Energy 101 (2016) 558–565

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks

Ripsy Bondia [a, 1], Sajal Ghosh [b, *], Kakali Kanjilal [c, 2]

[a] Management Development Institute (MDI), Mehrauli Road, Sukhrali, Gurgaon 122001, India
[b] Management Development Institute (MDI), Room No C-10, Scholar Building, Mehrauli Road, Sukhrali, Gurgaon 122001, India
[c] International Management Institute (IMI), B-10, Qutab Institutional Area, Tara Crescent, New Delhi, 110016, India

ARTICLE INFO

Article history:
Received 27 August 2015
Received in revised form
11 January 2016
Accepted 7 February 2016
Available online 24 March 2016

Keywords:
Alternative energy
Oil price
Cointegration
Structural break

ABSTRACT

Increasing greenhouse gas emissions, exhaustibility and geo-politics induced price volatility of crude oil has magnified the importance of looking for alternative sources of energy. In this paper, we investigate the long term relationship of stock prices of alternative energy companies with oil prices in a multivariate framework. To this end, we use threshold cointegration tests, which endogenously incorporate possible regime shifts in long run relationship of underlying variables. In contrast to the findings of the previous study by Managi and Okimoto (2013), our results indicate presence of cointegration among the variables with two endogenous structural breaks. This study confirms that ignoring the presence of structural breaks in a long time series data, as has been done in previous study, can produce misleading results. In terms of causality, while the stock prices of alternative energy companies are impacted by technology stock prices, oil prices and interest rates in the short run, there is no causality running towards prices of alternative energy stock prices in the long run. The study discusses the possible reasons behind the empirical findings and concludes with a discussion on short run and long run investment opportunities for the investors.

1. Introduction

Energy has become an integral part of our lives in some form or the other. An uninterrupted supply of energy is now a necessity for smooth functioning of our daily work and personal chores. At a national level, the importance of energy is further amplified as energy is one of the essential inputs for socio-economic development of a nation. In its International Energy Outlook, 2013 [1] published by EIA (Energy Information Administration), it has been projected that the world energy consumption would rise by 56%, from 524 quadrillion BTU (British Thermal Unit) to 820 quadrillion BTU, between 2010 and 2040. Moreover, more than 85 percent of this increased consumption is expected to come from non-OECD[3] countries, which have been witnessing high population and economic growth in recent years.

The sources of energy can be primarily clubbed into fossil, renewable and fissile[4] [2]. Fossils have historically been the largest source of energy globally and according to EIA, it is expected to remain so in future. While the consumption of energy is expected to be led by non-OECD countries through fossil fuels in coming years, one of the major problems in global economy is the geographical distribution of fossil fuels. The availability of fossil fuels, especially crude oil, is restricted only to certain parts of the world. Apart from scarcity of supply, combustion of fossil fuels results in emission of GHGs (Green House Gases), which is considered as one of the major causes of climatic change and global warming [3,4].

* Corresponding author. Tel.: +91 124 4560309; fax: +91 124 2340147.
E-mail addresses: fpm14ripsy_b@mdi.ac.in (R. Bondia), sghosh@mdi.ac.in, sajalg@yahoo.com (S. Ghosh), kakali@imi.edu (K. Kanjilal).
[1] Tel.: +91 124 4560010; fax: +91 124 2340147.
[2] Tel.: +91 11 47194100; fax: +91 11 26867539.

[3] Organization of Economic Cooperation and Development (OECD) is an international organization composed of the industrialized market economy countries, as well as some developing countries, by providing a forum in which to establish and coordinate policies. Non-OECD countries represent developing countries.
[4] Fossil fuel comprises of oil, natural gas, coal etc. Renewable energy comprises of hyro, wind, biomass, solar etc. and fissile fuel comprises of uranium, thorium etc.

http://dx.doi.org/10.1016/j.energy.2016.02.031

Crude oil gains immense importance in the world of energy as it has historically been a major source of energy supply worldwide. World oil production increased from 63,987.1 thousand barrels per day in 1980 to 90,904 thousand barrels per day in 2013, representing a CAGR (compound annual growth rate) of 1.07%. North America became the biggest supplier of oil during the period 1982–87 followed by Middle East. However, post 1987, Middle East has remained the top oil supplier with an average market share of 29% followed by North America with an average market share of 20%. In terms of consumption, Asia, North America and Europe remain the top consumers of oil. However, one can clearly see the gradual increase in oil consumption by Asian region over the period 1980–2013 (Fig. 1a and b).

During the past decade, AES (alternative energy sources) consisting primarily of RES (renewable energy sources), have been increasingly seen as one of the ways to combat climate change. As against the use of fossils, which result in anthropogenic GHG emissions, AES are considered sustainable source of energy which are environmentally benign in nature [5]. AES can also aid in energy security by diversification of the energy supply mix. In 2012, 13.2% of world's total primary energy supply came from RES. In its International Energy Outlook in 2013 [1], EIA expects government policies and incentives worldwide to support the rapid construction of facilities generating RES. While the total energy demand is expected to increase by 1.5 percent per year, RES are expected to be among the fastest-growing sources of world energy, increasing at an average annual rate of 2.5 percent during 2010–2040.

The conventional media wisdom suggests that increasing oil prices are favorable for financial performance of alternative energy companies since rising oil prices provide high incentive to shift to alternative energy. In this paper, we investigate the long term relationship of stock prices of alternative energy companies with oil prices in a multivariate framework.

The remainder of the article is organized as follows. Section 2 gives an overview of past studies. Section 3 provides data descriptions. Section 4 describes estimation methodology. Section 5 discusses empirical findings. Finally, section 6 concludes the study.

2. Literature review

Being one of the major sources of primary energy, oil price fluctuations have been considered to have a significant impact on economic growth and several macroeconomic variables for a long time. Several studies have been undertaken to examine the impact of oil price movements on economic growth [6–11], inflation [12–15], investment [16,17] and output [18,19]. There are several channels through which oil prices may impact economic activity. A rise in oil price leads to increase in energy bill for consumers and increased costs for producers. Further, from the classic supply-side effect, increasing oil prices are indicative of reduction in availability of a primary input in production, thereby leading to decrease in potential output. There is rise in production cost and a fall in growth of output and productivity. A drop in productivity in turn has an impact on employment, inflation, profits and investment [7,20,21].

There is also a large and growing body of literature that focuses on impact of oil price movements on financial markets [22–26]. The theoretical foundation of this relationship stems from the oil price effect diffusing to macroeconomic variables discussed above which in turn have an impact on investments and profits. On the supply side, increased oil prices increase cost of production thereby adversely impacting the profits of companies. On the

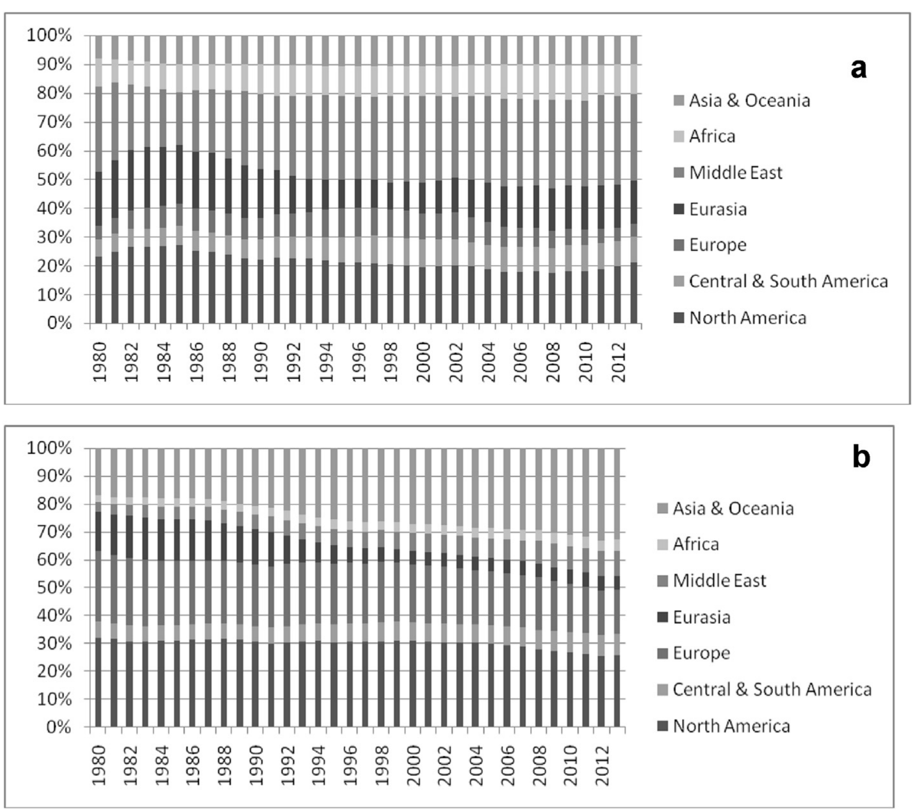

Fig. 1. (a): Oil production share in the world. (b) Oil Consumption share in the world.
Source: www.eia.gov

demand side, increased inflation resulting from oil price rise may deter investment in stock market due to increasing interest in bond market [6].

However, limited research has been done to study the dynamics between alternative energy stock prices and oil prices. Henriques and Sadorsky [27] use a four variable VAR (vector autoregressive) framework to study the relationships between stock prices of alternative energy companies, oil prices, technology stock prices and interest rates. They find oil prices, interest rates and technology stock prices Granger cause stock prices of alternative energy companies. The simulation results further show that shocks in technology stock prices have a positive and statistically significant impact on stock prices of alternative energy companies. However oil price shock does not have a statistically significant impact on stock prices of alternative energy companies. Since the success of clean energy companies depends upon the successful breakthrough or adoption of specific technologies, investors may perceive stocks of clean energy similar to stocks of technology companies [27,28].

Sadorsky [29] uses multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models to analyze conditional correlations and volatility spillovers between oil prices, clean energy stock prices and technology stock prices. The results of the study show that clean energy companies' stock prices correlate more with technology companies' stock prices than with oil prices. Kumar et al. [28] use Toda and Yamamoto [30] version of extended VAR framework to find clean energy stocks being explained by oil prices, technology stock prices and interest rates.

Managi and Okimoto [31] analyze the relationship between oil prices, clean energy stock prices and technology stock prices using Markov-switching VAR model. They find a structural change in late 2007. Their findings are consistent with Henriques and Sadorsky [27] for pre-structural break period. In post structural break period, they establish both oil prices and technology stock prices have positive impact on clean energy stock prices.

One of the criticisms of previous studies is that majority of works have not examined the existence of long-term association among the variables. Also, the study which investigates long-term relationship or cointegration [31] has some inherent flaws. Managi and Okimoto [31] have employed Johansen–Juselius [32] maximum likelihood procedure to detect cointegration among I(1) series namely the WilderHill Clean Energy index, the Arca Technology index, average of U.S. WTI (West Texas intermediate) and Brent crude oil future prices; and interest rates. The findings don't support the existence of cointegrating relationship among these variables.

One of the main disadvantages of Johansen–Juselius cointegration methodologies is that it assumes that the cointegrating relationship does not change over the entire period of the empirical study which is too unrealistic to be true especially when the time series is long. Structural breaks due to economic crises, technological shocks, external shocks or policy changes in a time series data often alter the long-run relationship among the underlying variables. Hence, application of Markov regime switching VAR and existence of different regimes in the study by Managi and Okimoto [31] raises question mark on the suitability of Johansen–Juselius methodology to detect cointegration. This raises the importance of re-investigating the long-run relationship among these variables where the cointegrating methodology endogenously determines the structural breaks or regime shifts of the underlying variables.

The objective of the current study is to re-visit the cointegrating relationship of stock prices of alternative energy companies with oil prices, technology stock prices and interest rates by deploying threshold cointegration tests of Gregory and Hansen [33] and Hatemi-J [34]. These cointegrating tests investigate long run relationship in the presence of possible regime shifts of underlying variables. Apart from this, the current study is different from the previous studies primarily on three other important aspects. First, the sample period of this study is different from earlier studies. Sadorsky [29] uses the daily data ranging from January 1, 2001 to December 31, 2010 and Managi and Okimoto [31] considers weekly data January 3, 2001 to February 24, 2010. Current study uses weekly data for the period January 3, 2003 to June 5, 2015. Second, current study uses average weekly spot price of WTI (West Texas Intermediate) and Brent crude. Third, the study employs VECM (Vector Error Correction Model) to ascertain the direction of Granger causality among the variables.

3. Data descriptions

In line with Henriques and Sadorsky [27] and Managi and Okimoto [31], current study uses four variables namely stock prices of alternative energy companies, oil prices, technology stock prices and interest rates. The variables are described below.

3.1. Stock prices of alternative energy companies

We use WilderHill New Energy Global Innovation Index for this variable. It is a modified dollar weighted index of publicly traded companies which are active in renewable and low-carbon energy. It is created by WilderHill New Energy Finance, LLC with a benchmark value of 100 as on 30th December, 2002. The index stands to benefit from responses to climate change and energy security concerns. Majority of index members are quoted outside the US. The data for the same has been sourced from Bloomberg.

3.2. Stock prices of technology companies

During 1990s it was observed that the stock prices of publicly traded alternative energy companies (like fuel cell companies) moved in the same direction as NASDAQ. As Henriques and Sadorsky [27] put that “it may be the case that investors view alterative energy companies as similar to other high technology companies”. Hence, it is imperative to investigate the relationship between stock prices of technology companies and stock prices of alternative energy companies.

We use New York Stock Exchange Arca Tech 100 Index for this variable. It is a price-weighted index of 100 multi-industry tech-related companies that deploy innovative technologies in their products. Companies are from 16 different industries, such as computer hardware, software, semiconductors, telecom, data storage, electronics and health care equipment. The index was established in 1982. The data for the same has been sourced from Bloomberg.

3.3. Oil prices

As mentioned earlier, the conventional media wisdom suggests a positive relationship between stock prices of alternative energy companies and oil prices because rising oil prices would encourage substitution towards non-petroleum energy sources. To examine this, we use the average of weekly closing spot prices of WTI (West Texas Intermediate) and Brent crude oil. The data is sourced from the website of EIA (Energy Information Administration), USA (see http://www.eia.gov/dnav/pet/pet_pri_spt_s1_w.htm).

3.4. Interest rates

A stream of literature shows significant relationship between interest rate and stock price movements [35,36] among others. We use 10-Year Treasury Constant Maturity Rate to investigate

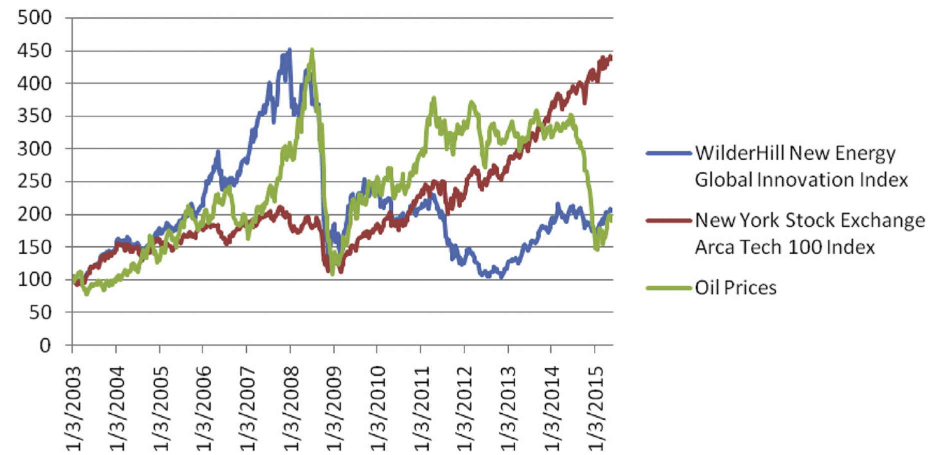

Fig. 2. Graphical representation of data.

relationship between interest rates and stock prices of alternative energy companies. The data is sourced from the website of Research Division of the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2).

The current study uses data ranging from January 3, 2003 to June 5, 2015. The choice of sample period plays a critical role for two reasons. Firstly, 2008 recession falls within the study period. All four variables witnessed a sudden drop during the period June 2008 to December 2008[5] demonstrating their lack of immunity to 2008 crisis. Post recession, Arca Technology index and oil price show a gradual increasing trend with improving economic conditions. However, the growing trend of oil price is halted by a second slump seen since June 2014 when the international oil price fell by 58.4%, between June 2014 and January 2015, as shown in Fig. 2. Secondly, it is also interesting to see two distinct behaviors of WilderHill New Energy Global Innovation index in relation to oil prices during the chosen study period. The two series exhibit a similar increasing trend before their fall in 2008. During 2008 recession, the WilderHill New Energy Global Innovation index shows a big drop like oil price. However, a careful examination of Fig. 2 shows the drifting behaviors of WilderHill New Energy Global Innovation index and oil price post recession. This is also supplemented by the fact that during the second major drop of oil price, WilderHill New Energy Global Innovation index does not show a major drop.[6]

NEX, PSE, AOP represent weekly WilderHill New Energy Global Innovation Index, New York Stock Exchange Arca Tech 100 Index and average oil price after natural logarithmic transformation respectively where as *INT* represents 10-Year Treasury Constant Maturity Rates.

4. Materials & methods

4.1. Cointegration methodology

Cointegration has been defined as systematic co-movement of two or more non-stationary series. Engle and Granger [37] showed that if the two series X and Y (say) are individually integrated of order one i.e. I(1) in nature and share a common stochastic trend then there exists a long-run relationship among the variables or, in other words, variables are cointegrated. In many cases economic theory tells us that two or more variables should be cointegrated and a test for cointegration is the test of the theory. The presence of cointegration among the variables also rules out the possibility of "spurious" correlation.

In the past two decades, cointegration techniques proposed by Engle and Granger [37], Johansen and Juselius [32] and Pesaran et al. [38] have been used extensively in empirical research to examine the long run relationship among variables in a bivariate or multivariate framework. One of the criticisms of these cointegration methodologies is that it assumes that the cointegrating relationship does not change over the entire period of the empirical study which is too unrealistic to be true especially when the time series is long. Gregory and Hansen [33] and Hatemi-J [34], GH and HJ henceforth, have argued that structural breaks in a long time series is a common phenomena whose presence can change the cointegrating relationship. In other words, the long run relationship is likely to witness one or two regime shifts in the sample period. In that case, conventional cointegration tests, stated above, may produce misleading or inconclusive results.

4.2. Threshold cointegration approach

As mentioned earlier, conventional cointegration methodologies proposed by Engle and Granger [37], Johansen and Juselius [32] and Pesaran et al. [38] may yield incorrect cointegrating relationship as they fail to capture the structural breaks in a long time series data. Hence to identify the robustness of long-term relationship, we use the regime shift model proposed by GH and HJ which incorporate regime changes endogenously with level and slope dummies. GH test is developed with one structural break whereas HJ test has incorporated two structural breaks. GH and HJ models are defined as follows:

GH Test:

$$\begin{aligned} NEX_t = {} & \alpha_0 + \alpha_1 D_{1t} + \beta_{01} PSE_t + \beta_{11} D_{1t} PSE_t + \beta_{02} AOP_t \\ & + \beta_{12} D_{1t} AOP_t + \beta_{03} INT_t + \beta_{13} D_{1t} INT_t + \varepsilon_t \; ; \end{aligned} \tag{1}$$

HJ Test:

[5] WilderHill Clean Energy index by 59%, Arca Technology index by 36%, international crude oil price by 73% and interest rate by 45%.

[6] The index drops by 17.7% in comparison to oil price drop of 58.4%.

$$
\begin{aligned}
NEX_t = {} & \alpha_0 + \alpha_1 D_{1t} + \alpha_2 D_{2t} + \beta_{01} PSE_t + \beta_{11} D_{1t} PSE_t \\
& + \beta_{21} D_{2t} PSE_t + \beta_{02} AOP_t + \beta_{12} D_{1t} AOP_t + \beta_{22} D_{2t} AOP_t \\
& + \beta_{03} INT_t + \beta_{13} D_{1t} INT_t + \beta_{23} D_{2t} INT_t + \varepsilon_t
\end{aligned} \tag{2}
$$

α_0 represents 'base dummy'. α_1 and α_2 represent the coefficient estimates of intercept dummies which differ from the common intercept α_0. In equation (1), α_1 captures the differential effect of one structural break over α_0 whereas in equation (2) it demonstrates the change in intercept for the first endogenous structural break. Similarly, α_2 in equation (2) shows the change from the base level α_0 due to second structural break. $\beta_{0i\ (i\,=\,1,\,2,\,3)}$ represents base slope coefficients of *PSE, AOP* and *INT*. $\beta_{1i\ (i\,=\,1,\,2,\,3)}$ and $\beta_{2i\ (i\,=\,1,\,2,\,3)}$ are differential slope coefficients due to endogenous structural breaks. The dummy variables D_{1t} and D_{2t} for endogenous structural breaks at time $t = 1, 2, \ldots,$ n are defined as

$$
\begin{aligned}
D_{1t} &= 0; \quad \text{if } t < = [n\tau_1] \\
&= 1; \quad \text{if } t > \ [n\tau_1] \\
D_{2t} &= 0; \quad \text{if } t < = [n\tau_2] \\
&= 1; \quad \text{if } t > \ [n\tau_2]
\end{aligned}
$$

τ_1 and τ_2 are two known parameters which belong to the set (0 1) implying the relative timing of regime change point or the structural break points. The bracket denotes the integer part. The standard methods of testing the null hypothesis of no cointegration in the context of the model (1) and (2) when there are no dummies for structural breaks are residual based [37]. According to Engle and Granger [37], variables Y_t (dependent) and X_t (independent) are cointegrated if they are integrated of order one (Y_t and $X_t \sim I(1)$) and their residual ε_t is stationary or integrated of order zero ($\varepsilon_t \sim I(0)$). So, the underlying variables Y_t and X_t are first tested for the presence of unit root. If the null hypothesis of unit root is accepted, then their linear combination approximated by regression error ε_t obtained from running OLS (ordinary least square) of Y_t on X_t is tested for unit root. Three residual based tests namely 'Augmented Dickey–Fuller test' (proposed by Engle and Granger [37]) and Z_α, Z_t tests (proposed by Perron [39]) are applied to its regression errors to test the hypothesis of no cointegration. GH [33] has shown direct application of these tests to the regression errors leads to misspecification of cointegration if the structural breaks are unknown and proposed bias-corrected modified ADF^*, Z_α^*, and Z_t^* tests for testing cointegrating relationship of the underlying variables.

$$ADF^* = \inf_{(\tau)\in T} ADF(\tau) \tag{3}$$

$$Z_t^* = \inf_{(\tau)\in T} Z_t(\tau) \tag{4}$$

$$Z_\alpha^* = \inf_{(\tau)\in T} Z_\alpha(\tau) \tag{5}$$

To test the null hypothesis of no cointegration, one has to first estimate equations (1) and (2) for each possible structural breaks $\tau \in T = (0.15,\ 0.85)$ for GH test and $\tau_1 \in T_1 = (0.15,\ 0.70)$ and $\tau_2 \in T_2 = (0.15 + \tau_1,\ 0.85)$ for HJ test. Equations (3)–(5) are then used for residuals of each possible structural break. Finally, the smallest value of (3), (4) and (5) is compared with the critical values of one-break point and two-break point tests developed by GH and HJ respectively to draw inference on the existence of cointegrating relationship among the variables under study.

4.3. Granger causality

Engle and Granger [37] showed that if two or more time series are individually I(1) and cointegrated then there must be a causal relationship at least in one direction. The direction of causality can be detected through the VECM (Vector Error Correction model) of long-run cointegrating vectors.

For current study, VECM can be written as

$$
\begin{aligned}
(1-L)\begin{bmatrix} NEX \\ PSE \\ INT \\ AOP \end{bmatrix} = {} & \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} + \sum_{i=1}^{p} (1-L) \begin{bmatrix} d_{11i} d_{12i} d_{13i} d_{14i} \\ d_{21i} d_{22i} d_{23i} d_{24i} \\ d_{31i} d_{32i} d_{33i} d_{34i} \\ d_{41i} d_{42i} d_{43i} d_{44i} \end{bmatrix} \\
& \times \begin{bmatrix} NEX_{t-i} \\ PSE_{t-i} \\ INT_{t-i} \\ AOP_{t-i} \end{bmatrix} + \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} [EC_{t-1}] + \begin{bmatrix} \gamma_{1t} \\ \gamma_{2t} \\ \gamma_{3t} \\ \gamma_{4t} \end{bmatrix}
\end{aligned} \tag{6}
$$

where, '*L*' is backward shift operator and EC_{t-1} is ECT (error-correction term), which represents speed of adjustment. $d_{(ij)}$ are parameters to be estimated and γ_t's are serially uncorrelated error terms, The *F*-statistics on the lagged explanatory variables of VECM indicates the significance of the short-run causal effects. The *t*-statistics of the coefficients of the ECT, on the other hand, indicate the significance of long-run causal effect. The lag length p of VECM would be detected from Schwarz-Bayessian (SBC) and/or Akaike (AIC) information criteria.

5. Results and discussions

In the beginning, the stationary property of the variables has been investigated. Keeping in mind the merits and demerits of numerous unit root tests [40,41], current study employs four unit root tests namely ADF (Augmented Dickey–Fuller), PP (Phillips-Perron), KPSS (Kwiatkowski-Phillips-Schmidt-Shin) and NP (Ng-Perron) tests. In ADF, PP and NP tests, the null hypothesis is defined as 'the series has a unit root against the alternative of stationarity', while for KPSS the null hypothesis states 'the series is stationary'.

Results of unit root tests on the levels and first differences of the logarithmic series are presented in Table 1. Majority of these unit root test results infer that series are integrated of order one, i.e. I(1) in nature.[7]

Once the stationary property of the underlying variables is examined, we proceed to investigate the presence of cointegration among the variables using threshold cointegration tests. The results of threshold cointegration tests are reported in Table 2. Modified ADF^* and Z_t^* test statistics reject the null hypothesis of no cointegration at 5% level of significance. This is true for both one break point (GH test) and two break point tests (HJ test).[8]

So, contrary to Managi and Okimoto [31] which fails to establish cointegration among the variables, threshold cointegration tests ascertain a long-run relationship among the variables with two endogenous structural breaks. However, the timing of each structural break is endogenously determined. This means that the cointegrating relationship among stock prices of alternative energy companies, oil prices, technology stock prices and interest rates are not time invariant. There have been two structural shifts in the relationship at two unknown points of time during the period of the study.

[7] NP tests suggest that *PSE* and *INT* are I(2) in nature. These types of divergences are not uncommon in the empirical literature.

[8] We use the GAUSS 9.0 software to test GH and HJ threshold cointegration tests. The code for GH test is taken from Bruce Hansen's website (http://www.ssc.wisc.edu/~bhansen/. The Gauss code for HJ test is obtained from Hatemi J A.

Table 1
Unit Root test results.

		ADF	PP	KPSS	NPZa
Level					
Intercept	*NEX*	−1.9839[a]	−2.1442[a]	0.4841[b],[c]	−0.484[a]
	PSE	−0.7209[a]	−0.7050[a]	2.4532[b]	1.4341[a]
	AOP	−2.1469[a]	−2.1729[a]	1.8394[b]	−0.8508[a]
	INT	−1.5262[a]	−1.4062[a]	2.3750[b]	−3.3224[a]
Intercept & Trend	*NEX*	−2.0663[a]	−2.2053[a]	0.4434[b]	−1.8817[a]
	PSE	−1.9314[a]	−1.9436[a]	0.4118[b]	−6.7752[a]
	AOP	−1.7298[a]	−1.8852[a]	0.3137[b]	−5.7485[a]
	INT	−2.9012[a]	−2.9615[a]	0.2669[b]	−10.319[a]
First Difference					
Intercept	*ΔNEX*	−24.3102[b]	−24.6803[b]	0.2088[a]	−44.0079[b]
	ΔPSE	−26.3102[b]	−26.2963[b]	0.0901[a]	−3.9903[a]
	ΔAOP	−20.2767[b]	−20.5643[b]	0.1730[a]	−33.3085[b]
	ΔINT	−20.3096[b]	−20.4785[b]	0.0598[a]	−2.1618[a]

All values significant at 1% level, unless indicated.
[a] Null hypothesis accepted.
[b] Null hypothesis rejected.
[c] Significant at 5% and 10% level.

Table 2
Threshold cointegration results.

$NEX_t = f(PSE_t, AOP_t, INT_t)$	ADF^*	Z_t^*	Z_α^*
GH Test	−6.15[a]	−5.65	−62.07
	(0.44)	(0.44)	(0.44)
HJ Test	−8,79[a]	−7.60[a]	−110.89[a]
	(0.26, 0.31)	(0.26, 0.31)	(0.26, 0.31)

Numbers in parentheses represent break points.
[a] Significant at 5% level of significance. The critical values for GH and HJ tests are available in GH (1996, pp 109) and HJ (2008, pp 501).

Table 3
Results of Granger causality tests.

Dependent Variable	*ΔNEX*	*ΔPSE*	*ΔAOP*	*ΔINT*	ECT [*t*-statistic]
ΔNEX	–	8.8387[a]	6.8906[a]	8.7821[a]	−0.002
		(0.012)	*(0.031)*	*(0.012)*	[−1.08]
ΔPSE	−0.0028	–	1.3481	5.9326[b]	0.002
	(0.422)	*(0.509)*		*(0.061)*	[1.462]
ΔAOP	2.931	1.8784	–	2.2790	0.001
	(0.230)	*(0.390)*		*(0.326)*	[0.527]
ΔINT	8.6664[a]	6.8578[a]	0.3686	–	0.0168[a]
	(0.013)	*(0.032)*	*(0.831)*		[2.354]

Figures in parenthesis are probability values.
[a] Significant at 5% level.
[b] Significant at 10% level.

Once a cointegrating relationship has been established, VECM needs to be estimated to understand the short-run dynamics.[9] The coefficient of the lagged error correction term in *ΔINT* equation, where '*Δ*' represents first-differenced operator, is found to be statistically significant at 5% level (Table 3). Because the ECT measures the speed at which the endogenous variable adjusts to changes in the explanatory variables before converging to its equilibrium level, the coefficient of 0.01 suggests that the speed of adjustment would be slow.

The existence of cointegration among *NEX, PSE, INT* and *AOP* also suggests that there must be Granger causality at least in one direction. Table 3 reveals results of short and long run Granger causality within VECM framework. Beginning with the short-run effect, the null hypothesis of non-causality from *ΔPSE*, *ΔINT* and *ΔAOP* to *ΔNEX*, which are asymptotically distributed as a chi-square variate with two degrees of freedom is rejected at 5% level of significance. Similarly, null hypothesis is rejected from *ΔNEX* to *ΔINT*, *ΔPSE* to *ΔINT* and from *ΔINT* to *ΔPSE*.

In summary, this study establishes short-run bidirectional Granger causality between *ΔINT* and *ΔNEX* and between *ΔINT* and *ΔPSE*. This bi-directional causality between interest rates and stock prices of technology companies; and between interest rates and stock prices of alternative energy companies can be explained by the relation between the stocks and bonds; where both (stocks and bonds) act as investment alternatives for investors thereby substituting or complimenting each other. Unidirectional causality is found from *ΔPSE* to *ΔNEX*, indicating that stock prices of alternative energy companies are impacted by stock prices of technology companies. This provides support to the argument given in existing literature [27,28] that investors perceive alternative energy companies similar to high technology companies since clean energy are based on specific technologies. Unidirectional causality is also found from *ΔAOP* to *ΔNEX*.

Turning to the long-run causality result, the statistical significance of the coefficient of the lagged error correction term in *ΔINT* equation indicates that there is Granger causality running from *NEX*, *PSE* and *AOP* to *INT*. No causality running towards oil strengthens the argument on exogenous nature of oil [22,42]. Also, no causality towards prices of alternative energy stock prices in long run is an indication in the direction that adoption of alternative energy is not a result of increasing oil prices in the long-run. Countries are making an effort to move towards alternative sources of energy which are not harmful to the environment.

A battery of diagnostic tests, which includes testing for heteroscedasticity, miss-specification of functional form, auto correlation and normality of the residuals, do not find any significant evidence of departures from standard assumptions.

6. Conclusions

Crude oil has historically been one of the major sources of primary energy worldwide. However, exhaustible nature and increasing greenhouse gas emissions from the use of fossils have been forcing many countries to think about shifting to alternative sources of energy which are renewable and cleaner in nature.

This study examines the cointegrating relationship between stock prices of alternative energy companies, oil prices, technology stock prices and interest rates for the period January 3, 2003 to June 5, 2015. The study uses cointegration tests of Gregory and Hansen [33] and Hatemi-J [34] which incorporate regime changes endogenously. Hence these tests are considered to be more robust for analysis of long term relationships among underlying variables.

In contrast to the previous study by Managi and Okimoto [31], which ignores the presence of structural breaks during the period of study, threshold cointegration test results suggest the existence of long-run relationship among stock prices of alternative energy companies, oil prices, technology stock prices and interest rates for one and two endogenous break points. This implies that the cointegrating relationship has witnessed two regime shifts and changed twice during the period of the study. This explains that the existence of structural breaks in the period of the study can produce misleading results if they are not incorporated in the cointegration testing model.

In terms of directions of Granger causality, our key findings are:

- A bi-directional short-run[10] Granger causality between interest rates and technology stock prices; and a bi-directional short-run

[9] Johansen-Juselius maximum likelihood tests suggest cointegration among the variables at 10% level of significance.

[10] In short-run the variables are represented in their respective growth rates.

causality between interest rates and stock prices of alternative energy companies: These bi-directional causalities suggest that stocks and bonds are either substitutes or complements to each other. The assets tend to be substitutes or complements depending on whether or not the actual returns are subject to similar deviation from the expected values due to a particular reason. The economic behavior of investors in the connection between stocks and bonds can be explained as follows. When the interest rates fall, the prices of existing bonds (giving higher interest) increase, thereby reducing bond yields. Lower interest rates create an upward pressure on stock prices mainly in two ways. First, the investors prefer to shift to buying stocks for higher return. Second, lower interest rates make borrowing less expensive for companies and individuals. This leads to higher corporate earnings, higher stock prices and high economic growth. Similarly, higher interest rates make bonds an attractive investment opportunity which leads to investors rebalancing their portfolio by selling stocks and buying bonds, thereby suppressing stock prices [36].

- A unidirectional short run causality from technology stock prices to stock prices of alternative energy companies: The stock prices of alternative energy companies are impacted by technology stock prices and oil prices in the short run. This strengthens the argument by Henriques and Sadorsky [27] and Kumar et al. [28] that investors perceive alternative energy companies similar to high technology companies since successful clean energy are based on specific technologies.
- A unidirectional short-run causality from oil price to the stock price of alternative energy companies. According to international agencies like IEA (International Energy Agency) and EIA, global crude oil prices are expected to be sluggish in near future. The increasing oil supply from OPEC nations, which reached a three year high in June 2015 in spite of lower price in international market, U.S shale gas revolution, continuing growth in global petroleum inventories and availability of Iranian oil in international market post US-Iran nuclear deal are some factors which are likely to put a downward pressure on crude oil prices from the supply side [43]. On the demand side, the growth in global oil demand has been easing since the first quarter of 2015. This scenario is expected to continue in near future due to lethargic demand from Europe, Asia and US. A possible Greek exit from European Union and concerns on lower economic growth in China could also add to the dampening oil demand, thereby putting further pressure on oil prices. Under such circumstances, existence of unidirectional causality from oil price to the stock price of alternative energy companies, as established in our study, may lead to a possible decline in the stock price of alternative energy companies in the short-run.
- No causality running towards prices of alternative energy stock prices in the long run. The absence of long run causality towards process of alternative energy companies, especially from oil prices is an indication in the direction that adoption of alternative energy is not a result of increasing oil prices in the long run. Rising levels of GHG, oil supply disruptions and oil geopolitics, technological innovation and development on clean energy sources and, most importantly, public sentiments are pushing countries to move towards alternative energy sources. Adoption of alternative energy sources also provides a welcome diversity to energy supply thereby enhancing national energy security.
- No impact on international crude oil price due to any of the variables considered in the study in short-run and long-run: This strengthens the argument of exogenous nature of international crude oil price as a variable established earlier by Ghosh and Kanjilal [22] and Bouri [42] among others.

The results of the current study provide valuable insights on short run and long run investment opportunities. Since there is no short run causality running between oil prices and technology prices, an investor can diversify his portfolio by holding assets in oil markets and technology stocks in the short run. However, from a long term investment perspective, the presence of cointegration among oil prices, prices of alternative energy companies, technology stock prices and interest rate implies that diversifying portfolio by simultaneously holding assets in oil markets, alterative energy stock, technology stocks and bond markets does not result in a significant reduction of unsystematic risk or increase long-term benefits.

Acknowledgements

The authors would like to thank anonymous referees for their valuable comments and suggestions. We also extend our thanks to the editor of the journal for his support.

References

[1] EIA US. International energy outlook 2013. Washington, DC: US Energy Information Administration; 2013.
[2] Ferreira G. Alternative energies: updates on progressVol. 34. Springer Science & Business Media; 2013.
[3] Akhmat G, Zaman K, Shukui T, Sajjad F. Does energy consumption contribute to climate change? Evidence from major regions of the world. Renew Sustain Energy Rev 2014;36:123–34.
[4] Auffhammer M, Mansur ET. Measuring climatic impacts on energy consumption: a review of the empirical literature. Energy Econ 2014;46:522–30.
[5] Lee CW, Zhong J. Construction of a responsible investment composite index for renewable energy industry. Renew Sustain Energy Rev 2015;51:288–303.
[6] Jones DW, Leiby PN, Paik IK. Oil price shocks and the macroeconomy: what has been learned since 1996. Energy J 2004:1–32.
[7] Brown SP, Yücel MK. Energy prices and aggregate economic activity: an interpretative survey. Q Rev Econ Finance 2002;42(2):193–208.
[8] Hamilton JD. What is an oil shock? J Econ 2003;113(2):363–98.
[9] Rahman S, Serletis A. Oil price uncertainty and the Canadian economy: evidence from a VARMA, GARCH-in-Mean, asymmetric BEKK model. Energy Econ 2012;34(2):603–10.
[10] Kilian L, Vigfusson RJ. Are the responses of the US economy asymmetric in energy price increases and decreases? Quant Econ 2011;2(3):419–53.
[11] Jiménez-Rodríguez R, Sánchez M. Oil price shocks and real GDP growth: empirical evidence for some OECD countries. Appl Econ 2005;37(2):201–28.
[12] Ghosh S, Kanjilal K. Oil price shocks on Indian economy: evidence from Toda Yamamoto and Markov regime-switching VAR. Macroecon Finance Emerg Mark Econ 2014;7(1):122–39.
[13] Wu MH, Ni YS. The effects of oil prices on inflation, interest rates and money. Energy 2011;36(7):4158–64.
[14] Blanchard OJ, Riggi M. Why are the 2000s so different from the 1970s? A structural interpretation of changes in the macroeconomic effects of oil prices. J Eur Econ Assoc 2013;11(5):1032–52.
[15] Cunado J, De Gracia FP. Oil prices, economic activity and inflation: evidence for some Asian countries. Q Rev Econ Finance 2005;45(1):65–83.
[16] Elder J, Serletis A. Oil price uncertainty. J Money Credit Bank 2010;42(6):1137–59.
[17] Henriques I, Sadorsky P. The effect of oil price volatility on strategic investment. Energy Econ 2011;33(1):79–87.
[18] Ferderer JP. Oil price volatility and the macroeconomy. J Macroecon 1997;18(1):1–26.
[19] Serletis A, Istiak K. Is the oil price–output relation asymmetric? J Econ Asymmetries 2013;10(1):10–20.
[20] Allegret JP, Mignon V, Sallenave A. Oil price shocks and global imbalances: lessons from a model with trade and financial interdependencies. Econ Model 2015;49:232–47.
[21] Kilian L. Exogenous oil supply shocks: how big are they and how much do they matter for the US economy? Rev Econ Statistics 2008;90(2):216–40.
[22] Ghosh S, Kanjilal K. Co-movement of international crude oil price and Indian stock market: evidences from nonlinear cointegration tests. Energy Econ 2014. http://dx.doi.org/10.1016/j.eneco.2014.11.002.
[23] Creti A, Ftiti Z, Guesmi K. Oil price and financial markets: multivariate dynamic frequency analysis. Energy Policy 2014;73:245–58.
[24] Broadstock DC, Filis G. Oil price shocks and stock market returns: new evidence from the United States and China. J Int Financial Mark Institutions Money 2014;33:417–33.

[25] Ewing BT, Malik F. Volatility spillovers between oil prices and the stock market under structural breaks. Glob Finance J 2015. http://dx.doi.org/10.1016/j.gfj.2015.04.008.
[26] Sadorsky P. Oil price shocks and stock market activity. Energy Econ 1999;21(5):449–69.
[27] Henriques I, Sadorsky P. Oil prices and the stock prices of alternative energy companies. Energy Econ 2008;30(3):998–1010.
[28] Kumar S, Managi S, Matsuda A. Stock prices of clean energy firms, oil and carbon markets: a vector autoregressive analysis. Energy Econ 2012;34(1):215–26.
[29] Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ 2012;34(1):248–55.
[30] Toda HY, Yamamoto T. Statistical inference in vector autoregressions with possibly integrated processes. J Econ 1995;66(1–2):225–50.
[31] Managi S, Okimoto T. Does the price of oil interact with clean energy prices in the stock market? Jpn World Econ 2013;27:1–9.
[32] Johansen S, Juselius K. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. Oxf Bull Econ Statistics 1990;52(2):169–210.
[33] Gregory AW, Hansen BE. Practitioners corner: tests for cointegration in models with regime and trend shifts. Oxf Bull Econ Statistics 1996;58(3):555–60.
[34] Hatemi-J A. Tests for cointegration with two unknown regime shifts with an application to financial market integration. Empir Econ 2008;35(3):497–505.
[35] Chen NF, Roll R, Ross SA. Economic forces and the stock market. J Bus 1986:383–403.
[36] Moya-Martínez P, Ferrer-Lapeña R, Escribano-Sotos F. Interest rate changes and stock returns in Spain: a wavelet analysis. BRQ Bus Res Q 2015;18(2):95–110.
[37] Engle RF, Granger CW. Co-integration and error correction: representation, estimation, and testing. Econ J Econ Soc 1987:251–76.
[38] Pesaran M Hashem, Shin Yongcheol, Smith Richard J. Bounds testing approaches to the analysis of level relationships. J Appl Econ 2001;16(3):289–326.
[39] Perron P. The great crash, the oil price shock, and the unit root hypothesis. Econometrica 1989;57(6):1361–401.
[40] Patterson K. Unit root tests in time series volume 1: key concepts and problems. Palgrave Macmillan; 2011.
[41] Patterson K. Unit root tests in time series volume 2: extensions and developmentsVol. 2. Palgrave Macmillan; 2012.
[42] Bouri Elie. Return and volatility linkages between oil prices and the Lebanese stock market in crisis periods. Energy 2015;89:365–71.
[43] Greene DL, Liu C. US oil dependence 2014: is energy independence in sight? Energy Policy 2015;85:126–37.