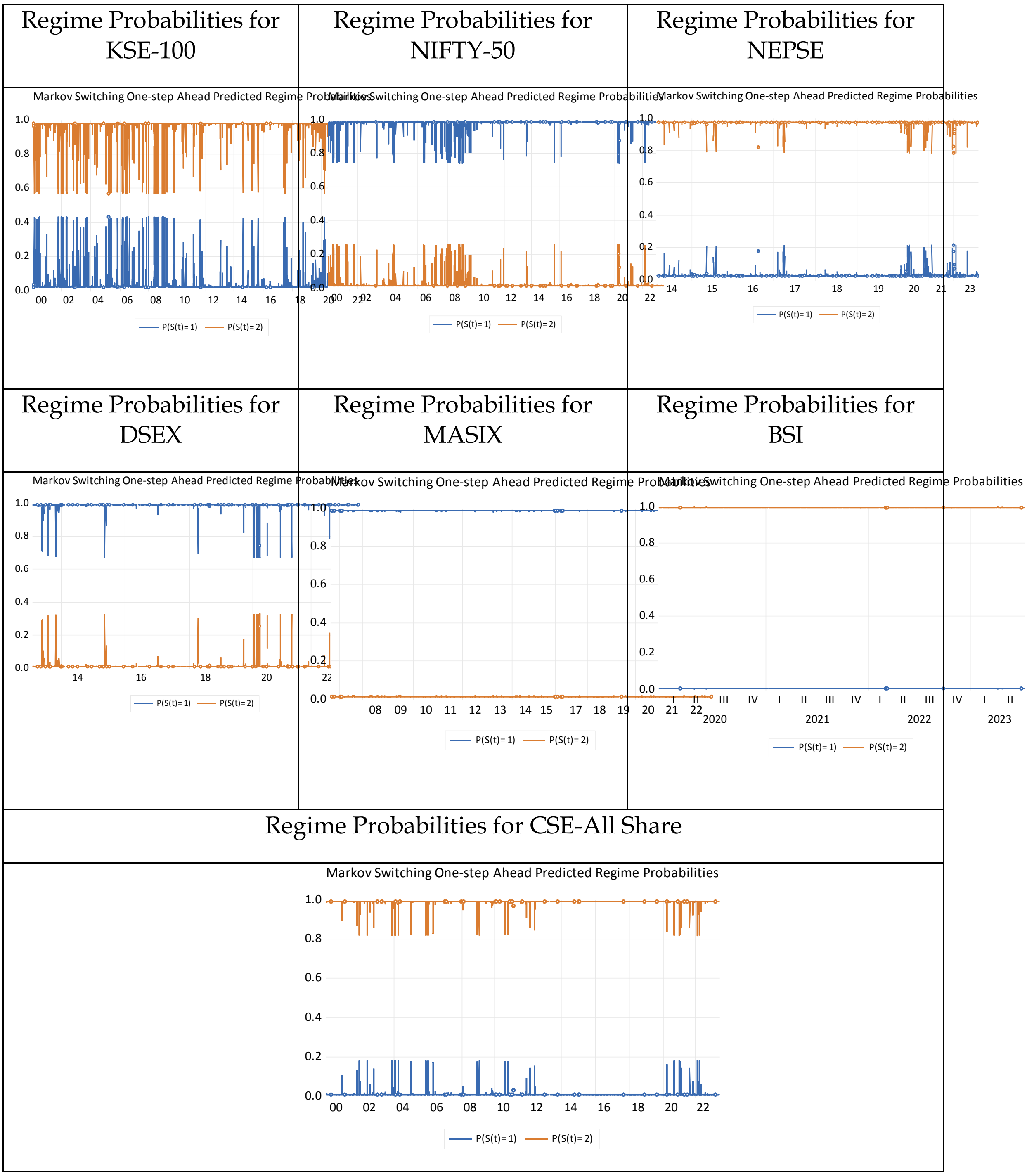

Figure 1. Regime Switching Probabilities for all the South Asian Stock Markets

Short and Long Run Volatility Spillover among Oil and South Asian Stock Markets

To check the volatility spillover in the long and short run between the oil and stock market, the study has employed the DCC-GARCH model, and its results have been reported in Table 7. It shows the dynamic association between the oil and stock markets of Pakistan, India, Nepal, Dhaka, Maldives, Bhutan, and Sri Lanka.

The results show the values of whole means (μ), constant (ω), ARCH term (α), GARCH term (β), DCC α, and DCC β. The ARCH term (α) shows the value of the ARCH coefficient based on the values of lagged squared residuals. GARCH term (β) shows the value of GARCH coefficients that help forecast the volatility based on its conditional variance. Moreover, DCC α shows the spillover effect in the short run because of the persistence of the standardized residuals from their preceding values. Whereas the DCC β shows the spillover effect in the long run because it shows the lingering effect of the shock and how it impacts the conditional correlation, which is the persistence of the process of conditional correlation.

The results show that α and β are significant for the KSE-100, which confirms the dependence on the lagged squared residuals and persistence of volatility. Similarly, α is significant for all the stock markets under study countries except the Dhaka Stock Exchange (DSEX), The Royal Securities Exchange of Bhutan Limited (BSI), and the Colombo Stock Exchange (CSE-All Share). Secondly, the persistence of volatility is also observed for all the stock markets except Dhaka (DSEX). The Dhaka Stock Exchange (DSEX) stock markets have the insignificant α and β. The Royal Securities Exchange of Bhutan Limited (BSI) has insignificant α and significant β, which means the value of conditional volatility can be estimated by looking at their past values instead of focusing on its squared residuals. Moreover, the sum of α and β is less than for all the series, which signifies the deterioration in the persistence of volatility with time, and the conditional correlation of the model is also not continuous. Volatility persistence over time and the conditional correlation in the model is not constant. Overall, it confirms the diffusion of information from South Asia's oil to stock markets.

The value of DCCα is significant for all the stock markets, excluding the Nepal Stock Exchange (NEPSE), The Royal Securities Exchange of Bhutan Limited (BSI), and the Colombo Stock Exchange (CSE-All Share). This shows that transmission of spillover from oil to stock markets does not exist for the markets of Nepal, Bhutan, and Sri Lanka in the short run. Moreover, the value of DCCβ is significant for all the South Asian stock markets except the Colombo Stock Exchange (CSE-All Share), which means there does not exist any spillover of volatility from the crude oil to the Sri Lankan Stock market in the long run. Nevertheless, volatility spillover does exist from the crude oil to stock markets of South Asia in the long run. This shows that investors have the options for diversifying their portfolios in Nepal, Bhutan, and Sri Lanka because the volatilities do not influence these in the international crude oil market.

Table 7
DCC Approach for Finding Volatility Spillover among Oil and South Asian Stock Markets

Stock Markets	Estimates	μ	ω	A	β	DCC α	DCC β	Elapsed Time
KSE-100	Coefficients	0.00094	0.000007	0.151643	0.806382	0.006533	0.976403	18.73114
	Sig-Value	0.000000	0.000001	0.000000	0.000000	0.062211	0.000000	
NIFTY-50	Coefficients	0.000900	0.000003	0.117613	0.870176	0.016838	0.966601	11.6741
	Sig-Value	0.000000	0.035940	0.000000	0.000000	0.023345	0.000000	
NEPSE	Coefficients	0.000780	0.000022	0.156525	0.762032	0.000000	0.905055	3.472712
	Sig-Value	0.027266	0.059216	0.000337	0.000000	0.999771	0.057697	
DSEX	Coefficients	0.000245	0.000001	0.122669	0.876331	0.031995	0.927533	5.708716
	Sig-Value	0.465427	0.992888	0.952806	0.651988	0.000015	0.000000	
MASIX	Coefficients	0.000294	0.000002	0.012055	0.985700	0.002583	0.993892	9.729987
	Sig-Value	0.426785	0.390225	0.000689	0.000000	0.032747	0.000000	
BSI	Coefficients	0.000086	0.000000	0.084307	0.914693	0.000000	0.939513	3.335598
	Sig-Value	0.655316	0.857065	0.259031	0.000000	0.997762	0.000574	
CSE-All Share	Coefficients	0.000207	0.000003	0.246710	0.752289	0.011895	0.725376	14.56358
	Sig-Value	0.533867	0.886362	0.167761	0.029459	0.271311	0.151997	

DCC GARCH Forecasts

The forecasts for the Conditional Correlation Matrices are shown in Table 8. The forecasted conditional correlation between all the series is almost close to zero, which suggests that no significant relationship exists among the forecasted returns of both series. Overall, the strength of the relationship is weak, and the conditional correlation remains constant over 5 periods, which suggests that the model expects a constant and stable relationship between both series in the near future.

Table 8
DCC GARCH Forecasts

Stock Markets	1	2	3	4	5
KSE-100	0.03676	0.03666	0.03657	0.03648	0.03639
NIFTY-50	0.1596	0.1591	0.1586	0.1581	0.1576
NEPSE	0.009425	0.009425	0.009425	0.009425	0.009425
DSEX	0.0293	0.02812	0.02698	0.02589	0.02484
MASIX	0.04119	0.04168	0.04217	0.04267	0.04316
BSI	0.07057	0.07057	0.07057	0.07057	0.07057
CSE-All Share	0.06309	0.05689	0.05231	0.04894	0.04645

Correlation between Oil and South Asian Stock Markets

The correlation among the oil and stock markets is shown in Table 9. And graphically in Figure 2. The results demonstrate a weak and positive relationship between crude oil and stock markets. This shows that these series show independence from each other, and a weak and positive relationship exists between them. Figure 4 also shows that patterns of their correlation are not constant. Instead, it keeps changing with time and returns to its mean position that exists in the long term. These findings are analogous to the findings of (Sehgal et al., 2015; Yadav et al., 2023).

Table 9
Correlation among Oil and South Asian Stock Markets

Stock Markets	Correlation
KSE-100	0.03335403
NIFTY-50	0.1501401
NEPSE	0.009425086
DSEX	0.02988248
MASIX	0.1834372
BSI	0.07057511

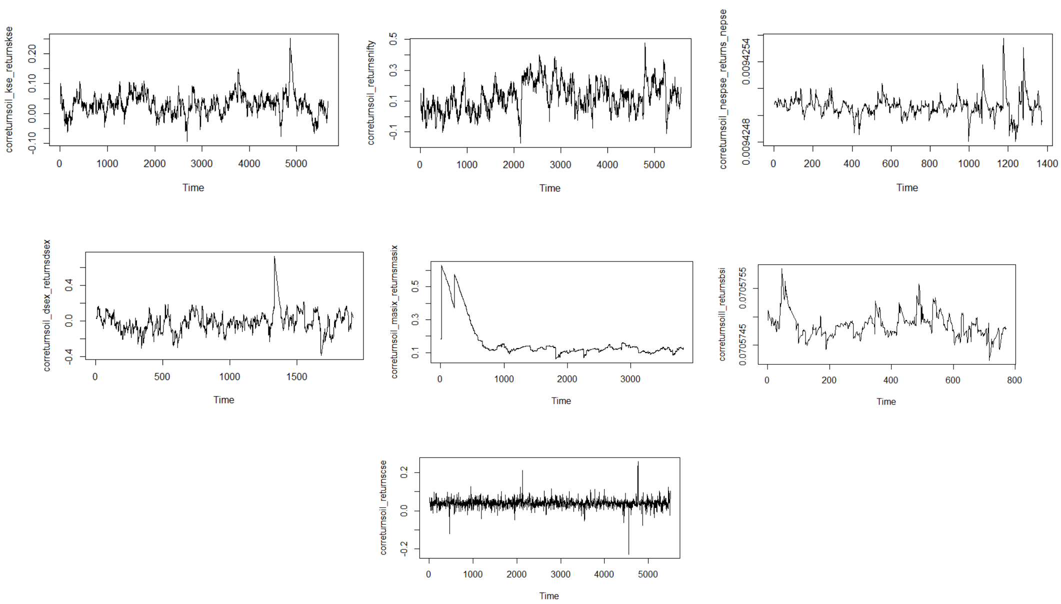

Figure 2. Correlation among Oil and South Asian Stock Markets

Covariance among Oil and South Asian Stock Markets

The covariance among oil and stock markets is shown in Table 10 and graphically in Figure 3. The results show that covariance between both the series is weak and propose the fluctuations in the international oil markets cannot strongly predict the volatility in the South Asian' stock markets. Overall, they have their inherent variability.

Table 10
Covariance among Oil and Stock Markets of South Asia

Stock Markets	Variance of Oil Returns	Variance of Stock Market Returns	Covariance
KSE-100	7.165800e-04	1.723619e-04	1.172199e-05
NIFTY-50	7.268377e-04	2.773002e-04	6.740473e-05
NEPSE	9.773060e-04	2.470625e-04	4.631311e-06
DSEX	7.577363e-04	7.840551e-06	7.840551e-06
MASIX	0.0009956827	0.0006732237	0.0001501853
BSI	1.781890e-03	6.156237e-05	2.337489e-05
CSE-All Share	5.48119e-04	1.71807e-04	1.65235e-05

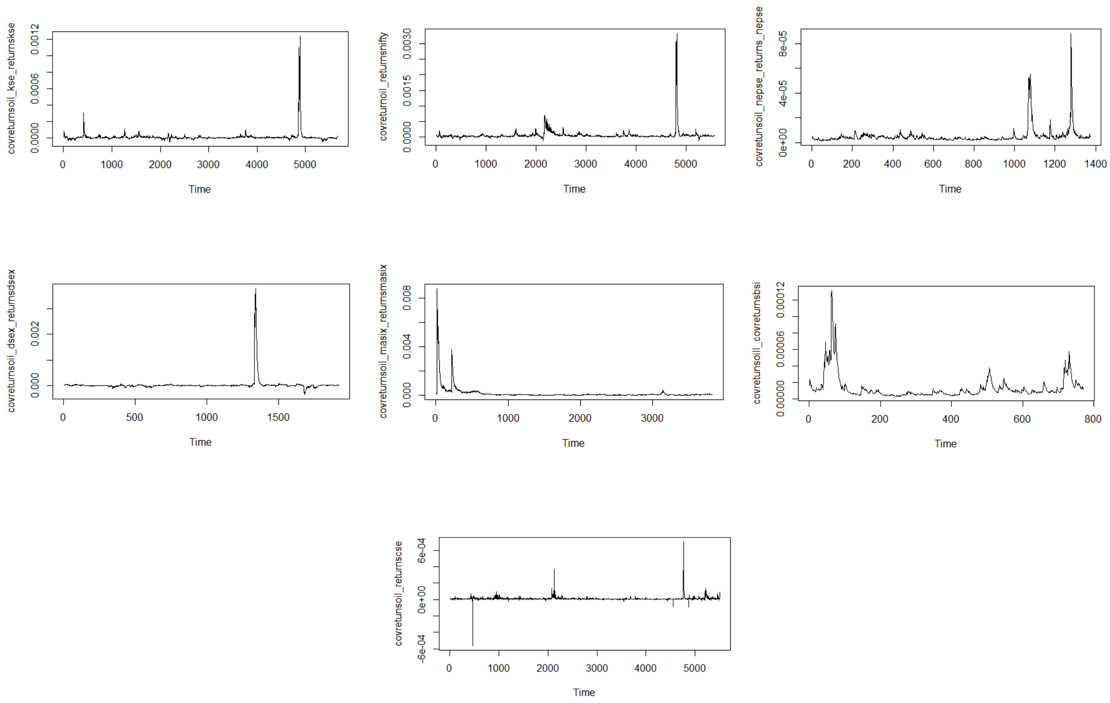

Figure 3. Covariance among Oil and stock markets in South Asia

Conclusion

The dynamic association between stock and oil market is of sound importance because of their dynamic relation and is also subjected to economic changes. The changing economic and political conditions create shocks in the economy that introduce fluctuations in terms of volatility in the oil markets. Later on, this volatility gets spillover to the stock markets of developing economies like South Asian stock markets. The study has used daily data to study the spillover from the crude oil markets to South Asian stock markets. Then, it employed the Markov Switching Model and DCC-GARCH approach to explore the spillover of diffusion of information from oil to stock markets of South Asia.

Markov-Switching Model's results have found that for regime 1, the effect of oil on the National Stock Exchange of India Limited (NIFTY-50) stock markets and Nepal Stock Exchange (NEPSE) is positive and significant at a 5% level. Conversely, this effect is negative and significant at a 5% level for the Royal Securities Exchange of Bhutan Limited (BSI) and the Colombo Stock Exchange (CSE-All Share). In contrast, its impact is insignificant for the remaining stock markets. Moreover, the study has found a significant and positive impact of crude oil prices on the stock markets of South Asia except the Nepal Stock Exchange (NEPSE) for the second Regime. This positive effect of oil prices on the stick markets demonstrates that high levels of volatility in the international oil markets are bringing positive shocks or spillovers in the stock markets. Findings of transition probabilities show that the first Regime is relatively stable compared to the second Regime, and the transition process from the first to the second Regime is comparatively slow. Besides, the probable duration of the second Regime is large for the stock exchanges of India, Dhaka, and Maldives.

Then, the findings of the DCC-GARCH model show that α and β terms are significant for the majority of the stock exchange markets. This shows that volatility can be forecasted by looking at its lagged values. Moreover, the sum of α and β is less than for all the series, which signifies the deterioration in the persistence of volatility with time, and the conditional correlation is not continuous. Overall, it shows the spread of information from the oil to the stock markets of South Asia. The value of DCCα is significant for all the stock markets, excluding the Nepal Stock Exchange (NEPSE), The Royal Securities Exchange of Bhutan Limited (BSI), and the Colombo Stock Exchange (CSE-All Share). This demonstrates that volatility does not spill over from the crude oil to the stock markets of Nepal, Bhutan, and Sri Lanka in the short run. Moreover, the value of DCCβ is significant for all the stock markets except the Colombo Stock Exchange (CSE-All Share), which means there does not exist any spillover of volatility from the crude oil to the Sri Lankan Stock market in the long run. However, volatility spillover does exist from the crude oil to the stock markets in the long run, which accepts the alternate hypothesis by rejecting the null hypothesis. This shows that investors can diversify their portfolios in Nepal, Bhutan, and Sri Lanka because these are not affected by the volatilities in the crude oil market.

Policy Implications

The findings of this study have suggestions for academia, investors, and portfolio managers. Portfolio managers can spread their risks by observing the spillover relationship between the markets. The study results demonstrate that a diversification opportunity exists for financiers to invest in Nepal, Bhutan, and Sri Lanka because these are independent of the international volatilities in the crude oil markets. Investors can diversify their portfolios in these countries. On the other hand, all the other markets have a strong association with the crude oil market. Proper consideration should be given to the shocks in oil prices for making a well-diversified portfolio. This would increase the accuracy of hedging against the risk induced by this oil market. Moreover, the study's findings can help policymakers make the appropriate strategies for stabilizing the oil price to prevent financial contagion and spillover in other markets. Overall, the study provides valuable insight for policymakers and investors on risk management by portfolio diversification and the spillover effect of international markets.

References

Adekoya, O. B., Oliyide, J. A., & Oduyemi, G. O. (2021). How COVID-19 upturns the hedging potentials of gold against oil and stock markets risks: Non-linear evidence through threshold regression and markov-regime switching models. *Resources Policy*, *70*, 101926.

Aruna, B., & Acharya, R. H. (2020). Is the effect of Indian energy price shocks asymmetric on the stock market at the firm level? A panel SVAR approach. *Economics and Policy of Energy and the Environment*(2020/1).

Aruna, B., & Rajesh, A. H. (2020). Impact of COVID-19 virus cases and sources of oil price shock on Indian stock returns. Structural VAR Approach. IAEE Energy Forum/COVID-19 Issue,

Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, *5*(2), 217-249.

Balcilar, M., Gupta, R., & Miller, S. M. (2015). Regime switching model of US crude oil and stock market prices: 1859 to 2013. *Energy Economics*, *49*, 317-327.

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global finance journal*, *17*(2), 224-251.

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash in 2013. *Economics*, *11*(1), 2.

Brunner, A. D. (1992). Conditional asymmetries in real GNP: a seminonparametric approach. *Journal of Business & Economic Statistics*, *10*(1), 65-72.

Caggiano, G., Castelnuovo, E., & Figueres, J. M. (2017). Economic policy uncertainty and unemployment in the United States: A non-linear approach. *Economics Letters*, *151*, 31-34.

Enwereuzoh, P. A., Odei-Mensah, J., & Junior, P. O. (2021). Crude oil shocks and African stock markets. *Research in International Business and Finance*, *55*, 101346.

Gao, R., Zhao, Y., & Zhang, B. (2021). The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. *International Journal of Finance & Economics*, *26*(2), 2134-2141.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of political economy*, *91*(2), 228-248.

Hung, N. T., & Vo, X. V. (2021). Directional spillover effects and time-frequency nexus between oil, gold and stock markets: evidence from pre and during COVID-19 outbreak. *International Review of Financial Analysis*, *76*, 101730.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. *International economic review*, *50*(4), 1267-1287.

Lee, Y.-H., & Chiou, J.-S. (2011). Oil sensitivity and its asymmetric impact on the stock market. *Energy*, *36*(1), 168-174.

Lin, L., Kuang, Y., Jiang, Y., & Su, X. (2019). Assessing risk contagion among the Brent crude oil market, London gold market and stock markets: Evidence based on a new wavelet decomposition approach. *The North American Journal of Economics and Finance*, *50*, 101035.

Liu, M., Lee, C.-C., & Choo, W.-C. (2021). The role of high-frequency data in volatility forecasting: evidence from the China stock market. *Applied Economics*, *53*(22), 2500-2526.

Lv, X., Lien, D., & Yu, C. (2020). Who affects who? Oil price against the stock return of oil-related companies: Evidence from the US and China. *International Review of Economics & Finance*, *67*, 85-100.

Mensi, W., Vo, X. V., & Kang, S. H. (2022). COVID-19 pandemic's impact on intraday volatility spillover between oil, gold, and stock markets. *Economic Analysis and Policy*, *74*, 702-715.

Naeem, M. A., Pham, L., Senthilkumar, A., & Karim, S. (2022). Oil shocks and BRIC markets: Evidence from extreme quantile approach. *Energy Economics*, *108*, 105932.

Nagarakatte, S. G., & Natchimuthu, N. (2022). Return and volatility spillover between India, UK, USA and European stock markets: The Brexit impact. *Investment Management and Financial Innovations*, *19*(1), 121-134.

Neftci, S. N. (1984). Are economic time series asymmetric over the business cycle? *Journal of political economy*, *92*(2), 307-328.

Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Oil price and stock returns of consumers and producers of crude oil. *Journal of International Financial Markets, Institutions and Money*, *34*, 245-262.

Phoong, S. W., Mahi, M. A., & Phoong, S. Y. (2023). A markov switching approach in assessing oil price and stock market nexus in the last decade: the impact of the COVID-19 pandemic. *SAGE open*, *13*(1), 21582440231153855.

Phoong, S. W., Phoong, S. Y., Moghavvemi, S., & Phoong, K. H. (2019). Multiple breakpoint test on crude oil price. *Foundations of Management*, *11*(1), 187-196.

Ready, R. C. (2018). Oil prices and the stock market. *Review of Finance*, *22*(1), 155-176.

Ren, X., Wang, R., Duan, K., & Chen, J. (2022). Dynamics of the sheltering role of Bitcoin against crude oil market crash with varying severity of the COVID-19: A comparison with gold. *Research in International Business and Finance*, *62*, 101672.

Ruta, M. (2022). The impact of the war in Ukraine on global trade and investment.

Sahabuddin, M., Islam, M. A., Tabash, M. I., Alam, M. K., Daniel, L. N., & Mostafa, I. I. (2023). Dynamic Conditional Correlation and Volatility Spillover between Conventional and Islamic Stock Markets: Evidence from Developed and Emerging Countries. *Journal of Risk and Financial Management*, *16*(2), 111.

Sarwar, S., Tiwari, A. K., & Tingqiu, C. (2020). Analyzing volatility spillovers between oil market and Asian stock markets. *Resources Policy*, *66*, 101608.

Sehgal, S., Ahmad, W., & Deisting, F. (2015). An investigation of price discovery and volatility spillovers in India's foreign exchange market. *Journal of Economic Studies*, *42*(2), 261-284.

Shear, F., Ashraf, B. N., & Sadaqat, M. (2020). Are investors' attention and uncertainty aversion the risk factors for stock markets? International evidence from the COVID-19 crisis. *Risks*, *9*(1), 2.

Singhal, S., Choudhary, S., & Biswal, P. C. (2019). Return and volatility linkages among International crude oil price, gold price, exchange rate and stock markets: Evidence from Mexico. *Resources Policy*, *60*, 255-261.

Tursoy, T., & Faisal, F. (2018). The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration. *Resources Policy*, *55*, 49-54.

Wang, G., Meng, J., & Mo, B. (2023). Dynamic Volatility Spillover Effects and Portfolio Strategies among Crude Oil, Gold, and Chinese Electricity Companies. *Mathematics*, *11*(4), 910.

Xu, W., Ma, F., Chen, W., & Zhang, B. (2019). Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. *Energy Economics*, *80*, 310-320.

Yadav, M. P., Sharma, S., & Bhardwaj, I. (2023). Volatility spillover between Chinese stock market and selected emerging economies: a dynamic conditional correlation and portfolio optimization perspective. *Asia-Pacific Financial Markets*, *30*(2), 427-444.

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