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The nexus between oil prices and stock prices of oil, technology and transportation companies under multiple regime shifts

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ABSTRACT
This study investigates the interaction between crude oil prices and the stock prices of oil, technology and transportation companies listed on U.S. stock exchanges, using weekly data covering the period from 2 January 1990 to 3 February 2015. Considering the importance of regime shifts or structural breaks in econometric analysis, this study employs the Carrion-i-Silvestre, Kim, and Perron unit root tests and the Maki cointegration tests, allowing for multiple breaks. Cointegration results confirm the existence of long-run equilibrium relationships between these stock indices, crude oil prices, short-term interest rates and the S&P 500. These findings indicate that crude oil prices and the other explanatory variables are long-run determinants of the stock prices of oil, technology and transportation firms. Stock prices of oil companies are positively affected by crude oil prices to a greater degree than that of technology and transportation stocks. Time-varying causality results show that West Texas Intermediate crude oil (WTI) is relatively more likely to affect the stock prices of these companies rather than to be affected by them. Evidently, it is confirmed that financial crises have a substantial ability to intensify the causal linkages between WTI and the stock indices of these companies.

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Crude oil prices; stock prices; structural breaks; breakpoint regression; time-varying causality

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1. Introduction

Crude oil is one of the most closely watched commodities in the world and its price is determined by global oil demand and supply conditions. The driving forces behind oil price movements include: increasing global demand for oil by emerging markets, environmental issues like global warming and energy security issues like potential supply disruptions due to political instability in oil exporting countries. Moreover, concerns of future oil shortages due to the estimates of reaching 'peak oil' between 2016 and 2040 affect oil prices as well (Appenzeller, 2004).

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Predicting the future of the oil market is intricate, as the largest oil-consuming nations do not have the largest oil reserves. North America and Asia Pacific account for approximately 60% of the world's oil consumption, while they just comprise 15% of the world's proved oil reserves. On the other hand, five Middle Eastern countries (Saudi Arabia, Iran, Iraq, Kuwait and United Arab Emirates) have almost 50% of the world's proved oil reserves, but their share of the world's oil consumption is less than 10% (BP Statistical Review of World Energy, 2014). Therefore, this oil-rich region has a great export potential and plays a substantial role in the global energy market.

Furthermore, member-nations of the Organisation of the Petroleum Exporting Countries (OPEC) possess almost 81% of the world's proved oil reserves (1200 billion barrels) and their respective governments control these reserves through their national oil companies (OPEC Annual Statistical Bulletin, 2014). This creates a great opportunity for these countries to pursue their petropolitics in line with their national and international interests, thus benefiting from this natural wealth. Since, most OPEC member-nations are located in geopolitical hotspots; their political instability and social unrest create concerns about energy security for the larger oil-consuming countries.

Developed economies heavily rely on the consumption of oil for their economies to thrive, despite the fact that a major proportion of it must be imported from other countries. Therefore, oil price swings, regardless of their causes, can have severe impacts on these economies. Oil price movements affect the production process and financial performance of companies, ultimately influencing their dividend payments, retained earnings and stock prices (Huang, Masulis, & Stoll, 1996). Higher oil prices force businesses to slash their consumption and purchase more energy-efficient products in an attempt to shift toward renewable energy sources in the long-term. This also encourages technology companies to allocate more funds towards the research and development of new, 'green' technologies, in order to reduce energy use and costs.

Furthermore, higher oil prices are less likely to have similar impacts on different economic sectors as they have dissimilar dependencies on the oil industry. For instance, according to an estimate, higher oil prices will stimulate investment in cutting-edge technologies for more efficient oil extraction methods, leading to higher oil production by drilling companies in the next 5 years (International Energy Agency (IEA), 2013). Consequently, the expected boost in oil production can be translated into more cash flow and better financial performance for these companies. However, unlike the oil companies, technology and transportation companies may suffer due to higher oil prices. In the short-run, their production costs may rise, but, in the medium- to long-run, they might even experience better financial performance by developing and consuming new energy-efficient products.

A good example of this is the production of the Airbus A350 XWB by EADS in June 2013. This lightweight, carbon composite airliner burns 25% less fuel than the previous generation of comparable aircraft. This is equal to 10.5 million litres of fuel savings per year, which is equivalent to the fuel consumption of roughly 7500 mid-size cars per year.[1] Although Airbus spent a significant amount of money on the development of this new aircraft, immediately after its first flight in June 2013 the company secured 613 orders worth billions of dollars (the number of orders increased to 780 by the end of February 2015).[2] This implies that, even with higher oil prices, technology companies can achieve better financial performance in the long-term. In addition, those transportation firms which utilise these energy-conserving products can benefit a lot in terms of fuel cost savings and lower maintenance costs, thus directly affecting their profitability.

The purpose of this paper is to empirically investigate the long-run and spillover impacts of crude oil prices on the stock prices of oil, technology and transportation companies listed in U.S. stock markets. The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 discusses the empirical methodology and data. Empirical analysis and results are presented in Section 4, while Section 5 provides concluding remarks.

2. Literature review

While it is broadly accepted that oil price fluctuations have important effects on the financial performance of a wide variety of companies, there have been relatively few empirical works conducted to examine how sensitive the stock prices of oil, technology and transportation companies are to changes in oil prices. Nandha and Faff (2008) studied the impact of oil price changes on 35 Datastream global industry indices over the period of April 1983 to September 2005. They demonstrated that oil price increases have a negative impact on stock returns of all sectors except mining and oil and gas companies. Memis and Kapusuzoglu (2015) found significant effects of oil fluctuations occurred in national and world oil prices on the financial and macroeconomic factors in the case of 19 OECD (Organisation for Economic Co-operation and Development) countries. Al-Abdulhadi (2014) analysed demand characteristics of oil in the case of Middle East countries using various computational approaches, while Jumadilova (2012) analysed the status of the oil and gas industry in the economy of Kazakhstan and emphasised the growing role of the oil and gas sector in Kazakhstan's economy.

Henriques and Sadorsky (2008) measured the impact of oil prices on the stock market performance of alternative energy firms. They employed a four-variable vector autoregressive model to examine the nexus between oil prices, interest rates, stock prices alternative energy and technology companies. Their results confirm the existence of unidirectional Granger causality running from both oil prices and technology stock prices to the alternative energy stock prices. Using impulse response functions, they demonstrate that a shock to stock prices of technology firms has a larger effect on the stock prices of alternative energy companies than does a shock to oil prices.

Aggarwal, Akhigbe, and Mohanty (2012) examined the effect of oil price changes on the Standard & Poor's (S&P) transportation companies. They used the daily data of WTI over 2 decades and found that transportation firms' returns are affected negatively by oil price rises. Scholtens and Yurtsever (2012) study the industry impact of oil price shocks in the European Union (E.U.) for the period 1983–2007. They construct dynamic vector autoregressive (VAR) models with various oil price specifications to assess the impact of oil price shocks on 38 different industries. They assert that the influence of oil price shocks considerably varies across the industries under the study. Results indicate that most of the industries are positively affected by negative price shocks, while they are not considerably influenced by increasing oil prices. On the other hand, some industries, like oil and gas and mining, positively respond to oil price surges and negatively respond to plunging oil prices.

Mohanty, Nandha, Habis, and Juhabi (2014) explore the exposure of the U.S. travel and leisure industry to oil price risk. They apply the four-factor asset pricing model of Fama–French–Carhart (1997) along with the oil price as a risk factor. The results show various degrees of oil price risk exposure across six sub-sectors. The exposure sign is mostly negative, but it is only significant for some sub-sectors, including airlines, restaurants and bars and recreational services. The results also suggest that the exposure of the sub-sectors to oil price risk vary significantly over time. For instance, the oil price risk exposure of the airline industry was the most during the 2007–2008 U.S. sub-prime mortgage crisis.

Chang, McAleer, and Tansuchat (2013) examined the volatility spillovers and conditional correlations between the oil and financial markets. They use daily data of the spot, futures and forward prices of the WTI and Brent crude oils, and the NYSE, FTSE100, Dow Jones and S&P 500 stock index returns from 2 January 1998 to 4 November 2009. They use multiple Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) family models such as vector autoregressive moving average GARCH (VARMA-GARCH), VARMA-AGARCH, constant conditional correlation (CCC) and dynamic conditional correlation (DCC) models. By using the CCC model, they explore the conditional correlations of returns across markets. They find that conditional correlations are very low and some cases are not statistically significant. They conclude that the shocks are conditionally correlated only in the same market and not between markets. They also find little evidence of volatility spillovers between the crude oil and financial markets using the VARMA-GARCH and VARMA-AGARCH. models.

Wang and Zhang (2014) study the responsiveness of China's major industries to oil price shocks using an autoregressive jump intensity-GARCH (ARJI-GARCH) method. They concentrated on four major industries: metals, grains, oil fats and petrochemicals. They also examined the impact of extreme price fluctuations, called jumps. The asymmetric impacts of oil price shocks have been confirmed. According to the results, the negative oil price shocks had tougher effects on the four industries. The least sensitive to oil price shocks was the grains market and the most sensitive was the petrochemical market. In the presence of jumps in the crude oil market, the reactions of four commodity markets would be different. In fact, the petrochemicals and oil fats markets had a tendency to over-react to oil price jumps, but there was no such behaviour in the grain and metal markets.

Reboredo and Rivera-Castro (2014) investigated the relationship between oil and stock markets by using wavelet multi-resolution analysis in the E.U. and the U.S. at the aggregate and sectoral levels. They used data for the period June 2000 to July 2011. They employed wavelet decomposition analysis in order to measure interdependence and contagion effects between oil and stock price at various time frames. They found that, except for oil and gas companies, oil price fluctuations had no impact on stock market returns in the pre-crisis period at either the sectoral or aggregate level. Contrariwise, they found evidence of positive interdependence and contagion between these markets at the time of financial crisis at both levels.

Demirer, Jategaonkar, and Khalifa (2015) examined the oil price risk exposure in the stock markets of net oil exporting countries. They used cross-sectional data for the period of 2004M03 to 2013M03. They integrate both the oil price risk element and an idiosyncratic volatility factor into the Fama-French three-factor model. Results suggest that the oil-sensitive stocks receive significantly higher returns, indicating that oil price exposure can be used as a predictor of return in Gulf Cooperation Council (GCC) stock markets. Their results also show that oil price variations can be considered as a source of stock return premia in these markets.

Tsai (2015) inspected the reaction of stock returns to oil price shocks before, during and after a financial crisis. He used daily data of 682 U.S. firms for the period of 1990M01 to 2012M12. By using the firm-level data, he confirmed the asymmetric effects of oil price shocks on stock returns during and after the crisis. Within and after the crisis, the oil-intensive industries are more positively affected by oil price shocks compared to the less oil-intensive industries. In order to investigate the effect oil price shocks across various firm sizes, he used different variables, such as total assets, number of employees and total revenue, to assess each firm's size. Results suggest that oil price shocks can influence big-sized firms more considerably and negatively prior to the crisis. Nonetheless, medium-sized companies are positively impacted by oil price shocks in the post-crisis period.

Shaeri, Adaoglu, and Katircioglu (2016) investigated the oil price risk exposure of U.S. financial and non-financial industries over the period of January 1983 to March 2015. They incorporated the oil price risk factor into the Fama and French (2015) five-factor asset pricing model. They used the Bai and Perron (2003) method to detect multiple structural breaks in the relationship between equity returns and multifactor model variables. Later, they estimated the multifactor model by using the breakpoint regression, which takes into account the previously identified structural breaks. They estimated the oil price risk exposures of financial and non-financial industries at the sub-sector level. The results suggest that the level of oil price sensitivity varies remarkably across sub-sectors and over time. The extent of impact of oil prices on the financial sub-sectors is substantially lower than the extent of its effect on the non-financial sub-sectors. For the financial sub-sectors, Real Estate Services and Mortgage Finance have the largest positive and negative exposures to oil price risk, correspondingly. For the non-financial sub-sectors, Oil Equipment Services and Airlines have the largest positive and negative oil price risk exposures, respectively.

3. Data and methodology

3.1. Data

This study uses weekly data over the period of 2 January 1990 to 3 February 2015 to assess the short-run and long-run relationships between crude oil prices and the stock prices of oil, technology and transportation companies. All data were obtained from Thomson Reuters's Datastream for a total of 1310 weekly observations for each variable. Weekly data is selected as it is less noisy compared to daily data and it relatively captures market movements better than monthly data. The stock market performance of oil companies is measured using the NYSE Arca Oil Index (OIL). This is a price-weighted stock index of the world's top oil companies who deal with the exploration and production of petroleum. The performance of the oil industry is measured by this index through changes in total stock prices of the component. The index was introduced on 27 August 1984 with a base level of 125.[3]

Further, the NYSE Arca Tech 100 Index (TEC) is used to examine the stock market performance of leading technological companies. This is a price-weighted stock index of technology-related firms listed on various U.S. exchanges. The main aim of the index is to benchmark the performance of the firms using technological innovations across different types of industries. The index covers top companies from numerous industries, such as aerospace, biotechnology, electronics, computer software and hardware, semiconductors, telecommunications and defence. The index was developed by the Pacific Stock Exchange in 1982 and still operates with the ticker symbol of PSE under NYSE Euronext supervision.[4]

Another selected index for this study is the Dow Jones Transportation Average, DJTA (TRA). It is known as the best indicator for the U.S. transportation sector. Its founding date backs to 1884 by Dow Jones & Company, making it the oldest U.S. stock index still in use.

The index was initially composed of only railroad companies, but now it includes airlines, trucking, marine transportation and logistics companies as well. The DJTA is also a price-weighted stock index and maintained by Dow Jones Indexes.[5]

The 3-month U.S. Treasury bill is chosen as the short-term interest rate (SIR) because, according to many researchers (Chen, 1991; Chen, Roll, & Ross, 1986; Sadorsky, 1999, 2001), it can explain stock price movements. The Standard and Poor's 500 Index (SPX) is also selected to capture market movements at aggregate level. This study uses West Texas Intermediate crude oil (WTI) spot prices in order to measure the effect of oil prices on stock market performance of oil, technology and transportation companies. Hereafter, the natural logarithm of the data is being used in order to reduce unwanted variability (heteroskedasticity) in the series.

Figure 1 illustrates the time series plot of the data. This shows that these stock indices tend to move together and also their movements are very similar to the oil price fluctuations. This means that these variables are highly correlated. The global financial crisis of 2008–2009 had a great impact on the stock prices of oil, technology and transportation companies and also on crude oil prices. As a result, all of the indices experienced a huge plunge, ranging from 39% to almost 70% between September 2008 and March 2009. To understand better the correlation conditions between these variables, the correlation plot matrix is presented in Figure 2.

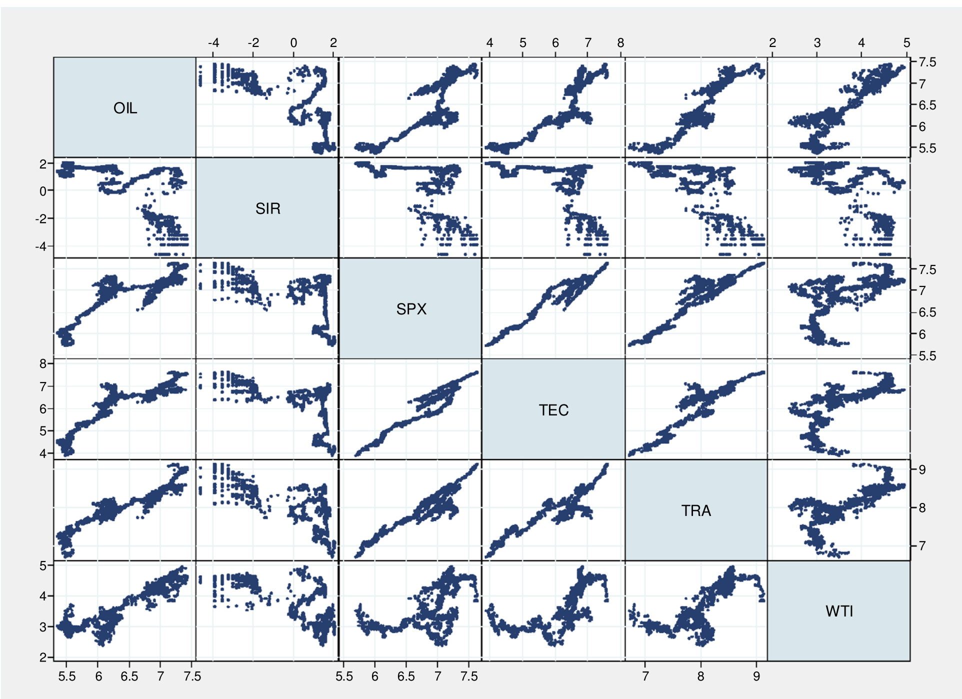

Figure 1. Correlation plot matrix. Source: Authors' calculation.

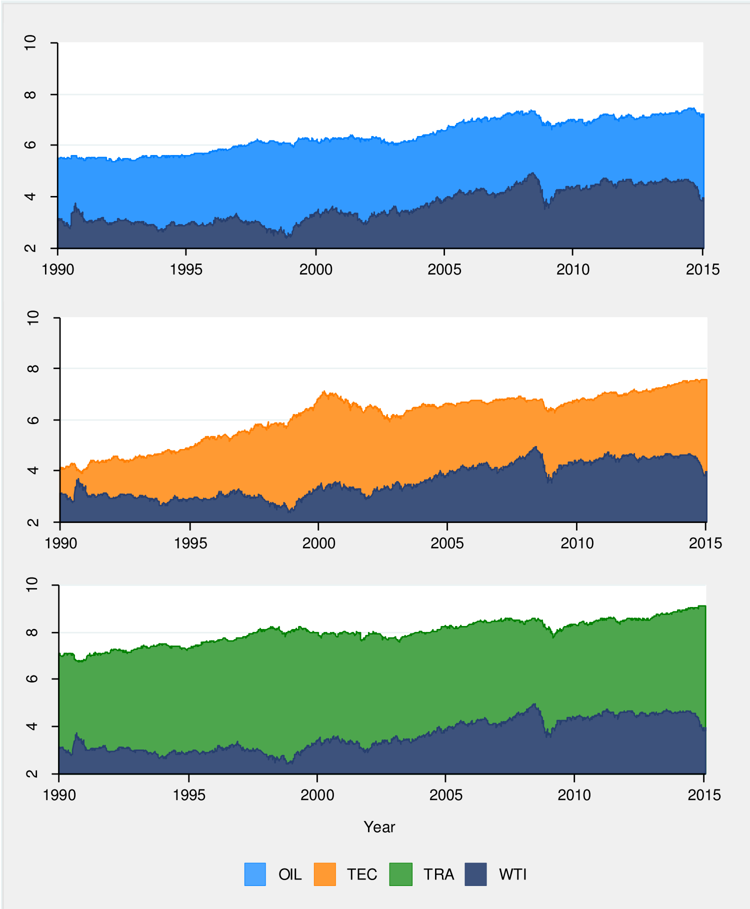

Figure 2. Time series graph of stock indices vs WTI Source: Authors' calculation.

3.2. Empirical model

In this study, we assume the short-term interest rate and the oil prices can explain fluctuations in the aforementioned stock price indices. Thus, the following equations are suggested:

$$OIL_t = \beta_1 + \beta_2 SIR_t + \beta_3 SPX_t + \beta_4 WTI_t + \varepsilon_t \tag{1}$$

$$TEC_t = \alpha_1 + \alpha_2 SIR_t + \alpha_3 SPX_t + \alpha_4 WTI_t + \varepsilon_t \tag{2}$$

$$TRA_t = \gamma_1 + \gamma_2 SIR_t + \gamma_3 SPX_t + \gamma_4 WTI_t + \varepsilon_t \tag{3}$$

Where, at period t, OIL, TEC and TRA are the natural logarithms of stock indices of oil, technology and transportation companies; SIR is the natural logarithm of short-term interest rate; SPX is the natural logarithm of S&P500 Index; WTI is the natural logarithm of West Texas Intermediate crude oil spot prices; and ε is the error disturbance.

3.3. Methodology

3.3.1. Testing for breaks in a time series

Perron and Yabu (2009) introduce a method in an attempt to test the existence of a structural break or regime shift in a univariate time series. The method computes the exponential Wald test (EXP-W$_{RQF}$) test in order to find a break in a time series that is valid, regardless of whether the error term is stationary or not. In other words, the EXP-W$_{RQF}$ test can be employed without knowing whether the series contains an autoregressive unit root or is trend stationary. By using robust quasi-flexible GLS (generalised least squares), this test can detect an unknown break in the intercept, deterministic trend or in both.

3.3.2. Unit root tests under multiple structural breaks

When the existence of regime shifts is the case, the conventional unit root tests like Phillips and Perron and Augmented Dickey-Fuller cannot be applied due to lack of power (Katircioglu, 2009). As a result, various unit roots tests in the econometrics literature consider structural breaks. Some of these tests can consider one or two structural breaks (see, for example, Lee & Strazicich, 2003; Lumsdaine & Papell, 1997; Ng & Perron, 2001; Zivot & Andrews, 1992). The newest unit root testing technique available is the one developed by Carrion-i-Silvestre, Kim, and Perron (2009), which allows for up to five breaks in the series. Hence, the unit root test that we apply in this study is superior to other unit root tests employed in the relevant literature, allowing us to be more confident about the unit root test results (Katircioglu, 2014).

The unit root test of Carrion-i-Silvestre et al. (2009) uses the algorithm of Bai and Perron (2003) in order to identify structural breaks through a quasi-GLS method and it minimises the residual sum of squares through a dynamic programming process. Regarding the stochastic data generation process, $y_t = d_t + \mu_t$ (where $\mu_t = \alpha\mu_{t-1} + v_t$ for $t = 0, 1, ..., T$), Carrion-i-Silvestre et al. (2009) developed the following five different statistics for testing the null hypothesis of a unit root under multiple structural breaks (see Katircioglu, 2014):

$$P_T(\lambda^0) = \frac{\left[S(\bar{\alpha}, \lambda^0) - \bar{\alpha}S(1, \lambda^0)\right]}{S^2(\lambda^0)} \tag{4}$$

where P_T stands for Gaussian point optimal statistic and S stands for spectral density function.

$$MP_t(\lambda^0) = \frac{\left[c^{-2}T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2 + (1-\bar{c})T^{-1}\tilde{y}_T^2\right]}{S(\lambda^0)^2} \tag{5}$$

where MP_T stands for the modified feasible point optimal statistic according to Ng and Perron (2001).

$$MZ_\alpha(\lambda^0) = \left(T^{-1}\tilde{y}_T^2 - s(\lambda^0)^2\right)\left(2T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{-1} \tag{6}$$

$$MSB(\lambda^0) = \left(s(\lambda^0)^{-2}\, T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{1/2} \tag{7}$$

$$MZ_t\left(\lambda^0\right) = \left(T^{-1}\tilde{y}_T^2 - s\left(\lambda^0\right)^2\right)\left(4s\left(\lambda^0\right)^2 T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{1/2} \tag{8}$$

where MZ_α, MSB, and MZ_t are M-class test statistics which can be obtained using a GLS detrending approach (see Carrion-i-Silvestre et al., 2009). The asymptotic critical values are generated through a bootstrapping approach. Rejection of the null hypothesis indicates the stationarity of the series (Katircioglu, 2014; Katircioglu & Taspinar, 2017).

3.3.3. Maki (2012) cointegration test under multiple structural breaks

According to Westerlund and Edgerton (2006), the conventional cointegration tests for non-stationary series, which do not consider the existence of structural breaks, are likely to provide biased results (Katircioglu, 2014; Katircioglu & Taspinar, 2017). To deal with this risk, various methods are available in the relevant literature. For instance, cointegration tests of Carrion-i-Silvestre and Sansó (2006) and Westerlund and Edgerton (2006) allow for one or two breaks in the series. However, when dealing with a long sample period like in this study, the probability of existence of more than two structural breaks is higher and, if they are not detected, may compromise the reliability of the results. To address this issue, we employ the newest cointegration test developed by Maki (2012), which allows for consideration of up to five structural breaks. In Maki's (2012) cointegration test, every period can be a possible breaking point and, for this reason, a t-statistic for each period is computed. Periods with the lowest t-ratios are recognised as breaking points. Maki (2012) developed four different models that are called 'regime shift models' for testing the cointegration, as illustrated below.

Model 1, with a break in the level:

$$y_t = \mu + \sum_{i=1}^{k}\mu_i K_{i,t} + \beta x_t + \upsilon_t \tag{9}$$

Model 2, with a break in the level and coefficients:

$$y_t = \mu + \sum_{i=1}^{k}\mu_i K_{i,t} + \beta x_t + \sum_{i=1}^{k}\beta_i x_i K_{i,t} + \upsilon_t \tag{10}$$

Model 3, with a break in the level and coefficients, and with trend:

$$y_t = \mu + \sum_{i=1}^{k}\mu_i K_{i,t} + \gamma x + \beta x_t + \sum_{i=1}^{k}\beta_i x_i K_{i,t} + \upsilon_t \tag{11}$$

Model 4, with a break in the level, coefficients, and trend:

$$y_t = \mu + \sum_{i=1}^{k}\mu_i K_{i,t} + \gamma t + \sum_{i=1}^{k}\gamma_i t K_{i,t} + \beta x_t + \sum_{i=1}^{k}\beta_i x_i K_{i,t} + \upsilon_t \tag{12}$$

where K_i stands for dummy variables that are defined by Maki (2012) as:

$$K_i = \begin{cases} 1 & when\ t > T_B \\ 0 & Otherwise \end{cases}$$

where T_B stands for break point. The Monte Carlo simulations are used for computation of critical values to test the null hypothesis of 'no cointegration' under multiple structural breaks (see Maki, 2012).

3.3.4. Estimation of long-run coefficients using DOLS

Once a cointegrating vector is determined, then the dynamic ordinary least square (DOLS) approach can be used to estimate the long-run coefficients of equations (1–3). As suggested by Stock and Watson (1993), by addition of lagged structures and differences of independent variables to their level forms, consistent estimators can be obtained by eradicating any autocorrelation, endogeneity and simultaneity problems. Therefore, DOLS models can be employed, regardless of the order of integration of the variables. The DOLS models will be used to estimate equations (1–3), which can be expressed as follows:

$$OIL_t = B'X + \sum_{i=-q}^{q} \mu_i \Delta SIR_{t-i} + \sum_{i=-q}^{q} \eta_i \Delta SPX_{t-i} + \sum_{i=-q}^{q} \lambda_i \Delta WTI_{t-i} + \varpi D_i + \varepsilon_t \qquad (13)$$

$$TEC_t = B'X + \sum_{i=-q}^{q} \mu_i \Delta SIR_{t-i} + \sum_{i=-q}^{q} \eta_i \Delta SPX_{t-i} + \sum_{i=-q}^{q} \lambda_i \Delta WTI_{t-i} + \varpi D_i + \varepsilon_t \qquad (14)$$

$$TRA_t = B'X + \sum_{i=-q}^{q} \mu_i \Delta SIR_{t-i} + \sum_{i=-q}^{q} \eta_i \Delta SPX_{t-i} + \sum_{i=-q}^{q} \lambda_i \Delta WTI_{t-i} + \varpi D_i + \varepsilon_t \qquad (15)$$

where $B = [c, \alpha, \beta, \gamma]$, $X = [1, \mathrm{SIR}_t, \mathrm{SPX}_t, \mathrm{WTI}_t]$, and q stands for the lag structure to be determined by the Akaike Information Criterion and t is a time trend. D_i stands for dummy variables of week breaks which are allowed, up to a maximum of five, and they are selected based on Model 4 of Maki's (2012) cointegration test.

3.3.5. Breakpoint regression

Given the occurrence of some structural changes in oil and financial markets over the last 3 decades, it is necessary to test the existence of structural breaks in the relationship between the stock prices of oil, technology, transportation companies and crude oil price. This can be done using the method introduced by Bai and Perron (2003). This approach allows testing for multiple structural breaks in a linear model. Then, via using least squares estimation, it can detect breaks at *a priori* unknown dates. Allowing for multiple breaks in the explanatory factors, equations (1–3) can be reformulated and use the following regression model with m breaks ($m + 1$ regimes[6]:

$$OIL_t = \alpha_j + \beta_j SIR_t + \gamma_j SPX_t + \delta_j WTI_t + \varepsilon_t \qquad (16)$$

$$TEC_t = \alpha_j + \beta_j SIR_t + \gamma_j SPX_t + \delta_j WTI_t + \varepsilon_t \qquad (17)$$

$$TRA_t = \alpha_j + \beta_j SIR_t + \gamma_j SPX_t + \delta_j WTI_t + \varepsilon_t \tag{18}$$

where $t = T_{j-1}+1, \ldots, T_j$ and $j = 1, \ldots, m + 1$. The breakpoints $(T_1, \ldots, T_m)$ are explicitly treated as unknown, and by convention, $T_0 = 0$ and $T_{m+1} = T$, where T is the total sample size. The Bai-Perron sequential test statistics detects the number of breaks. The SupF $(l + 1 \mid l)$ test is a sequential test of the null hypothesis of l breaks vs the alternative of $l + 1$ breaks. Later, the breakpoint regression is used to estimate equations (16–18) for the sub-periods, based on breakpoint(s) determined by the Bai-Perron sequential test results.

3.3.6. Time-varying causality

In order to test the spillover between oil prices and the stock indices of the industries, the causal linkages between them should be examined. The most conventional way of testing this causal relationship has been the Granger causality test in finance and economic literature. According to Brooks (2014), the concept of Granger causality (Granger, 1969, 1980) does not imply a 'causes-and-effects' relationship between two variables. Instead, it merely indicates a 'correlative' relationship among the past values of one variable and the current value of another. Hong, Liu, and Wang (2009) describe Granger causality as 'incremental predictive ability', which can be utilised as a proper tool for inspecting and forecasting risk spillovers between different financial assets and markets. Although this method has been used in a large body of the literature, it is unable to capture the non-linear causal linkages (Billio, Lo, Getmansky, & Pelizzon, 2012). Several methods have been introduced for testing causality, since Granger presented the causality concept for the first time in 1969. Most of these tests use the VAR model introduced by Sims (1972).

In 1976, an asymptotically Chi-squared test was introduced by Haugh, based on the residual cross correlations in order to check Granger causality in mean. As an extension to the work of Haugh (1976), Cheung and Ng (1996) introduced the test of causality in variance. Due to convenience of Granger-type causality tests for forecasting and causal inferences, they have been extensively adopted in finance and economics. Recently, time-varying Granger causality has gained great attention from scholars. As a result, a limited number of new tests have been introduced. For instance, Aaltonen and Östermark (1997) proposed a fixed-length rolling window Granger causality test to measure the time-varying Granger causality among the Japanese and Finnish security markets in the 1990s. Moreover, a Bayesian VAR model with time-varying parameters was introduced by Cogley and Sargent (2001) to test the causal dynamics between inflation, interest rate and unemployment in the U.S.

Given the structural breaks and crises in the financial time series, non-linear causal relationships may exist due to volatility and return spillover effects. As the linear and non-linear causal relationships are dependent to the sample data, a causality framework with dynamic rolling window is employed. In this study, Hill's (2007) fixed-length rolling window causality test will be used. He suggests a successive multi-horizon non-causality test, which can be adopted to detect non-linear causalities in terms of linear parametric restrictions for a trivariate process. The Wald-type test statistic is used in this causality test under the joint null hypothesis of zero parameter linear constraints. This time-varying causality test has a VAR structure of order p at horizon h, as the following:

$$W_{t+h} = \alpha + \sum_{k=1}^{p} \pi_k^{(h)} W_{t+1-k} + u_{t+h} \tag{19}$$

where W_t is a m-vector process with stationarity, $m \geq 2$, α is the constant term, $\pi_k^{(h)}$ are matrix-valued coefficients and u_t is a zero mean white noise process ($m \times 1$ vector) with non-singular covariance matrix. This study utilises the bivariate case where $m = 2$. Therefore, the aim is to test the null hypothesis of non-causality running from oil prices (WTI) to the stock indices of the industries. Causality takes place at any horizon if and only if it takes place at horizon 1 (first month in each window). W_t is a 2-vector stationary process, $W_t = \{S_t, R_t\}$, where R does not linearly cause S at 1-step ahead if and only if the RS-block $\pi_{RS,1}^{(h)} = 0$ for $k = 1$. Due to the likely sub-standard performance of the Chi-squared distribution in small samples, Hill (2007) proposed a parametric bootstrapping approach for estimating small sample p-values.

4. Empirical analysis and results

The Perron and Yabu (2009) EXP-W_{RQF} test statistics and the corresponding breaking weeks are reported in Table 1. The EXP-W_{RQF} test statistic is estimated based on Model 3 of Perron and Yabu (2009), which permits a structural break in both level and trend. According to the results that are shown in Table 1, we can strongly reject the null hypothesis of not having structural break in both level and trend. Alternatively, it is indicated that there is at least one regime shift in each series under consideration.

Table 2 provides the Carrion-i-Silvestre et al. (2009) unit root tests results for the variables under consideration. The results suggest five structural breaks in each series. Given these breaks, all the series seem to be non-stationary in levels, because the null hypothesis of having a unit root cannot be rejected. On the other hand, all the series become stationary in their first differences. Evidently, it is concluded that the series of the present study are integrated of order one, $I(1)$. Since all the series are integrated of the same order, $I(1)$, the existence of any cointegrating relationship can be examined by using cointegration tests. As mentioned before, this study employs Maki's (2012) approach to test for cointegration.

Table 3 present Maki's (2012) cointegration tests results. As can be seen from the results, in the presence of multiple structural breaks or regime shifts, the null hypothesis of 'no cointegration' can be rejected by all of the four models suggested by Maki (2012). The results reveal that Equations (1–3) cointegrate and, thus, there are long-run equilibrium relationships between these variables. It should be noted that the breaking weeks that have been identified by model 4 of Maki (2012) are added to the estimation of the long-run coefficients via dummy variables (D1–D5).

Table 4 exhibits the level coefficients of the long-run models shown in equations (13–15) that are estimated via the DOLS method. The results suggest that SIR exerts a negative significant impact on the stock price indices of oil, technology and transportation companies. The S&P 500 (SPX) has a positive and significant effect on the stock price indices. However, as expected, the impact magnitude of SPX is much higher than that of SIR and

Table 1. Perron and Yabu (2009) break test results.

	OIL	SIR	SPX	TEC	TRA	WTI
EXP-W_{RQF}	31.2509[a]	46.8299[a]	24.6342[a]	23.5144[a]	15.3095[a]	14.2044[a]
TB	2005W38	2008W43	2008W21	2001W30	1999W42	2004W16

Note: [a] Statistical significance at 1% level. The asymptotic critical values for the EXP-W_{RQF} are 2.48, 3.12 and 4.47 (for a break in the constant and time trend slope) at 10, 5 and 1% significance level, respectively (Perron & Yabu, 2009).
Source: Authors' calculation.

Table 2. Carrion-i-Silvestre et al. (2009) unit root test results.

	Levels					
	P_T	MP_T	MZ_a	MSB	MZ_t	Breaking weeks
OIL	11.55	11.4	−39.17	0.11	−4.41	1996W22; 1998W18; 2001W36; 2003W32; 2005W45
	(9.56)	(9.56)	(−46.49)	(0.10)	(−4.75)	
SIR	24.72	20.95	−16.86	0.17	−2.9	1999W41; 2001W36; 2005W49; 2008W52; 2011W15
	(7.92)	(7.92)	(−44.01)	(0.10)	(4.70)	
SPX	19.15	17.37	−25.94	0.14	−3.57	1994W50; 1999W41; 2002W41; 2005W42; 2008W21
	(9.33)	(9.33)	(−47.10)	(0.10)	(4.83)	
TEC	12.76	11.38	−39.7	0.11	−4.45	1998W40; 2000W35; 2002W39; 2004W30; 2009W09
	(9.51)	(9.51)	(−46.97)	(0.10)	(−4.80)	
TRA	13.29	11.1	−39.92	0.11	−4.46	1997W27; 1999W18; 2003W10; 2006W18; 2009W09
	(9.21)	(9.21)	(−47.48)	(0.10)	(−4.86)	
WTI	18.74	17.06	−26.27	0.13	−3.62	1997W02; 1999W01; 2000W02; 2003W39; 2008W29
	(9.36)	(9.36)	(−47.11)	(0.10)	(−4.82)	
	First differences					
DOIL	0.19[a]	0.19[a]	−471.27[a]	0.03[a]	−15.34[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	
DSIR	0.19[a]	0.19[a]	−472.34[a]	0.03[a]	−15.36[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	
DSPX	0.19[a]	0.19[a]	−473.64[a]	0.03[a]	−15.39[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	
DTEC	0.19[a]	0.19[a]	−469.23[a]	0.03[a]	−15.31[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	
DTRA	0.19[a]	0.19[a]	−470.79[a]	0.03[a]	−15.34[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	
DWTI	0.19[a]	0.19[a]	−465.13[a]	0.03[a]	−15.24[a]	—
	(5.54)	(5.54)	(−17.32)	(0.16)	(−2.89)	

Note: [a] The rejection of the null hypothesis of a unit root at the 5% level. Numbers in brackets are critical values derived from the bootstrap approach after 1000 simulations. Breaking weeks are automatically estimated and determined by Carrion-i-Silvestre et al. (2009) unit root tests in GAUSS software.
Source: Authors' calculation.

Table 3. Maki (2012) cointegration tests.

Model options	Statistics	CV 1%	CV 5%	Break weeks
Cointegration model: OIL = f (SIR, SPX, WTI)				
Model 1	−7.53[a]	−6.55	−6.03	1991W47; 1994W28; 1996W04; 2004W21; 2008W36
Model 2	−7.76[a]	−6.78	−6.25	1996W04; 1999W21; 2001W14; 2004W21; 2007W01
Model 3	−9.21[a]	−8.67	−8.11	1994W34; 1996W11; 1999W21; 2004W21; 2008W37
Model 4	−9.97[a]	−9.43	−8.81	1991W47; 1996W40; 2000W36; 2003W48; 2007W12
Cointegration model: TEC = f (SIR, SPX, WTI)				
Model 1	−37.07[a]	−6.55	−6.03	1996W46; 1999W24; 2000W20; 2004W31; 2008W12
Model 2	−37.82[a]	−6.78	−6.25	1998W01; 2000W25; 2001W11; 2006W39; 2008W11
Model 3	−37.51[a]	−8.67	−8.11	2001W21; 2006W38; 2008W12; 2010W46; 2012W06
Model 4	−38.30[a]	−9.43	−8.81	2002W19; 2004W32; 2008W21; 2012W05; 2013W23
Cointegration model: TRA = f (SIR, SPX, WTI)				
Model 1	−5.43	−6.55	−6.03	1996W37; 2000W21; 2001W27; 2005W10; 2008W09
Model 2	−6.80[a]	−6.78	−6.25	1991W17; 1995W13; 2000W21; 2004W41; 2007W11
Model 3	−7.43	−8.67	−8.11	1994W32; 2001W28; 2005W11; 2008W19; 2012W21
Model 4	−9.30[b]	−9.43	−8.81	1996W37; 1998W43; 2001W26; 2005W08; 2009W19

Notes: [a, b] The rejection of the null hypothesis of no cointegration at the 1% and 5% levels, respectively. Critical values (CV) were gathered from Table 1 of Maki (2012): which allows breaks in trend and intercept through two independent variables.
Source: Authors' calculation.

WTI on the stock price indices, which indicates the importance of the broad market index in determining stock prices. On the other hand, WTI has a positive and statistically significant impact on all of the stock price indices. The positive oil coefficient of technology stocks suggests that even high oil prices can improve the financial performance and profitability of technology companies as they move toward innovating more new energy-efficient and sustainable products. For instance, in June 2012, Tesla Motors unveiled an all-electric sedan (Model S), which is one of the most advanced electric vehicles. Due to its rapidly growing sales, the company's stock price skyrocketed from almost $30 in June 2012 to $282 in July 2015, which is equivalent to a 940% return in 2 years! This shows that the market is moving toward a future less reliant on fossil fuels.

Moreover, it should be noted that the extent of impact of WTI on oil companies is much higher than that of WTI on technology and transportation companies. This suggests that the oil-sensitive stocks have a tendency to be affected relatively more by crude oil price fluctuations. This result is in accordance with the findings of Click (2001), Sadorsky (2001), Hammoudeh and Li (2004), Nandha and Faff (2008), Gogineni (2010), Mohanty et al. (2014), Demirer et al. (2015) and Shaeri et al. (2016). The majority of dummy variables are also significant and have mixed signs.

Table 5 reports the results of the Bai and Perron (2003) test for identifying the multiple structural breaks in the relationship between the stock indices and the explanatory variables.

Table 4. Estimation of level coefficients in the long-run models using DOLS

	SIR	SPX	WTI	D1	D2	D3	D4	D5	C	R^2	DW
OIL	−0.005[c]	0.601[a]	0.569[a]	−0.053	−0.051	−0.325[a]	−0.270[b]	0.163	0.221[a]	0.963	1.87
	(0.003)	(0.092)	(0.085)	(0.124)	(0.124)	(0.125)	(0.124)	(0.124)	(0.056)		
TEC	−0.056[c]	1.664[b]	0.204[b]	0.496[c]	0.222	−0.884[b]	−0.041	−0.683[c]	−0.598	0.778	1.92
	(0.033)	(0.710)	(0.101)	(0.298)	(0.297)	(0.390)	(0.304)	(0.399)	(0.659)		
TRA	−0.034[c]	0.762[b]	0.210[b]	0.304	1.498[b]	−1.194[b]	−0.231	−0.096	2.027	0.901	2.04
	(0.019)	(0.350)	(0.101)	(0.642)	(0.686)	(0.659)	(0.645)	(0.701)	(1.961)		

Notes: [a, b, c] Significance at 1, 5 and 10% levels, respectively. Standard errors of the estimated coefficients are corrected for heteroscedasticity by the White procedure. Dummy variables have been assigned for breaking weeks (D1–D5) and these breaks are selected based the Model 4 of Maki's (2012) cointegration test. DW shows the Durbin-Watson test statistics.
Source: Authors' calculation.

Table 5. Structural breaks in the relationship between stock indices and the explanatory variables.

	$SupF_t$					Number of breaks			
Company	(1 | 0)	(2 | 1)	(3 | 2)	(4 | 3)	(5 | 4)	Seq.	BIC	LWZ	Break dates
OIL	472.09[a]	159.38[a]	83.72[a]	84.76[a]	0.00	4	3	2	1997W22; 2001W20;
	(16.19)	(18.11)	(18.93)	(19.64)	(20.19)				2005W07; 2008W47
TEC	514.18[a]	413.60[a]	149.33[a]	336.12[a]	0.00	4	1	1	1996W02; 1999W49;
	(16.19)	(18.11)	(18.93)	(19.64)	(20.19)				2006W19; 2010W09
TRA	543.03[a]	231.82[a]	172.52[a]	67.88[a]	0.00	4	2	1	1994W31; 1999W32;
	(16.19)	(18.11)	(18.93)	(19.64)	(20.19)				2002W19; 2008W14

Note: This table shows the test results for the endogenous structural breaks as developed by Bai and Perron (2003). Five breaks are allowed at most and the trimming parameter is 0.15. The $SupF_t$ (l + 1 | l) is a sequential test of the null of l breaks vs the alternative of l + 1 breaks. Sequential, BIC and LWZ denote the procedure of sequentially determined breaks, Bayesian Information Criterion and Information Criterion proposed by Liu, Wu, and Zidek (1997), respectively.
[a]Statistical significance at 5% level.
Source: Authors' calculation.

The results of the sequential test show that the oil, technology and transportation companies have four structural breaks at 5% significance level. This implies that assuming the oil price sensitivity is constant over time is not true. Thus, it confirms the shortcomings of prior studies based on this assumption. In this table, columns seven, eight and nine show the number of breaks identified by the sequential approach of the Bai and Perron (2003) test and the Bayesian information criterion (BIC) and Liu, Wu, and Zidek (LWZ) information criteria, accordingly.

Once the structural breaks in the relationship between the stock indices and the explanatory variables are identified, equations (16–18) are estimated for the sub-periods based on the breakpoints identified by the Bai-Perron sequential test. This method, instead of putting break dates as the dummy variables into the regression model, segments the regression into multiple regimes based on the identified break dates. Results of the breakpoint regressions are presented in Table 6. The results help us to see how regression coefficients are evolving throughout the time. Due to the existence of four breaks in each regression, there are five different regimes and each regime has its own coefficients. For instance, the negative effect of SIR changes over time and, in some periods, becomes positive. The results also show that the SPX is a key factor in determining the stock prices of these companies and its coefficients are statistically significant and positive for all companies. Overall, TEC companies receive

Table 6. Breakpoint regression results.

Company	Breaks	Obs.	Sub-samples	SIR	SPX	WTI	C	R^2	DW
OIL	4	387	1990W01–1997W21	0.142[a]	0.623[a]	0.157	1.082[b]	0.812	1.95
				(0.053)	(0.058)	(0.095)	(0.467)		
		206	1997W22–2001W19	−0.360[c]	0.053	0.253[a]	1.616[a]		
				(0.207)	(0.155)	(0.085)	(1.008)		
		196	2001W20–2005W06	0.091	0.832[a]	0.380[a]	−0.845		
				(0.058)	(0.203)	(0.083)	(1.349)		
		196	2005W07–2008W46	−0.140[b]	1.384[a]	0.213[c]	−1.630		
				(0.060)	(0.333)	(0.112)	(2.034)		
		325	2008W47–2015W05	−0.017	0.545[a]	0.140[c]	2.511[a]		
				(0.023)	(0.082)	(0.072)	(0.509)		
TEC	4	314	1990W01–1996W02	0.226[a]	2.192[a]	−0.109[a]	−1.697[a]	0.921	1.96
				(0.010)	(0.029)	(0.025)	(0.323)		
		204	1996W02–1999W48	−0.350	1.518[a]	0.482[c]	−1.473		
				(0.756)	(0.369)	(0.281)	(0.911)		
		335	1999W48–2006W18	−0.056[c]	1.800[a]	0.068	−1.309		
				(0.030)	(0.059)	(0.106)	(0.724)		
		199	2006W19–2010W08	−0.040	0.874[a]	0.075[b]	0.185		
				(0.046)	(0.215)	(0.033)	(1.607)		
		258	2008W09–2015W05	−0.011[a]	1.216[a]	0.034[a]	−1.874[a]		
				(0.002)	(0.007)	(0.008)	(0.073)		
TRA	4	239	1990W01–1994W30	0.106[a]	1.617[a]	−0.193[a]	−1.082[a]	0.597	1.96
				(0.016)	(0.054)	(0.023)	(0.389)		
		262	1994W31–1999W31	0.535[a]	0.936[a]	0.065	0.506		
				(0.092)	(0.192)	(0.279)	(2.105)		
		143	1994W32–2002W18	−0.050	0.223	0.128	1.982		
				(0.242)	(0.418)	(0.571)	(1.661)		
		308	2002W19–2008W13	0.066	1.050[a]	0.187	−0.037		
				(0.214)	(0.298)	(0.504)	(0.390)		
		358	2008W14–2015W05	−0.001	1.182[a]	−0.057[a]	0.293[a]		
				(0.002)	(0.009)	(0.008)	(0.067)		

Notes: This table reports the breakpoint regression results of linear models in equations (16–18). Sub-samples are based on the breakpoints identified by the test of Bai and Perron (2003). Five breaks are allowed at most. Standard errors of the estimated coefficients are corrected for heteroscedasticity by the White procedure. Breaks denote the number of breaks selected by the sequential procedure of Bai and Perron (2003) at 5% statistical significance level. DW shows the Durbin-Watson test statistics. Obs. shows the number of observations in each sub-sample.

[a, b, c]Statistical significance at the 1, 5 and 10% levels, respectively.

Source: Authors' calculation.

the highest impact from SPX compared to OIL and TRA companies. Regarding the impact of crude oil on stock prices of the companies, it is clear that oil companies (OIL) relatively receive the highest impact from WTI price movements. However, the impact magnitude of WTI on the companies' stocks are changing over time and regimes. The results are almost consistent with the results of DOLS

In order to test the spillover effect between oil prices and the stock indices of the companies, the causal linkages between them should be examined. This study employs Hill's (2007) fixed-length rolling window causality test. He suggests a successive multi-horizon non-causality test, which can be adopted to detect non-linear causalities in terms of linear parametric restrictions for a trivariate process (two different time series plus an auxiliary variable). This study utilises the bivariate case where causality between two different time series is measured. Causality takes place at any horizon if and only if it takes place at horizon 1 (first week in each window). Due to likely substandard performance of the Chi-squared distribution in small samples, Hill (2007) proposed a parametric bootstrapping approach for estimating small sample *p*-values. Also, the length of rolling window is fixed at 250 weeks and the maximum order of the VAR model is four lags. Table 7 presents the time-varying causality between oil prices and the stock prices of the oil, technology and transportation companies.

The results show that the null hypotheses of non-causality running from WTI to the stock indices of oil, technology and transportation companies are rejected at 51.6, 22.8 and 30.2% of the time, respectively. In other words, the strongest causality exists from WTI to oil companies, which is quite logical, as crude oil is the main product of these companies. Furthermore, the second-strongest causal linkage exists between WTI and transportation companies, since fuel is the key input for this industry. The results also show that the null hypotheses of non-causality running from the stock indices of oil, technology and transportation companies to WTI are rejected at 9.6, 21.7 and 16.6% of the time, respectively. Unlike the previous causality results, OIL has a little causal impact on WTI, as the causality degree has dropped from 51.6% to 9.6%. Therefore, we can say that WTI is relatively more likely to affect the stock prices rather than to be affected by them. The results suggest that technology companies have relatively more ability to influence crude oil prices, most probably through the channel of technological changes and innovations. Figures 3 and 4 illustrate the time-varying causality between WTI and the stock indices.

By means of this method we can easily understand the causal dynamics between these variables in a time-varying manner. As can be seen from Figure 3, after the global financial

Table 7. Time-varying causality using bootstrap rolling-window approach.

Null hypothesis (H_0)		Avg. VAR order	Avg. BPV	Rejection rate of H_0
WTI $\nrightarrow$	OIL	1.5655	0.2026	51.6494
WTI $\nrightarrow$	TEC	1.9877	0.3981	22.8087
WTI $\nrightarrow$	TRA	1.5749	0.3550	30.2544
OIL $\nrightarrow$	WTI	1.5655	0.4311	9.6136
TEC $\nrightarrow$	WTI	1.9877	0.3444	21.6776
TRA $\nrightarrow$	WTI	1.5749	0.4068	16.5881

Notes: This table reports the results of Hill's (2007) time-varying causality test. $\nrightarrow$ denotes the non-causality null hypothesis. VAR denotes Vector Autoregressive model and BPV denotes the bootstrap *p*-values. The maximum order of the VAR model is four lags. The size of the fixed rolling-window is 250 weeks. Bootstrap iterations are 1000 times. BPVs of less than 5% indicate causality within that window.
Source: Authors' calculation.

crisis of 2008–2009, there are high levels of causality running from WTI to all of the stock indices of companies. However, except from the crisis period, there is not a strong causal relationship running from WTI to the companies. Thus, we can say that return spillovers from WTI to these companies mainly occur during financial crises. On the other hand, Figure 4 exhibits the time-varying causality running from stock indices of the companies

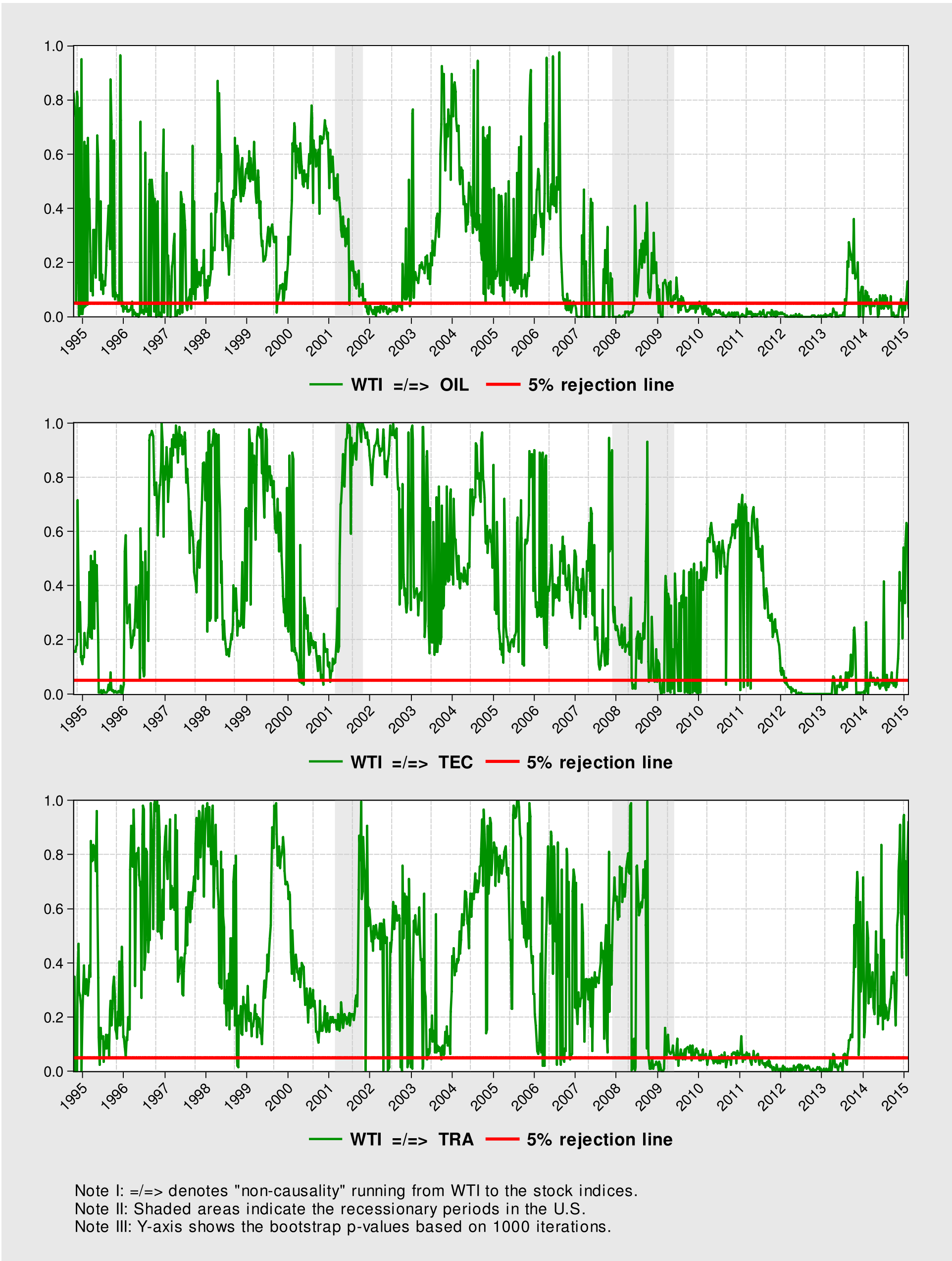

Figure 3. Time-varying causality (from WTI to the stock indices). Source: Authors' calculation.

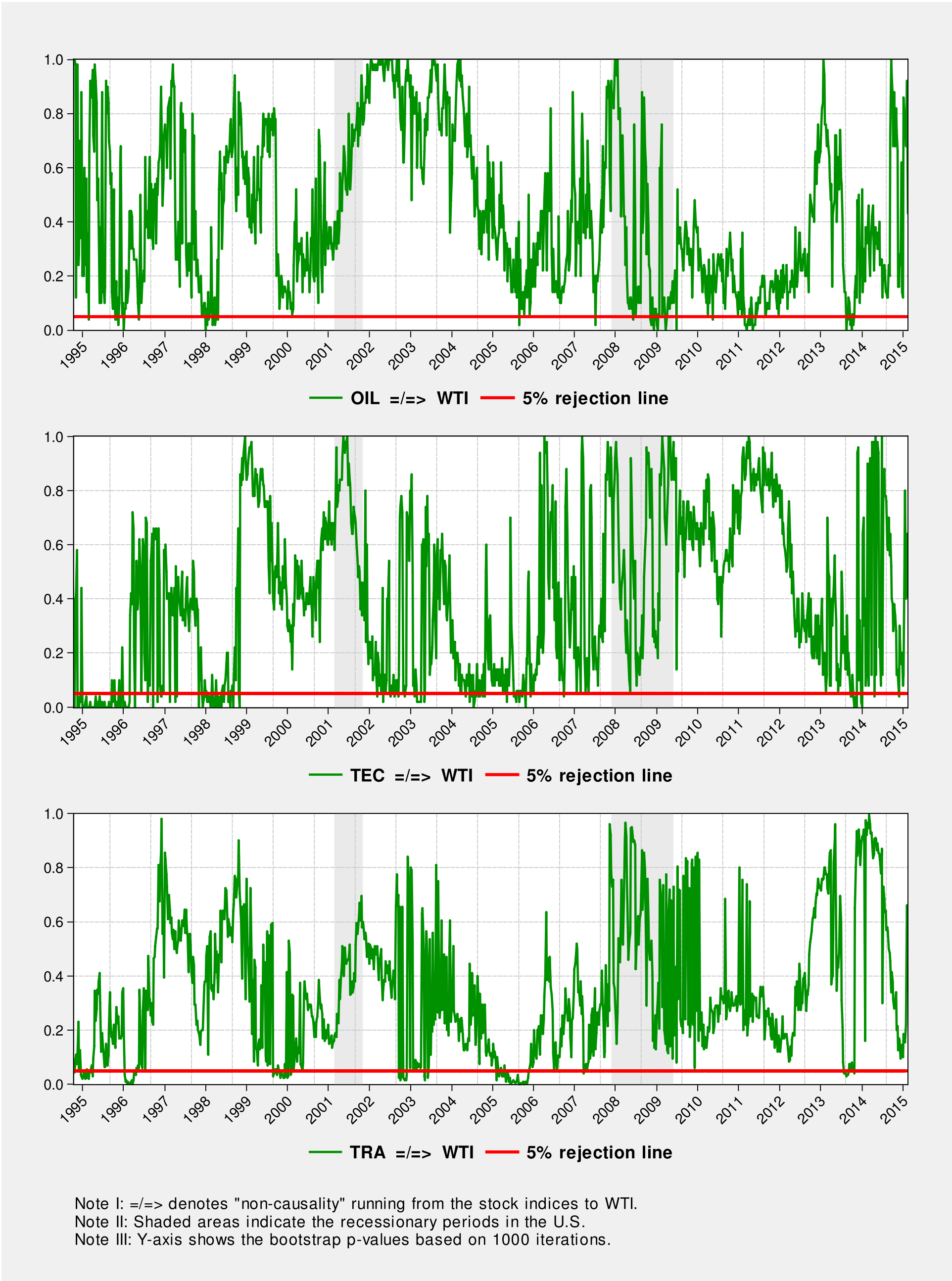

Figure 4. Time-varying causality (from the stock indices to WTI). Source: Authors' calculation.

to WTI. This figure shows that the degree of causality from OIL, TEC and TRA to WTI is relatively low. This demonstrates that the stock prices of these companies are not relatively powerful enough to affect crude oil prices. This also implies that the causal linkage between WTI and these stock indices is more unidirectional rather than bidirectional.

5. Conclusion

The present study has investigated the impact of crude oil prices on the stock prices of oil, technology and transportation companies listed on U.S. stock exchanges, using weekly data covering the period from 2 January 1990 to 3 February 2015. The Maki (2012) cointegration test results reveal that long-run equilibrium relationships exist between these stock indices, crude oil prices, short-term interest rate and S&P 500 in the presence of multiple structural breaks. These findings indicate that crude oil prices, short-term interest rates and the S&P 500 are long-run determinants of the stock prices of oil, technology and transportation firms. The DOLS results show that stocks prices of oil companies are positively and significantly affected by crude oil prices to a greater degree than that of technology and transportation stocks. This implies that the oil-sensitive stocks have a tendency to be affected relatively more by crude oil price fluctuations. Results also point out that technology stocks are positively and significantly affected by crude oil prices, which indicates that increasing crude oil prices put more pressure on technology firms to lower their energy-related costs and innovate more energy-conserving products due to high demand from other sectors. Therefore, if technology companies are successful in meeting these demands, their financial performances will also improve. Consequently, as these demanding industries utilise these innovative products, they can benefit a lot in terms of fuel cost savings and lower maintenance costs, thus directly affecting their profitability. The results of the breakpoint regressions are almost in line with the DOLS results, but it gives us a hint about how the oil price exposure of these companies changes over time as it takes multiple regimes into account and provides regime-dependent coefficients. Time-varying causality results show that WTI is relatively more likely to affect the stock prices of oil, technology and transportation companies rather than to be affected by them. Evidently, it is confirmed that financial crises have a substantial ability to intensify the causal linkage between WTI and the stock indices of these companies.

These findings contribute to the relevant literature, suggesting that, although oil price swings may not be the main reasons behind the stock price movements of technology and transportation companies, they have enough power to stimulate a movement toward a business environment that would be less reliant on fossil fuels. This is because investors may perceive technological advancements and innovations as the most important factors that influence the profitability of these companies and, therefore, affect their stock prices. We believe that the implications of this study are important and beneficial for financial managers, CFOs, hedge funds and portfolio managers. They have to pay special attention to the oil prices exposure of their companies or portfolios, as the degree of causality and cross-market spillover tends to be amplified between these markets in the event of financial crises. Finally, it should be noted that, in the future, crude oil will probably lose more of its influence on the stock prices of these firms due to the dominance of renewable energies and the proliferation of energy-efficient and sustainable products.

Notes

1. http://www.a350xwb.com/cost-effectiveness
2. http://www.a350xwb.com/
3. http://www.nyse.com/listed/lcddata.html?ticker=xoi.
4. http://www.nyse.com/about/listed/pse_i.shtml.

5. http://www.djaverages.com/?go=transportation-overview
6. A 'regime' means a period. If there is one break, there will be two regimes.

Disclosure statement

No potential conflict of interest was reported by the authors.

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