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Volatility Spillover, Hedging and Portfolio Diversification Between Oil Market and S&P Sectoral Indices

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ABSTRACT

The study aims to analyze the volatility spillover between the oil market (WTI) and the S&P (Stand and Poor's) Energy, Financial, and Industry sector indices through conditional correlation and variance causality. The DCC-GARCH (Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroscedasticity) and Hafner-Herwartz (2006) Variance Causality models were used to analyze the daily data for the period between January 3, 2012 and December 31, 2019. The results indicate a positive time-varying conditional correlation between the oil market and sector indices. In addition, the hedge ratios and risk-minimizing portfolio weights (which are vital for investors) have been calculated based on these data. The cheapest hedging transaction with the oil market occurs in the financial sector, while the most expensive one occurs in the energy sector. It has also been determined that volatility is transmitted from the sector indices to the oil market. This situation means that the S&P sector indices play a leading role (resource of information- emit information) in volatility spillover. The results provide important information to researchers, investors, and policymakers.

Keywords: Oil Market, Sector Indices, Multivariate GARCH, Variance Causality, Spillover.

JEL Classification Codes: C58, G11, Q40

INTRODUCTION

While the global markets are affected by many factors (such as economic, political, and social events), economic developments, which are reflected by specific indicators, play a key role in influencing the markets. Some vital economic indicators include stock indexes, securities-based futures, exchange rates, and the value of gold and oil in commodity prices.

Crude oil is both an essential resource of energy and raw material. Crude oil is an indispensable source of energy that directly or indirectly affects the economic activities of many countries. Many studies have shown the oil market's numerous macro and micro effects on the economy. Increasing oil prices lead to higher input costs and so higher output prices (cost inflation). These situations cause less output quantity and consumption, so the GDP rate (Gross Domestic Product) decreases. During these processes, unemployment and interest rates go up. In addition, increasing oil prices induces decreasing cash flows (except for companies that benefit from higher oil prices), therefore stock prices also decline. Moreover, increasing interest rates shifts the investor's preference from risky assets (stocks) to fixed-income securities, leading to stock prices falling (Pindyck,1980; Brown and Yucel; 2002: Basher and Sadorksy,2006; Soytas and Oran, 2011).

In addition to its effects on the economy, the financialization of commodity markets (Domanski and Heath, 2007) and increasing integration between commodity and financial markets have made the price of oil much more significant for policymakers and investors in recent years.

Previous studies analyzing crude oil's impact on the economy have generally focused on price (level) or return relationships (see Balabanoff, 1995; Ferderer, 1996; Hooker, 1996; Jones and Kaul,1996, etc) because the VAR (Vector Autoregression) model, the VAR based Classical Granger Causality model, the VECM (Vector Error Correction) based Granger Causality model, the Engle-Granger Cointegration model and the Toda-Yamamoto

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Causality model allow the level values or first moment of series. These models are not useful for high-frequency data. However, some studies have also indicated a potential relationship between volatilities (second moment of series, conditional variance). The literature defines the relationship between variables' volatilities as the volatility spillover or volatility transmission effect.

The volatility notion is important because it is considered a risk measure (Yu, 2002) which contains information (Ross,1989) and expectations (Kalotychou and Staikouras, 2009). Investors can utilize volatility within efficient risk management strategies (diversification and hedging). Additionally, examining the volatility structure of stocks and commodities provides information about substitution strategies (Creti et al., 2013). When the variables are negatively correlated (uncorrelated), this situation indicates a strong (weak) hedging process. The vital hedging process is known as a safe haven if the financial markets are in a period of turmoil. Positively correlated variables reflect the diversification property but are not considered perfect (Baur and Lucey, 2010; Baur and McDermott, 2010). In addition, policymakers pay attention to volatility to avoid the negative consequences of large fluctuations in the financial markets (Wang et al., 2020). This is because volatility is considered a measurement of the sensitivity and stability of financial markets and the economy (Yu, 2002; Poon and Granger, 2003).

This study provides a significant and original approach to the topic by exploring the risk management property of sector-based stock market indexes against the oil market. Sector-based stock market indexes are of interest because several studies have found that sectoral diversification effectively reduces risk (Cavaglia et al., 2000). In addition, using them removes the offsetting effect of aggregate stock market indexes (Soytas and Oran, 2011). We calculated the hedging ratios and optimal portfolio weights to observe the risk management property of sector-based equity indexes. This paper also contributes to the literature by analyzing the spillover direction in the context of causality. To achieve the paper's aim we utilized the DCC-GARCH and Hafner Herwartz Variance Causality methods.

This paper has shown that there are positive time-varying correlations between the oil market and the equity sector indices (Energy, Industry, and Financial), with the highest average correlation observed between the oil market and the energy sector. In addition, there are volatility spillovers from the equity sector indices to the oil market. Following this brief introduction, this paper is organized as follows: Literature Review (section 2), Data Set and Methodology (section 3), Results and Discussion (section 4), and Conclusion.

LITERATURE REVIEW

This section indicates the studies investigating the relationship between crude oil and the economy. This part of the paper consists of two subtitles in the form of (1) Macro-Level Interaction, and (2) Micro-Level Interaction. Moreover, both subtitles are also discussed for developing and developed countries.

Macro-Level Interaction

The macro-level interaction remarks the relationship between the growth rate, inflation rate, exchange rate, employment rate, and crude oil. A seminal work by Hamilton (1983) has shown that the changes in oil prices substantially affect the real output and production in the US. The majority of studies indicate that a rise in oil price shocks leads to a slower growth rate and higher inflation rate (see Huang et al., 2005; Rahman and Serletis, 2009; Bala and Chin, 2018; Bawa et al., 2021, etc). However, these linkages can vary from a developing country to a developed country and from an oil-importing country to an oil-exporting country.

Many papers have analyzed the relationship between crude oil and economic growth in developing countries. For example, Farzanegan and Markwardt (2009) indicate a significantly positive link between crude oil prices and the GDP (Gross Domestic Product) of Iran by using the Vector Error Correction Model (VECM) and Variance Decomposition Analysis (VDC). Contrary to Farzanegan and Markwardt (2009), Jbir and Zouari-Ghorbel (2009) remark no direct links between oil price shocks and economic indicators in Tunisia. Kumar (2009) shows that oil price shock is influenced negatively by the growth rate of industrial production in India. That said, oil price shocks positively affect inflation and interest rates. Akinlo and Apanisile (2015)(20 sub-Saharan countries) and Quero-Virla (2016) (Colombia) reveal that the crude oil market has a statistically significant and positive effect on economic growth. Trang et al. (2017) indicate the positive impact of increasing crude oil prices on inflation and the budget deficit for Vietnam. Nyangarika et al. (2018) show a strong correlation between crude oil prices and GDP growth in oil-producing nations. Akinsola and Odhiambo (2020) specify a statistically significant negative effect of oil prices on economic growth for seven low-income oil-importing sub-Saharan African nations by employing the Non-linear Autoregressive Distributed Lag (NARDL) approach. A further study by Syaharuddin et al. (2021) provides evidence of a positive transmission from oil prices to growth, exchange rates, and inflation rates. Finally, Liaqat et al. (2022) show crude oil price shocks prevent short- and long-term economic growth, in Pakistan.

The papers considering the impact of crude oil on the economic growth of developed countries are as follows: Mork et al., (2013) show the negative transmission effects of oil price shocks on GDP growth within seven members of the OECD. Similarly, Eyden et al. (2019) confirm the statistically significant and negative effect on economic growth for OECD countries. Bu using VAR (Vector Autoregressive) model, Alekhina and Yoshino (2018) indicate the positive impact of crude oil on GDP growth, inflation, interest rates, and exchange rates for oil-exporting nations. Aka (2020) shows a spillover from crude oil prices to economic growth in Turkey.There are also several studies only conducted on the relationship between oil price shocks and inflation. For instance, Bala and Chin (2018) (Nigeria) and Bawa et al. (2021) (OPEC) reveal the impact of negative crude oil shocks on inflation. LeBlanc and Chinn (2004), Sek et al. (2015), Choi et al. (2018), Kilian and Zhou (2021), and Wen et al. (2021) considered the impacts of crude oil on inflation in developed countries.

The literature is also replete with studies of the effects of crude oil prices on exchange rate markets. By using VAR-GARCH (Vector Autoregression- Generalized Autoregressive Conditional Heteroscedasticity) model, Salisu and Mobolaji (2013) remark on the bi-directional volatility spillover transmission between oil and the exchange markets for Nigeria. Mishra and Debasish (2016) also corroborate Salisu and Mobolaji's (2013) result. By considering MENA (Middle East, North Africa) countries, Nouira et al. (2019) indicate substantial evidence of volatility spillovers from crude oil markets to exchange rate markets. There are plethora of further studies (Basher et al., 2012; Abed et al., 2016; Bangura et al., 2021; Geng and Guo, 2021; Huang and Li, 2022) which dive into the volatility transmission between the price of crude oil and the exchange rate across numerous nations.

The studies covering developed countries are as follows: Jawadi et al. (2016) show a negative link between oil prices and the U.S. dollar/Euro exchange rate. Ji et al. (2019) reveal a statistically significant spillover from crude oil prices to the exchange rate markets in the U.S. and China. By considering major oil-exporting and oil-importing nations, Malik and Umar (2019) indicate the connectedness relationship between oil price shocks and the exchange rate, which was significantly positive and high after the financial crisis. By considering major oil exporter and importer countries, Hameed et al. (2021) remark that the exchange rate has a more volatile spillover effect on oil-exporting countries than on oil-importing countries. Finally, Adi et al. (2022) demonstrate a bi-directional volatility spillover and shock impact between the exchange rate and crude oil. The other studies considering developed countries are Wu et al. (2012), Mokengoy (2015), Siami-Namini (2019), Liu et al. (2020).

When we assess the literature mentioned above, we see that crude oil shocks' economic impacts are different for oil-importing and oil-exporting countries. In oil-importing countries the links are negative, but in oil-exporting countries are positive. In the following section, we will present the micro-level interaction.

Micro-Level Interaction

This interaction shows the relationship between crude oil and stock markets. As is known, crude oil impacts on stock markets can occur in different channels: (1) Cash flow, (2)Discount rate, and (3) Investors' demand shifting.

Some of the studies have considered the level and/or return value of the data set. For instance, Papapetrou (2001) remarks on the importance of crude oil in explaining Greece's stock market change, by using the VAR model. Eryigit (2012) shows that crude oil shocks have an impact on stock market index return in Turkey, by using the VAR model. Dagher and Hariri (2013) indicate that there is only uni-directional Granger causality from crude oil to the Lebanese stock market. By using panel cointegration and causality models, Li et al. (2012) reveal the long- run impact of oil prices on sectoral stock indices and causality from crude oil to the stock market of China. Halac et al. (2013) remark on a positive connection and significant cointegrated relationship between oil prices and the Turkish stock market. Broadstock et al. (2014) indicate that crude oil shocks have a direct impact on the stock markets in Asia-Pacific Countries. Gil-Alana and Yaya (2014) reveal the positive relationship between crude oil and the Nigerian stock market. Sensoy and Sobacı (2014) demonstrate the existence of volatility spillover between bond and stock markets in Turkey. Aydogan and Berk (2015) suggest that oil price variations significantly and rationally affect the Turkish stock market, by utilizing the VAR model. Similarly, Toparlı et al. (2019) reveal the impact of crude oil shocks on the Turkish stock market, but they show that this impact is less than the exchange rate and interest rate. Çatık et al. (2020) indicate the significant impact of crude oil on energy-dependent sector indices. Caporale et al. (2022) show that the crude oil market has a significantly positive (negative) effect on energy sectors (financial sectors) by considering BRICS (Brazil, Russia, India, China, and South Africa). Lastly, Le and Do (2022) specify that crude oil has a positive (negative) impact on oil-exporting (oil-importing) Asian countries' stock markets.

The works of literature covering developed countries are as follows: By using the structural VAR model, Kang and Ratti (2013) show that the oil market's typical demand shocks harm stock returns in the U.S. Kang et al. (2015) found similar results corroborating this study. Balcilar and Ozdemir (2013) indicate that there is no Granger causality in different regimes between crude oil and S&P 500. By focusing on Central and Eastern European Countries, Asteriou and Bashmakova (2013) remark on the impact of crude oil price changes on the stock market. Cunado and Gracia (2014) show the negative impact of the crude oil market on some European Countries. Moreover, they specify that the effects become different in underlying causes of oil price changes. Reboredo and Rivera-Castro (2014) indicate that oil price changes did not affect aggregate and sector indices in the pre- 2008 financial crisis period in Europe and U.S. Jiang et al. (2020) demonstrate no significant correlation between crude oil and the stock market in G7 (Group of Seven) countries. Finally, Akdeniz et al. (2021) remark on the changing of the positive impact of crude oil to a negative impact during the pandemic period.Many studies also investigate the volatility spillover relationship between oil and stock markets. Table 1 below summarizes the methodology and key findings of the literature reviewed in this section.

DATA SET AND METHODOLOGY

While the daily sector indices (energy-SP5EENE, industrial-SP5EIND, and financial-SP5FIN) have been obtained from Thomson Reuters Datastream, crude oil (WTI) was obtained from EIA (U.S. Energy Information

Table 1. Literature Review

Author	Data and Sample Period	Methodology	Key Findings
Malik and Hammoudeh (2007)	S&P 500, BSE, KSE, Tadawul WTI Crude Oil, Daily Data (1994-2001)	BEKK-GARCH	Indirect shock spillover is determined from the S&P 500 and Tadawul indices to the oil market. Volatility transmission from the oil market to BSE, KSE, and Tadawul indices is detected.
Malik and Ewing (2009)	Dow Jones Financial, Technology, Consumer Service, Health Care, Industrials Indices, WTI Crude Oil Weekly Data (1992-2008)	BEKK-GARCH	Volatility spillover from the oil market to the financial sector is not determined. Indirect shock and volatility spillover from the oil market to the technology sector is identified. Bi-directional volatility spillover is observed between the consumer service sector and the health sector and the oil market. Volatility spillover is determined from the industry sector to the oil market.
Arouri et al. (2011)	Dow Jones Stoxx 600 S&P 500 Sector Indices BRENT Oil Weekly Data (1998-2009)	CCC-GARCH, DCC-GARCH, BEKK-GARCH, VAR-GARCH,	It is determined that the volatility spillover has a one-way effect from the oil market to the European stock market indices. A bi-directional effect was found between the oil market and U.S. stock market indices of volatility spillover.
Chang et al. (2013)	FTSE 100, NYSE, Dow Jones, S&P 500 WTI, and Bent Oil Daily Data (1998-2009)	CCC-GARCH, DCC-GARCH, VARMA-GARCH,	No volatility spillover between the crude oil spot prices and stock indices was determined in this study. A slight volatility spillover between crude oil forward and future prices and stock indices has occurred.
Mensi et al. (2013)	S&P 500 WTI and BRENT Oil Daily Data (2000-2011)	VAR-GARCH	Volatility spillover is determined from the past shocks of S&P 500 Index to WTI crude oil, and from the past volatility of S&P 500 to WTI and Brent crude oil. In addition, volatility spillover is detected from past WTI and Brent crude oil shocks to S&P 500.
Mollick and Assefa (2013)	S&P 500, Dow Jones, NASDAQ, Russell 2000 WTI Crude Oil Daily Data (1999-2011)	DCC-GARCH GARCH	Before the financial crisis, stock returns were affected negatively by the oil market. During the crisis, it was determined that the oil market's stock returns were positively affected.
Maghyereh et al. (2016)	U.S, Canada, UK, India, Mexico, Japan Sweeden, And Oil Implied Volatility Indices Daily Data (2008-2015)	Diebold-Yılmaz	It is determined that there is a bi-directional volatility spillover between the stock and oil markets. Such a condition that the oil market is dominant in these relations.

Singhal and Ghosh (2016)	S&P BSE SENSEX and Sector Indices Brent Crude Oil Weekly Data (2006-2015)	VAR-DCC GARCH	No volatility spillover from the oil market to the S&P, BSE, SENSEX index has been identified. Volatility spillover from the oil market to the auto, power and finance sectors is determined.
Wang and Liu (2016)	SSEC, FCHI, GDAXI, BSESN, NIKKEI 225, KS11, FTSE, S & P 500, TSX, TASI, SEWI, MXX, OSEAX, MICEX, SMSI, IBVC WTI Crude Oil Weekly Data (2000-2011)	BEKK-GARCH DCC-GARCH	Among oil-exporting countries, there is a volatility transmission to IBVC (Venezuela), OSEAX (Norway), and MICEX (Russia) indices from the oil market. Among the oil-importing countries, a volatility spillover from GDAXI (Germany), FTSE (UK) and S&P 500 indices to the oil market has occurred.
Liu et al. (2017)	S&P500, MICEX, WTI Crude Oil, Daily, Weekly, Bimonthly, Monthly Data (2003-2014)	Wavelet BEKK-GARCH	Before the crisis period, there was no volatility spillover between S&P 500 and WTI in daily data. During and after the crisis, there is a volatility transmission from S&P 500 to WTI in the daily data. There is a bi-directional volatility spillover in all periods when considering weekly data.
Çevik et al. (2018)	MSCI G7 Index, MSCI Emerging Market Index Brent and WTI Daily Data (1988-2018)	Cheung and Ng Mean and Variance Causality Test	The causality of variance from WTI and Brent crude oil prices to MSCI G7 has not been determined. The causality of variance has been detected from MSCI G7 to Brent oil.
Ashfaq et al. (2019)	MSCI G7 Index, MSCI Emerging Market Index Brent and WTI Crude Oil Daily Data (1988-2018)	BEKK-GARCH DCC-GARCH	There is a bi-directional volatility spillover between oil-exporting countries' stock markets and the oil market (namely, Saudi Arabia and Iraq). Additionally, it is determined that there is a volatility spillover from the oil market to the South Korean stock market, which is one of the oil-importing countries
Sarwar et al. (2019)	Shangai, Nikkei, Bombay WTI Crude Oil Daily Data (2000-2016)	BEKK-GARCH DCC-GARCH cDCC-GARCH GO-GARCH	No spillover of shock and volatility spillover was determined between the Shangai Index and the oil market. Bi-directional shock and volatility spillover is detected between the Nikkei Index and the oil market. The results indicate that there is a shock and volatility transmission from Bombai Index to the oil market
Belhassine (2020)	Eurozone Sectors Brent Oil Daily Data (2004-2015)	VAR-BEKK-GARCH	The results showed that the presence or direction (bi-directional, uni-directional) of volatility spillover varies according to the period analyzed.
Liu et al. (2020)	OVX and VIX Daily Data (2007-2018)	DCC-GARCH cDCC-GARCH GO-GARCH	It is determined that there is a positive conditional correlation relationship between OVX and VIX, depending on time. This relationship strengthened during the financial crisis with a bi-directional volatility spillover.
Mensi et al. (2021)	Chinese Sector Stock Market Indices, WTI Futures Daily Data (2005-2020)	Diebold-Yılmaz	The energy sector is the most affected sector by crude oil. The financial and industrial sectors are the other most affected sectors, respectively.
Tiwari et al. (2021)	S&P500, Crude Oil (1990-2017) Monthly Data	Barunik-Krehlik	There is a similar interaction between S&P 500 and crude oil in the short term (1-6 Months). The interactions between data set become very small after that period.
Hussain and Rehman (2022)	GCC Stock Indices, S&P Global Oil Index (2012-2022) Daily Data	Diebold-Yılmaz	There is no spillover (too small to be considered) between the data set.
Hernandez et al. (2022)	OVX and U.S Sector Indices (2007-2020) Daily Data	Diebold-Yılmaz Markov Regime Switching Granger Causality	There is a Granger causality from the oil volatility to the sector indices, and the causality's impact is stronger in high volatility regimes.

Administration). The study covers the period between January 1, 2012, and December 31, 2019. The paper aims to analyze the relationship between stochastic processes, so level values were converted to returns series with the formula ln (P_t / P_{t-1})x100.

Several techniques have been developed to analyze volatility spillover. These are as follows: (1) Multivariate Autoregressive Conditional Heteroscedasticity Models (CCC, DCC, VEC, VAR, VARMA BEKK, etc.), (2) Variance Causality Methods (Cheung and Ng, Hong, Hafner-Herwartz), and (3) Volatility Connectedness Model-(Diebold & Yılmaz and Barunik & Krehlik). We utilized DCC-GARCH and Hafner Herwatz Variance Causality.

Christodoulakis and Satchell (2002), Engle (2002), and Tse and Tsui (2002) developed the Constant Conditional Correlation GARCH (CCC-GARCH) model for a structure in which the conditional correlation matrix is time-dependent. These models are collectively known as the Dynamic Conditional Correlation GARCH (DCC-GARCH) model. The model which was suggested by Christodoulakis and Satchell (2002) can only be applied to models with two variables. On the other hand, the DCC-GARCH models suggested by Engle (2002) and Tse & Tsui (2002) can be applied to multivariate and high-dimensional data sets.

The DCC (Engle) model can be formulated as follows:

$$r_t|\zeta_{t-1} \sim N(0, D_t R_t D_t), \tag{1}$$

$$D_t^2 = diag\{\omega_i\} + diag\{\mathrm{K}_i\} \circ r_{t-1}r_{t-1}' + diag\{\lambda_i\} \circ D_{t-1}^2 \tag{2}$$

$$\varepsilon_t = D_t^{-1} r_t \tag{3}$$

$$Q_t = S \circ (\iota\iota' - A - B) + A \circ \varepsilon_{t-1}\varepsilon_{t-1}' + B \circ Q_{t-1} \tag{4}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{5}$$

Within the equations: R_t refers to the symmetric positive matrix of correlations, S is the unconditional correlation matrix of ε_t, and A and B indicate non-negative scalar parameters, which must be lower than 1. If A=B=0, the Dynamic Conditional Correlation Model becomes the Constant Conditional Correlation Model (Wang and Liu, 2016).

Hafner and Herwartz (2006, 2008) have used the Lagrange Multiplier instead of the Portmanteau statistics model that Cheung and NG (1996) considered. As a result of their Monte Carlo simulation indicated that the test based on CCF (Cross-Correlation Function) has two shortfalls compared to the LM test. Firstly, if the conditional heteroskedastic process is leptokurtic, the Portmanteau test suffers from an oversizing problem. Secondly, $P_m = T\sum_{i=1}^{m} r_{ij,t}^2$ such that cross-correlation is the problem of correctly determining the *m* value. If *m* is determined too small, causality can be overlooked at high lags. If it is too large, the degree of freedom increases, and the strength of the test decreases.

The variance causality hypothesis put forward by Hafner and Herwatz (2006) is formulated as follows:

$$H_0: Var\left(\varepsilon_{it}|\mathrm{F}_{t-1}^{(j)}\right) = Var(\varepsilon_{it}|\mathrm{F}_{t-1}); \tag{6}$$

j=1,………N, i≠ j

$$F_t^{(j)} = F_t(\varepsilon_{j\tau}, \tau \leq t) \tag{7}$$

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2 g_t};\, g_t = 1 + z_{jt}'\pi = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2\right) \tag{8}$$

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{jt}'\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{jt}\right) \tag{9}$$

The expression ξ_{it} in Equation 8 indicates the standardized residual of variable *i*, while σ_{it}^2 is the conditional variance of variable *i*. Expressions ε_{jt-1}^2 and σ_{jt-1}^2 indicates the square of the error terms and the conditional variance of the series *j*, respectively (Nazlıoğlu et al, 2015:281). The Hafner and Herwatz Variance Causality Model tests the null hypothesis to ensure that there is no causality in variance. The following chapter will present and discuss the results.

RESULTS AND DISCUSSION

Before explaining the results, it is necessary to do a preliminary analysis of the data set. Figure 1 indicates the price (level) of the series.

Figure 1 shows that the WTI and the Energy Sector Index have moved on a similar upward trajectory. This situation became apparent after the year 2014. The period between 2014 and 2016 is crucial for the energy sector due to the following reasons (Investopedia; Eraydın, 2015; Ellwanger et al., 2017):

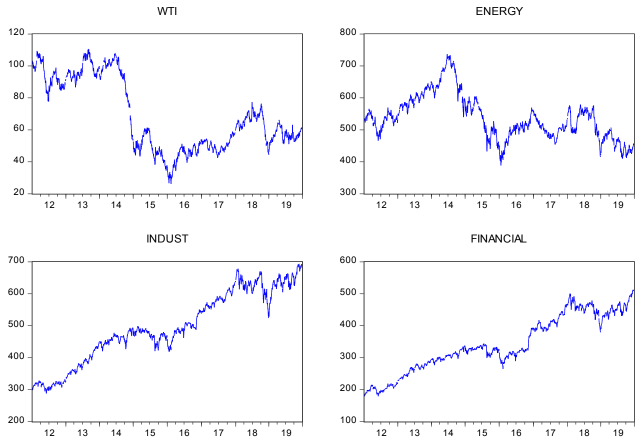

Figure 1. Price Series Graphs

- Due to rising oil prices, the U.S. and Canada increased their oil production and decreased imports.
- The growing trend after the global financial crisis (2008) didn't occur as expected.
- The economic slowdown in China caused a shrink in demand.
- The oil supply was not reduced by OPEC (The most Important Factor).
- Shale gas was used in the U.S.
- Increasing energy efficiency via technological advances.

Figure 1 displays a clear trend of increase in the Industry Sector Index and the Financial Sector Index, which is contrary to the WTI and the Energy Sector Index.

The data set has been converted to the return series with the formula ln (P_t / P_{t-1})x100. Figure 2 below represents the return series.

The results, as shown in Table 2, indicate that among the sector indices, the mean value is only negative in the energy sector, the highest risk is seen in the oil market, and the lowest risk is in the industry sector. The kurtosis value greater than 3 indicates a leptokurtic structure. This means that negative and positive outliers occur more frequently than normally distributed variables, and values scatter around the mean (Franke et al., 2007). While the sector indices are all skewed to the left, the crude oil market is skewed to the right. Left skewness indicates that negative values are more likely to occur. The skewness and kurtosis values of the data set reveal that the series has not been normally distributed. The Jarque-Bera test, which examines whether the series is normally distributed, also supports this result.

From the data presented in Table 3, the greatest correlation observed within the oil market occurs in the energy sector, while the lowest correlation is found within the financial sector.

While ADF and PP test the null hypothesis that the variables include unit roots, KPSS tests the null hypothesis that the series is stationary (Dickey and Fuller, 1981; Phillips and Perron, 1998; Kwiatkowski et al., 1992). In Table 4, it can clearly be observed that all series are stationary. ADF, PP, and KPSS are all traditional unit root models which ignore structural breaks. Because structural breaks may cause an acceptance of the null hypothesis even if they are false, researchers developed several unit root models which consider structural breaks. Zivot-Andrews (1992) is one such researcher.

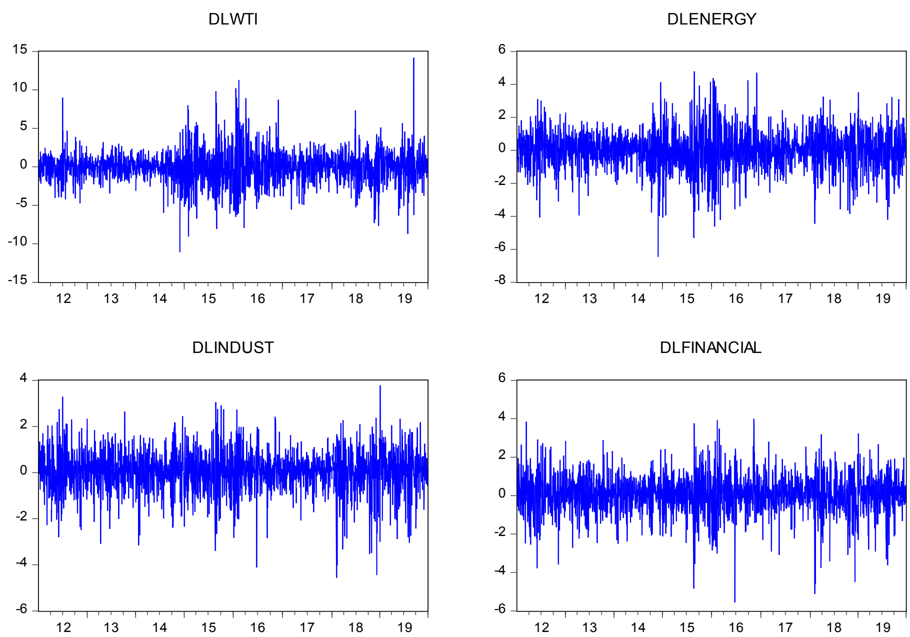

Figure 2. Return Series Graphs

Table 2. Descriptive Statistics of Return Series

	WTI	ENERGY	INDUSTRY	FINANCIAL
Mean	-0.025788	-0.007798	0.041303	0.051650
Maximum	14.17608	4.794393	3.778237	3.988712
Minimum	-11.12576	-6.469567	-4.562463	-5.558890
Std. Dev	2.104095	1.211535	0.915808	1.022031
Skewness	0.228042	-0.236570	-0.460161	-0.399910
Kurtosis	6.924854	4.754890	4.957872	5.314217
Jarque-Bera	1314.702***	278.1825***	394.1165***	504.8552***

Note: **** significance at %1*

Table 3. Correlation Table

	WTI	ENERGY	INDUSTRY	FINANCIAL
WTI	1	0.613449	0.276431	0.254263
ENERGY	0.613449	1	0.681491	0.634577
INDUSTRY	0.276431	0.681491	1	0.826177
FINANCIAL	0.254263	0.634577	0.826177	1

Table 4. Results of Unit Root Tests

	ADF		PP		KPSS	
	C	C + T	C	C + T	C	C + T
WTI						
Test Statistic	-48.22966	-48.23160	-48.20070	-48.20496	0.138728	0.066477
Test Critical (%5)	-2.862768	-3.412034	-2.862768	-3.412034	0.463000	0.146000
ENERGY						
Test Statistic	-18.86657	-18.87098	-44.63919	-44.63420	0.063265	0.039113
Test Critical (%5)	-2.862772	-3.412040	-2.862768	-3.412034	0.463000	0.146000
INDUSTRY						
Test Statistic	-21.57650	-21.57781	-44.41673	-44.41283	0.060401	0.025557
Test Critical (%5)	-2.862771	-3.412039	-2.862768	-3.412034	0.463000	0.146000
FINANCIAL						
Test Statistic	-21.77032	-21.77607	-45.75552	-45.75715	0.087273	0.041825
Test Critical (%5)	-2.862771	-3.412039	-2.862768	-3.412034	0.463000	0.146000

Table 5 shows that the null hypothesis of the Zivot–Andrews Unit Root Test (there is a unit root with a structural break in intercept and trend) is rejected. This indicates that the return series is a stationary process.

The DCC-GARCH (Engle Two-Step Procedure) model provides three kinds of information about the data set. These are as follows: (1) Univariate autoregressive conditional heteroscedastic structure of the series- *Panel A.*, (2) Existence of volatility spillover between series - *Panel B.,* and (3) The static and dynamic (time-varying) power of spillover.

Within the equation, ω ($\omega > 0$), α ($\alpha \geq 0$), and β serving as the constant, the effect of shock on the volatility and the effect of volatility in the previous period on current

Table 5. Zivot–Andrews Unit Root Test

Variables	At level		At 1st difference	
	T-statistic	Time Break	T-statistic	Time Break
Ln WTI	-4.619 (1)	9/29/2014	-48.514 (0)*	2/12/2016
Ln ENERGY	-3.450 (0)	5/04/2015	-19.096 (5)*	1/21/2016
Ln INDUSTRY	-4.210 (0)	4/23/2013	-21.667 (4)*	1/26/2016
Ln FINANCIAL	-3.309 (5)	7/23/2015	-21.958 (4)*	2/12/2016

Note: ** indicates % 1 level of significance. The critical value at %1 is –5.57 and 5% is –5.08. Parenthesis represents the lag order.*

Table 6. DCC-GARCH Model

PANEL A	ω		α		β
ω_{wti}	0.036915* [1.867]	α_{wti}	0.064668*** [4.946]	β_{wti}	0.928916*** [60.67]
ω_{energy}	0.024776** [2.123]	α_{energy}	0.067040*** [4.330]	β_{energy}	0.916610*** [43.67]
$\omega_{industry}$	0.062236*** [2.705]	$\alpha_{industry}$	0.115398*** [3.783]	$\beta_{industry}$	0.812123*** [16.53]
$\omega_{financial}$	0.136221*** [3.900]	$\alpha_{financial}$	0.160646*** [4.407]	$\beta_{financial}$	0.712711*** [12.96]
PANEL B	ρ		α		β
$\rho_{wti\text{-}energy}$	0.584879***	$\alpha_{wti\text{-}energy}$	0.006242**	$\beta_{wti\text{-}energy}$	0.989167***
$\rho_{wti\text{-}indutry}$	0.259151***	$\alpha_{wti\text{-}indutry}$	0.012739**	$\beta_{wti\text{-}industry}$	0.980529***
$\rho_{wti\text{-}financial}$	0.210281***	$\alpha_{wti\text{-}financial}$	0.012369***	$\beta_{wti\text{-}financial}$	0.981386***

Note: *Panel A shows Univariate Generalized Autoregressive Conditional Heteroscedasticity Model to consider ARMA(1,0).*

The variance equation is $\sigma^2=\omega+\alpha\mu^2_{t-1}+\beta\sigma^2_{t-1}$.

Note: *Panel B indicates the conditional correlation part of the DCC-GARCH Model.*

Note: **** significance at %1, ** significance at %5, * significance at %10.*

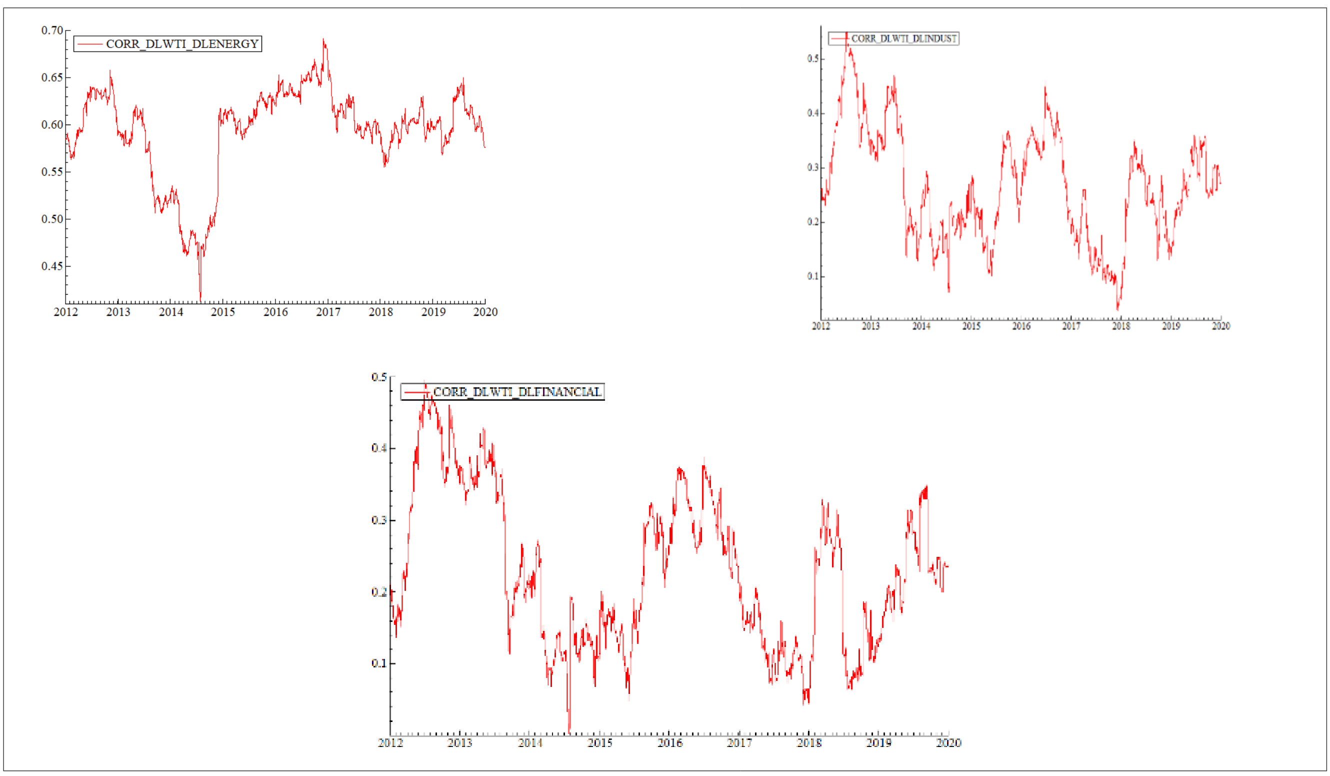

Figure 3. Time-Varying Conditional Correlation

Table 7. Results of Variance Causality

From/to	LM (prob)
WTI/ ENERGY	2.319(0.3137)
ENERGY/ WTI	11.121(0.0038)
WTI /INDUSTRY	3.281(0.1939)
INDUSTRY/WTI	6.852(0.0325)
WTI /FINANCIAL	2.191(0.3344)
FINANCIAL/ WTI	7.309(0.0259)
WTI/ ENERGY	2.319(0.3137)

***H_{0a}:** There is no causality in variance from the oil market to the sector indices*

***H_{0b}:** There is no causality in variance from the sectoral indices to the oil market*

volatility is determined, respectively. In addition, $\alpha + \beta$ indicates volatility persistence and must be less than 1. Persistence reveals whether the effect of the shock in the relevant data set is long or short. It can be seen from PANEL A in Table 6 that the highest volatility persistence is 0.99358 in WTI and the lowest is 0.873357 in the financial sector. The persistence of WTI leads researchers to consider long memory models (such as FIGARCH, FIEGARCH, FIAPARCH, and HYGARCH). The results of volatility spillover are shown in PANEL B (Table 6). Table 6 indicates that there is a volatility spillover (uni-directional or bi-directional) between the crude oil and the sector indices because ρ (average conditional correlation term), α (ARCH), and β (GARCH) are all statistically significant.

The interval of correlations between crude oil and the sector indices ranges from 0 to 0.7. This situation indicates that the sector indexes and crude oil do not have strong hedging and are not a safe haven instrument, but instead serve as a diversifier for each other over some period. As shown in Figure 3, the correlation between the WTI and the sector indices of industry and the financial sector increased from 0.2 to 0.5 in 2012. During this period, the price of crude oil increased from \$80 to \$100 per barrel. At the same time, the industry and financial sector indices were trending upward because of the global economic recovery after 2008. Therefore, we can infer that the recovery increased the demand for crude oil, which led to a demand-based volatility spillover (risk and information) from the sector indexes to crude oil. This indicates that during the recovery period of the economy, sector indexes should not be used as a risk management instrument for crude oil. In Figure 3, a clear downward correlation trend from 2013 to mid-2014 can be seen because the crude oil supply exceeded the demand. Despite this, OPEC did not reduce the supply. Therefore, the divergence between crude oil and the sector indexes (industry and financial) increased. This means that demand-based risk and information transfer from the sector indices to crude oil have decreased. The more surprising correlation occurred with the Energy Sector Index from 2013 to mid-2014. This occurred because the expectation was that there would be a tough divergence between crude oil and the energy sector. Two possible reasons for this are (1) Technological progress in clean energy and (2) Shale Gas. These assumptions (which have supply-side and demand-side effects) may have led the energy companies to not consider crude oil volatility (caused by a fall in the price) as an uncertainty and risk factor. Another crucial decrease in correlation is noticed from mid-2016 to 2018 (as shown in Figure 3). Although there was a supply-side effect (caused by lower global production and issues in oil fields, economic issues, the Zika virus in Venezuela, etc.), the divergence between the sector indices and crude oil increased. A possible explanation for this might again be the progression of clean energy technologies and the use of shale gas. Determining the existence of the volatility spillover lack of direction will be insufficient for investors, researchers, and policy makers. Detecting the presence of volatility spillovers without the direction of the relationship is insufficient for investors, researchers, and policy makers. Therefore, we utilized the variance causality model to capture the spillover direction. The results of the spillover direction are shown in Table 7.

Table 7 indicates that H_{0a} is not rejected for all the sector indices. That means there is no volatility spillover from the crude oil market to the sector indices. The statistical explanation of this result is that the past and current volatility of crude oil cannot be used to forecast the future volatility of stock markets. That result implies that the crude oil market is not a useful information resource for determining the sector indices. The other null hypothesis *H0b* is rejected for all the sectoral indices, as seen in Table 7. This means that the past and current volatility of the stock markets can be used to forecast the future volatility of the crude oil market or in brief, sector indexes have a leading role against crude oil. From the economic point of view, we can say that the transmission between crude oil and S&P indices is related to the demand and supply side because the U.S. is one of the biggest oil importers and exporters. For instance, slowing economic growth leads to increased industry sector uncertainty, and this situation based on lower demand also affects the crude oil market uncertainty. In terms of the supply side, we can say that energy producers' uncertainty condition is useful information for crude oil market volatility. The variance causality results indicate that policy makers in the U.S. do not need to monitor the oil market when developing policies to curb the stock market's fragility, but policy makers in the crude oil market should consider the sector indices in the U.S. For investors, the existence of variance causality remarks on the possibility of a weak risk management process. To observe that clearly, the hedge ratio and the optimal portfolio weight should be calculated.

The DCC-GARCH model allows us to calculate the Hedge Ratio and the Optimal Portfolio Weight. Kroner and Sultan (1993) formulated the Hedge Ratio as follows:

$$b_t = h_{xy,t}/h_{yy,t} \tag{10}$$

In the equation, b_t , $h_{xy,t}$, $h_{yy,t}$ and denote hedge ratio, conditional covariance, and conditional variance at time t, respectively.

The hedge ratio represents the cost of hedge transactions. According to the hedge ratio, a $1 long position in one asset should be hedged (short position) in the other asset. As such, Table 8 indicates that a $1 long position in crude oil should be hedged 0.46 (0.60, 1.01) cents with the financial sector (Industry, Energy) and a $1 long position in the financial sector (Industry, Energy) should be hedged 0.12 (0.13, 0.36) cents with crude oil. These results coincide with the correlation relationships (0.58-Energy; 0.25-Industry; 0.21-Financial). This means that if the conditional correlation relationship rises (volatility spillover impact), the hedging transactions become more expensive. When Table 7 and Table 8 are considered together, the financial sector has the lowest demand-side effect, as expected. Table 8 also shows that cheaper hedging transactions occur if crude oil is in a short position. The short position is used as a hedging transaction when assets are falling in a downward trajectory. This situation (decreasing trend of crude oil) can be observed in Figure 1 above. The time-varying hedge ratios are illustrated in Figure 4 below.

In Figure 4, graphics on the right (left) side show the short position (long-position) of the crude oil. It is apparent from Figure 4 that generally a short position in crude oil is more beneficial than a long position while considering the hedging ratio's ranges. This inference is corroborated by Figure 1 because crude oil has had a continuously decreasing trend since 2012. For example in 2014, suitable hedging transactions occurred when the crude oil in short position. In 2014 the crude oil price decreased because of the OPEC decision, and the slowdown in China's economy, therefore short position in crude oil was appropriate. The divergence (decreasing conditional correlation) between crude oil and the sector indices peaked at that period, especially between crude oil and financial sector indices. Therefore, the cheapest hedge process occurred between crude oil and financial sector (so close to zero). In some periods, the relationship between the correlation and hedge ratios is interesting considering Baur and Lucey (2010) and Baur and McDermott (2010) because they determined that only negative correlations (uncorrelated) related to strong (weak) hedging transactions. However, this paper shows that the positive low correlation can lead to strong or weak hedge ratio.

Table 8. Descriptive Statistics of Hedge Ratio

Long/Short	Mean	Maximum	Minimum	Std.Dev
WTI/ENERGY	1.014838	1.921916	0.400338	0.278724
ENERGY/WTI	0.365447	0.804299	0.186468	0.078290
WTI/ INDUSTRY	0.603219	1.931511	0.057544	0.326856
INDUSTRY/WTI	0.131432	0.414067	0.020591	0.072093
WTI/FINANCIAL	0.465828	1.644864	0.005224	0.280090
FINANCIAL/WTI	0.128307	0.467909	0.001954	0.082798

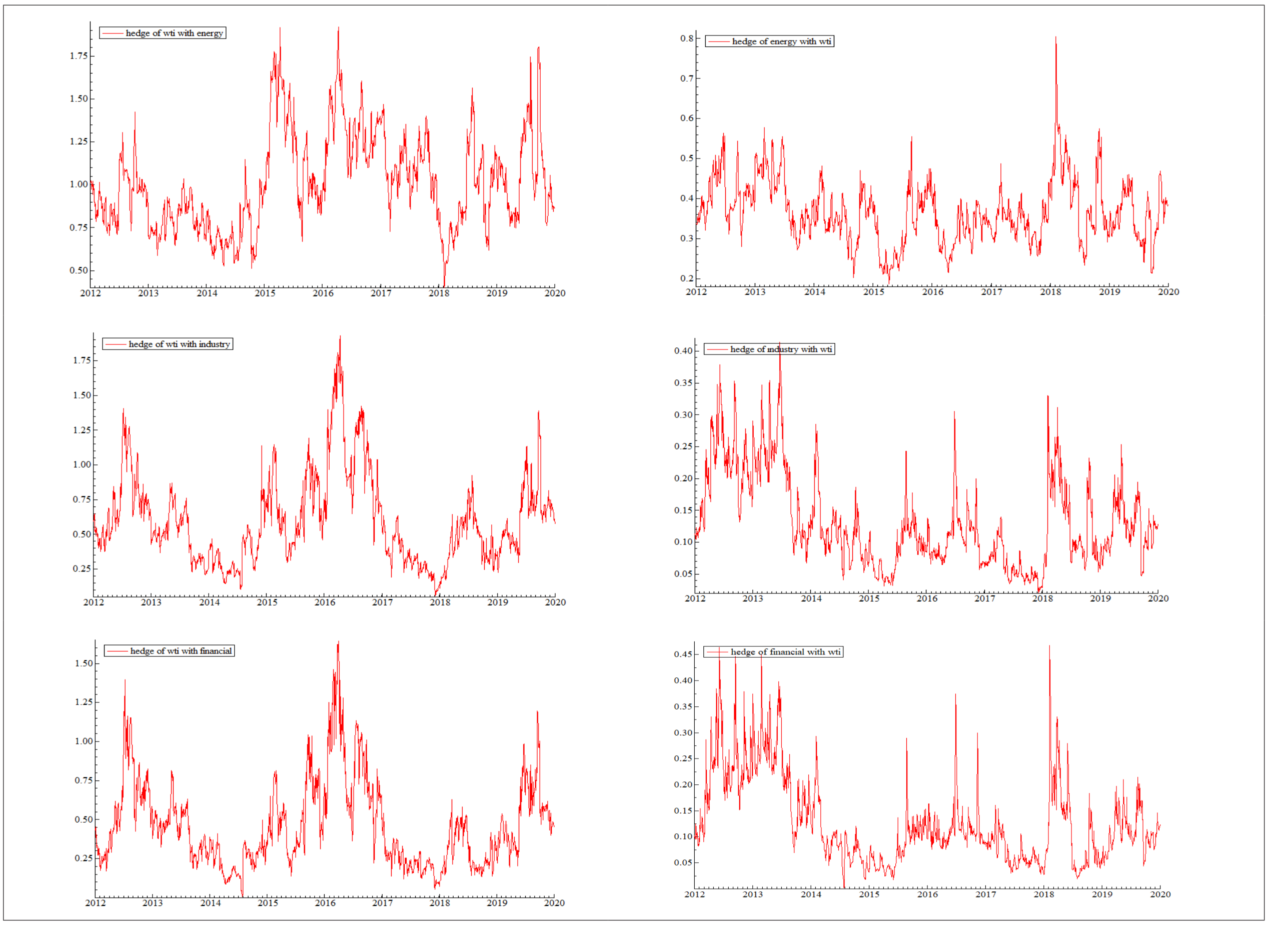

Figure 4. Time-Varying Hedge Ratio

The equation of risk-minimizing portfolio weight described by Kroner and Ng (1998) is as follows:

$$\omega_t = h_{yy} - h_{xy}/h_{xx} - 2h_{xy} + h_{yy} \tag{11}$$

$$\omega_t = \begin{cases} 0, if\,\omega_t < 0 \\ \omega_t, if\,0 \le \omega_t \le 1 \\ 1, if\,\omega_t > 1 \end{cases} \tag{12}$$

In the equation, h_{xx} and h_{yy} relate to the conditional variance of asset x and asset y, while h_{xy} is the conditional ω_t covariance between asset x and asset y. In addition, remarks the portfolio weight of the first asset, while $1\text{-}\omega_t$ states the second asset weight in the portfolio.

Table 9 indicates that in the \$1 portfolio, w_{jt} cents should be invested in j and 1- wjt cents in t. The WTI/Financial portfolio is approximately 0.18. This reveals that in a portfolio of \$100,000, \$18,000 should be invested in crude oil, the remaining \$82,000 should be invested in the financial sector, or \$13,000 should be invested in crude oil, and the rest should be invested in the industry sector. While creating a bivariate portfolio consisting of crude oil and sector indices, investors should include sector indices, predominantly.

The results presented in this chapter indicate a volatility spillover from the sector indices to crude oil. Sector indices are the indicators of crude oil's information, risk, and uncertainty. The cheapest hedging cost occurs between crude oil and the financial sector because the financial sector has the lowest effect (inferred from conditional correlations and hedging theories) on crude oil. The hedging cost will increase if the sector indices are used in a short position. There may be two possible explanations for this result: (1) Being an indicator and (2) Showing bull market tendencies. These findings have important implications for developing strategies for risk management for investors. The present results are also significant for policymakers. Policymakers should, therefore, not consider crude oil a source of vulnerability for the sector indices. These results corroborate the findings of Malik and Ewing (2009) and Singhal and Ghosh (2016).

Table 9. Descriptive Statistics of Optimal Portfolio Weights

$w_{jt/1-}\ w_{jt}$	Mean	Maximum	Minimum	Std.Dev
WTI/ENERGY	0.084675	0.860259	0.000000	0.120698
WTI/INDUSTRY	0.128078	0.707930	0.000000	0.111657
WTI/FINANCIAL	0.177895	0.836605	0.000000	0.133819

CONCLUSION

Financial liberalization and developing technology cause increased integration between markets. This leads investors and policymakers to investigate volatility spillover. Volatility spillover can be defined as the effect of risk perception in one market on the risk perception of another market.

This paper has proposed the answers to two questions: (1) Are crude oil and the sector indices risk management instruments for each other? (2) Is crude oil a source of vulnerability and uncertainty for the stock markets? According to these questions, the WTI, energy, industry, and financial sector indices were considered. We utilized the DCC-GARCH and Hafner-Herwartz Variance Causality methods to tackle these research questions. This paper has five major findings: (1) There is a volatility spillover from sector indices to the crude oil market, (2) Volatility transmissions are positive (3) The minimum average positive conditional correlation occurs between crude oil and finance sector, so the cheapest hedge transaction occurs together, (4) To do cheaper hedge transaction, investors should take a short position in the crude oil market, and (5) The sector indices are the leading indicators of crude oil, while the energy sector is most important. The dependence between WTI and the Energy Sector Index was at its lowest level in 2014. Technological progress in terms of clean energy and the increased use of shale gas may be the reasons for this.

The findings of this study have three practical implications for investors. First, investors do not need to consider the changes in crude oil when investing in sector indices in the U.S. Instead, they should consider the sector indices when investing in crude oil. Second, investors should consider the leading and lagging properties of assets and the conditional correlation together. Risk management results are limited in this paper because hedge effectiveness has been disregarded. As hedge effectiveness allows investors to learn the best risk management strategies (hedge or portfolio diversification), further research into this topic is required. Another practical implication of this research affects policymakers. Policymakers do not need to consider crude oil when developing policies for the stock market's stability.

Future research should consider contemporary methodologies. These methodologies include: Risk Spillover (Hong, Copula), Frequencies Spillover (Breitung and Calderon, 2006), Quantile Causality, Fourier Causality, Wavelet Causality, and Connectedness Models (Diebold Yılmaz, Barunik, and Krehlik), and more.

REFERENCES

Abed, R. El, Amor, T. H., Nouira, R., & Rault, C. (2016). Asymmetric effect and dynamic relationships between Oil prices shocks and exchange rate volatility: Evidence from some selected MENA countries. *Topics in Middle Eastern and African Economies, 18(2), 1–25.*

Adi, A.A., Adda, S.P. & Wobilor, A.K. (2022). Shocks and volatility transmission between oil price and Nigeria's exchange rate. *SN Bus Econ*, 2-47.

Akdeniz, C., Çatık, A. N. & Kışla Huyugüzel, G. (2021). The impact of oil prices on oil-gas stock returns: A fresh evidence from the covid-affected countries. *Economic Computation and Economic Cybernetics Studies and Research,55(3), 221-236.*

Akinlo, T., & Apanisile, O. (2015). The impact of volatility of oil price on the economic growth in Sub-Saharan Africa. In British Journal of Economics, Management & Trade, 5(3), 338–349.

Akinsola, M. O., & Odhiambo, N. M. (2020). The asymmetric effect of oil price on economic growth: A panel analysis of low-income oil-importing countries. Energy Reports, 6, 1057–1066.

Alekhina, V., & Yoshino, N. (2018). An Energy Exportıng Economy, Asian Development Bank Institute. 828.

Arouri, M. E.H., Jouni, J. & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International Money and Finance, 30, 1387-1405.

Ashfaq, S., Tang, Y., &Maqbool, R. (2019). Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies stock returns. Energy, 188, 1-13.

Asteriou, D., & Bashmakova, Y. (2013). Assessing the impact of oil returns on emerging stock markets: A panel data approach for ten Central and Eastern European Countries. Energy Economics, 38, 204-211.

Aydogan, B., & Berk, I. (2015). Crude oil price shocks and stock returns: Evidence from Turkish stock market under global liquidity conditions. International Journal of Energy Economics and Policy, 5(1), 54-68.

Bala, U., & Chin, L. (2018). Asymmetric impacts of oil price on inflation: An empirical study of African OPEC member countries. Energies, 11(11), 1-21.

Balabanoff, S. (1995). Oil futures prices and stock management A cointegration analysis. Energy Economics, 17(3), 205-210.

Balcilar, M., & Ozdemir, Z. A. (2013). The causal nexus between oil prices and equity market in the US: A regime switching model. Energy Economics, 39, 271-282.

Bangura, M., Boima, T., Pessima, S., & Kargbo, I. (2021). Modeling returns and volatility transmission from crude oil prices to Leone-US dollar exchange rate in Sierra Leone: aA GARCH approach with structural breaks. Modern Economy, 12(03), 555–575.

Basher S.A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. Global Finance Journal, 17, 224-251.

Basher, S. A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. Energy Economics, 34(1), 227–240.

Baur, D.G., & Lucey, B.M., (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. The Financial Review, 45,217-229.

Baur, D.G., & McDermott, T.K. (2010). Is gold a safe haven? International evidence. Journal of Banking & Finance,34,1886-1898.

Bawa, S., S. Abdullahi, I., Tukur, D., I. Barda, S., & J. Adams, Y. (2021). Asymmetric impact of oil price on inflation in Nigeria. Central Bank of Nigeria Journal of Applied Statistics, 11(2), 85–113.

Belhassine, O. (2020). Volatility spillovers and hedging effectiveness between the oil market and eurozone sectors: A tale of two crises. Research in International Business and Finance, 53, 1-19.

Broadstock, D. C., Wang, R., & Zhang, D. (2014). Direct and indirect oil shocks and their impacts upon energy related stocks. Economic Systems, 38(3), 451-467.

Brown S.P.A., & Yücel. M.K. (2002). Energy prices and aggregate economic activity: An interpretative survey. The Quarterly Review of Economics and Finance, 42, 193-208.

Caporale, G. M., Catik, A. N., Kışla, G. Ş. H., Helmi, M. H., & Akdeniz, C. (2022). Oil prices, exchange rates and sectoral stock returns in the BRICS-T countries: A time-varying approach. SSRN Electronic Journal, September.

Cavaglia, S., Brightman, C., & Aked, M. (2000). The increasing importance of industry factors. Portfolio Management, 41-54

Chang, C-L., McAleer, M., & Tansuchat, R. (2013). Conditional correlations and volatility spillovers between crude oil and stock index return. North American Journal of Economics and Finance, 25, 116-138.

Cheung, Y.W., & L.K. Ng (1996), A causality in variance test and its application to financial market prices, Journal of Econometrics, 72, 33-48.

Choi, S., Furceri, D., Loungani, P., Mishra, S., & Poplawski-Ribeiro, M. (2018). Oil prices and inflation dynamics: Evidence from advanced and developing economies. Journal of International Money and Finance, 82, 71–96.

Christodoulakis, G.A., & Satchell, S.E., (2002). Correlated ARCH (CorrARCH): Modelling the Time-Varying Conditional Correlation Between Financial Asset Returns. European Journal of Operational Research, 139, 351-370.

Creti,A., Joets,M., & Mignon, V. (2013). On the links between stock and commodity markets' volatility. Energy Economics, 37,16-28.

Cunado, J., & de Gracia, F. P. (2014). Oil price shocks and stock market returns: Evidence for some European countries. Energy Economics, 42, 365-377.

Çatık, A. N., Kışla, G. H., & Akdeniz, C. (2020). Time-varying impact of oil prices on sectoral stock returns: Evidence from Turkey. Resources Policy, 69, 101845.

Çevik, E.İ., Atukeren, E., & Korkmaz, T. (2018). Oil prices and global stock markets: A time-varying causality-in-mean and causality-in-variance Analysis. Energies, 11, 1-22.

Dagher, L., & El Hariri, S. (2013). The impact of global oil price shocks on the Lebanese stock market. Energy, 63, 366-374.

Dickey, D.A., & Fuller, W.A. (1981). Likelihood ratio statistics for autoregressive time series with a Unit Root, Econometrica, 49(4), 1057-1072.

Domanski, D., & Heath, A. (2007). Financial investors and commodity markets. BIS Quarterly Review, 53-67.

Ellwanger, R., Sawatzky, B., & Zmitrowicz, K. (2017). Factors behind the 2014 oil price decline. *Bank of Canada Review.1-13.*

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20(3), 339-350.*

Eraydın, K. (2015). causes and effects of the fall in crude oil price. *Department of Economic Studies of Türkiye İş Bankası, January 2015 Report, 1-22.*

Eryiğit, M. (2012). The dynamical relationship between oil price shocks and selected macroeconomic variables in Turkey. Economic Research, 25(2), 263-276.

Farzanegan, M. R., & Markwardt, G. (2009). The effects of oil price shocks on the Iranian economy. *Energy Economics, 31(1), 134–151.*

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy. Journal of macroeconomics, 18(1), 1-26.

Franke, J., Hardle, W. K., & Hafner, C. M. (2007). Statistics of Financial Markets. Berlin: Springer.

Geng, X., & Guo, K. (2021). The spillover effect of VIX and oil price on the exchange rate volatility among Belt and Road countries. Procedia Computer Science, 199, 765–772.

Gil-Alana, L. A., & Yaya, O. S. (2014). The relationship between oil prices and the Nigerian stock market. An analysis based on fractional integration and cointegration. Energy Economics, 46, 328-333.

Habiba, U. E., & Zhang, W. (2020). The dynamics of volatility spillovers between oil prices and stock market returns at the sector level and hedging strategies: evidence from Pakistan. Environmental Science and Pollution Research, 27(24), 30706–30715.

Hafner, C.M., & Herwartz, H. (2006). A Lagrange multiplier test for causality in variance. Economics Letters, 93, 137-141.

Hafner, C.M., & Herwartz, H. (2008). Testing for causality in variance using multivariate GARCH models. Annales d'Économie et de Statistique, 89, 215-241.

Halaç, U., Taşkın, F. D., & Çağlı, E. Ç. (2013). The Turkish stock market integration with oil prices: Cointegration analysis with unknown regime shifts. Panoeconomicus, 60(4), 499-513.

Hameed, Z., Shafi, K., & Nadeem, A. (2021). Volatility spillover effect between oil prices and foreign exchange markets. Energy Strategy Reviews, 38:10,100712.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. The University of Chicago Press, 91(2), 228–248.

Hernandez, J. A., Shahzad, S. J. H., Sadorsky, P., Uddin, G. S., Bouri, E., & Kang, S. H. (2022). Regime specific spillovers across US sectors and the role of oil price volatility. Energy Economics, 107, 105834.

Hooker, M. A. (1996). What happened to the oil price-macroeconomy relationship? Journal of monetary Economics, 38(2), 195-213.

Huang, Y., & Li, F. (2022). Research on the time-varying spillover effect of international crude oil price on China's exchange rate. Energy Reports, 8, 138–148.

Huang BN, Hwang MJ., & Peng HP. (2005). The asymmetry of the impact of oil price shocks on economic activities: an application of the multivariate threshold model. Energy Econ, 27(3), 455–476.

Hussain, M., & Rehman, R. U. (2022). Volatility connectedness of GCC stock markets: how global oil price volatility drives volatility spillover in GCC stock markets?. Environmental Science and Pollution Research, 1-11.

Jawadi, F., Louhichi, W., Ameur, Ben. H., & Cheffou, A. I. (2016). On oil-US exchange rate volatility relationships: An intraday analysis. Economic Modelling, 59, 329–334.

Jbir, R., & Zouari-Ghorbel, S. (2009). Recent oil price shock and Tunisian economy. Energy Policy, 37(3), 1041–1051.

Ji, Q., Liu, B. Y., & Fan, Y. (2019). Risk dependence of CoVaR and structural change between oil prices and exchange rates: A time-varying copula model. Energy Economics, 77, 80–92.

Jiang, Y., Tian, G., & Mo, B. (2020). Spillover and quantile linkage between oil price shocks and stock returns: new evidence from G7 countries. Financial Innovation, 6(1).

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. The journal of Finance, 51(2), 463-491.

Kalotychou, E., & Staikouras, S.K. (2009). An Overview of the Issues Surrounding Stock Market Volatility, Stock Market Volatility, Edt by. Gregoriou, G. N. 3-29. Chapman&Hall:NY

Kang, W., & Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets, Institutions and Money, 26, 305-318.

Kang, W., Ratti, R. A., & Yoon, K. H. (2015). Time-varying effect of oil market shocks on the stock market. Journal of Banking & Finance, 61, S150-S163.

Kilian, L., & Zhou, X. (2021). The impact of rising oil prices on U.S inflation and inflation expectations in 2020-23. Federal Reserve Bank of Dallas, Working Papers, 2021(2116).

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. The Journal of Financial and Quantitative Analysis, 28: 4, 535-551.

Kroner, K.F., & Ng, V.K., (1998). Modeling asymmetric movements of asset prices. Review of Financial Studies,.11, 817–844.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econometrics, 54(1-3), 159-178.

Kumar, S. (2009). The macroeconomic effects of oil price shocks: empirical evidence for India. Business Valuation Review, 29(1), 1–43.

Le, H. A., & Do, D. T. (2022). The impacts of crude oil market structure on stock market growth : Evidence from Asian Countries. Hindawi Complexity, 2022.

LeBlanc, M., & Chinn, M. D. (2004). Do high oil prices presage inflation? The evidence from G-5 countries. SUC Santa Cruz Working Paper Series.

Li, S. F., Zhu, H. M., & Yu, K. (2012). Oil prices and stock market in China: A sector analysis using panel cointegration with multiple breaks. Energy Economics, 34(6), 1951-1958.

Liaqat, M., Ashraf, A., & Nisar, S. (2022). The İmpact of oil price İnflation on economic growth of oil İmporting economies: Empirical evidence from Pakistan. Journal of Asian Finance, 9(1), 167–0176.

Liu, X., An, H.,Huang, S., & Wen, S. (2017). The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH-BEKK model. Physica A: Statistical Mechanics and its Applications, 465, 374-383.

Liu, Y., Failler, P., Peng, J., & Zheng, Y. (2020). Time-varying relationship between crude oil price and exchange rate in the context of structural breaks. Energies, 13(9), 1–17.

Liu, Z., Tseng, H-K.,Wu, J.S., & Ding, Z. (2020). Implied volatility relationships between crude oil and the U.S. Stock Markets: Dynamic correlation and spillover effects. Resources Policy,.66, 1-10.

Maghyereh, A.I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Economics, 57, 78-93.

Malik, F., & Ewing, B.T. (2009). Volatility transmission between oil prices and equity sector returns. International Review of Financial Analysis, 18, 95-100.

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil, US and Gulf Equity Markets. International Review of Economics and Finance, 16, 357-368.

Malik, F., & Umar, Z. (2019). Dynamic connectedness of oil price shocks and exchange rates. Energy Economics, 84, 104501.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. Economic Modelling, 32, 15-22.

Mensi, W., Al Rababa'a, A. R., Vo, X. V., & Kang, S. H. (2021). Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. Energy Economics, 98, 105262.

Mishra, S., & Debasish, S. S. (2016). Analysis of volatility spillover between oil price and exchange rate in India: GARCH Approach, 8.

Mokengoy, M. B. (2015). Volatility transmission between the oil price , the exchange rate and the stock market index. Thesis Universite Laval.

Mollick, A. V., & Assefa, T. A. (2013). U.S. stock returns and oil prices: The tale from daily data and the 2008–2009 financial crisis. Energy Economics, 36, 1-18.

Mork, K.A, Olsen,O., & Mysen, H.T. (2013). Macroeconomic responses to oil price increases and decreases in seven OECD countries. The Energy Journal,15(4), 19-35.

Nazlıoğlu, S., Hammoudeh, S., & Gupta, R. (2015). Volatility transmission between Islamic and conventional equity markets: Evidence from causality in-variance test. Applied Economics, 1-15.

Nouira, R., Hadj Amor, T., & Rault, C. (2019). Oil price fluctuations and exchange rate dynamics in the MENA region: Evidence from non-causality-in-variance and asymmetric non-causality tests. Quarterly Review of Economics and Finance, 73, 159–171.

Nyangarika, A. M., Mikhaylov, A. Y. & Tnag, B-J. (2018). Correlation of oil prices and Gross Domestic Product in oil-producing countries. International Journal of Energy Economics and Policy, 8(5), 42-48.

Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. Energy economics, 23(5), 511-532.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75(2), 335-346.*

Pindyck, R. S. (1980). Energy price increases and macroeconomic policy. The Energy Journal, 1: 4, 1-20.

Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. Journal of Economic Literature, 41(2), 478-539.

Quero-Virla, L. (2016). Macroeconomic effects of oil price fluctuations in Colombia. Ecos de Economía, 20(43), 23–38. https://doi.org/10.17230/ecos.2016.43.2

Rahman, S., & Serletis, A. (2009). The effects of exchange rate uncertainty on exports. Journal of Macroeconomics, 31(3), 500–507.

Reboredo, J. C., & Rivera-Castro, M. A. (2014). Wavelet-based evidence of the impact of oil prices on stock returns. International Review of Economics & Finance, 29, 145-176.

Ross, S. A. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *The Journal of Finance*, 44(1), 1-17

Salisu, A. A., & Mobolaji, H. (2013). Modeling returns and volatility transmission between oil price and US-Nigeria exchange rate. *Energy Economics, 39, 169–176.*

Sarwar, S., Khalfaoui, R., Waheed, R., & Dastgerdi, H.G. (2019). Volatility spillovers and hedging: Evidence from Asian oil-ımporting countries. Resources Policy, 61, 479-488.

Sek, S. K., Teo, X. Q., & Wong, Y. N. (2015). A comparative study on the effects of oil price changes on inflation. Procedia Economics and Finance, 26(15), 630–636.

Sensoy, A., & Sobaci, C. (2014). Effects of volatility shocks on the dynamic linkages between exchange rate, interest rate and the stock market: The case of Turkey. Economic Modelling, 43, 448-457.

Siami-Namini, S. (2019). Volatility transmission among oil price, exchange rate and agricultural commodities prices. Applied Economics and Finance, 6(4), 41.

Singhal,S., & Ghosh, S. (2016). Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. Resources Policy, 50, 276-288.

Soytas, U., & Oran, A. (2011). Volatility spillover from world oil spot markets to aggregate and electricity stock ındex returns in Turkey. Applied Energy, 88, 354-360.

Syaharuddin, Y., Purwadi, P., & Sampeliling, A. (2021). Attention of economic growth and oil prices: Evidence from Indonesia. International Journal of Energy Economics and Policy, 11(5), 425–433.

Tiwari, A. K., Mishra, B. R., & Solarin, S. A. (2021). Analysing the spillovers between crude oil prices, stock prices and metal prices: The importance of frequency domain in USA. Energy, 220, 119732.

Toparlı, E. A., Çatık, A. N., & Balcılar, M. (2019). The impact of oil prices on the stock returns in Turkey: A TVP-VAR approach. Physica A: Statistical Mechanics and its Applications, 535, 122392.

Trang, N. T. N., Tho, T. N., & Hong, D. T. T. (2017). The impact of oil price on the growth, inflation, unemployment and budget deficit of Vietnam. International Journal of Energy Economics and Policy, 7(3), 42–49.

Tse, Y.K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time varying correlations. Journal of Business & Economic Statistics. 20: 3, 351-362.

Van Eyden, R., Difeto, M., Gupta, R., & Wohar, M. E. (2019b). Oil price volatility and economic growth: Evidence from advanced economies using more than a century's data. Applied Energy, 233–234, 612–621. https://doi.org/10.1016/j.apenergy.2018.10.049

Wang,Y., & Liu, L. (2016). Crude oil and world stock markets: Volatility spillovers, dynamic correlations, and hedging. Empir Econ, 50, 1481-1509.

Wang, L., Ma, F., Liu, J., & Yang, L. (2020). Forecasting stock price volatility: New evidence from the GARCH-MIDAS model. *International Journal of Forecasting*, 36(2), 684-694.

Wen, F., Zhang, K., & Gong, X. (2021). The effects of oil price shocks on inflation in the G7 countries. *North American Journal of Economics and Finance, 57(June 2020), 101391.*

Wu, C. C., Chung, H., & Chang, Y. H. (2012). The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. Energy Economics, 34(1), 270–282.

Yu, J. (2002). Forecasting volatility in the New Zealand stock market. *Applied Financial Economics*, 12(3), 193-202.

Zivot, E., & Andrews, D. (1992). Further evidence of great crash, the oil price shock and unit root hypothesis, *Journal of Business and Economic Statistics, 10, 251-270.*

INTERNET ACCESS

Depersio, G. (2019). Why Did Oil Prices Drop So Much in 2014? www.investopedia.com.

Tarver, E. (2019). Why the Price of Crude Oil Dropped in 2015. www.investopedia.com.