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2012

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Abstract

This study investigates the dynamic linkages between oil prices and stock markets, also known as the oil price-stock price nexus. Within the framework of a VAR we examine dynamic interactions between daily Brent spot prices and several Lebanese stock prices. As expected, we find evidence of oil prices Granger causing stock prices, but no evidence of the opposite relationship. To better understand how shocks in the oil market are transmitted to the stock market, the orthogonalized impulse response function is examined. The behavior of all stocks examined is very similar; they all respond positively to a shock in crude oil prices on the same day and the day after the shock, with the impact of the shock disappearing thereafter. As for the variance decomposition analysis, it shows that the forecast errors of the stocks are largely attributable to their own innovations and the percentages do not change much with time. Only around 1% is attributable to oil shocks, increasing to around 3% after a few days and remaining at that level. Thus, our main conclusion is that the estimated level of the impact of an oil price shock on the Lebanese stock market is positive but marginal.

Keywords: oil price shocks; Beirut Stock Exchange; impulse response function; variance decomposition

JEL Classifications: C32, C51, G15, Q43

1. Introduction

The role of oil prices as a crucial determinant of economic growth and international stability has been widely documented starting with Hamilton's [1] influential study. In his paper, Hamilton [1] shows that in the period since World War II every single recession in the USA except one has been preceded by a spike in oil prices. In a recent testimony to the Joint Economic Committee of the US Congress, Hamilton [2] states that:
"Big increases in the price of oil that were associated with events such as the 1973-74 embargo by the Organization of Arab Petroleum Exporting Countries, the Iranian Revolution in 1978, the Iran-Iraq War in 1980, and the First Persian Gulf War in 1990 were each followed by global economic recessions."

A related strand of literature has investigated the impact of oil price fluctuations on the stock market performance. Theoretically, this relationship can best be explained using an equity pricing model, which suggests that the current price of any equity can be calculated as the present value of the discounted future cash flows. Based on the discounted cash flow method, a stock valuation model, changes in oil prices affect stock prices through two main transmission channels. First, in the absence of substitutes and given that oil is a direct or indirect factor of production for most firms, a rise in oil prices causes a decline in firms' expected earnings resulting in lower cash flows and thus leading to a fall in the stock price [3,4]. Second, higher oil prices imply inflationary pressures leading Central Banks to raise interest rates in order to control prices. Both inflation and higher interest rates result in the use of higher discount rates in the discounted cash flow method, leading to lower stock prices [5].

Practically, it is suggested that traders look at both the commodity (particularly oil) and stock market movements to predict the directions of both stock indices and commodity prices and make their investment decisions [6]. Also, as a result of oil spikes, economic downturns and/or higher inflation will negatively affect consumer confidence, slowing overall consumption and investments [7]. Consequently, it is natural to expect that oil fluctuations will somehow impact the stock markets.

As the world increases its dependence on oil today, and as stock markets continue to grow and develop, researchers are showing growing interest in the relationship between the two. One of the earliest of such studies was that by Kling [8] who investigated the effects of oil shocks on the US stock markets for the period 1973-1982. Although, earlier studies were mostly focused on developed countries, this past decade has witnessed greater interest in examining the relationship between international oil prices and stock markets of developing countries [9-14]. However, research on the MENA region markets remains very scant including only a few studies focusing on the Gulf Cooperation Countries (GCC) countries [15-23], and none on Lebanon.

Studying the relationship between oil prices and the Lebanese stock market is important for several reasons. First, the Lebanese economy in contrast to most other MENA countries, is highly dependent on imported oil products used as fuel for transportation, heating, electricity generation as well as for other sectors. Therefore, the economy is expected to be highly sensitive to global oil prices and variations in oil prices are expected to eventually propagate to profits, dividends, investments, and stock prices. According to the United Nations Economic and Social Commission of Western Asia [24], the share of total primary energy consumption in 2010 was 96.2% from imported oil products and only 3.8% from domestic sources, specifically from hydro.

Second, oil consumption in recent years is growing at a fast rate making the country even more dependent on imported oil and hence more vulnerable to oil price shocks. Lebanon ranked third among the 14 ESCWA Arab member countries experiencing high oil consumption changes in the period 2007-2010, a period during which the Lebanese oil consumption increased by 34% in just three years [24].

Third, existing studies have produced conflicting results; some find that there is no significant effect of oil price shocks on stock prices, others find a significant positive relationship, while still others find a significant negative effect. Hence, the evidence from the existing literature on the magnitude and sign of the impact of oil price changes on stock prices is still inconclusive.

Lebanese stocks are traded at the Beirut Stock Exchange (BSE), which is the second oldest stock market in the region following the Cairo and Alexandria Stock Exchanges in Egypt. It was primarily established by a decree of the French Commissioner in 1920. Throughout the 1950s and 1960s, the Lebanese stock market was significantly active. However, during the civil war, the BSE witnessed a decline in its trading activity and eventually halted its operations in 1983. The BSE remained closed for thirteen years before it re-opened in January of 1996. Global Depository Receipts (GDR), investment funds shares, preferred stocks, priority shares, and other forms of tradable derivatives were listed and traded at the BSE starting in 2000 [25]. As of January 2013, 28 different types of stocks (common, preferred and GDR stocks) are listed on the BSE. The stocks are categorized into five main sectors, namely: development and reconstruction, banking, trading, industrial, and funds. Table 1 lists the issuers of the Lebanese securities classified under each sector. It is worth noting that the most active stocks on the BSE are those belonging to the banking and development and reconstruction sectors.

The Lebanese market capitalization amounted to approximately $10,163 million in 2011 making it one of the smallest market capitalizations in the region, while Gulf countries have the highest market caps with Saudi Arabia ranking first ($338,874 million). Comparing the size of the Lebanese market cap on a world scale, it is close to that of Kenya, Panama, and Zimbabwe [26].

Table 1
Issuers at the Beirut Stock Exchange.

Sector	Issuer
Banking	Bank Audi BLC Bank Bank of Beirut Byblos Bank Banque Bemo BLOM Bank
Development and Reconstruction	Solidere
Funds	Beirut Preferred Funds
Industrial	Holcim Liban S.L. des Ciments Blancs
Trading	Rasamny Younis Motor Co.

Source: Beirut Stock Exchange [25]

Understanding the type of relationship between oil prices and stock prices is beneficial to portfolio managers, investors, financial market regulators, and energy analysts and policymakers. The findings can be utilized to build profitable portfolio strategies for traders. In particular, international investors and their portfolio managers can use this relationship to help them in managing the risk inherent in their portfolios [27,28] by identifying which stocks (or sectors) offer a means of diversification during large swings in oil prices [29]. Stocks of industries or specific companies which are positively correlated to oil prices are recommended when oil prices are expected to rise. On the other hand, stocks with negative sensitivity are considered better investments in times of declining oil price forecasts. Also, portfolio managers can benefit by rebalancing portfolios with stocks from different sectors if these stocks react differently to changes in oil prices. This will allow for risk diversification opportunities to be achieved through investing in stocks across sectors rather than within a sector [27].

Also, in case oil prices are proven to affect the stock market of a certain country, Fayyad and Daly [19] advise policymakers to raise the contribution of non-oil sensitive sectors to GDP and to take appropriate measures in order to minimize the impact of any oil shock on the market. Furthermore, governments of oil-importing countries can protect themselves from oil-supply shocks by increasing strategic oil reserves and saving measures through improving energy efficiency, promoting energy conservation and using alternative fuels whose prices are independent from oil prices. Governments of oil-importing countries can also enhance dialogue with oil-exporting countries to increase multilateral cooperation and to minimize shocks with unpleasant effects on the economies [12].

This paper contributes to the literature that examines the linkages between oil prices and stock markets of developing oil-importing countries. We use the unrestricted vector autoregression approach together with the impulse response and variance decomposition analyses to investigate the relationship in question. Given the strong evidence provided by existing studies that the impact of oil price shocks differs between sectors, we examine the stocks listed under the development and reconstruction sector in addition to the aggregate stock index. The findings in all cases indicate a significant positive effect. However, this effect is not persistent and disappears within two days of the initial shock.

The remainder of this paper is structured as follows. Section 2 provides a review of the existing literature. In Section 3 we describe the data and the methodology used followed by a presentation and discussion of the empirical results in Section 4. Finally, in Section 5 we offer some concluding remarks on the findings together with suggestions for future research.

2. **Literature Review**

There exists a substantial body of literature investigating the relationship between oil price changes and stock prices. The first study in this strand of literature was conducted by Kling [8] who employed vector autoregression analysis to examine the effect of oil spikes on the S&P500 and the price indexes of five US industries using monthly data for the period 1973-1982. Later, Hamao [30], using multi-factor analysis for the Japanese market, again employed monthly data for a similar time period 1975-1984.

However, the availability of data that goes back to the early 1970s in some countries allowed researchers to examine both the 1973-1974 and the 1979-1980 price hikes. For example, Chen at al. [31] used a multivariate factor model with monthly US data for the period 1953 to 1983. Jones and Kaul [32] investigated the effects of oil shocks on the stock markets of four countries: US, Canada, Japan, and UK during 1970-1991. Furthermore, Miller and Ratti [33] analyzed the long-run relationship between the US and European stock markets and world prices of crude oil via the use of vector autoregressions on selected sample periods (Jan 1971-May 1980; June 1980-Jan 1988; Feb 1988-Sep 1999; Sep 1999-May 2008).

While only a few papers covered the period before and during the 1970s [34], many more papers have investigated the period from 1980 and onwards, especially with the increasing availability of financial data [3,35-38]. Aloui and Jammazi [4] justified the usage of the regime switching model to the period 1989-2007, by noting the multiple political and economic events during this time period that have caused dramatic changes in both oil and international stock prices; the stock market crash in 1987, the 1990 Gulf war, the 1997 East Asian currency crisis, the 9/11 terrorist attacks in 2001, the oil price hikes in 2007-2008, and the 2008 financial crisis. These events have motivated many scholars to study the linkage between the two variables during this period across many countries. For example, Hammoudeh and Li [39] used dummies for all the major events listed above to examine oil sensitivity and systematic risk of oil-producing countries (Mexico and Norway) and oil-sensitive industries (US oil and transportation industries). Hammoudeh and Choi [40] investigated the permanent (or fundamental) components and the transitory (or fad) components of the Gulf Cooperation Council (GCC) stock markets in comparison to the Mexican stock market. Although their selection of the 1994-2004 period was primarily determined by the availability of data, the time series permitted the examination of the impacts of the Mexican crisis in 1994, the East Asian crisis in 1997, the collapse of oil prices in 1998, the oil price and Asian economy recoveries in 1999, the adoption of the target zone oil pricing mechanism and the NASDAQ collapse in 2000, the New York terrorist attacks in September 2001, and the Iraq war in 2003.

Another important reason for focusing on the first decade of this century is the significant rise in demand for oil, specifically in developing countries. The rapid growth in oil consumption has motivated many scholars to research the relationship between oil prices and stock markets [5]. The rising oil demand was also accompanied by high volatility in prices during the 2000s. Although the 2008 global financial was considered to be an important event and was taken into account by many researchers [14, 41], others chose to exclude it from their sample periods to avoid possible distortions in the oil-stock linkage that could be caused by this specific event [28].

While studies concerned with developed countries date as far back as the 1980s, studies on developing countries did not appear until the mid 2000s. The majority of these studies examine the Asian-Pacific region, probably because this region is more energy intensive and has more developed financial markets compared to other developing regions. Therefore, many researchers focused their attention on exploring how changes in oil prices influence Asian stock markets' performance [9-14, 41-43]. Accounting for approximately 40% of global oil reserves and 25% of total world crude oil exports in 2012, several researchers have shown interest in the Gulf Cooperation Council (GCC) countries. Additionally, the GCC markets (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates) are characterized as being segmented from international markets thus making them promising areas for portfolio diversification. These reasons have motivated several researchers to investigate the relationship between oil prices and stock returns of these markets [15-21,23]. Only one study explored the effects of oil prices on financial markets in the MENA region [22]. The countries analyzed were Morocco, Tunisia, Egypt, Jordan, and Turkey, which are oil importers sharing borders with big oil exporting countries. Since no study to date has looked at the oil–stocks relationship in Lebanon, we attempt to fill this gap by focusing on the Lebanese market.

In most cases, Brent or WTI spot prices have been used as proxies for international oil prices. Being more relevant to the Middle East region, we will use the Brent prices. To reflect the performance of stock markets, most papers have used broad based stock market indices, while a few others studied stock prices of specific industries [36, 37, 39, 44-46]. Given the strong evidence provided by existing studies that the impact of oil price shocks differs between sectors, we examine the stocks listed under the development and reconstruction sector in addition to the aggregate Lebanese stock index.

In general, the frequency of the data in previous studies has varied between daily and yearly, with earlier papers using lower frequencies such as quarterly, monthly, or even yearly. The usage of low frequency data has been criticized as averaging out too much important information. For this reason, Broadstock *et al.* [14] and others [6, 16, 18, 27, 29, 40, 45, 48] chose to use weekly time series. In the present study, we will preserve the original frequency of the data and hence use daily values.

The majority of researchers have conducted bivariate analyses; yet, others have chosen to use multivariate models to control for the impact of additional factors such as: interest rates [3,10, 34, 36, 44, 45, 49-52], exchange rates [11] , industrial production [53], global oil production [51], global real economic activity [33,46], inflation [50], export/import price index of a country [30, 54], or unemployment rates [49,50, 54]. In this paper, we limit our investigation to a bivariate analysis given that none of the relevant variables exists on a daily basis.

Moreover, a wide range of specifications, estimation techniques, and testing methodologies have been used in an effort to investigate the relationship between oil prices and stock markets. A common approach is to estimate multifactor market models [5, 27-29, 32, 35, 36, 44, 55-57]. Another approach is to use the Markov switching models that switch between regimes [4, 7, 40, 58] or the Autoregressive Conditional Jump Intensity method (ARJI) which assumes that the jump intensity has an autoregressive moving average (ARMA) process [43, 59]. Some researchers have used the wavelet methodology that enables the simultaneous examination of the behavior of a time-series in both frequency and time domains (see e.g. Akoum *et al*. [23] and Jammazi [60, 61]). The most frequently used model has been the vector autoregression model (VAR), or in case of cointegration, the vector error correction model (VECM). Kaneko and Lee [54] were one of the first researchers who used the VAR approach to test for the relationship between oil and stock prices of the Japanese market. The approach was later used by various authors for different countries [15, 49, 62-65]. This framework has been mainly chosen due to its characteristics that treat all variables as endogenous and allow studying the direction of causality as well as the short-term dynamics of these variables. Because of its many advantages for time series data, this study will apply the VAR model to facilitate the comparison of results to previous research done following the same methodology.

As for estimation methods, we list here a few of the methods used in this body of literature besides the OLS method: Seemingly Unrelated Regression [18], quantile regression [66], and the quasi-maximum likelihood [27].

The results describing the relationship between oil and stock prices have been contradictory even when the same country is studied. While some researchers found that no linkage exists [3, 10, 16, 40, 57, 63, 67-69], many others provided evidence of a relationship between the two variables. In most cases, the relationship was negative [4, 33, 37, 48, 49], while in other cases, oil prices were found to positively impact stock prices, in particular in sectoral or industry-based studies [11, 13, 14, 18, 21, 36, 41, 44, 50].

3. Data and Methodology

Daily closing prices for the period 10/16/2006 to 7/10/2012 were obtained from the BSE website for the stock prices and the EIA for the oil prices. As a proxy for the world price of crude oil, we use the Brent spot price (measured in US dollars per barrel), which is the most commonly used benchmark for pricing in the crude oil market. Following Arouri and Nguyen's [27] advice regarding the drawbacks of limiting the stock price information to the national market index, we use in addition to the BLOM Beirut Stock Index (BSI), the stocks that fall under the development and reconstruction sector, Solidere A (SOLA) and Solidere B (SOLB). These two stocks, being the most actively traded on the BSE, have been chosen to be included in the new Dow Jones MENA index. To be consistent with other studies, all variables are expressed in natural logarithms. None of the other variables commonly used in such an analysis are available at frequencies higher than annual, and hence we limit our analysis to a bivariate one.

3.1 Unit root and cointegration testing

Typically, the first step in any time-series analysis is to investigate the order of integration of the variables used in the empirical study. The Augmented Dickey Fuller (ADF) test [70, 71] will be used, complemented with the Phillips Perron (PP) test [72]. Both tests are based on equation 1 in which the null hypothesis is $H_o\colon \gamma = 0$, i.e. y has a unit root, and the alternative hypothesis is $H_1\colon \gamma < 0$, but the test statistics are calculated differently.

$$\Delta y_t = \alpha + \gamma y_{t-1} + \theta t + \sum_{i=1}^{p} \varphi_i \, \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is assumed to be a Gaussian white noise error, *t* is a time trend, and the number of lags *p* is selected by the Akaike information criterion [73] from a maximum number of lags based on Schwert's [74] formula $p_{max} = 12 * (\frac{T}{100})^{0.25}$. The distribution of γ does not follow the conventional *t* distribution, and hence the appropriate critical values are taken from MacKinnon [75].

If the unit root tests confirm that at least some of the variables are I(1), then the next step would be to test if they are cointegrated, i.e. if they are bound by a long-run relationship. Cointegration exists between a set of non-stationary variables when a certain linear relationship of the series is stationary [76]. To test for cointegration both Engle and Granger's [77] and Johansen's [78, 79] approaches will be used. If cointegration is found then the remaining analysis can be performed using a VECM, otherwise the I(1) variables are differenced and a simple unrestricted VAR can be used.

3.2 VAR model

The vector autoregression (VAR) model, originally advocated by Sims [80] as an alternative to simultaneous equation models, carries many advantages. Its ease of estimation (OLS),[1] ease of construction by treating all variables as endogenous, and good forecasts have made it one of the most widely used models in spite of some criticism surrounding the model (see for e.g. Cooley and Leroy [82]; Runkle [83]; Harvey [84]). It is worth noting that its major drawback is the large number of parameters to be estimated ($N+pN^2$), which may severely limit degrees of freedom. VARs have been used primarily in forecasting, testing Granger causality, and studying the effects of policy through impulse response characteristics [85]. The VAR model in reduced form is given by:

$$y_t = \Lambda + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{2}$$

where y_t is a vector of N stationary variables, ε_t is a vector of Gaussian white noise errors, and p is the order of the VAR. If the variables being studied are I(1) but not cointegrated, they can be used in differenced form in a VAR. Otherwise, if the variables are I(1) and cointegrated, a vector error correction model can be employed.

It is essential to appropriately specify the lag length p for the VAR system; if p is too small the model is misspecified and the missing variables create an omitted variables bias, while overparameterizing involves a loss of degrees of freedom and introduces the possibility of multicollinearity [86]. In general, VAR estimates are known to be sensitive to the number of lags included. The lag length p will be determined based on Akaike's Information Criterion [73] (AIC), where the maximum number of lags is again calculated by Schwert's [74] formula $p_{max} = 12 * (\frac{T}{100})^{0.25}$.

This method of analysis permits us to test for the direction of causality, if it exists, as discussed next. Moreover, it captures the dynamics of the interrelationships between the variables through impulse responses and variance decomposition.

3.3 Granger Causality Testing

One of the earliest methods to test for causality was proposed by Granger [87]. Granger [88] defines causality as "if y_t causes x_t, then x_{t+1} is better forecast if the information in y_{t-j} is used than if it is not used." To determine the direction of causality, a simple Wald test in an unrestricted VAR setting is applied to a group of coefficients to test whether they are jointly significant or not.

Consider the VAR model presented in equations 3 and 4, where O denotes the logarithm of oil prices and *BSI* denotes the logarithm of the Beirut Stock Index. In order to identify the direction of the causality between O and *BSI*, Granger Causality tests are applied to the VAR model as follows.

In Equation 3 if $\beta_1 = \beta_2 = \cdots = \beta_p = 0$ then *BSI* does not Granger cause oil prices, while if the opposite is true then *BSI* can be said to Granger cause oil prices. Similarly, in Equation 4 we test whether the group of μ coefficients are jointly significant or not to conclude whether oil prices Granger cause *BSI* or not. p is usually determined based on a lag selection criterion such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC).

$$O_t = \alpha + \sum_{i=1}^{p} \gamma_i O_{t-i} + \sum_{i=1}^{p} \beta_i BSI_{t-i} + \varepsilon_{1t} \tag{3}$$

$$BSI_t = \delta + \sum_{i=1}^{p} \rho_i BSI_{t-i} + \sum_{i=1}^{p} \mu_i O_{t-i} + \varepsilon_{2t} \tag{4}$$

where ε_{1t} and ε_{2t} are white noise error processes. This simple Wald test, however, is only valid if all variables are stationary [87, 89].

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[1] It can be shown that OLS applied to each equation separately is asymptotically efficient [81].

3.4 Impulse Response Function (IRF)

Impulse response analysis is a useful tool to examine the effect of a shock over time on the various variables in a system. For example, if we introduce a one period shock to O by increasing ε_1 by one standard deviation at time t=0 (see equation 3), we can observe how this impulse will affect *BSI* immediately and several periods later. However, if the errors are correlated as is usually the case, we cannot associate a shock with any one particular variable. In that case and in order to be able to isolate the effects of any specific shock, researchers have used orthogonalized impulses based on the Cholesky decomposition.

Assuming that the VAR in equation 2 is stable, by repetitive substitution we obtain the following moving average representation of the VAR:

$$y_t = \bar{y} + \sum_{\tau=0}^{\infty} A_\tau \varepsilon_{t-\tau} \tag{5}$$

where

$$\bar{y} = E(y_t) = \Lambda(I - \Gamma_1 - \Gamma_2 - \cdots - \Gamma_p)^{-1}$$

and

$$A_\tau = \sum_{j=1}^{\tau} \Gamma_j A_{\tau-j} = \Gamma_1 A_{\tau-1} + \Gamma_2 A_{\tau-2} + \cdots + \Gamma_p A_{\tau-p} \text{ with } A_0 = I$$

A shock to a stationary time series is known to be transitory. In other words, for an I(0) series the impact of a shock will disappear after some time period when the series will revert to its mean value. It should be noted that Cholesky factorization is not invariant to the ordering of the variables in the VAR. Since the first variable in the ordering explains all of its one-step forecast variance, it should be the one least influenced by other variables in the model such as an exogenous variable. The variable that is influenced by other variables the most is chosen as the last variable in the ordering. To overcome the arbitrariness in order selection, Sims [90] suggests attempting various orderings and checking the robustness of the results.

Using the Cholesky decomposition, the variance-covariance matrix Ω of the errors can be uniquely decomposed into $\Omega = PDP'$, where P is a lower triangular matrix with ones on the diagonal and D is a diagonal matrix [91]. The errors ε_t can thus be transformed into orthogonal errors $\theta_t = P^{-1}\varepsilon_t$ with a variance-covariance matrix D.

$$y_t = \bar{y} + \sum_{\tau=0}^{\infty} A_\tau P \theta_{t-\tau} \tag{6}$$

or more compactly

$$y_t = \bar{y} + \sum_{\tau=0}^{\infty} \phi_\tau \theta_{t-\tau} \tag{7}$$

where

$$\phi_\tau = A_\tau P$$

Applying the Cholesky decomposition to the moving average representation of equations (3) and (4), we obtain

$$\begin{bmatrix} O_t \\ BSI_t \end{bmatrix} = \begin{bmatrix} \overline{O_t} \\ \overline{BSI_t} \end{bmatrix} + \sum_{\tau=0}^{\infty} \begin{bmatrix} \phi_{11}(\tau) & \phi_{12}(\tau) \\ \phi_{21}(\tau) & \phi_{22}(\tau) \end{bmatrix} \begin{bmatrix} \theta_{1,t-\tau} \\ \theta_{2,t-\tau} \end{bmatrix}$$

The four sets of ϕ coefficients are called the impulse response functions. For example, $\phi_{11}(1)$ and $\phi_{21}(1)$ are the one-period responses of an impulse in $\theta_{1,t-1}$ on O_t and BSI_t, respectively.

3.5 Variance Decomposition (VD)

Another way of characterizing the dynamics of a VAR is via the variance decomposition. Forecast error variance decomposition is applied to identify the relative importance of a variable in generating its own variation. Similarly to the IRF, the results are sensitive to the ordering of the variables. In general, the n-step ahead conditional forecast of y_t using equation 7 is:

$$y_{t+n} = \bar{y} + \sum_{\tau=0}^{\infty} \phi_\tau \theta_{t+n-\tau} \quad (8)$$

And hence the n-period forecast error will be

$$y_{t+n} - E_t y_{t+n} = \sum_{\tau=0}^{n-1} \phi_\tau \theta_{t+n-\tau} \quad (9)$$

The corresponding covariance matrix will be equal to $\sum_{\tau=0}^{n-1} A_\tau PDP' A'_\tau$

For example, if we focus solely on the O_t sequence in (9), the n-step ahead forecast error is:

$$O_{t+n} - E_t O_{t+n} = \phi_{11}(0)\theta_{1,t+n} + \phi_{11}(1)\theta_{1,t+n-1} + \cdots + \phi_{11}(n-1)\theta_{1,t+1} + \phi_{12}(0)\theta_{2,t+n} + \phi_{12}(1)\theta_{2,t+n-1} + \ldots + \phi_{12}(n-1)\theta_{2,t+1}$$

And its variance denoted by $\sigma_1^2(n)$ is:

$$\sigma_1^2(n) = \sigma_1^2[\phi_{11}^2(0) + \phi_{11}^2(1) + \cdots + \phi_{11}^2(n-1)] + \sigma_2^2[\phi_{12}^2(0) + \phi_{12}^2(1) + \cdots + \phi_{12}^2(n-1)]$$

We are now ready to decompose the n-step ahead forecast error variance into the proportions due to each of the θ_1 and θ_2 shocks, shown below respectively:

$$\frac{\sigma_1^2[\phi_{11}^2(0) + \phi_{11}^2(1) + \cdots + \phi_{11}^2(n-1)]}{\sigma_1^2(n)}$$

$$\frac{\sigma_2^2[\phi_{12}^2(0) + \phi_{12}^2(1) + \cdots + \phi_{12}^2(n-1)]}{\sigma_1^2(n)}$$

The sum of the variance decompositions of any variable as shown above should equal 100 per cent. Note that if the variance decomposition due to an impulse in θ_2 for example is zero for all *n*, then we can say that O_t is exogenous. Enders [92] recommends examining the variance decompositions at various forecast horizons. Consequently, we will look at the 1 day, 15 day, and 30 day variance decompositions.

4. Empirical Results

To test the stationarity properties of the data, ADF and PP unit root tests are employed. Two separate specifications are applied; one with a constant and trend and the other with a constant only. With respect to the ADF test, the appropriate lag length is automatically selected based on the Akaike Information Criterion. As for the PP test, the bandwidth is determined by the Newey-West method. The results for both the level and differenced variables are reported in Table 2, from which it can be concluded that all variables are I(1).

Table 2
Unit Root Test Results.

Variables	ADF[a]			PP[b]		
	Order of Integration	Constant and Trend	Constant	Order of Integration	Constant and Trend	Constant
OIL	I(1)	-1.93 (0.64)	-1.80 (0.38)	I(1)	-1.78 (0.71)	-1.70 (0.43)
Δ OIL	I(0)		-6.61 (0.00)	I(0)		-37.20 (0.00)
BSI	I(1)	-2.54 (0.31)	-2.49 (0.12)	I(1)	-1.30 (0.89)	-1.24 (0.66)
Δ BSI	I(0)		-5.41 (0.00)	I(0)		-33.87 (0.00)
SOLA	I(1)	-2.41 (0.37)	-2.12 (0.24)	I(1)	-1.64 (0.78)	-1.40 (0.59)

Δ SOLA	I(0)		-6.03 (0.00)	I(0)		-34.75 (0.00)
SOLB	I(1)	-2.40(0.38)	-2.10 (0.25)	I(1)	-1.56 (0.81)	-1.30 (0.63)
Δ SOLB	I(0)		-8.85 (0.00)	I(0)		-34.97 (0.00)

Notes: probability values are in parentheses. [a] AIC is used to select the lag length. [b] Barlett Kernel is used as the spectral estimation method. Newey-West is used as the bandwidth selection method.

We now proceed to examine the cointegration properties of each pair of variables; OIL-BSI, OIL-SOLA, and OIL-SOLB. We perform both the Engle and Granger [77] and the Johansen [78] tests. According to the Johansen test results, both the Maximum Eigenvalue and Trace statistics indicate the absence of cointegration. Similarly, Engle and Granger test results do not find any evidence of a common stochastic trend shared by any two series. Consequently, we will continue with our VAR analysis using the variables in differences. The next step involves choosing the appropriate lag length according to the AIC, with the maximum number of lags being 23 based on Schwert's formula. For all three models, the selected number of lags is 13.

In Table 3 we report the results of the Granger causality tests performed on each of our three models. At the 5% level of significance we conclude that BSI does not Granger cause OIL but that OIL Granger causes BSI. With respect to Model 2, the results reveal that SOLA does not Granger cause OIL, but OIL Granger causes SOLA. Similar results are found for SOLB and OIL. These findings are expected for smaller economies such as that of Lebanon, even though for larger economies and at the global level that might not be the case since the same economic shocks that affect stock returns also affect oil prices [46].

Table 3
Causality Test Results.

VAR Granger Causality/Block Exogeneity Wald Tests			
Model	Dependent Variable	Independent Variable	Chi-Square
Model 1	OIL	BSI	20.06 (0.09)
	BSI	OIL	27.92 (0.01)
Model 2	OIL	SOLA	20.74 (0.08)
	SOLA	OIL	27.58 (0.01)
Model 3	OIL	SOLB	21.63 (0.06)
	SOLB	OIL	27.49 (0.01)

Note: Probability values are in parentheses.

To better understand how shocks in the oil market are transmitted to the stock market, the orthogonalized impulse response function is examined. Following the ordering of the variables suggested by Cong *et al.* [10] and Park and Ratti [93], oil prices are placed before stock prices when estimating the VAR models. Based on this ordering, oil prices can have possible contemporaneous effects on the stock prices but not vice versa. The plots of the impulse responses from a Cholesky one standard deviation innovation in oil prices are shown in Figures 1-3. The behavior of the stock index BSI and the two stocks SOLA and SOLB are very similar; they all respond positively to a shock in crude oil prices on the same day and the day after the shock, with the the impact of the shock disappearing thereafter. The two standard error confidence intervals are shown in dashed lines.

Not many studies have used daily data, so it would be hard to compare the duration of the responses to other studies. However, the direction of the response, which is surprising for a net oil importer such as Lebanon, is similar to that found by a few studies, notably Sadorsky [36] for Canadian oil and gas stocks; El-Sharif *et al.* [44] for English oil and gas stocks; Bjornland [50] for Norway; Narayan and Narayan [11] for Vietnam; Arouri and Rault [21] for GCC countries except Saudi Arabia; Mohanty *et al.* [18] for GCC countries except Kuwait; Broadstock *et al.* [14] for Chinese energy stocks; Li *et al.* [41] for China at the sectoral level; Nguyen and Bhatti [13] for Vietnam. The more commonly found result in the literature however, is that increases in oil prices tend to depress stock prices [51]. Figures 4-6 display the response of oil prices to shocks in the domestic financial markets. As expected, there appears to be no significant response by oil prices to a shock in the Lebanese stock market.

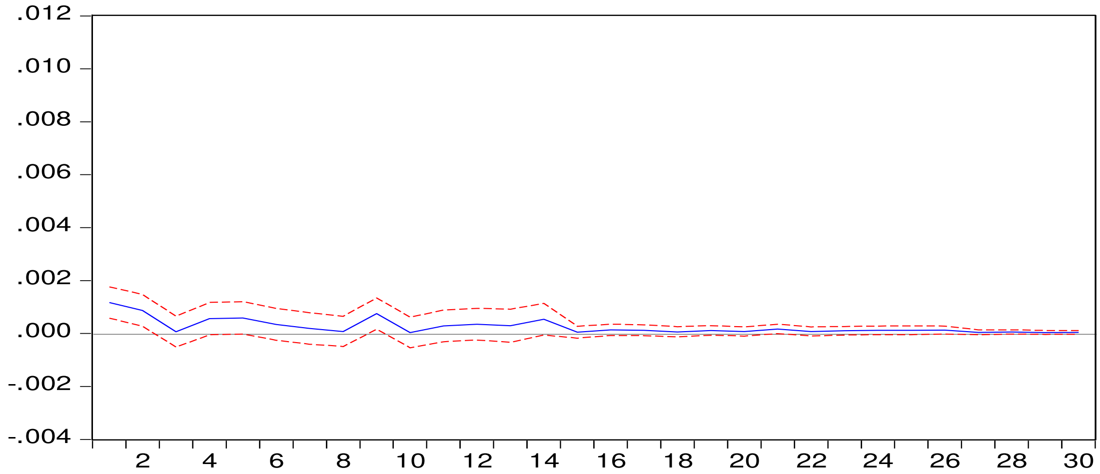

Fig. 1. Orthogonalized Impulse Response of BSI to a shock in OIL.

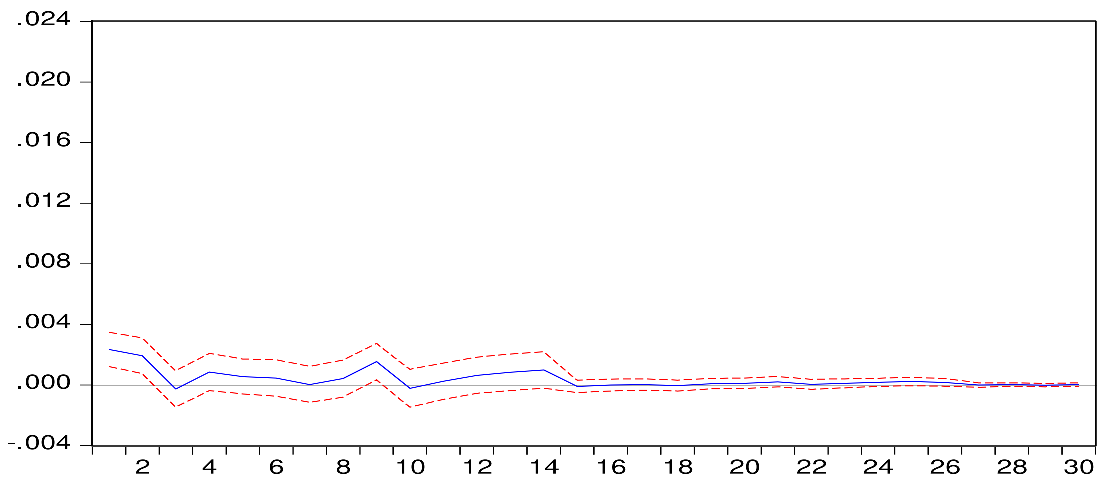

Fig. 2. Orthogonalized Impulse Response of SOLA to a shock in OIL.

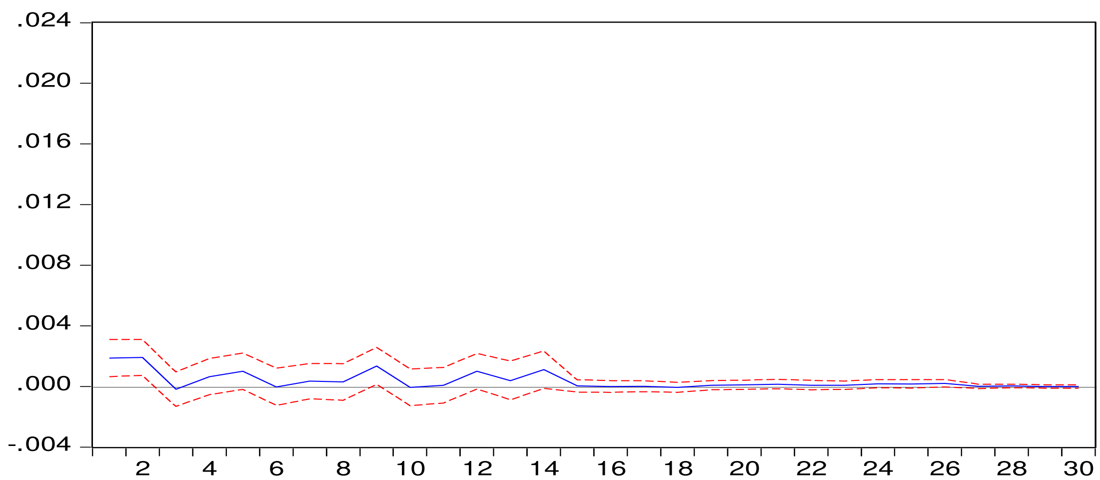

Fig. 3. Orthogonalized Impulse Response of SOLB to a shock in OIL.

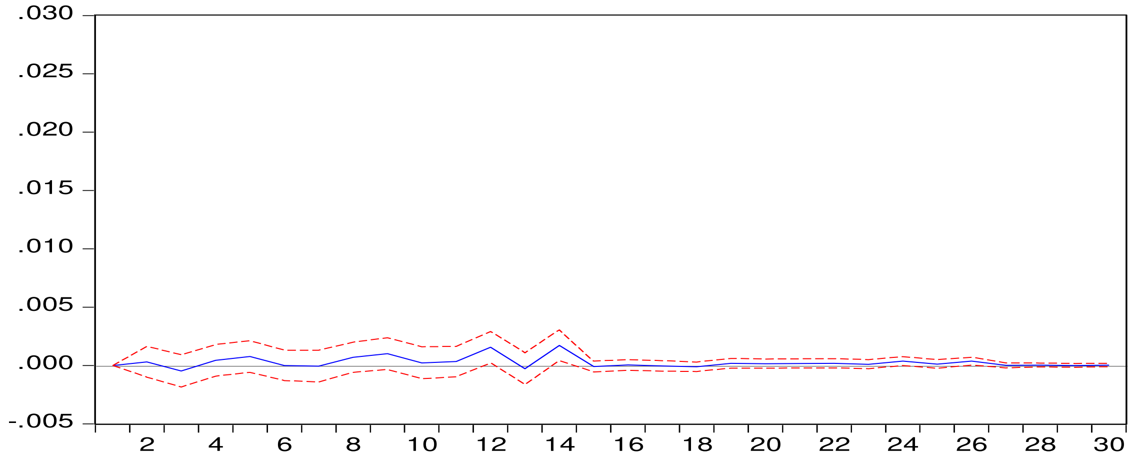

Fig. 4. Orthogonalized Impulse Response of OIL to a shock in BSI.

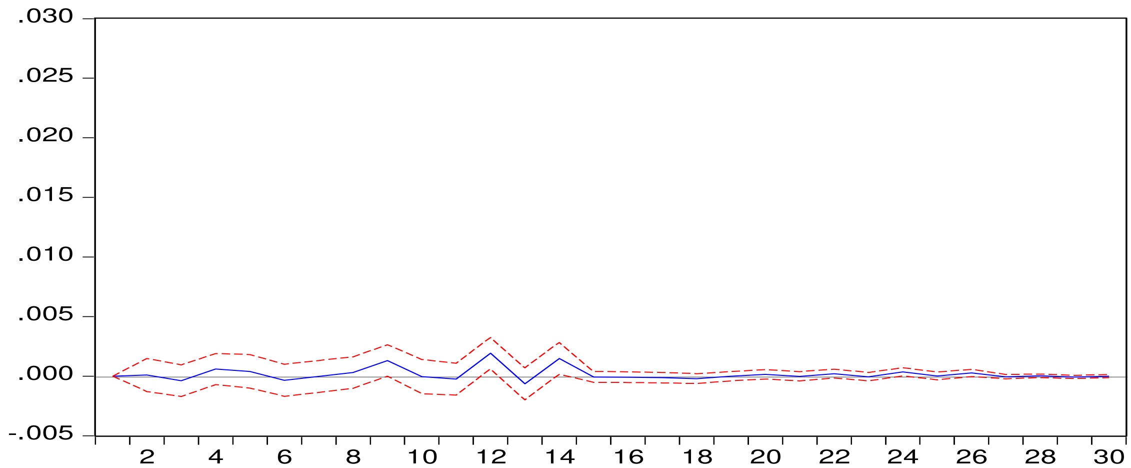

Fig. 5. Orthogonalized Impulse Response of OIL to a shock in SOLA.

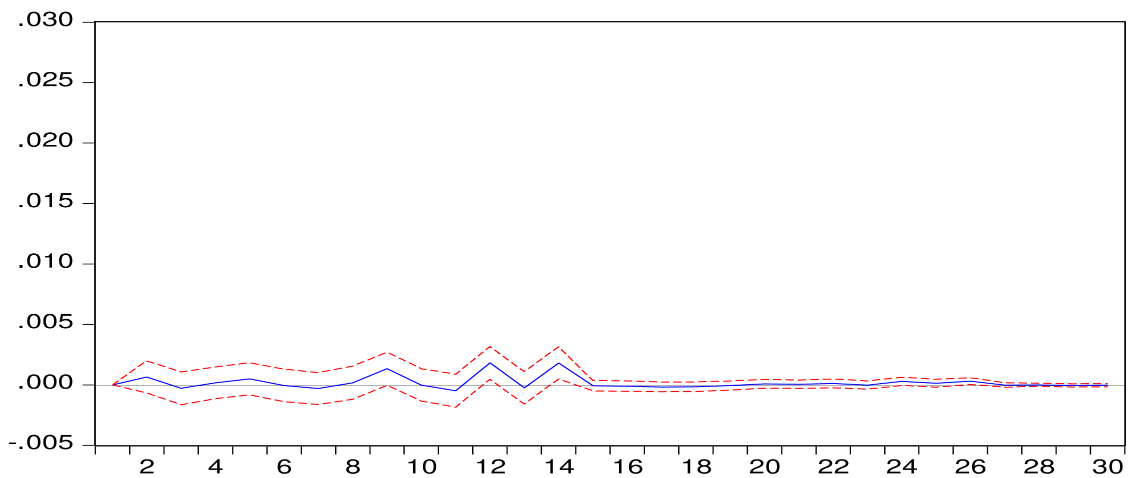

Fig. 6. Orthogonalized Impulse Response of OIL to a shock in SOLB.

We finally turn to the results of the orthogonalized variance decomposition analysis that are presented in Table 4. The values indicate the percentage of the forecast error variance in BSI, SOLA, and SOLB attributed to their own innovations versus innovations from crude oil prices. The time horizons chosen are: one day, 15 days, and 30 days ahead. For BSI, 98.82% of the variability in BSI changes is explained by its own innovation for one day ahead. This percentage only declines to 96.68% after 15 days and to 96.57% after 30 days. Similarly, the orthogonalized variance decomposition of SOLA (SOLB) reveals that most of the variability is explained by its own shock; 98.85% (99.27%) after one day and decreases slightly to 96.95% (97.41%) after 30 days. In summary, for all three variables their forecast errors are largely attributable to their own innovations and the percentages do not change much with time. Only around 1% is attributable to oil shocks, increasing to around 3% after a few days and remaining at that level. In other words, the results of the variance decomposition suggest that crude oil price shocks barely have an impact on changes in BSI, SOLA, or SOLB. In all three models, oil price shocks explain less than 3.5% of the forecast error variances at the end of the 30-day period considered in the variance decomposition analysis.

Table 4
Orthogonalized Variance Decomposition Results.

Model 1	Period	S.E.	OIL	BSI
	1	0.01	1.18	98.82
Variance Decomposition of BSI	15	0.02	3.32	96.68
	30	0.01	3.43	96.57
Model 2	Period	S.E.	OIL	SOLA
	1	0.02	1.15	98.85
Variance Decomposition of SOLA	15	0.02	3.02	96.98
	30	0.02	3.05	96.95
Model 3	Period	S.E.	OIL	SOLB
	1	0.02	0.73	99.27
Variance Decomposition of SOLB	15	0.02	2.56	97.44
	30	0.02	2.59	97.41

5. Conclusions

This study investigates the dynamic linkages between oil prices and stock markets, also known as the oil price-stock price nexus. Within the framework of a VAR we examine dynamic interactions between daily Brent spot prices and Lebanese stock prices. Given the strong evidence provided by existing studies that the impact of oil price shocks differs between sectors, we examine the stocks listed under the development and reconstruction sector, Solidere A (SOLA) and Solidere B (SOLB), in addition to the aggregate stock index (BSI).

As expected, we find evidence of oil prices Granger causing stock prices, but no evidence of the opposite relationship. These findings are expected for smaller economies such as that of Lebanon, even though for larger economies and at the global level that might not be the case since the same economic shocks that affect stock returns also affect oil prices [46].

To better understand how shocks in the oil market are transmitted to the stock market, the orthogonalized impulse response function is examined. An oil price shock produces a slight increase in the stock market that rapidly dissipates; they all respond positively to a shock in crude oil prices on the first day after the shock, but starting the second day and onwards the impact of the shock disappears. Not surprisingly, shocks in the stock market do not seem to have any effect on oil prices, judging by the statistical insignificance of the response function. Not many studies have used daily data, so it would be hard to compare the duration of the responses to other studies. However, the direction of the response, is similar to that found by Sadorsky[36]; El-Sharif *et al.*[44]; Bjornland [50]; Narayan and Narayan [11]; Arouri and Rault [21]; Mohanty *et al.* [18]; Broadstock *et al.* [14]; Li *et al.* [41]; Nguyen and Bhatti [13]. Oil price shocks have been commonly found to stimulate the stock markets of oil exporting countries. But for Lebanon, an oil importer, this is a surprising result, which can be partly explained by the fact that a substantial number of investors in Lebanese stocks are from neighboring oil exporting Arab countries.

As for the variance decomposition analysis, it shows that the forecast errors of the stocks are largely attributable to their own innovations and the percentages do not change much with time. Only around 1% is attributable to oil shocks, increasing to around 3% after a few days and remaining at that level. Thus, our main conclusion is that the estimated level of the impact of an oil price shock on the Lebanese stock market is positive but marginal. Our results are in line with Apergis and Miller's [68] who conclude that international stock markets do not respond in a large way to oil market shocks.

Acknowledgments

Part of this research was completed while the first author was visiting the Joint Institute for Strategic Energy Analysis at the National Renewable Energy Lab. Financial aid by the American University of Beirut's URB is gratefully acknowledged. The authors would like to thank two anonymous reviewers for their valuable comments on an earlier draft.

References

[1] Hamilton JD. Oil and the macroeconomy since World War II. Journal of Political Economy 1983; 91:228-248.

[2] Hamilton,J.D. Oil prices and Economic downturn. Testimony Prepared for the Joint Economic Committee of the U.S. Congress 2009. University of California, San Diego. Available from: http://www.jec.senate.gov/public/?a=Files.Serve&File_id=a6fca8ca-4c4f-4006-bca5-67e972dc19e2

[3] Huang RD, Masulis RW, Stoll HR. Energy shocks and financial markets. The Journal of Futures Markets 1996; 16:1-27.

[4] Aloui C, Jammazi R. The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach. Energy Economics 2009; 31:789–799.

[5] Basher SA, Sadorsky P. Oil price risk and emerging stock markets. Global Finance Journal 2006; 17: 224–251.

[6] Choi K, Hammoudeh S. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Policy 2010; 38: 4388–4399.

[7] Chen SS. Do higher oil prices push the stock market into bear territory? Energy Economics 2010; 32: 490–495.

[8] Kling JL. Oil price shocks and stock market behavior. Journal of Portfolio Management 1985; 12(1): 34-39.

[9] Nandha M, Hammoudeh S. Systematic risk, and oil price and exchange rate sensitivities in Asia-Pacific stock markets. Research in International Business and Finance 2007; 21: 326–341.

[10] Cong R, Wei Y, Jiao J, Fan, Y. Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy 2008; 36: 3544–3553.

[11] Narayan PK, Narayan S. Modelling the impact of oil prices on Vietnam's stock prices. Applied Energy 2010; 87: 356–361.

[12] Masih R, Peters S, De Mello L. Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea. Energy Economics 2011; 33: 975–986.

[13] Nguyen, CC, Bhatti MI. Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam. International Financial Markets, Institutions and Money 2012; 22: 758–773.
[14] Broadstock DC, Cao H, Zhang D. Oil shocks and their impact on energy related stocks in China. Energy Economics 2012; 34: 1888–1895.
[15] Abou Zarour B. Wild oil prices, but brave stock markets! The case of GCC stock markets. An International Journal 2006; 6: 145-162.
[16] Hammoudeh S, Choi K. Behavior of GCC stock markets and impacts of US. Research in International Business and Finance 2006; 20: 22–44.
[17] Arouri M, Rault C. Oil prices and stock markets: what drives what in the Gulf Corporation Council countries? William Davidson Institute Working Paper 2009: 960.
[18] Mohanty S, Nandha M, Turkistani AQ, Alaitani MY. Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. Global Finance Journal 2011; 22; 42–55.
[19] Fayyad A, Daly K. The impact of oil price shocks on stock market returns: Comparing GCC countries with the UK and USA. Emerging Markets Review 2011; 12: 61-78.
[20] Hammoudeh, S., Aleisa, E. Dynamic relationships among the GCC stock markets and the NYMEX oil prices. Contemporary Economic Policy 2004;22: 250–269..
[21] Arouri MH, Rault C. Oil prices and stock markets in GCC countries: empirical evidence from panel analysis. International Journal of Finance and Economics. Wiley Online Library 2011; DOI: 10.1002/ijfe.443.
[22] Al-Nahleh M, Al-Zaubia K. Oil prices and financial markets activity: Empirical evidence from some MENA countries. International Business Research 2011; 4 (2): 193-200.
[23] Akoum I, Graham M, Kivihaho J, Nikkinen J, Omran M. Co-movement of oil and stock prices in the GCC region: A wavelet analysis. The Quarterly Review of Economics and Finance 2012; http://dx.doi.org/10.1016/j.qref.2012.07.005 :1-10.
[24] United Nations Economic and Social Commission of Western Asia. Statistical abstract of the ESCWA region 2011; 30. Available from: http://www.escwa.un.org/
[25] Beirut Stock Exchange 2013. Available from: http://www.bse.com.lb/
[26] The World Bank 2013. Available from: http://data.worldbank.org/indicator/CM.MKT.LCAP.CD .
[27] Arouri MH, Nguyen DK. Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. Energy Policy 2010; 38: 4528– 4539.
[28] Aloui C, Nguyen DK, Njeh H. Assessing the impacts of oil price fluctuations on stock returns in emerging markets. Economic Modelling 2012; 29: 2686–2695.
[29] Arouri, MH. Does crude oil move stock markets in Europe? A sector investigation. Economic Modelling 2011; 28: 1716–1725.
[30] Hamao Y. An empirical examination of the arbitrage pricing theory: Using Japanese data. Japan and the World Economy 1988; 1: 45−61.
[31] Chen NF, Roll R, Ross, SA. Economic forces and the stock market. Journal of Business 1986; 59: 383−403.
[32] Jones CM, Kaul G. Oil and stock markets. The Journal of Finance 1996; LI (2): 464-492.
[33] Miller JI, Ratti RA. Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics 2009; 31: 559–568.
[34] Sadorsky P. Oil price shocks and stock market activity. Energy Economics 1999; 21: 449-469.
[35] Faff RW, Brailsford TJ. Oil price risk and the Australian stock market. Journal of Energy Finance and Development1999; 4: 69–87.

[36] Sadorsky P. Risk factors in stock returns of Canadian oil and gas companies. Energy Economics 2001; 23:17-28.
[37] Nandha, M., Faff, R. Does oil move equity prices? A global view. Energy Economics 2008; 30: 986–997.
[38] Scholtens B, Yurtsever C. Oil price shocks and European industries. Energy Economics 2012; 34: 1187–1195.
[39] Hammoudeh S, Li H. Oil sensitivity and systematic risk in oil-sensitive stock indices. Journal of Economics and Business 2005; 57: 1-21.
[40] Hammoudeh S, Choi K. Characteristics of permanent and transitory returns in oil-sensitive emerging stock markets: The case of GCC countries. Journal of International Financial Markets, Institutions & Money 2007; 17: 231-245.
[41] Li S, Zhu H, Yu K. Oil prices and stock market in China: A sector analysis using panel cointegration with multiple breaks. Energy Economics 2012; 34: 1951–1958.
[42] Lin C, Fang C, Cheng H. Relationships between oil price shocks and stock market: An Empirical analysis from the greater China. China Economic Journal 2009; 3 (3); 241-254.
[43] Zhang C, Chen X. The impact of global oil price shocks on China's stock returns: Evidence from the ARJI (-ht)-EGARCH model. Energy 2011; 36: 6627-6633.
[44] El-Sharif I, Brown D, Burton B, Nixon B, Russsell A. Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Economics 2005; 27:819–830.
[45] Henriques I, Sadorsky P. Oil prices and the stock prices of alternative energy companies. Energy Economics 2008; 30: 998–1010.
[46] Kilian L, Park C. The impact of oil price shock on the U.S stock market. International Economic Review 2009; 50(4): 1267-1287.
[47] Lescaroux F, Mignon V. On the influence of oil prices on economic activity and other macroeconomic and financial variables. OPEC Energy Review 2008; 848-855.
[48] Cifarelli G, Paladino G. Oil price dynamics and speculation: A multivariate financial approach. Energy Economics 2010; 32: 363–372.
[49] Papapetrou E. Oil price shocks, stock market, economic activity and employment in Greece. Energy Economics 2001; 23: 511-532.
[50] Bjornland HC. Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy 2009; 56 (2): 232-253.
[51] Basher S, Haug AA, Sadorsky P. Oil prices, exchange rates and emerging stock markets. Energy Economics 2012; 34: 227–240.
[52] Lee B, Yang CW, Huang, B. Oil price movements and stock markets revisited: A case of sector stock price indexes in the G-7 countries. Energy Economics 2012; 34: 1284–1300.
[53] Ewing BT, Thompson MA. Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. Energy Policy 2007; 35: 5535–5540.
[54] Kaneko T, Lee B. Relative importance of economic factors in the U.S and Japanese stock markets. Journal of the Japanese and International Economies 1995; 9: 290-307.
[55] Ghouri, SS. Assessment of the relationship between oil prices and US oil stocks. Energy Policy 2006; 34: 3327–3333.
[56] Oberndorfer U. Energy prices, volatility, and the stock market: Evidence from the Eurozone. Energy Policy 2009; 37: 5787–5795.
[57] Mohanty S, Nandha M, Bota G. Oil shocks and stock returns: The case of the Central and Eastern European (CEE) oil and gas sectors. Emerging Markets Review 2010; 11: 358–372.

[58] Jammazi R, Aloui C. Wavelet decomposition and regime shifts: Assessing the effects of crude oil shocks on stock market returns. Energy Policy 2010; 38: 1415–1435.
[59] Chiou JS, Lee YH. Jump dynamics and volatility: Oil and the stock markets. Energy 2009; 34: 788–796.
[60] Jammazi R. Cross dynamics of oil-stock interactions: A redundant wavelet analysis. Energy 2012; 44: 750-777.
[61] Jammazi R. Oil shock transmission to stock market returns: Wavelet-multivariate Markov switching GARCH approach. Energy 2012; 37: 430-454.
[62] Ciner C. Energy shocks and financial markets: Nonlinear linkages. Studies in Nonlinear Dynamics and Econometrics 2001; 5(3): 203–212.
[63] Maghyereh A. Oil price shocks and emerging stock markets: A generalized VAR approach. International Journal of Applied Econometrics and Quantitative Studies 2004; 1-2: 27-40.
[64] Hammoudeh S, Dibooglu S, Aleisa A. Relationships among U.S. oil prices and oil industry equity indices. International Review of Economics and Finance 2004; 13: 427–453.
[65] Huang B, Hwang MJ, Peng H. The asymmetry of the impact of oil price shocks on economic activities: An application of the multivariate threshold model. Energy Economics 2005; 27: 455– 476.
[66] Lee C, Zeng J. The impact of oil price shocks on stock market activities: Assymetric effect with quantile regression. Mathematics and Computers in Simulation 2011; 81: 1910-1920.
[67] Sari R, Soytas U. The relationship between stock returns, crude oil prices, interest rates, and output: Evidence from a developing economy. The Empirical Economics Letters 2006; 5(4): 205-220.
[68] Apergis N, Miller SM. Do structural oil-market shocks affect stock prices? Energy Economics 2009; 31: 569–575.
[69] Fowowe B. Jump dynamics in the relationship between oil prices and the stock market: Evidence from Nigeria. Energy 2013. Available from: http://dx.doi.org/10.1016/j.energy.2013.04.062
[70] Dickey D, Fuller W. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 1979; 74 (366): 427–431.
[71] Dickey DA, Fuller WA. The likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 1981; 49: 1057-1072.
[72] Phillips PE, Perron PI. Testing for a unit root in time series regression. Biometrika 1988; 75 (2): 335–346.
[73] Akaike H. Information theory and an extension of the maximum likelihood principle. Second International Symposium on Information Theory. BN Petrov and F Csaki ed. Budapest : Academia Kiado 1973; 267-281.
[74] Schwert G William. Why Does Stock Market Volatility Change over Time? Journal of Finance, American Finance Association 1989; 44 (5): 1115-1153.
[75] MacKinnon JG. Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics 1996; 11 (6): 601–618.
[76] Wang P. Financial econometrics: Methods and Models. New York: Routledge; 2003.
[77] Engle RF, Granger CWJ. Cointegration and error correction: representation, estimation and testing. Econometrica 1987; 55: 251– 276.
[78] Johansen S. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control 1988; 12: 231–254.
[79] Johansen S. Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. Econometrics 1991; 59 (6): 1551-1580.
[80] Sims CA. Macroeconomics and reality. Econometrica 1980; 48: 1-48.
[81] Harvey AC. Forecasting structural time series models and the kalman filter. Press Syndicate of the University of Cambridge 1989; 554.

[82] Cooley, TF, Leroy, SF. A theoretical macroeconometrics: A Critique. Journal of Monetary Economics 1985; 16: 283–308.
[83] Runkle DE. Vector autoregressions and reality. Journal of Business and Economic Statistics 1987; 5: 437-442.
[84] Harvey A. Trends, cycles and autoregressions. Economic Journal 1997; 107 (440): 192-201.
[85] Greene WH. Econometric analysis. 5th ed. New Jersey: Prentice Hall; 2003.
[86] Gujarati D, Porter D. Basic econometrics. 5th ed. New York: McGraw-Hill; 2009
[87] Granger CWJ. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 1969; 37 (3): 424-438.
[88] Granger CWJ. Some recent development in a concept of causality. Journal of Econometrics 1988; 39 (1-2): 199-211.
[89] Granger CWJ, Newbold P. Spurious regressions in econometrics. Journal of Econometrics 1974; 2: 111–20.
[90] Sims CA. An autoregressive index model for the U.S 1948– 1975, in J Kmenta and JB Ramsey (eds.). Large-Scale Macro-Econometric Models. Amsterdam: North-Holland Publishing 1981; 283 – 327.
[91] Kennedy P. A guide to econometrics. 5th ed. Cambridge: MIT press; 2003.
[92] Enders W. Applied econometric time series. 3rd ed. Wiley; 2010.
[93] Park J, Ratti RA. Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Economics 2008; 30: 2587–2608.