

Stock market and crude oil relationship: A wavelet analysis

shafaai, Shafizal and Masih, Mansur

INCEIF, Malaysia, INCEIF, Malaysia

15 August 2013

Online at https://mpra.ub.uni-muenchen.de/62363/ MPRA Paper No. 62363, posted 25 Feb 2015 15:12 UTC

Stock market and crude oil relationship: A wavelet analysis

Shafizal Bin Shafaai $^1\,$ and Mansur Masih $^2\,$

Abstract

Financialisation of crude oil and its frequent inclusion into investment portfolios raise the demand for analysis of crude oil and stock market indices relationship at various time scales. In this paper, the relationships between crude oil and stock markets in three Islamic stock market indices and three non-Islamic indices are examined by using a time-scale decomposition based on the theory of wavelets. This study employs daily closing price data of Brent crude oil index and the six stock market indices. The oil and stock return series are first decomposed into different time components and then their relationships are investigated over different time scales through wavelet's estimated correlations. We also characterized the crude oil and stock market relationship for different timescales in an attempt to disentangle the possible existence of comovement during the global financial crisis. The results mainly show evidence of significant time scale effects on the behavior of the oil-stock market links, and that investors should consider these effects when diversifying their portfolios of stocks into the oil asset. The paper specifies the investment horizons that should be considered to maximize diversification properties of crude oil. These findings also have important implications for risk management, monetary policies to control oil inflationary pressures and fiscal policy in oil-exporting countries.

¹ Shafizal Bin Shafaai, Graduate student at INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia.

² **Corresponding author**, Professor of Finance and Econometrics, INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia. Phone: +60173841464 Email: mansurmasih@inceif.org

Stock market and crude oil relationship: A wavelet analysis

1.0 Introduction

With oil prices cascading to new highs over the past few years, the topic of energy prices has once again come to the fore. Oil has played a significant role in the economic and political development of the industrialised countries in the world. Oil price shocks are an important determinant of the future economic growth and stability of the developing countries of today. The economic impact of higher oil prices on developing countries is generally more severe than that for industrialised countries. This is mainly because of the energy intensiveness of these economies as they experience a rapid economic growth and, generally, energy is used less efficiently. According to the International Energy Agency report (2010), on average, developing countries use more than twice as much oil to produce a unit of economic output as do OECD countries. Economic liberalisation and integration of international markets is characterised by an increased level of capital flow and international investment in emerging markets. Given the oil intensity of the emerging economies of today, it is important for global portfolio investors to understand the level of susceptibility of stock prices in these markets to movements in global oil prices.

As investors turned more upbeat on oil prices, financial demand for crude oil fueled by cheap liquidity, has also picked up as what happened in 2008 as well as in early 2011. Recall that crude oil price was pushed up to an all time high of US\$146.3 a barrel on 11 July 2008, partly caused by strong financial demand. In early 2011, crude oil prices rose again to a 30-month high of US\$113.93 a barrel on 29 April. Indeed, data compiled by the commodity market regulator in the US shows that speculators are boundlessly bullish on a surge in oil prices. Their net long position on benchmark New York Mercantile Exchange crude oil contract is now as large as 259 million barrels, a huge one-way bet on prices to rise. When oil prices were soaring in 2007 and 2008, investors' net long position hardly ever exceeded 150 million barrels. According to US Commodity Futures Trading Commission, financial demand could have added as much as

US\$26 to a barrel of the crude oil price. The presence of financial demand has increased oil price volatility, making forecasting oil price movements more challenging in recent years.

Another interesting feature of crude oil as commodity is that world oil markets were gradually unifying into a global market. Prices of crude oils with different characteristics were moving close to each other and shocks in one region were transferred into other regions (Fattouh 2010). For this reason, oil prices can be the aggregation of all kinds of market information, and are likely to reflect the changes in market forces, including structural characteristics of market mechanism (Fan & Xu 2011).

In globalized financial markets with growing trading volumes and liquidity, the integration and co-movements are becoming stronger in time so that the use of diversification has been becoming more limited. Therefore, examination and research on different types of co-movements and correlations in time is of a great importance. In addition to the time dimension of the market dynamics, there are different types of investors who are influenced by such dynamics. Starting with noise traders with an investment horizon of several minutes or hours, the spectrum of investors ranges through technicians with the horizon of several days to fundamentalists with the horizon of several weeks or months to pension funds with the investment horizon of several years. Thus, apart from the time domain, there is a frequency domain, which represents various investment horizons.

The profound understanding of interdependence between crude oil prices makes it possible for investors to make across-market hedging decisions and create a balanced portfolio. However, correlation can be highly dynamic. It can change significantly over time and what is more, also over different frequencies. Most of research on financial data is performed in time domain, thus it is very familiar environment and does not need additional comments. Frequency domain is less popular term, but it is possible to meet expressions in the literature such as long-term relationship or short-term responses, which describe changes over different frequencies. We want to combine those two approaches into time-frequency domain, which would bring results extremely valuable for investors and other decision makers.

1.1 Overview of Global Crude Oil

Reflecting the weak global economic recovery in 2013, global commodity prices have been inching down in recent months, dragged down by falling demand due to a recession in the Eurozone, a modest US economic recovery and less robust China's economic growth. This was indicated by the Commodity Research Bureau's (CRB) commodity price index, which fell to 475.5 on 23 April 2013, from 491.5 in January 2013. The CRB commodity price index tracks the price movements of 22 sensitive basic commodities whose prices are presumed to be among the first to be influenced by changes in economic conditions. The easing in commodity prices came as no surprise given the sluggish global economic recovery. Not until the sharp fall in gold prices, followed by a decline in crude oil prices that caught investors' attention for fear that the plunge in prices may signal some unwarranted development in the global economy. Indeed WTI crude oil price fell by 5.0% from a high of USD91.29/barrel on 12 April 2013 to USD86.68/barrel on 17 April 2013. The situation was exacerbated by a weaker growth in the Chinese economy and a drop in demand from the US following the shale energy revolution. A combination of horizontal drilling and hydraulic fracturing has unlocked supplies from shale formations in the US including North Dakota, where output surged by 44% in 2012. Rising production helped the US meet 84% of its energy needs in 2012, the most since 1991, according to the US Energy Information Administration. The measure of self-sufficiency rose to 88% in December 2012, the highest level since February 1987. Crude oil price, however, had since climbed back to USD91.06/barrel on 24 April 2013.

Unlike 2011 when the price subsequently pulled back, the rise in crude oil prices appears to be on a more solid ground of late, as investors expect fuel demand to pick up given that the global economic outlook is becoming less gloomy after the Eurozone averted from a brink of a meltdown and the Eurozone Central Bank injected more than €1 trn liquidity into the financial system in December 2011 and February 2012 to defuse a liquidity crunch. This was aided by the US Federal Reserve keeping its interest rates low until late 2014 and introducing the third round of quantitative easing.

2.0 Motivation of the Study

The modern portfolio theory suggests that investors seek to diversify their portfolios in order to reduce the risk on the market. The previous literature has showed that commodities asset class, and in particular crude oil asset, may provide good diversification potential due to their different nature and low correlations with stocks. However, most of the previous research ignores the effects of different time horizon problem when studying the relationships between crude oil prices and stock markets.

To solve the above issue and in order to better understand the underlying dynamics of the oil price variable, it is my humble attempt to better assess the impact of oil price on the stock price by applying the wavelet methodology. It is my humble effort to focus on the usefulness and performance of wavelets in providing out of sample forecasts for the oil prices. I will then proceed to deal with several associated issues and provide a balanced account of the problems and promises. The applied procedure is motivated by some basic properties of wavelets and is based on the application of the maximum overlap discrete wavelet transform (MODWT). The idea is to subdivide the price data/signal in low and high frequency part. By relying on MODWT, the data is decomposed in several scales and coarse and fine parts of the data are obtained. The coarse scales reveal the trend, while the finer scales might be related to seasonal influences, singular events and noise. This is followed by an appropriate and adaptive extension of the signal (which is depending on the behaviour on each scale). Consequently, (out of sample) forecast values on each scale are calculated and the inverse wavelet transform is used to generate a forecast for the whole signal.

In addition to this change relating to the data level, the paper intends to set up a new time level. The oil price specifications usually used in the literature (Mork, 1989; Lee et al., 1995; Hamilton, 1996), implicitly consider that the relevant sphere of analysis of the oil price–stock Market relationship is the simple time dimension. Despite the application of filters, the use of VAR (Vector Auto Regressive) approach and other standard econometric tools, these constructions only enable to separate short term fluctuations from the time trend. They do not take into account the fact that the factors determining oil price fluctuations, as well as the indicators of the economic activity, all operate at very different time scales. A tool that would provide more subtle information, and would allow room for intermediate cycles' sizes, would prove very useful in this matter. Such a tool does exist, and has been developed by the theory of signal: the wavelet decomposition. In this paper, we rely on the new framework offered by wavelets to analyse the oil price cycles and to investigate the oil price–stock market relationship.

Our contributions to the related literature are in two principal aspects. First, there is still little empirical evidence on how oil prices are associated with stock markets in the context of Islamic stock market indices. The investigation of such relationship is thus interesting because the Islamic stock markets have recently become attractive due to the innovation and rapid expansion of Islamic finance, as well as global investors seeking for new international diversification destinations. This paper could also help governments and regulatory authority to make sound decisions when they have to regulate stock markets and oil price policies. Second, empirical findings related to the oil-stock market relationship are not consistent across past studies due to the differences in terms of methodological approaches, sample periods, and data used are important sources. Consequently, it is highly difficult to make comparison among related studies.

In this paper, the relationship between the price of crude oil and stock markets in three Islamic stock market indices and three non-Islamic indices from 15 January 2007 to 15 December 2012 are analysed. The wavelet decomposition approach is employed. A clear relationship will suggest significant time scale effects on the behavior of the oil-stock market links, and that investors should consider these effects when diversifying their portfolios of stocks into the oil asset.

3.0 Main Objectives/ Issues

Previous contributions have already attempted to provide a relevant decomposition of the oil price, in order to better understand the oil price impact on the stock price. In addition to Mork's (1989) decomposition of the oil price into two components, increases and decreases, Lee et al.'s (1995) "surprise effect" measure, and Hamilton's NOPI (1996), Kilian (2006) also decomposed the oil price shocks into 3 shocks, using a Structural VAR model: supply shocks, aggregate demand shocks (that also affect other commodities) and oil specific demand shocks (that only

affect the oil demand). Thanks to this decomposition, he could show that oil supply shocks, that have been the most studied ever since the early 1970s, only explain a marginal part of the oil price variations, compared with both kinds of demand shocks. These "transformations" of the oil price, prove that the oil price should not be studied as a gross variable anymore, since a lot of information is lost by doing so.

However, despite the precious information they yield, these specifications do not address an essential characteristic of the oil price: the diversity of the factors causing its variations. At best, Kilian (2006) manages to decompose the oil price into three global components, but it does not suffice to fully take into account the complexity of the factors driving the oil price.

The causes of the oil price rises we have witnessed for the last decade are indeed numerous. Regarding the supply side first, we can find the following explanations:

(i) The low investment in the oil industry during the 1990s has led today to an under-capacity of oil facilities (exploration, production and refining)

(ii) The scarcity of the resource (some countries have already reached their oil peak) creates uncertainty which also contributes to drive oil prices up

(iii) Geopolitical instability affects many of the oil producing countries (gulf wars, the nuclear crisis with Iran, aggressive nationalism in South America)

(iv) The rise of the costs of many production factors (price of other commodities, costs of subcontractors) increases the cost of major energy projects;

(v) OPEC's decisions of cuts in production

(vi) Information about low US' oil stocks

(vii) Some extreme climate events which damage oil facilities

Turning now to the demand side, the rise in oil demand stemming from China, India and other emerging countries, and the stable energy demand from advanced countries constitute potential explanations of the oil price increases.

These factors, whether on the offer or on the demand side, all operate at very different time horizons: a few hours for an OPEC meeting, a few days for strikes in Venezuela, a few months for attacks in Nigeria, a few years for the Iran–Iraq war and the 2nd Gulf war and up to 20 years

or more for energy investment policy in the oil sector or in substitution energy sources. The diversity of these time horizons induces diverse underlying cycles in the variations of the oil price. Shocks that may affect these cycles do not have the same impact on the oil price: a hurricane in the United States will damage the capacity of some refineries or off shore platforms for a while, but their impacts on the oil price cannot be compared to a permanent rise in Chinese demand for oil or to the lasting cut in Iraq's oil production. In order to better understand the underlying dynamics of the oil price variable, and in fine to better assess its impact on the stock price, it is essential to separate these various contributions according to their own time scales. To reach this objective, the wavelet theory, part of the theory of signal, is a powerful tool.

As far as the analysis of economic time series (e.g. commodity prices) are concerned, the presence of scaling relations can be used to characterize the statistical properties of the underlying process and to provide alternative means for dealing with the volatility issue and other issues related to conditional moments (mean, variance, etc.). With regards to this paper, it is my humble attempt to apply the multi-scale analysis as understood in wavelet literature. The basic idea is to consider a signal which can be decomposed by wavelet transform in different scales. The scales contain contributions of the signal of different frequencies. When embedded in an appropriate function space, the multi-scale analysis of a function can be performed.

4.0 Literature Review – Theoretical

Economic theory suggests that any asset price should be determined by its expected discounted cash flows (Fisher 1930; Williams 1938). Thus, any factor that could alter the expected discounted cash flows should have a significant effect on these asset prices. Consequently, any oil price increase would result to increased costs, restraining profits and in greater extend, would cause a decrease in shareholders' value. Hence, any oil price increase should be accompanied by a decrease in the stock prices. Should that effect be the same for oil-importing and oil-exporting countries, though? Many authors argue that oil price effect on stock markets is an indirect effect and it is fed through the macroeconomic indicators. According to Bjornland (2009) and Jimenez-Rodriguez and Sanchez (2005), an oil price increase is expected to have a positive effect in an oil exporting country, as the country's income will increase. The consequence of the income

increase is expected to be a rise in expenditure and investments, which in turn creates greater productivity and lower unemployment. Stock markets tend to respond positively in such event.

For an oil-importing country, any oil price increase will tend to have the opposite results; see LeBlanc and Chinn (2004) and Hooker (2002). Oil price increase will lead to higher cost of productions, as oil is one of the most important production factors (Arouri & Nguyen 2010; Backus & Crucini 2000; Kim & Loungani 1992). The increase cost will be transferred to the consumers, whichwill, in turn, lead to lower demand and thus consumer spending, due to higher consumer prices; see for example, Bernanke (2006), Abel and Bernanke (2001), Hamilton (1996), Hamilton (1988a, 1988b) and Barro (1984). Lower consumption could lead to lower production and thus increased unemployment; see Lardic and Mignon (2006), Brown and Yücel (2002) and Davis and Haltiwanger (2001). Stock markets would react negatively in such case; see Sadorsky (1999), and Jones and Kaul (1996).

However, the oil price shocks could affect stock markets due to the uncertainty that they create to the financial world, depending on the nature of the shock (demand side or supply-side). In this case stock markets could respond positively to an oil price shock, which originates from the demand side, and negatively if the shock originates from the supply side. Having briefly discussed the possible transmission mechanisms of an oil price shock to the stock market, we proceed to the analysis of the previous studies in this area.

Oil is one of the most important production factors in an economy. Not surprisingly, a growing theoretical and empirical literature has been devoted to the study of oil and its impact on the economy. Rising oil prices lead to higher production costs which affect inflation, consumer confidence and therefore economic growth. Several studies report a clear negative correlation between energy prices and aggregate output or employment. For instance, Hamilton (1983) and Gisser and Goodwin (1986) demonstrate that rising oil prices are responsible for recessions. Rotemberg and Woodford (1996) estimate that a 10% increase in oil prices leads to an average GDP decline of 2.5% five or six quarters later. Jones et al. (2004) estimate that the oil price – GDP elasticity (the ratio of percentage change in GDP to percentage change in oil price) is around -0.06. However, Lee et al. (1996), Hamilton (1996), Huntington (1998), among others,

report an asymmetric relationship between oil prices and the macroeconomy. Rising oil prices seem to decrease the aggregate economic activities more than falling oil prices stimulate them. Furthermore, Bernanke (1983) and Pindyck (1991) show that large oil price movements increase uncertainty about future prices and thus cause delays in business investments. Nevertheless, Hooker (1996) indicates that the correlation between oil prices and economic activity appears to be much weaker in data since 1985, so the suggestion that oil shocks contribute directly to the economic downturn remains controversial.

The connection between oil and stock prices appears to be quite natural. Theoretically, the value of a firm is the present value of expected future cash flows. Rising oil prices affect the future cash flows of a firm, either negatively or positively depending on whether the firm is producing or consuming oil. In addition, oil prices also affect interest rates in the economy via inflation and monetary policy of the central bank. Rising oil prices lead to high inflation which increases interest rates. Furthermore, the central bank often uses contractionary monetary policy to fight inflation. This further increases interest rates. As a result, the discount rate of the firm also increases. Increasing discount rate leads to lower stock price, other things equal.

Nowadays, the majority of the countries have turned the focus of their monetary policy on inflation stability putting an effort to the absorption of any shocks that could cause inflationary pressures – e.g. oil price shocks –(Bernanke et al. 1997; Blanchard & Gali 2007; Lescaroux & Mignon 2008). Furthermore, due to increased productivity, investments and renewable energy sources, firms are able to absorb increased production input costs without the need of price increases (International Energy Agency 2010). Wage flexibility plays an important role on the reduced impact of oil price shocks, as well. Nordhaus (2007) suggested that due to the greater wage flexibility in some countries, responses to oil price shocks tend to be more neoclassical rather than Keynesian. Similar evidence was adduced by Blanchard and Gali (2007). Neoclassical theory, in contrast to the Keynesians, argues that effect on output is much smaller and thus oil price shocks should have minimum impact in the economy. Hence, according to this theory, oil price shocks should have small or no impact on stock markets today, as well.

5.0 Literature Review – Empirical

On the issue of the effect of oil price shocks on stock market returns, it has been investigated by a number of researchers. Jones and Kaul (1996), Sadorsky (1999) and Ciner (2001) report a significant negative connection, while Chen et al. (1986) and Huang et al. (1996) do not. A negative association between oil price shocks and stock market returns has been reported in several recent papers. Nandha and Faff (2008) find oil prices rises have a detrimental effect on stock returns in all sectors except mining and oil and gas industries, O'Neill et al. (2008) find that oil price increases lead to reduced stock returns in the United States, the United Kingdom and France, and Park and Ratti (2008) report that oil price shocks have a statistically significant negative impact on real stock returns in the U.S. and 12 European oil importing countries (Nandha and Faff (2008) review work on the effect of oil price on equity prices. Recently papers have focused on the effect of oil price for stock market risk as in Basher and Sadorsky (2006) and Sadorsky (2006)) In newstrands in the literature, Kilian and Park (2007) report that only oil price increases driven by precautionary demand for oil over concern about future oil supplies negatively affect stock prices, and Gogineni (2007) finds that industry stock price returns depends on demand and cost side reliance on oil and on size of oil price changes. Research on the effect of oil prices on stock prices parallels a larger literature on the connection of oil price shocks with real activity. Much of this research has been influenced by Hamilton's (1983) connection of oil price shocks with recession in the U.S. Hamilton's finding has been elaborated on and confirmed by Mork (1989), Lee et al. (1995), Hooker (1996), Hamilton (1996, 2003) and Gronwald (2008), among others Cologni and Manera (2008), Kilian (2008a) Jimenez-Rodriguez and Sanchez (2005), Cunado and Perez de Garcia (2005) and Lee et al. (2001) have confirmed a negative link between oil price shocks and aggregate activity for other countries. Huntington (2005), Barsky and Kilian (2004) and Jones et al. (2004) provide reviews on the effect of oil shocks on the aggregate economy. The research in the two areas is clearly connected, since oil price shocks influence stock prices through affecting expected cash flows and/or discount rates. Oil price shocks can affect corporate cash flow since oil is an input in production and because oil price changes can influence the demand for output at industry and national levels. Oil price shocks can affect the discount rate for cash flow by influencing the expected rate of inflation and the expected real interest rate. The corporate investment decision can be affected directly by changes in the latter and by changes in stock price relative to book value.

Mounting evidence suggests a negative relationship between oil prices and stock market returns. Jones and Kaul (1996) were the first to reveal the negative impact of oil price on stock markets, which occurs due to the fact that oil price, is a risk factor for stock markets. Other authors, such as Filis (2010), Chen (2009), Miller and Ratti (2009), Nandha and Faff (2008), O'Neill, Penm, and Terrell (2008), Park and Ratti (2008), Driesprong, Jacobsen, and Maat (2008), Ciner (2001) and Gjerde and Sættem (1999) have also provide evidence towards such a negative relationship. Sadorsky (1999) argued that oil price volatility has also an impact on stock returns. Oberndorfer (2009) seconds that opinion in his study on the effect of oil price volatility on European stock markets. A negative relationship between the volatilities of oil price returns and three stock market sectors returns in US (namely, technology, health care and consumer services) was identified by Malik and Ewing (2009). Similar results were obtained by Chiou and Lee (2009). More specifically, Chiou and Lee (2009), using an Autoregressive Conditional Jump Intensity (ARJI) model, found evidence that oil price volatility negatively influence the S&P500 index. More importantly, their study concluded that periods of increased oil price volatility tend to cause unexpected asymmetric negative effects on S&P500 returns. Hammoudeh and Li (2008) provided an interesting finding in this area of concern. They suggested the major events that cause changes in oil prices tend to increase the stock market volatility of the GCC countries. In addition, Arouri and Nguyen (2010) used a two-factor GARCH model to examine the effect of oil prices on European sectors' returns rather than only on aggregate stock market index returns. They concluded that oil prices tend to exercise a significant influence on various European sectors (such as, Oil and Gas, Financials, Industrials and Utilities, among others); however, the magnitude and the direction of the effect differ from one sector to another. Specifically for the oil-exporting countries, Arouri and Rault (2011) employed a bootstrap panel cointegration technique and a seemingly unrelated regression (SUR) method and provided evidence that positive oil price shocks have positive impact on the stock market performance of GCC countries. Similar results were also documented by Bashar (2006). Hammoudeh and Aleisa (2004), on the otherhand, found a bidirectional relationship between oil prices and stock markets, in oil-exporting countries.

Other studies concentrate their interest in the investigation of the oil price shock origin, i.e. demand-side or supply-side shock. These studies include Hamilton (2009a,b), Lescaroux and

Mignon (2008), Barsky and Kilian (2004) and Terzian (1985). The origin of an oil price shock is an important component when studying the relationship between oil prices and stock markets. In particular, Lescaroux and Mignon (2008) suggest that supply-side shocks could be related to higher oil price volatility, although it may not be the only reason. Demand-side shocks also justify high oil price volatility. In addition, Hamilton (2009b) argued that demand-side shock deriving from industrialization of countries such as China could have a significant impact. He also voiced the opinion that lack of immediate response of oil-supply to a large scale increase in oil-demand could result to a demand-side shock. Kilian and Park (2009) advocated that demand side oil price shocks influence stock prices more than the supply-side oil price shocks. Demandside oil price shocks exercise a negative influence on stock prices due to the precautionary demand for crude oil, which echoes the uncertainty of future oil supply availability. However, they suggested that if the demand-side oil price shock is driven by global economic expansion, then higher oil prices will cause a positive effect on stock prices, which is in line with Hamilton's (2009b) views.

Another study regarding only the Chinese market is made by Cong et al.(2008). This paper investigates the interactive relationships between oil price shocks and Chinese stock market using multivariate vector auto-regression. Oil price shocks do not show statistically significant impact on the real stock returns of most Chinese stock market indices, except for manufacturing index and some oil companies. Increase in oil volatility may increase the speculations in mining index and petrochemicals index, which raise their stock returns. Both the world oil price shocks and China oil price shocks can explain much more than interest rates for manufacturing index. As for the GCC stock markets, Akoum et al. (2010) consider data from six oil-countries of GCC and two non-oil countries, over the period 2002 -2009. Their result is that for a long period of time the stock returns in these countries have not shown strong correlation with crude oil prices, but this behavior has changed from 2007 onwards, as they observed stronger correlations. Meanwhile, Abu Zarour (2008) investigated the effect of sharp increases in oil prices on stock market returns for five of the six GCC countries. Using VAR analysis and daily data from mid 2001 to mid 2005, he concluded that sharp oil price increases can predict GCC stock market prices, except for Abu Dhabi Stock Market.

All that said, a wealth of literature suggests that there is no relationship between oil price and stock markets; see for example Cong, Wei, Jiao, and Fan (2008), Haung, Masulis, and Stoll (1996) and Chen, Roll, and Ross (1986). Concerning the oil-exporting countries, Al Janabi, Hatemi-J, and Irandoust (2010) used bootstrap test for causality appropriate for non-normal financial data with time varying volatility and concluded that GCC stock markets are informationally efficient with regard to oil prices, i.e. oil prices do not tend to affect these stock markets and thus oil prices cannot be used as predictors for the GCC stock markets. Specifically for oil-importing countries, Al- Fayoumi (2009) found no evidence that oil price shocks affect the stock markets. Other authors suggest that oil prices do not seem to have any effect in the economy after the 1980s (Bernanke, Gertler, & Watson 1997; Blanchard & Gali 2007; Hooker 1996, 2002; Lescaroux & Mignon 2008; Nordhaus 2007). Miller and Ratti (2009) concluded that oil price effects are insignificant after 1999 due to oil price bubbles which have taken place since the early 2000. Jammazi and Aloui (2010) and Apergis and Miller (2009) painted the same picture suggesting that oil prices do not affect stock market performance. Such conclusions could originate from the fact that oil prices are not any more a significant source for economic downturn, as was suggested by Hamilton (1983).

6.0 Methodology and Data

6.1 Methodology

The paper intends to confine the methodology to a general application of multi-scale analysis as it is understood in wavelet literature. The basic idea is to consider a signal which can be decomposed by wavelet transform in different scales. The scales contain contributions of the signal of different frequencies. When embedded in an appropriate function space, the multiresolution (or multi-scale) analysis of a function (or signal or time series) can be performed. As was mentioned above, previous contributions have already attempted to provide a relevant decomposition of the oil price, in order to better understand the oil price impact on the stock price. The DWT is implemented practically via a pyramid algorithm derived by Mallat (1989). As described in Gencay et al. (2002) the analysis begins with data X_t , which is filtered by h_t and g_t . h_t are wavelet filters while g_t are scaling filters. It subsamples both filter outputs to half of their original length, keeps the sub-sampled output from the ht as wavelet coefficients and then repeats the process described above on the sub-sampled output of the scaling filter g_t . The major limitation of the method is that data must have a dyadic length.

Whitcher et al. (1999, 2000) have extended the notion of wavelet variance for the maximal overlap DWT (MODWT) and introduced the definition of wavelet covariance and wavelet correlation between the two processes, along with their estimators and approximate confidence intervals. To determine the magnitude of the association between two series of observations X and Y on a scale-by-scale basis the notion of wavelet covariance has to be used.

We employ the time-scale decomposition analysis by applying the maximal overlap discrete wavelet transform (MODWT). The MODWT is a variant of the discrete wavelet transform (DWT) that, unlike the classical DWT, can handle any sample size, is translation invariant (as a shift in the signal does not change the pattern of wavelet transform coefficients), provides increased resolution at coarser scales, and produces a more asymptotically efficient wavelet variance estimator than DWT.

There are different wavelets families available. These may include Haar wavelets, Daubechies wavelet, Minimum Bandwidth Discrete-Time Wavelets (MBDT) etc. Among them, Haar wavelets is the only symmetric compactly supported orthonormal wavelet. Daubechies wavelet can be viewed as a generalized version of Haar wavelet. Different wavelet families could accentuate different data characteristics in time scale domain and serve as a potential pattern recognition tool.

Though there are no universal criteria for the choice of the type of wavelets and their width, this choice must be dictated by the objective to balance two considerations. On the one hand, wavelet filters of too short width can introduce undesirable artifacts (unrealistic blocks) into the multi-

resolution analysis. As the width of the wavelet filter increases, it can better match to the characteristics of the time series, but on the other hand, the influence of boundary conditions becomes more severe, the localization of DWT coefficients decreases and the computation becomes more difficult. Percival and Walden (2000) suggest that the best strategy is to choose the smallest width of wavelet that brings "reasonable" results. They also point out that this strategy often results in the choice of the least asymmetric filter with width equal to 8, denoted LA(8).

The choice of the number of scales is a difficult issue. In some applications of multi-resolution analysis, it is dictated by some physical considerations of scale. Unfortunately, no such easy rule can be established for financial time series. Apparently for the data sampled at 15-minute intervals (32 observations per day) the level of decomposition must be higher than 5 in order to isolate intraday fluctuations (Percival & Walden, 2000). Our choice of the number of horizons is a compromise between the high enough portion of energy, explained by the details, and the accuracy of the approximation, which declines as the number of scales increases for a given number of observations.

To be able to study the interaction between two time series, how closely X and Y are related by a linear transformation, we need to apply a bivariate framework which called wavelet coherence. The best wavelet for feature extraction purposes is the Morlet wavelet, since it provides a good balance between time- and frequency localization. Also for the Morlet wavelet the Fourier period is almost equal to the wavelet scale used (Grinsted et al. 2004).

6.2 Data

We collect daily data for the three Islamic stock market indices and three non-Islamic indices The stock market indices are: the FTSE Bursa Malaysia Shariah index (FBMSHA), the Dow Jones Islamic Market index (DJIM), the Dow Jones Islamic Asia Pacific index (DJIAP), the Standard & Poor's 500 index (S&P 500), the Financial Times Stock Exchange index (FTSE 100) and the Tokyo stock exchange index (NIKKEI). The data are collected over the period from 15 January 2007 to 15 December 2012. The Brent spot prices are used to represent the international crude-oil market since they usually serve as reference prices for pricing crude oil and many other derivatives products using oil as underlying asset. All prices from both markets (oil and stock) are expressed in dollar terms and have been extracted from Datastream and Bloomberg Database.

Unlike the majority of previous studies which employ low frequency data (yearly, quarterly, monthly, and weekly), we use daily data in order to adequately capture the rapidity and intensity of the dynamic interactions between oil and stock prices. All price data are denominated in US dollars to take into account the impacts of exchange rates and to ease the comparison across countries. Daily returns are calculated from daily price data by taking the natural logarithm of the ratio of two successive prices. The statistical properties of the data are summarized in Table 1.

Table 1	Crude Oil	S&P500	FTSE100	NIKKEI	FBMSHA	DJIM	DJIAP
Mean	0.052	-0.045	-0.026	-0.033	-0.007	-0.015	-0.003
Minimum	-16.832	-10.188	-10.421	-11.566	-14.225	-9.637	-13.512
Maximum	18.13	11.569	12.161	11.844	15.394	11.589	10.713
Standard							
Deviation	2.455	2.269	1.909	2.071	2.747	2.017	1.946
Skewness	0.005	-0.051	-0.071	0.037	-0.379	-0.049	-0.202
Kurtosis	9.013	6.199	9.344	8.018	6.988	7.606	8.106
Jarque-Bera	1883.428	533.718	2096.979	1312.009	858.337	1105.308	1366.545
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

This table provides the basic statistics of daily crude-oil returns for 6 stock market indices. Data are over the period from 15 January 2007 to 15 December 2012.

The average daily returns on the stock market indices are all negative over our sample period under the effects of the recent global financial crisis 2007–2009, sparked by the US subprime crisis. The stock index S&P500 realised the worst performance (-0.045%), followed by NIKKEI and FTSE100. Inversely, the oil market experienced a positive average return, which is not surprising in view of the increasing trend in the price of oil over the last decade. Skewness is

negative for all stock markets except for NIKKEI, and positive for the oil market. This means that extreme negative and positive returns are likely to be realized for stock and oil markets respectively. Kurtosis coefficients are important in size and highly significant, indicating that outliers may occur with a probability higher than that of a normal distribution (They have fatter tails and longer left tails than a normal distribution). Accordingly, the Jarque–Bera test statistics strongly reject the null hypothesis of normality for all series.

7.0 Interpretations

7.1 Return Decompositions: A Multi-resolution Analysis of the Oil Price and Stock Returns

As variable for the oil price, we use the logarithm of the spot price Brent on a daily basis, from 15 January 2007 to 15 December 2012 and we use 7 levels of wavelet decomposition. As mentioned above, we use the MODWT transform for the decomposition.

The method used to decompose the time series in this thesis is the Maximum Overlap Discrete Wavelet Transform (MODWT), as it allows us to use a sample which size is not necessarily a multiple of a power of 2, and because its wavelet variance estimator is asymptotically more efficient than the one based on the DWT. Regarding the choice of the wavelet function, we follow the advice given by Gençay et al. (2002) which states that the longer the length of the wavelet, the better it approximates an ideal band pass filter. Given the shape of the original series, which is rather smooth, we therefore choose the Least Asymmetric wavelet of level 8, LA(8) (8 is the width of the filter), as the wavelet function.

The various decomposition levels we obtain correspond to time scales: D1 (2 to 4 months), D2 (4 to 8 months), D3 (8 to 16 months), D4 (16 to 32 months), D5 (2.7 to 5.3 years), D6 (5.3 to 10.6 years), D7 (10.6 to 21.3 years). We also obtain a smooth S7 which corresponds to the trend of the signal, while the details Dj correspond to fluctuations of various sizes. From Figure 1 to 7 represent the details of D1 to D7 and the smooth S7, obtained by applying the LA(8) to the oil price & stock market returns variables.

Given the properties of the wavelet decomposition, each detail represents the contribution of fluctuations of a specific time scale to the oil price variations & stock market returns variations, while the smooth S7 represents its trend. From these figures, we can see that, in a stock index each time scale has a dynamic of return and dynamics of the six stock market indices are different at the same levels. The shape of the smooth, which is continuously increasing & decreasing throughout the whole sample.

Turning to the wavelet details on the figures 1-7, we note that they are able to capture the classical oil shock events & stock returns. At the smallest level D1 (2 to 4 month scale), we observe a clear rupture in 2009, corresponding to the economic crisis 2008-2009. At level D2, (4 to 8 month scale) we can see an additional significant rupture in 4/2010. At levels D5 (app. 2.7 to 5.3 years scale) and D6 (app. 5.3 to 10.6 years scale), smaller shocks are merged into larger oil price movements. Another feature which can be observed from figure 1-7 is the cyclical shape of all details, especially of the larger ones, which exhibit troughs and peaks in a regular manner. This fact does not constitute a surprise in itself, as it is common for macroeconomic variables to follow cycles.



Figure 1: Multi-resolution of oil price (Logarithm of the Brent between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 2: Multi-resolution of stock market returns (Logarithm of S&P 500, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 3: Multi-resolution of stock market returns (Logarithm of FTSE100, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 4: Multi-resolution of stock market returns (Logarithm of NIKKEI, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 5: Multi-resolution of stock market returns (Logarithm of FBMSHA, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 6: Multi-resolution of stock market returns (Logarithm of DJIM, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.



Figure 7: Multi-resolution of stock market returns (Logarithm of DJIAP, between 15 January 2007 to 15 December 2012 on a daily basis). The top right cell represents the trend (S7) and the original oil price curve.

7.2 Wavelet Correlations

When analysing the relationship between oil price and stock price, one major concern is whether one is leading the other. To investigate this issue, figure 8 shows the wavelet correlation between the two variables at all seven levels corresponding to 6 pairs (S&P 500-Brent, FTSE 100-Brent, NIKKEI– Brent, FBMSHA–Brent, DJIM-Brent and DJIAP-Brent).

Regarding figure 8, we can see that

- i) Each country has a different correlation between oil price and stock price
- ii) Most of the correlations between the two variables appear to be significant at level 6 except for correlations Brent –FBMSHA and Brent–DJIAP are always positive. The correlation of FBMSHA and crude oil can be explained by the fact that FBMSHA is based in Malaysia, a net oil-exporting country.
- iii) The correlations between the two variables (S&P500– Brent and FTSE100-Brent, DJIM-Brent) only appear to be significant at level 6, with negative values. At the other levels, the correlation between the two variables is not significantly different from zero or positive. In fact, it is suitable to US (S&P500) and UK (FTSE100) as the countries are engaged in both oil-exporting and oil-importing activities.
- iv) The correlations between the two variables (Brent-NIKKEI) is negative or is not significantly different from zero. This finding was due to NIKKEI being based in the Japan, a resource scarce country that resorts to importing crude oil to support its economic activities.



Figure 8: Wavelet correlation of BRENT and Stock Market Indices

7.3 Co-movement of Crude Oil and Stock Markets: Wavelet Coherence Analysis

The research on comovement of different stock markets, commodity markets, exchange rates and many other variables have been discussed by Dajcman et al. (2012). Different methods can be applied to find the co-movement, with such methods as linear correlation (the Pearson's correlation coefficient), Vector autoregressive models, the co-integration, the family of GARCH models, regime switching models and the wavelet analysis. In this paper, we will focus on wavelet analysis and more precisely on the wavelet coherence (WTC).

Rua & Nunes (2009) analyzed monthly returns in the period 1973- 2007 among stock markets of four developed countries, namely USA, UK, Germany and Japan. Their analysis led to a discovery that the comovement among these stock markets is stronger on higher frequencies, from which they concluded that international diversification of portfolio might play a key role especially for short term investors. Barunik et al. (2011) did research on the comovement between Central European Economies, more precisely, they analyzed the comovement of stock market index returns between Czech Republic, Poland, Hungary and Germany, which was used as a benchmark. Their results based on high frequency data revealed that the comovement differed in time and also in frequency between economies during the period 2008 - 2009. Ranta (2010) used the WTC for an analysis of contagion among stock markets like USA, UK, Japan and Germany between years 1984 and 2009. Results indicate that after a crisis the co-movement between stock markets increased, especially on high frequencies and this suggests the existence of contagion.

The comovement of commodities and stock markets was a subject of several papers too. Starting with Aguiar-Conraria & Soares (2011), they used the WTC to analyze the comovement between S&P500 and Oil prices. Their dataset included monthly returns for the period starting in July 1954 and ending in December 2010. By using the wavelet partial coherence with controlling variables they concluded that there was a significant comovement in mid-1970s and mid-1980s and also in the early 1990s. Another paper written by Vacha & Barunik (2012) is studying the comovement between crude oil, gasoline, heating oil and natural gas. Based on their results they concluded that comovement varied a lot during the analyzed period, which started in 1993 and

ended in 2010. Moreover, the comovement did not vary only in time, but also in terms of frequencies, which provides a completely new information about the development of studied returns.

The wavelet coherence is a very efficient tool how we can study when and at what scales examined time series comove. Following figures depict the wavelet coherence into a contour plot. The time domain is represented by x-axis and the frequency by y-axis. In addition, the frequency is represented by the period, i.e. the higher frequency the lower the period. We focus on the comovement between each of stock indices and crude oil.

The interpretation of the figures is based on the color of regions, blue color means that there is low or even no comovement. On the other hand, red regions with a thick black outline mean that there is a significant comovement between time series. As a result of this we can obtain very detailed results based on the time domain and the frequency domain at the same time. Another thing that helps us to interpret results are so called phase arrows, which show the relative phasing of time series at given scale. If arrows are pointing to the right that means that time series are in phase, opposite direction means anti-phase. If they are pointing down then the first variable is leading the second one and if they are pointing up then the second variable is leading the first one. Based on the wavelet coherence, we analyse the interdependence of crude oil and stock market indices.

Starting with S&P500 and its comovement with crude oil, we observe that S&P500 did not comove with crude oil significantly from 2007 to 2009, only some periodic episodes of interdependence at lower frequencies. The interdependence of crude oil and S&P500 became significant in the second half of 2009 and also in 2010 at certain frequencies. In addition we observed a very strong comovement at almost all frequencies starting in 2011.

We continue with FTSE100 and crude oil, the wavelet coherence revealed very similar patterns as in case of S&P500. We observe that crude oil comoved with the stock market index in different periods and only on certain frequencies. More significant comovement is in the second half 2009 as there was a strong comovement at higher frequency. In 2010 we observed a

comovement starting at quite low frequencies and last one in 2011 at almost all frequencies. In the case of NIKKEI and crude oil, we observe a significant comovement in 2008 at low frequencies. There is a also very significant comovement on 8 - 64 day period in 2010. Time series seem to be in phase, because arrows point to the right. Also in the second half of 2011 there is a significant comovement at low frequencies.

We also observe some significant comovement among FBMSHA and crude oil. We observe a very significant comovement with crude oil in the first half of 2010 on 10 - 35 day period and also on 30- 40 day period in the second half of 2010 and throughout 2011 at lower frequency. DJIAP and crude oil provide very similar results with FBMSHA comovement with crude oil. Both comovement of FBMSHA and DJIAP are not significant in 2007 and 2008, before the onset of the global financial crisis. The comovement between DJIM and crude oil reveals comovement in 2009 on 8 - 64 day period and then continues in 2010 on 30 - 62 day period. We can conclude that there is any significant comovement between DJIM and crude oil in 2010 at 32 day period.





8.0 Conclusions

While most previous studies rely on a VAR-type methodology to tackle the issue of the stock market impact of oil price disruptions, this paper uses a more innovative approach based on the wavelet theory. This decomposition enables us to decompose a signal into various timescales without losing time related information and to capture the various time scales at which the factors that influence the oil price operate. It is useful in revealing that the nature of the oil price–stock market relationship is not the same through all time scales, and that a multi-scale analysis can help unravel the changes that can occur in such relationships when various timescales are considered. Our main findings may be summarized as follows.

First, in a country, each time scale has a corresponding dynamics of return. Second, the higher variance when the level increases, it means that if bigger horizon is higher risk. Third, investigating the relationship between the oil price and stock markets indices, we show that at low wavelet levels (high frequency cycles), both the oil price and the stock index seem to entertain a feedback relationship, where they are both leading and lagging each other. At larger wavelet levels however, only the stock index happens to be leading the oil price with a positive correlation. And this relationship is different corresponding to each different stock index. We then analysed comovement in the frequency and the time domain using wavelet coherence. Crude oil market comoved with stock markets especially in the second half of 2009 and at almost all frequencies. So even during the crisis, when markets become volatile, crude oil was not comoving with indices significantly in most of the periods. As a whole, investors should adjust their portfolios at different countries to attain maximum portfolio diversification strategy based on their multi investment horizons.

9.0 Future Recommendations

The results reported in this present analysis can be extended in several ways in future research. For instance, given the rapidly increase of emergent economies share of the overall energy demand and the world economic growth, it would be interesting to investigate the cyclical co-movements and causality relationships between the world demand on oil prices, oil prices and GDP in order to deepen our understanding to the link between oil prices and macroeconomic variables. Another interesting topic for future research, using the same methodology, the dynamic cyclical co-movements of oil prices can be empirically investigated with other macroeconomic variables such as consumer prices, unemployment, and stock prices.

There are also other avenues for future research. First, a sector analysis of the long-run linear and nonlinear links between oil and stock prices would be informative. Second, the econometric tools applied in this paper could be used to examine the effects of other energy products, such as natural gas. Third, a study of nonlinear causality between oil or other energy products and sector stock returns should be relevant. Finally, one of the future challenges would be to investigate whether oil price constitutes a common business cycle component across a few countries, that is affecting their sectoral indices indirectly.

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

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

Arouri, M.E.H., & Khuong, N.D. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. Energy Policy, 38(8), 4528-4539.

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

Bernanke, S.B., Gertler, M., & Watson, M. (1997). Systematic monetary policy and the effects of oil price shocks. Brookings Papers on Economic Activity, 1, 91-148.

Berument, M.H., Ceylan, N.B., & Dogan, N. (2010). The impact of oil price shocks on the economic growth of selected MENA1 countries. Energy Journal, 31(1), 149-176.

Bharn, R., & Nikolovann, B. (2010). Global oil prices, oil industry and equity returns: Russian experience. Scottish Journal of Political Economy, 57(2), 169-186.

Bjornland, C.H. (2009). Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy, 2(5), 232-254.

Blanchard, J.O., & Gali, J. (2007). The macroeconomic effects of oil price shocks. Why are the 2000s so different than the 1970s? National Bureau of Economic Research, Working Paper 13368.

Chen, S.S. (2009). Do higher oil prices push the stock market into bear territory? Energy Economics, 32(2), 490-495.

Cifarelli, G., & Paladino, G. (2010). Oil price dynamics and speculation: A multivariate financial approach. Energy Economics, 32, 363-372.

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

Du, L., He, Y., & Wei, C. (2010). The relationship between oil price shocks and China's macroeconomy: An empirical analysis. Energy Policy, 38, 4142–4151.

Gisser, M., & Goodwin, T.H. (1986). Crude oil and the macroeconomy: Tests of some popular notions. Journal of Money, Credit and Banking, 18(1), 95-103.

Hamilton, D.J. (2009). Causes and consequences of the oil shock of 2007-08. Brookings Papers on Economic Activity, Spring 2009, 215-261.

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

Hammoudeh, S., Bhar, R., & Thompson, M.A. (2010). Re-examining the dynamic causal oilmacroeconomy relationship. International Review of Financial Analysis, 19, 298–305.

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

International Energy Agency. (2010). The impact of the financial and economic crisis on global energy investment. IEA background paper for the G8 energy ministers' meeting 24-25 May 2010.

Jammazi, R., & Aloui, C. (2010). Wavelet decomposition and regime shifts: Assessing the effects of crude oil shocks on stock market returns. Energy Policy, 38(3), 1415-1435.

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

Jimenez-Rodriguez, R. (2009). Oil price shocks and real GDP growth: Testing for nonlinearity. Energy Journal, 30(1), 1-24.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053–1069.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. International Economic Review, 50, 1267-1287.

Lee, Y-H., & Chiou, J-S. (2011). Oil sensitivity and its asymmetric impact on the stock market. Energy, 36, 168-174.

Lescaroux, F., & Mignon, V. (2008). On the influence of oil prices on economic activity and other macroeconomic and financial variables. OPEC Energy Review, 32(4), 343-380.

Malik, F., & Ewing, B. (2009). Volatility transmission between oil prices and equity sector returns. International Review of Financial Analysis, 18(3), 95-100.

Miller, J.I., & Ratti, R.A. (2009). Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics, 31(4), 559-568.

Mork, A.K., Olsen, O., & Mysen, H.T. (1994). Macroeconomic responses to oil price increases and decreases in seven OECD countries. Energy Journal, 15(4), 19-35

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

Oberndorfer, U. (2009). Energy prices, volatility, and the stock market: Evidence from the Eurozone. Energy Policy, 37(12), 5787-5795.

O'Neill, J.T., Penm, J., & Terrell, D.R. (2008). The role of higher oil prices: A case of major developed countries. Research in Finance, 24, 287–299.

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

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

Stiglitz, J. (2009). The current economic crisis and lessons for economic theory. Eastern Economic Journal, 35, 281–296.