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Oil Price, Stock Market and Economic Growth of the United States: Empirical Evidence based on Dynamic Statistical Models

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Abstract: *This paper investigates the linkages and the long-run equilibrium relationship among oil price, stock market, and the economic growth of the U.S. using the quarterly data from 2010 to 2019 by applying the advanced econometric models. Economic growth rate (proxied by GDP growth) and the oil price are collected from the Bureau of Economic Analysis and the World Bank World Economic Indicators. The data of the U.S. market (proxied by S&P 500) is collected from the Bloomberg database. The econometric models are estimated by applying the most recent version of Econometric Software (**EViews 11**). In addition to graphical analysis and descriptive statistics, this study applied stationary tests Augmented Dickey Fuller (ADF), Johansen multivariate Cointegration as well as the Granger Causality tests. The graphical analysis and the descriptive statistics show the non-normal and skewed distributions with fat tails. The ADF test results indicates S&P 500 indices and the oil prices are nonstationary in level series and stationary in their first differences. Johansen Cointegration test results indicate that there is a long-run relationship among these variables. However, the pair wise Ganger Causality test fails to detect any causality between the oil price changes and economic growth, between oil price changes and S&P 500 index returns, or between economic growth and the S&P 500 returns.*

Keywords: *oil price, economic growth, stock market, cointegration, causality.*

I. Introduction

Crude oil is considered to be the important source of energy in industrial processes, transportation, and generation of electricity. The crude oil prices have experienced significantly wider swings since the mid-1980s. The WTI crude oil price experienced a continuous rise from $18.2/barrel in 2002 to $145.31/barrel in 2008 followed by a heavy decline to $34.03/barrel till 2009. Since 2010 the price of crude oil fell sharply from nearly $146 per barrel to recently about $50 per barrel. Many analysts argue that this sharp decline and volatility in oil prices will have significant long-run negative effects on the global economy through financial and equity markets. Theoretically, crude oil price fluctuations can affect the global economy in many different and significant ways. Rising oil prices can be passed on to consumers in the form of higher prices for final goods and services, consequently will reduce demand for final goods and services. However, the size of the impact will depend on the underlying drivers of the price decline and the extent of pass-through to households and firms. There is a wide range of empirical studies of the relationship between oil prices and the stock markets. These studies have mainly focused on oil exporting countries. Some evidences show that the price of oil has a direct effect on real trade, disposable income, stock market and hence the state of the economy (discussed in section II).

The significant fluctuations in crude oil prices have adverse influence on the economic growths of the oil importing countries as well. This also influences the decisions of portfolio managers, risk managers and investors in their pursuit of rebalancing their exposure to oil-based investments. The accurate forecast of crude oil volatility thus plays a very important role in policy-making, designing diversified portfolios, managing market risk, pricing derivatives securities, and in implementing trading strategies. Academicians, policy makers and the market participants have thus focused on forecasting and modelling oil prices by quantifying and managing the risks inherent in their frequent volatilities. In particular, the information transmission of crude oil prices has drawn the attention of various academics and practitioners as crude oil prices play a prominent role in national economies.

Over the past decade, the U.S. stock market has reached a record high. Big companies with a sizeable presence in overseas have helped fuel the rally in the stock markets. According to some analysts this rally in the stock markets is related to years of easy monetary policy, substantial increase in corporate earnings, and stronger economic growth. Many others argue that the abnormal profits of technology companies are the major gainers in the stock market. Others believe that the global economic growth and a weak US dollar are argued to boost profits of major U.S. transnational companies resulting in higher economic growth and record high performance of U.S stock indexes. According to the Federal Reserve, U.S GDP growth on average was 2.2% in 2019. The volatility in oil prices, stock indices and economic growth is a cause of concern to regulators, policy makers, financial institutions and portfolio managers. Empirical evidence of the impact of these fluctuations on stock returns has been mixed (Discussed in section II). Moreover, a more accurate test for linkages between different financial variables is based on cointegration techniques developed by Engle and Granger (1987), and Johansen and Juselius (1990). Since then, cointegration tests have become the standard methodology for investigating long-run relationship between financial and equity markets, and among other macroeconomic variables. Testing cointegration has thus become the standard method of investigating long-run stationary relationship between variables and markets. To the best of my knowledge, no study has yet analyzed the linkages and the relationship among oil price, economic growth and stock markets of the U.S using recent statistical data with advanced econometric techniques. So empirical investigations in this study will be conducted primarily by applying this methodology.

The first test will check for long-run relationships among oil prices, stock markets and GDP growth by applying the multivariate cointegration test of Johansen and Juselius (1990). The second test will be conducted on the Granger (1998) causality test to investigate the lead-lag feedback between oil prices and stock indexes, and between stock prices and economic growth. Therefore, the major objectives of this study are to investigate empirically

(i) the stochastic properties of the variables,

(ii) the Johansen cointegration test to examine the long-run relationship among the stock market, oil prices and economic growth, and

(iii) the Granger causality between the oil prices and economic growth, between oil price and the stock market, and between the economic and S&P 500.

The rest of the paper is organized as follows: Section II is devoted to the Review of the Literature. Section III presents Econometric Methodology. Section IV reports the Empirical Results, while Section V Concludes the paper.

II. Literature Review

Many researchers analyzed the relationship between oil prices and stock markets. Jones and Kaul (1996) examined the impact of oil price changes to stock markets. They found that for the USA and Canada, stock markets reaction can be accounted for entirely by the impact of oil shocks on cash flows. Huang *et al.* (1996) in their study concentrated on the relationship between daily oil futures returns and daily US stock returns. Using a vector autoregressive (VAR) approach, they found that oil futures returns did lead some individual oil company stock returns but oil futures returns did not have much impact on broad-based market indices though oil futures volatility led to the petroleum stock index volatility. Ferderer (1996) provided the same conclusion but at more general and indecisive level by indicating that oil price shocks may have an adverse impact on the macro economy indicators, not only because they increase the level of oil prices, but also because they raise oil price volatility. Gjerde and Saettem (1999) demonstrated that stock returns have a positive and delayed response to changes in industrial production and that the stock market responds rationally to oil price changes in the Norwegian market. Sadorsky (2001, 2003) investigated the impact of oil prices using industry level data in Canada and the USA, respectively. He found a significant impact from oil to stock price returns in the oil and gas industry for Canada; and for the US case, he reports a link between oil price shocks and technology stock prices using monthly data from 1986 to 1999. Basher and Sadorsky (2004), using a multi-factor arbitrage pricing model, find strong evidence that oil price risk impacts returns of emerging stock markets. Papapetrou (2001) in his study investigated the dynamic relationship between oil price shocks, stock exchange prices and economic activities in Greece during period from 1989 to 1999. He concluded that the changes in the oil prices affect the real economic activities and they are important factors in studying the movements between the prices of oil crude and stock exchange. Ciner (2001) examined the causality between oil prices and stock return in the U.S proving that a significant nonlinear correlation exists. Hammoudeh and Aleisa (2002) found spillovers from oil markets to the stock indices of oil exporting countries, including Bahrain, Indonesia, Mexico and Venezuela. In his study, Maghyereh (2004) looked into the interaction between shocks that occurred in oil prices and stock markets of relevant countries, and found that shocks that occurred in oil prices did not have meaningful effect on stock index returns of developing countries. Hammoudeh and Elesia (2004) used a VAR model and cointegration tests in their study to check the bidirectional relationship between Saudi stock returns and oil price. Their findings also suggested that the other GCC markets are not directly linked to oil prices and are less dependent on oil exports and are more influenced by domestic factors. El-Sharif *et al.* (2005) examined the links between oil price movements and stock returns in the UK oil and gas sector. They found a strong interrelationship between the two variables.

Several other studies have examined whether oil price changes affect stock markets in terms of return and volatility. Most existing research concerning the relationship between the crude oil market and stock markets mainly concentrated on major European, Asian and Latin American emerging markets. A number of papers are dedicated to crude oil futures. Part of the existing literature exhibits low and negative correlations between crude oil and stock markets, concluding on the diversification properties of crude oil futures. Other studies investigated the distributional characteristics of those futures returns and concludes to their nonnormality. A majority of these works showed the negative impact of oil price shocks on international stock returns (see, *e.g.*, Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Chiou and Lee, 2009; Narayan and Narayan, 2010; Lee and Chiou, 2011). This evidence indicated that oil price increases lead to higher stock returns of oil-related firms. In terms of methodologies, some of the studies applied VAR and vector error correction (VEC) models to analyze the relationship between oil and commodity prices (see, *e.g.*, Park and Ratti, 2008; Arouri and Fouquau, 2009; Miller and Ratti, 2009; Fayyad and Daly, 2011; Masih *et al.*, 2011). Park and Ratti (2008) show that in most oil importing countries oil price shocks have a significantly negative effect on the stock market in the same month or in one month.

Furthermore, the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model has been used to examine temporal volatility spillovers between oil and stock markets (see, *e.g.*, Chang *et al.*, 2009; Sadorsky, 2012; Arouri *et al.*, 2011a, 2012; Mollick and Assefa, 2013; Hamma *et al.*, 2014). Sadorsky (1999) showed that oil prices and oil price volatility both play important roles in affecting real stock returns Moreover, some authors have based on other related methodologies to investigate the relationship between the oil and stock markets. Only a minor group of studies uses the cointegration tests. Malik and Ewing (2009) investigated volatility spillover between oil prices and five US equity sector indices and concluded in favors of significant transmission of return and volatility shocks. Arouri and Nguyen (2010) examined the short-term links between oil and stock prices in the aggregate as well as sector-by-sector in Europe. Their findings, obtained through various econometric techniques, suggest that the sensitivity of sector stock returns to oil price changes differs greatly from one sector of activity to another. The fact that the volatility in stock markets is associated with depreciation or appreciation of the oil prices.

Adebiyi *et al.* (2009) showed an immediate and significant negative real stock returns to oil price shock in Nigeria, the Granger causality test indicates that causation runs from oil price shocks to stock returns. El-Sharif *et al.* (2005) illustrated that the relationship is always positive and highly significant between volatility in the price of crude oil and share values within the sector. Meyer (2010) finds a significant long-run positive beta for the three factors (NASDAQ high tech index, oil price and the US interest rate. Gogineni (2010) finds that stock returns of some industries that use little oil also are sensitive to oil prices. Anoruo and Mustafa (2007) revealed that the oil and stock market returns are co-integrated. The results from the modified Vector Error Correction Model suggest that causality runs from stock market to oil market but not vice versa. Hyde and Bredin (2005) reveal that oil prices are not a strong determinant of stock returns. Moreover, Mujahid *et al.* (2007) indicate that there is no significant effect of oil prices is found on stock returns.

The relationship between oil prices and stock markets in oil-exporting countries have been examined by various authors in the last decade (for example, Ahmad Al-Kandari (2007), Anoruo and Mustafa (2007) Basher and Sadorsky (2006), Eltony (1999), Hammoudeh (2009), Maghyereh (2004). From their side, Davis and Aliaga-Diaz (2008) showed that increases oil price do not uniformly lead to lower stock returns. Agusman and Deriantino (2008) suggested that in general oil price changes do not have significant impacts on industry stock returns. Discussing this issue further, Cong *et al.* (2008) illustrate that oil price shocks do not show a statistically significant impact on the real stock returns of most Chinese stock market indices. From his side, Kandir (2008) revealed that oil prices do not appear to have any significant effect on stock returns. Miller and Ratti (2009) analyzed the long-run relationship between the world price of crude oil and international stock markets for six OECD countries using a cointegrated VEC Model with additional regressors. They found a long-run relationship between these series for the six countries, suggesting that stock market indices respond negatively to increases in the oil price in the long run. Al-Fayoumi's (2009) study did not support the hypothesis that oil prices lead to changes in stock market returns in Turkey, Jordan and Tunisia.

In the case of group of oil exporting countries, Basher and Sadorsky (2006) found a strong evidence that oil prices risk impacts stock price returns in emerging markets. Hammoudeh and Choi (2005) concluded that a positive oil shock will benefit most of GCC markets. Moreover, Maghyereh and Al-Kandari (2007) supported a non-linear modelling of the relationship between oil and economy in GCC countries. Abdelaziz and Chortareas (2008) from their side indicated that the oil prices have a long-run positive effect on stock market in each country of the followings: Egypt, Saudi Arabia, Oman and Kuwait. Investigating this issue further, Arouri and Fouquau (2009) show that Bahrain, Kuwait and Saudi Arabia were found that oil price changes do not affect their stock market returns. Arouri and Rault (2009) showed that stock market price changes in the other GCC member countries do not Granger cause oil price changes, whereas oil price shocks Granger cause stock price changes. They showed a significant links between the two variables in Qatar, Oman and UAE, thus, stock markets in these countries react positively to oil price increases. Bjørnland (2008) found that following a 10% increase in oil prices, stock returns increase by 2.5% in Norway.

III. Methodology and Hypotheses

Unit Root Test (Stationary)

Augmented Dickey Fuller (ADF) test is applied in advanced economic research to determine whether time series represented by economic variables are nonstationary (have unit root). ADF requires running a regression of the first difference of the series against the series lagged once, lagged difference terms, a constant and a time trend such as

$$\Delta x_t = \lambda_0 + \lambda_1 X_{t-1} + \lambda_2 T + \Sigma\, \lambda_i\, \Delta x_{t-I} + \in_t \; i = 1 \ldots k \qquad (1)$$

where Δ is the first difference operator, $\in_t$ is an error term, k is the number of lagged first difference term and is determined such that t approaches to white noise. The null hypothesis specifies nonstationary series or unit root $(H_0\!: \lambda_1 = 0)$. Output of the ADF test consist of the t-statistic on the estimated coefficient of the lagged variable (λ_1) and the Mackinnon critical values for the test of a zero coefficient. If the estimated coefficient is significantly different from zero then the H_0 is rejected, suggesting the series are stationary.

Cointegration Test

The theory of cointegration, first introduced first by Granger (1981) and further developed by Granger (1986) and Engle and Granger (1987), integrates the short-run dynamics with long-run equilibrium relationship. A set of time-series variables are said to be cointegrated if they are integrated of the same order and a linear combination of them is stationary. Such linear combination would then point to the existence of a long-term relationship among the variables. Since our interest is searching for long run linkages among these variables, we consider the three macroeconomic variables to investigate the presence of potential common trends among them. This study first investigates on the first order nonstationary integrated process *i.e.* $I(1)$. The implications of cointegration are numerous, both from economic and statistical points of view. In particular if there are r stable long-run relationships (cointegrating equations) in k dimensional vector of time series, then these k series share $k - r$ common stochastic trends. On the other hand, given the unique relationship between cointegration and the error correction models, then there must be some Granger causality (*i.e.*, precedence) in at least one direction. This paper exploits these relationships and investigates the presence of common stochastic trends by means of the vector autoregressive representation. We derived a maximum likelihood approach for estimating and testing the number of cointegrating relationships among the components of a k-vector x_i of variables. Assuming a simple vector autoregressive (VAR) model for x_i:

$$A(L)\ x_i = \in_t \tag{2}$$

which can be reparametrized in a vector autoregressive Error Correction Model (ECM):

$$\Delta x_t = \Sigma_i\ \Pi_i\ \Delta x_{t-I} + \Pi p x_{t-p} + \in_t \tag{3}$$

where $I = 1, 2, \ldots p - 1.$

$$\Pi_i = -1 + A_1 + A_2 + \ldots + A_i \text{ with } I = 1, \ldots, p.$$

If rank $(\Pi_p) = r < k$, there are $r - k$ unit roots in the system and r linear combinations which are stationary, that is, there are r cointegrating relationships. Π_p can be written as $\alpha\beta'$ where both α and β are $(k \times r)$ matrices of full column rank. The first r rows of β' are the r cointegrating vectors in the different equations. The maximum likelihood estimate of the cointegrating vector is given by the empirical canonical variates of X_{t-p} with respect to Δx_t corrected for the short-run dynamic and the deterministic components. The number of cointegrating relationships is given by the number of significant canonical correlations. Their significance can be tested by means of a sequence of likelihood ratio tests. Once the number of cointegrating relationships has been determined, it is possible to test particular hypothesis concerning α and β using standard ξ^2 (chi-square) distributed likelihood ratio test. We consider the above three variables jointly in a model such as equation (4). The specification of the lag length of the model is tested sequentially using likelihood ratio test statistics.

The Granger Test for Causality

The Granger approach to the question of whether X and Y are Granger causality related is thus to see how much of the current Y can be explained by past values of Y and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients on the lagged values of X are statistically significant. The two-way causation is frequently the case; x Granger causes y and y Granger causes x. It is important to note that the statement 'x Granger causes y' does not imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. In the causality test, the null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression.

More specifically let us consider the following two variable VAR model:

$$Y_t = \alpha_{10} + \Sigma\ \alpha_{1i}\ X_{t-i} + \Sigma\beta_{1j}\ Y_{t-j} + \varepsilon_{1t} \tag{4}$$

$$X_t = \alpha_{20} + \Sigma\alpha 2i\, X_{t-i} + \Sigma\beta_{2j}\, Y_{t-j} + \varepsilon_{2t} \quad (5)$$

where ε_t is white noise, p is the order of the lag for X, and q is the order of the lag for Y.

With respect to this model we can distinguish the following cases:

(i) If $[\alpha_{11}, \alpha_{12}, ..., \alpha_{1p}] \neq 0$ and $[\beta_{12}, \beta_{13}, ..., \beta_{1q}] = 0$, there exists a unidirectional causality from X_t to Y_t, denoted as $X \rightarrow Y$.

(ii) If $[\alpha_{21}, \alpha_{22}, ..., \alpha_{2p}] = 0$ and $[\beta_{21}, \beta_{22}, ..., \beta_{2q}] \neq 0$, there exists a unidirectional causality from Y_t, to X_t, denoted as $Y \rightarrow X$.

(iii) If $[\alpha_{11}, \alpha_{12}, ..., \alpha_{1p}] \neq 0$ and $[\beta_{21}, \beta_{22}, ..., \beta_{2q}] \neq 0$, there exists a bidirectional causality between X_t to Y_t, denoted as $X \rightarrow Y$.

The testable hypotheses are as follows

H_0: X does not Granger-cause Y, *i.e.* $[\alpha_{11}, \alpha_{12}, ..., \alpha_{1p}] = 0$, if F-statistic < critical value of F.

H_1: X does Granger-cause Y, *i.e.* $[\alpha_{11}, \alpha_{12}, ..., \alpha_{1p}] \neq 0$, if F-statistic > critical value of F. and

H_0: Y does not Granger-cause X, *i.e.* , $[\beta_{21}, \beta_{22}, ..., \beta_{2q}] = 0$ if F-statistic < critical value of F.

H_1: Y does Granger-cause X, *i.e.* $[\beta_{21}, \beta_{22}, ..., \beta_{2q}] \neq 0$, if F-statistic > critical value of F.

Data and the Sample

The GDP growth rate (proxy for economic growth) and the oil prices are collected from the Bureau of Economic Analysis and the World Bank World Economic Indicators. The S&P500 is a value weighted index representing approximately 75% of the total market capitalization of the U.S. stock market. The data of the U.S. market index S&P 500 is collected from the Bloomberg database. The study uses the quarterly data covering from 2010:Q1 to 2019:Q2. 9

IV. Empirical Results

In order to estimate the above described models, this study applied the recent version of the Econometric software (Eviews 11). Empirical results reported here are also comprised of descriptive statistics, stationarity tests, Johansen multivariate cointegration and the Granger causality tests. The time series properties and the dynamics of the variables over the study period are plotted in Figures 1 through 10. Figure 1 depicts the behavior of oil prices and the S&P 500 index and the GDP growth, while Figure 3 and 4 exhibit the behaviors of oil prices and S&P 500 in levels. Figures 5, 6 and 7 depict their behaviors in terms of changes. While Figures 8, 9 and 10 show histograms with descriptive statistics for each variable in levels. Level series of oil prices and S&P500 indicate significant time trends.

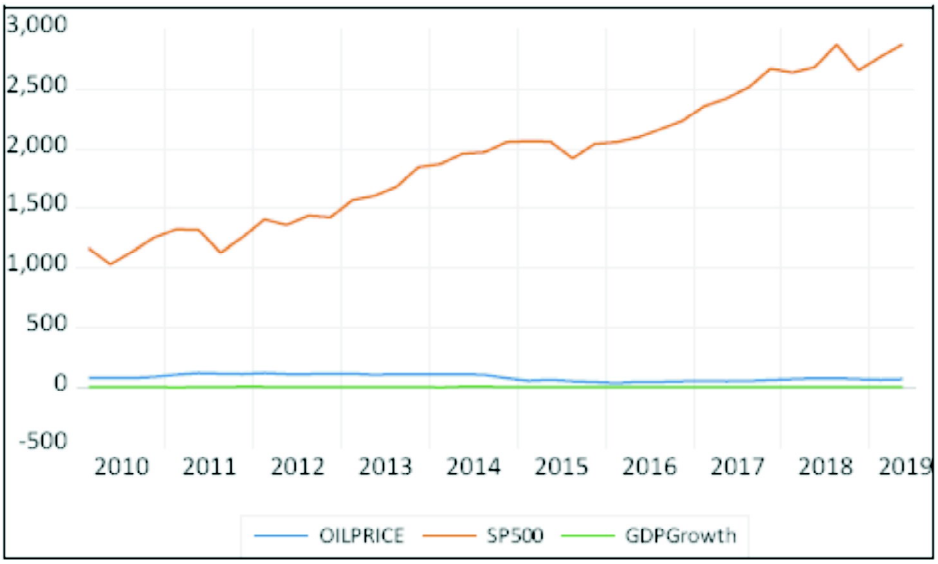

Figure 1: Level series

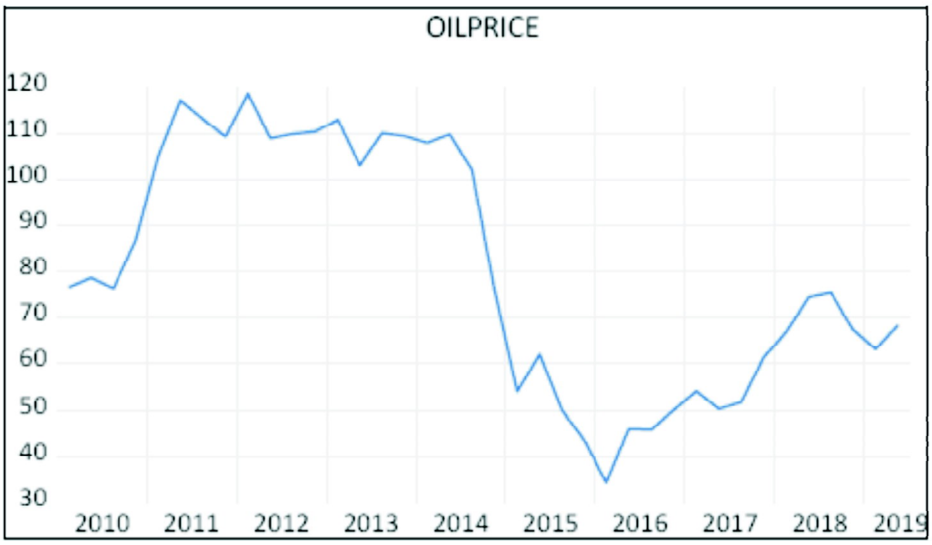

Figure 2: Oil price in level

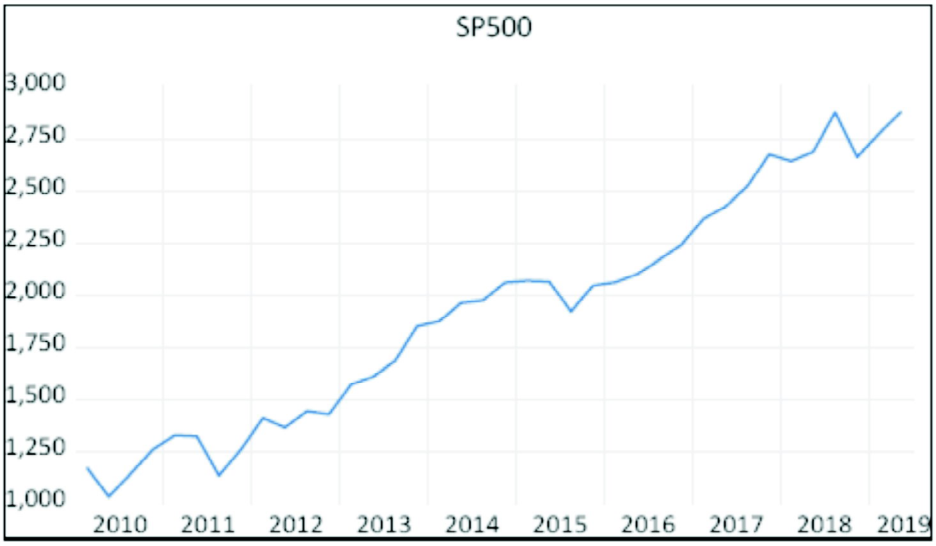

Figure 3: S&P 500 index in level

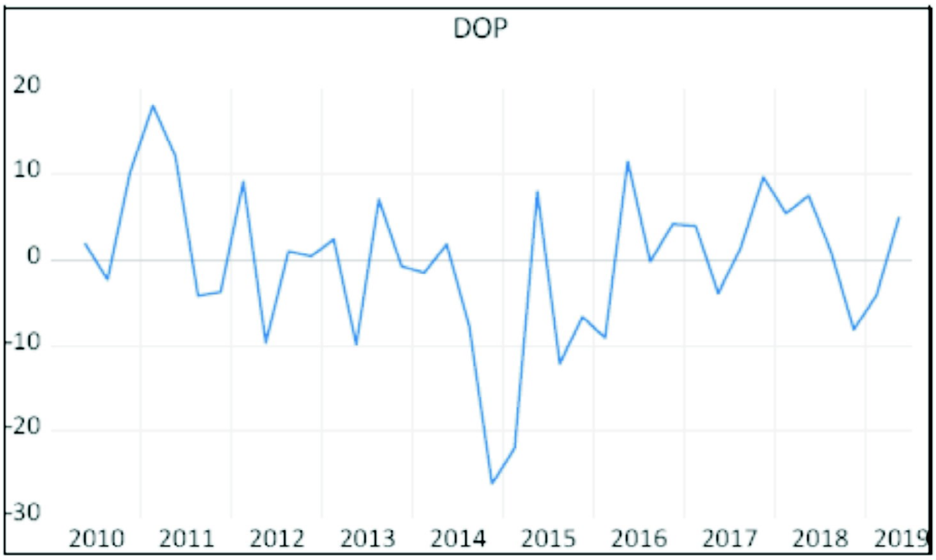

Figure 4: Change in oil price

The descriptive statistics for each variable both in levels and in first differences are presented in Table 1. These statistics including mean (Mean), standard deviations (Std. dev.), maximum (Max), minimum (Min), skewness (Skew.) and kurtosis (Kurt.). Jarque–Bera (J-B) statistics are the empirical tests for normality based on skewness and excess kurtosis. From

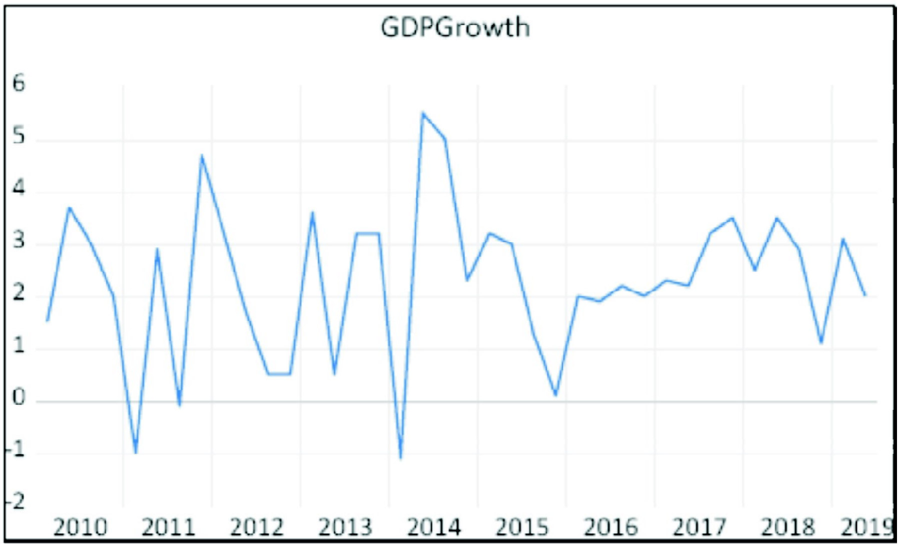

Figure 5: Economic growth

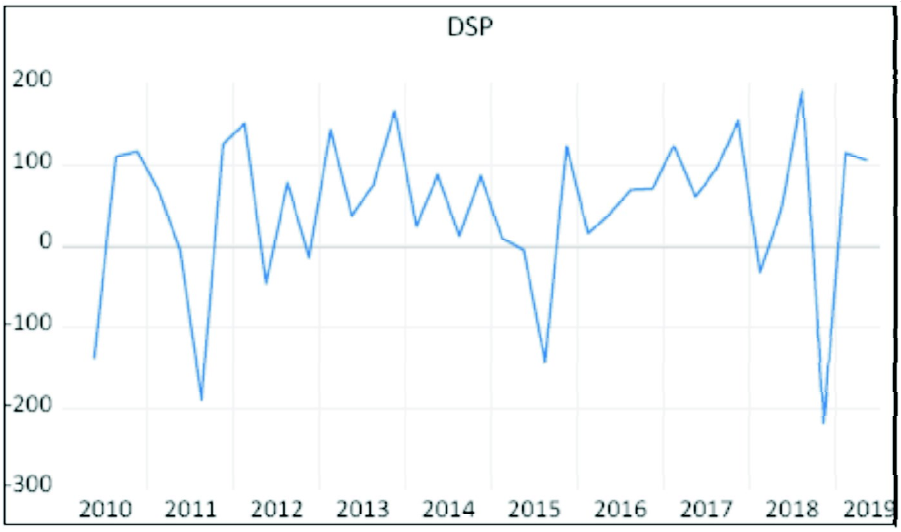

Figure 6: SP500 index returns

Table 1 (A&B), the measures for skewness and excess kurtosis show that most return series are skewed and highly leptokurtic with respect to the normal distribution. All variables in levels display "stylized' facts common to most financial and macroeconomic data such as non-normality in the form of fat tails. As indicated by skewness statistics, all variables are either positively or negatively skewed indicating right or left tail; supporting

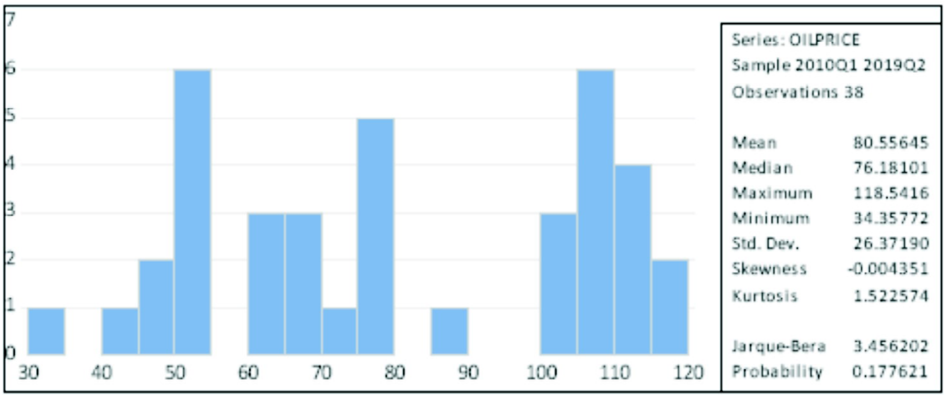

Figure 7: Oil price (Descriptive statistics)

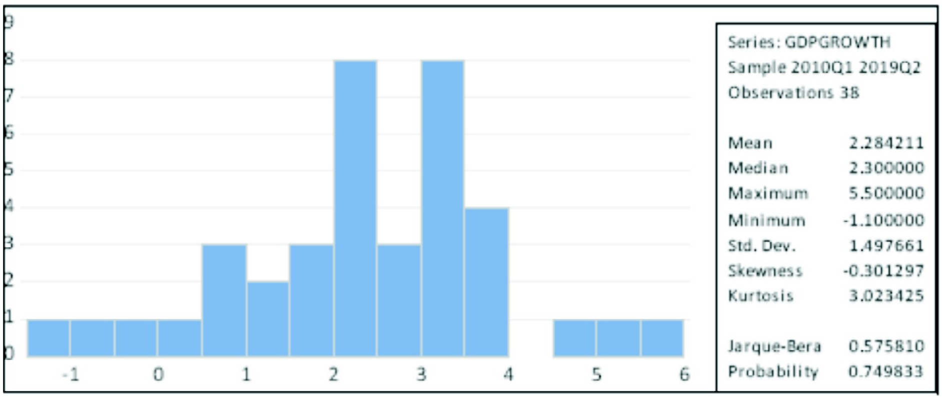

Figure 8: Economic growth (Descriptive statistics)

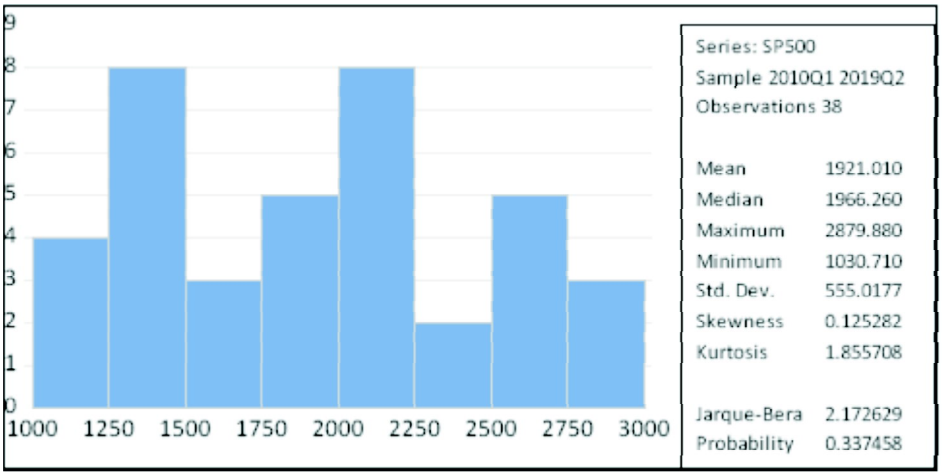

Figure 9: S&P 500 (Descriptive statistics)

asymmetric distributions. The kurtosis of variables indicate the non-normal distributions. The J-B test which combines both the skewness and the kurtosis, strengthens the above conclusion that the null hypothesis of normality is rejected decisively for all variables at the conventional level of significance. The second part of the analysis is based on the correlation matrix, indicating weak correlations between the economic growth and the stock return as well as between the oil price change and the S&P returns (Table 1C). No correlation is detected between the oil price change and the economic growth. These findings provide the first hand useful information for further investigations of the stated hypotheses by applying the above discussed advanced statistical methodologies.

Table 1A: Descriptive Statistics

	Oilprice	*SP500*	*GDP growth*
Mean	80.55645	1921.010	2.284211
Median	76.18101	1966.260	2.300000
Maximum	118.5416	2879.880	5.500000
Minimum	34.35772	1030.710	–1.100000
Std. Dev.	26.37190	555.0177	1.497661
Skewness	–0.004351	0.125282	–0.301297
Kurtosis	1.522574	1.855708	3.023425
Jarque-Bera	3.456202	2.172629	0.575810
Probability	0.177621	0.337458	0.749833
Sum	3061.145	72998.40	86.80000
Sum Sq. Dev.	25732.66	11397651	82.99053
Observations	38	38	38

Table 1B: Descriptive Statistics

Oil Price Change (DOP) S&P500 Return (DSP) GDP Growth (Econ Growth)			
	DOP	*DSP*	*GDPGrowth*
Mean	–0.225043	46.22835	2.305405
Median	0.986806	69.41000	2.300000
Maximum	18.10215	191.6600	5.500000
Minimum	–26.12373	–217.6700	–1.100000
Std. Dev.	9.124808	96.59636	1.512530
Skewness	–0.678269	–1.104759	–0.339430
Kurtosis	3.803343	3.845687	3.005201
Jarque-Bera	3.831900	8.628947	0.710518
Probability	0.147202	0.013374	0.700992
Sum	–8.326608	1710.449	85.30000
Sum Sq. Dev.	2997.436	335910.8	82.35892

Table 1C: Covariance and Correlation

Covariance Analysis: Ordinary
Sample: 2010Q1 2019Q2
Included observations: 38

Covariance Correlation	*Oil Price*	*SP500*	*GDP Growth*
Oil Price	677.1753		
	1.000000		
SP500	–8548.934	299938.2	
	–0.599854	1.000000	
GDP Growth	0.376603	133.3264	2.183961
	0.009793	0.164732	1.000000

Table 1D: Covariance and Correlation

Covariance Correlation	*Oil Price*	*SP500*	*GDP Growth*
DOP	81.01179		
	1.000000		
DSP	216.1525	9078.672	
	0.252043	1.000000	
GDP Growth	0.360125	42.18773	2.225917
	0.026818	0.296770	1.000000

Unit Root Tests

As the study uses the time series data and aims at possible long-run equilibrium relationships among them, it is necessary to check whether the variables are stationary in levels and in difference in order to avoid spurious results. Therefore the study applies the Augmented Dickey-Fuller (ADF) test for stationarity (unit root) to each variable. Table 2 provides the summary results of the ADF test on both level series and in their first differences. The S&P and the Oil prices are found to be non-stationary in levels, but found to be stationary in their first differenced. Since the economic growth is proxied by percentage changes in GDP, this variable is stationary.

Cointegration Test

Engel and Granger (1987) suggest if two non-stationary variables converge to long-run equilibrium, then a stationary combination of these two variables should exists. Such variables are then called cointegrated; and the vector that transforms the no-stationary variables into stationary is called cointegration vector. Test for cointegration suggested by Engle and Granger was extended by Johansen to a multivariate case. Both tests rely on the assumption that stability of the cointegration vector is stable over time. We

Table 2: ADF Unit Root Tests

Null Hypothesis: SP500 has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag = 9)

		t-Statistic	*Prob.**
Augmented Dickey–Fuller test statistic		–0.018384	0.9508
Test critical values:	1% level	–3.621023	
	5% level	–2.943427	
	10% level	–2.610263	

**MacKinnon (1996) one-sided p-values.*

Augmented Dickey–Fuller Test Equation
Dependent Variable: D(SP500)
Method: Least Squares
Included observations: 37 after adjustments

Variable	*Coefficient*	*Std. Error*	*t–Statistic*	*Prob.*
SP500(–1)	–0.000516	0.028049	–0.018384	0.9854
D(SP500(–1))	–0.255730	0.159172	–1.606626	0.1174
C	65.01630	55.62623	1.168806	0.2506
R-squared	0.073137	Mean dependent var		52.19324
Adjusted R-squared	0.018616	S.D. dependent var		91.54026
S.E. of regression	90.68420	Akaike info criterion		11.93025
Sum squared resid	279603.2	Schwarz criterion		12.06086
Log likelihood	–217.7096	Hannan–Quinn criter.		11.97630
F-statistic	1.341445	Durbin–Watson stat		2.090504
Prob (F-statistic)	0.274955			

Null Hypothesis: D(SP500) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag = 9)

		t-Statistic	*Prob.**
Augmented Dickey–Fuller test statistic		–8.146198	0.0000
Test critical values:	1% level	–3.621023	
	5% level	–2.943427	
	10% level	–2.610263	

**MacKinnon (1996) one-sided p–values.*

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SP500,2)
Method: Least Squares
Sample (adjusted): 2010Q3 2019Q3
Included observations: 37 after adjustments

Variable	*Coefficient*	*Std. Error*	*t–Statistic*	*Prob.*
D(SP500(–1))	–1.256268	0.154215	–8.146198	0.0000
C	64.04007	16.33206	3.921126	0.0004
R-squared	0.654698	Mean dependent var		5.964892
Adjusted *R*-squared	0.644832	S.D. dependent var		149.9762
S.E. of regression	89.37977	Akaike info criterion		11.87620
Sum squared resid	279606.0	Schwarz criterion		11.96328
Log likelihood	–217.7098	Hannan-Quinn criter.		11.90690
F-statistic	66.36054	Durbin–Watson stat		2.090661
Prob (*F*-statistic)	0.000000			

With trend and Intercept:
Null Hypothesis: SP500 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic – based on SIC, maxlag = 9)

		t–Statistic	*Prob.**
Augmented Dickey–Fuller test statistic		–3.591777	0.0440
Test critical values:	1% level	–4.219126	
	5% level	–3.533083	
	10% level	–3.198312	

**MacKinnon (1996) one-sided p-values.*

Null Hypothesis: D(SP500) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic – based on SIC, maxlag = 9)

		t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		–8.036897	0.0000
Test critical values:	1% level	–4.226815	
	5% level	–3.536601	
	10% level	–3.200320	

**MacKinnon (1996) one-sided p-values.*

No trend and no intercept
Null Hypothesis: SP500 has a unit root
Exogenous: None
Lag Length: 0 (Automatic-based on SIC, maxlag = 9)

		t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		2.952417	0.9988
Test critical values:	1% level	–2.627238	
	5% level	–1.949856	
	10% level	–1.611469	

**MacKinnon (1996) one-sided p–values.*

Null Hypothesis: D(SP500) has a unit root
Exogenous: None
Lag Length: 2 (Automatic – based on SIC, maxlag = 9)

		t–Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		–2.087010	0.0371
Test critical values:	1% level	–2.632688	
	5% level	–1.950687	
	10% level	–1.611059	

**MacKinnon (1996) one–sided p–values.*

Null Hypothesis: USGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic-based on SIC, maxlag = 9)

		t–Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		–6.799110	0.0000
Test critical values:	1% level	–3.615588	
	5% level	–2.941145	
	10% level	–2.609066	

**MacKinnon (1996) one-sided p-values.*

Augmented Dickey-Fuller (ADF) Test Equation
Dependent Variable: D(USGDP)
Method: Least Squares
Sample (adjusted): 2010Q2 2019Q3
Included observations: 38 after adjustments

Variable	*Coefficient*	*Std. Error*	*t–Statistic*	*Prob.*
USGDP(–1)	–1.121117	0.164892	–6.799110	0.0000
C	2.574026	0.448602	5.737884	0.0000
R-squared	0.562192	Mean dependent var		0.013158
Adjusted R–squared	0.550031	S.D. dependent var		2.239350
S.E. of regression	1.502150	Akaike info criterion		3.702867
Sum squared resid	81.23232	Schwarz criterion		3.789056
Log likelihood	–68.35448	Hannan–Quinn criter.		3.733533
F-statistic	46.22790	Durbin–Watson stat		1.970651
Prob (F-statistic)	0.000000			

Null Hypothesis: USGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic – based on SIC, maxlag = 9)

		t-Statistic	Prob.*
Augmented Dickey–Fuller test statistic		–6.759656	0.0000
Test critical values:	1% level	–4.219126	
	5% level	–3.533083	
	10% level	–3.198312	

**MacKinnon (1996) one-sided p-values.*

Null Hypothesis: D(OILPRICE) has a unit root
Exogenous: None
Lag Length: 0 (Automatic-based on SIC, maxlag = 9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		–5.911053	0.0000
Test critical values:	1% level	–2.628961	
	5% level	–1.950117	
	10% level	–1.611339	

*MacKinnon (1996) one-sided *p*-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(OILPRICE,2)

Method: Least Squares

Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t–Statistic	Prob.
D(Oil Price (–1))	–0.988793	0.167279	–5.911053	0.0000
R-squared	0.492406	Mean dependent var		–0.174595
Adjusted R-squared	0.492406	S.D. dependent var		11.20913
S.E. of regression	7.986013	Akaike info criterion		7.019915
Sum squared resid	2295.951	Schwarz criterion		7.063454
Log likelihood	–128.8684	Hannan–Quinn criter.		7.035265
Durbin–Watson stat	1.981156			

Null Hypothesis: Oil Price has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic-based on SIC, maxlag = 9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		–2.715007	0.2366
Test critical values:	1% level	–4.219126	
	5% level	–3.533083	
	10% level	–3.198312	

**MacKinnon (1996) one-sided p-values.*

Null Hypothesis: D(Oil Price) has a unit root
Exogenous: None
Lag Length: 0 (Automatic – based on SIC, maxlag = 9)

		t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		–5.911053	0.0000
Test critical values:	1% level	–2.628961	
	5% level	–1.950117	
	10% level	–1.611339	

**MacKinnon (1996) one-sided p-values.*

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(Oil Price, 2)

Method: Least Squares

Included observations: 37 after adjustments

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
D(Oil Price(–1))	–0.988793	0.167279	–5.911053	0.0000
R-squared	0.492406	Mean dependent var		–0.174595
Adjusted *R*-squared	0.492406	S.D. dependent var		11.20913
S.E. of regression	7.986013	Akaike info criterion		7.019915
Sum squared resid	2295.951	Schwarz criterion		7.063454
Log likelihood	–128.8684	Hannan-Quinn criter.		7.035265
Durbin-Watson stat	1.981156			

thus applied Johansen Cointegration techniques and the maximum likelihood estimator to determine the number of cointegrating equations (relationships) in equity markets. The purpose is to detect the long-run (equilibrium). The summary results of the Johansen's cointegration test are reported in Table 3. Both the trace and the maximum eigenvalue tests support the hypothesis of at most one cointegrating equation, implying long-run equilibrium relationship among the stock market, oil price and the economic growth.

Granger Causality Tests

Results of Granger Causality tests are reported in Table 4. We test the null hypothesis that one variable market does not Granger cause another variables both at the 1 percent and 5 percent significance levels with one to four-quarter lag interval. No causality has been detected between the oil price and economic growth or between oil price and the stock market or between the economic growth and the stock market.

Table 3A: Johansen Cointegration Tests

Series: GDP GROWTH SP500 OILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	*Eigenvalue*	*Trace Statistic*	*0.05 Critical Value*	*Prob.***
None *	0.511492	39.47127	24.27596	0.0003
At most 1 *	0.311249	13.68090	12.32090	0.0294
At most 2	0.007124	0.257371	4.129906	0.6716

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*
***MacKinnon–Haug–Michelis (1999) p-values*

Unrestricted Cointegration Rank Test (Maximum Eigen value)

Hypothesized No. of CE(s)	*Eigen value*	*Max-Eigen Statistic*	*0.05 Critical Value*	*Prob.***
None *	0.511492	25.79037	17.79730	0.0026
At most 1 *	0.311249	13.42353	11.22480	0.0202
At most 2	0.007124	0.257371	4.129906	0.6716

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level*
***MacKinnon–Haug–Michelis (1999) p–values*

Single Equation Cointegration Tests

Series: GDPGROWTH SP500 OILPRICE
Sample: 2010Q1 2019Q2
Null hypothesis: Series are not cointegrated
Cointegrating equation deterministics: C
Automatic lags specification based on Schwarz criterion (maxlag = 4)

Dependent	*tau-statistic*	*Prob.**	*z-statistic*	*Prob.**
GDPGROWTH	–6.945831	0.0000	–42.53989	0.0000
SP500	–1.335779	0.9280	–3.796765	0.9393
OILPRICE	–1.653621	0.8594	–4.814579	0.8973

**MacKinnon (1996) p-values.*

Intermediate Results:

	GDPGrowth	*SP500*	*Oil Price*
Rho - 1	–1.149727	–0.102615	–0.130124
Rho S.E.	0.165528	0.076821	0.078690
Residual variance	2.150207	37112.32	98.38602
Long-run residual variance	2.150207	37112.32	98.38602
Number of lags	0	0	0
Number of observations	37	37	37
Number of stochastic trends**	3	3	3

***Number of stochastic trends in asymptotic distribution*

Table 3B: Summary of Johansen Cointegration

Tests Series: GDPGROWTH SP500 OILPRICE
(Lags interval: 1 to 1)
Selected (0.05 level) Number of Cointegrating Relations by Model*

Data Trend:	*None*	*None*	*Linear*	*Linear*	*Quadratic*
Test Type	*No Intercept No Trend*	*Intercept No Trend*	*Intercept No Trend*	*Intercept Trend*	*Intercept Trend*
Trace	2	1	1	1	1
Max-Eig	2	1	1	1	1

**Critical values based on MacKinnon–Haug–Michelis (1999)*

Information Criteria by Rank and Model

Data Trend: *Rank or* *No. of CEs*	*None* *No Intercept* *No Trend*	*None* *Intercept* *No Trend*	*Linear* *Intercept* *No Trend*	*Linear* *Intercept* *Trend*	*Quadratic* *Intercept* *Trend*
Log Likelihood by Rank (rows) and Model (columns)					
0	–416.4328	–416.4328	–409.2882	–409.2882	–409.1118
1	–403.5376	–403.4917	–396.8113	–392.7218	–392.5472
2	–396.8258	–396.7599	–393.7481	–388.7321	–388.6988
3	–396.6971	–393.7412	–393.7412	–385.9822	–385.9822
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	23.63515	23.63515	23.40490	23.40490	23.56176
1	23.25209	23.30510	23.04507	22.87343*	22.97485
2	23.21255	23.31999	23.20823	23.04067	23.09438
3	23.53873	23.54118	23.54118	23.27679	23.27679
Schwarz Criteria by Rank (rows) and Model (columns)					
0	24.03103	24.03103	23.93274	23.93274	24.22156
1	23.91189	24.00888	23.83683	23.70918*	23.89857
2	24.13627	24.33168	24.26391	24.18432	24.28202
3	24.72637	24.86077	24.86077	24.72835	24.72835

Table 4A: Pairwise Granger Causality Tests

Oil Price, SP500 Index, GDP Growth

Null Hypothesis:	*Obs*	*F–Statistic*	*Prob.*
Lags: 1			
OILPRICE does not Granger Cause GDPGROWTH	37	1.1E–05	0.9973
GDPGROWTH does not Granger Cause OILPRICE		1.99301	0.1671
SP500 does not Granger Cause GDPGROWTH	37	0.53188	0.4708
GDPGROWTH does not Granger Cause SP500		0.03555	0.8516
SP500 does not Granger Cause OILPRICE	37	2.25029	0.1428
OILPRICE does not Granger Cause SP500		0.18640	0.6687
Lags: 2			
OILPRICE does not Granger Cause GDPGROWTH	36	0.43294	0.6525
GDPGROWTH does not Granger Cause OILPRICE		2.49811	0.0987
SP500 does not Granger Cause GDPGROWTH	36	1.55939	0.2263
GDPGROWTH does not Granger Cause SP500		0.03735	0.9634
SP500 does not Granger Cause OILPRICE	36	1.42026	0.2569
OILPRICE does not Granger Cause SP500		0.42649	0.6566
Lags: 3			
OILPRICE does not Granger Cause GDPGROWTH	35	0.34600	0.7923
GDPGROWTH does not Granger Cause OILPRICE		1.93313	0.1471
SP500 does not Granger Cause GDPGROWTH	35	0.90152	0.4528
GDPGROWTH does not Granger Cause SP500		0.01018	0.9986
SP500 does not Granger Cause OILPRICE	35	1.33194	0.2839
OILPRICE does not Granger Cause SP500		0.18846	0.9034
Lags: 4			
OILPRICE does not Granger Cause GDPGROWTH	34	0.96635	0.4433
GDPGROWTH does not Granger Cause OILPRICE		1.81052	0.1584
SP500 does not Granger Cause GDPGROWTH	34	1.20490	0.3335
GDPGROWTH does not Granger Cause SP500		1.83018	0.1546
SP500 does not Granger Cause OILPRICE	34	0.96426	0.4444
OILPRICE does not Granger Cause SP500		0.41429	0.7967

Table 4B: Pairwise Granger Causality Tests

Oil Price Change, SP500 Index Return, GDP Growth			
Lags: 1			
Null Hypothesis:	*Obs*	*F–Statistic*	*Prob.*
DSP does not Granger Cause DOP	36	0.02711	0.8702
DOP does not Granger Cause DSP		0.53211	0.4709
GDPGROWTH does not Granger Cause DOP	36	2.13158	0.1537
DOP does not Granger Cause GDPGROWTH		0.65346	0.4247
GDPGROWTH does not Granger Cause DSP	36	0.01816	0.8936
DSP does not Granger Cause GDPGROWTH		1.68548	0.2032
Lags: 2			
Null Hypothesis:	*Obs*	*F–Statistic*	*Prob.*
DSP does not Granger Cause DOP	35	0.03384	0.9668
DOP does not Granger Cause DSP		0.20999	0.8118
GDPGROWTH does not Granger Cause DOP	35	2.21954	0.1262
DOP does not Granger Cause GDPGROWTH		0.51335	0.6036
GDPGROWTH does not Granger Cause DSP	35	0.00933	0.9907
DSP does not Granger Cause GDPGROWTH		0.64360	0.5325
Lags: 3			
Null Hypothesis:	*Obs*	*F–Statistic*	*Prob.*
DSP does not Granger Cause DOP	34	0.37185	0.7739
DOP does not Granger Cause DSP		0.42370	0.7375
GDPGROWTH does not Granger Cause DOP	34	2.50692	0.0802
DOP does not Granger Cause GDPGROWTH		1.49322	0.2387
GDPGROWTH does not Granger Cause DSP	34	0.00981	0.9986
DSP does not Granger Cause GDPGROWTH		0.90738	0.4504
Lags: 4			
Null Hypothesis:	*Obs*	*F–Statistic*	*Prob.*
DSP does not Granger Cause DOP	33	0.18626	0.9433
DOP does not Granger Cause DSP		0.41648	0.7951
GDPGROWTH does not Granger Cause DOP	33	2.85711	0.0455
DOP does not Granger Cause GDPGROWTH		2.10642	0.1113
GDPGROWTH does not Granger Cause DSP	33	1.53879	0.2228
DSP does not Granger Cause GDPGROWTH		0.56667	0.6892

V. Conclusions

The high performance of the U.S. stock markets with lowest unemployment and inflation over past several years before led many analysts to further examine the relationship among oil prices, stock markets, and the economic growths in oil importing countries. Previous studies have focused exclusively on this relationship of some oil exporting countries. In the empirical literature, there is a lack of studies focusing on the relationships among oil prices, economic growths and stock markets in oil importing countries applying advanced econometries techniques based on the recent information. This paper thus investigates the long-run relationship and causality among oil prices, stock market, and the economic growth of the U.S. using the quarterly data from 2010:Q1 through 2019:Q2.

The descriptive statistics including the Jarque-Bera (J-B) test show non-normal and skewed distributions with fat tails for all variables. In addition to descriptive statistics, the estimated models include Johansen cointegration technique to test the long-run relationship among oil prices, stock market, and economic growth of the U.S. The co-integration test indicates the presence of two cointegrating vectors under the (ë-trace) among oil price, stock index and the economic growth. Johansen Cointegration test results thus indicate that there is a long-run relationship among these three variables. Pairwise Granger Causality test is applied to examine any unidirectional or bidirectional causality between these variables. However, the Ganger causality test fails to detect any causality between the oil prices and economic growth or between oil prices and stock market or between economic growth and the stock market in the United States. These findings have important implications for the policy-makers to implement effective monetary and fiscal policies. Though the findings of this research are important, however, further investigations are recommended based on applying more statistical tests since COVID-19, not done in this study. However, this study has contributed to the existing literature on linkages among oil price, stock market and economic growth.

References

Alsarhan, A. A ., Khalifa A.A., and Al-Titi. O. (2013) ' Oil price volatility and the dynamic systematic risk in Kuwait's equity sector portfolio using the Kalman filter approach.' *American Journal of Finance and Accounting*, Vol. 3, No. 1, pp.24–40.

Al-Fayoumi, A.N. (2009). Oil prices and stock market returns in oil importing countries: The case of Turkey, Tunisia and Jordan. *European Journal of Economics, Finance and Administrative Sciences*, 16, 86-101.

Aloui, C. and Jammazi, R. (2009) 'The effects of crude oil shocks on stock market shifts behavior: a regime switching approach', *Energy Economics*, Vol. 31, pp.789–799.

Anoruo, E. and Mustafa, M. (2007) 'An empirical investigation into the relation of oil to stock market prices', *North American Journal of Finance and Banking Research*, Vol. 1, pp.22–36.

Arouri, M. and Nguyen, D.K. (2010) 'Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade', Energy Policy, Vol. 38, pp.4528–4539.

Arouri, M.E.H., Jouini, J. and Nguyen, D. (2012) 'On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness', Energy Economics, Vol. 34, pp.611–617.

Asteriou, D. and Bashmakova, Y. (2014) 'Assessing the impact of oil returns on emerging stock markets: a panel data approach for ten central and eastern European countries', Energy Economics, Vol. 38, pp.204–211.

Asprem, M. (1989), "Stock Prices, Asset Portfolios and Macroeconomic Variables in Ten European Countries," *Journal of Banking and Finance* 13, pp. 589-612.

Awartani, B. and Maghyereh, A.I. (2013) 'Dynamic spillovers between oil and stock markets in the gulf cooperation council countries', Energy Economics, Vol. 36, pp.28–42.

Broadstock, D.C. and Filis, G. (2014) 'Oil price shocks and stock market returns: new evidence from the United States and China', Int. Fin. Markets, Inst. and Money, Vol. 33, pp.417–433.

Chang, C.L., McAleer, M. and Tansuchat, E. (2013) 'Conditional correlations and volatility spillovers between crude oil and stock index returns', *The North American Journal of Economics and Finance*, Vol. 25, pp.116–138.

Chkili, W., Aloui, C. and Nguyen, D.K. (2014) 'Instabilities in the relationships and hedging strategies between crude oil and US stock markets: do long memory and asymmetry matter?', *Journal of International Financial Markets. Institutions and Money*, Vol. 33, pp.354–366.

Cong, R-G., Wei, Y-M., Jiao, J-L. and Fan, Y. (2008) 'Relationships between oil price shocks and stock market: an empirical analysis from china', Energy Policy, Vol. 36, pp.3544–3553.

El-Sharif, I., Brown, D., Burton, B., Nixon, B. and Russell, A. (2005) 'Evidence on the nature and extent of the relationship between oil prices and equity values in the UK', Energy Economics, Vol. 27, No. 6, pp.819–830. 13

Engle, R.F. and C.W.J. Granger (1987), "Cointegration and Error Correction Representation, Estimation and Testing," Econometrica Vol. 55 pp. 251-276.

Fama, E. F. (1990), "Stock Returns, Expected Returns and Real Activity," *The Journal of Finance* 45(4), pp. 1089-1108.

Ferderer, J. (1996) 'Oil price volatility and the macroeconomy', *Journal of Macroeconomics*, Vol. 18, pp.1–26.

Filis, G., Degiannakis, S. and 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,* Vol. 20, pp.152–164.

Granger, C.W. J. and P. Newbold (1971) 'Spurious Regressions in Econometrics' *Journal of Econometrics*. Vol. 26. pp. 1045-1066.

Granger, C.W. J. (1981) 'Some Properties of Time Series Data and Their Use in Econometric Model Specification.' *Journal of Econometrics* pp. 121-130.

Granger, C.W. J. and J. Lin (1995) 'Causality in the Long-Run.' Econometric Theory Vol. 11 pp 530-36.

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

Hamilton, J.D. and Herrera, A.M. (2004) 'Oil shocks and aggregate macroeconomic behavior: the role of monetary policy', *Journal of Money. Credit and Banking*, Vol. 36, pp.265–286.

Hammoudeh, S. and Choi, K. (2006) 'Behavior of GCC stock markets and impacts of US oil and financial markets', Research in International Business and Finance, Vol. 20, pp.22–44.

Hammoudeh, S., Dibooglu, S. and Aleisa, E. (2004) 'Relationships among US oil prices and oil industry equity indices', International Review of Economics and Finance, Vol. 13, pp.427–453.

Islam, Mazhar M. (2004). 'Linkages between the Kuala Lumpur Stock Returns and Macroeconomic Variables: Cointegrati and the Error Correction Tests' *Journal of the Academy of Finance*, Vol. 2 No.1

Johansen, S. (1988) 'Statistical Analysis of Cointegrated Vectors.' *Journal of Econometric Dynamics and Control.* Vol. 12. pp 429-44.

Johansen, S. and K. Juselius (1990), "Maximum Likelihood Estimation and Inference on Co integration with Application to the Demand of Money," Oxford Bulletin of Economics and Statistics 52, pp. 169-210.

Johansen, S. (1991). 'Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models.' Econometrica Vol, 59. pp 155180..

Johansen, S. (1992). 'Cointegration in Partial Systems and the Efficiency of Single Equation Analysis.' *Journal of Econometrics.* Vol.52. pp. 389-402.

Jones, C.M. and Kaul, G. (1996) 'Oil and the stock markets', *Journal of Finance*, Vol. 51, pp.463–491. 14

Jouini, J. (2013) 'Return and volatility interaction between oil prices and stock markets in Saudi Arabia', *Journal of Policy Modeling*, Vol. 35, pp.1124–1144.

Lee, B.R., Lee, K. and Ratti, R.A. (2001) 'Monetary policy, oil price shocks and the Japanese economy', Japan and the World Economy, Vol. 13, pp.321–349.

Li, S-F., Zhu, H-M. and Yu, K. (2012) 'Oil prices and stock market in china: a sector analysis using panel cointegration with multiple breaks', *Energy Economics,* Vol. 34, pp.1951–1958.

Maghyereh, A. and Al-Kandari, A. (2007) 'Oil prices and stock markets in GCC countries: new evidence from nonlinear cointegration analysis', *Managerial Finance,* Vol. 33, pp.449–460.

Malik, F. and Ewing, B.T. (2009) 'Volatility transmission between oil prices and equity sector returns', International Review of Financial Analysis, Vol. 18, pp.95–100.

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

Miller, J.I. and Ratti, R.A. (2009) 'Crude oil and stock markets: stability, instability and bubbles', Energy Economics, Vol. 31, pp.559–568.

Mollick, A.V. and Assefa, T.A. (2013) 'U.S. stock returns and oil prices: the tale from daily data and the 2008–2009 financial crisis', Energy Economics, Vol. 36, pp.1–18.

Naifar, N. and Al Dohaiman, M.S. (2013) 'Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables', International Review of Economics and Finance, Vol. 27, pp.416–431.

Oberndorfer, U. (2009) 'Energy prices, volatility and the stock market: evidence from the Eurozone', Energy Policy, Vol. 37, pp.5787–5795.

Papapetrou, E. (2001) 'Oil price shocks, stock market, economic activity and employment in Greece', Energy Economics, Vol. 23, pp.511–532.

Park, J. and Ratti, R.A. (2008) 'Oil price shocks and stock markets in the US and 13 European countries', Energy Economics, Vol. 30, pp.2587–2608.

Sadorsky, P. (2012) 'Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies', Energy Economics, Vol. 34, pp.248–255.

Salameh, H. M., Al-Zubi, B., Al-Zubi. K. A, and Magablel, I. K. (2012) 'Oil price and stock market index in exporting and importing countriesL evidence from MENA'. *American Journal of Finance and Accounting*, Vol. 2, No 4 pp.363-379.

Wang, Y., Wu, C. and Yang, L. (2013) 'Oil price shocks and stock market activities: evidence from oil-importing and oil-exporting countries', *Journal of Comparative Economics*, Vol. 41, pp.1220–1239.

Zarour, B.A. (2006) 'Wild oil prices, but brave stock markets: the case of GCC stock market', *International Journal Operation Research*, Vol. 6, pp.145–162.