Economic Modelling 76 (2019) 172–181

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Oil price and automobile stock return co-movement: A wavelet coherence analysis

Debdatta Pal [a,*], Subrata K. Mitra [b]

[a] Indian Institute of Management Lucknow, Lucknow, 226013, India
[b] Indian Institute of Management Raipur, India

ARTICLE INFO

JEL Code:
C32
C63
Q41

Keywords:
Co-movement
Crude oil
Automobile stock
Wavelet analysis

ABSTRACT

This paper explores possible co-movement between oil price and automobile stock return in a joint time-frequency domain. Daily price series from August 01, 1996 to June 20, 2017 is used in this analysis. The results indicate that the co-movement between oil price and automobile stock return is strong during November, 2000–December, 2002 and March, 2006–December, 2009. The co-movement is found to be more pronounced in the long-term and stock return is sensitive to the higher oil price emanating from the demand shock. This contravenes the conventional wisdom that crude oil is always counter-cyclical to the automobile stocks. For investor, this weakens the probable gain from including oil asset in a portfolio of automobile stocks as crude oil does not offer cushion against bearish automobile stock markets during the crisis period.

1. Introduction

Since Jones and Kaul (1996) suggest that oil price rise has a considerable negative influence on stock market returns in the U.S., numerous studies (e.g., Huang et al., 1996; Sadorsky, 1999; Wei, 2003; Park and Ratti, 2008; Apergis and Miller, 2009) have examined possible effect of oil price fluctuations on aggregate market indices. In parallel, several studies (e.g., Nandha and Faff, 2008; Kilian and Park, 2009; Narayan and Sharma, 2014; Chiang et al., 2015; Phan et al., 2015a, 2015b; Chiang and Hughen, 2017; Narayan et al., 2018) have investigated whether influence of oil price shocks varies across sectors. Narayan and Sharma (2011) have extended the literature with micro-level data across 560 firms spread over 14 sectors and find that returns of firms from the energy and transportation sectors respond positively to oil price hike. Sector as well as firm level exploration of oil price-stock return relationship is important as sectors have different market structure and their dependence on oil is also not homogenous.

We revisit sectoral analysis and sets the objective to extend the understanding of the link between oil price shock and stock return at the intra-sector level. Based on Narayan and Sharma (2011) that highlights that firm returns from the transportation sector respond positively to oil price rise, this study explores whether returns of major stock market indices in the automobile sector differ to oil price changes. Secondly, we want to examine whether the strength of co-movement between crude oil and automobile stock return varies over time across frequency. An investor needs to detect the time-varying characteristics as the co-movement may be significant only during specific periods (Devpura et al., 2018). At the same time, if the degree of the co-movement of oil price with automobile stock return varies across frequencies the risk for a long-term investor will differ from her short-term counterpart as the former is more concerned to long-run oscillations while the latter group is more interested on the fluctuations in the short-run (Rua and Nunes, 2009).

To achieve this objective, we focus on modelling the co-movement of daily returns of four major stock indices in the automobile sector (a prime oil-consuming sector), namely, MSCI ACWI automobiles and components index, STOXX Europe 600 automobiles and parts index, S&P 500 auto and component index, and MSCI world automobile index with the crude oil (West Texas Intermediate - WTI) price returns. We choose the automobile sector as it is broadly believed to be extremely prone to oil price shock (e.g., Nandha and Faff, 2008; Arouri, 2011) as a higher oil price is probable to carry a dampening effect on the demand of passenger vehicle, thus, may repress the stock prices of the automobile companies (Cameron and Schulenburg, 2009; Hamilton, 2009). The study period spans over August 01, 1996–June 20, 2017. The choice of the study period is guided by the fact that it covers the phases of both energy crisis and financial turmoil during 2007–2009. This would help us to unearth possible changes in the strength of co-movement (if any) during the crisis periods.

* Corresponding author.
E-mail address: debdatta@iiml.ac.in (D. Pal).

https://doi.org/10.1016/j.econmod.2018.07.028
Received 28 February 2018; Received in revised form 26 June 2018; Accepted 29 July 2018
Available online 10 August 2018

On the methodological front, we distinct our work from the majority of the empirical analysis, by using wavelet coherence, a technique that pools information from time as well as frequency domain. Conventional time series techniques, namely, vector autoregressive models, Granger causality, generalized autoregressive conditional heteroscedastic processes, capture information solely from the time domain and ignore any information from the frequency sphere. On the other hand, the frequency-based methods, for example Fourier transformation techniques, completely ignore information from the time sphere. Contrary to the approaches that focus either on the time sphere or on the frequency space, wavelet coherence analysis covers both. The novelty of wavelet coherence is that it decomposes time series data into time-frequency domain. This breakdown to frequency modules allows for differentiation between short- and long-term activities.

In 2009, flow in commodity assets, more specifically in crude oil, was as high as $250 billion from an investment of only $15 billion during 2003 (Irwin and Sanders, 2011). Causes behind this financialization of energy commodities are seemed to be: (a) given poor returns from conventional asset class, namely stocks and bonds, investors were exploring non-traditional assets expecting more returns (Brooks and Prokopczuk, 2013); (b) as the causes behind crude oil price changes (e.g., aggregate demand shock, oil supply shock, and precautionary demand shock as advanced by Kilian, 2008) are dissimilar from those guiding stocks and bonds markets, oil prices hold weak correlation with conventional assets (Geman and Kharoubi, 2008). Hence, crude oil is included as a “diversifier” in the portfolio as it holds a weak positive correlation with stocks (Bouri et al., 2016). Similarly, a strong positive correlation (co-movement) of oil price with automobile stock return involves lesser gains from the diversification of portfolio. By using wavelet analysis, it is possible to assess concurrently the degree of the co-movement at diverse frequencies over time. In this manner, one can isolate phases in the combined time–frequency sphere where the co-movement is stronger and the payback from diversified portfolio is low (Rua and Nunes, 2009).

Our analysis implies significant wavelet coherence between oil price and automobile stock return and contravenes the traditional wisdom that crude oil is always countercyclical in regard to the stock markets. For example, following a weak positive correlation between crude oil and stock indices, Arouri et al. (2012) and Khalfaoui et al. (2015) suggest that inclusion of crude with stocks would substantially improvise the portfolio's diversification benefits. However, we find strong co-movement i.e., significant positive correlation of oil price with automobile stock return during 2000–2002 and 2006–2009. For investor, this weakens the probable gain from diversification and crude oil does not continue to offer cushion against bearish automobile stock markets during the crisis periods.

The following section briefly covers the relevant literature. Section 3 narrates the wavelet coherence method. In Section 4, we offer the empirical evidence from our study. Section 5 draws conclusions with regard to the implications in the financial market.

2. Relevant literature

The association between oil price variations and stock return may be explained in the discounted cash flow valuation model (Fisher, 1930) which suggests that value of a stock is its discounted expected cash flows. Oil price can influence a firm's future cash flows in the following ways. First, given oil is a key input, an augmented oil price would raise the production cost, which would carry a dampening effect on firm's profit margin, and hence, suppress the stock price (Sadorsky, 1999; Narayan and Sharma, 2011; Filis et al., 2011). Second, fluctuations of oil price may carry a negative influence on demand of goods and services produced by a firm; as consumers might raise their precautionary savings in anticipation of recession and unemployment due to increased crude price and postpone purchase of consumer durables, thus, adversely affecting both top and bottom line of a firm along with its stock price (Kilian, 2008; Xu, 2015). Third, reacting to the oil price shocks, firms may postpone their investment decisions which would repress their future cash flows, in turn, would carry a negative impact on stock price (Edelstein and Kilian, 2009). Finally, policy makers may raise interest rate to counter the inflationary pressure of increased oil price. An increased interest rate would lead to an augmented discount rate which is expected to have a strong dampening influence on stock price (Miller and Ratti, 2009; Ghosh and Kanjilal, 2016).

While literature is yet to reach a consensus on oil-stock nexus, majority of the studies indicate that oil price hike carry a substantial negative influence on stock return (e.g., Jones and Kaul, 1996; Sadorsky, 1999; Ciner, 2001; Driesprong et al., 2008; Park and Ratti, 2008). However, there are dissenting outcome (e.g., Narayan and Narayan, 2010; Lee et al., 2012; Zhu et al., 2014) that have even documented positive stimulus of oil price variations on stock return. Another set of researches (e.g., Cong et al., 2008; Park and Ratti, 2008; Bjornland, 2009) suggest that while oil price rise is expected to carry a dampening effect of stocks of oil-importing nations, it would boost the stock price in oil exporting nations. In turn, Kilian and Park (2009) have argued, based on the causes of oil price variation, stock return responds differently to the oil price movement. They suggest that an aggregate demand shock augments the demand for crude oil along with its price, thus, boosts the stock price. This occurs as because both oil and stock market respond positively to economic stimulation. In contrast, precautionary demand shock arising from concerns regarding restricted supply of crude oil in future, dampens the stock market. However, the supply-side price shock, attributed to the short fall in oil availability, does not carry much influence on stock return. Similar result has also been suggested by Abhyankar et al. (2013) in Japanese stock market. Lastly, there are studies (e.g., Huang et al., 1996; Al Janabi et al., 2010) supporting neutrality hypothesis that could not identify any relation of oil price movement with stock return.

Among the studies that explore sector-wise oil price - stock return linkage, Nandha and Faff (2008) suggest that oil price shocks depress the stock returns for all sectors including automobile and transport, however, carries a positive impact on stocks in mining and oil sectors. Along the same line, Scholtens and Wang (2008) find that increased oil price boosts stock return from oil industry. Henriques and Sadorsky (2008) exhibit that oil price movement Granger-cause stock price of the firms from the domain of alternative energy. Cameron and Schulenburg (2009) find that oil price hike depresses the stock returns in the automobile sector and more specifically for the manufacturer of sports utility vehicles. Kilian and Park (2009) suggest that precious metal stocks appreciate in reaction to higher oil price, whereas stocks in petroleum and natural gas industries hardly appreciates, and stocks in the retail sector show a persistent and strong negative relationship with the oil price shock. Arouri (2011) also confirms that the nature and the degree of fluctuation in stock return in reaction to the oil shock varies across sectors; while oil and gas sector stocks react positively to higher oil prices, reaction of the stocks in the automobile sector is negative. Narayan and Sharma (2011) suggest that returns of firms from the energy and transportation sectors respond positively to oil price rise. Similarly, Chiang et al. (2015) offer corroborative evidence that oil-related stock return is highly reactive to oil price changes. Ready (2016) also suggests substantial negative link between oil price movement and stock return in industries related to consumer durable and a positive link of oil price with stock return in the energy sector. Kang et al. (2016) suggest that U.S. oil production shocks could explain 9.6 percent of automobile stock returns. In a more recent attempt, Chiang and Hughen (2017) find that stocks in the non-oil industry react negatively to higher oil price, whereas reaction of the stocks in the oil-related industry is positive to rising oil prices.

From the geographical perspective, present literature on the relationship of oil price movement with stock return has mostly concentrated in developed nations (Park and Ratti, 2008; Apergis and Miller, 2009; Miller and Ratti, 2009; Abhyankar et al., 2013; Cuñado and Pérez de Gracia, 2014; Degiannakis et al., 2014; Moya-Martínez et al., 2014; Ding et al., 2016; Chiang and Hughen, 2017; Jammazi et al., 2017). However, literature is increasingly dealing with emerging markets (e.g., Basher and Sadorky, 2006; Narayan and Narayan, 2010; Aloui et al., 2012; Singhal and Ghosh, 2016; Peng et al., 2017).

On the methodological front, following Huang et al. (1996) that have adopted vector autoregressive (VAR) framework, a wide body of literature (e.g., Sadorsky, 1999; Kilian and Park, 2009; Abhyankar et al., 2013; Degiannakis et al., 2014; Kang et al., 2015) has followed VAR model. Studies have also explored other time series techniques, namely, co-integration analysis (e.g., Zhu et al., 2011; Narayan and Narayan, 2010; Ghosh and Kanjilal, 2016), vector error correction framework (e.g., Miller and Ratti, 2009), generalized autoregressive conditional heteroskedasticity model (e.g., Aloui and Jammazi, 2009; Sadorsky, 2012; Guesmi and Fattoum, 2014; Jouini and Harrathi, 2014; Narayan and Sharma, 2014; Peng et al., 2017), copula function (e.g., Aloui et al., 2013; Zhu et al., 2014; Aloui and Ben Aïssa, 2016; Kayalar et al., 2017) as well as Markov regime switching models (e.g., Balcilar and Ozdemir, 2013; Naifar and Al Dohaiman, 2013; Jammazi and Nguyen, 2015).

Furthermore, literature has also explored Granger causality from oil price movement to stock return in a linear framework (e.g. Henriques and Sadorsky, 2008; Lee et al., 2012; Dagher and El Hariri, 2013). Recently, studies have also explored whether stock returns respond asymmetrically to oil price movement (e.g., Arouri, 2011; Rafailidis and Katrakilidis, 2014; Alsalman and Herrera, 2015; Reboredo and Ugolini, 2016; Ding et al., 2016; Salisu and Isah, 2017).

All the studies noted above have looked into the time sphere, while information originated from the frequency sphere has been obviated. To jointly include information from time and frequency spheres, a growing body of literature is increasingly focusing on wavelet analysis (e.g., Madaleno and Pinho, 2014; Reboredo and Rivera-Castro, 2013; Huang et al., 2015; Khalfaoui et al., 2015; Martín-Barragán et al., 2015; Ftiti et al., 2016; Jammazi and Reboredo, 2016; Jammazi et al., 2017). In this study, we also employ wavelet coherence analysis.

3. Methodology

A wavelet is made of two distinct parameters: time (l) and scale (m). Originating from mother wavelet ψ, "wavelet daughters" family ($\psi_{l,m}$) can be produced over scaling and translating ψ (see for example, Torrence and Compo, 1998; Percival and Walden, 2000; Gençay et al., 2002; Ramsey, 2002):

$$\psi_{l,m}(t) = \frac{1}{\sqrt{m}}\psi\left(\frac{t-l}{m}\right), \quad l,\ m\ \in \mathbb{R}, m \neq 0. \tag{1}$$

Given a finite time series $g(t)$, it is plausible to obtain the continuous wavelet transform, $W_g(l,m)$, from the specific wavelet $\psi(\cdot)$ which is a function of time (l) as well as scale (m), by "comparing" g with a full "wavelet daughters" family:

$$W_g(l,m) = \int_{-\infty}^{\infty} g(t)\frac{1}{\sqrt{m}}\overline{\psi\left(\frac{t-l}{m}\right)}\mathrm{d}t, \tag{2}$$

where the bar denotes a complex conjugate.

Variance distribution of an underlying time series over time-scale (time-frequency) sphere can be generated from a *wavelet power spectrum* (WPS) as follows:

$$\mathrm{WPS}_g(l,m) = \left|W_g(l,m)\right|^2. \tag{3}$$

Wavelet coherence between two time series, $g(t)$ and $h(t)$, over a joint time-frequency sphere, can be expressed through cross wavelet transform (CWT) as:

$$W_{gh}(l,m) = W_g(l,m)\overline{W_h(l,m)}, \tag{4}$$

where $W_g(l,m)$ and $W_h(l,m)$ indicate the CWT of $g(t)$ and $h(t)$, respectively. The bar shows a complex conjugate.

Following Torrence and Compo (1998), definition of a squared wavelet coherence is as follows:

$$R^2(l,m) = \frac{\left|S\left(m^{-1}W_{gh}(l,m)\right|^2}{S\left(m^{-1}\left|W_g(l,m)\right|^2\right)S\left(m^{-1}\left|W_h(l,m)\right|^2\right.}, \tag{5}$$

where S represents a smoothing procedure over time along with frequency (scale), with $0 \leq R^2(l,m) \leq 1$. A value of $R^2(l,m)$ approaching 1 represent dependence of the two underlying time series for a distinct frequency.

As the wavelet coherence coefficient is squared value, it may not be feasible to isolate the positive correlation from its negative counterpart. Thus, Torrence and Compo (1998) suggested a way for differentiating between positive and negative coherence by signs of deferments in the oscillating of the underlying time series. The difference of the phase of wavelet coherence is expressed as:

$$\phi_{gh}(l,m) = \tan^{-1}\left(\frac{\Im\left\{S\left(m^{-1}W_{gh}(l,m)\right)\right\}}{\Re\left\{S\left(m^{-1}W_{gh}(l,m)\right)\right\}}\right), \tag{6}$$

where, $\Im$ refers to an imaginary operator and $\Re$ indicates a real part operator. In this article, we portray a bi-dimensional plot where the black arrows show the results of the wavelet coherence phase difference. When two underlying time series exhibit are positive correlation, the wavelet coherence phase difference evolves to be zero for a particular scale, and reflected through rightward pointed arrows. Alternatively, when two underlying time series exhibit negative correlation (i.e., anti-phase of two underlying series), arrows will be pointing leftward. A downward pointed arrow denotes that the first series is leading the second by $\frac{\pi}{2}$ and *vice versa*.

4. Empirical evidence

4.1. Data

Our data comprises of four stock market indices that belong to the automobile sector, namely, MSCI ACWI automobiles and components index (MXWDOAC), STOXX Europe 600 automobiles and parts index (SXAP), Standard & Poor's 500 automobiles and components index (S5AUCO), and MSCI world automobile index (MXWO0AU) along with crude oil (WTI) price (in U.S. dollar per barrel) spanning from August 01, 1996 to June 20, 2017, yielding a total of 5449 observations for each series. The MSCI ACWI automobiles and components index consists of large and mid-cap stocks of the manufacturer of automobile and its components spread over 23 developed and 24 emerging market economies. The STOXX Europe 600 automobiles and parts index acts as a performance measurement yard of the key automobile firms and parts suppliers from 18 European nations. The Standard and Poor's 500 automobiles and components index is an automobile industry subset of Standard and Poor's 500 (Industry Group) index. The MSCI world automobiles index is comprised of large- as well as mid-cap stocks that belong to the automobile industry and spreads across 23 developed market economies. While we have obtained the data sets of the automobile indices from Bloomberg, crude oil price data is availed from United States Energy Information Administration.

The choice of daily data over monthly series is guided by the fact that the former carries richer information over the monthly data set (Bannigidadmath and Narayan, 2016). Secondly, as hypothesis testing based on single data frequency is not beyond question (Narayan and Sharma, 2015; Narayan et al., 2015), we use daily data for examining the robustness of our results with monthly data set.

To assess the order of integration of the underlying time series (converted in their logarithmic form), we employ the following unit root tests: Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP). As expected, that returns are found to be stationary after first differencing. We offer summary statistics in Table 1 and unit root test results are provided in Table 2.

Following Narayan and Liu (2018), we ascertain the higher order moments of the underlying return series as they are important for asset pricing. With reference to Table 1, the third moment denotes that distributions of the return series of MSCI ACWI automobiles and components index, STOXX Europe 600 automobiles and parts index, and MSCI world automobile index are positively skewed. As the return distribution of these three automobile stock indices are concentrated on the positive side, investors are expected to pay a premium for these assets and hence, they are likely to attract higher prices (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Narayan and Ahmed. 2014). The fourth moment specifies that all the underlying return series are leptokurtic with excess positive kurtosis greater than three, indicating that risks might be emanating from the outlier events.

As the underlying variables are of order one, we conducted Johansen test to ascertain cointegrating relationships among the I(1) level variables, so that, further analysis can be done using vector error correction model (VECM). However, in absence of any cointegrating relationship among the underlying variables, VECM has not been carried out. As return series variables are found stationary (I(0)), relationship among variables are analysed using returns series.

4.2. Wavelet analysis

To evaluate the co-movement of oil price with automobile stock indices, a wavelet power spectrum for daily returns of four underlying indices representing the automobile sector along with crude oil (WTI) price return is developed (as portrayed in Fig. 1). The analysis is undertaken using "biwavelet" (*R* project) proposed by Tarik C. Gouhier and Aslak Grinsted. Given the length of the time series (5449 data points) the scale of 1024 periods (2^{10}) has been used. With reference to Fig. 1, the white curve corresponds to the cone of influence referring an edge under which the wavelet power is discontinued, and therefore hard to infer. The thick black contours refer to the wavelet power spectrum, significant at the five percent level, where significance test results are obtained by the means of Monte Carlo simulations. The color referring to the power spectrum varies from red (strong) to blue (weak).

In Fig. 1, all four stock market returns exhibit some commonality on account of wavelet power. All of them have shown high power over a time span between July 1998 and September 2015, but at scales as high as 256 periods (low frequency) and above. In contrast, wavelet power is low at upper frequencies over the entire study period. The crude oil price return also has exhibited high power during April 2000 to September 2015 only at higher scales.

In Fig. 2, we display the wavelet coherence of crude oil with four automobile stock market performance indices in the joint time-frequency sphere. The wavelet coherence will denote the strength of correlation between examined return pairs, and the bright red (hotter) the color, the higher the correlation value with regard to $R^2(l,m)$ as in *Eq.* 5. Black contours refer to the wavelet power spectrum, significant at 5 percent. Following the discussion in Section 3, the direction of the arrows would specify whether the underlying pair is in phase besides identifying the lead series.

Fig. 2(a) illustrates coherence between the return series of crude oil price and MSCI ACWI automobiles and components index. In Fig. 2(a), we find that during November, 2000–December, 2002, oil price return exhibits relatively strong correlation with the stock return of the MSCI ACWI automobiles and components index, with statistically significant at close to 264 days scale. The right and down pointing arrows confirm that, first, both the series are in phase and second, oil price return has led the stock return of the aforementioned automobile index by $\frac{\pi}{2}$, that is, by one quarter of this given scale. The correlation of the underlying variables has become stronger since March, 2006 and continued till December, 2009, the phase that coincides with the phase of energy crisis when the oil price has touched a historically high at $145 per barrel during July, 2008. And this correlation is again found in relatively higher scales of 264 days and above (low frequency). The rightward pointing arrows indicate that both the underlying series are in phase. Furthermore, as those arrows are pointing down, it confirmed that the stock return of the examined automobile index is led by the oil price return during the period of energy crisis as well as financial turmoil.

Fig. 2(b) portrays the coherence of oil price returns with STOXX Europe 600 automobiles and parts index (SXAP) returns. Crude oil price returns are found to be weakly correlated with stock market returns of the SXAP during the majority of the study period, except between November, 2000 and December, 2002, when the underlying pair is in phase and the particular stock return is led by the oil price return at relatively long-term scales (low frequency). Although Fig. 2(b) indicates strong correlation between the underlying return series during March, 2006–December, 2009, it is hard to infer from the trend of arrows, whether oil price returns lead SXAP returns or vice-versa. The outcome of our analysis extends support to that of Arouri et al. (2012) who have analysed the volatility spill over from crude oil to STOXX Europe 600 automobiles and parts index. They also could not identify any evidence of cross-volatility spill over. They account this absence of cross-volatility spill over to the inherent risk-management strategies followed by the automobile manufacturers, an industry prone to oil price risk, to cover up any sudden oil shock. However, Cameron and Schulenburg (2009) attribute this weak correlation of oil price with automobile stock return in Europe to the European legislation, which manifests greater usage as well as production of fuel-efficient vehicles, besides extending financial aid to the automobile sector during the period of energy crisis.

With reference to Fig. 2(c), we show the wavelet coherence between the return series of crude oil price and Standard & Poor's 500 automobiles and components index (S5AUCO). The underlying return series exhibit correlation during November, 2000–December, 2002 at relatively long-term scales (low frequencies). During the corresponding period the pair is found to be in phase and crude oil price return led the sectoral S & P stock market return. Existence of coherence between the underlying pair of series is also evident during March, 2006–December, 2009 and the direction of arrows confirmed that the underlying automobile sector stock returns are led by the oil price returns during the crisis. These findings are consistent with Kumar (2017) who found linkage of crude oil prices with S & P 500 automobiles and components index.

In Fig. 2(d), we find that crude oil price return is strongly correlated with the returns of MSCI World Automobile Index (MXWO0AU), specifically during November, 2000–December, 2002 and March, 2006–December, 2009; rightward-down arrows indicate the underlying series are in phase; moreover, oil price returns have led the market returns of MXWO0AU during the period of the energy crisis in the relatively long-term scales of 264 days and above.

Table 1
Summary statistics of return series.

	Mean	Variance	Skewness	Kurtosis
MSCI ACWI automobiles & components index	0.00016	0.00016	0.81986	21.27815
STOXX Europe 600 automobiles & parts index	0.00025	0.00038	1.97936	87.39425
S & P 500 automobiles & components index	0.00001	0.00035	−0.18952	6.31429
MSCI World automobiles index	0.00013	0.00019	1.06258	26.76001
Crude oil (West Texas Intermediate) price	0.00014	0.00059	−0.09531	4.69140

4.3. Robustness test

Following the growing body of literature (e.g., Narayan and Sharma, 2015; Narayan et al., 2013) to identify whether choice of data frequency

Table 2
Unit root tests of the return series.

Return series (first log-difference series)	Intercept			Intercept and trend		
	ADF t-statistics	KPSS LM statistics	PP Adj t-statistics	ADF t-statistics	KPSS LM statistics	PP Adj t-statistics
MSCI ACWI Automobiles & Components Index	−63.84935***	0.045422	−63.30779***	−63.84441***	0.033651	−63.30175***
STOXX Europe 600 Automobiles & Parts index	−75.03964***	0.067556	−75.03971***	−75.03301***	0.070061	−75.03308***
S & P 500 Automobiles & Components Index	−36.45313***	0.063222	−72.29115***	−36.45335***	0.033933	−72.29163***
MSCI World Automobiles Index	−66.04608***	0.033129	−65.64467***	−66.04003	0.033598	−65.63798***
Crude oil (WTI) price	−77.38226***	0.137903	−77.38377***	−77.38226	0.137903	−77.38377***

Note: *** significant at 1%. Under KPSS test the return series are found to be stationary as the LM statistics do not reject null of return series is stationary.

critically impacts the results of time-series modelling, we re-estimated our results of wavelet analysis by changing the data frequency from daily to monthly. Our results (Fig. 3) with the monthly return series are almost robust to the changes in frequency of the underlying variables.

To confirm the linkage between crude oil and four automobile stock indices, we administer Granger causality (Granger, 1969) test. Following Rodríguez-Caballero and Ventosa-Santaulària (2014) that suggest that results of Granger-causality test are not reliable when the series are integrated to the first order, we have undertaken Granger-causality test with the return series and results are given in Table 3. Our findings suggest some evidence of bi-directional causality between oil price and STOXX Europe 600 automobiles and parts index (SXAP). Similar results are obtained between oil price and Standard & Poor's 500 automobiles and components index (S5AUCO). The causality test results corroborate our findings from wavelet analysis and indicate strong interactions of crude oil price with both SXAP and S5AUCO.

4.4. Discussion

The findings from our wavelet analysis indicate that the coherence of oil price with automobile stock return differs in time and across scale (frequency). We find corroborative evidence that the co-movement between crude oil and stock returns in the automobile sector is time-varying in nature i.e., the co-movement is existing only over particular periods rather than remaining present during the entire sample (Devpura et al., 2018). We find that automobile stock returns are strongly correlated with the oil price returns during 2000–2002 and 2006–2009. The latter phase not only corresponds to the period of the energy crisis but also overlaps with financial turmoil during 2007–2009. Hamilton (2009) suggests that the period over the fourth quarter of 2007 to the second quarter of 2008 is the most severe oil price shock on record. The pre-crisis period (with exception during 2000–2002) along with the post-crisis period has marked a relatively weak coherence between crude oil and automobile stock indices in short- along with long-term scales. That is, the inter-dependence between oil price and automobile stock returns is relatively weak during the stable periods, however, rises significantly during financial crisis. Hence, the use of crude oil as a predictor of automobile stock return is likely to hold true only during the crisis periods, not in general.

Another noteworthy finding of our study is that the strength of the co-movement between crude oil and automobile stock returns is frequency dependent. Our empirical outcomes indicate that the co-movement of oil price and automobile stock return is more prominent in relatively long-term scales of 264 days and above (low frequency) and this co-movement is weak for short-term scale (high frequency). That is, the co-movement is stronger at the lower frequencies suggesting a minimum diversification benefit in the long- term scales. This is because higher oil prices attributed to oil demand shocks carry a persistent augmenting influence on stock returns within a year, as the impetus stemming from the economic expansion initially outweighs the stagnation induced by rising oil prices (Kilian and Park, 2009). Therefore, the interest of the investor, in regards to the long- and short-term horizon, to be considered for addressing the issue of portfolio diversification with crude oil.

Furthermore, in terms of lead-lag relationship, the evidence from our wavelet analysis suggests that crude oil returns have led the automobile stock returns during the period of financial crisis. Such lead-lag linkages show that crude oil market processes new information much faster than the automobile stock market. However, the lead-lag relationship has remained mostly unclear in pre- as well as post-crisis periods.

Our findings add to that of Madaleno and Pinho (2014) that suggest stronger coherence between oil and MSCI World index as well as its sectoral indices during 2007–08 and confirm that crude oil is not counter cyclic to stock market representing the major automotive manufacturers and the firms producing automobile components. The counter-cyclic role is more prominent when high oil price originates from the oil-supply shocks. However, when oil price shock is rooted in growing demand of oil from economies to augment higher economic growth, oil price and stock return are likely to move together (Kilian, 2009). Our findings are also consistent with Ftiti et al. (2016) that demonstrate that inter-dependence between oil price and stock return in G7 countries is more pronounced during 2007–2008. In a more recent attempt, Jammazi et al. (2017) have also detected stronger link between oil price fluctuation and stock return of six key oil-importing industrialized nations (France, Germany, Italy, Spain, U.S., U.K.,) during the period of financial turmoil.

A critical inference from significant wavelet coherence of oil price with automobile stock return during 2006–2009 is that crude oil no longer continues to be a safe haven to offer cushion against bearish automobile stock markets, specifically in crisis. Hence, from the perspective of diversification benefit, crude oil does not always serve as counter-cyclic in regards to automobile stock market, as generally envisaged by the previous literature. Given weaker coherence during the stable periods crude oil may add potential diversification benefit to the portfolio. However, identification of strong co-movement between crude oil and automobile stock returns during the period of finial crisis limits the potential advantage of including crude oil as a diversifier in the portfolio. Investors need to pay adequate attention to such strong co-movement of oil price with automobile stock return as such coherence during crisis periods adds complexity to the diversification strategies.

5. Conclusion

This study inspects the link of oil price with automobile stock return. It covers four major global automobile stock indices, namely, MSCI ACWI automobiles and components index, STOXX Europe 600 automobiles and parts index, Standard & Poor's 500 automobiles and components index, and MSCI World automobile index. By using the wavelet coherence analysis, it has modelled the co-movement of daily oil price and automobile stock return spanning over August 01, 1996 and June 20, 2017. Choice of the wavelet method over conventional econometric techniques is rooted in its unique ability of decomposing time series into bi-dimensional time-frequency space.

The findings of the wavelet analysis indicate that the co-movement between oil price and stock return of MSCI ACWI automobiles and components index is significantly strong during March, 2006–December, 2009, the phase that not only corresponds to the period of energy crisis, but also overlaps with financial turmoil, i.e., during 2007–2009. This correlation is observed to be prevalent at comparatively long-term scales

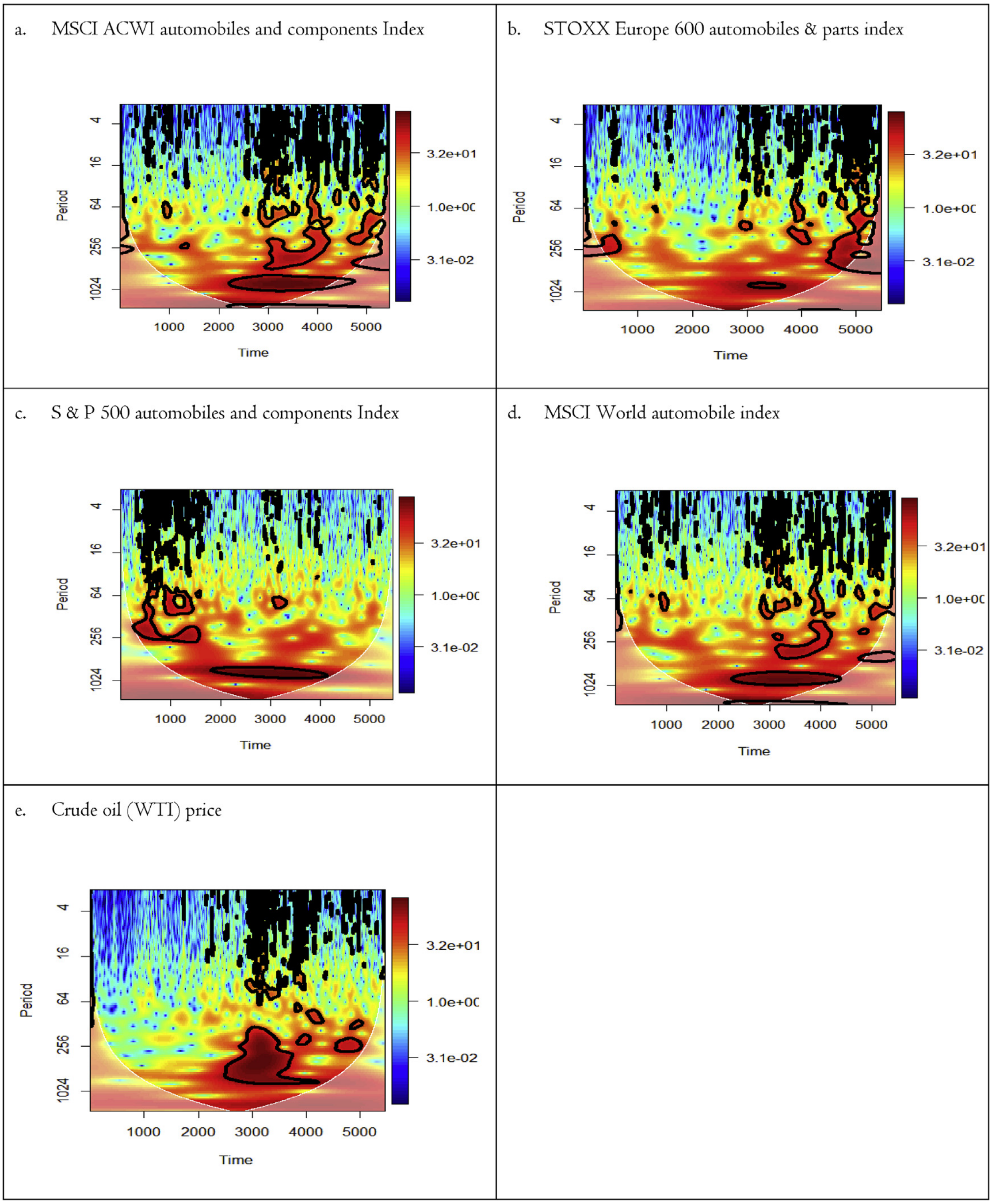

Fig. 1. Wavelet power spectrum for the returns of MSCI ACWI Automobiles and Components Index, MSCI World Automobile Index (MXWO0AU), STOXX Europe 600 Automobiles & Parts index (SXAP), S & P 500 Automobiles and Components Index (S5AUCO), and crude oil (WTI) price. Vertical axis refers to time in days and horizontal axis represents period. White curve corresponds to the cone of influence referring an edge under which the wavelet power is discontinued, and therefore, hard to infer. Black contours refer to the wavelet power spectrum, significant at 5%. The color indicating the power spectrum varies from red (strong) to blue (weak). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of 264 days (lower frequency) where stock returns are led by the oil prices. For STOXX Europe 600 automobiles and parts index, though the strength of the correlation is visible during March, 2006–December, 2009, lead-lag relationship has remained inconclusive. During the same period, i.e., between March, 2006 and December, 2009, stock returns of both Standard & Poor's 500 automobiles and components index and MSCI World automobile index have exhibited significantly stronger coherence with the oil price returns at scales of 264 days and above (i.e., lower frequency) with oil price leading stock returns of both the indices.

Our results have following useful implications for the investors along with the policy makers. First, upon synthesizing the outcomes, we favor to disagree with the prevailing literature, for example Arouri et al. (2012), that advocate that inclusion of the oil asset in a portfolio of automobile stocks would substantially improvise the portfolio's diversification benefits. Rather, our analysis provides corroborative evidence that oil is not counter-cyclic to automobile stock returns and oil is not always a cushion against bearish automobile stock markets, as envisaged. The significant co-movement of oil price with automobile stock return during 2000–2002 and 2006–2009 at relatively long-term scales of 256 days and above is plausibly attributed to the higher oil prices emanating

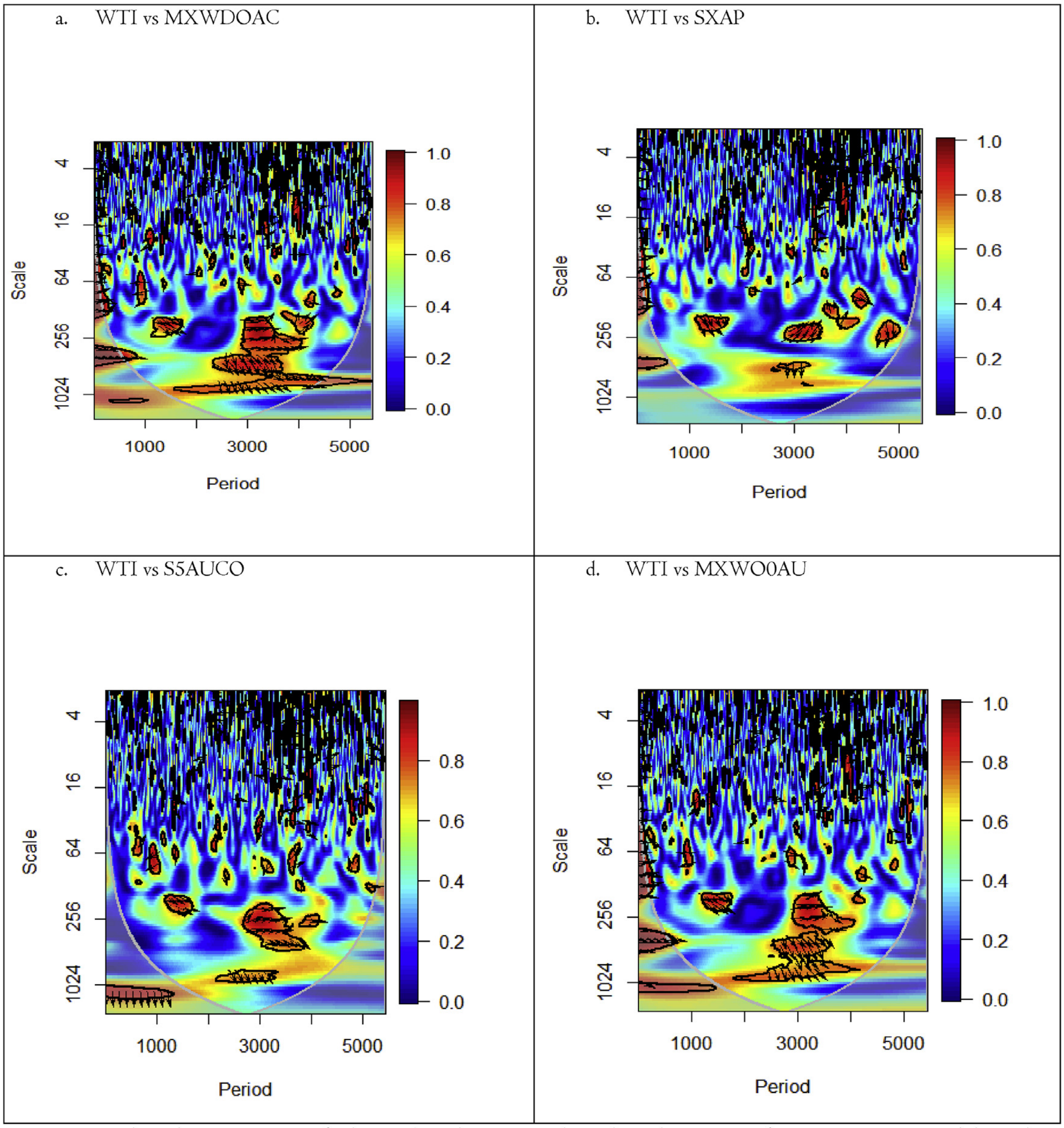

Fig. 2. Wavelet coherence in pairs of oil price (WTI) returns with stock market returns of MSCI ACWI automobiles and components index (MXWDOAC), MSCI World automobile index (MXWO0AU), STOXX Europe 600 automobiles and parts index (SXAP), and S & P 500 automobiles and components index (S5AUCO). Vertical axis denotes time in days and horizontal axis represents period. White curve corresponds to the cone of influence referring an edge under which wavelet power will be discontinued, and therefore, hard to infer. Color shown on the right hand side of the charts indicate degree of correlation; hotter the color the greater the absolute correlation value according to $R^2(l, m)$ in *Eq.* 5. Black contour denotes the significance testing at the 5% level tested for AR(1). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

from the augmented oil demand due to global economic activities. This is because higher oil prices due to oil demand shocks positively influence the stock returns within a year, as the growth associated with expanded economic activity initially outweighs the stagnation levied by oil price hike (Kilian and Park, 2009). In contrast, a counter-cyclic association between oil price and stock return is likely to be driven by higher oil price originating from oil supply shocks or precautionary demand shocks (Kilian, 2009). Hence, an immediate inference of our study is that as all oil price shocks are not same, investors need to disentangle oil demand shock from the oil supply shock as well as precautionary demand shock while crafting diversification strategies.

Second, upon scanning a sufficiently longer period of two decades from August 01, 1996 to June 20, 2017, oil prices are found to be weakly correlated with automobile stock return during the majority of the study period, except during November, 2000–December, 2002 and March, 2006–December, 2009. Anticipating a weak positive correlation of oil price with automobile stock return, an investor may add oil asset in a portfolio of automobile stocks to derive diversification benefit. However, sudden stronger positive correlating relationship during November, 2000–December, 2002 and March, 2006–December, 2009 would have eroded the possible diversification benefit. Therefore, investors should be careful towards such co-movements while diversifying their portfolio.

Finally, our findings will also be of use to the monetary authorities for deciding policy rate as well as exchange rates to counter the oil price shock and foster a positive investment environment. This is because fluctuations in oil prices are related with a firm's financial performance and therefore, with its stock prices and market capitalization. This, in turn, would push the economic activity and employment scenario in an economy.

In the future, this study can be expanded to other sectors, namely, oil

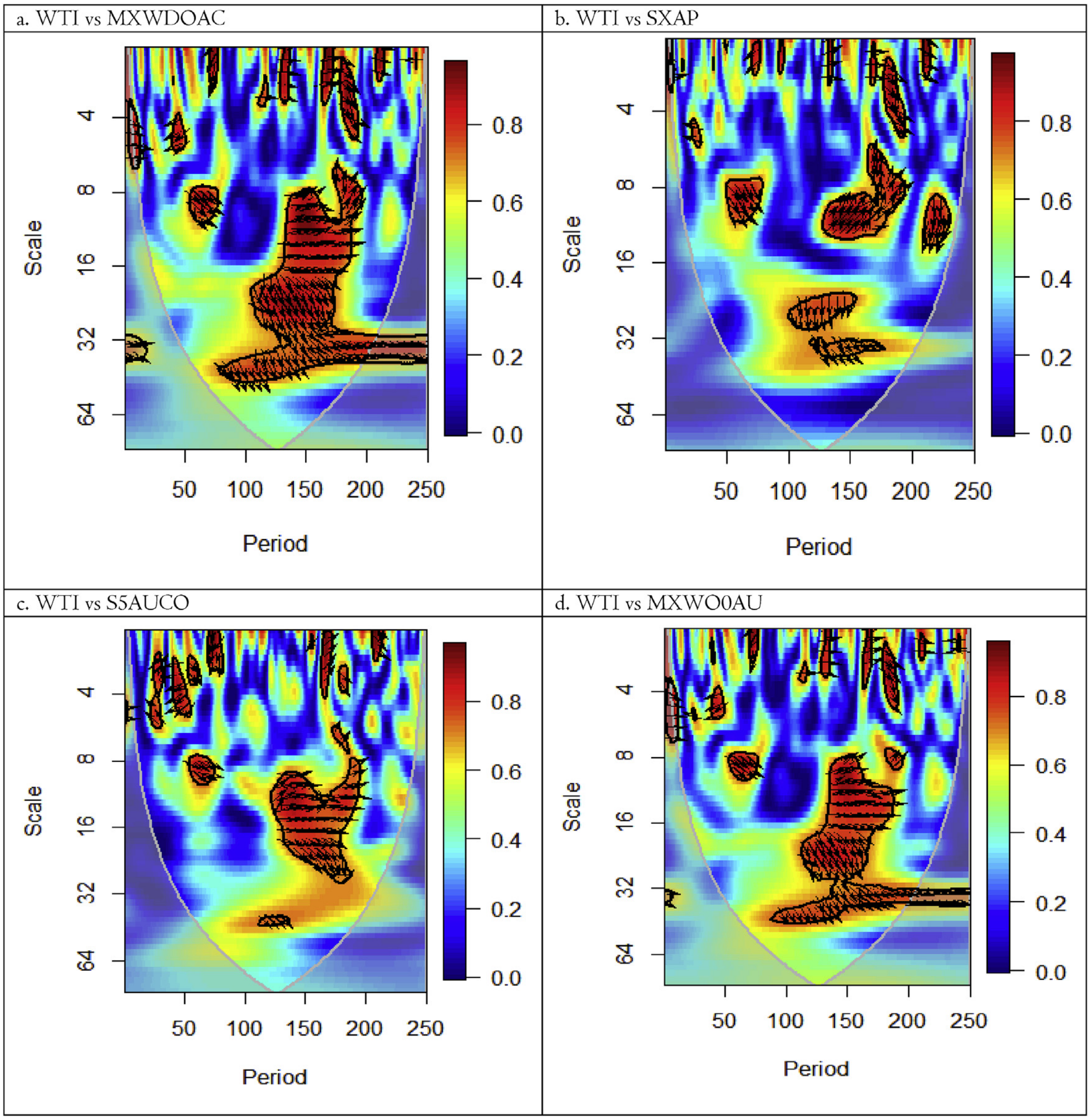

Fig. 3. Pairwise wavelet coherence for oil (WTI) price returns with stock market returns of MSCI ACWI automobiles and components index (MXWDOAC), MSCI World automobile index (MXWO0AU), STOXX Europe 600 automobiles and parts index (SXAP), and S & P 500 automobiles and components index (S5AUCO) with monthly return series. Vertical axis denotes time in days and horizontal axis represents period. White curve corresponds to cone of influence referring an edge under which wavelet power will be discontinued, and therefore, hard to infer. Color provided on the right hand side of the charts denotes degree of correlation; hotter the color the greater the absolute correlation value according to $R^2(l, m)$ in *Eq.* 5. Black contour denotes significance testing at the 5% level tested for AR(1). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Results of Granger-causality.

Null Hypothesis	Test-Statistic	p-value	Decision
MXWDOAC does not Granger Cause WTI	1.88	0.1528	Do not Reject
WTI does not Granger Cause MXWDOAC	1.72	0.1787	Do not Reject
SXAP does not Granger Cause WTI	2.57	0.0769	Reject*
WTI does not Granger Cause SXAP	4.74	0.0087	Reject***
S5AUCO does not Granger Cause WTI	9.41	0.0001	Reject***
WTI does not Granger Cause S5AUCO	2.75	0.0642	Reject*
MXWO0AU does not Granger Cause WTI	2.11	0.1212	Do not Reject
WTI does not Granger Cause MXWO0AU	1.82	0.1615	Do not Reject

Note: ***, * Significant at 1% and 10%, respectively.

and natural gas industries, retail industry, along with precious metals. Another possible extension could be to examine the association of oil price with sectoral stock return in the context of developing and under-developed nations that are highly vulnerable to positive oil price shocks.

Acknowledgements

We are thankful to the Editor and three anonymous referees for their detailed and helpful comment. This has enriched our paper significantly.

References

Abhyankar, A., Xu, B., Jiayue, W., 2013. Oil price shocks and the stock market: evidence from Japan. Energy J. 34 (2), 199–222.
Aloui, C., Jammazi, R., 2009. The effects of crude oil shocks on stock market shifts behaviour: a regime switching approach. Energy Econ. 31 (5), 789–799.
Aloui, R., Nguyen, D.K., Njeh, H., 2012. Assessing the impacts of oil price fluctuations on stock returns in emerging markets. Econ. Modell. 29, 2686–2695.
Aloui, R., Hammoudeh, S., Nguyen, D.K., 2013. A time-varying copula approach to oil and stock market dependence: the case of transition economies. Energy Econ. 39, 208–221.

Aloui, R., Ben Aïssa, M.S., 2016. Relationship between oil, stock prices and exchange rates: a vine copula based GARCH method. N. Am. J. Econ. Finance 37, 458–471.
Al Janabi, M.A.M., Hatemi, J.A., Irandoust, M., 2010. An empirical investigation of the informational efficiency of the GCC equity markets: evidence from bootstrap simulation. Int. Rev. Financ. Anal. 19, 47–54.
Apergis, N., Miller, S.M., 2009. Do structural oil-market shocks affect stock prices? Energy Econ. 31 (4), 569–575.
Arouri, M., 2011. Does crude oil move stock markets in Europe? A sector investigation. Econ. Modell. 28 (4), 1716–1725.
Arouri, M., Jouini, J., Nguyen, D.K., 2012. On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. Energy Econ. 34 (2), 611–617.
Alsalman, Z., Herrera, A.M., 2015. Oil price shocks and the U.S. Stock market: do sign and size matter? Energy J. 36 (3), 171–188.
Bannigidadmath, D., Narayan, P.K., 2016. Stock return predictability and determinants of predictability and profits. Emerg. Market. Rev. 26, 153–173.
Balcilar, M., Ozdemir, Z.A., 2013. The causal nexus between oil prices and equity market in the U.S.: a regime switching model. Energy Econ. 39, 271–282.
Basher, S., Sadorky, P., 2006. Day-of-the-week effects in emerging stock markets. Appl. Econ. Lett. 13, 621–628.
Bjornland, H.C., 2009. Oil price shocks and stock market booms in an oil exporting country. Scot. J. Polit. Econ. 56, 232–254.
Bouri, E., Awartani, B., Maghyereh, A., 2016. Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. Energy Econ. 56, 205–214.
Brooks, C., Prokopczuk, M., 2013. The dynamics of commodity prices. Quant. Finance 13, 527–542.
Cameron, K., Schulenburg, O., 2009. Oil prices, SUVs, and Iraq: an investigation of automobile manufacturer oil price sensitivity. Energy Econ. 31 (3), 375–381.
Chiang, E., Hughen, K., Sagi, J., 2015. Estimating oil risk factors using information from equity and derivatives markets. J. Finance 70 (2), 769–804.
Chiang, E., Hughen, W.K., 2017. Do oil futures prices predict stock returns? J. Bank. Finance 79 (6), 129–141.
Ciner, C., 2001. Energy shocks and financial markets: nonlinear linkages. Stud. Nonlinear Dynam. Econom. 5, 203–212.
Cong, R.G., Mei, Y.M., Jiao, J.-L., Fan, Y., 2008. Relationships between oil price shocks and stock market: an empirical analysis from China. Energy Pol. 36, 3544–3553.
Cuñado, J., Pérez de Gracia, F., 2014. Oil Price shocks and stock market returns: evidence for some European countries. Energy Econ. 42, 365–377.
Dagher, L., El Hariri, S., 2013. The impact of global oil price shocks on the Lebanese stock market. Energy 63, 366–374.
Degiannakis, S., Filis, G., Renatas, K., 2014. The effects of oil price shocks on stock market volatility: evidence from European data. Energy J. 35 (1), 35–56.
Devpura, N., Narayan, P.K., Sharma, S.S., 2018. Is stock return predictability time-varying? J. Int. Financ. Market. Inst. Money 52, 152–172.
Ding, H., Kim, H.-G., Park, S.Y., 2016. Crude oil and stock markets: causal relationships in tails? Energy Econ. 59 (9), 58–69.
Driesprong, G., Jacobsen, B., Maat, B., 2008. Striking oil: another puzzle. J. Financ. Econ. 89, 307–327.
Edelstein, P., Kilian, L., 2009. How sensitive are consumer expenditures to retail energy prices? J. Monetary Econ. 56, 766–779.
Filis, G., Degiannakis, S., Floros, C., 2011. Dynamic correlation between stock market and oil prices: the case of oil-importing and oil-exporting countries. Int. Rev. Financ. Anal. 20, 152–164.
Fisher, I., 1930. The Theory of Interest. Macmillan, New York.
Ftiti, Z., Guesmi, K., Abid, I., 2016. Oil price and stock market co-movement: what can we learn from time-scale approaches? Int. Rev. Financ. Anal. 46 (4), 266–280.
Geman, H., Kharoubi, C., 2008. WTI crude oil futures in portfolio diversification: the time-to- maturity effect. J. Bank. Finance 32, 2553–2559.
Gençay, R., Selçuk, F., Whitcher, B., 2002. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Academic Press, London.
Ghosh, S., Kanjilal, K., 2016. Co-movement of international crude oil price and Indian stock market: evidences from nonlinear cointegration tests. Energy Econ. 53, 111–117.
Granger, C.W.J., 1969. Investigating causal relations by econometric methods and crossspectral methods. Econometrica 34, 424–438.
Guesmi, K., Fattoum, S., 2014. Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. Econ. Modell. 38, 305–310.
Hamilton, J.D., 2009. Causes and Consequences of the Oil Shock of 2007–08. Brookings Papers on Economic Activity, Spring, pp. 215–261.
Harvey, C., Siddique, A., 2000. Conditional skewness in asset pricing tests. J. Finance 55 (3), 1263–1295.
Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Econ. 30 (3), 998–1010.
Huang, R.D., Masulis, R.W., Stoll, H.R., 1996. Energy shocks and financial markets. J. Futures Market. 16 (1), 1–27.
Huang, S., An, H., Gao, X., Huang, X., 2015. Identifying the multiscale impacts of crude oil price shocks on the stock market in China at the sector level. Phys. Stat. Mech. Appl. 434, 13–24.
Irwin, S.H., Sanders, D.R., 2011. Index funds, financialization, and commodity futures markets. Appl. Econ. Perspect. Pol. 33, 1–31.
Jammazi, R., Nguyen, D.K., 2015. Responses of international stock markets to oil price surges: a regime-switching perspective. Appl. Econ. 47, 4408–4422.
Jammazi, R., Reboredo, J.C., 2016. Dependence and risk management in oil and stock markets. A wavelet-copula analysis. Energy 107, 866–888.
Jammazi, R., Ferrer, R., Francisco Jareño, F., Shahzad, S.J.H., 2017. Time-varying causality between crude oil and stock markets: what can we learn from a multiscale perspective? Int. Rev. Econ. Finance 49 (5), 453–483.
Jones, C.M., Kaul, G., 1996. Oil and the stock markets. J. Finance 51 (2), 463–491.
Jouini, J., Harrathi, N., 2014. Revisiting the shock and volatility transmissions among GCC stock and oil markets: a further investigation. Econ. Modell. 38, 486–494.
Kayalar, D.E.C., Cskun, K.A., Sevtap, S.K., 2017. The impact of crude oil prices on financial market indicators: copula approach. Energy Econ. 61, 162–173.
Khalfaoui, R., Boutahar, M., Boubaker, H., 2015. Analyzing volatility spillovers and hedging between oil and stock markets: evidence from wavelet analysis. Energy Econ. 49, 540–549.
Kang, W., Ratti, R.A., Yoon, K.H., 2015. Time-varying effect of oil market shocks on the stock market. J. Bank. Finance 61 (12), S150–S163.
Kang, W., Ratti, R.A., Vespignani, J., 2016. The impact of oil price shocks on the U.S. stock market: a note on the roles of U.S. and non-U.S. oil production. Econ. Lett. 145, 176–181.
Kilian, L., 2008. Exogenous oil supply shocks: how big are they and how much do they matter for the US economy? Rev. Econ. Stat. 90 (2), 216–240.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am. Econ. Rev. 99 (3), 1053–1069.
Kilian, L., Park, C., 2009. The impact of oil price shocks and the U.S. stock market. Int. Econ. Rev. 50 (4), 1267–1287.
Kraus, A., Litzenberger, R., 1976. Skewness preference and the valuation of risky assets. J. Finance 21 (4), 1085–1094.
Kumar, D., 2017. Realized volatility transmission from crude oil to equity sectors: a study with economic significance analysis. Int. Rev. Econ. Finance 49 (5), 149–167.
Lee, B.J., Yang, C.H., Huang, B.H., 2012. Oil price movements and stock market revisited: a case of sector stock price indexes in the G7 countries. Energy Econ. 34, 1284–1300.
Madaleno, M., Pinho, C., 2014. Wavelet dynamics for oil-stock world interactions. Energy Econ. 45 (9), 120–133.
Martín-Barragán, B., Ramos, S.B., Veiga, H., 2015. Correlations between oil and stock markets: a wavelet-based approach. Econ. Modell. 50, 212–227.
Miller, J.I., Ratti, R.A., 2009. Crude oil and stock markets: stability, instability, and bubbles. Energy Econ. 31, 559–568.
Moya-Martínez, P., Ferrer-Lapeña, R., Escribano-Sotos, F., 2014. Oil price risk in the Spanish stock market: an industry perspective. Econ. Modell. 37, 280–290.
Naifar, N., Al Dohaiman, M.S., 2013. Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. Int. Rev. Econ. Finance 27, 416–431.
Nandha, M., Faff, R., 2008. Does oil move equity prices? A global view. Energy Econ. 30 (3), 986–997.
Narayan, P.K., Narayan, S., 2010. Modelling the impact of oil prices on Vietnam's stock prices. Appl. Energy 87, 356–361.
Narayan, P.K., Sharma, S.S., 2011. New evidence on oil price and firm returns. J. Bank. Finance 35, 3253–3262.
Narayan, P.K., Narayan, S., Sharma, S.S., 2013. An analysis of commodity markets: what gain for investors? J. Bank. Finance 37, 3878–3889.
Narayan, P.K., Ahmed, H., 2014. Importance of skewness in decision making: evidence from the Indian stock market. Global Finance J. 25 (3), 260–269.
Narayan, P.K., Sharma, S.S., 2014. Firm return volatility and economic gains: the role of oil prices. Econ. Modell. 38 (2014), 142–151.
Narayan, P.K., Sharma, S.S., 2015. Does data frequency matter for the impact of forward premium on spot exchange rate? Int. Rev. Financ. Anal. 39, 45–63.
Narayan, P.K., Ahmed, H.A., Narayan, S.S., 2015. Do momentum-based trading strategies work in the commodity futures markets? J. Futures Market. 35, 868–891.
Narayan, P.K., Liu, R., 2018. A new GARCH model with higher moments for stock return predictability. J. Int. Financ. Market. Inst. Money. https://doi.org/10.1016/j.intfin.2018.02.016.
Narayan, P.K., Phan, D.H.B., Sharma, S.S., 2018. Does Islamic stock sensitivity to oil prices have economic significance? Pac. Basin Finance J. https://doi.org/10.1016/j.pacfin.2018.04.003.
Park, J., Ratti, R., 2008. Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Econ. 30 (5), 2587–2608.
Peng, C., Zhua, H., Jiaa, X., Wanhai, Y., 2017. Stock price synchronicity to oil shocks across quantiles: evidence from Chinese oil firms. Econ. Modell. 61 (2), 248–259.
Percival, D., Walden, A., 2000. Wavelet Methods for Time Series Analysis. Cambridge University Press.
Phan, D., Sharma, S., Narayan, P.K., 2015a. Oil price and stock returns of consumers and producers of crude oil. J. Int. Financ. Market. Inst. Money 34, 245–262.
Phan, D.H.B., Sharma, S.S., Narayan, P.K., 2015b. Stock return forecasting: some new evidence. Int. Rev. Financ. Anal. 40, 38–51.
Rafailidis, P., Katrakilidis, C., 2014. The relationship between oil prices and stock prices: a nonlinear asymmetric cointegration approach. Appl. Financ. Econ. 24 (12), 793–800.
Ramsey, J.B., 2002. Wavelets in economics and finance: past and future. Stud. Nonlinear Dynam. Econom. 6 (3), 1–69.
Ready, R., 2016. Oil prices and the stock market. Rev. Finance. https://doi.org/10.1093/rof/rfw071.
Reboredo, J.C., Rivera-Castro, M.A., 2013. A wavelet decomposition approach to crude oil price and exchange rate dependence. Econ. Modell. 32, 42–57.
Reboredo, J.C., Ugolini, A., 2016. Quantile dependence of oil price movements and stock returns. Energy Econ. 54, 33–49.
Rodríguez-Caballero, C.V., Ventosa-Santaulària, D., 2014. Granger causality and unit roots. J. Stat. Econom. Meth. 3 (1), 97–114.
Rua, A., Nunes, L.C., 2009. International comovement of stock market returns: a wavelet analysis. J. Empir. Finance 16 (4), 632–639.

Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Econ. 21 (5), 449–469.
Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34 (1), 248–255.
Salisu, A.A., Isah, K.O., 2017. Revisiting the oil price and stock market nexus: a nonlinear Panel ARDL Approach. Econ. Modell. 66, 258–271.
Scholtens, B., Wang, L., 2008. Oil risk in oil stocks. Energy J. 29 (1), 89–112.
Singhal, S., Ghosh, S., 2016. Returns and volatility linkages between international crude oil price, metal and other stock indices in India: evidence from VAR-DCC-GARCH models. Resour. Pol. 50, 276–288.
Torrence, C., Compo, G.P., 1998. A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. 79 (1), 61–78.
Wei, C., 2003. Energy, the stock market, and the putty-clay investment model. Am. Econ. Rev. 93 (1), 311–323.
Xu, B., 2015. Oil prices and UK industry-level stock returns. Appl. Econ. 47, 2608–2627.
Zhu, H.M., Li, S.F., Yu, K., 2011. Crude oil shocks and stock markets: a panel threshold cointegration approach. Energy Econ. 33, 987–994.
Zhu, H.M., Li, R., Li, S., 2014. Modelling dynamic dependence between crude oil prices and Asia- Pacific stock market returns. Int. Rev. Econ. Finance 29, 208–223.