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Research paper

Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis

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HIGHLIGHTS

- The link between oil prices and clean energy stock prices is revisited.
- Using a NARDL model, we study the asymmetric linkages between these variables.
- Ignoring the presence of nonlinear relations leads to misleading findings.
- We find the presence of significant asymmetric effects among the variables.
- These impacts significantly vary in the short- and long-run.

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ABSTRACT

There is an ongoing debate on how oil prices affect the stock prices of clean energy companies. We contribute to this debate by questioning the possibility of asymmetric linkages between oil prices, interest rates, and the stock prices of clean energy and technology firms. Using a recently developed approach (nonlinear auto-regressive distributed lag (NARDL) model), we document that ignoring the presence of nonlinearities leads to misleading results. The analyses reveal significant asymmetric effects among the variables of interest. Our findings suggest that the impacts of positive and negative changes in the oil prices, interest rates and technology stock prices on clean energy stock prices substantially vary in the short-and long-run. More specifically, our results point out that the increased investments in clean energy stocks appear to be due to speculative attacks along with an increase in oil prices in the short-run. But, in the long-run, the increased oil price has a negative impact on clean energy stock prices and this impact is asymmetric. Last but not least, the results also emphasize the importance of business cycle fluctuations for the clean energy stock performance in the long-run. The implications of this paper are noteworthy for energy economists, policymakers, and investors in the energy and financial markets.

1. Introduction

A number of studies showing a significant impact of oil markets on sector stocks and global stock markets are available in the existing energy and finance literature (e.g. Jones and Kaul, 1996; Sadorsky, 1999; Kocaarslan et al., 2017). Rising oil prices lead to a deterioration in economic activity through the negative impacts on aggregate output and consumption. This is due to increases in production costs (Brown and Yucel, 1999) and reductions in household income levels (Edelstein and Kilian, 2009). On one hand, the increases in production costs reduce firms' profits and thereby negatively influence their current and future cash flows (Jones and Kaul, 1996). On the other hand, an increase in oil prices creates inflationary pressures in global markets (Darby, 1982). The increased inflationary pressure has a significant impact on the discount rate of cash flows and hence leads to lower stock prices. Previous studies generally provide strong evidence of negative relationships between oil and stock prices (Jones and Kaul, 1996; Sadorsky, 1999). In addition to these macroeconomic and financial risks induced by an increase in oil prices, geopolitical uncertainties and political insecurity in regions where oil reserves exist and climate change, which is caused by fossil fuels such as oil, act as a threat to global markets and natural environment. All these macroeconomic, financial and political risks and growing concern about global warming have triggered an increasing interest in alternative energy sources, especially during the last decade.

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Nomenclature

ARDL	Auto-regressive distributed lag (ARDL)
NARDL	Nonlinear auto-regressive distributed lag (NARDL)
IEA	International Energy Agency
GHG	Greenhouse gas
OECD	Organisation for Economic Co-operation and Development
VAR	Vector auto-regressive
GARCH	Generalized auto-regressive conditional heteroskedasticity
VECM	Vector error correction model
ECO	WilderHill Clean Energy Index
PSE	Arca Tech 100 index
WTI	West Texas Intermediate
LECO	Logarithmic prices of clean energy stocks
LPSE	Logarithmic prices of technology stocks
LOP	Logarithmic crude oil spot prices of West Texas Intermediate
IR	Interest rate on the three-month Treasury bill
DECO	Identified dummy variable for clean energy stocks based on a structural break
DPSE	Identified dummy variable for technology stocks based on a structural break
DOP	Identified dummy variable for crude oil prices based on a structural break
DIR	Identified dummy variable for interest rate based on a structural break
PP	Phillips and Perron test
ZA	Zivot and Andrews test
SIC	Schwarz information criterion
AIC	Akaike information criterion

Along with the accelerated economic growth of emerging markets (e.g. China, Brazil, Turkey, and India), energy demand has increased remarkably in recent years. Currently, a great majority of global energy needs are still met from fossil fuels. However, because these resources are depletable, investments in renewable energy resources have increased strikingly. The renewable energy investments have gained momentum since 2004 (Eyraud et al., 2011; New Energy Finance, 2010). According to the International Energy Agency's (IEA) Medium-Term Renewable Market Report 2016, renewables are predicted to grow 13% more between 2015 and 2021 than between 2014 and 2020, which is supported by strong policies in China, Mexico, India, and the United States. However, not all renewable energy sources are considered as clean energy sources. Clean energy includes energy sources that contribute to a low carbon future and do not have adverse effects on human health. There is a line of literature showing that consumers' willingness to pay for green energy is positive (see Sundt and Rehdanz (2015) for a meta-analysis of this literature). The literature on the links between oil and stock markets is also focusing more on clean energy sources (e.g. Managi and Okimoto, 2013) as a responsible investment. Kaminker and Stewart (2012) argue that to meet the greenhouse gas (GHG) emission reduction targets of the OECD, institutional investors must be involved more in clean energy investments to meet the financing needs in the sector. One way of meeting the financing gap is through the capital markets. However, investors need more information on the dynamics of the stocks in this sector to make sound portfolio allocation decisions and determine hedging strategies. The scientific literature on clean energy stocks is recently emerging and there is an information gap in this area.

The main purpose of this study is to contribute to filling this gap by studying the factors driving clean energy stock prices. Crude oil is a major energy commodity that influences macroeconomic variables and financial asset prices in general and the opportunity cost of investments in alternative energy sources in particular. Hence, we consider the oil price as a major factor and examine the asymmetric linkages between oil prices and clean energy stock prices. Although sustainability concerns make renewable energies attractive, they require large initial investments that need to be financed carefully. Therefore, alternative energy investments are very sensitive to business cycles. The business cycle literature indicates that interest rates play a key role in stock market valuations (Sadorsky, 1999). Some studies provide evidence of strong relationships between interest rates and clean energy stock prices (Henriques and Sadorsky, 2008; Kumar et al., 2012). It could be also argued that the high technology level is necessary for successful clean energy projects (Kumar et al., 2012). Furthermore, investors' perceptions of the stocks of clean energy and technology companies are very similar. (Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013). Based on these arguments, we also take into consideration the interest rates and the stock prices of technology companies to better capture variations in the stock prices of clean energy companies due to oil price changes.

It is important to identify the transmission mechanisms from oil prices and interest rates to clean energy stock prices. The effect of oil price increases on the stock prices is expected to be negative in the long-run through negative impacts on overall economy while this effect varies depending on the source of oil price shocks (e.g. oil-specific demand, aggregate demand, and oil supply shocks) in the short-run (Kilian and Park, 2009; Smyth and Narayan, 2018). On one hand, conventional wisdom suggests that an increase in oil prices could lead to an increase in clean energy stock prices due to substitution motives and speculative trader behavior in the short-run. On the other hand, higher oil prices associated with worsening economic conditions might result in a worse investment climate for clean energy projects in the long-run. Therefore, it could be argued that the substitution demand for clean energy is negatively influenced by worsening economic conditions due to permanently higher oil prices in the long-run. We test this argument in this study.

Rising interest rates tend to coincide with increasing economic growth (Mishkin, 2006; Henriques and Sadorsky, 2008). Due to a greater increase in the supply of bonds than in the demand for bonds during business cycle expansions, an increase in interest rates is frequently observed in periods of high economic activity (Mishkin, 2006). Hence, increasing interest rates due to faster economic growth might motivate investors to change the weights of sector stocks in an optimal portfolio. Namely, in a period of higher interest rates associated with an expanding economy, investors prefer to invest in sectors that benefit from increased economic growth. Among these sectors, clean energy investments come to the forefront as an important contributor to higher economic activity. Therefore, we argue that the stock prices of clean energy firms may tend to rise along with rising interest rates during an expansionary period. Based on this argument, we investigate whether the above economic mechanism holds or not.

Some traditional economics and finance theories are found to be insufficient in explaining individuals' economic and financial decisions (Kahneman and Tversky, 1979). One possible reason is the linearity assumption. Therefore, the nonlinear characteristics of a significant majority of macroeconomic risk factors should not be neglected in econometric research (Shin et al., 2014). The assumption of linear relationships in the short- and long-run in advance excessively restricts economic and financial analyses. Hence, analyses using a linear model may lead to misleading results. Several studies reveal that oil prices asymmetrically influence economic activities (e.g. Mork, 1989). The negative impact of rising oil prices on economic activity is significantly stronger than the positive impact of declining oil prices on the economy. Asymmetric impacts may also be subject to change during different phases of the business cycle. The asymmetric behavior of market participants towards risk could be strongly associated with business cycle shocks (Acemoglu and Scott, 1997). Main macroeconomic variables show an asymmetric behavior during different periods of economic activity (Neftci, 1984; Kocaarslan et al., 2018). The asymmetric effects also play a central role across global markets (Ang and Bekaert, 2002). In this study, we consider nonlinear interactions among the variables under consideration, which are strongly influenced by business cycle fluctuations.

Previous studies have dedicated very little effort to investigating asymmetric linkages between oil prices, interest rates, and the stock prices of clean energy and technology firms in the short- and long-run. Among these studies, Managi and Okimoto (2013) take into account asymmetric effects and structural changes using Markov regime-switching VAR approach. In a similar study, Bondia et al. (2016) criticize the methodology applied in the study of Managi and Okimoto (2013) by questioning the appropriateness of Johansen–Juselius methodology and alternatively employ threshold cointegration approaches developed by Hatemi-j (2008) and Gregory and Hansen (1996) and vector error correction model (VECM). The choice of the regime-switching variables could be of immense importance in the empirical investigations (Shin et al., 2014). The use of nonlinear threshold vector error correction models (VECM) may also lead to a convergence problem due to the large number of parameters involved. Moreover, the integration order of the variables should be the same in the applications of these models. In order to overcome these difficulties, we use a recent approach (nonlinear autoregressive distributed lag (NARDL) model) introduced by Shin et al. (2014) to not only examine nonlinear relationships but also to jointly model short- and long-run asymmetries. This model does not suffer from the problems listed above and follows standard bounds testing procedure (Pesaran and Shin, 1998; Pesaran et al., 2001) to test long-run relationships between the variables of interest regardless of the integration order of the variables. Due to these advantages, recently, the NARDL method has been used to make rigorous nonlinear analysis in various studies in the energy literature (e.g. Tugcu and Topcu, 2018). Very little is known about the direction, magnitude and significance of asymmetric effects between oil prices, technology stock prices, interest rates, and clean energy stock prices. The aim of this study is to contribute to closing this gap. In this sense, this study differs from the relevant literature and makes important contributions to the discussion on the linkages between interest rates, oil prices, technology stock prices, and clean energy stock prices.

This paper proceeds as follows. Section 2 briefly summarizes the relevant literature. Section 3 includes the data sources and characteristics. Section 4 introduces the empirical methodology. Then, Section 5 presents empirical findings. We present a detailed discussion on the implications of this paper in Section 6 and finally conclude with main remarks in Section 7.

2. Literature review

There are a limited number of studies that examine the dynamic relationship between oil prices and clean energy stock prices. Using a VAR (vector autoregressive) model, Henriques and Sadorsky (2008) demonstrate that interest rates, oil prices, and technology stock prices explain the variations in clean energy stock prices. Furthermore, they show a positive and stronger impact of a shock to technology stock prices on clean energy stock prices than a shock to oil prices. Using a similar methodology to that adopted by Henriques and Sadorsky (2008), Kumar et al. (2012) reveal that the fluctuations in clean energy stock prices are captured by past movements in technology stock prices, interest rates, and oil prices, but, they do not find a significant relationship between clean energy stock prices and carbon prices. Sadorsky (2012) estimates multivariate GARCH models and documents higher dynamic correlations of clean energy stock prices with technology stock prices than with oil prices. Managi and Okimoto (2013) report a significant and positive impact of oil prices on clean energy stock prices after structural break in late 2007 by applying Markov-switching VAR (vector autoregressive) models.

More recently, employing the cointegration tests of Hatemi-j (2008) and Gregory and Hansen (1996), Bondia et al. (2016) conclude that clean energy stock prices are influenced by interest rates, oil prices, and technology stock prices in the short run, but not in the long-run. Dutta (2017) demonstrates the impact of oil price uncertainty on the variance of clean energy stock returns. Ahmad (2017) reports the importance of technology stocks in influencing clean energy stocks by using the directional spillover index approach developed by Diebold and Yilmaz (2012) and multivariate GARCH models.

As shown in the background literature, previous studies have not jointly modeled short- and long-run asymmetries between the stock prices of clean energy and technology companies, oil prices, and interest rates. To fill this void, we use the NARDL model. As explained in the introduction part, this model also has the ability to overcome some difficulties that other nonlinear methods face.

3. Data sources and characteristics

We use the WilderHill Clean Energy Index (ECO) for clean energy stock prices which is a modified dollar weighted index of clean energy stocks. It is a selective index of clean energy stocks. In order to be included in this index, a company must either be exposed to clean energy or contribute to advancing or developing clean energy.[1] The Arca Tech 100 index (PSE) is used as a proxy for technology stock prices. The PSE is composed of leading firms from industries containing software, telecommunications, computer hardware, aerospace and defense, semiconductors, electronics, biotechnology and healthcare equipment. ECO and PSE are widely used indices to represent the stock prices of clean energy and technology companies, respectively, in the related literature. Following the literature, interest rates are represented by the yield on a 3-month US Treasury bill and oil prices are measured as the crude oil spot prices of the West Texas Intermediate (WTI). All stock data (ECO and PSE) are sourced from Bloomberg and the interest rate and oil price data are obtained from the Federal Reserve Board of St. Louis. We use daily data and concentrate our focus on the period between 2004 and 2018 as the great majority of increases in renewable energy investments have occurred since 2004 (Eyraud et al., 2011; New Energy Finance, 2010). Our observation period spans from January 5, 2004 to January 18, 2018, including 3502 observations.

Table 1 provides the descriptive statistics of the stock and oil prices. The statistics demonstrate the non-normal and asymmetric distributions of the time series. The logarithmic transformations of the daily closing prices of the Arca Tech 100 index (PSE), the WilderHill Clean Energy Index (ECO) and the West Texas Intermediate (WTI) are used to reduce heteroscedasticity and non-normality in the data for the empirical investigations (LPSE, LECO,

[1] See more details about the ECO index at https://wildershares.com/about.php.

and, LOP henceforth). Unconditional correlation coefficients suggest positive links between the daily returns of the ECO, PSE, and WTI indexes, among which the strongest correlation appears to be between the ECO and PSE (see Table 2). These findings are consistent with the evidence presented by previous studies (e.g. Kumar et al., 2012; Sadorsky, 2012).

The variables should be integrated of order 0 or 1, but not 2, to apply the linear and nonlinear ARDL models (Pesaran and Shin, 1998; Pesaran et al., 2001; Shin et al., 2014). To investigate the stationarity characteristics of the time series variables, we conduct the unit root tests with and without an unknown structural break accounting for intercept and both intercept and trend. Phillips and Perron (1988) (PP) test is broadly used in the literature. However, the findings of the PP test could be biased in the presence of structural breaks in the time series (Perron, 1989; Zivot and Andrews, 1992). Since energy and financial markets have experienced global shocks during our sample period (e.g. global financial crisis in 2008, the sharp decline of oil prices in 2014), along with the PP test, we also use Zivot and Andrews (1992) (ZA) unit root test allowing for an endogenously determined structural break. Table 3 reports the unit root test results for the variables analyzed. To better understand the stationarity characteristics of the variables, the summarized test results for unit root are also presented in Table 4. The structural breakpoints suggested by the Zivot and Andrews (1992) (ZA) unit root tests are used to code and create dummy variables for the empirical tests. The unit root tests generally indicate similar results suggesting that the variables are integrated of order 0 or 1. Hence, we can continue our analysis using the ARDL and NARDL models without any hesitation.

4. Methodology

As explained in the introduction part, although some regime-switching models take asymmetric effects into consideration they are known to cause some difficulties in the estimation procedure. The concept of "hidden cointegration" is developed by Granger and Yoon (2002). In their study, it is argued that the cointegration relationship could be identified between the negative and positive components of the underlying factors. To investigate hidden cointegration, Schorderet (2003) suggests an asymmetric cointegrating regression model in which only one component of each series is incorporated into the cointegration relationship. In a cornerstone study, Shin et al. (2014) introduce a nonlinear ARDL framework, which utilizes negative and positive partial sum decompositions of the predetermined independent variables. This approach enables us to easily detect asymmetric interactions between variables in the short- and long-run.

We first consider the linear ARDL model. Following the bounds-testing procedure (Pesaran and Shin, 1998; Pesaran et al., 2001), the error correction representations of the linear ARDL models can be represented as follows (Eqs. (1)–(4));

$$\begin{aligned}\Delta LECO_t &= \mu + \alpha_1 LECO_{t-1} + \alpha_2 LPSE_{t-1} + \alpha_3 LOP_{t-1} + \alpha_4 IR_{t-1} \\ &+ \sum_{i=1}^{p-1} \lambda_1 \Delta LECO_{t-i} + \sum_{i=0}^{q-1} \lambda_2 \Delta LPSE_{t-i} \\ &+ \sum_{i=0}^{q-1} \lambda_3 \Delta LOP_{t-i} + \sum_{i=0}^{q-1} \lambda_4 \Delta IR_{t-i} + \psi DECO_t + \varepsilon_t \end{aligned} \quad (1)$$

$$\begin{aligned}\Delta LPSE_t &= \mu + \alpha_1 LECO_{t-1} + \alpha_2 LPSE_{t-1} + \alpha_3 LOP_{t-1} + \alpha_4 IR_{t-1} \\ &+ \sum_{i=1}^{p-1} \lambda_1 \Delta LPSE_{t-i} + \sum_{i=0}^{q-1} \lambda_2 \Delta LECO_{t-i} \\ &+ \sum_{i=0}^{q-1} \lambda_3 \Delta LOP_{t-i} + \sum_{i=0}^{q-1} \lambda_4 \Delta IR_{t-i} + \psi DPSE_t + \varepsilon_t \end{aligned} \quad (2)$$

$$\begin{aligned}\Delta LOP_t &= \mu + \alpha_1 LECO_{t-1} + \alpha_2 LPSE_{t-1} + \alpha_3 LOP_{t-1} + \alpha_4 IR_{t-1} \\ &+ \sum_{i=1}^{p-1} \lambda_1 \Delta LOP_{t-i} + \sum_{i=0}^{q-1} \lambda_2 \Delta LPSE_{t-i} \\ &+ \sum_{i=0}^{q-1} \lambda_3 \Delta LECO_{t-i} + \sum_{i=0}^{q-1} \lambda_4 \Delta IR_{t-i} + \psi DOP_t + \varepsilon_t \end{aligned} \quad (3)$$

$$\begin{aligned}\Delta IR_t &= \mu + \alpha_1 LECO_{t-1} + \alpha_2 LPSE_{t-1} + \alpha_3 LOP_{t-1} + \alpha_4 IR_{t-1} \\ &+ \sum_{i=1}^{p-1} \lambda_1 \Delta IR_{t-i} + \sum_{i=0}^{q-1} \lambda_2 \Delta LPSE_{t-i} \\ &+ \sum_{i=0}^{q-1} \lambda_3 \Delta LOP_{t-i} + \sum_{i=0}^{q-1} \lambda_4 \Delta LECO_{t-i} + \psi DIR_t + \varepsilon_t \end{aligned} \quad (4)$$

The above regression equations are estimated to investigate symmetric cointegration relationships between the variables. LECO, LPSE, and LOP are the prices of clean energy and technology stocks and oil prices in logarithms, respectively. IR is the interest rate on the three-month Treasury bill. DECO, DPSE, DOP, and DIR stand for the dummy variables which are created and coded based on the structural break dates suggested by the Zivot and Andrews (1992) (ZA) unit root tests for the dependent variables in the relevant equations. The value of the dummy variable is 1 if the period is after structural break time and 0 otherwise. The most significant dummy variables are incorporated into the models estimated. The Δ denotes the first difference of variables. The coefficient λ_j refers to the short-run coefficients of the model as the α_j represents the long-run coefficients for the variables with j=1, 2, 3, 4. The F statistics are used to test the null hypothesis of no cointegration, which is $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$.

If the relationships between variables are not linear, the application of the linear ARDL model may lead to drawing misleading conclusions about the actual relationships. To overcome this potential bias, we utilize an asymmetric ARDL (NARDL) model that captures possible long- and short-run nonlinearities (Shin et al., 2014). Following Shin et al. (2014), the below nonlinear long-run cointegrating regression is considered;

$$y_t = \beta^+ x_T{}^+ + \beta^- x_t{}^- + u_t \quad (5)$$

with y_t and x_t referring to $LECO_t$, $LPSE_t$, LOP_t, and IR_t. β^+ and β^- represent the associated long-run parameters. x_t is a k*1 vector of regressors defined as $x_{t=}x_0{}^+x_t{}^+ + x_t^-$ where x_0 is the initial value. The NARDL model employs the decomposition of the exogenous variables into their negative and positive partial sums for decreases and increases as follows;

$$\text{For positive partial sums;}\ x_t{}^+ = \sum_{i=1}^{t} \Delta x_i{}^+ = \sum_{i=1}^{t} \max(\Delta x_i, 0) \quad (6)$$

$$\text{and for negative partial sums;}\ x_t{}^- = \sum_{i=1}^{t} \Delta x_i{}^- = \sum_{i=1}^{t} \min(\Delta x_i, 0) \quad (7)$$

The extended version of the linear ARDL models including asymmetries (NARDL) can be indicated as below (Eqs. (8)–(11));

$$\begin{aligned}\Delta LECO_t &= \mu + \chi LECO_{t-1} + \omega_1{}^+ LPSE_{t-1}{}^+ + \omega_1{}^- LPSE_{t-1}{}^- \\ &+ \omega_2{}^+ LOP_{t-1}{}^+ + \omega_2{}^- LOP_{t-1}{}^- + \omega_3{}^+ IR_{t-1}{}^+ + \omega_3{}^- IR_{t-1}{}^- \\ &+ \sum_{i=1}^{p-1} \tau \Delta LECO_{t-i} + \sum_{i=0}^{q-1} \phi_1{}^+ \Delta LPSE_{t-i}{}^+ + \sum_{i=0}^{q-1} \phi_1{}^- \Delta LPSE_{t-i}{}^-\end{aligned}$$

$$+\sum_{i=0}^{q-1}\phi_2{}^{+}\Delta LOP_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_2{}^{-}\Delta LOP_{t-i}{}^{-}+\sum_{i=0}^{q-1}\phi_3{}^{+}\Delta IR_{t-i}{}^{+}$$
$$+\sum_{i=0}^{q-1}\phi_3{}^{-}\Delta IR_{t-i}{}^{-}+\psi DECO_t+\varepsilon_t \quad (8)$$

$$\Delta LPSE_t=\mu+\chi LPSE_{t-1}+\omega_1{}^{+}LECO_{t-1}{}^{+}+\omega_1{}^{-}LECO_{t-1}{}^{-}$$
$$+\omega_2{}^{+}LOP_{t-1}{}^{+}+\omega_2{}^{-}LOP_{t-1}{}^{-}+\omega_3{}^{+}IR_{t-1}{}^{+}+\omega_3{}^{-}IR_{t-1}{}^{-}$$
$$+\sum_{i=1}^{p-1}\tau\Delta LPSE_{t-i}+\sum_{i=0}^{q-1}\phi_1{}^{+}\Delta LECO_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_1{}^{-}\Delta LECO_{t-i}{}^{-}$$
$$+\sum_{i=0}^{q-1}\phi_2{}^{+}\Delta LOP_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_2{}^{-}\Delta LOP_{t-i}{}^{-}+\sum_{i=0}^{q-1}\phi_3{}^{+}\Delta IR_{t-i}{}^{+}$$
$$+\sum_{i=0}^{q-1}\phi_3{}^{-}\Delta IR_{t-i}{}^{-}+\psi DPSE_t+\varepsilon_t \quad (9)$$

$$\Delta LOP_t=\mu+\chi LOP_{t-1}+\omega_1{}^{+}LPSE_{t-1}{}^{+}+\omega_1{}^{-}LPSE_{t-1}{}^{-}$$
$$+\omega_2{}^{+}LECO_{t-1}{}^{+}+\omega_2{}^{-}LECO_{t-1}{}^{-}+\omega_3{}^{+}IR_{t-1}{}^{+}+\omega_3{}^{-}IR_{t-1}{}^{-}$$
$$+\sum_{i=1}^{p-1}\tau\Delta LOP_{t-i}+\sum_{i=0}^{q-1}\phi_1{}^{+}\Delta LPSE_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_1{}^{-}\Delta LPSE_{t-i}{}^{-}$$
$$+\sum_{i=0}^{q-1}\phi_2{}^{+}\Delta LECO_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_2{}^{-}\Delta LECO_{t-i}{}^{-}+\sum_{i=0}^{q-1}\phi_3{}^{+}\Delta IR_{t-i}{}^{+}$$
$$+\sum_{i=0}^{q-1}\phi_3{}^{-}\Delta IR_{t-i}{}^{-}+\psi DOP_t+\varepsilon_t \quad (10)$$

$$\Delta IR_t=\mu+\chi IR_{t-1}+\omega_1{}^{+}LPSE_{t-1}{}^{+}+\omega_1{}^{-}LPSE_{t-1}{}^{-}$$
$$+\omega_2{}^{+}LOP_{t-1}{}^{+}+\omega_2{}^{-}LOP_{t-1}{}^{-}+\omega_3{}^{+}LECO_{t-1}{}^{+}+\omega_3{}^{-}LECO_{t-1}{}^{-}$$
$$+\sum_{i=1}^{p-1}\tau\Delta IR_{t-i}+\sum_{i=0}^{q-1}\phi_1{}^{+}\Delta LPSE_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_1{}^{-}\Delta LPSE_{t-i}{}^{-}$$
$$+\sum_{i=0}^{q-1}\phi_2{}^{+}\Delta LOP_{t-i}{}^{+}+\sum_{i=0}^{q-1}\phi_2{}^{-}\Delta LOP_{t-i}{}^{-}+\sum_{i=0}^{q-1}\phi_3{}^{+}\Delta LECO_{t-i}{}^{+}$$
$$+\sum_{i=0}^{q-1}\phi_3{}^{-}\Delta LECO_{t-i}{}^{-}+\psi DIR_t+\varepsilon_t \quad (11)$$

Similar to the linear model, initially, we employ the F-statistic to test the null hypothesis of no asymmetric cointegration relationship that $\chi = \omega_1{}^{+} = \omega_1{}^{-} = \omega_2{}^{+} = \omega_2{}^{-} = \omega_3{}^{+} = \omega_3{}^{-} = 0$. Then, employing the standard Wald test, the short- and long-run symmetries are tested (Shin et al., 2014). To examine the existence of long-run nonlinearities, we test the null hypothesis of long-run symmetry that is $\beta^{+} = \beta^{-}$ where $\beta^{+} = -\omega_j{}^{+}/\chi$ and $\beta^{-} = -\omega_j{}^{-}/\chi$ with j=1, 2, and 3. The presence of short-run symmetry can be assessed by testing the null hypothesis that $\sum_{i=0}^{q-1}\phi_k{}^{+}=\sum_{i=0}^{q-1}\phi_k{}^{-}$ with $k = 1, 2,$ and 3. The findings provided by these empirical investigations are discussed in the following sections.

5. Empirical findings

In this section, we present the empirical test results obtained from the linear and nonlinear models introduced above. In the first step, we investigate the presence of symmetric and then asymmetric cointegration relationships between the variables of interest using the linear ARDL (Pesaran and Shin, 1998; Pesaran et al., 2001) and nonlinear ARDL models (Shin et al., 2014), respectively. We determine the optimal lag length in the unrestricted error correction models (ARDL and NARDL models) using the Schwarz information criterion (SIC).[2] The maximum lag length is chosen as twelve for the lagged levels of the variables. A series of stability and diagnostic tests are applied to check the robustness of the ARDL and NARDL models.[3] We do not detect any significant departures from standard assumptions except for heteroscedasticity problem. To correct for heteroscedasticity leading to inefficient estimations and thus to provide accurate estimates, we use Newey and West (1987) standard errors with lags determined based on the SIC criterion for the estimated coefficients from the models.

Table 5 provides the F-statistics testing the linear and nonlinear cointegration relationships respectively, in Panel A and B. The estimated F-statistics fail (do not fail) to reject the null hypothesis of no cointegration relationship if the statistics are smaller (larger) than the lower (upper) critical values. If the statistics fall between lower and upper critical values the results are inconclusive. The F-statistics reported in Panel A indicate the absence of linear cointegration relationships between the variables.[4] This finding leads to the examination of asymmetric impacts via the NARDL approach. Panel B presents the F-statistics testing the null hypothesis of no asymmetric cointegration relationship. The results suggest nonlinear cointegration relationships between the stock prices of clean energy (LECO) and technology firms (LPSE) and other explanatory variables. The overall evaluation shows that ignoring nonlinearity may lead to wrong inferences about the real relationships among the variables.

The LECO is significantly affected by the other variables in the short- and long-run, as shown in Table 6. We also report the summarized results for the impact of the determinants of clean energy stock prices in Table 7, since one of the focal points of this study is to examine these determinants. We find that the LPSE has a positive and significant impact on the LECO in the short- and long-run and this impact is asymmetric in the long-run. Namely, in the long-run, a negative change in the LPSE has a greater impact on the LECO, which leads to more decreases in the LECO than increases sourcing from a positive change in the LPSE. The LOP is a significant and positive factor on the LECO in the short-run. However, interestingly, the effect of the LOP on the LECO changes from being positive and symmetric to being negative and asymmetric in the long-run. An increase in the LOP has a larger negative effect on the LECO than a positive effect on the LECO in response to a decrease in the LOP in the long-run. The IR asymmetrically and positively influences the LECO in the long-run in such a way that the larger impact on the LECO is resulting from a positive change in the IR.

The effects of explanatory variables on the LPSE are indicated in Table 8. The findings mainly demonstrate that the LECO has positive and asymmetric effects on the LPSE in the short and long-runs. The greatest impact on the LPSE is due to a negative change in the LECO, which significantly decreases the LPSE, rather than a positive change in the LECO leading to an increase in the LPSE in the short-run. But, the opposite of this situation holds true in the long-run. We do not find an asymmetric impact of LOP on the LPSE. However, an increase in the LOP significantly and negatively affects the LPSE in the short-run, but the size of this effect is relatively low. The Wald test results also suggest the asymmetric effect of the IR on the LPSE in the long run, but the coefficients are not statistically significant. A decrease in the IR has a significant and negative, but relatively small effect on the LPSE in the short-run. In the following sections, we discuss the implications of our results mentioned in this part and then conclude with highlights of the main findings and further research directions.

[2] We also employ Akaike information Criterion (AIC) to select the optimal lag length for the cointegration tests and obtain similar findings regarding the cointegrating relationships. The results are provided upon request.

[3] The findings are available from authors upon request.

[4] We also apply the Johansen and Juselius (JJ) (1990) cointegration test and do not find cointegration between the variables of interest. This finding suggests that the first set of results is robust. For brevity, the JJ cointegration test results are not reported. The results are provided upon request.

Table 1
Descriptive statistics (on stock data and oil prices).

	ECO	PSE	OP
Mean	107.0399	1286.864	71.46862
Median	87.295	1043.56	69.215
Maximum	297.05	3031.23	145.31
Minimum	36.53	516.89	26.19
Std. Dev.	63.84746	583.3687	23.62898
Skewness	0.738268	0.854202	0.31371
Kurtosis	2.262455	2.604717	2.195263
Jarque–Bera	397.4958	448.6783	151.9367
Probability	0	0	0
Observations	3502	3502	3502

Notes: Table 1 presents the descriptive statistics of all stock data and oil prices for the sample period. ECO, PSE, and OP represent clean energy stocks, technology stocks, and oil prices respectively.

Table 2
Pairwise correlations between daily returns.

	RECO	RPSE	ROP
RECO	1	0.799907476	0.326810398
RPSE	0.799907476	1	0.236169614
ROP	0.326810398	0.236169614	1

Notes: Table 2 presents daily return correlations between variables for the sample period. RECO, RPSE, and ROP represent the daily returns of clean energy stocks, technology stocks, and oil prices respectively.

6. Discussion

Ignoring the variety of market player reactions over different phases of business cycles may lead to misleading inferences and incorrect economic analysis. Identifying the asymmetric linkages between interest rates, oil prices, and the stock prices of clean energy and technology firms is of great importance to reflect investor behavior. Hence, the NARDL results are vital for risk management and policy-making in energy and financial markets. Using the ARDL and NARDL models, we first examine the linear and nonlinear cointegration relationships between the variables. Our findings show the absence of linear cointegration relationships between the variables and suggest a nonlinear link.

The NARDL results indicate the combined asymmetric effect of explanatory variables on the stock prices of clean energy and technology firms in both the short- and long-run. The results demonstrate significant and positive effects of the LPSE on the LECO in the short- and long-run and the magnitudes of these effects are higher in the long-run than those in the short-run. This result confirms the existing evidence that investors consider the clean energy stocks to be like technology stocks. This impact can be explained by the use of high technology in alternative energy investments (Kumar et al., 2012). On the other hand, the larger impact of the LPSE on the LECO is stemming from the negative changes in the LPSE rather than the positive changes in the long-run. To this respect, it could be argued that investors display more pessimistic behaviors towards clean energy stocks depending on the changes in the LPSE in the long-run.

As for the impacts of the LOP on the LECO, the results show a significant and positive impact of the LOP on the LECO in the short-run. This finding supports the argument that oil prices are driving forces behind the increases in clean energy stock prices, since clean energy is considered as a promising alternative to fossil fuels. Conversely, the positive impact of the LOP on the LECO is reversed in the long-run and this negative impact is stronger along with oil price increases than the positive impact resulting from the decreases in oil prices. In the short-run, the positive link is probably due to speculative trader behavior in the asset markets. Whereas, in the long-run, high oil prices suppress investments in clean energy due to the increased opportunity cost of responsible investment in the energy markets. On one hand, the increases in oil prices considerably worsen economic activity due to the negative effects on household income levels and firms' production costs. This distorts economic balance and ultimately causes a worse investment climate. On the other hand, renewable energy sources are considered as the input for the economy (Sadorsky, 2012). When one considers this economic mechanism, in the long-run, one sees that an increase in oil prices negatively influences clean energy stock prices against common belief. This implies that the reason behind the short-run positive impact of oil price increases on the LECO could be the speculative investments in clean energy stocks. Also, the analysis of the asymmetric impact of the LOP on the LECO, as in the impact of LPSE on the LECO, points out more pessimistic behaviors of investors towards clean energy stocks in the long-run based on the shifts in overall economic conditions caused by oil price changes.

Interest rates play a central role in the economy and the linkages among energy, stock, and bond markets are of key importance in macroeconomic analysis. According to our results, the interest rate (IR) has a strong, asymmetric and positive effect on the LECO in the long-run. More clearly, a positive change in the IR has a greater positive effect on the LECO than a negative effect on the LECO stemming from a negative change in the IR. Mostly, rising interest rates are strongly associated with increased economic growth (Henriques and Sadorsky, 2008). As criticized by Milton Friedman, other variables than interest rates in the economy are influenced as a result of the increase in money supply, and thereby, interest rates may rise rather than decline (Mishkin, 2006). In addition, an increase in both the demand and supply in the bond market is accompanied by increased economic activity and the resulting increase in income. It appears that the supply of bonds significantly increases during business cycle expansions and hence, the interest rates increase in periods of high economic activity and decrease during recessions (Mishkin, 2006). When considering the input characteristics of clean energy investments for economic activity,

Table 3
Unit root tests without and with a structural break.

		PP Statistics	ZA Statistics	Break Points		PP Statistics	ZA Statistics	Break Points
LECO	Intercept	−1.049483	−3.487134	[8/29/2008]	Intercept and Trend	−2.216675	−3.966749	[8/29/2008]
LPSE		0.439108	−4.196228	[11/01/2007]		−1.865731	−4.678536	[8/18/2008]
LOP		−2.548274	−4.595184*	[9/29/2014]		−2.533696	−4.105553	[9/29/2014]
IR		−0.807374	−5.906256***	[8/09/2007]		−1.080239	−5.703241***	[8/09/2007]
DLECO	Intercept	−57.00499***	−14.13276***	[12/27/2007]	Intercept and Trend	−56.99686***	−14.14512***	[3/10/2009]
DLPSE		−63.50755***	−13.00346***	[3/10/2009]		−63.54180***	−13.14011***	[11/21/2008]
DLOP		−61.24003***	−14.43560***	[12/24/2008]		−61.25179***	−14.59973***	[12/24/2008]
DIR		−50.09753***	−10.91984***	[2/21/2007]		−50.08845***	−11.57379***	[3/24/2008]

Notes: Table 3 provides the results of Phillips–Perron (PP) and Zivot–Andrews (ZA) tests used by this paper. D and L are the first differences and natural log operators, respectively. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively. Numbers in square brackets refer to the structural break dates suggested by the Zivot–Andrews (ZA) tests.

Table 4
Summarized test results for unit root.

	PP		ZA	
	Level	First difference	Level	First difference
LECO	Not stationary	Stationary	Not stationary	Stationary
LPSE	Not stationary	Stationary	Not stationary	Stationary
LOP	Not stationary	Stationary	Not stationary	Stationary
IR	Not stationary	Stationary	Stationary	Stationary

Notes: Table 4 presents the stationarity characteristics of the variables at 1% significance level for the levels and first differences of the variables. PP and ZA refer to the Phillips–Perron, and Zivot–Andrews unit root test results, respectively. LECO, LPSE, and LOP represent the logarithmic prices of clean energy and technology stocks, and logarithmic crude oil spot prices of West Texas Intermediate, respectively. IR is the interest rate on the three-month Treasury bill.

Table 5
Bounds testing procedure results.

Panel A. F-test results for the ARDL models		Panel B. F-test results for the NARDL models	
Cointegration hypotheses	F stat.	Cointegration hypotheses	F stat.
$F(LECO_t/LPSE_t, LOP_t, IR_t)$	0.855957	$F(LECO_t/LPSE_t^+, LPSE_t^-, LOP_t^+, LOP_t^-, IR_t^+, IR_t^-)$	4.584091***
$F(LPSE_t/LECO_t, LOP_t, IR_t)$	2.080296	$F(LPSE_t/LECO_t^+, LECO_t^-, LOP_t^+, LOP_t^-, IR_t^+, IR_t^-)$	7.078305***
$F(LOP_t/LPSE_t, LECO_t, IR_t)$	3.258601	$F(LOP_t/LPSE_t^+, LPSE_t^-, LECO_t^+, LECO_t^-, IR_t^+, IR_t^-)$	2.763848
$F(IR_t/LPSE_t, LOP_t, LECO_t)$	2.860117	$F(IR_t/LPSE_t^+, LPSE_t^-, LOP_t^+, LOP_t^-, LECO_t^+, LECO_t^-)$	3.449311

Notes: Table 5 provides Bounds testing procedure results. For the ARDL models in Panel A, the critical values are 3.23–4.35 and 4.29–5.61 for 5%, and 1% significance levels, respectively. For the NARDL models in Panel B, the critical values are 2.45–3.61and 3.15–4.43 for 5%, and 1% significance levels, respectively. Superscript *** represents significance at 1% level. LECO, LPSE, and LOP represent the logarithmic prices of clean energy and technology stocks, and logarithmic crude oil spot prices of West Texas Intermediate, respectively. IR is the interest rate on the three-month Treasury bill.

Table 6
NARDL estimation results (Dependent variable: $\triangle LECO_t$).

Panel A. Estimated coefficients (Adj. $R^2 = 0.671788$)				
EV	Coefficient	Robust Std. error	t-statistic	Prob.
C	0.040523	0.010421	3.888762	0.000
$LECO_{t-1}$	−0.007767	0.002013	−3.858145	0.000
${LPSE_{t-1}}^+$	0.018487	0.003514	5.260831	0.000
${LPSE_{t-1}}^-$	0.02134	0.004242	5.030547	0.000
${LOP_{t-1}}^+$	−0.003204	0.001353	−2.3682	0.018
${LOP_{t-1}}^-$	−0.002124	0.001043	−2.035364	0.042
${IR_{t-1}}^+$	0.001798	0.00045	3.995277	0.000
${IR_{t-1}}^-$	0.000818	0.000288	2.842666	0.005
$\triangle LPSE_t^+$	1.179029	0.050212	23.48079	0.000
$\triangle {LPSE_{t-1}}^+$	0.230187	0.037769	6.094603	0.000
$\triangle {LPSE_{t-2}}^+$	0.097013	0.037519	2.585678	0.010
$\triangle LPSE_t^-$	1.416551	0.053906	26.27823	0.000
$\triangle LOP_t^+$	0.107487	0.017427	6.167836	0.000
$\triangle LOP_t^-$	0.128675	0.02398	5.365871	0.000
$\triangle IR_t^+$	0.00917	0.008677	1.056895	0.291
$\triangle IR_t^-$	−0.006662	0.007526	−0.885224	0.376
$DUM^{[3/10/2009]}$	0.003505	0.001602	2.188194	0.029
Panel B. Long-run coefficients and symmetry test results				
$LPSE^+$	2.380198***	$LPSE^-$	2.747521***	
LOP^+	−0.412514**	LOP^-	−0.273464**	
IR^+	0.231492***	IR^-	0.105317***	
$W_{LR,LPSE}$	7.795751***	$W_{SR,LPSE}$	0.94643	
$W_{LR,LOP}$	5.859507**	$W_{SR,LOP}$	0.36761	
$W_{LR,IR}$	16.79228***	$W_{SR,IR}$	1.63714	

Notes: EV denotes the explanatory variables. The Newey and West (1987) autocorrelation and heteroskedasticity robust standard errors and t-statistics are presented. LECO, LPSE, and LOP represent the logarithmic prices of clean energy and technology stocks, and logarithmic crude oil spot prices of West Texas Intermediate, respectively. IR is the interest rate on the three-month Treasury bill. The superscripts "+" and "−" refer to positive and negative partial sums, respectively. $LPSE^+$, $LPSE^-$, LOP^+, LOP^-, IR^+, and IR^- are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR,LPSE}$, $W_{LR,LOP}$, and $W_{LR,IR}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. $W_{SR,LPSE}$, $W_{SR,LOP}$, and, $W_{SR,IR}$ refer to the standard Wald test for the null of the additive short-run symmetry condition for the corresponding variable. $DUM^{[3/10/2009]}$ is a dummy variable for the structural break date suggested by the Zivot and Andrews test (1992) for the dependent variable. Superscripts **, *** represent the significance at 5% and 1% levels, respectively.

this economic mechanism explains the reason why an increase in interest rates strongly increases the clean energy stock prices.

Additionally, our results suggest that the LECO asymmetrically and positively influences the LPSE in the short and long-runs. More specifically, the larger effect on the LPSE is stemming from a negative (positive) change in the LECO in the short-run (long-run). The size of these impacts is greater in the short-run than that in the long-run. The demand for technology products is considered as a new desire of consumers (Sadorsky, 2012). In the short-run, the greater negative impact on the LPSE sourcing from the decreases in the LECO and negative impacts of oil price increases and interest

Table 7
Summarized results for the impact of explanatory variables on clean energy stocks.

Explanatory variables	The direction of the impact		The characteristic of the relationship	
	In the short-run	In the long-run	In the short-run	In the long-run
LPSE	Positive	Positive	Not asymmetric	Asymmetric
LOP	Positive	Negative	Not asymmetric	Asymmetric
IR	Not significant	Positive	Not asymmetric	Asymmetric

Notes: Table 7 reports the summarized results for the impact of the determinants of clean energy stock prices. LPSE and LOP represent the logarithmic prices of technology stocks, and logarithmic crude oil spot prices of West Texas Intermediate, respectively. IR is the interest rate on the three-month Treasury bill.

Table 8
NARDL estimation results (Dependent variable: $\triangle LPSE_t$).

Panel A. Estimated coefficients (Adj. $R^2 = 0.659351$)				
EV	Coefficient	Robust Std. error	t-statistic	Prob.
C	0.104485	0.016171	6.461297	0.000
$LPSE_{t-1}$	−0.015916	0.002478	−6.423132	0.000
$LECO_{t-1}{}^{+}$	0.00407	0.001065	3.82042	0.000
$LECO_{t-1}{}^{-}$	0.002448	0.000873	2.805381	0.005
$LOP_{t-1}{}^{+}$	0.001004	0.000749	1.340231	0.180
$LOP_{t-1}{}^{-}$	0.000857	0.000573	1.494483	0.135
$IR_{t-1}{}^{+}$	−0.000418	0.000243	−1.720721	0.085
$IR_{t-1}{}^{-}$	0.0000519	0.000163	0.318059	0.751
$\triangle LPSE_{t-1}$	−0.059036	0.020395	−2.894624	0.004
$\triangle LPSE_{t-2}$	−0.029525	0.012597	−2.343821	0.019
$\triangle LECO_t{}^{+}$	0.423085	0.017896	23.64153	0.000
$\triangle LECO_{t-1}{}^{+}$	−0.054637	0.019592	−2.788802	0.005
$\triangle LECO_t{}^{-}$	0.524362	0.014957	35.05691	0.000
$\triangle LOP_t{}^{+}$	−0.025027	0.012074	−2.0728	0.038
$\triangle LOP_t{}^{-}$	−0.003249	0.014805	−0.219457	0.826
$\triangle IR_t{}^{+}$	0.006322	0.004015	1.574694	0.115
$\triangle IR_t{}^{-}$	0.013701	0.005052	2.711851	0.007
$DUM^{[11/21/2008]}$	−0.00331	0.001187	−2.788879	0.005
Panel B. Long-run coefficients and symmetry test results				
$LECO^{+}$	0.255717***	$LECO^{-}$	0.153807***	
LOP^{+}	0.063081	LOP^{-}	0.053845	
IR^{+}	−0.026262	IR^{-}	0.00326	
$W_{LR,LECO}$	19.17257***	$W_{SR,LECO}$	23.38819***	
$W_{LR,LOP}$	0.292875	$W_{SR,LOP}$	0.925741	
$W_{LR,IR}$	11.46401***	$W_{SR,IR}$	1.038585	

Notes: EV denotes the explanatory variables. The Newey and West (1987) autocorrelation and heteroskedasticity robust standard errors and t-statistics are presented. LECO, LPSE, and LOP represent the logarithmic prices of clean energy and technology stocks, and logarithmic crude oil spot prices of West Texas Intermediate, respectively. IR is the interest rate on the three-month Treasury bill. The superscripts "+" and "−" refer to positive and negative partial sums, respectively. $LECO^{+}$, $LECO^{-}$, LOP^{+}, LOP^{-}, IR^{+}, and IR^{-} are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR,LECO}$, $W_{LR,LOP}$, and $W_{LR,IR}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. $W_{SR,LECO}$, $W_{SR,LOP}$, and, $W_{SR,IR}$ refer to the standard Wald test for the null of the additive short-run symmetry condition for the corresponding variable. $DUM^{[11/21/2008]}$ is a dummy variable for the structural break date suggested by the Zivot and Andrews test (1992) for the dependent variable. Superscript *** represents the significance at 1% level.

rate decreases might be related to worsening economic circumstances influencing consumer demands. On the other hand, in the long-run, the larger positive effect on the LPSE sourcing from the increases in the LECO could be due to business cycle expansions.

7. Conclusions

Market players are experiencing complex and asymmetric relationships in the energy and financial markets. Moreover, the increased interest in energy markets is promoting policy-makers and investors to further examine their investment and risk potential considering asymmetric linkages between energy and financial assets. The exhaustion of fossil-based fuels turns policy-makers' attention to seeking alternative energy sources. In addition, recently, there is increased interest in clean energy investments due to environmental issues. Previous studies demonstrate the considerable effects of interest rates, oil and technology stock prices on the clean energy stock prices. Following this line of research, our paper examines the asymmetric effects between these variables using the NARDL approach. Our study reveals that asymmetric impacts play a central role in the dynamic relationships between clean energy stocks and other factors. Furthermore, these impacts shift considerably between the short- and long-runs in terms of both magnitude and direction. This suggests that investors interpret positive and negative signals differently both in the short- and long-run. Sound economic policy decisions and risk management strategies require information on asymmetric linkages between financial and energy markets. In this regard, our NARDL findings are of immense importance for the relevant market players, such as policymakers, speculators, fund managers, and investors.

Our results point out that the increased investments in clean energy stocks appear to be due to speculative attacks along with an increase in oil prices in the short-run. On the other hand, clean energy stocks are more vulnerable to business cycle fluctuations in the long-run than in the short-run. This implies that investors do not tend to invest in clean energy stocks during a period of low economic activity. In order to be able to eliminate this perception and push investment tendencies to clean energy stocks, it is necessary to increase government subsidy for clean energy investments and to raise public awareness about the destructive impacts of fossil-based fuels on the environment such as climate change. Our results emphasize that taking into account the expected direction of changes (negative or positive) in macroeconomic conditions, policy-makers concerned about environmental issues should follow more sensible and dynamic strategies in the short- and long-run. Furthermore, they should promote the necessity of renewable and sustainable energy investments to better adjust the risk exposure of clean energy stock portfolios in response to shifts in macroeconomic fundamentals.

For future research, the asymmetric effects of interest rate, oil, and technology stock prices on the stock prices of different alternative energy sectors (e.g. wind, solar and etc.) might be further analyzed. It would also be useful to simulate the short- and long-run risk-return performance of different investment strategies. Moreover, research investigating the asymmetric linkages between clean energy stocks and macroeconomic fundamentals in different developing and developed countries could illuminate the potentials and problems in the financing of clean energy investments. This would help understand the vulnerability of clean energy investments to various macroeconomic risks in these countries.

Appendix

See: Tables 1–8.

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