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The Relationship between the Returns and Volatility of Stock and Oil Markets in the Last Two Decades: Evidence from Saudi Arabia

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ABSTRACT

Using daily data from 2000 to 2019, this study examines the sensitivity of Saudi market returns and volatility to changes in oil prices. This study employs the threshold general autoregressive conditional heteroskedastic in mean model (TGARCH-M) and three multivariate general autoregressive conditional heteroskedastic (MGARCH) models. Overall, it is found that oil price changes have a significant positive impact on Saudi stock market returns. More, there is a positive relationship between the volatility of stock and oil markets, and this positive relationship has increased significantly in the last decade. Thus, Saudi Arabia is recommended to diversify its economy away from oil income to enhance their stock market efficiency and stability.

Keywords: Saudi Arabia, Tadawul, Oil, Volatility, TGARCH-M, MGARCH
JEL Classifications: C32, E44, G12

1. INTRODUCTION

Oil price movements play a vital role in changing economic activity (Sadorsky, 1999). Despite the importance of oil to the world economy, there is a lack of academic literature that tries to examine the impact of oil price changes on stock markets performance (Apergis and Miller, 2009). According to Huang et al. (1996), the oil price can impact the stock prices throw altering the company's cash flow and discount rates. However, the size and the sign of this impact depend on the economic condition whether it is a net importer or exporter of oil (Salisu and Isah, 2017).

Saudi Arabia plays a vital role in the global oil market and it is the largest oil producer in the OPEC organization with oil production capacity of 9.8 million barrels a day that accounts for 33% of the total OPEC members production in 2019. Further, the Saudi stock market exchange (Tadawul) is considered as one of the largest stock markets in the world with a value of USD 2.41 trillion by the end of 2019 (Tadawul, 2019). However, despite the importance of the Saudi stock market exchange, fewer studies that try to analyze the market sensitivity to changes in oil prices such as (Abdalla, 2013) and (Jouini, 2013).

Therefore, this study aims to contribute to the literature by examining the impact of oil price changes on the returns and the volatility of the Saudi stock market exchange over the last two decades from 2000 to 2019. This study employs the threshold general autoregressive conditional heteroskedastic in mean model (TGARCH-M) and three multivariate general autoregressive conditional heteroskedastic (MGARCH) models to capture the sensitivity of Saudi market returns and volatility to changes in oil prices. The study relies on a highly frequent daily data set that can efficiently capture the sensitivity of market stock returns and volatility to changes in oil prices. This paper is divided into six sections. Section 2 summarizes related literature. Section 3 discusses the study methodology, while Section 4 describes the study data. Section 5 discusses the empirical results and finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

The 1970s price oil shock has encouraged several studies to examine the impact of oil prices on stock market returns. However, the majority of these studies has been focused on developed countries. Jones and Kaul (1996) analyzed the reaction of stock markets to oil price shock in four developed countries, which are the United States, Canada, Japan and the United Kingdom by relying on a quarterly data set. They found that changes in oil prices have a negative impact on stock returns in these countries and US and Canadian stock markets have a rational reaction to oil price shocks, while for Japan and UK, the reaction is ambiguous. More, Huang et al. (1996) examined the relationship between the prices of a future oil market and a stock market in the US by using a multivariate vector autoregressive (VAR) approach and daily data from 1979 to 1990. They concluded that oil future returns were only correlated with oil company stock returns and there was no correlation between the volatility of oil and stock markets. Further, Sadorsky (1999) examined the relationship between oil prices and stock market returns in the US over the period 1947-1996 by using an unrestricted vector autoregression model. He found that oil price changes had an adverse influence on stock market returns and this effect is dynamic. He also reported that oil price volatility had an asymmetric impact on US economic activity. Ciner (2001), more, found there is a nonlinear relationship between oil prices and US stock market movements and this relationship is dynamic by employing linear and non-linear Granger-causality tests. Based on monthly data, Nandha and Faff (2008) investigated the impact of changes in oil prices on global equity indices and they found that oil price changes have a negative effect on stock market returns except for companies that work at oil, gas and mining sectors. In the same manner, Park and Ratti (2008) used an unrestricted vector autoregression model to analyze the impact of oil price shocks on stock market return in the US and 13 European countries over the period 1986 to 2005. In general, they found that oil prices shocks and volatility harm stock market returns, except in Norway. Apergis and Miller (2009), moreover, employed a vector error-correction or vector autoregressive model to study the impact of oil price changes on stock market returns in eight developed countries. They pointed out that oil price changes had a minimal effect on international stock market returns.

For emerging markets, using weekly data from 1994 to 2004, Nandha and Hammoudeh (2007) examined the sensitivity of stock market returns to changes in oil prices and exchange rates in 15 Asia-Pacific countries by employing an international factor model. They showed that countries are only sensitive to changes in oil prices in local currency only. They also found stock markets in two oil importer countries (South Korea and Philippines) react negatively to oil price changes, while stock markets in two oil importer countries (Indonesia and Malaysia) react negatively only when there is a decrease in oil prices. More, Ono (2011) used a multivariate vector autoregressive (VAR) model to examine the impact of oil prices changes on stock market returns in Brazil, China, India and Russia over the period 1999-2010. They reported that oil price shocks have a positive impact on stock markets returns in China, India and Russia only and these shocks contribute significantly to the volatility of stock markets in Russia and China only. Recently, Salisu and Isah (2017) examined the relationship between oil and stock markets in 13 countries by using a nonlinear panel autoregressive distributed lag model over the period 2000-2015. They found that there is a positive relationship between changes in oil and stock prices for both oil-exporting and oil-importing countries, where the former exhibit a larger impact. Therefore, the results of the impact of oil price changes on stock market performance vary between countries and this paper aims to extend the literature by examining the impact of oil price changes on stock market exchange in Saudi Arabia, one of the largest oil producer and exporter in the world, over the last two decades.

3. METHODOLOGY

This section describes the employed models and their properties. Firstly, the threshold general autoregressive conditional heteroskedastic in mean model (TGARCH-M) is used to analyze the impact of oil returns on Saudi stock market returns in the last two decades.[1] This model specification has several advantages. First, it allows capturing the volatility clustering and leptokurtosis in the financial time series.[2] Second, it allows capturing the asymmetric effect as in financial markets the good and bad news usually have an asymmetric effect on volatility. Lastly, it allows estimating the ARCH in-mean effect or the direct feedback between volatility and returns.

$$\mathrm{R_t} = \theta + \beta_1 \mathrm{R}_{t-1} + \beta_2 \mathrm{Oil}_t + \delta\sqrt{\sigma_t^2} + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \gamma\, \varepsilon_{t-1}^2 I_{t-1} \quad (2)$$

where R_t is the stock market return at time t; R_{t-1} is the return lagged term; Oil_t the OPEC basket return at time t; $\sqrt{\sigma_t^2}$ is the square root of the conditional variance at time t. For the variance equation σ_t^2 is the conditional variance at time t; ε_{t-1}^2 and σ_{t-1}^2 are the last surprise and conditional variance respectively; I_{t-1} is a dummy variable equals one if $\epsilon_{t-1}<0$ or equals 0 otherwise.

In addition, the multivariate general autoregressive conditional heteroskedastic (MGARCH) approach is used to estimate the conditional covariance matrix of the dependent variables to examine the co-movement in the volatility or the volatility spillover effect between stock and oil markets. However, in the literature, many parameterizations methods have been used that try to provide an optimal trade-off between flexibility and parsimony.

1 Different extensions of ARCH models (e.g., GARCH, EGARCH and PGARCH) have been applied and it is found that the TGARCH-M fits the data better based on the criteria of Akaike information criterion (AIC) and Schwarz-Bayesian criterion (BIC). The TGARCH model is proposed by Glosten et al. (1993).

2 The presence of ARCH effect is tested and is highly statistically significant indicating that the use of OLS estimator will result in inefficient estimates.

This study employs three common parametrization methods: (1) the constant conditional correlation (CCC) model (Bollerslev, 1990); (2) the dynamic conditional correlation (DCC) model (Engle, 2002); (3) the time-varying conditional correlation (VCC) model (Tse and Tsui, 2002).

$$R_t=\theta+\delta R_{t-1}+\varepsilon_t \quad (3)$$

$$\mu_t = H_t^{1/2} v_t \quad (4)$$

Where R_t is an m × 1 vector containing the set of market or OPEC basket prices at time t; θ is a vector of constants; δ is a vector of parameters of the returns lagged terms R_{t-1}; H_t is the conditional covariance matrix; v_t is an m × 1 vector of the white noise errors. However, under the three conditional correlation models, nonlinear combinations of univariate GARCH models are used to estimate the conditional covariance matrix.

$$H_t = D_t^{1/2} COR_t D_t^{1/2} \quad (5)$$

where COR_t a matrix of conditional correlations and D_t a diagonal matrix of conditional variances. Nonetheless, the CCC MGARCH model assumes that the conditional correlation matrix is time invariant, whereas the DCC MGARCH and the VCC MGARCH models allow the conditional correlations to vary over time. Thus, the DCC MGARCH and the VCC MGARCH models are more flexible than the CCC MGARCH model.

4. DATA

The sample consists of the Saudi stock market index (Tadawul) and the OPEC basket oil price. The OPEC basket is chosen as a proxy for oil prices because Saudi Arabia is the largest oil producer in the OPEC organization. However, the daily

Figure 1: The indexes of Tadawul and OPEC basket from 2000 to 2019

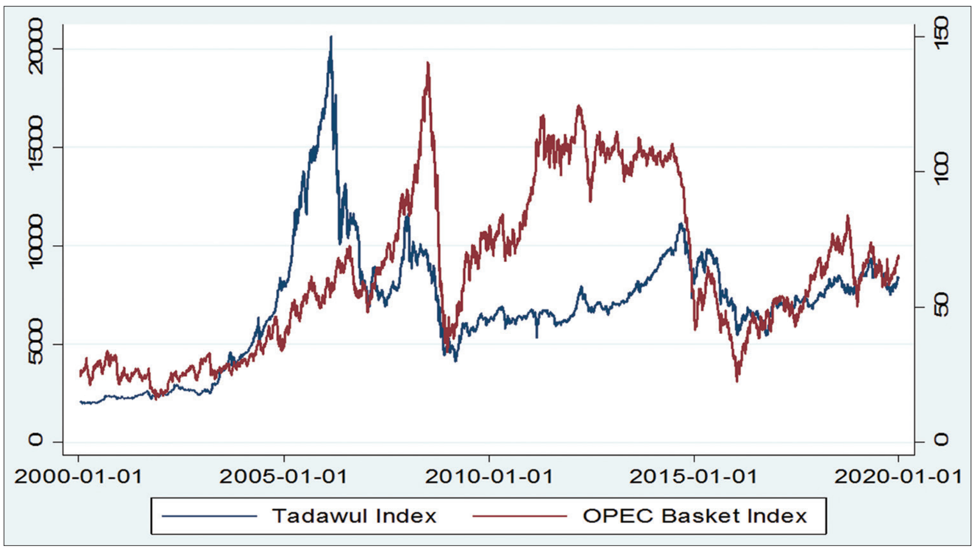
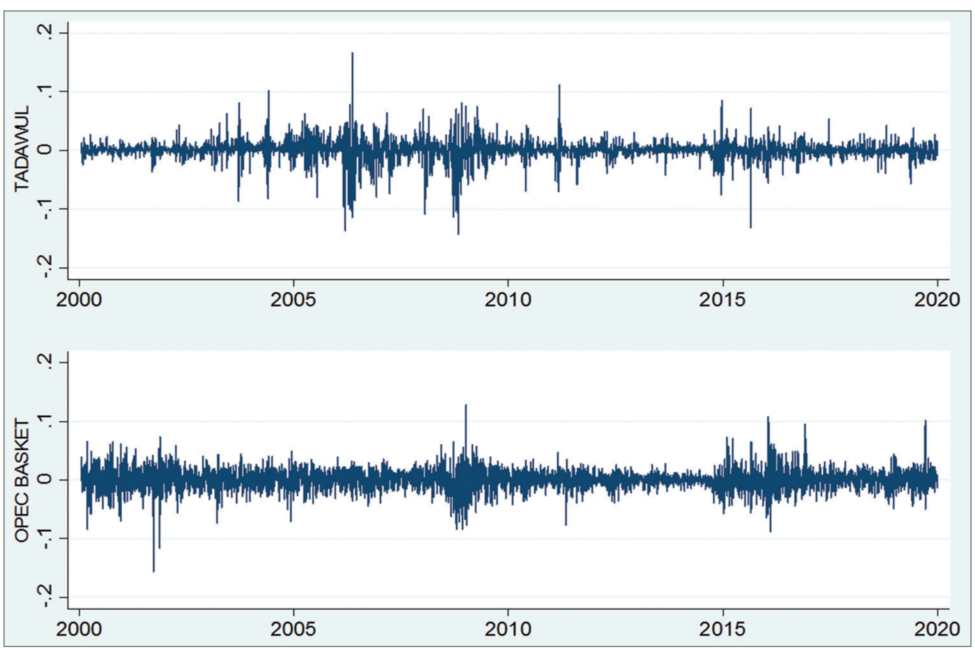
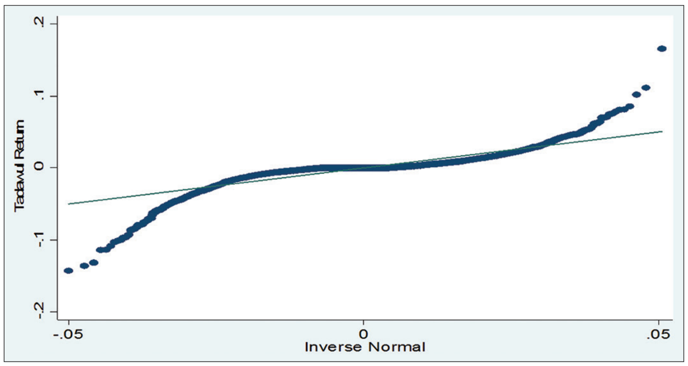


Figure 2: The volatility of Tadawul and OPEC basket from 2000 to 2019



data covers the period from 2000 to 2019 (Figure 1). More, the continuous compound daily returns for the data are computed as $r_t=\ln(p_t/p_{t-1})$ to observe the data volatility and to eliminate the unit root problem (Figure 2). Table 1 presents the descriptive statistics of the data. The Saudi stock market on average is more profitable and less volatile as measured by the mean and standard deviation. However, the daily returns of both indexes are negatively skewed and have large kurtosis statistics implying that the data are leptokurtic or having fat tails. Figures 3 and 4 show that the daily returns of the two indexes do not lie on the line especially at the end

Figure 3: Compare the Tadawul return distribution with the normal distribution



indicating the data distributions are leptokurtic. Nonetheless, the Dickey-Fuller unit root test is significant implying that the data are stationary.

5. RESULTS

5.1. The Impact of Oil Price Changes on Tadawul Returns

Table 2 shows the TGARCH-M model results. The model fits better under the generalized distribution, which is not surprising as this distribution is suitable for many types of series. The oil coefficient has a positive impact on the Saudi stock market returns implying higher oil returns will result in higher stock market returns in Saudi Arabia. This result disagrees with the result found by Dhaoui and Khraief (2014) in developed stock markets and consists with the result reported by Park and Ratti (2008) who found that although an increase in oil prices had a negative impact on most developed countries stock market returns, it has a positive impact on stock market returns in an oil exporter country such as Norway. This can be explained by the fact that Saudi Arabia is one of the largest oil producers and exporters in the world and it relies heavily on oil income. Thus, higher oil prices will lead to more money in the economy that can boost the Saudi economy and as a result increases the Saudi stock market prices. However, Saudi investors seem to be risk

Table 1: Data descriptive statistics

Variables	Obs.	Mean	Std.	Min	Max	Skew	Kurtosis	DF statistics
Tadawul	5,209	0.0003	0.0142	−0.1432	0.1659	−1.1359	23.5120	−99.02*
OPEC	5,209	0.0002	0.0172	−0.1563	0.1280	−0.2291	7.8753	−51.78*

DF is the Dickey–Fuller test. *means the statistic is significant at the 1% level

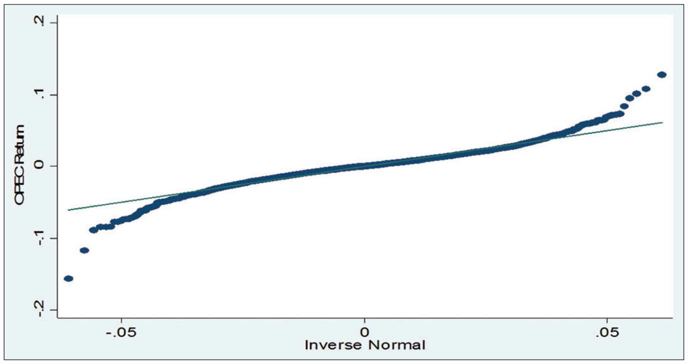
Table 2: TGARCH-M estimation with Gaussian and generalized distributions

Parameters	Whole period		2000-2009		2010-2019	
	Normal	Generalized	Normal	Generalized	Normal	Generalized
Mean-equation						
θ	0.0006	0.0000***	0.0007	-0.0001***	0.0005	0.0000***
	(0.0004)	(0.0000)	(0.0004)	(0.0000)	0.0006	(0.0000)
β_1	0.0386**	0.0000***	0.0156	0.0000***	0.0561***	0.0000***
	(0.0151)	(0.0000)	(0.0213)	(0.0000)	(0.0179)	(0.0000)
β_2	0.0745***	0.0000***	0.0362***	0.0000***	0.1149***	0.0000
	(0.0072)	(0.0000)	(0.0090)	(0.0000)	(0.0109)	(0.0000)
δ	−0.0203	0.0000***	−0.0090	0.0028***	−0.0391	0.0020***
	(0.0392)	(0.0000)	(0.0434)	(0.0000)	(0.0762)	(0.0000)
Variance-equation						
ω	0.0000***	0.0003***	0.0000***	0.0001***	0.0000***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0619***	−0.0041***	0.0945***	−0.0011***	−0.0058**	0.0001*
	(0.0028)	(0.0000)	(0.0052)	(0.0000)	(0.0023)	(0.0000)
α_2	0.9086***	0.9856***	0.9236***	0.8955***	0.8848***	0.7929***
	(0.0027)	(0.0000)	(0.0029)	(0.0000)	(0.0063)	(0.0000)
γ	0.0405***	0.0073***	−0.0240***	0.0018***	0.1473***	−0.0003***
	(0.0036)	(0.0000)	(0.0058)	(0.0000)	(0.0075)	(0.0000)
ν		0.0752***		0.1180***		0.1886***
		(0.0002)		(0.0007)		(0.0011)
Observations	5208	5208	2600	2600	2608	2608
AIC	-6.2003	−11.0928	−5.8726	−8.9688	−6.6064	−9.1290
BIC	-6.1903	-11.0814	-5.8545	−8.9485	−6.5884	−9.1087
Log-likelihood	16154	28895	7642	11668	8623	11913

***, **, * imply significance at 1%, 5% and 10% levels respectively. ν is the estimated generalized distribution degree of freedom. AIC and BIC are Akaike information and Schwarz-Bayesian criteria averse since the conditional standard deviation has a positive sign with the stock index returns.

With regard to the variance estimates, the sum of α and β are significant and close to unity, which indicates the model fits well.

Figure 4: Compare the OPEC return distribution with the normal distribution



Nonetheless, the asymmetry effect is positive and significant for the whole period. This means a negative surprise has a large impact on Saudi stock market volatility. However, after the data split, interestingly, it is found that in the last decade (2010-2019), the asymmetry effect is negative implying that positive news has more effect on the volatility of Tadawul in the last years in comparison with the first decade (2000-2009). This means that in last years, a positive shock will result in higher next period volatility than negative shock. A possible explanation is that in last years, Saudi investors seem to react more to an increase in the market price by engaging in the market than when there is a decrease in the market price.

5.2. The Volatility of Tadawul and Oil Price

In the model selection, the orders of lags are selected based on the criteria of Akaike information criterion (AIC) and Schwarz-Bayesian criterion (BIC) in which the model with the lowest AIC and BIC will be selected. In general, the main model is estimated with two lags and their results are presented in Table 3.

Table 3: MGARCH models CCC, DCC and VCC with Gaussian & Student's t distributions (whole period)

Parameters	(1)	(2)	(3)	(4)	(5)	(6)
	CCC	CCC	DCC	DCC	VCC	VCC
	Normal	Student's t	Normal	Student's t	Normal	Student's t
Tadawul						
Mean-constant	0.0006***	0.0005***	0.0006***	0.0006***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0006)	(0.0000)	(0.0001)	(0.0001)
Lag 1	0.0343**	0.0322***	0.0325*	0.0328***	0.0316**	0.0322***
	(0.0163)	(0.0110)	(0.0194)	(0.0114)	(0.0157)	(0.0110)
Lag 2	0.0339**	0.0206**	0.0333*	0.0197**	0.0362***	0.0238***
	(0.0166)	(0.0101)	(0.0178)	(0.0086)	(0.0119)	(0.0083)
Variance-constant	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0805***	0.0851***	0.0801***	0.0835***	0.0801***	0.0839***
	(0.0050)	(0.0105)	(0.0104)	(0.0128)	(0.0049)	(0.0103)
GARCH	0.9128***	0.9063***	0.9136***	0.9077***	0.9129***	0.9067***
	(0.0046)	(0.0081)	(0.0085)	(0.0113)	(0.0046)	(0.0080)
Oil						
Mean-constant	0.0004**	0.0007***	0.0005**	0.0009***	0.0005***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Lag 1	0.2458***	0.2241***	0.2544***	0.2219***	0.2436***	0.2227***
	(0.0144)	(0.0136)	(0.0152)	(0.0150)	(0.0142)	(0.0134)
Lag 2	−0.0633***	−0.0635***	−0.0601***	−0.0654***	−0.0634***	−0.0638***
	(0.0143)	(0.0137)	(0.0149)	(0.0151)	(0.0139)	(0.0138)
Variance-constant	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0761***	0.1000***	0.0774***	0.0997***	0.0758***	0.0988***
	(0.0074)	(0.0151)	(0.0125)	(0.0154)	(0.0074)	(0.0148)
GARCH	0.9222***	0.9464***	0.9214***	0.9462***	0.9225***	0.9464***
	(0.0072)	(0.0065)	(0.0116)	(0.0069)	(0.0072)	(0.0065)
ρ	0.1059***	0.1056***	0.0977**	0.0831**	0.1522**	0.1360**
	(0.0138)	(0.0155)	(0.0472)	(0.0388)	(0.0627)	(0.0630)
ν		2.8037***		2.8128***		2.8189***
		(0.1067)		(0.1135)		(0.1075)
λ_1			0.0087***	0.0072***	0.0068***	0.0054***
			(0.0019)	(0.0016)	(0.0020)	(0.0020)
λ_2			0.9876***	0.9904***	0.9908***	0.9925***
			(0.0028)	(0.0023)	(0.0027)	(0.0029)
Observations	5,207	5,207	5,207	5,207	5,207	5,207
AIC	−11.7966	−12.1967	−11.8070	−12.1266	−11.8015	−12.2000
BIC	−11.7803	−12.1790	−11.7882	−12.1064	−11.7827	−12.1799
Log-likelihood	30726	31768	30761	31802	30740	31779

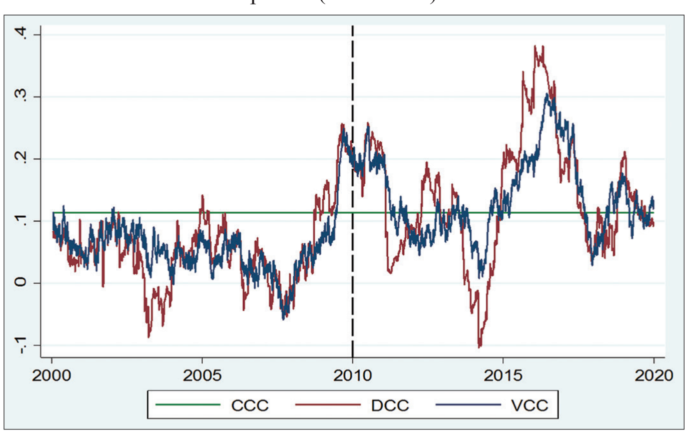
***, **, * imply significance at 1%, 5% and 10% levels respectively. ρ is the conditional correlation between the volatility of Tadawual and oil markets. ν is the estimated student's t degree of freedom. λ_1 and λ_2 are the adjustment parameters for the dynamic conditional correlation. AIC and BIC are Akaike information and Schwarz-Bayesian criteria

Table 4: MGARCH models CCC, DCC and VCC with Gaussian & Student's t distributions (2000-2009)

Parameters	(1)	(2)	(3)	(4)	(5)	(6)
	CCC	CCC	DCC	DCC	VCC	VCC
	Normal	Student's t	Normal	Student's t	Normal	Student's t
Tadawul						
Mean-constant	0.0005***	0.0008***	0.0005*	0.0008***	0.0005***	0.0008***
	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0001)
Variance-constant	0.0000***	0.0000***	0.0000**	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0841***	0.1121***	0.0835***	0.1145***	0.0841***	0.1118***
	(0.0066)	(0.0201)	(0.0128)	(0.0220)	(0.0066)	(0.0200)
GARCH	0.9213***	0.9021***	0.9219***	0.9019***	0.9213***	0.9022***
	(0.0051)	(0.0096)	(0.0090)	(0.0123)	(0.0051)	(0.0096)
Oil						
Mean-constant	0.0008***	0.0017***	0.0011***	0.0021***	0.0009***	0.0017***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Lag 1	0.2323***	0.2023***	0.2354***	0.2013***	0.2323***	0.2028***
	(0.0198)	(0.0184)	(0.0205)	(0.0203)	(0.0198)	(0.0171)
Variance-constant	0.0000***	0.0000***	0.0000**	0.0000**	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0642***	0.0909***	0.0653***	0.0926***	0.0641***	0.0910***
	(0.0101)	(0.0225)	(0.0205)	(0.0227)	(0.0101)	(0.0224)
GARCH	0.9234***	0.9526***	0.9225***	0.9522***	0.9235***	0.9526***
	(0.0124)	(0.0087)	(0.0233)	(0.0080)	(0.0124)	(0.0087)
ρ	0.0463**	0.0385*	0.0459**	0.0403**	0.0670	0.0453
	(0.0197)	(0.0222)	(0.0214)	(0.0183)	(0.0501)	(0.0447)
ν		2.6189***		2.6029***		2.6202***
		(0.1341)		(0.1395)		(0.1342)
λ_1			0.0000	0.0075	0.0037	0.0036
			(0.0000)	(0.0282)	(0.0028)	(0.0029)
λ_2			0.8385	0.2114	0.9923***	0.9922***
			(2.7534)	(0.5627)	(0.0051)	(0.0064)
Observations	2,600	2,600	2,600	2,600	2,600	2,600
AIC	−11.1868	−11.5852	−11.1863	−11.4935	−11.1861	−11.5844
BIC	−11.1642	−11.5604	−11.1570	−11.4619	−11.1590	−11.5551
Log-likelihood	14553	15072	14555	15078	14554	15073

***, **, * imply significance at 1%, 5% and 10% levels respectively. ρ is the conditional correlation between the volatility of Tadawual and oil markets. ν is the estimated student's t degree of freedom. λ_1 and λ_2 are the adjustment parameters for the dynamic conditional correlation. AIC and BIC are Akaike information and Schwarz-Bayesian criteria

Figure 5: The conditional correlations between Tadawul and OPEC basket under CCC, DCC and VCC MGARCH models over the whole period (2000-2019)



The results are reported under two distributional assumptions, Gaussian and Student's t-distribution, to compare their results. A close inspection to Table 3 shows that the three models' likelihood, AIC and BIC has improved when the Student's t-distribution assumed implying that the distribution with fat tails fits the data better and improves the model quality. However, the VCC MGACH model with Student's t distribution seems to fit the data better than the other two models based on the AIC and BIC criteria. The conditional correlation between the two indexes returns is significant and positive implying that the volatility of the two markets is moving together by 0.1360 on average under the VCC MGARCH model.

The conditional correlations between the Saudi Stock Market (Tadawul) and the OPEC oil basket volatility are illustrated in Figure 5. This result is in line with the result found by Malik and Hammoudeh (2007). The conditional correlation, furthermore, has increased in the last decade (2010-2019) compared to the first decade (2000-2009). This indicates that the volatility spillover effect between the two markets has increased in the last years. For further inspection, the sample has been split into two periods (2000-2009) and (2010-2019) and the three MGARCH models have been re-estimated for each period. The results are presented in Tables 4 and 5. The results further confirm the initial finding that the conditional correlation between Tadawul and the OPEC oil basket volatility has increased significantly in the last decade (2010-2019).

Table 5: MGARCH models CCC, DCC and VCC with Gaussian & Student's t distributions (2010-2019)

Parameters	(1)	(2)	(3)	(4)	(5)	(6)
	CCC	CCC	DCC	DCC	VCC	VCC
	Normal	Student's t	Normal	Student's t	Normal	Student's t
Tadawul						
Mean-constant	0.0006***	0.0004***	0.0006***	0.0004***	0.0006***	0.0004***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Lag 1	0.0549**	0.0333**	0.0499**	0.0332**	0.0516**	0.0334**
	(0.0230)	(0.0155)	(0.0228)	(0.0155)	(0.0217)	(0.0152)
Variance-constant	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0830***	0.0633***	0.0820***	0.0622***	0.0826***	0.0627***
	(0.0081)	(0.0125)	(0.0079)	(0.0122)	(0.0081)	(0.0124)
GARCH	0.8760***	0.9088***	0.8784***	0.9107***	0.8771***	0.9097***
	(0.0115)	(0.0159)	(0.0112)	(0.0154)	(0.0113)	(0.0157)
Oil						
Mean-constant	0.0002	0.0002	0.0003	0.0002	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Lag 1	0.2266***	0.2107***	0.2198***	0.2069***	0.2257***	0.2091***
	(0.0197)	(0.0190)	(0.0196)	(0.0189)	(0.0196)	(0.0189)
Variance-constant	0.0000***	0.0000***	0.0000***	0.0000**	0.0000***	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0905***	0.1114***	0.0911***	0.1100***	0.0908***	0.1112***
	(0.0124)	(0.0229)	(0.0121)	(0.0222)	(0.0124)	(0.0228)
GARCH	0.9052***	0.9287***	0.9054***	0.9290***	0.9052***	0.9286***
	(0.0123)	(0.0126)	(0.0120)	(0.0124)	(0.0122)	(0.0126)
ρ	0.1733***	0.1646***	0.1008*	0.1007	0.1785***	0.1667***
	(0.0192)	(0.0214)	(0.0588)	(0.0740)	(0.0386)	(0.0444)
ν		3.0180***		3.0484***		3.0273***
		(0.1685)		(0.1712)		(0.1693)
λ_1			0.0167***	0.0081***	0.0065**	0.0050*
			(0.0039)	(0.0028)	(0.0032)	(0.0030)
λ_2			0.9725***	0.9880***	0.9869***	0.9900***
			(0.0057)	(0.0042)	(0.0056)	(0.0060)
Observations	2,607	2,607	2,607	2,607	2,607	2,607
AIC	−12.4210	−12.8079	−12.4310	−12.8128	−12.4220	−12.8085
BIC	−12.3962	−12.7809	−12.4018	−12.7813	−12.3927	−12.7770
Log-likelihood	16202	16707	16217	16715	16205	16710

***, **, * imply significance at 1%, 5% and 10% levels respectively. ρ is the conditional correlation between the volatility of Tadawual and oil markets. ν is the estimated student's t degree of freedom. λ_1 and λ_2 are the adjustment parameters for the dynamic conditional correlation. AIC and BIC are Akaike information and Schwarz-Bayesian criteria

6. CONCLUSION

This study investigates the sensitivity of Saudi stock market returns and volatility to oil price changes in the last two decades from 2000 to 2019 by using TGARCH-M and three MGARCH models. In general, it is found that higher oil prices have a significant positive impact on Saudi stock market returns. More, in Saudi stock market exchange, there is a significant positive relationship between the stock market returns and its conditional volatility implying that the Saudi investors are risk averse and bad news have a more asymmetric effect on stock market volatility than good news. About volatility spillover, there is a positive relationship between the volatility of stock and oil markets, and this positive relationship has increased significantly in the last decade. Hence, Saudi Arabia should diversify away from oil to reduce market volatility and this agrees with the argument of Hammoudeh and Choi (2007) that oil exporter countries should diversify their economies away from oil to mitigate their stock market volatility. In the end, further studies are recommended to investigate this relationship at sector levels to examine the asymmetric sensitivity between oil-related and none-oil-related companies.

REFERENCES

Abdalla, S.Z.S. (2013), Modelling the impact of oil price fluctuations on the stock returns in an emerging market: The case of Saudi Arabia. Journal of Research in Business, 2(10), 10-20.

Apergis, N., Miller, S.M. (2009), Do structural oil-market shocks affect stock prices? Energy Economics, 31(4), 569-575.

Bollerslev, T. (1990), Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model. The Review of Economics and Statistics, 72(3), 498.

Ciner, C. (2001), Energy shocks and financial markets: Nonlinear linkages. Studies in Nonlinear Dynamics and Econometrics, 5(3), 203-212.

Dhaoui, A., Khraief, N. (2014), Empirical Linkage Between Oil Price and Stock Market Returns and Volatility: Evidence from International Developed Markets (Economics Discussion Papers 2014-12), Economics Discussion Papers, No. 2014-12. Germany: Kiel Institute for the World Economy. Available from: http://www.hdl.handle.net/10419/94193.

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

Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993), On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.

Hammoudeh, S., Choi, K. (2007), Characteristics of permanent and transitory returns in oil-sensitive emerging stock markets: The case of GCC countries. Journal of International Financial Markets, Institutions and Money, 17(3), 231-245.

Huang, R.D., Masulis, R.W., Stoll, H.R. (1996), Energy shocks and financial markets. Journal of Futures Markets, 16(1), 1-27.

Jones, C.M., Kaul, G. (1996), Oil and the Stock Markets. The Journal of Finance, 51(2), 463-491.

Jouini, J. (2013), Return and volatility interaction between oil prices and stock markets in Saudi Arabia. Journal of Policy Modeling, 35(6), 1124-1144.

Malik, F., Hammoudeh, S. (2007), Shock and volatility transmission in the oil, US and Gulf equity markets. International Review of Economics and Finance, 16(3), 357-368.

Nandha, M., Faff, R. (2008), Does oil move equity prices? A global view. Energy Economics, 30(3), 986-997.

Nandha, M., Hammoudeh, S. (2007), Systematic risk, and oil price and exchange rate sensitivities in Asia-Pacific stock markets. Research in International Business and Finance, 21(2), 326-341.

Ono, S. (2011), Oil price shocks and stock markets in BRICs. The European Journal of Comparative Economics, 8(1), 29-45.

Park, J., Ratti, R.A. (2008), Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Economics, 30(5), 2587-2608.

Sadorsky, P. (1999), Oil price shocks and stock market activity. Energy Economics, 21(5), 449-469.

Salisu, A.A., Isah, K.O. (2017), Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach. Economic Modelling, 66, 258-271.

Tadawul. (2019), Annual Statistical Report (Main Market). Riyadh, Saudi Arabia. Available from: http://www.tiny.cc/tadawul.

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