Impact of oil price changes on stock returns of UK oil and gas companies: A wavelet-based analysis

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Abstract

The relationship between oil and stock is important because oil is the key production input for most industries and stock market performance, to some extent, reflects the economic conditions. However, the relationship between oil price and stock prices of oil and gas industry companies is more complex because oil plays the roles as both costs and profits for this kind of company. Unlike previous research of the relationship between oil and oil and gas companies using randomly chosen data frequencies and only based on time domain, we examine the impact of oil price changes on stock returns of UK oil and gas companies through various time scales during the sample period from June 19, 1996 to December 30, 2016 by using both continuous wavelet transform and discrete wavelet transform. We found the following several important results: First, the dependence between oil and UK oil and gas companies' stocks is weak in the short term but higher in the medium-run and long-run. Second, the Granger causality running from oil to stock on daily basis is limited but the significant bidirectional Granger causality relations running between the oil price and oil and gas stock prices can be observed at scale 3, 4 and 5. Moreover, the oil price shocks at these scales have significant negative and positive effects on stock prices of UK oil and gas companies. Third, the short term oil price risk is weak, which means that short-term UK oil and gas industry investors can still diversify their portfolios' risk by adding oil, however, the long-term investors should be more concerned about oil price risk.

Keywords: Oil prices; Oil and gas; Granger causality; Multiscale; Wavelet coherence

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1. Introduction

Starting with the previous study of Hamilton (1983), oil price has been widely documented as a crucial determinant of economic growth and international political stability. The impact of oil price changes on the stock market performance has been focused and investigated by a variety of literature. Based on the theoretical equity pricing model which suggests that the current value of stocks is dependent with the discounted future cash flows, the oil price changes can affect stock prices through two aspects. On the one side, since the crude oil is a direct or indirect production factor for most companies, the increased oil price will cause a increase in companies' production cost and then decrease the companies' expected future profits and the current companies' stock prices(Huang et al. (1996) and Aloui and Jammazi (2009)). On the other side, in the long-run, the continuing increasing oil price will imply inflation pressures, which leads Central Banks to control prices in terms of increasing interest rates. Consequently, the stock prices are supposed to be lower due to the higher discount rates in the equity valuation method(Basher and Sadorsky (2006)).

In the prominent studies of Jones and Kaul (1996) and Sadorsky (1999), they found a negative relationship between oil prices and stock returns, which is consistent with the expectation derived from the above mentioned theoretical equity valuation model. However, the impact of oil price returns on the stock returns of oil and gas companies is more complex because the companies' production cost and profit are both dependent on the oil price. Oil and gas industry occupies a large market capitalization proportion of the stock market for most countries and the largest volume products of this industry are fuel oil and gasoline which is the key production input for other industries. Therefore, the investigation of the stock performance for oil and gas companies is important for both investors and policy makers. Ramos and Veiga (2011) indicate that the evolution of companies' revenues rely on whether the companies can pass oil price hikes on to customers to offset the increased production and operation cost due to the growth of oil price. A variety empirical evidence of previous studies, such as Faff and Brailsford (1999), Sadorsky (2001), Boyer and Filion (2007), Ramos and Veiga (2011) and Moya-Martínez et al. (2014), indicates that oil price changes have a positive effect on stock returns of oil and gas companies. This means, for oil and gas companies, increased oil price does not depress oil demand much and the companies can pass oil price increases on to customers easily.

However, all the previous research about the relationship between oil price changes and stock price returns of oil and gas companies rely on time domain analysis and the results are restricted to two time scales, namely, the short and the long run which are randomly chosen. This means that the time-domain analysis of the relationship between oil and stock markets may miss the effects caused by using different time intervals such as daily basis, weekly basis or monthly basis. In addition, the arbitrary choice of data basis can also cause information loss problem, which brings about bias for the investigation of the linkage between oil and stock. Therefore, in this study, we investigate the impact of oil price changes on the stock returns of UK oil and gas companies by using wavelet transform analysis which characterizes the oil-stock price relationship at different time scales. Moreover, decomposing the return series of oil-stock into different time scales can mimic the heterogeneity of different agents who have different consumption requirements, risk tolerance level, heterogeneous assimilation of information and heterogenous belief in the financial market(Chakrabarty et al. (2015)). Based on the Fractal Market Hypothesis (FMH) proposed by Peters (1996), the dynamic of stock prices is because of the different responses of heterogenous investors to the information. For example, negative news may trigger short-term investors to sell stock, while long-term investors may consider the same news as a good signal for buying stock.

We employed continuous and discrete wavelet transform to examine the dependence and correlation between oil and stock returns of oil and gas companies at different time and across different time scales. We also explored the direction of causality between oil and oil and gas stock returns for different time horizons through linear Granger causality tests based vector autoregressive model (VAR) and discrete wavelet transform. The Granger causality test across different time scales allows to justify whether the investors with different investment horizons or policy makers for designing policies of different time length can utilize the past information of oil and stock markets for prediction. After investigating the Granger causality, we examined the response direction and duration of the stock returns of oil and gas companies to the oil price shocks using impulse response function. This enables us to analyze how stock price of oil and gas companies respond to the oil price increases in different time horizons. Furthermore, we used variance decomposition to quantify the contribution to the volatility of stock returns of oil and gas companies from oil price changes across different time scales, which allows to examine the influence of oil price on stock prices of oil and gas companies in different time horizons. Finally, we explored the oil price risk for oil and gas industry investors with different investment horizons by estimating the oil price risk exposure using the wavelet covariance and wavelet variance.

Our research has several contributions to the current literature: First, we applied wavelet-based analysis to assess the strength of the co-movement between returns of oil price and stock price of oil and gas companies over different time horizons (or scales) and how such strength has changed over time. We also identify the lead-lag relationship between oil price and stock price returns across different time scales over time based on wavelet transform analysis. Second, we conducted Granger casuality test on return pairs of oil and stock on different time scales, which is important for investors and policy makers to know about the information transmission between the stock and oil markets. Third, we investigated the response direction and duration of the oil and gas stocks to the oil price changes using impulse response function and variance decomposition method based on VAR model. Fourth, we estimated the oil price risk exposure for oil and gas stocks on different time scales, which is important for investors and hedgers who have different investment horizons. We selected 11 UK oil and gas companies quoted on the London Stock Exchange and they have been traded continuously more than 20 years. The sample companies cover companies belonging to different sub-sectors, namely, integrated companies, oil & gas exploration and production companies and oil & gas equipment and service companies. The companies from different sub-sectors may response to oil price changes in different ways because of different business and service fields. Very little research has directly examined the impact of oil prices on the equity values of UK-listed oil and gas companies, which is a substantive omission from the literature.

We focus on UK oil and gas industry due to the following two main reasons. First, according to El-Sharif et al. (2005), the UK oil and gas industry remains the largest in the European Union and accounted for 8% of Britains exports in June 2004. But the UK returned to being an energy importer in 2004[1]. So the transfer from oil exporting country to oil importing country may also change the relationship between oil and stock price of UK oil and gas industry. Second, oil and gas industry is also vital for UK economy because it pays high corporate taxes to the government and the supplies large number of job opportunities. Specifically, over £330 billion has been paid in corporate taxes since production on the UKCS (UK Continental Shelf) began and around 330,000 jobs are currently supported by the offshore oil and gas industry across the UK[2]. The sample period spans from June 19, 1996 to December 30, 2016 which is more than 20 years and covers the global financial crisis period and recent oil price slump since 2014.

Our empirical results can be summarized into several aspects as follows: First, co-movement strength for stock prices of UK oil and gas companies and oil price is small in the short term but become bigger in the long term, which suggests that

[1] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/516837/UK_Energy_in_Brief_2015.pdf

[2] http://oilandgasuk.co.uk/wp-content/uploads/2016/09/Economic-Report-2016-Oil-Gas-UK.pdf

no significant contagion effects exist but positive interdependence exists. Moreover, during global financial crisis, oil and gas stock returns led oil price changes significantly at higher scales. Second, the Granger causality running from oil to stock on daily basis is limited, however, significant Granger causality running from stock to oil can be observed for all companies. The bidirectional Granger casuality relationship between oil and UK oil and gas stocks evident in medium and medium-long term. This above results are consistent with previous studies in which monthly or quarterly price changes and oil and gas stock returns are used such as Boyer and Filion (2007), Ramos and Veiga (2011) and Diaz and de Gracia (2017). Third, by using impulse response function and variance decomposition, we found that the oil price can only cause UK oil and gas stock prices to fluctuate in a short period. However, the oil price has significant effects on stock prices of UK oil and gas companies at scale 3, 4, 5 corresponding to 8-16 days, 16-32 days and 32-64 days, respectively and the effects can be both negative and positive. This means that the oil price shocks measured by weekly, semi-monthly, monthly and quarterly basis are important. Fourth, we also found that short-term investors of UK oil and gas industry bear very small oil price risk but the oil price risk is higher for long-term investors.

The rest of the paper is laid out as follows. Section 2 provides a brief review of two literature strands. One is about the relationship between oil price and oil and gas stock returns. The other is about the wavelet analysis implications on relationship between oil price and stock markets. Section 3 describe the data used in this research. Section 4 introduces continuous and discrete wavelet transform, VAR model, impulse response function and variance decomposition methods. Section 5 describe our empirical findings and Section 6 concludes this paper.

2. Literature review

2.1. Relationship between oil price changes and oil and gas companies' stock returns

There exists a strand of literature investigating the relationship between oil price changes and stock price returns of oil and gas industry by using econometrics methods on time domain. Faff and Brailsford (1999) examined the influence of oil price changes on the stock returns oil Australian oil and gas companies using a two-factor model including market beta and oil price changes as risk factors. The oil price risk exposure was found to be significantly positive. The same results were also found by Sadorsky (2001) and Boyer and Filion (2007) for Canadian oil and gas industry as well as El-Sharif et al. (2005) for UK oil companies. However, because El-Sharif et al. (2005) used London Brent Crude Oil Index spot barrel prices in US $, the currency risk of the pair UK Sterling/US Dollar may be embedded in the oil price risk and brought about bias. Park and Ratti (2008) also found empirical evidence suggesting that oil price rises have a positive impact on stock returns of oil and gas industries of 13 European countries. Similarly, Oberndorfer (2009) found that oil price growth led to an appreciation in gas stocks in European countries. In addition, from a global angle, Ramos and Veiga (2011) investigated risk factors for the equities of oil and gas industry in 34 countries and found that oil price was a global priced risk factor. By dividing the countries into developed countries and emerging countries, they found that oil and gas industry in developed countries responded stronger to oil price changes than emerging countries. Moreover, their empirical evidence indicated that oil price rises had a greater impact than oil price drops. Furthermore, Chang et al. (2009) investigated the volatility spillover effects between the returns of crude oil futures and stock prices of oil companies during the period from November 14, 1996 to February 20, 2009 based on daily data. They indicated that conditional correlations between oil price changes and oil company stock returns were very low and they did not found significant spillover effects between oil and stock returns. Recently, Phan et al. (2015) investigated the effect of oil price changes on stock returns of oil producers and oil consumers and empirical evidence showed that stock returns of oil producers were affected positively by oil price changes. Sanusi and Ahmad (2016) analyzed the determinants of the U.K. oil and gas stock returns through multi-factor asset pricing model and they found that oil price shock had impact on the stock returns of oil and gas companies. On the other hand, Diaz and de Gracia (2017) found a significant positive impact of oil price shocks on real stock returns in oil and gas companies by using an unrestricted VAR model. Moreover, the research of Kang et al. (2017) indicated that oil demand-side shock had a positive effect on the stock returns of oil and gas companies, while shocks to policy uncertainty have a negative effect on the returns. In general, co-integration analysis, Granger causality test, multi-factor regression model and volatility spill-over analysis are most commonly used methods for examining the relationship between oil price and oil and gas companies' stock returns. Comparing the empirical evidence of Chang et al. (2009) and others, we found that the effects of oil price changes are heterogeneous by using different data frequencies.

2.2. Wavelet analysis for relationship between oil price changes and stock markets' performance

The other strand of literature is about the utilization of wavelet analysis for investigating the relationship between oil price changes and the performance of stock market index.The details of the literature are displayed in the subsequent parts.

After denoising the price series with wavelet method, Jammazi and Aloui (2010) investigated the impact of the crude oil shocks on the stock market returns for UK, France and Japan over the period from January 1989 to December 2007 using a Markov-Switching Vector Autoregressive approach. Their results indicated that crude oil shocks did not affect the recession stock market periods(except for Japan) but they significantly reduce moderate and/or expansion stock market periods temporarily. By using continuous wavelet transform, Akoum et al. (2012) studied the dependence between stock market returns and OPEC basket oil price changes for the six Gulf Cooperation Council (GCC) countries and two non-oil producing countries in the region across different time scales. Their evidence showed that oil and stock returns in these countries were not strongly linked in the short term but the dependencies were much stronger in the long term. Madaleno and Pinho (2014) investigated the relationship between oil prices and world general and stock market indices on a daily scale by scale basis by using continuous wavelet transform during the period from December 1992 and October 2012. Their results showed that the relationship between oil prices and sector stock returns was unclear where mostly stock led oil. They also found a bidirectional relationship between both series for large time scales, which could be associated with fundamentalist traders. Reboredo and Rivera-Castro (2014) examined the relationship between oil and stock markets in Europe and the USA at the aggregate and sectoral levels using wavelet multiresolution analysis during the period from June 2000 to July 2011. They showed that oil price changes had no effect on stock market returns in the before global financial crisis except for oil and gas companies, however, they found evidence of contagion and positive interdependence since the financial crisis happened. They also indicated that no lead-lag effects existed in the pre-crisis period but oil price led stock prices and vice versa for higher frequencies after financial crisis. By proposing a wavelet-based MGARCH approach, Khalfaoui et al. (2015) studied the linkage of crude oil market (WTI) and stock markets of the G-7 countries and explored the mean and volatility spillovers of the oil and stock markets across different time scales. Empirical evidence confirmed the existence of significant volatility spillovers and dynamic time-varying correlations for various market pairs. Moreover, they found WTI market was leading in most time. By using the similar method, Liu et al. (2017) studied the mean and volatility spillovers between WTI crude oil prices and stock indices of US and Russia for the period January 2003-December 2014. Their results indicated that spilover effects were different in terms of strength and direction across wavelet scales. Martín-Barragán et al. (2015) examined the impact of the crashes in oil and stock markets on the correlations between stock and oil markets by using discrete wavelet transform. Their results showed that correlation between oil and stock markets tended to be stable in non-shock phases, around zero, but changed due to the shocks of the oil and stock markets and the contagion effect during the 2008 and 2011 was also confirmed empirically. Reboredo et al. (2017) examined co-movement and causality between oil and renewable energy stock indices' prices using continuous and discrete wavelets for the period 2006-2015. They found no linear causality at higher frequencies but unidirectional and bidirectional linear causality at lower frequencies. Moreover, the dependence between oil and renewable energy returns was weak in the short term but gradually strengthened as the time horizons increase. Huang et al. (2015), Huang et al. (2016) and Huang et al. (2017) investigated the impact of oil price on the stock market performance in China using wavelet-based analysis. They found the bidirectional Granger causality relationships between energy sector stock index and the crude oil price existed in the short, medium and long terms and the energy sector index responded to crude oil price shocks negatively in the short run but positively in the medium and long runs. Moreover, the Granger causality tests for the pair of Brent oil price and Shanghai Composite index were heterogeneous for different time scales. Specifically, Brent and stock had stronger correlation in the high (1-14 days) and medium frequency (14-128 days) bands. In addition, both oil price growth and decrease had significant effects on Chinese stock returns for each time horizon, however, the response amplitude of the stock market to the oil price changes was enhanced as the time horizon lengthens and the response direction varies across different time scales. Furthermore, they found no persistent asymmetric effects of the oil price on the stock market across time scales but the impact of oil price shocks for longer time horizons should be paid more attention by the policy makers and investors. In summary, the relationship between oil and stock markets is different at different time scales and also heterogeneous across different sectors and countries.

3. Data and descriptive statistics

In this study, we focus on the individual stocks because the dependence structures between stock and oil may be changed after grouping stocks into portfolios or indices. We chose 11 UK oil and gas companies listed on the London Stock Exchange and they are also the components of Thomson Reuters datastream UK oil and gas stock index where the stocks are group together based on the Industry Classification Benchmark (ICB). These companies' stocks have been traded for more than 20 years and the sample companies include integrated companies, oil & gas exploration and production companies as well as oil & gas equipment and service companies, which enables us to analyze the impact of oil price changes on different sub-sector companies. We used WTI crude oil spot price which is considered as a world benchmark for oil prices.

We collected daily basis data for both oil and stock prices during the period from June 19, 1996 to December 30, 2016 from Thomson Reuters datastream. The sample covers several important periods for both oil and stock market such as Iraq War in 2003, quotas cut decisions of OPEC in 1999, 2002, 2004, 2008, Global Financial Crisis(2008-2010), European Sovereign Debt Crisis(2009-2012) and the recent oil price downward movement period (2014-2016). We excluded the non-trading days of stocks for the pairs of oil/stock, therefore, the length of WTI prices was dependent on the length of each individual stock. We chose the UK sterling as the reference currency to avoid the bias caused by foreign exchange currency risk to impact of oil price changes. We computed the stock returns and oil price changes as the first difference of the natural logarithm of the daily prices.

Figure 1 illustrates the price dynamics for WTI and different UK oil and gas stocks during the sample period. It shows that the price of oil and gas stocks did not always co-move with WTI oil price. For most companies, the stock price had the similar increasing trend with oil price during the period from 2002 to 2008 which can be seen as the first oil price increasing period. Then, during the financial crisis period, namely, 2008, all the oil and gas stocks suffered from a decreasing movement. After that, almost all the companies's stock prices experienced a second increasing trend together with the increasing oil price during the period from 2008 to 2010 except BP and Northern Petroleum. However, from 2010 to 2014, the oil price started to fluctuate and during this period, the stock prices of Cape, Premier Oil, Cairn Energy, Tullow Oil, Jkx Oil & Gas and Northern Petroleum began to decrease, which was earlier than the starting point of oil price decline, namely, 2014.

Table 1 reports the companies' names and sub-sector names and Table 2 reports the descriptive statistics for stock returns of selected companies. The mean and median of daily returns for all companies are close to zero. According to the difference between maximum and minimum values as well as standard deviations, we found that integrated oil and gas companies, BP and Royal Dutch Shell were less volatile compared with other companies. Skewness was negative for BP, Cape, Hunting, Amec Foster Wheeler and Jkx Oil & Gas whereas positive for other companies. The high kurtosis values indicate that all series exhibited fat tails in their distributions. The Jarque-Bera(JB) test rejected the normality of the unconditional distribution strongly and consistently. Moreover, the empirical statistics of Ljung-Box(LB) and autoregressive conditional heteroscedasticity-Lagrange multiplier (ARCH-LM) tests confirm the existence of serial correlation in the mean (except Tullow Oil) and volatility. Finally, the unconditional Pearson correlation coefficients showed that the linear correlation between oil price changes and oil and gas stocks returns was heterogeneous for different companies, which is not consistent with previous studies.

4. Methodology

Wavelets are signal processing techniques in finance and economics, which is developed from filtering approaches and Fourier analysis(Percival and Mofjeld (1997) and Percival and Walden (2006)). The main advantages of wavelet analysis are the fact that we can combine information from both time and frequency domains and strong assumptions about the data generating process for the series under investigation are not necessary, which overcomes most of the liminations of filtering methods and Fourier analysis. Wavelets allow us to decompose a given time series $x(t)$ into different series each associated with a different time scale, which is known as multiresolution analysis. The decomposed sub-series with different frequencies represent short-term, medium-term and long-term dynamics of the original time series. Therefore, investors with short-term horizons will focus on the lower scale (high frequency) components of the original series, while long-term investors will focus on the upper scale (low frequency) components. Detailed descriptions of the wavelet analysis can be found in literatures such as Torrence and Compo (1998), Ramsey and Lampart (1998), Rua and Nunes (2009) and Rua (2010). We will describe the details of the methods in following sections.

4.1. Continuous wavelets

Wavelets are functions generated from a single mother wavelet, $\psi(\cdot)$, given by:

$$\psi_{\tau,t} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right), \tag{1}$$

where τ and s are the location and scale parameters that determine the exact time position and dilation that is related to frequency and where $1/\sqrt{s}$ is a normalization factor to make certain that the wavelet has unit variance. Following most previous studies, in our empirical analysis, we used the Morlet wavelet, which allows good identification and isolation of periodic signals since it provides a balance between localization of time and frequency. The Morlet wavelet including a Gaussian-windowed Fourier transform with sine and cosine oscillating at the central frequency, is given by:

$$\psi(t) = \pi^{\frac{-1}{4}} e^{iw_0 t} e^{\frac{-t^2}{2}}, \tag{2}$$

where $\pi^{\frac{-1}{4}}$ is a normalization constant that ensures that the wavelet has unit energy, $e^{\frac{-t^2}{2}}$ is a Gaussian envelope with unit standard deviation and $e^{iw_0 t}$ is a complex sinusoid. We set $w_0 = 6$ to represent a suitable trade-off between time and frequency localization.

4.1.1. Continuous wavelet transform

The continuous wavelet transform, with respective to the Morlet wavelet, is a function $W_x(s)$ defined as:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t - \tau}{s} \right), \tag{3}$$

where * refers to the complex conjugate and where the scale parameter, s controls the length of the wavelet and we can extract frequency information from the time series by changing the values of s, and where τ denotes the position.

4.1.2. Wavelet coherence

Following Rua and Nunes (2009), we computed the wavelet coherence of two time series to capture their dependence in the time and frequency domains. First, we specify the two financial time series, namely, oil and gas stock returns and oil price changes (denoted by $x(t)$ and $y(t)$) with the wavelet transforms $W_x(\tau, s)$ and $W_y(\tau, s)$ and the the cross-wavelet spectrum $W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s)$ (* denotes the complex conjugate) which depicts the local covariance between two time series at each scale or frequency. Then, we calculated the wavelet squared coherence that is defined as:

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau, s))|^2}{S(s^{-1}|W_x(\tau, s)|^2)S(s^{-1}|W_y(\tau, s)|^2)}, \tag{4}$$

where S indicates a smoothing operator in time and scale which guarantees that the squared coherence is not always equal to 1(see Priestley (1981)). $R^2(\tau, s)$ is closely similar with the correlation coefficient, with values close to zero indicating weak dependence and values close to one indicating strong dependence. Due to the unknown theoretical distribution of the wavelet coherence coefficient, we computed the statistical significance using Monte Carlo procedures(Torrence and Compo (1998)).

4.1.3. Phase difference

We cannot know whether the dependence is positive or negative by using wavelet coherence since it is squared, therefore, we use the phase difference to identify the dependence signs and the lead-lag relationship.The phase difference between $x(t)$ and $y(t)$ is defined as follows(Bloomfield et al. (2004)):

$$\phi_{xy}(\tau, s) = tan^{-1} \left(\frac{\Im S(s^{-1}W_{xy}(\tau, s))}{\Re S(s^{-1}W_{xy}(\tau, s))} \right), \text{ with } \phi_{xy} \in [-\pi, \pi], \tag{5}$$

where $\Im$ and $\Re$ are the imaginary and real parts, respectively, of the smooth power spectrum. We identified the phase relationships between oil and gas stock returns and oil price changes in the coherence phase by using the arrows: (1) the two series are in phase (anti-phase) or the dependence is positive (negative) when the arrows point to the right(left); and (2) when the arrows point down (up) the oil price changes (oil and gas stock returns) lead the oil and gas stock returns (oil price changes) by 90°.

4.2. Discrete wavelets

In the continuous wavelet analysis, the position parameter and translation parameter, τ and s can be varied continuously, which brings about redundant information. Therefore, we also used discrete wavelet transform to analyze the correlation, causality between oil price changes and oil and gas stock returns across different time scales and we also calculated the oil price risk across different scales for oil and gas stock returns based on discrete wavelet transform. The discrete and continuous wavelet analysis can be considered as robustness check for each other. The approach uses discrete values of scale and translation parameters to reduce redundancy. The motivation of discrete wavelet transform is to decompose the original time series into components associated with different scales of resolution. There are two basic wavelets for each wavelet family, namely, father wavelet and mother wavelet. Father wavelet extract low frequent components from the original series whereas the mother wavelet captures deviation from the trend. The mother (φ) and father (ψ) wavelets satisfies the following fundamental properties:

$$\begin{aligned} &\int_{t=-\infty}^{\infty} \varphi(t)dt = 1 \\ &\int_{t=-\infty}^{\infty} \psi(t)dt = 0 \\ &\int_{t=-\infty}^{\infty} |\psi(t)|^2 dt = 1. \end{aligned} \tag{6}$$

Their definitions are given by:

$$\begin{aligned} &\varphi_{j,k}(t) = 2^{-j/2}\varphi(2^{-j}t-k)\ j=1,2,...,J;\ k=1,2,...,K_j \\ &\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k)\ J \leq log_2 N,\ K_j = N, \end{aligned} \tag{7}$$

where J refers to the number of multi-resolution levels and N is the number of coefficients in each level. Any function $f(t)$ in $L^2(R)$, under wavelet transform, can be decomposed as follows:

$$f(t) = \sum_{k=1}^{N} s_{J,k}\varphi_{J,k}(t) + \sum_{k=1}^{N} d_{J,k}\psi_{J,k}(t) + \sum_{k=1}^{N} d_{J-1,k}\psi_{J-1,k}(t) + ... + \sum_{k=1}^{N} d_{1,k}\psi_{1,k}(t), \tag{8}$$

where the coefficients $s_{J,k} = \sum_{k=1}^{N} \varphi_{J,k} f(t)$ and $d_{j,k} = \sum_{k=1}^{N} \psi_{j,k} f(t)$. Therefore, the original series under wavelet approximation can be expressed as follows:

$$f(t) = S_{J,k}(t) + D_{J,k}(t) + D_{J-1,k}(t) + ... + D_1(t), \tag{9}$$

where $S_{J,k}$ represents the smooth signal and $D_{J,k}$, D_{J-1}, k,...,$D_{1,k}$ represent detailed ones and $S_{J,k}$ and $D_{j,k}$ are given by:

$$\begin{aligned} S_{J,k} &= \sum_{k=1}^{N} s_{J,k} \varphi_{J,k}(t) \\ D_{j,k} &= \sum_{k=1}^{N} d_{j,k} \psi_{j,k}(t),\ j = 1, 2, ..., J. \end{aligned} \tag{10}$$

In this study, we used the maximum overlap discrete wavelet transform (MODWT) which overcomes some of the difficulties associated with discrete wavelet transform (DWT). Moreover, the variance estimator based on coefficients of MODWT is asymptotically more efficient than that based on DWT. Thus, we can calculate the wavelet variance and covariance in different time scales efficiently. We used a compact Daubechies wavelet least asymmetric function (designated LA8) for empirical application and established $J = 6$ for the multi-resolution level J. Since we used daily data, the different frequent components, D1, D2, D3, D4, D5 and D6 correspond to the following time scales, namely, 2-4 days, 4-8 days, 8-16 days, 16-32 days, 32-64 days and 64-128 days, respectively. The DWT description and its developments regarding the MODWT can be found in Tiwari et al. (2013).

4.2.1. Multi-scale analysis of correlation

Since DWT decomposes the time series into different scales, we can obtain statistical moments for different frequency components, such as wavelet variance, covariance and correlation (Percival and Walden (2006)). Based on Whitcher et al. (2000), the wavelet variance at scale j for time series $x(t)$, $\tilde{\sigma}_x^2(j)$, is given by:

$$\tilde{\sigma}_x^2(j) = Var(d_{j,t}), \tag{11}$$

if the wavelet coefficients for that level obtained by MODWT exists and finite. Similar with the variance, we can model the wavelet covariance and the relevant correlation between two time series on a scale-by-scale basis. Thus, the wavelet correlation between two time series $x(t)$ and $y(t)$ for scale j, $\tilde{\rho}_{xy,j}$, is given by:

$$\tilde{\rho}_{xy,j} = \frac{\tilde{\sigma}_{xy,j}}{\tilde{\sigma}_x(j)\tilde{\sigma}_y(j)}, \tag{12}$$

where $\tilde{\sigma}_{xy,j}$ is the covariance between the decomposed time series $x(t)$ and $y(t)$ at scale j. According to Gençay et al. (2001) and Reboredo and Rivera-Castro (2014), to use the asymptotic normality of $\tilde{\rho}_{xy,j}$, we used a nonlinear transformation to produce reasonable confidence intervals for the Fischer's z-transformation correlation coefficient defined as $h(\rho) = tanh^{-1}(\rho)$. For an estimated correlation coefficient $\hat{\rho}$ of N independent Gaussian observations, $\sqrt{N-3}[h(\hat{\rho}) - h(\rho)] \sim N(0,1)$. Consequently, we can estimate the $(1-\alpha)$ confidence interval for the wavelet correlation which is given by:

$$tanh\left\{ h[\hat{\rho}_{xy(j)}] \pm \eta_{\frac{\alpha}{2}} \left(\frac{1}{\hat{N}_j} - 3 \right)^{0.5} \right\}, \tag{13}$$

where $\hat{N}_j$ is the number of MODWT corresponds to scale j and $\eta_{\frac{\alpha}{2}}$ satisfies $P[-\eta_{\frac{\alpha}{2}} \leq \eta_{\frac{\alpha}{2}}] = 1 - \alpha$ if Z has a standard Gaussian distribution and no systematic trend or geostationary features exist in the wavelet coefficients.

4.3. Granger causality relationship

We tested for the existence of linear causality introduced by Granger (1969) in the original return series and in their different scale components that obtained from the DWT analysis based on bivariate vector autoregressive (VAR) model. For two stationary series x_t and y_t, the VAR model can be expressed as follows:

$$\begin{aligned} x_t &= c_1 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_{1t}, \\ y_t &= c_2 + \sum_{i=1}^{p} \gamma_i x_{t-i} + \sum_{i=1}^{p} \delta_i y_{t-i} + \epsilon_{2t}, \end{aligned} \tag{14}$$

where p is the lag length of the x_t and y_t variables and ϵ_{1t} and ϵ_{2t} are assumed to be independently and identically normal distributed. Thus, we can test whether y does not cause x by testing whether the null hypothesis $H_0^1 : \beta_1 = ... = \beta_q = 0$ can be rejected. Similarly, we can test whether x does not cause y by testing whether the null hypothesis $H_0^2 : \gamma_1 = ... = \gamma_q = 0$. The test statistic follows a standard F distribution with $(q, T - 2q - 1)$ degrees of freedom asymptotically, where T is the sample size.

4.4. Impulse response function

We used the Impulse Response Function (IRF) to determine the response function of oil and gas stock returns at time 0 and subsequent periods when the oil price changes increase by one standard deviation at time 0. For a bivariate VAR model,

$$Y_t = (I_2 + \Theta_1 L + \Theta_2 L^2 + ...)\epsilon_t,\ t = 1, 2, ..., T, \tag{15}$$

where $Y_t = [x_t, y_t]'$ and $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}]'$. Therefore,

$$\begin{aligned} x_t &= \sum_{j=1}^{2} \left(\theta_{1j}^{(0)}\epsilon_{jt} + \theta_{1j}^{(1)}\epsilon_{jt-1} + \theta_{1j}^{(2)}\epsilon_{jt-2} + ...\right), \\ y_t &= \sum_{j=1}^{2} \left(\theta_{2j}^{(0)}\epsilon_{jt} + \theta_{2j}^{(1)}\epsilon_{jt-1} + \theta_{2j}^{(2)}\epsilon_{jt-2} + ...\right), \end{aligned} \tag{16}$$

where $t = 1, 2, ..., T$. If we introduce one standard deviation at time 0 to x, thus, we have:

$$\epsilon_{1t} = \begin{cases} 1,\ t = 0 \\ 0,\ t \neq 0 \end{cases} \tag{17}$$

Thus, $\epsilon_{2t} = 0,\ t = 1, 2, ..., T$. Then we can obtain the impulse response of y to x as follows:

$$y_t = \sum_{j=1}^{2} \left(\theta_{2j}^{(0)}\epsilon_{jt} + \theta_{2j}^{(1)}\epsilon_{jt-1} + \theta_{2j}^{(2)}\epsilon_{jt-2} + ...\right), \tag{18}$$

where $\theta_{2j}^{(q)} = \frac{\partial_{y,t+q}}{\partial_{\epsilon_{jt}}},\ q = 0, 1, ..., N,\ t = 1, 2, ..., T$ and where N is the response period.

4.5. Variance decomposition

We also used the variance decomposition method to examine the contribution of changes in oil price to the oil and gas stock price fluctuation. Based on Eq.18 and assuming that ϵ_j has no correlation, we have the following equation:

$$\begin{aligned} &E[(\theta_{2j}^{(0)}\epsilon_{jt} + \theta_{2j}^{(1)}\epsilon_{jt-1} + \theta_{2j}^{(2)}\epsilon_{jt-2} + ...)^2] \\ &\sum_{q=0}^{\infty}(\theta_{2j}^{(q)})^2\sigma_{22}, \end{aligned} \tag{19}$$

where σ_{22} is the variance of ϵ_2. Assuming that the covariance matrix Σ of the error terms ϵ_1 and ϵ_2 is diagonal, the variance of y is given by:

$$var(y) = \sum_{j=1}^{2} \left\{ \sum_{q=0}^{\infty}(\theta_{2j}^{(q)})^2 \right\}. \tag{20}$$

Thus, the variance of y can be consider as a combination of 2 types of separated disturbance effects given by:

$$RVC_{x\to y}(\infty) = \frac{\sum_{q=0}^{\infty}(\theta_{2j}^{(q)})^2\sigma_{22}}{var(y)} = \frac{\sum_{q=0}^{\infty}(\theta_{2j}^{(q)})^2\sigma_{22}}{\sum_{j=1}^{2}\left\{\sum_{q=0}^{\infty}(\theta_{2j}^{(q)})^2\right\}}. \tag{21}$$

Because $\theta_{2j}^{(q)}$ would decrease in a geometrical progression as q increases if the model satisfies the stationary conditions, we use limiting number instead of ∞ to approximate contribution ratio of the variance, which allows to avoid excessively complex computation.

4.6. Oil price risk across different time scales

To quantify the oil price risk for oil and gas companies in different time scales (investment horizons), we follow a similar method used by Gençay et al. (2005). We use the oil price beta β_i^j for each stock i at scale j to represent the oil price risk, which is given by:

$$\beta_i^j = \frac{\tilde{\sigma}_{i,oil,j}}{\tilde{\sigma}_{oil,j}}, \tag{22}$$

where $\tilde{\sigma}_{i,oil,j}$ is the wavelet covariance of stock i and oil at scale j, and $\tilde{\sigma}_{oil,j}$ is the wavelet variance of oil at scale j. The oil price risk at different time scales is important for us. Specifically, if β_i^j is essentially similar across scales j, then the data frequency is not important for calculating oil price risk, in other words, oil and gas industry investors with different horizons bear similar oil price risk.

5. Empirical Results

5.1. Evidence from continuous wavelet analysis

Figure 2 shows the wavelet transform coherence (WTCs) and phase difference for the pairs of oil and gas stock and WTI , which offers information about varying dependence between oil and UK oil and gas stock returns across different frequencies and over time. The vertical axis shows the frequencies from scale 1 corresponding to one day up to scale 1024 corresponding to approximately four trading years, while the horizontal axis shows the whole sample period. Wavelet coherence allows to identify regions where two series are highly dependent in both time and frequency domains. It is showed that values of coherence range from zero to one corresponding to blue and red by the colourful bar on the right-hand side for each sub-figure. Therefore, those regions with warmer colours indicate highly dependent areas, whereas the regions with cooler colours refer to less dependence. The statistically significant local correlations in the time-frequency domain was evaluated using Monte Carlo simulations and highlighted by solid-curved lines. The cone of influence which indicates the region affected by edge effects is also shown by a solid curved line. Moreover, Figure 2 also displays phase evidence for prices of oil and gas stocks and oil by using phase arrows, which indicate the cause-effect relationships. An arrow pointing right means the dependence is positive, whereas an arrow pointing left means the dependence is negative. An arrow pointing down indicates the oil price changes lead the oil and gas stock returns and vice versa.

Figure 2 shows that, for most companies, the dependence between oil price and oil and gas stock price is low at higher frequencies corresponding to one to sixteen days. The coherence values tend to be higher and significantly dependent areas appear in the mid-term regions corresponding to 16-64 days. Based on the positions of the big red colour regions corresponding to 64-512 days, we found that long-term dependencies were very high. According to Bodart and Candelon (2009) and Saiti et al. (2016), the dependence between oil and UK oil and gas companies' stocks should be classified as "interdependence" rather than "contagion" because of the strong wavelet coherence at lower frequencies. Moreover, during the period from 2008 to 2010, the long-term dependencies were very high for all the oil and gas companies, which means financial crisis had an important effect. However, the dependence at higher frequencies did not become higher during the financial crisis period, which suggests a weak contagion effect. Since the oil price began to fall from 2014, the dependencies at middle scales corresponding to 32-64 days, also started to increase for all companies except Cape, Jkx Oil & Gas and Northern Petroleum. As for the phase patterns, the arrow directions were time-varying and different across time scales. In most cases, we observed in-phase patterns for all the companies, which means oil price and stock prices of UK oil and gas companies moved along the same direction in most time. In addition, we found stock price of UK oil and gas companies led oil price at lower frequencies in most time. However, for Royal Dutch Shell, the big integrated company, during the global financial crisis period and the period of recent downward movement of oil price, we found its stock price was led by oil price at lower scale. The similar pattern can be also found for Northern Petroleum from 2013 to 2015.

5.2. Evidence from wavelet correlation

Figure 3 shows the wavelet correlation between WTI and UK oil and gas stocks based on discrete wavelet transform during the sample period. The 95% confidence intervals are also shown through red dashed lines, which permit reliable statistical inference as to whether the correlations are significantly different from zero. It shows that the wavelet correlation between oil price changes and returns of oil and gas stocks varies across considered time scales, which confirms a multiscale phenomenon in the link of oil-stock markets.

For all the companies (except Cape, Jkx Oil & Gas and Northern Petroleum), the wavelet correlation does not keep increasing as the time horizons increase but experience a drop at scale 3 corresponding to 8-16 days. The negative wavelet correlation at scale 3 is even significant for Bp, Hunting, Premier Oil, Amec Foster Wheeler, Cairn Energy, Tullow Oil and Amerisur Resources. The wavelet correlation tend to be higher in long-term horizons such as scale 5 and scale 6 for all the companies, which is consistent with the evidence from continuous wavelet transform. The wavelet correlation at scale 5 was significant and highest for Bp, Royal Dutch Shell, Premier Oil, Cairn Energy, Tullow Oil and Northern Petroleum, whereas the wavelet correlation at scale 4 was significant and highest for Amec Foster Wheeler and Amerisur Resources. For all the companies, the wavelet correlation at scale 1 and scale 2 was non-significant during the sample period.

5.3. Evidence from Granger causality tests

We first investigated causality between WTI and stock returns of oil and gas companies in the original return series and the empirical results are reported in Table 3[1]. Interestingly, on daily basis, we found that stock returns Granger cause oil price changes at 5% significance level, however, oil price changes only Granger cause stock returns of Bp, Royal Dutch Shell, Premier Oil and Tullow Oil. This evidence shows that it is difficult to use the daily changes of oil price to predict the following daily stock returns of UK oil and gas companies.

Table 4 reports the empirical evidence of Granger causality tests across different frequent components for the oil and gas companies. At scale 1, the bidirectional Granger causality is unchanged for Royal Dutch Shell, Premier Oil and Tullow Oil but not for Bp. Moreover, the Granger causality running from WTI to stock can be found at higher scales for all the companies, which means temporary oil price changes have little impact on stock prices for most oil and gas companies but the long term and persist changes are more important. The heterogeneous evidence of Granger causality tests on original series and recomposed series confirms the multi-resolution nature of the lead-lag relationship between oil and the stock returns of oil and gas companies over the medium and long term. In addition, we observe that the bidirectional Granger casuality exists at scale 3, scale 4 and scale 5 for all companies,

[1]All the recomposed series for stock returns and oil price changes are stationary according to ADF, PP and KPSS tests, the results are available on request

which means investors with investment horizons from 8 to 64 days are able to use the past information from oil market to predict stock prices of oil and gas companies. This evidence also supports the perspective that oil and stock markets adjust prices towards medium and long run equilibrium by using information from each other. The policy makers and investors should pay more attention to weekly, semi-monthly, monthly and quarterly oil price changes.

5.4. Evidence from impulse response function

Figure 4-9 show the impulse response function which helps to discover the response direction and duration of the UK oil and gas stocks to one standard deviation of the oil price across different time scales. The red dashed lines refer to the 95% confidence interval. We fix the response period at 100 days. First, at scale 1 and scale2, the oil and gas stocks responded to the oil price shocks in a sustained fluctuating manner and the response gradually become zero around 70 days at scale 1 and 100 days at scale 2 and both significant positive and negative impact of oil price shocks on the stock returns can be observed. In addition, the positive and negative impact shift very quickly. Therefore, short-run oil price shocks only could induce the UK oil and gas stocks to fall into a fluctuated condition in a short period. Second, we can observe that the significant impact of oil price shocks exist for all companies at scale 3 and scale 4 corresponding to 8-16 days and 16-32 days. The impact of oil price shock at these two scales can be either positive or negative and do not disappear in 100 days. This result may be related to the weekly and monthly seasonality due to the existence of short term investors and the steps taken by oil and gas companies themselves. Thus, the oil price changes measured on weekly, semi-monthly and monthly basis should be focused by policy makers and investors. Similar with the response at scale 2, the responses of oil and gas stocks to oil price shocks at scale 3 and scale 4 can be either negative or positive over time. For Bp and Royal Dutch Shell, the two integrated companies, we can observe that positive impact exists on the 20th, 40th and 60th days approximately. This evidence is consistent with the empirical findings of Diaz and de Gracia (2017) in which the authors found significant positive impact of monthly oil price shocks on monthly stock prices of the above two companies in the first and second months. As for the scale 5 and scale 6, the oil price shocks have fewer significant impact on the stock prices of oil and gas companies although they generate longer oscillation. One potential explanation is that the UK policy makers and oil and gas companies may take steps to response the long-term and persist oil price shocks. Another potential explanation is that the market agents, oil and gas companies and policy makers may respond differently for long-term demand or supply shocks. Moreover, although the impact of oil price shocks may be either positive and negative but the amplitude is similar at different scales.

5.5. Evidence from variance decomposition

In this section, we introduce the variance decomposition to quantify the contribution to the stock prices' fluctuation from the oil price. Table 5 reports the evidence of variance decomposition at different scales. We find that the contribution percentage of the oil price is lowest at scale 1 for all the companies, which means that short-run oil price changes have less impact on stock prices of UK oil and gas companies. However, for most companies, the contribution percentage increases at scale 2 and scale 4, which means that weekly and monthly oil price changes exert more influence. However, for Cape, Cairn Energy and Northern Petroleum, the oil price changes have impact on their stock prices in the long term.

5.6. Evidence from oil price risk across different scales

Table 6 shows the results of oil price beta coefficients β_i^j for each stock at scale j. As we can see, the oil price beta coefficients show a multiscale tendency for all oil and gas companies. Beta coefficients are very low at scale 1 and scale 2 but the beta values are negative and the absolute values are larger at scale 3 for Hunting, Amec Foster Wheeler, Cairn Energy and Tullow Oil. The oil price betas are larger and positive for all companies (except Amerisur Resource at scale 6) at scale 4,5,6. This result suggests that long-term investors are more exposed to oil price risk than short-term investors. In other words, short-term oil and gas industry investors who have investment horizons from 1 day to 16 days can still benefit from diversification by adding oil into their portfolios, while long-term investors should short sell oil when they hold oil and gas companies' stocks.

6. Conclusion

Oil price has been concentrated on by policy makers and researchers because oil is the production input for most industries. However, the impact of oil price changes on stock returns of oil and gas companies is complex because oil price determines both operation costs and profits. Most previous empirical literature has studied oil and oil and gas companies' stock dependence at one time domain, such as daily basis or monthly basis, we analyzed the influence of oil price changes at different time scales using wavelet analysis. Wavelet transform decomposes original return series into multiscale orthogonal components, which allows to analyze the impact of oil price changes in short-run, medium-run and long-run. Due to existence of heterogenous market anticipants with different investment horizons, analyzing the impact of oil price changes at different time scales is important.

We used both continuous wavelet coherence and discrete wavelet correlation to analyze the dependence, lead-lag relationship between oil price changes and stock returns of UK oil and gas companies during the period from June 19, 1996 to December 30, 2016. These two methods provide robust evidence about the dependence between oil price changes and stock returns of oil and gas companies at different time scales and over time. In addition, we used the Granger causality test, impulse response function and variance decomposition approaches in time-frequency domain to investigate the causality direction, response amplitude and direction and the contribution of oil price changes to oil and gas stocks' variance in different time horizons. We also employed wavelet covariance and wavelet variance to estimate the oil price risk at different time horizons. Our empirical evidence can be summarized as follows:

First, we find that the dependence between oil and UK oil and gas companies is low in the short term corresponding to one day to eight days, while the dependence increases in the medium and long term indicating the positive interdependence. Second, stock returns Granger cause oil price changes on daily basis, however, oil price changes have no significant effects on stock returns in the short term but the bidirectional casuality between oil and stock can be found in the mid-and-long term. Third, short-run oil price shocks can only cause the oil and gas stocks to fall into constant fluctuation lasting for around 70 days but the medium-run shocks can cause stock prices fluctuate for longer time. However, the oil price shocks have both negative and positive impact on stock returns across different time scales. Fourth, we observed that oil price risk is higher for long-term investors but very low for short-term investors.

Our empirical results are important for both policy makers and investors. The policy makers should pay more attention on oil price changes in medium and medium-long term such as monthly or quarterly basis when they design medium-run or long-run energy policies. They can also make use of information from oil and gas stocks in medium and medium-long term to predict future oil price. For UK oil and gas industry investors, the short-term investors can still add oil to their portfolios for diversifying risk but it is difficult for them to use short-run oil price changes to predict future stock price. As for mid-term and long-term investors, they should keep alert to oil price risk but they can also use past oil price information to improve the forecasting quality of future stock prices.

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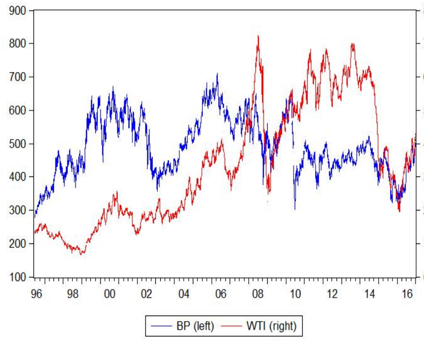
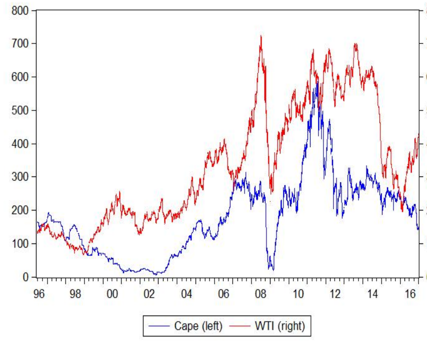
Figures



(a) Bp & WTI



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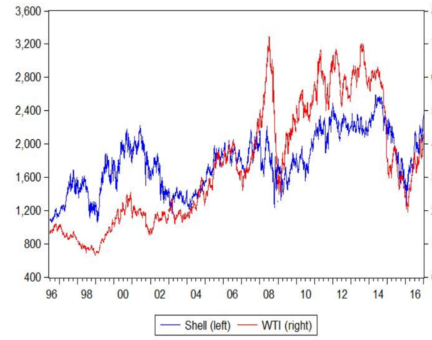
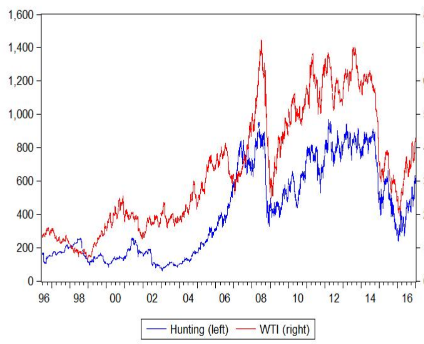


(c) Royal Dutch Shell B & WTI



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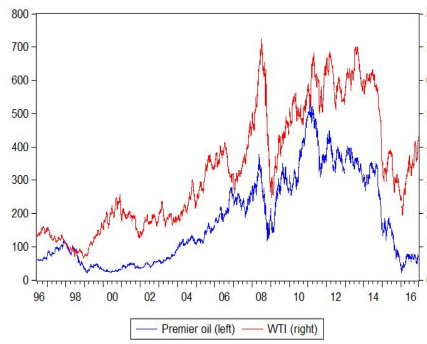
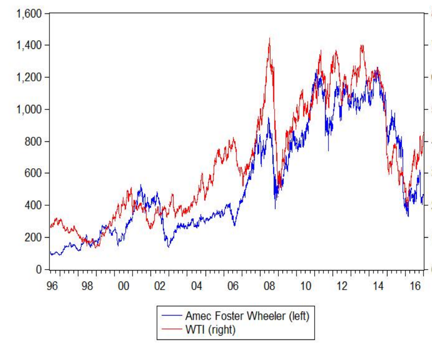
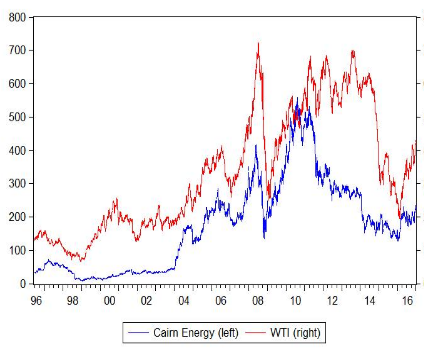


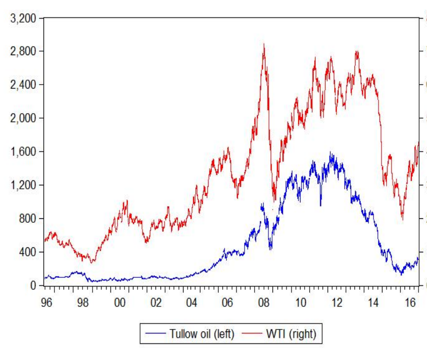
(e) Premier Oil & WTI



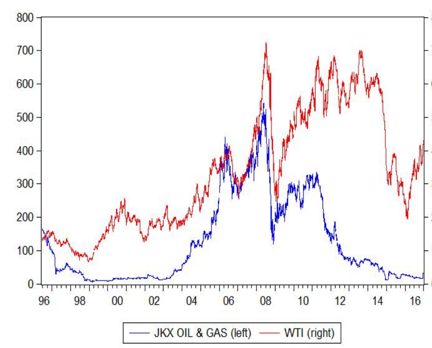
(f) Amec Foster Wheeler & WTI



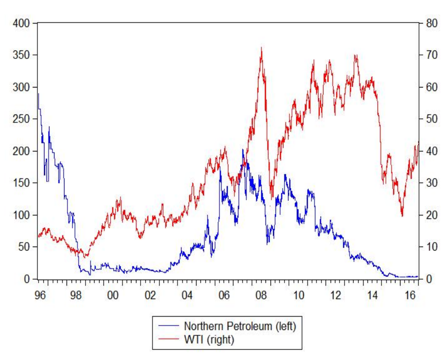
(g) Cairn Energy & WTI



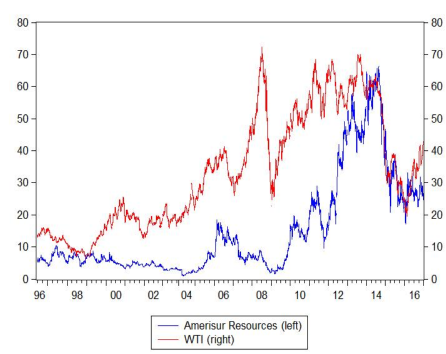
(h) Tullow Oil & WTI



(i) Jkx Oil & Gas & WTI

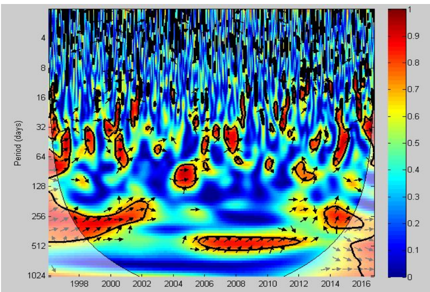


(j) Northern Petroleum & WTI

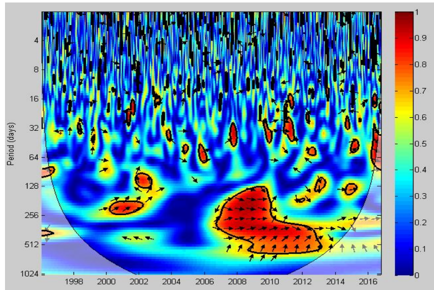


(k) Amerisur Resources & WTI

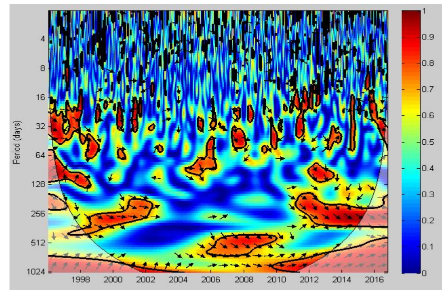
Figure 1: Oil and oil and gas stock prices for the period from June 19, 1996 to December 30, 2016



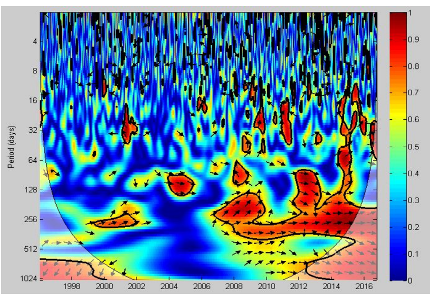
(a) Bp & WTI



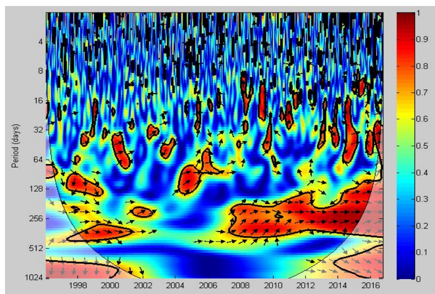
(b) Cape & WTI



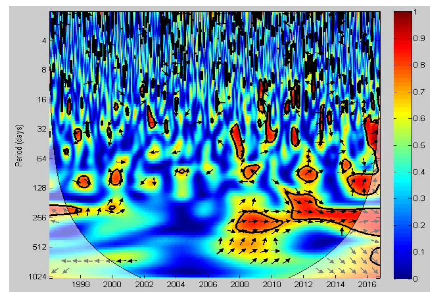
(c) Royal Dutch Shell B & WTI



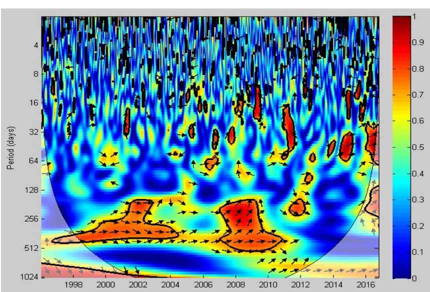
(d) Hunting & WTI



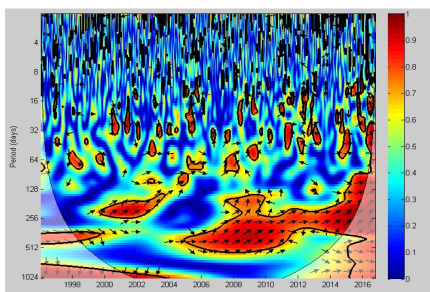
(e) Premier Oil & WTI



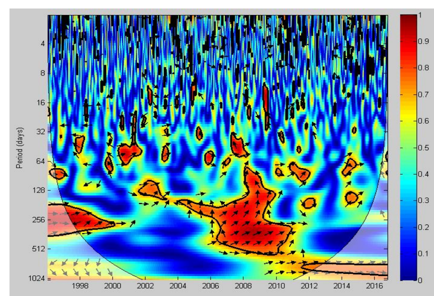
(f) Amec Foster Wheeler & WTI



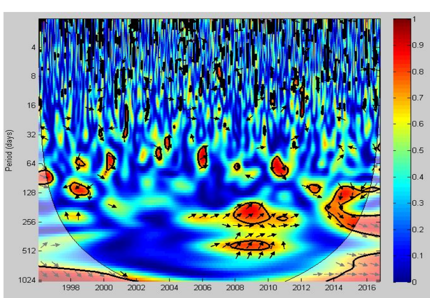
(g) Cairn Energy & WTI



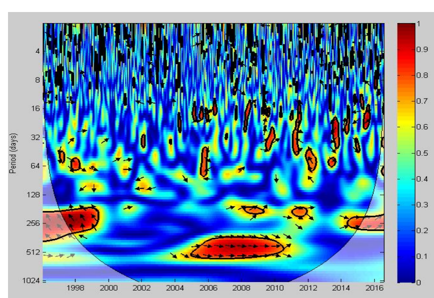
(h) Tullow Oil & WTI



(i) Jkx Oil & Gas & WTI

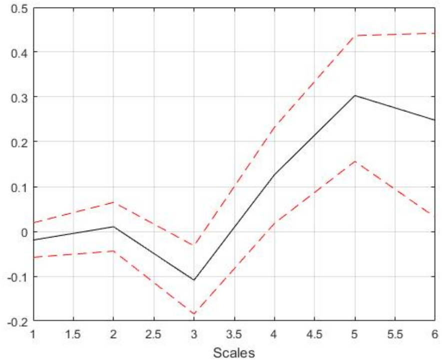


(j) Northern Petroleum & WTI

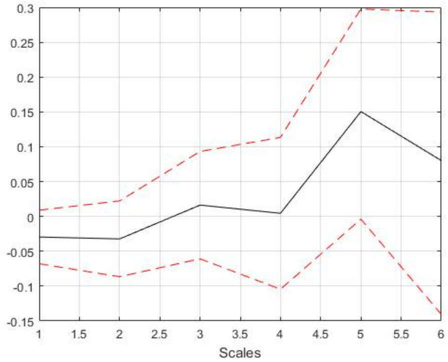


(k) Amerisur Resources & WTI

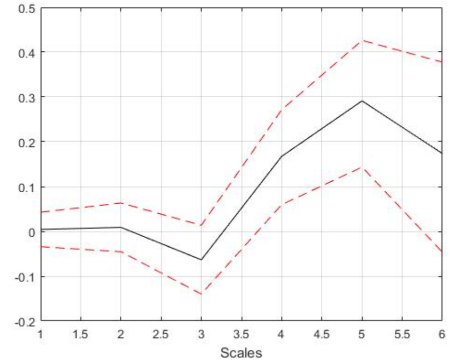
Figure 2: Coherence and phase difference for oil and oil and gas stocks



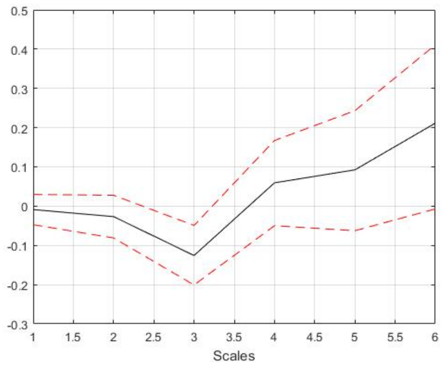
(a) Bp & WTI



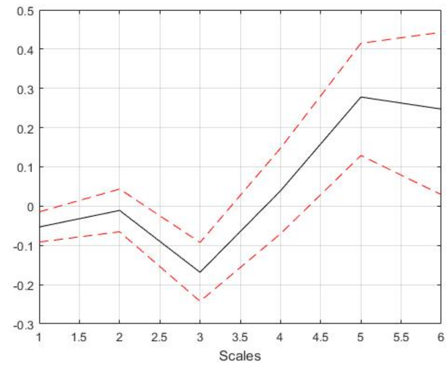
(b) Cape & WTI



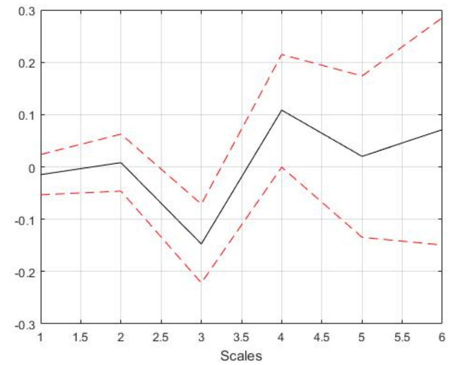
(c) Royal Dutch Shell B & WTI



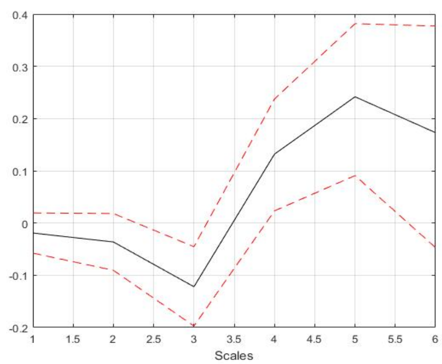
(d) Hunting & WTI



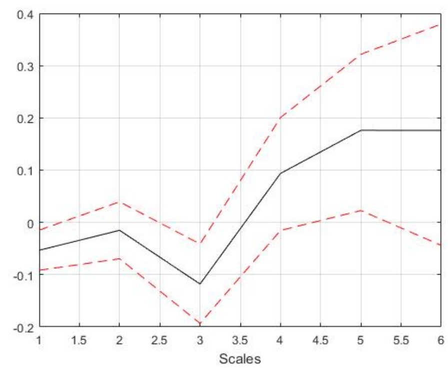
(e) Premier Oil & WTI



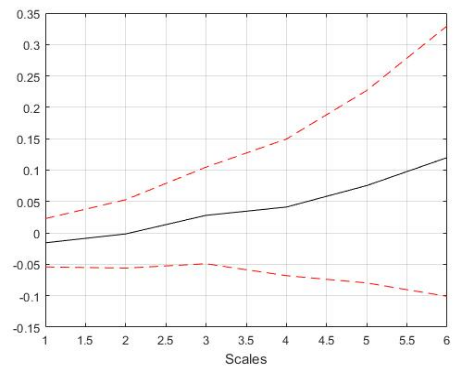
(f) Amec Foster Wheeler & WTI



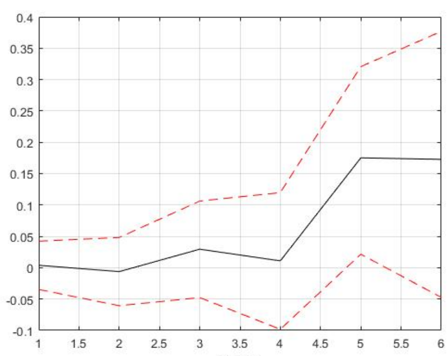
(g) Cairn Energy & WTI



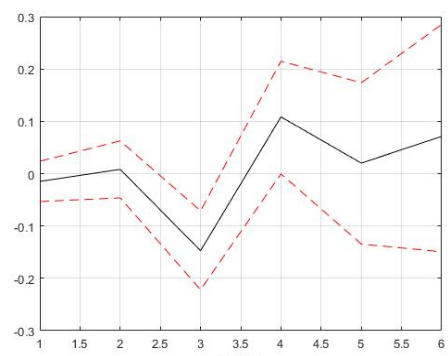
(h) Tullow Oil & WTI



(i) Jkx Oil & Gas & WTI

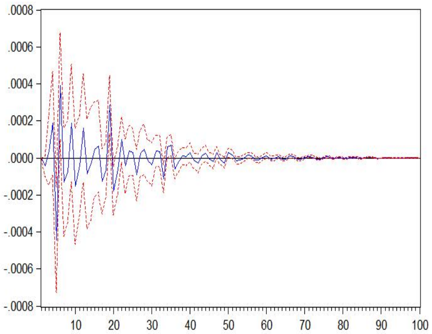


(j) Northern Petroleum & WTI

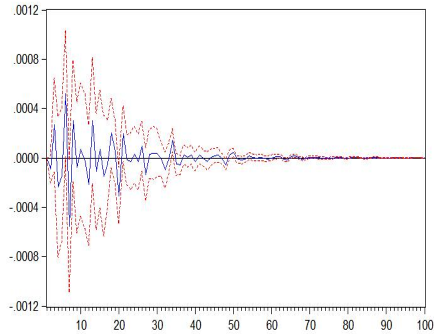


(k) Amerisur Resources & WTI

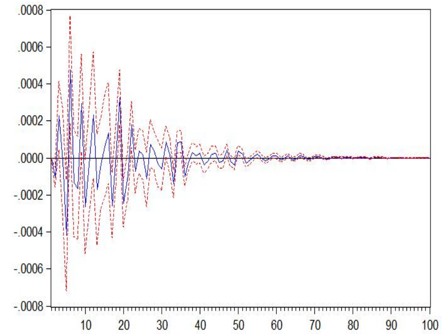
Figure 3: Wavelet correlation between oil and oil and gas stocks



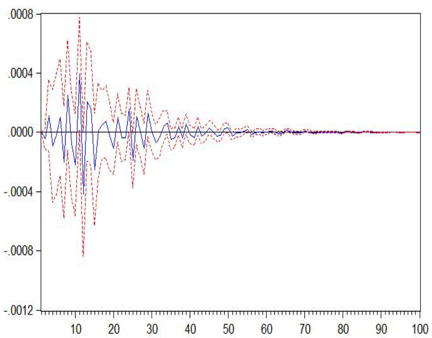
(a) Bp



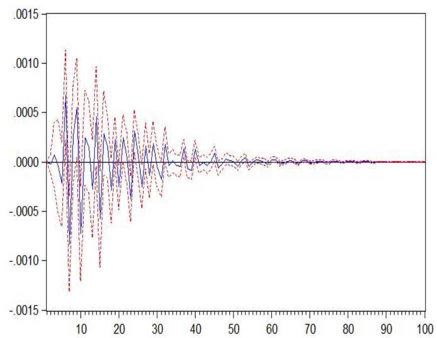
(b) Cape



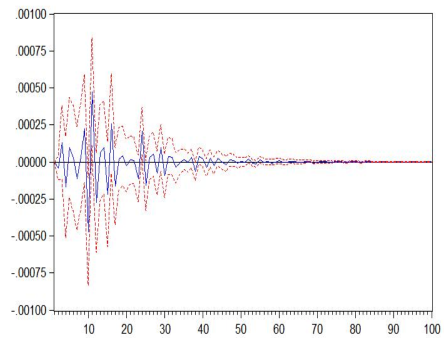
(c) Royal Dutch Shell B



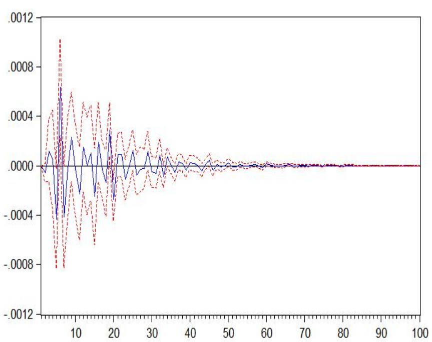
(d) Hunting



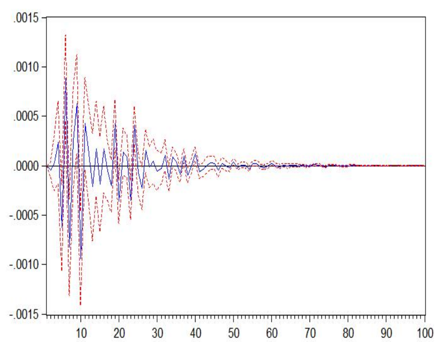
(e) Premier Oil



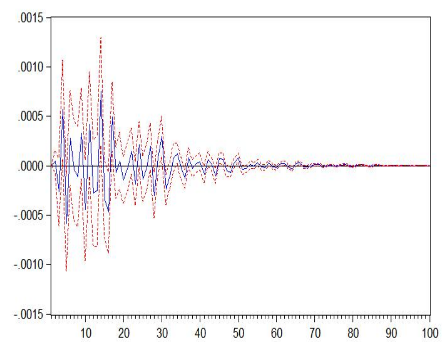
(f) Amec Foster Wheeler



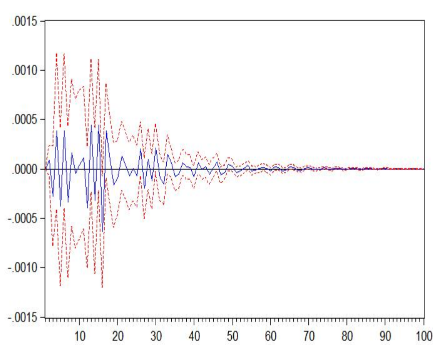
(g) Cairn Energy



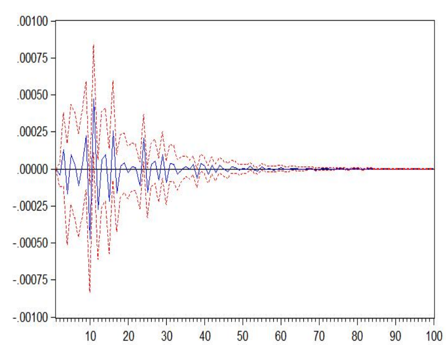
(h) Tullow Oil



(i) Jkx Oil & Gas

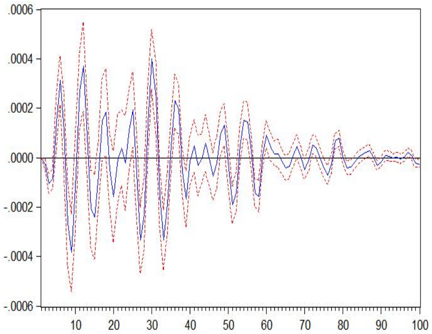


(j) Northern Petroleum

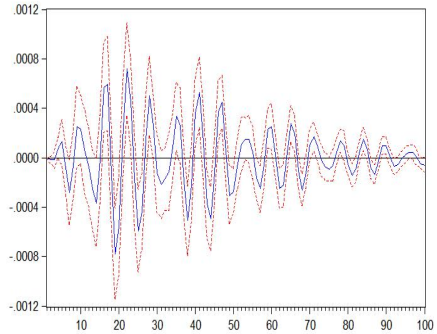


(k) Amerisur Resources

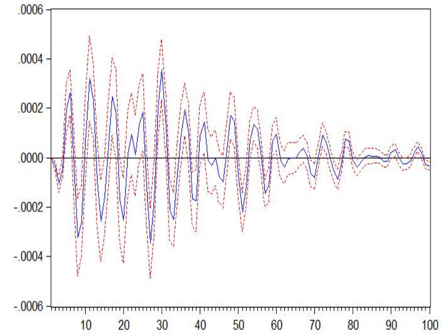
Figure 4: The impulse responses of oil and gas stocks to the oil price change shocks at scale 1



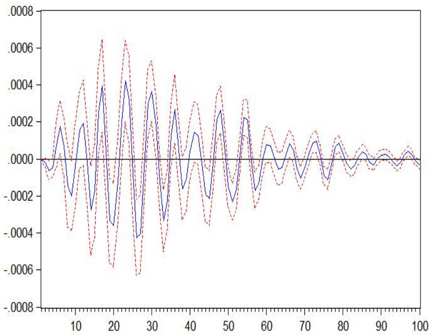
(a) Bp



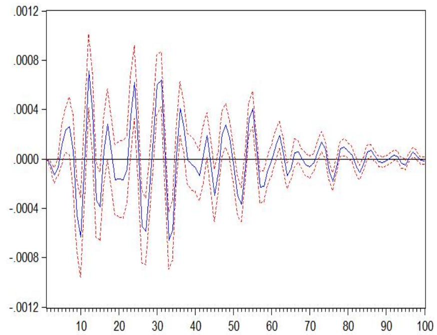
(b) Cape



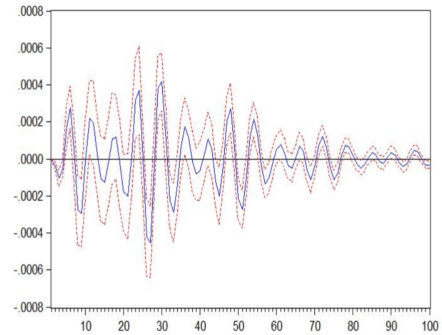
(c) Royal Dutch Shell B



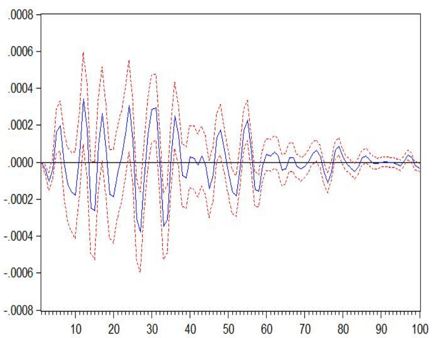
(d) Hunting



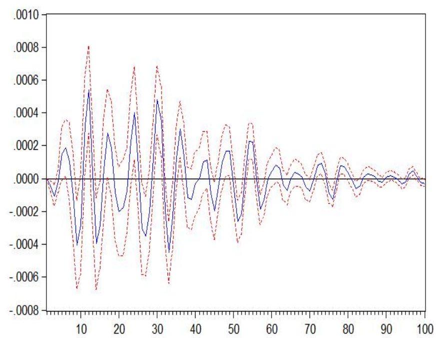
(e) Premier Oil



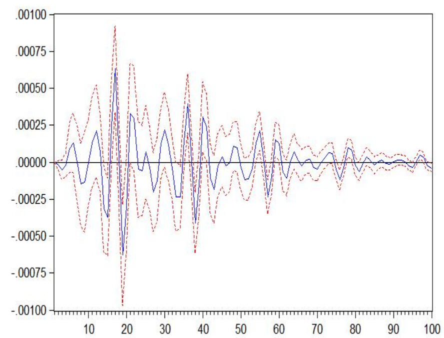
(f) Amec Foster Wheeler



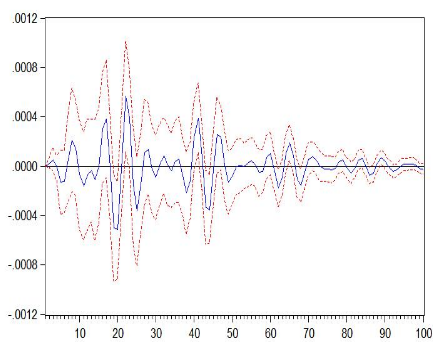
(g) Cairn Energy



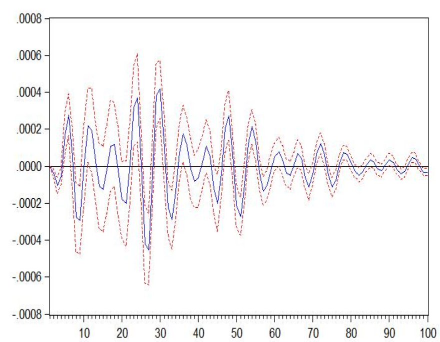
(h) Tullow Oil



(i) Jkx Oil & Gas

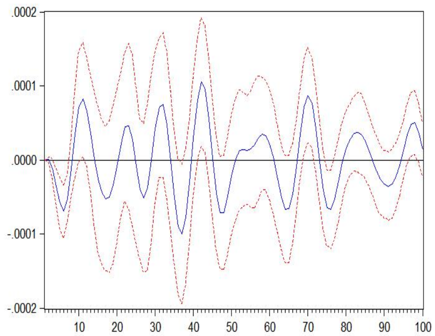


(j) Northern Petroleum

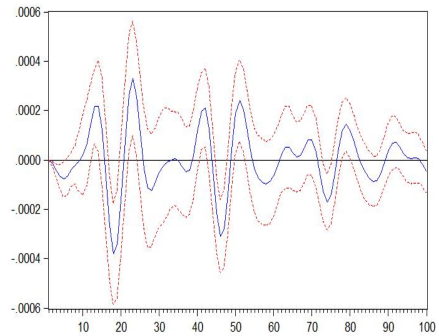


(k) Amerisur Resources

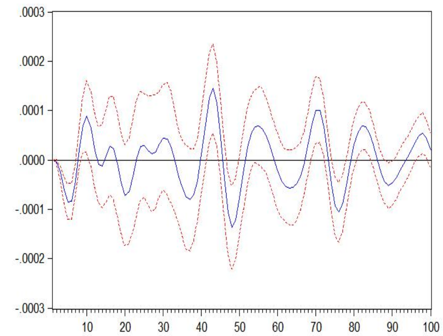
Figure 5: The impulse responses of oil and gas stocks to the oil price change shocks at scale 2



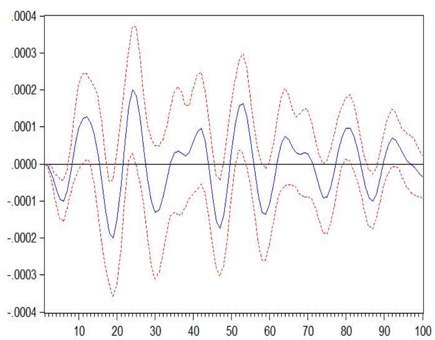
(a) Bp



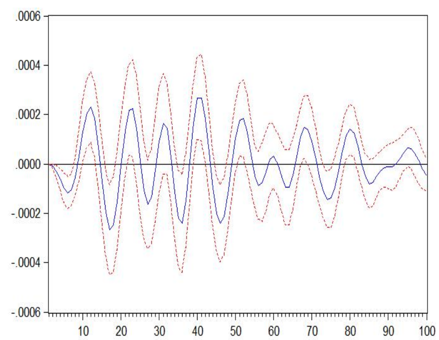
(b) Cape



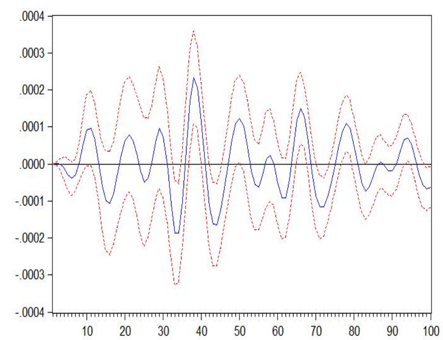
(c) Royal Dutch Shell B



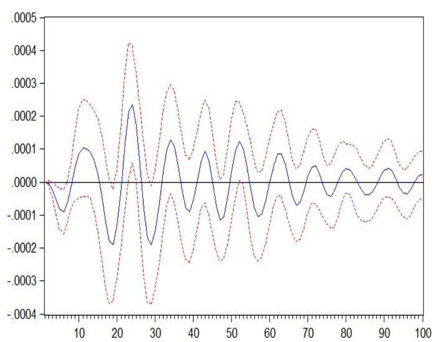
(d) Hunting



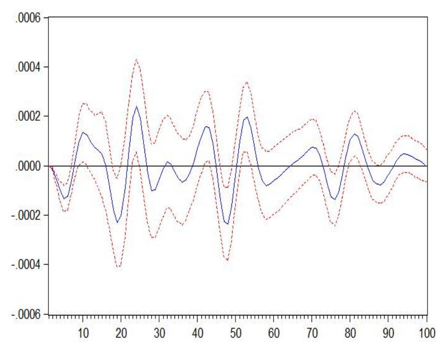
(e) Premier Oil



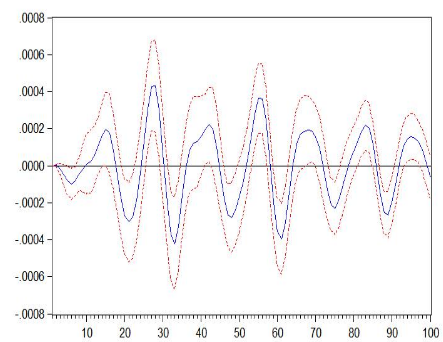
(f) Amec Foster Wheeler



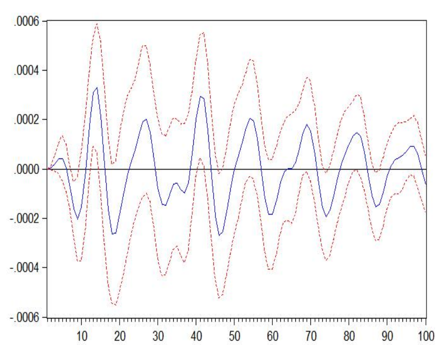
(g) Cairn Energy



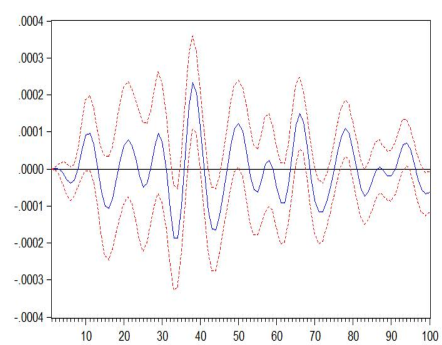
(h) Tullow Oil



(i) Jkx Oil & Gas

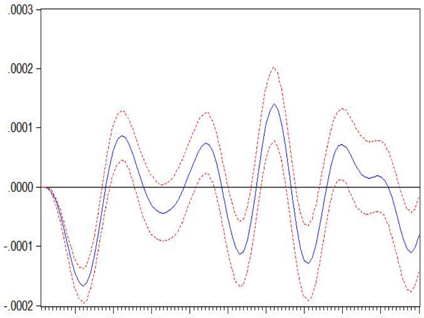


(j) Northern Petroleum

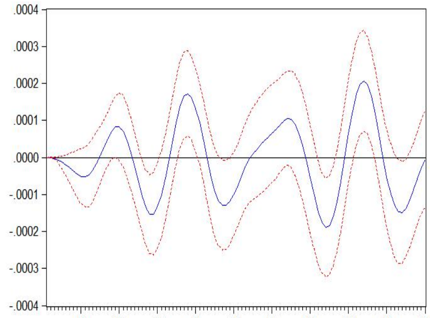


(k) Amerisur Resources

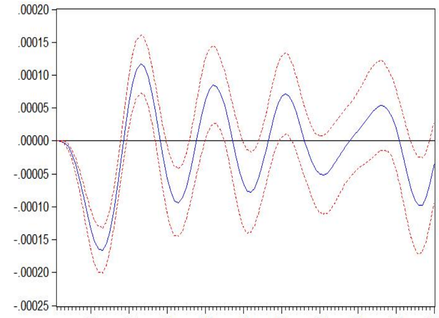
Figure 6: The impulse responses of oil and gas stocks to the oil price change shocks at scale 3



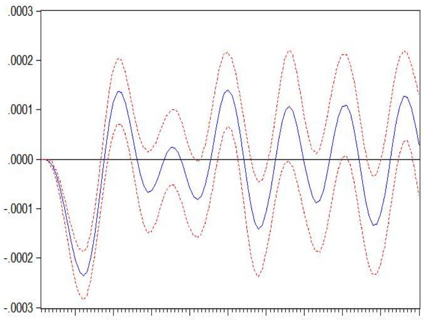
(a) Bp



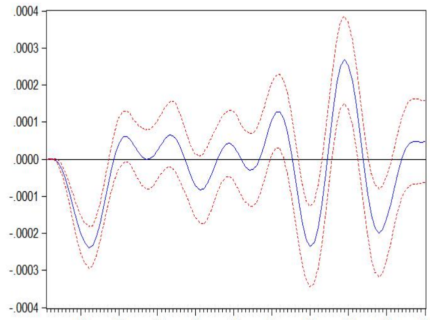
(b) Cape



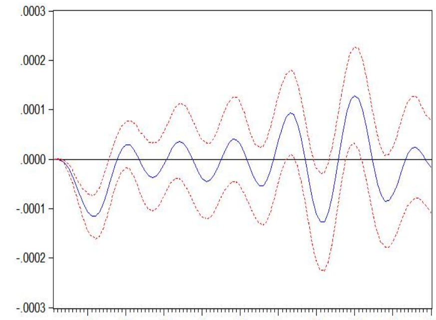
(c) Royal Dutch Shell B



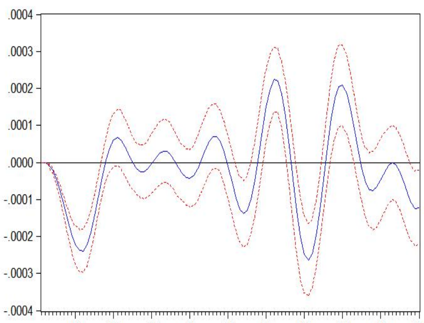
(d) Hunting



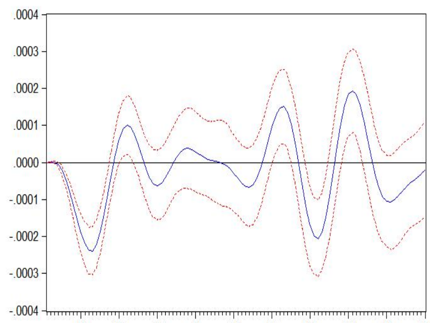
(e) Premier Oil



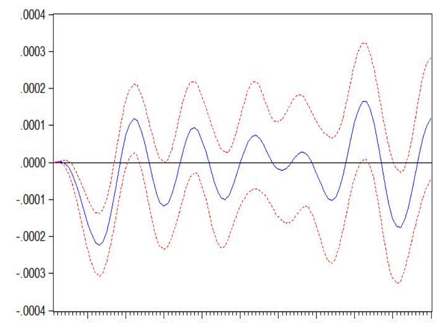
(f) Amec Foster Wheeler



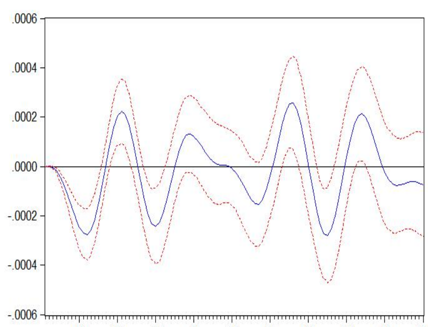
(g) Cairn Energy



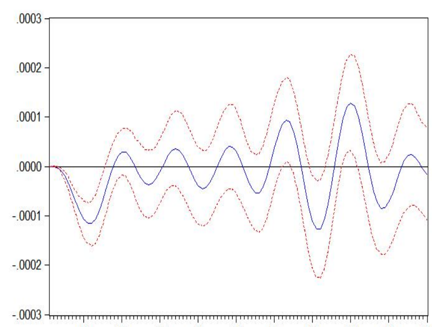
(h) Tullow Oil



(i) Jkx Oil & Gas

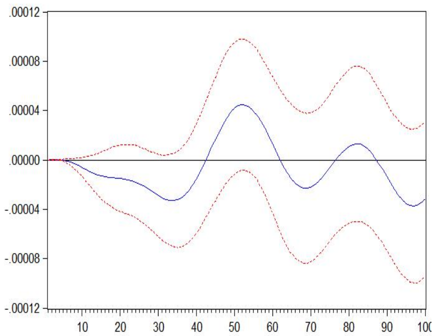


(j) Northern Petroleum

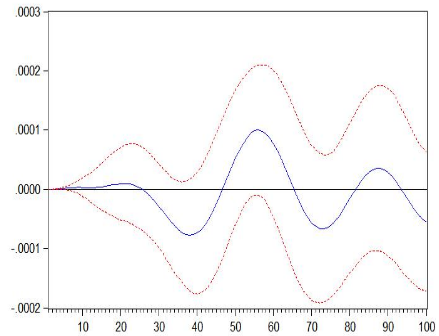


(k) Amerisur Resources

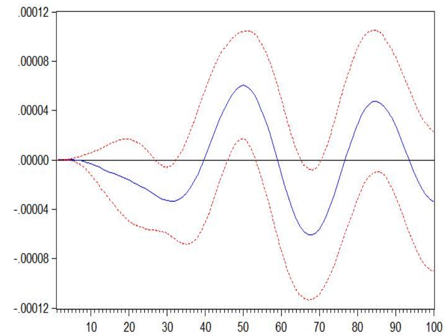
Figure 7: The impulse responses of oil and gas stocks to the oil price change shocks at scale 4



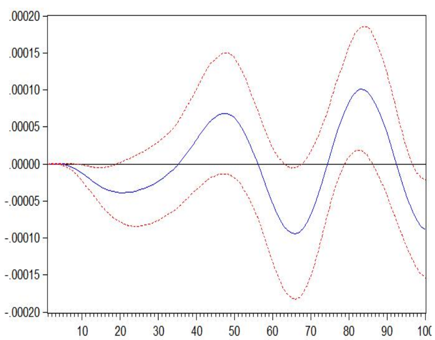
(a) Bp



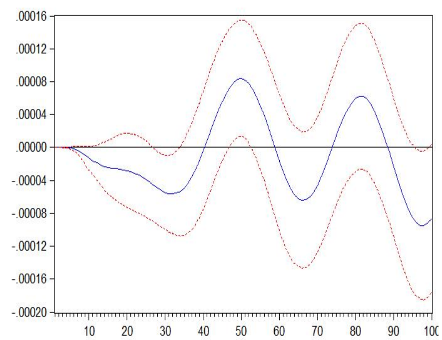
(b) Cape



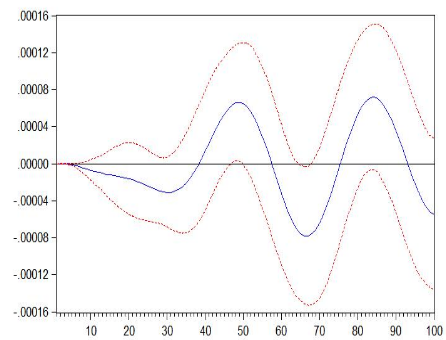
(c) Royal Dutch Shell B



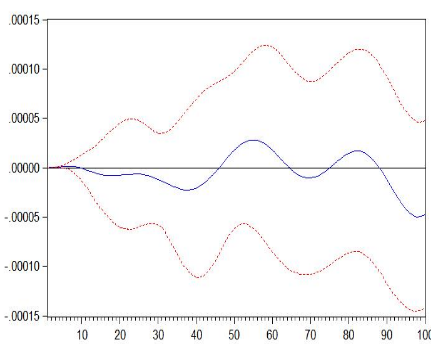
(d) Hunting



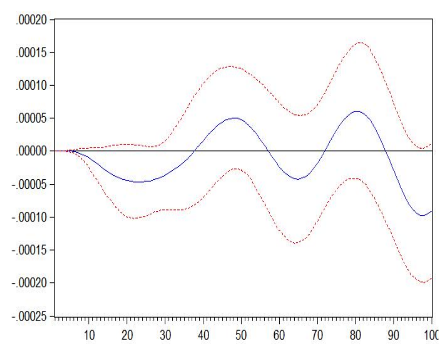
(e) Premier Oil



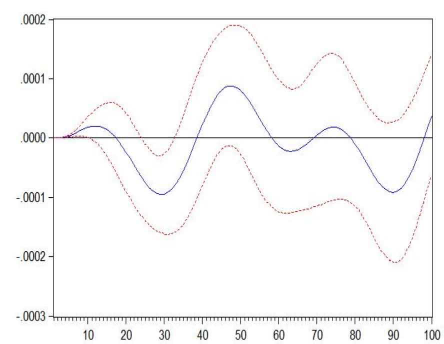
(f) Amec Foster Wheeler



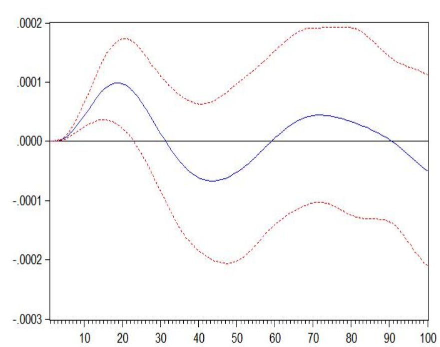
(g) Cairn Energy



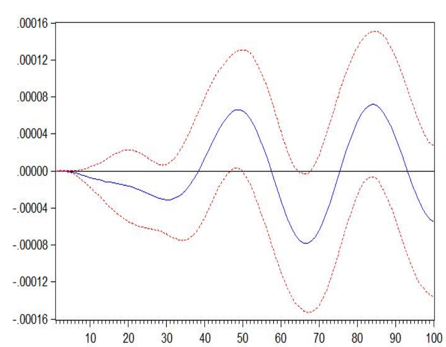
(h) Tullow Oil



(i) Jkx Oil & Gas

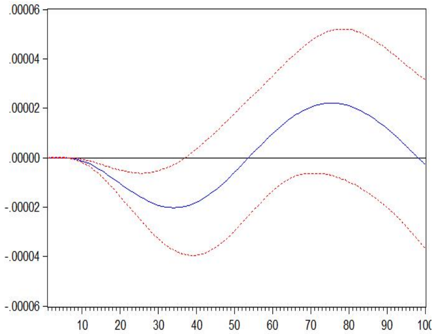


(j) Northern Petroleum

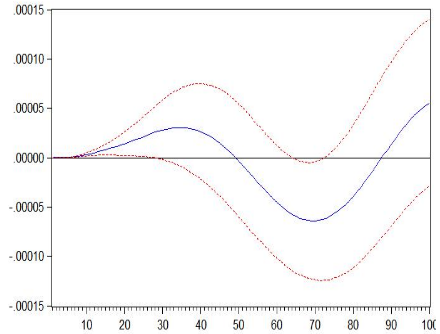


(k) Amerisur Resources

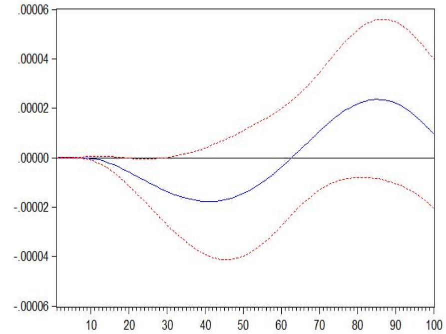
Figure 8: The impulse responses of oil and gas stocks to the oil price change shocks at scale 5



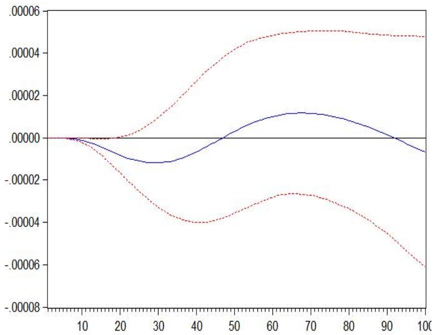
(a) Bp



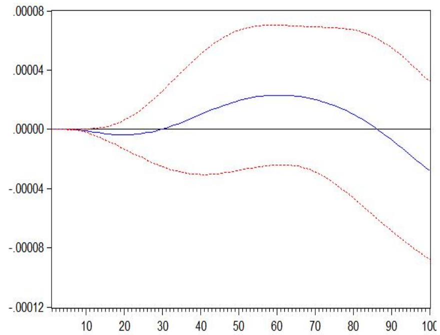
(b) Cape



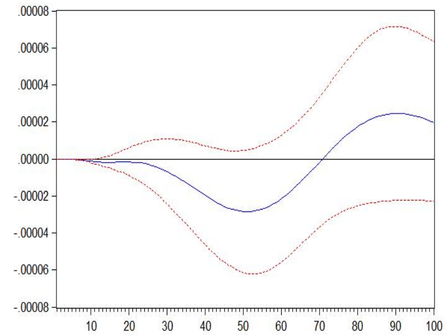
(c) Royal Dutch Shell B



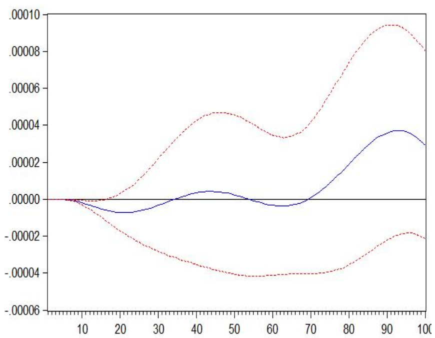
(d) Hunting



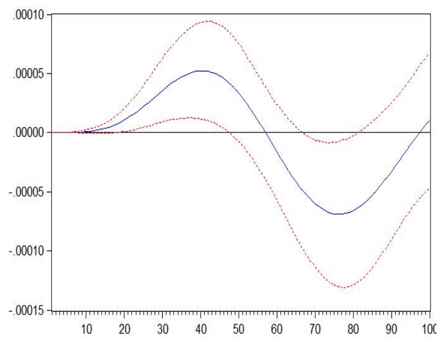
(e) Premier Oil



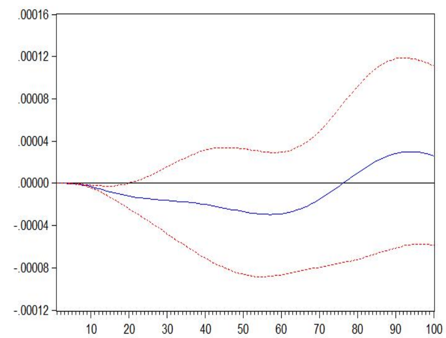
(f) Amec Foster Wheeler



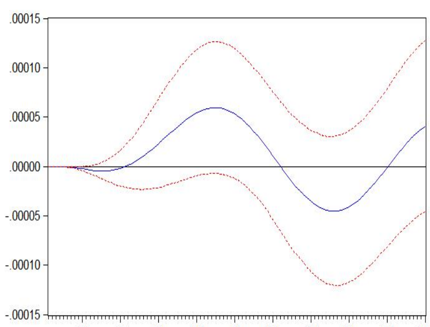
(g) Cairn Energy



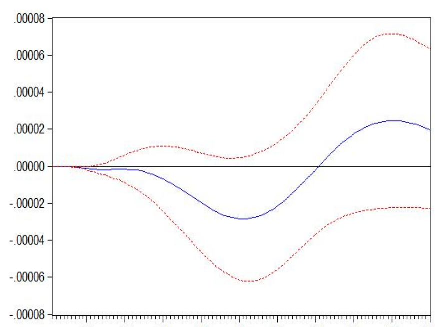
(h) Tullow Oil



(i) Jkx Oil & Gas



(j) Northern Petroleum



(k) Amerisur Resources

Figure 9: The impulse responses of oil and gas stocks to the oil price change shocks at scale 6

Tables

Table 1: Name and sub-sector name for the oil and gas companies

Name	Sub-sector name
Bp	Integrated Oil & Gas
Cape	Oil Equip. & Services
Royal Dutch Shell B	Integrated Oil & Gas
Hunting	Oil Equip. & Services
Premier Oil	Exploration & Prod.
Amec Foster Wheeler	Oil Equip. & Services
Cairn Energy	Exploration & Prod.
Tullow Oil	Exploration & Prod.
Jkx Oil & Gas	Exploration & Prod.
Northern Petroleum	Exploration & Prod.
Amerisur Resources	Exploration & Prod.

Notes: This table reports the name of selected companies and their sub-sector names. Integrated Oil & Gas, Oil Equip. & Services and Exploration & Prod. represent integrated oil and gas companies, oil equipment and service companies and oil and gas exploration and production companies, respectively.

Table 2: Descriptive statistics for oil and gas stock returns

	Bp	Cape	Royal Dutch Shell B	Hunting	Premier Oil	Amec Foster Wheeler
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.106	0.547	0.132	0.161	0.639	0.135
Minimum	-0.140	-0.460	-0.098	-0.237	-0.405	-0.263
Std.Dev.	0.017	0.034	0.017	0.024	0.030	0.022
Skewness	-0.053	-0.537	0.060	-0.009	1.607	-0.719
Kurtosis	7.057	67.657	6.878	11.402	54.965	14.925
JB	3560.52*	903947.70*	3255.14*	15261.39*	584709.20*	31194.89*
LB	59.59*	195.18*	69.29*	76.93*	107.67*	52.00*
ARCH-LM	50.58*	17.77*	60.55*	16.08*	40.27*	17.41*
Observations	5169	5188	5189	5169	5177	5189
Corr.vs WTI	0.009	-0.003	0.025	-0.003	-0.022	-0.004
	Cairn Energy	Tullow Oil	Jkx Oil & Gas	Northern Petroleum	Amerisur Resources	
Mean	0.000	0.000	0.000	-0.001	0.000	
Median	0.000	0.000	0.000	0.000	0.000	
Maximum	0.400	0.216	0.317	0.693	0.452	
Minimum	-0.213	-0.312	-0.464	-0.486	-0.505	
Std.Dev.	0.026	0.028	0.033	0.045	0.040	
Skewness	0.905	0.236	-0.383	1.335	0.215	
Kurtosis	21.551	11.897	29.605	31.704	19.726	
JB	75117.20*	17150.76*	153140.60*	179683.70*	59829.04*	
LB	97.50*	26.75	184.41*	46.68*	46.24^{8}	
ARCH-LM	8.00*	20.38*	20.23*	18.08*	11.02*	
Observations	5169	5165	5168	5189	5109	
Corr.vs WTI	-0.004	-0.019	0.013	0.018	-0.007	

Notes: This table reports basic statistics of daily return series for the period between June 19, 1996 to December 30, 2016. The statistics include mean, median, maximum, minimum, standard deviation, skewness, kurtosis and observations for each oil/stock pair. JB refers to the empirical statistics for the Jarque-Bera normality test and LB represents the empirical statistics for the Ljung-Box test for serial correlation in the return series calculated with 20 lags. ARCH-LM refers to the empirical statistics of the test for autoregressive conditional heteroscedasticity of order 20. Corr. is the Pearson's correlation coefficient. * indicates rejecting the null hypothesis of relevant tests at the 5% significance level.

Table 3: The Granger causality test results based on a VAR model for the raw data

Pairs	Lags	Result	Null hypothesis			
			Oil does not cause stock		Stock does not cause oil	
			F-test	p-value	F-test	p-value
Bp&WTI	7	stock $\Leftrightarrow$ WTI	2.431	0.017	23.199	0.000
Cape&WTI	10	stock $\Rightarrow$ WTI	1.534	0.120	4.041	0.000
Royal Dutch Shell B&WTI	7	stock $\Leftrightarrow$ WTI	4.158	0.000	21.057	0.000
Hunting&WTI	10	stock $\Rightarrow$ WTI	0.570	0.840	11.759	0.000
Premier Oil & WTI	6	stock $\Leftrightarrow$ WTI	4.210	0.000	28.051	0.000
Amec Foster Wheeler & WTI	10	stock $\Rightarrow$ WTI	1.612	0.096	7.507	0.000
Cairn Energy & WTI	7	stock $\Rightarrow$ WTI	1.602	0.130	16.025	0.000
Tullow Oil & WTI	7	stock $\Leftrightarrow$ WTI	4.738	0.000	15.659	0.000
Jkx Oil & Gas & WTI	10	stock $\Rightarrow$ WTI	1.529	0.122	3.762	0.000
Northern Petroleum & WTI	5	stock $\Rightarrow$ WTI	1.572	0.164	2.519	0.028
Amerisur Resources & WTI	5	stock $\Rightarrow$ WTI	0.684	0.635	8.955	0.000

Notes: Lags in tests were selected using the Akaike information criterion(AIC).

Table 4: The Granger causality test results based on a VAR model for time-scaled components on original data

Pairs	Lags	Result	Null hypothesis			
			Oil does not cause stock		Stock does not cause oil	
			F-test	p-value	F-test	p-value
Bp&WTI						
Scale 1(2-4 days)	10	stock $\Leftarrow$ WTI	2.859	0.001	1.824	0.051
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	8.030	0.000	4.617	0.000
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	6.397	0.000	13.131	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	25.058	0.000	39.368	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	5.553	0.000	18.490	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	4.493	0.000	22.956	0.000
Cape&WTI						
Scale 1(2-4 days)	10	No causality	1.475	0.142	1.541	0.118
Scale 2(4-8 days)	10	stock $\Rightarrow$ WTI	1.714	0.072	2.882	0.001
Scale 3(8-16 days)	9	stock $\Leftrightarrow$ WTI	4.323	0.000	2.742	0.003
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	3.127	0.001	3.343	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	3.990	0.000	6.357	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	5.193	0.000	7.412	0.000
Royal Dutch Shell B&WTI						
Scale 1(2-4 days)	10	stock $\Leftrightarrow$ WTI	5.008	0.000	2.412	0.007
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	7.577	0.000	4.367	0.000
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	9.879	0.000	11.445	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	18.172	0.000	29.950	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	6.695	0.000	14.291	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	3.047	0.001	10.537	0.000
Hunting&WTI						
Scale 1(2-4 days)	10	No causality	1.748	0.065	1.378	0.183
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	3.460	0.000	7.237	0.000
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	3.931	0.000	6.718	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	13.786	0.000	20.542	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	2.652	0.003	14.041	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	3.093	0.001	8.861	0.000
Premier Oil & WTI						
Scale 1(2-4 days)	10	stock $\Leftrightarrow$ WTI	2.516	0.005	3.330	0.000
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	9.335	0.000	10.915	0.000
Scale 3(8-16 days)	9	stock $\Leftrightarrow$ WTI	4.363	0.000	9.464	0.000

Table 4 (Continued)

Pairs	Lags	Result	Null hypothesis			
			Oil does not cause stock		Stock does not cause oil	
			F-test	p-value	F-test	p-value
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	19.765	0.000	34.767	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	4.862	0.000	19.065	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	3.960	0.000	16.212	0.000
Amec Foster Wheeler & WTI						
Scale 1(2-4 days)	10	stock $\Rightarrow$ WTI	1.338	0.203	2.252	0.013
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	4.151	0.000	4.668	0.000
Scale 3(8-16 days)	9	stock $\Leftrightarrow$ WTI	4.027	0.000	3.349	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	6.998	0.000	10.720	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	3.274	0.000	7.448	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	9.837	0.000	16.148	0.000
Cairn Energy & WTI						
Scale 1(2-4 days)	10	No causality	1.795	0.056	1.211	0.278
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	4.257	0.000	5.853	0.000
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	3.769	0.000	8.650	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	18.057	0.000	25.469	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	4.968	0.000	13.600	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	3.428	0.000	14.365	0.000
Tullow Oil & WTI						
Scale 1(2-4 days)	10	stock $\Leftrightarrow$ WTI	4.243	0.000	2.187	0.016
Scale 2(4-8 days)	10	stock $\Leftrightarrow$ WTI	5.267	0.000	4.230	0.000
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	5.352	0.000	5.885	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	17.351	0.000	21.844	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	8.943	0.000	12.882	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	7.709	0.000	11.852	0.000
Jkx Oil & Gas & WTI						
Scale 1(2-4 days)	10	stock $\Leftarrow$ WTI	3.063	0.001	1.772	0.060
Scale 2(4-8 days)	10	stock $\Leftarrow$ WTI	2.393	0.008	1.695	0.076
Scale 3(8-16 days)	10	stock $\Leftrightarrow$ WTI	8.169	0.000	6.812	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	5.202	0.000	8.656	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	7.811	0.000	2.576	0.004
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	7.213	0.000	5.089	0.000

Table 4 (Continued)

Pairs	Lags	Result	Null hypothesis			
			Oil does not cause stock		Stock does not cause oil	
			F-test	p-value	F-test	p-value
Northern Petroleum & WTI						
Scale 1(2-4 days)	10	No causality	0.929	0.505	0.805	0.624
Scale 2(4-8 days)	10	No causality	0.460	0.916	0.540	0.863
Scale 3(8-16 days)	9	No causality	1.398	0.183	1.196	0.292
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	4.664	0.000	5.287	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	6.549	0.000	5.796	0.000
Scale 6(64-128 days)	10	stock $\Leftrightarrow$ WTI	3.483	0.000	5.271	0.000
Amerisur Resources & WTI						
Scale 1(2-4 days)	10	stock $\Rightarrow$ WTI	0.670	0.753	2.175	0.016
Scale 2(4-8 days)	10	stock $\Rightarrow$ WTI	1.227	0.267	3.484	0.000
Scale 3(8-16 days)	9	stock $\Leftrightarrow$ WTI	1.988	0.037	5.367	0.000
Scale 4(16-32 days)	10	stock $\Leftrightarrow$ WTI	2.732	0.002	6.817	0.000
Scale 5(32-64 days)	10	stock $\Leftrightarrow$ WTI	4.857	0.000	9.896	0.000
Scale 6(64-128 days)	10	stock $\Rightarrow$ WTI	1.464	0.146	4.344	0.000

Notes: Lags in tests were selected using the Akaike information criterion(AIC).

Table 5: Variance decomposition results of the stock returns due to the oil price changes

	Scale1	Scale2	Scale3	Scale4	Scale5	Scale6
Bp	0.565	2.780	1.003	13.498	3.187	1.204
Cape	0.310	3.088	1.518	3.302	1.037	10.536
Royal Dutch Shell B	0.800	3.057	1.718	8.211	2.390	2.093
Hunting	0.437	2.797	1.389	5.191	4.010	0.282
Premier Oil	1.272	3.693	1.950	13.296	4.449	3.129
Amec Foster Wheeler	0.463	2.622	1.409	4.621	1.733	2.228
Cairn Energy	0.542	1.705	1.076	10.532	1.108	6.333
Tullow Oil	1.474	2.129	1.370	9.859	2.997	2.320
Jkx Oil & Gas	0.826	1.527	3.799	3.447	3.597	1.569
Northern Petroleum	0.289	0.710	1.223	3.287	1.486	4.883
Amerisur Resources	0.364	0.752	1.218	1.502	3.291	2.241

Table 6: Oil price risk estimated based on daily return series and recomposed series at different scales

	raw return	scale1	scale2	scale3	scale4	scale5	scale6
Bp	0.008	-0.017	0.009	-0.102	0.102	0.234	0.220
Cape	-0.005	-0.045	-0.053	0.031	0.008	0.287	0.172
Royal Dutch Shell B	0.021	0.004	0.007	-0.060	0.147	0.224	0.127
Hunting	-0.003	-0.010	-0.030	-0.174	0.076	0.099	0.258
Premier Oil	-0.032	-0.075	-0.016	-0.291	0.058	0.324	0.325
Amec Foster Wheeler	-0.004	-0.016	0.009	-0.184	0.125	0.022	0.071
Cairn Energy	-0.005	-0.016	0.009	-0.184	0.125	0.022	0.071
Tullow Oil	-0.026	-0.073	-0.020	-0.189	0.136	0.250	0.245
Jkx Oil & gas	0.021	-0.023	-0.002	0.056	0.079	0.121	0.254
Northern Petroleum	0.040	0.008	-0.013	0.077	0.028	0.399	0.351
Amerisur Resource	-0.014	-0.036	-0.087	-0.058	0.261	0.330	-0.074

Notes: This table reports the oil price risk estimated based on daily return series and recomposed series at different scales for the selected oil and gas companies.