The Impact of Oil Price Fluctuations on Saudi Arabia Stock Market: A Vector Error-Correction Model Analysis

Nouf Bin Ayyaf Al-Mogren*

Department of Finance, College of Business Administration, Prince Sultan University, Riyadh, Saudi Arabia. *Email: nbinayyaf@psu.edu.sa

ABSTRACT

This paper examine the relationship between oil prices and the Saudi Stock Market by testing the null hypothesis that oil prices are statistically significant predictors of the Saudi stock market's movements for the period 2000-2019. Finding the time series to be cointegrated, the paper performs the testing procedure by employing a Vector Error Correction Model (VECM) and results obtained indicate that oil prices are not statistically significant predictors of Saudi stock market movements, thus giving us reason to reject our null hypothesis. We also find evidence that the New York Stock Exchange NYSE is a better predictor of both the Saudi stock index and oil price fluctuations, paving the way for further research into these correlations in the future.

Keywords: Oil Price, Stock Exchange, Vector Error Correction Model, Saudi Arabia
JEL Classifications: E44, G12, G15, C32
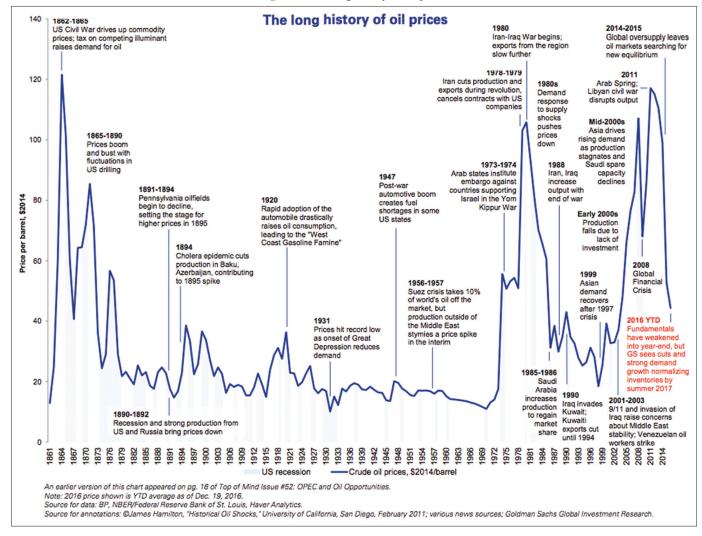
1. INTRODUCTION

As the Kingdom of Saudi Arabia is one of the largest oil market producers in the world, its stock market is widely expected to be affected by oil price shocks and fluctuations. Since its discovery in the early 1850s, oil has surpassed gold, coal and all other minerals in proving to be the most important commodity in modern times, as it is now considered the main driving force behind modernization and industrialization. Looking back at the history of oil prices in the last century, it is clear that oil is a volatile commodity which is very sensitive to changing political events, as seen in Figure 1.[1] As oil's role continues to increase, the importance of understanding the economies of the countries that produce and export it, including the main world exporters of oil, the Gulf Cooperation Council (GCC), increases as well.

The GCC, which was established in 1981, includes six member countries: Saudi Arabia, Kuwait, United Arab Emirates (UAE),

Bahrain, Qatar, and Oman. The GCC's oil output accounts for two thirds of the Organization of the Petroleum Exporting Countries' (OPEC) oil production and reserves. As James D. Hamilton said regarding the detriments of oil prices, 'In the modern era, it is sovereign countries rather than private companies which would be calling the shots', stating that the role of OPEC in influencing oil prices cannot be emphasized enough (Hamilton, 2008). Therefore, understanding the complex structure of the GCC economies is important for many reasons: First, the GCC is one of the major oil exporting area in the world, with economies that heavily depend on oil's price performance. Second, all GCC countries achieved high economic growth rates in the wake of oil price surges in the last decade. As a result, GCC countries are now considered as an attractive investment hub for international investors looking for diversification, due to its high growth and profit potential. Lastly, GCC markets are an enticingly unique area to study in the sense that they differ from both developed and emerging markets; they are predominately–segmented markets, largely isolated from the international markets, and are overly sensitive to regional and political events (Arouri and Rault, 2012). As Mohanty et al. (2011) explained that GCC countries, oil exports largely determine foreign earnings and the governments' budget

---

1   Goldman Sachs, 2016, The long history of oil prices, *Business Insider*, http://uk.businessinsider.com/timeline-155-year-history-of-oil-prices-2016-12.

Figure 1: The long history of oil prices

revenues and expenditures; thus, they are the primary determinant of aggregate demand. The aggregate demand effect influences corporate output and domestic price levels, which eventually impacts corporate earnings. Such a strong oil influence on the national economy of these countries presumably makes share prices in their stock markets very vulnerable to oil prices and changes in the oil market. Thus, one would expect that an increase in oil price would positively affect economic output and corporate earnings at the aggregate level for GCC countries, but the impact of oil price movements on stock prices at the country and industry level is ambiguous. It is an empirical question, determining which of the positive (increased revenues, cash flows, and earnings) and negative (inflation, interest rate, and discount rate) effects offset the other.

To be able to accurately assess an economy, one must take a closer look at the driving factors behind it. A major indicator of a country's economy is its stock exchange, which in Saudi Arabia is referred to as Tadawul (Arabic for *trade*). The main index in Tadawul is called TASI (Tadawul All Share Index), with twenty sectors listed, amounting to 171 different companies.[2] In addition to TASI, in the

first quarter of 2017 Tadawul launched another index called Nomu (Arabic for *growth*), which is a parallel equity market but with less strict listing requirements serving as an alternative platform for growing companies to go public. Nomu was created with the aim of developing a more advanced capital market open to the world, allowing greater capital inflows which in turn stimulate economic growth. Nomu was launched with seven companies, requiring a market value of at least ten million SAR (2.6 million USD), a minimum shareholder size of 35–50 shareholders, and an offering percentage of at least 20%. With the goal of creating greater stock price stability, traders at Nomu are restricted to institutional and qualified investors only.[3] The share price movement of TASI, and more recently Nomu, can be quite volatile and sometimes seem disconnected from company fundamentals, which highlights the existence of other factors that might be influencing returns and stock prices. This begs the important question: is the fluctuation in oil prices one of those factors?

The foremost goal of a thriving Saudi economy for achieving Vision 2030 is diversifying revenue streams and raising non–oil

2 Official Saudi Tadawul website, knowledge center, Capital Market Overview, https://www.tadawul.com.sa/wps/portal/tadawul/knowledge-center/about/Capital-Market-Overview.

3 Official Saudi Tadawul website, knowledge center, Nomu parallel market, https://www.tadawul.com.sa/wps/portal/tadawul/knowledge-center/about/parallel-market.

exports share of GDP from 16% to 50% by the year 2030. Doing so can be achieved by many methods, such as increasing foreign direct investment from 3.8% to the targeted international level of 5.7% of GDP, as well as the privatization of state-owned assets and government services. The main example and forefront project of this objective is the plan to offer a 5% stake of Saudi–Aramco, the huge state–owned oil company, to the public in an IPO in late 2018. This is expected to be the largest IPO in history with an expected value of $2 Trillion. For that reason, closely examining the relationship between oil price volatility and stock market return, especially for a country as heavily reliant on oil as Saudi Arabia, is of great importance. The motivation behind this paper is to fill the gaps in existing literature regarding understanding this ambiguous yet important area.

For investors, understanding the drivers behind the Saudi stock market's movements and its relationship with oil prices is more important now than ever, especially after the major efforts being implemented to position the Saudi market as a major world player. Saudi Arabia represents a promising new area for regional and international portfolio diversification. Thus, understanding the main drivers behind its stock return movements is integral to making sound investment decisions by local and foreign investors alike. As for policy makers, being able to correctly determine and understand whether such a relationship exists can play a vital role in creating relevant policies and implementing appropriate regulations, based on facts that would help in creating the coherent, motivating and competitive working environment they aspire to reach. Basing decisions on a clear understanding of all surrounding factors can indeed aid in making the Saudi market a safe and attractive world–ranked investment hub.

The purpose of this paper is to investigate the dynamic relationship by using a Vector Error Correction Model (VECM). More precisely, VECM's variance decomposition and impulse responses techniques will be executed after running the necessary diagnostic tests of assessing stationarity by the Modified Dickey–Fuller test, determining the correct equation order by the VAR Lag order test, and examining if the variables are cointegrated by using the Johansen procedure.

The remaining structured as follows: Section 2 will provide related literature. Section 3 will explain the data, testing methodology implemented and results respectively. Findings and analysis of results will be discussed in full in Section 6. Finally, the conclusion of the paper will be presented in Section 4.

2. THEORY AND EVIDENCE

Although numerous studies have been conducted relating to the correlation between oil prices and different world–wide stock indices, the results found are rather conflicting. And with the majority of the available papers examining this relationship in the context of developed economies such as the US, Europe, Australia and Japan, very few have endeavored to investigate the existence and degree of such a connection in emerging markets which happen to also be major oil exporters, such as Saudi Arabia. Samontaray et al. (2014) examined the relationship between

stocks in the Saudi stock market —denoted by the Saudi Stock Index TASI—and a number of diverse macroeconomic variables. Their investigation came to conclusion based on empirical testing by using the factors into three independent variables: Oil WT, Saudi exports and the PE ratio and they found that a significant correlating relationship does in fact exist between the chosen factors and the movement of the Saudi Stock Market Index.

Mohanty et al. (2011) using a linear factor pricing model, tried to evaluate whether a relationship exists between oil prices and equity returns in both country–level and industry–level in the GCC countries. The testing showed that a significant positive relationship does exist between fluctuations in oil prices and stock market returns in all of the GCC countries, except Kuwait, but found that the exposure is asymmetric between a rise and a fall in prices. As for the industry–level correlation, the test finds that twelve out of the twenty industries tested have a positive significant relationship, which indicates that the exposure differs significantly between different industries and countries even within the similar GCC area.

On the other hand, Arouri and Fouquau (2009), who endeavored to examine the short-term relationship, and Arouri and Rault (2012), who intended to study the long–term relationship between stock markets in the GCC region and oil prices, came to an opposite conclusion. The short–term test was conducted by using a non–parametric method, after testing for heteroscedasticity, correlation and homogeneity of error terms; the long–term test used bootstrap panel cointegration techniques along with regression SUR methods. Surprisingly, both studies found that positive evidence suggest a significant link in all the countries *except* Saudi Arabia on the long–term and all countries except Saudi Arabia, Kuwait and Bahrain on the short–term. Lastly, a paper focusing on Kuwait approached the examination of this complex relationship from a new angle.

Al Hayky and Naim (2016) attempted to assess whether or not the degree of volatility in the stock market affected the extent of the relationship with oil prices. The paper first ran the Augmented Dickey Fuller (ADF) test, as well as a unit root test and Johansen (1988) and Johansen and Juselius (1990) cointegration analysis, then applied Markov Switching Model to examine oil price's effect on both high and low volatility regimes. Interestingly, the paper found that different volatility periods yielded different results, with low volatility periods showing no relationship, and a positive and significant relationship in high volatility periods.

Fayyad and Daly (2011), who investigated the relationship between oil prices and stock markets by employing Vector Autoregressive (VAR), Variance Decomposition and Impulse Response techniques, then compared the results between major exporters of oil (the five GCC countries of Kuwait, Oman, UAE, Bahrain, and Qatar) and advanced countries who are major importers of oil (USA and UK). The overall empirical findings were that all of the tested countries exhibited a significant inter–relationship with oil prices, but to varying degrees. Another study, aiming to investigate whether a rise in oil price affects its relationship with stock markets, focused mainly on the GCC countries in the period between 2001 and 2005.

Zarour (2006) divided the study into two sub–periods (the first being 2001–2003 which represent normal/low prices and the second being 2003–2005 representing the period when the huge surge in prices occurred) and estimated a separate VAR for each. The paper found that oil price, as a predictive mechanism, does in fact increase in power the more its price increase, so does the speed of response of the markets to any shocks in oil prices. Furthermore, the study found that the Saudi market is more responsive to changes in oil prices and vice versa, as well as, alongside Oman, have the power to predict oil prices.

Sadorsky (1999) used a similar methodology by first applying a cointegration test for nonstationary variables, which showed that no long–run relationship exists and hence the Vector Autoregressive (VAR) model can be used. Then the VAR test was carried out through Variance Decomposition Analysis and Impulse Responses Function. Unsurprisingly, it was found that oil prices and oil price volatility are both significant affecting factors on the US stock market, but not vice–versa. It is noticed that similar findings are discovered when studying different parts of the world as well. Taking the case of Turkey, which is neither a major oil exporter nor importer, Eryiğit (2012) examined the short–term relationship between interest rates, the Istanbul Stock Exchange Market index, and the exchange rate with the changing oil prices by using weekly data from the period 2005-2008. The paper found that oil price shocks affect the main Turkish stock market, which is explained by the author as perhaps due to the fact that Turkey is a net oil importing country with the majority of the listed companies affected directly or indirectly by the changes in world–wide oil prices.

But just as there are studies supporting each other's findings, some studies contradict the notion that oil price must have an effect on stock markets. Such results were found by Cong et al. (2008), who used a Multivariate Vector Autoregressive model to uncover a result that oil price shocks do not show a statistically significant impact on the Chinese stock market index, except for some indices of specific sectors which are heavily reliant on oil.

Masih et al. (2011) also investigated the relationship between South Korea's stock market and oil fluctuations and found that a long–term relationship exists among the factors included in their study (*interest rates, economic activity, real stock returns, real oil prices, and oil price volatility*) and that fluctuations in oil price significantly affects the South Korean stock market. Similarly, Cuñado and de Gracia (2013) uncovered similar results that oil price fluctuations (whether shocks in supply or in demand) have significant negative effects on most of the European countries, but with the supply shocks generating a greater negative impact than demand shocks.

Filis (2010) found a significant negative relationship between oil prices and the Greek stock market. However, interesting results have been obtained when this relationship was studied with regards to oil prices and three Turkish stock market indices in the period between 2000 and 2010 in Istanbul, Turkey. Kapusuzoglu (2011) found that all stock indices examined were cointegrated with oil prices, but that a one–way causal relationship existed between the indices and oil prices but not vice–versa, meaning oil price does not have a causal relationship with any of the three indices.

Falzon and Castillo (2013), examined same relationship in the US and UK across ten industries by using ARCH and GARCH modelling methodology and found that each industry's dependence on oil. More precisely, first, changes in oil price do not impact every industry. Second, changes in oil prices can explain changes in equity returns for several industries in both countries. And finally, oil has a positive effect on oil–producing industries and negative effect on oil–consuming industries.

Even if it is evident that a relationship does exist in most of the world–wide stock indices, the nature of this relationship, whether positive or negative, still needs to be examined. For the case of Hasan and Ratti (2012), who examined this relationship in the context of the Australian stock market using conditional volatility as a measure oil price risk and employed the GARCH–M model to find the risk and return patterns in some chosen sectors: an inverse relationship was found between oil and index fluctuations, where an increase in oil price return or volatility decreased the index's return or volatility. Similarly, Regarding the relationship between oil price volatility and stock market returns using an EGARCH–M model to specify the effect on each of the country's stock market returns and volatility, Dhaoui and Khraief (2014) found a negative relationship in all of the eight developed economies tested (US, UK, Canada, Switzerland, France, Australia, Japan) except Singapore, where no relationship was found. In contrast, a significant positive relationship was noticed between oil price volatility and stock market volatility in all countries except France and the UK, where again, no relationship was empirically found.

Furthermore, a study by Aloui and Jammazi (2009) used the two–regime Markov–switching EGARCH model to examine this relationship in the context of the UK, France and Japan for the period between 1989-2007 using monthly data. It was found that the volatility of these countries' stock market returns as well as their probability to transition across political regimes are greatly influenced by an increase in oil prices. Finally, Filis et al. (2011) investigated this dynamic correlation by focusing on three oil–exporting countries (Canada, Mexico and Brazil) and then contrasting the results with tests on three oil–importing countries (US, Germany and The Netherlands). Their findings suggested that the time–varying correlation is similar in both oil–importing and oil–exporting economies and that, in periods of international uncertainties, the oil market does not provide protection against stock market losses.

After considering the previously mentioned studies and their testing methodologies, it becomes clear that the researchers prefers to use either a VAR model or an ARCH/GARCH model to examine closely any existing relationship—or lack thereof—between oil prices and stock indices. That is why the paper by Constantinos et al. (2010) is unique as it applied both VAR and ARCH/GARCH models alongside each other to do their investigation. The VAR model in conjunction with Granger–Causality analysis was used to investigate the linkage between the Greek stock market and the international oil prices,

and the volatilities were quantified using ARCH/GARCH modelling techniques. Focusing on the period between 2004 and 2006, the paper's findings confirm the mainstream notion and detect signs of a significant positive relationship between oil price fluctuations and the Greek stock market. Arouri et al. (2011) implemented the Vector Autoregressive Moving Average Generalized Autoregressive Conditional Heteroscedasticity technique (VAR-GARCH), mainly due to its computational ease and the fact that it allows the examination of both the volatility and the interdependence simultaneously. Their empirical findings suggest a considerable presence of volatility and return spillover between the examined GCC stock markets and oil prices.

In addition to VAR and ARCH/GARCH variations, other testing methods have been used to further examine this interrelated relationship as well. Such as the case of El-Sharif et al. (2005) who used a multi–factor model to focus their investigation on the relationship between crude oil prices and the UK oil and gas sector equity prices. The paper found that oil and gas stock returns are primarily impacted by the volatility of crude oil prices as the main risk factor. Moreover, it was found that a weak relationship exists between crude oil prices and non–oil and gas sectors equity returns. The evidence from the paper suggests that the relationship is always positive, highly significant, and reflects the direct impact of crude oil price volatility on oil and gas sector equity returns. Finally, Basher and Sadorsky (2006) focused their research on emerging markets and examined the correlation between oil price volatility and the respective stock market's returns. The paper used daily, weekly and monthly data for twenty–one emerging markets indices (including Brazil, India, Russia and China) in an international multi–factor model which allows for both unconditional and conditional risk factors—this model is related to the international capital asset pricing model (CAPM). The paper found that oil price risks affect stock prices significantly across all emerging markets.

Jarrah and Salim (2016) and Samontaray et al. (2014) found evidence of a strong correlation between TASI and several macroeconomic factors including oil prices in the context of Saudi Arabia. Also, the research conducted by Zarour (2006) found similar evidence in that the Saudi market is more responsive than the other tested countries to changes in oil prices and vice versa.

3. MODEL AND RESULTS

It is clear from previous studies that the relationship between oil price fluctuations and world indices in general, and the Saudi index in particular, are contradictory. Therefore, this paper hypotheses, while endeavoring to examine this relationship more closely in the context of the Saudi market, is based on the findings by the majority of previous world–wide research papers' results, such as Fayyad and Daly (2011), Sadorsky (1999) and Eryiğit (2012). The null and alternative hypotheses used are as follows:

H_o: Oil prices are statistically significant predictors of Saudi stock market movements

H_a: Oil prices are not statistically significant predictors of Saudi stock market movements.

The data used in this paper were gathered from the Bloomberg terminal, the Saudi Arabian Monetary Authority (SAMA) website, and the Saudi Stock Exchange (Tadawul) website. All data are reported on a monthly basis for the period 2000-2019. This period was chosen to account for the major fluctuations of both oil prices and world–wide stock markets.

The paper used the variable of interest represented by the Saudi Stock Index called Tadawul All Share Index (TASI). The main predictor will be oil price and its fluctuations, represented in this paper by the West Texas Intermediate (WTI), which is a grade of crude oil often used as the international benchmark for oil prices. Other variables thought to have some effect on the Saudi economy and thus be related to the fluctuations in TASI have been introduced as controlling variables. Seeing the importance of the United States' economy to the well–being of the Saudi economy, and due to the fact that the US is one of the major import and export countries from and to Saudi Arabia, certain key US indicators are vital to include. The first of which is the New York Stock Exchange (NYSE), which is included as a proxy for US market risk. Also, to represent the effects of changing interest rates, the US 1 month Interest Rate is added and named (US1M). Furthermore, to account for the effects of world–commodities on the changes of such macroeconomic variables, the PALLFNF index, which is the weighted average of all commodity prices, is included and renamed as 'Commodities' for ease.

Returns are calculated by taking the first difference of the natural logarithm. A summary of statistical properties of the data used is exhibited in the Table 1.

The methodological framework used in this paper is based on a p–th order VAR:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t \tag{1}$$

Where y_t is a vector of endogenous variable, a vector of constants, A_i for $i=1,\ldots,p$ are matrices of coefficients, and ε_t is a vector of disturbances.[4]

Estimation requires that the components of y_t are covariance stationary. A series is said to be covariance or weakly stationary

---

4   J. DiNardo, 1997, *Econometrics Methods, Fourth Edition* (New York, NY: McGraw–Hill Education).

Table 1: Descriptive statistics

Descriptives	TASI	WTI	NYSE	COMM	US1M
Mean	8.7000	4.0220	4.9648	4.7183	0.9983
Maximum	9.8653	4.9485	9.7218	5.3215	5.5000
Minimum	7.3215	3.0012	8.3416	3.9900	0.1500
Std. Dev.	0.5361	0.4899	0.2334	0.4185	1.5830
Skewness	–0.5340	–0.2750	–0.1510	–0.2526	1.9930
Kurtosis	2.6510	1.8650	2.1270	1.8280	5.4550
Probability	0.0000	0.0000	0.0000	0.0001	0.0002
Sum	1827.0020	844.6279	1882.6110	990.8451	124.7991
Observations	234	234	234	234	140

Source: Authors' estimation

when it has a constant mean, a constant variance and constant auto–covariances for each given lag.[5] Stationary variables tend to cross their mean frequently while the nonstationary differences can wander a long way from their mean value.

We determine the appropriate VAR equation's lag order through the Selection–Order Criteria. This test reports four criteria which are: the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC), as well as a sequence of likelihood ratios (LR), giving us the option of comparing among them to make the most appropriate decision for our model.

It is important to distinguish between stationary and nonstationary data before testing for many reasons, namely because this can strongly influence the properties and behavior of the time-series. Moreover, the use of nonstationary data can lead to a spurious regression (Granger and Newbold 1974), which is a regression that appears to be good but is worthless in reality, or to invalid assumptions, meaning that the usual 't-ratios' will not follow a t-distribution, and the F–statistic will not follow an F–distribution, and so on (Brooks, 2014).

This paper uses another extension of the ADF test (DF–GLS) as suggested by Elliott et al. (1996). Table 2 shows the DF-GLS test to verify the order of integration. The results show that all series are nonstationary at the level and stationary at the first difference.

We then proceed to test for cointegration between our variables using the Johansen procedure, the results of which are shown in Table 3.

---

5   C. Brooks, 2014, *Introductory Econometrics for Finance, third ed.* (Cambridge, UK: Cambridge University Press).

Table 2: Dickey–Fuller generalized least square (DF-GLS) test

Variables	Level		First difference	
	I(0)		I(1)	
	C	C & T	C	C & T
TASI	−1.062	−2.932*	−7.778	−2.933*
OIL	−1.72	−2.932*	−8.693	−2.933*
NYSE	−2.144	−2.932*	−5.69	−2.925*
COMM	−1.41	−2.932*	−6.904	−2.933*
US1M	−0.511	−2.997*	−8.085	−2.999*

McKinnon critical values for intercept (C); 1% level=−3.6394, 5% level=−2.9511, and for intercept & trend (C & T); 1% level=−4.2529, 5% level=−3.5485. Lag length in all cases is one. *Shows stationarity at the 1% level of significance. Source: Authors' estimation

Table 3: Co-integration test results

Hypothesized No. of CE(s)	t. Statistics	5% Critical values	Max-Eigenvalue statistics	5% Critical values
None	72.0869	68.5800	27.7100	27.0700
At most 1	36.5008*	47.2100	19.7400	20.9700
At most 2	17.5400	29.6800	8.0600	13.6000
At most 3	6.8500	15.4100	3.9800	14.0700
At most 4	0.6500	3.7600	1.0750	3.7600

Source: Authors' estimation

As indicated by the table, since the test statistic of 36.50 does not exceed the 5% critical value of 47.21, we fail to reject the null hypothesis that the rank of the cointegrating matrix is 1 at this significance level, against the alternative hypothesis that it is more than 1. This means that we find evidence for 1 cointegrating relationship. Since evidence of cointegration exists, we will now implement a Vector Error Correction Model (VECM) and results given in Table 4.

Different information criteria indicate different results (as shown in Table 4), but since three (LR, FPE, AIC) out of five (not SC, HQ) tests suggest that the appropriate lag should be 2 not 1, we will adopt 2 as our appropriate corresponding VECM lag of order p-1.

We then proceed with implementing our VECM to capture the dynamics of our cointegrated system. In the summarized results shown in Table 5, the error correction term for each variable represents the speed of mean reversion to equilibrium. At 5% significance, we find that only oil and commodities have statistically significant coefficient values, this indicates there is only evidence for error correction in these variables.

The VECM results (Table 5) indicate that, in the short run at a 5% significance level, TASI returns are predicted by NYSE lagged returns and by US1M 2 period lagged change. More precisely,

Table 4: VAR lag order selection criteria

LAG	LL	LR	FPE	AIC	SC	HQ
0	683.2000	-	8.50E-12	−11.3033	−11.1872	−11.2562
1	757.8060	149.2100	3.70E−12	−12.1301	−11.4332*	−11.8471*
2	791.7570	67.9020*	3.2e-12*	−12.2793*	−11.0017	−11.7604
3	809.0230	34.5310	3.70E-12	−12.1504	−10.2921	−11.3957
4	824.1380	30.2310	4.40E-12	−11.9856	−9.54658	−10.9951

* indicates lag order selected by the criterion. Source: Authors' estimation

Table 5: Results of vector error correction model

Variable	Variable relationship with	Coefficient	Probability
TASI	e*	−0.0237	0.3820
	NYSE LD	0.6746	0.0000
	US1M L2D	−0.0463	0.0440
WTI	e*	0.1165	0.0000
	NYSE LD	0.7435	0.0000
	Commodities LD	0.7444	0.0000
	Commodities L2D	0.4255	0.0420
NYSE	e*	0.0232	0.2220
	TASI LD	−0.1600	0.0180
	US1M L2D	0.0373	0.0210
Commodities	e*	0.0429	0.0210
	NYSE LD	0.3871	0.0000
	Commodities L2D	0.3022	0.0400
US1M	e*	0.0288	0.7910
	TASI L2D	−0.8906	0.0190
	NYSE L2D	1.7027	0.0090

e* = error correction. Source: Authors' estimation

Table 6: Vector error correction model—cointegrating vector results

Variables	Coef.	Std. Err.	t. statistic	Probability	5% Critical values	10% Critical values
Constant	−1.6264	-	-	-	-	
TASI	1.0000	-	-	-	-	
WTI	−3.7798	0.6849	−5.5200	0.0000	−5.1221	−2.4374
NYSE	−1.3368	0.2118	−6.3100	0.0000	−1.7519	−0.9218
COMM	4.2064	0.8869	4.7400	0.0000	2.4682	5.9446
US1M	0.8347	0.3255	2.5600	0.0100	0.0197	0.1473

Source: Authors' estimation

Table 7: VECM stability analysis result

Eigenvalue			Modulus
1			1
1			1
1			1
1			1
0.6638047	+	0.2864086i	0.722957
0.6638047	−	0.2864086i	0.722957
−0.00110266	+	0.686821i	0.686822
−0.00110266	−	0.686821i	0.686822
−0.4878489	+	0.733506i	0.493332
−0.4878489	−	0.733506i	0.49332
0.4746181			0.474618
−0.1935413	+	0.2085671i	0.284532
−0.194513	−	0.2085671i	0.284532
0.1762624	+	0.1845036i	0.255167
0.1762624	−	0.1845036i	0.255167

The VECM specification imposes 4-unit moduli. Source: Authors' estimation

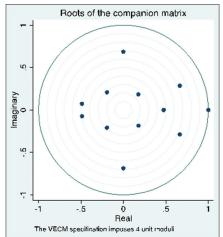**Figure 2:** VECM stability analysis graphical result

a 1% change in NYSE last period is associated with a 0.675% change in TASI, and a 1 percentage point change in US1M in the two previous periods is associated with a 0.046% change in TASI today. This is a significantly more modest association than that between NYSE and TASI, as may be expected. At the same significance level, we find no statistically significant short run relationship between TASI and WTI.

Taking a look at the other variables at the 5% significance level, in the short run we find evidence that WTI is predicted by both NYSE and commodities. With a significant error correction term in WTI, it is indicative of a long–run component of the dynamics of oil with respect to all the other variables.

As for NYSE, the first lag of TASI returns and US1M appear to be the only factors which are statistically significant short-run predictors of NYSE. TASI's predictive power over NYSE is counter intuitive and hence may be a result of omitted variable bias (OVB). The fact that NYSE is not the main focus of our study means that major factors influencing its daily movements are not included; thus TASI's relationship might be reflecting all other omitted factors resulting in a bias to the coefficient.

Furthermore, Commodities seem to be predicted only by NYSE. With its error correction term also statistically significant, this indicates a strong connection between commodities and NYSE in the short run and between commodities and all of the other variables in the long run. Finally, in the short run, changes in the US 1 month interest rates are predicted by both TASIs 2 period lagged returns and those of NYSE.

The results shown in Table 6 imply a long run relationship of the form:

$$logtasi=3.78logwti+ 1.34lognyse–4.21logcom+0.08US1M$$

Here, the coefficients on logwti, lognyse and logcom represent the long–run elasticities. Thus, a 1% change in WTI would in the long run be associated with a 3.78% change in TASI, and so on. These are signed as expected, particularly for WTI and NYSE, which both have positive long–run elasticities.

As we can see, the results in Table 7 indicate that the moduli of all real roots are far from 1, with the closest being at 0.722957, which is still not a concerning degree. These results provide no evidence that the cointegrating equations are non–stationary, resulting in a stable VECM. This finding is supported by the graph exhibited below:

Figure 2 plots the roots of the companion matrix of the VECM, and gives a visual indication of the distances between the roots and the unit circle. As we can see, all of the tested roots lie far from the unit circle, which reinforces the table's finding that our VECM is indeed stable.

4. CONCLUSION AND POLICY RECOMMENDATION

The paper found reason to test for cointegration after the DF–GLS unit root test indicated that the variables are first difference

stationary, and testing for cointegration thereafter using the Johansen procedure confirmed that our series are indeed cointegrated. For that reason, the Vector Error Correction Model (VECM) was used, which is the appropriate specification for cointegrating vectors because it differentiates among the vectors of endogenous variables and includes an error–correction term to capture long–run dynamics. The VECM results indicate that, at the 5% significance level, no predictive relationship exists between TASI and WTI in the short run, and that the biggest short–term predictor of TASI returns are NYSE lagged returns. Interestingly, NYSE is found to be a good short–term predictor of WTI at the 5% significance level as well, indicating that in the short term the NYSE can be used to predict both TASI and WTI. WTI is also thought to have long–term dynamics with all variables, as its error correction term was significant at the same significance level. Additionally, the results indicate that a 1% change in WTI would be associated with a 3.78% long–run change in TASI, and that a 1% change in NYSE would be associated with a 1.34% long–run change in TASI as well. These results suggest that WTI holds a greater magnitude of long–term effect over TASI, and that an increase in both WTI and NYSE will be associated with a positive increase in TASI in the long run.

The results revealed in this paper give us reason to reject our original null hypothesis that oil prices are statistically significant predictors of the Saudi stock market movements. The New York stock exchange (NYSE) is noticed to be a better predictor of TASI, and therefore additional research must be conducted to closely examine this relationship. Additionally, it is observed that the New York stock exchange holds predictive power over oil fluctuations as well, indicating the possibility of the NYSE being used as a projection instrument of future oil price fluctuations. These findings open the door for future research to study these relationships more closely and indicate the magnitude at which these relationships can be most observed.

REFERENCES

Al Hayky, A., Naim, N. (2016), The Relationship between Oil Price and Stock Market Index: An Empirical Study from Kuwait. Kuwait: Middle East Economic Association, 15th International Conference.

Aloui, C., Jammazi, R. (2009), The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach. Energy Economics, 31(5), 789-799.

Arouri, M., Fouquau, J. (2009), On the short-term influence of oil price changes on stock markets in GCC countries: Linear and nonlinear analyses. Economic Bulletin, 29(2), 795-804.

Arouri, M.E.H., Lahiani, A., Nguyen, D.K. (2011), Return and volatility transmission between world oil prices and stock markets of the GCC countries. Economic Modelling, 28(4), 1815-1825.

Arouri, M.E.H., Rault, C. (2012), Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis. International Journal of Finance and Economics, 17(3), 242-253.

Basher, S.A., Sadorsky, P. (2006), Oil price risk and emerging stock markets. Global Finance Journal, 17(2), 224-251.

Brooks, C. (2014), Introductory Econometrics for Finance. 3rd ed. Cambridge, United Kingdom: Cambridge University Press.

Cong, R.G., Wei, Y.M., Jiao, J.L., Fan, Y. (2008), Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy, 36(9), 3544-3553.

Constantinos, K., Ektor, L.A., Dimitrios, M. (2010), Oil price and stock market linkages in a small oil dependent economy: The case of Greece. Journal of Applied Business Research, 26(4), 55-64.

Cuñado, J., De Gracia, F.P. (2013), Environment and happiness: New evidence for Spain. Social Indicators Research, 112(3), 549-567.

Dhaoui, A., Khraief, N. (2014), Empirical Linkage between Oil Price and Stock Market Returns and Volatility: Evidence from International Developed Markets. Economics Discussion Papers. Germany: Kiel Institute for the World Economy.

Elliott, G., Rothenberg, T.J., Stock, J.H. (1996), Efficient tests for an autoregressive unit root. Econometrica, 64(4), 813-830.

El-Sharif, I., Brown, D., Burton, B., Nixon, B., Russell, A. (2005), Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Economics, 27(6), 819-830.

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

Falzon, J., Castillo, D. (2013), The impact of oil prices on sectoral equity returns: Evidence from UK and US stock market data. Journal of Financial Management, Markets and Institutions, 1(2), 247-68.

Fayyad, A., Daly, K. (2011), The impact of oil price shocks on stock market returns: Comparing GCC countries with the UK and USA. Emerging Markets Review, 12(1), 61-78.

Filis, G. (2010), Macro economy, stock market and oil prices: Do meaningful relationships exist among their cyclical fluctuations? Energy Economics, 32(4), 877-886.

Filis, G., Degiannakis, S., Floros, C. (2011), Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 20(3), 152-164.

Granger, C.W.J., Newbold, P. (1974), Spurious regressions in econometrics. Journal of Econometrics, 2(2), 111-120.

Hamilton, J.D. (2008), Oil and the macroeconomy. In: The New Palgrave Dictionary of Economics. London: Palgrave MacMillan.

Hasan, M., Ratti, R. (2012), Oil Price Shocks and Volatility in Australian Stock Returns. Melbourne: Global Accounting, Finance and Economics Conference, Business Conference Papers.

Jarrah, M., Salim, N. (2016), The Impact of Macroeconomic Factors on Saudi Stock Market (Tadawul) Prices. Saudi Arabia: International Conference on Advances in Big Data Analytics.

Johansen, S. (1988), Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2-3), 231-254.

Johansen, S., Juselius, K. (1990), Maximum likelihood estimation and inference on cointegration-with applications to the demand for money. Oxford Bulletin of Economics and Statistics, 52(2), 169-210.

Kapusuzoglu, A. (2011), Relationships between oil price and stock market: An empirical analysis from Istanbul Stock Exchange (ISE). International Journal of Economics and Finance, 3(6), 99-106.

Masih, R., Peters, S., Mello, L.D. (2011), Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea. Energy Economics, 33(5), 975-986.

Mohanty, S.K., Nandha, M., Turkistani, A.Q., Alaitani, M.Y. (2011), Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. Global Finance Journal, 22(1), 42-55.

Sadorsky, P. (1999), Stock markets and energy prices. Energy Economics, 21(5), 449-69.

Samontaray, D.P., Nugali, S., Sasidhar, B. (2014), A study of the effect of macroeconomic variables on stock market: Saudi perspective. International Journal of Financial Research, 5(4),120-27.

Zarour, B.A. (2006), Wild oil prices, but brave stock markets! The case of GCC stock markets. Operational Research, 6(2), 145-162.