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On the pursuit of energy security: evidence from the nexus between clean energy stock priceand energy security elements

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Abstract

Concerns for fossil fuel price volatility, environmental pollution and energy inefficiency drive the formulation of energy policies aimed at attaining energy security. We use a theoretical framework which integrates key elements of energy security into the context of natural capital theory to investigate the causal relationship between Nasdaq clean energy stock price and a range of variables including oil price, natural gas prices, carbon price and energy efficiency. Our ARDL results reveal that clean energy stock price is jointly and individually explained by the variables representing some elements of energy security. Carbon price and energy efficiency emerged as the most important elements of energy security driving the on-going transition from conventional to clean energy sources. Consequently, governments should take environmental sustainability and energy efficiency very seriously when formulating energy policies in the pursuit of energy security and the way they stimulate substitutions between clean energy sources and hydrocarbons.

Keywords: Oil and gas prices; sustainability; clean energy stock price; energy security; natural capital theory; substitutability; energy transition

1. Introduction

Evidently, the world is experiencing a gradual paradigm shift from non-renewable energy sources, mainly fossil fuels, to renewable energy sources (Waziri, Hassan, and Kouhy 2018; Khan, Hou, and Le 2021a, 2021b). This shift is notably propelled by the drive to pursue sustainability (Costanza and Daly 1992; Missemer 2018; Hassan 2019b) and energy security (Winzer 2012). In the context of natural capital theory (NCT), as a key theory underpinning sustainable development, substitutability condition for sustainability is one of the key facilitators of this paradigm shift (van Geldrop and Withagen 2000; Hassan 2019a). As another critical driver of the paradigm shift, energy security is vigorously pursued by developed countries that are vulnerable to fossil energy price volatility and its consequent negative environmental impacts (Yergins 2006; Winzer 2012; Khan and Hou 2021b). To address these problems and ensure the attainment of optimal energy efficiency, many advanced economies formulate energy policies. Energy policies, mainly formulated at national level, are deliberate efforts put in place to strategically influence the elements of energy security such as hydro- carbon prices, energy efficiency and environmental sustainability, to ensure efficient energy supply and utilisation (Lucas, Francés, and González 2016; Galinis et al. 2020). In this regard, Win- zer (2012) enumerates efficiency, sustainability and energy prices as the principal pillars of the European Union’s energy policy. These policies are designed to influence energy consumption pat- terns in many advanced countries such that fossil fuel energy sources are replaced by clean energy sources. Furthermore, the outcomes of the implementation of energy policies targeting the pursuit of energy security manifest in the form of changes in energy-related variables such as clean energy stock performance, clean energy consumption, fossil fuel prices, fossil fuel consumption and energy efficiency.

Despite the importance of energy security in the context described above, only a few studies explore the topic in examining the link between fossil fuel prices and clean energy stock performance (see, Henriques and Sadorsky 2008; Kumar, Managi, and Matsuda 2012; Sadorsky 2012; Pham 2019). These studies generally highlight the importance of energy security in motivating their research. For instance, Henriques and Sadorsky (2008) emphasise that energy security concerns such as rapidly diminishing supply; political instabilities in the oil and gas exporting countries and oil price volatility induce investments in clean energy companies' stocks. Similarly, Kumar, Managi, and Matsuda (2012) vaguely introduce energy security in their paper while providing back- ground information and establishing the justification for their study. Additionally, when establishing the justification for his study, Sadorsky (2012) mentions energy security as one of the key drivers which propel fast growth of the renewable energy segment of the overall energy sector. More recently, Pham (2019) focuses on the evaluation of alternative energy sources which emerge to strengthen energy security and environmental wellbeing issues. However, none of these studies has gone into more depth in unpacking and incorporating energy security concerns within any specific theoretical framework to underpin their research. Following a careful review of the relevant literature; we identify three key elements of energy security (oil and gas prices, energy efficiency and environmental sustainability). We then integrate these elements into the context of NCT to develop a framework to underpin our study. As such, examining the role of energy security via its three key elements in stimulating a substitution between the conventional and clean energy sources is the key motivation for our study.

There has been a growing concern for energy security stemming from fossil fuel prices' volatility and the adverse environmental impacts associated thereto. Fossil fuel prices represent the independent prices of the three hydrocarbons, namely crude oil, natural gas and coal (Song et al. 2019a, 2019b; Sun et al. 2019). Two dominant international oil prices, Brent and West Texas Intermediate (WTI), are mainly used as the benchmarks for the determination of crude oil prices across the world. While WTI dominates the American region, Brent is used by OPEC

members, European countries and several other countries around the globe. Due to the high similarity between the two, they are often used interchangeably by researchers to represent global oil price. In this study, we use Brent oil future to represent oil price to partly proxy for fossil fuel as an element of energy security. However, to represent the natural gas aspect, we employ natural gas price from four gas markets. They include Henry Hub, National Balancing Point (NBP), Title Transfer Facility (TTF) and Zeebrugge (ZEE). Additionally, we develop and use a simple composite gas price index which integrates the prices from the three European natural gas markets (NBP, TTF and ZEE). Following this choice and the development of the composite gas price index, our study exhibits features which set it apart from the rest of the studies in the research area.

Another important motivation for our paper relates to the inclusion of carbon price as a potential determinant of clean energy stock performance. Within the literature occupied with the relationship between fossil fuel prices and clean energy stock performance, only Kumar, Managi, and Matsuda (2012) include carbon price as a key explanatory variable. The authors, however, fail to document a significant relationship between carbon price and clean energy stock price. Like Kumar, Managi, and Matsuda (2012), we also include carbon price to capture concern for environmental sustainability. However, our motivation for including the variable extends to identifying carbon price to represent environmental sustainability concern as a key element of energy security. Furthermore, carbon price represents an important link between energy security and NCT. Consequently, we suspect that a change in carbon price will trigger a substitution between clean energy and fossil fuels in an energy mix and a resultant change in clean energy stock price.

Furthermore, attaining energy efficiency is among the key objectives which drive the pursuit of energy security. Consistent with NCT, this stems from the fact that the current generation ought to

be efficient in harnessing and utilising energy resources so that we do not encroach into the ability of future generation to benefit fro¶m these resources. These include renewable energy resources as Harte (1995, 158) observes: '… continued exploitation in excess of natural regeneration rate can turn potential renewable resources into non-renewable resources.' This motivates our inclusion of the variable, clean energy efficiency, to represent energy efficiency. Also consistent with the relevant literature, we include the variable to control for the investors' categorisation of clean energy companies as technology companies (Henriques and Sadorsky 2008; Kumar, Managi, and Matsuda 2012)

Therefore, informed by insights from NCT, this paper investigates whether the three elements of energy security identified above, which are operationalised by five variables (Brent oil price, natural gas price index, Henry hub price, carbon price and energy efficiency), jointly and/or individually explain variations in Nasdaq clean energy stock price. Thus, the purpose of the investigation is to establish whether the causal relationships stimulate substitutions between conventional and clean energy sources. The rest of the paper is organised as follows. Section 2 reviews the relevant literature and develops the theoretical framework for the study. Section 3 focuses on the methodology of the paper. Section 4 presents empirical results and these are discussed in the subsequent section 5. Section 6 presents our concluding remarks and policy implications.

2. Literature review and theoretical underpinnings

2. 1. Energy security

Energy security became a matter of national concern and strategy since the early 1900s. For instance, during the 1st World War, United Kingdom had to rely on the insecure supply of petroleum from Persia to make its ships faster than those of Germany (Yergins 2006). During that period, the insecurity referred to was mainly related to uncertainties concerning the supply of oil, the inefficiency of coal and the safety of oil as a new source of power (Yergins 2006). Notably, these remained the key elements of energy security until the incident of the initial oil crises in the 1970s occurred. Thus, modern concern for energy security was invoked by the first oil crises (Blum and Legey 2012) which specifically occurred in 1973 when the Arab members of OPEC placed an oil embargo on various advanced countries (Gasser 2020). This caused global oil price to shoot up by 300% – from $3 to $12 per barrel (Gasser 2020). The key lesson from this event is that the use of oil supply restriction as a political weapon exposed the vulnerability of advanced economies to energy insecurity.

Yergins (2006) predicted that the challenge of energy security would escalate as the world's energy markets became more integrated. Consistent with this prediction, energy security has become a complex and a multidimensional concept which lacks a specific definition applicable to all situations. For this reason, the concept has been described as blurred, lacks universal interpretation and is elusive (Checchi, Behrens, and Egenhofer 2009; Winzer 2012; Kruyt et al. 2009). Thus, Kruyt et al. (2009, 2166) describe the concept as having '… rather elusive nature and it is highly context dependent.' For example, the perception of energy security by oil and gas net-energy-importing countries differs from the way net-energy-exporting countries view the concept. Consequently, the definition of energy security as the availability of energy sources at affordable prices (Abdo and Kouhy 2016; Song et al. 2019a, 2019b) applies to oil and gas net-importing countries. However, for the oil and gas exporting countries such as Iran, Nigeria and Saudi Arabia, energy security extends to include economic security where a decline in oil and/or gas price may lead to financial difficulties. It is imperative to clarify that our paper is concerned with the conception of energy security from the net-energy-importing countries' perspective.

In their seminal paper, while trying to demonstrate the complex nature of energy security, Ang, Choong, and Ng (2015) add dynamism to the context-dependent nature. The authors specifically derive seven key energy security themes1 from 83 energy security definitions. In this regard, Galinis et al. (2020) highlight four principal elements in the provision of energy services, namely, afford- ability (price), efficiency, energy security and sustainability. Technically, the other three elements have a strong connection to energy security as their absence or weakness signals a concern for energy security. For example, if the affordability of oil is threatened by an excessive hike in its price, this indicates that oil-dependent countries are vulnerable to energy insecurity. However, on top of affordability and sustainability, Le and Nguyen (2019) identify availability, accessibility and acceptability as three additional aspects of energy security. Furthermore, Matsumoto, Doum- pos, and Andriosopoulos (2018) contend that these elements are used by policymakers to form indicators which inform national energy policies.

From the foregoing discussion, a closer look at the relevant literature shows that oil and gas prices, energy efficiency and environmental sustainability have been variously recognised as important elements of energy security (Yergins 2006; Abdo and Kouhy 2016; Ang, Choong, and Ng 2015;

Le and Nguyen 2019; Zaman and Kalirajan 2019; Galinis et al. 2020). In addition, these elements have been identified as parts of the critical factors studied, analyzed and shaped to inform the for- mulation of energy policies in facilitating the provision of the needed energy supplies and services in an economy (Winzer 2012). In particular, our paper focuses on the relationship that may exist between such key elements of energy security as prices of fossil fuels (particularly, oil and gas), environmental sustainability and energy efficiency on the one hand, and clean energy stock price on the other hand.

2. 2. Oil and gas price and clean energy stock performance nexus

On a broad spectrum, various studies have empirically examined the relationship between fossil fuel prices and clean energy stock performance but results reported so far remain mixed and rather inconclusive. Evidently, two principal measurement strategies for clean energy stock performance seem to be responsible for the mixed results. In measuring clean energy stock performance, while most studies use price indexes (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Kocaarslan and Soytas, 2019; Sun et al., 2019; Pham, 2019), some others employ stock returns (Dutta, 2007; Reboredo and Ugolini, 2018; Kyritsis and Serletis, 2019; Xia et al. 2019; Shao and Zhang, 2020).

Apparently, those who use clean energy stock price indexes have mainly employed WilderHill Clean Energy Index and have consistently documented similar results. For instance, Henriques and Sadorsky (2008) establish a weak positive relationship between oil price and clean energy stock price with causation flowing from oil price to alternative energy stock performance. An important implication of this result is that, oil price volatility as a key element of energy security induces fluctuations in the production, consumption and investment in alternative energy. Sadorky (2012) reports a similar but stronger positive relationship. An important implication drawn by Sadorky (2012, p.254) from the significant positive correlation they report between oil price and clean energy stock price is as follows: “the results of this paper show that a portfolio of clean energy stocks and oil futures can be built and that oil futures can be used to hedge an investment in clean energy stock prices.” Similarly, Kumar et al. (2012) report an independent significant positive effects of oil price and technology stock price on clean energy stock price, specifically noting that rising oil prices stimulate substituting clean energy sources for conventional sources. It is important to note that the authors employ two more clean energy price indexes in addition to WilderHill Clean Energy Index. Similarly, Managi and Okimoto (2013), who use Markov-switching VAR, also document a significant positive relation between oil price and clean energy stock price. Although, Bondia et al. (2016) did not find association between oil price and energy stock price in the long-run, they document a significant positive relationship between the two variables in the short-run. In the same vein, Kocaarslan and Soytas (2019) and Song et al. (2019) examine the dynamic conditional correlation between oil price and clean energy stock performance and technology stock prices, and report a significant positive relationship. Also, Song et al. (2019a, 2019b)’s results imply that crude oil price has a stronger positive impact on renewable energy stock performance than natural gas and coal prices.

However, in the category of studies that use stock price to measurement performance, Sun et al. (2019) document a differing result. Thus, they analyze the effect of composite price index on the stock price of new energy companies and report a mild effect of the combined prices of the three fossil fuels on newly quoted energy stock prices. This deviant finding may be attributed to the fact that the authors use a price index different from WilderHill Clean Energy Index. Pham (2019) is another study within this category that deviates from the dominant approach. Specifically, Pham (2019) differs from the previous studies in two ways. Pham (2019) is the only study, to the best of our knowledge, which uses the disaggregation of three Nasdaq OMX indexes in measuring clean energy stock performance. Secondly, the study reports varying relationships between indices in the renewable energy sub-sectors and oil price. A more recent study, also with a divergent result, conducted by Zhang, Cai, and Yang (2020) reports heterogeneous relationships across quantiles and investment horizons regarding the effect of oil price on renewable energy stock performance. Unlike Henriques and Sadorsky (2008), the authors find that oil price has a strong ability to predict renewable energy stock prices in the long run.

We encounter mixed results within the extant literature that employ stock returns to measure clean energy stock performance. For instance, Kyritsis and Serletis (2019) establish absence of statistically significant relationship between oil price uncertainty and clean energy stock returns. However, the authors document asymmetric relationship between oil price and clean energy stock returns. In contrast, however, Dutta (2017) discovers that oil price uncertainty has a significant positive impact on clean energy returns. Still within the same category, Reboredo and Ugolini (2018) examine the effect of quantile price fluctuations in oil, natural gas, coal and electricity on the quantiles of clean energy stock returns. The authors document empirical evidence showing that whilst oil price appears to be the major determinant of stock return in the US, electricity price is the key determinant in the EU States. However, Shao and Zhang (2019) focus on the effect of oil price fluctuations on clean energy metal price returns and finds that oil price had positive spill over effect on seven clean energy metal stock returns.

Considering the overall category of studies that used price indexes, only four studies reported results divergent from the dominant positive relationship between oil price and clean energy stock price. However, Henriques and Sadorsky (2008) is the only study that documented a weak positive relationship between oil price and clean energy stock price within the category of studies that specifically employed WilderHill Clean Energy Index. All other studies which used this index documented a significant positive relationship. In a different context, heterogeneous relationships across clean energy sub-sectors (Pham 2019) and quantile/investment horizons (Zhang, Cai, and Yang 2020) have been documented. The few studies that measured clean energy performance via returns reported results which are a mixture of significant positive, insignificant positive and heterogeneous (a combination of positive, negative, insignificant, symmetric and/or asymmetric). Evidently, the review in this section informs our conclusion that so far findings in the area are rather inconclusive.

2. 3. Theoretical Framework: the natural capital theory (NCT)

Substitutability condition for sustainability is conceptualized, within the context of NCT, to explain the rationale behind the paradigm shift that underlies the ongoing transition from non-renewable to renewable energy resources (see Figure 1). Thus, in advocating for sustainability, NCT states that substituting the harnessing and consumption of exhaustible natural resources with non-depreciable renewable natural capital to the extent that we, at the very least, keep the aggregate stock of natural capital intact facilitates sustainable development (Pearce, 1988; Costanza and Daly, 1992; Harte, 1995; Ekins et al, 2003; Barbier, 2019). According to this theory, it is when we implement this that we are able to achieve our present needs without compromising the ability of the future generations to achieve their needs (van Geldrop and Withagen, 2000; Fenichel and Hashida, 2019). On this note, Pearce (1988) equates the attainment of sustainable development to ensuring 'constancy of natural capital stock'. This implies maintenance of natural capital at the level at which humanity meets it by never allowing it to depreciate (Solow, 1974; Kornafel and Telega, 2020). Elaborating on the constancy of natural of natural capital, Costanza and Daly (1992; p.7) note that "A minimum necessary condition for sustainability is the maintenance of the total natural capital stock at or above the current level."

Various studies allude to the close substitutability between fossil fuels and clean energy sources in articulating and discussing the causes and the implications of the nexus between fossil fuel prices and clean energy stock performance (Henriques and Sadorsky, 2008; Kumar et al., 2012; Xia et al., 2019; Kocaarslan and Soytas, 2019; Kocaarslan and Soytas, 2019b; Song et al., 2019). For example, Henriques and Sadorsky (2008) argue that higher oil price and shortages in its supply induce substituting fossil fuels with alternative energy options. Similarly, the positive relationship hypothesized between oil price and alternative energy stock price by Kumar et al. (2012) is premised on the substitutability between the two competing energy sources. In articulating the implications of their findings, Xia et al. (2019) contend that fossil fuels and renewable energy have strong substitution relationship. Similarly, the studies by both Managi and Okimoto (2013) and Kocaarslan and Soytas (2019) refer to fossil fuels and renewable energy sources as close substitutes.

The close substitution between the two competing energy sources, which underpins the relationship between fossil fuel prices and renewable energy stock prices (Managi and Okimoto, 2013; Kumar et al., 2012), is linked to the substitutability condition for sustainability as advocated by the NCT via certain key elements of energy security. In reality, the substitution between fossil fuels and renewable energy sources is mainly driven by the elements of energy security such as energy prices, energy efficiency, climate change and environmental sustainability. Changes in fossil fuel prices may impact investments in renewable energy options in two ways. Firstly, increases in fossil fuel prices incentivise searching for a cheaper alternative to maintain affordability of energy. Secondly, reductions in fossil fuel prices motivate consumptions, thus increases emissions and cost of production due to carbon prices and tariffs; thus motivate investing in a more sustainable sources of energy. Therefore, this paper argues that in pursuit of energy security the society substitutes renewable energy away from fossil fuels in terms of production, consumption and investment. As such, changes in the elements (such as fossil fuel price, environmental conditions, and energy efficiency) stimulate increases in the consumption, production and investments in clean energy. This translates into rises in the clean energy stock performance (clean energy stock return or clean energy price).

Figure 1 shows how NCT classifies energy resources into exhaustible, renewable and ecosystem services and advocates substitutability as an important condition for achieving sustainability (Costanza and Dalley, 1992; Berkes and Folke, 1992; Harte, 1995; Fenichel and Hashida, 2019; Barbier, 2019). The Figure is a diagrammatic representation of our theoretical framework which advocates that in pursuit of energy security people, entities and governments substitute clean energy sources for fossil fuels. In this scenario, as shown in Figure 1, the elements of energy security would in differing individual ways and, perhaps in a joint way, affect the substitution between non-renewable and renewable energies. Unlike oil and gas, the clean energies such as solar, biofuel, wind energy etc, do not have specific markets where their prices could be determined. We can only see the reflection of their prices via their stock energy performances. For instance, it is argued that when stock prices of clean energies are rising as the prices of fossil fuels are increasing, it is an indication of a substitution away from fossil fuel to clean energy sources (Henrique and Sadorsky, 2008; Kumar et al, 2012; Managi and Okimoto, 2013).

3. Material and method

In this section, we describe the nature of the dependent and the independent variables and the various sources from which data on these variables are gathered. Next, we present statistical descriptions of the time-series data for each variable. Finally, we specify the appropriate time-series regression model based on the results of the conventional and breakpoint unit root tests.

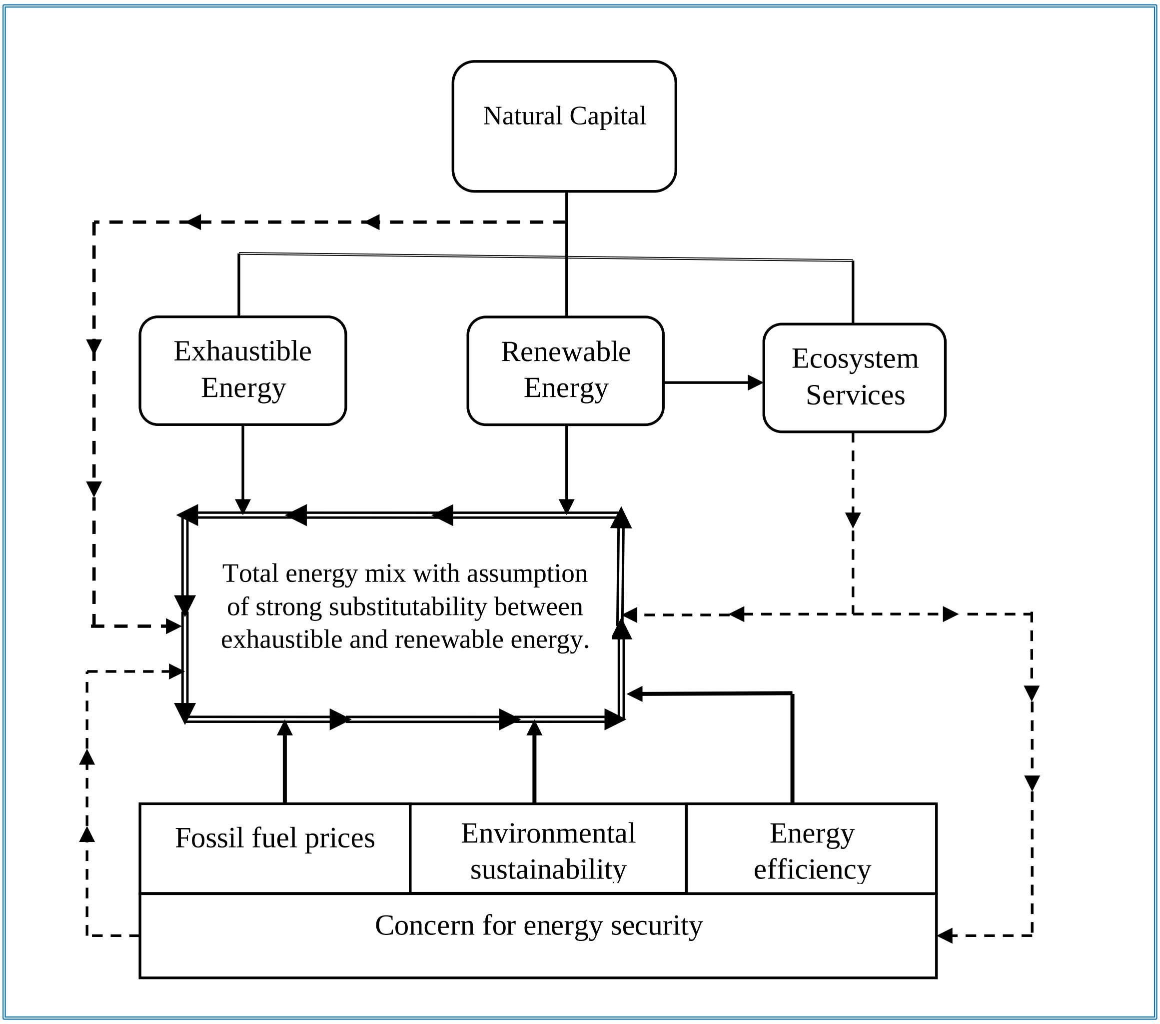


Figure 1 Theoretical framework. Source: Authors' creation, 2021

3. 1. Variables and data sources

3.1.1 Clean energy stock price index (CEI)

CEI, as the dependent variable in this study, is one of the key indexes that belongs to NASDAQ OMX Green Economy Sector Index Family. It tracks the price-related performance of companies from around the world included in the NASDAQ OMX Green Economy Index[1]. According to NASDAQ (2015, p.9)

> Clean Energy Focused Index is designed to track sectors of the Green Economy specifically enabling the advancement of energy generation via non-fossil-based sources inclusive of the sectors renewable energy generation, clean energy efficiency, advanced materials and bio/clean fuels.

The index began at the base value of 1000 on 10th October 2010. Data on this variable were collected from the NADAQ Global Indexes.

3.1.2 Oil price (OPR)

We use Brent oil futures to measure crude oil price. Choosing this price is informed by its wide usage as a benchmark in the international oil markets located in the Middle East, Europe and Africa. Brent is also used as the benchmark for pricing by the OPEC member countries considered as a powerful group that plays a significant role in the determination of international oil price. Brent crude oil is very similar to West Texas Intermediate (WTI) as the two are denominated in US dollar; are both light and their prices are highly correlated. Daily data on both Brent and WTI prices were collected from Investing.com.

3.1.3 Gas price index (GPI) and Henry Hub Natural gas price (HUB)

Unlike the two key international crude oil prices (Brent & WTI), international markets for natural gas are segmented and less unified (de Jong and Schneider, 2009). However, there are four dominant natural gas markets to which most international natural gas prices are bench-marked. They are Henry Hub (HUB) (United States),

[1] These are indexes whose computations are based on market capitalizations.

National Balancing Point (BP) (United Kingdom), Title Transfer Facility (TTF) and Zeebrugge (Continental Europe). Following this choice, our study exhibits a feature that sets it apart from the rest of the studies in this research area as we develop and use a simple composite gas price index which integrates the prices from the three European natural gas markets. Daily data for HUB price were collected from the US Energy Information Administration (EIA). However, daily data on NBP, ZEE and TTF prices were collected from Energy Market Price. In order to avaid multicollinearity, we decided to develop a simple composite price index that integrates the daily spot prices from the four markets into one. More specifically, we follow the steps outlined below to develop the gas price index.

In the first step, we calculate and examine the correlation amongst the four prices pair-wise. With correlation coefficient values of 0.97 (NBP and TTF), 0.99 (NBP and ZEE) and 0.97 (TTF and ZEE), we established that prices from the three European markets are highly correlated. An examination of their graphical representation shows high similarity as well. However, with Pearson's correlation coefficients of 0.53 (HUB and NBP), 0.47 (HUB and TTF) and 0.54 (HUB and ZEE), it is evident that Henry Hub price is quite different from prices in the three European markets. Secondly, we express the prices from the three European markets in the same scale such that the value of each price ranges between 0 and 1 by dividing each price by the maximum value in the series. The result of this exercise, not reported here, confirms that prices in NBP, ZEE and TTF for their maximum values at 1 occurred on the same date, 28th March 2013. But on this date the value of HUB was 0.6544. We take a simple average of the prices from the three European markets to generate the *GPI* and include the price from the Henry hub market as a separate variable.

3.1.3 Carbon emission futures (CEF)

Carbon emission futures are price quotations of carbon emission reduction contracts existing in the emissions trading markets. it is a derivative whose contract prices reflect the prices at which carbon emission reductions will be bought and sold. A rise in the price of CEF suggests that intensive-carbon-emission firms are buying more carbon emission reductions to meet their targets, thus implies an extensive production and consumption of fossil fuels. This encourages cleaner production including more usage of clean energy sources. Falling CEF prices implies the reverse. Daily data on this variable was sourced from Investing.com.

3.1.4 Clean energy efficiency (CEE)

In the main, we include the NASDAQ energy efficiency index to represent the efficiency element of energy security. The key components of this index suggest intensive use of advanced technology. The index started at the base value of 1000 on 10/13/2010. This very date marks the start date of the time period covered by our study. Additionally, technology companies stock performance is usually included to control for the clean energy firms' being essentially recognised as companies that use highly advanced technology. As energy efficiency index reflects the use of advanced technology by clean energy companies (Henriques and Sadorsky, 2008, Kumar et al., 2012), we included this index to more directly control for this feature. Daily data concerning this variable were collected from NASDAQ Global Indexes.

3.1.5 Volume of clean energy stock traded (VTD).

The inclusion of the quantity of clean energy stock bought and sold on the floor of NASDAQ security market is based on the reasoning that the number stock traded on daily basis may affect the dependent variables. Additionally, the volume traded may be affected by fossil fuel prices and the price of CEF. Data on this variable were collected from the NASDAQ Global Index.

3. 2. Data description

In this section, we present descriptive statistics, line graphs and Pearson's correlation matrix to provide information on the nature of our time-series dataset. While Table 1 presents the mean, median, maximum and standard deviation for each variable; Figure 1 presents the line graph for each variable and Table 3 provides information on pair-wise Pearson's correlations. All variables, except GPI which is in a ratio form, were transformed to natural logarithms before computing the descriptive statistics and generating the line graphs.

Table1 Descriptive statistics

Statistics/Variables	*ln(CEI)*	*ln(OPR)*	*ln(HUB)*	*GPI*	*ln(CEF)*	*(CEE)*	*ln(VTD)*
Mean	6.9572	4.3684	1.1734	0.6978	1.9804	7.0767	12.1226
Median	6.9775	4.6215	1.1913	0.7310	1.8825	7.0876	12.2415
Maximum	7.2659	4.8414	1.8163	1.0000	3.2359	7.3415	13.2023
Minimum	6.6130	3.3279	0.4941	0.3615	0.9933	6.7162	9.3518
Std. Dev.	0.1437	0.3986	0.2460	0.1577	0.4910	0.1247	0.5942
Observations	1,710	1,710	1,710	1,710	1,710	1,710	1,710

A careful observation of the line graphs in Figure 1 shows that six out of the seven variables are likely to be integrated of order one, *I(1)*. However, the logarithmic form of VTD seems likely to be integrated of order 0, *I(0)*.

3. 3. Model specification

Consistent with previous literature clean energy performance as a function of such regressors as fossil fuel prices and other control variables are generally modelled as follows:

$$AEP_t = \delta_0 + \delta_i FFP_t + \delta_j CV_t + \epsilon_t$$

(1)

Where AEP_t denotes the alternative energy stock performance in question; FFP_t represents a vector of fossil fuel prices (such as crude oil, natural gas and coal) and CVR_t a vector of other relevant regressors. While δ_0 is the time invariant constant, δ denotes the coefficients of the regressors in the model, $i = 1, 2, 3 \ldots\ldots n \; and \; j = n + 1, n + 2 \ldots\ldots n + m$

Kumar et al (2012) introduce carbon price as an additional explanatory variable in the model such that it becomes:

$$AEP_t = \delta_0 + \delta_i FFP_t + \delta_j CVR_t + \delta_k CPR_t + \epsilon_t$$

(2)

Where CPR_t represents the carbon price and $k = m + 1$.

Recently, McNown et al. (2018) assessed the application of the famous Pesaran et al.'s (2001) ARDL model and identified some problems associated with its implementation by various studies. The authors called the attention of researchers to the fact that if not implemented with caution, the Pesaran et. al. (2001) bounds cointegration test in ARDL may lead to incorrect conclusion. They implied two options researchers may choose from in order to produce ARDL cointegration test results that are not misleading. In the first option, McNown et al. (2018) clarify and remind us that Pesaran et al. (2001) lay down four conditions that must be satisfied before we conclude that two or more variables are cointegrated. These conditions are.

(i) The dependent variable is known to be *I(1)* with high degree of certainty.

(ii) Both F-bounds test on the lag level of all variables and the t-bounds test on lag level of the dependent variable reject the null hypothesis of 'no level relationship'.

there is no feedback at the levels from the dependent to the independent variables so that the independent variables are weakly exogenous.

Table 2 Correlation matrix

Variables	*ln(CEI)*	*ln(OPR)*	*ln(HUB)*	*GPI*	*ln(CEF)*	*(CEE)*	*ln(VTD)*
ln(CEI)	1.0000						
ln(BRT)	-0.5487	1.0000					
ln(HUB)	0.0060	0.6369	1.0000				
GPI	-0.5711	0.8337	0.5485	1.0000			
ln(CEF)	-0.3272	0.2848	0.2353	0.1769	1.0000		
ln(CEE)	0.9696	-0.4310	0.0675	-0.4338	-0.4595	1.0000	
ln(VTD)	0.1375	-0.2191	-0.1538	-0.1893	-0.1147	0.1183	1.0000

However, McNown, Sam, and Goh (2018) conclude that treating regressors as dependent variables in a system of ARDL equations (see, for example, Marques, Fuinhas, and Menegaki 2016) thereby making them weakly endogenous does not affect the validity of ARDL results under Pesaran, Shin, and Smith (2001). Consequently, this rules out the need to meet the requirement of condition (iii).3 The second option relates to the use of the bootstrap ARDL method introduced by

McNown, Sam, and Goh (2018). In this paper, we choose the first option and use relevant econometric tests to determine whether conditions (i) and (ii) outlined above are violated or not.

3. 4. Unit root tests

Establishing the stationarity status of each variable in a time-series dataset is among the key factors to consider in determining the appropriate regression model to use. To ensure that we satisfy the first condition, we conduct four unit root tests on the independent and the dependent variables. Thus, we subject all the variables in our model to Augmented Dickey Fuller (ADF) test, Phillips Perron (PP) test, KwiatKowski-Phillips-Schmidt-Smith (KPSS) test and the Perron and Vogelsang (1992) breakpoint unit root test.

Table 3 Conventional unit root tests

Variable	ADF		PP		KPSS		Stationarity Status
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.	
ln(CEI)	-1.0170	-38.3959***	-0.7936	-38.3068***	3.3500***	0.1337	*I(1)*
ln(OPR)	-0.7876	-44.1709***	-0.7525	-44.0982***	4.1848***	0.1627	*I(1)*
ln(HUB)	-2.3352	-43.2608***	-2.2500	-43.2891***	1.3425***	0.0461	*I(1)*
GPI	-1.4709	-45.6133***	-1.4322	-45.8838***	3.3864***	0.1393	*I(1)*
ln(CEF)	-2.0748	-27.9690***	-2.4504	-75.2675***	2.3220***	0.1470	*I(1)*
ln(CEE)	-1.5384	-39.3713***	-1.4458	-39.4070***	8.5563***	0.1180	*I(1)*
ln(VTD)	-3.5946***	-23.9137***	-28.9396***	-313.174***	0.378595	0.1278	*I(0)*

***significant @ 1%, **significant @ 5%, *significant @ 10%,

Table 3 presents three unit root tests that are known to perform well with large samples (Diebold and Kilian, 2000). Results reported in the Table reveal that all the three tests show that six out of the seven variables, including CEI, are *I(1)*. However, *ln(VTD)* is shown to be an *I(0)* variable by all the three tests.

A careful examination of *ln(OPR)* and *ln(CEF)* graphs it is obvious that they are characterized by significant structural breaks. Other variables that may have structural breaks, but not as pronounced as those of *ln(OPR)* and *ln(CEF),* include *ln(HUB), ln(CEI)* and *ln(CEE).* Tursoy and Faisal (2018) remind us that conventional unit root tests such as ADF, PP, NG-Perron and KPSS do not take structural break into consideration in processing data for variables to produce the relevant test statistics. For this reason, the tests might produce misleading results if the variables being tested are characterized by structural breaks (Perron, 1997; Murthy and Okunade, 2016; Sun et al., 2017). Consistent with Sun et al. (2017) and Tursoy and Faisal (2016), we conduct and present breakpoint unit root test on each variable and the results are presented in Table 4.

Table 4 Breakpoint unit root test

Variables	Level		First Difference		Stationarity Status
	t-Statistic	Break date	t-statistic	Break date	
ln(CEI)	-2.642	6/24/2013	-38.9363***	8/8/2011	*I(1)*
ln(OPR)	-4.6613**	9/29/2014	-44.8038***	1/22/2016	*I(0)*
ln(HUB)	-3.4161	11/20/2014	-43.6061***	2/19/2014	*I(1)*
GPI	-4.0964	1/24/2014	-48.7293***	12/27/2016	*I(1)*
ln(CEF)	-4.2211*	11/16/2011	-58.3022***	12/10/2010	*Inconclusive*
ln(CEE)	-3.1015	11/14/2012	-40.0393***	8/18/2011	*I(1)*
ln(VTD)	-40.0393***	12/16/2010	-61.6148***	12/16/2010	*I(0)*

***significant @ 0.1%, **significant @ 1%, *significant @ 5%, The results of the breakpoint unit root test serve three purses. Firstly, it enables us to confirm that none of the variables is *I(2)*. Secondly, it assists in double checking that the dependent variable *ln(CEI)* is definitely *I(1)* and not *I(0)*. Thirdly, it helps to identify *ln(OPR)* and *ln(CEF)* as the variables that are likely stationary at level due to presence of significant structural breaks. In view of the results relating to the third purpose, we generate two dummy variables, BRK1 and BRK2 for inclusion in our ARDL model to account for the significant breaks associated with *ln(OPR)* and *ln(CEF)* respectively.

As all the three conventional unit root tests (ADF, PP and KPSS) as well as the Perron and Vogelsang (1992) breakpoint unit root tests have shown that the dependent variable, *ln(CEI)*, is *I(1)*, we believe that we satisfy the condition of the dependent being strictly *I(1)*. The results of the three conventional unit root tests presented in Table 3 show a mixture of six *I(1)* and one *I(0)* variables, and the Breakpoint unit root test results in Table 4 show a mixture of four *I(1)*, two *I(0)* and one inconclusive case. We interpret this as a strong indication to use ARDL to estimate our model.

3. 5. The ARDL model specification

Given the standard ARDL specification (see, Pesaran et al., 2001; Narayan, 2004) we specify the following model:

$$
\begin{aligned}
&\Delta\, ln(CEI)_t \\
&= \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, \Delta\, ln(CEI)_{t-i} + \sum_{i=0}^{q} \alpha_{2i}\, \Delta\, ln(OPR)_{t-i} + \sum_{i=0}^{r} \alpha_{3i}\, \Delta (HUB)_{t-i} \\
&+ \sum_{i=0}^{s} \alpha_{4i}\, \Delta (GPI)_{t-i} + \sum_{i=0}^{u} \alpha_{5i}\, \Delta\, ln(CEF)_{t-i} + \sum_{i=0}^{v} \alpha_{6i}\, \Delta ln(CEE)_{t-i} \\
&+ \sum_{i=0}^{w} \alpha_{7i}\, \Delta ln(VTD)_{t-i} + \alpha_8 BRK1_t + \alpha_9 BRK2_t + \lambda_1\, ln(CEI)_{t-1} + \lambda_2\, ln(OPR)_{t-1} \\
&+ \lambda_3 (HUB)_{t-1} + \lambda_4 (GPI)_{t-1} + \lambda_5 ln(CEF)_{t-1} + \lambda_6 ln(CEE)_{t-1} + \lambda_7 ln(VTD)_{t-1} \\
&+ \mu_{it} \qquad (3)
\end{aligned}
$$

Where: Δ represents difference operator; ln represents natural logarithm operator and p, q, r, s, u, v, w are the variables' lag limits.

After estimating the ARDL model specified in equation (3), its goodness of fit is assessed and subjected to the relevant diagnostic tests. We then proceed with long run cointegration tests, if the model is found to be structurally and dynamically stable; its residuals are not serially correlated and it does not suffer from severe heteroskedasticity. In doing so, firstly, we conduct bounds F-test on the lagged levels of the dependent and the independent variables. Secondly, we conduct bounds t-test on the lagged level of the dependent variable only. If and only if both bounds test (F-test and t-test) reject the 'no level relationship' null hypothesis, we proceed to estimate the long run and the short run models (see, McNown et al., 2018).

Thus, the long run model, normally used to estimate level relationships, is specified as follows.

$$ln(CEI)_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, ln(CEI)_{t-i} + \sum_{i=0}^{q} \alpha_{2i}\, ln(OPR)_{t-i} + \sum_{i=0}^{r} \alpha_{3i}\,(HUB)_{t-i} + \sum_{i=0}^{s} \alpha_{4i}\,(GPI)_{t-i} + \sum_{i=0}^{u} \alpha_{5i}\, ln(CEF)_{t-i} + \sum_{i=0}^{v} \alpha_{6i}\, ln(CEE)_{t-i} + \sum_{i=0}^{w} \alpha_{7i}\,\Delta ln(VTD)_{t-i} + \upsilon_t \qquad (4)$$

However, the short run error correction model is specified as follows.

$$\Delta\, ln(CEI)_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\,\Delta\, ln(CEI)_{t-i} + \sum_{i=0}^{q} \alpha_{2i}\,\Delta\, ln(OPR)_{t-i} + \sum_{i=0}^{r} \alpha_{3i}\,\Delta(HUB)_{t-i} + \sum_{i=0}^{s} \alpha_{4i}\,\Delta(GPI)_{t-i} + \sum_{i=0}^{u} \alpha_{5i}\,\Delta\, ln(CEF)_{t-i} + \sum_{i=0}^{v} \alpha_{6i}\,\Delta ln(CEE)_{t-i} + \sum_{i=0}^{w} \alpha_{7i}\,\Delta ln(VTD)_{t-i}\alpha_8 BRK1_t + \alpha_9 BRK2_t + \varphi ECT_{t-1} + \vartheta_t \qquad (5)$$

The short run model is an error correction model that presents the dynamic relationship between the dependent and the independent variables in an ARDL regression. It estimates the first difference stationery relationship between the dependent and the independent variables. Unlike the long run level model, it includes the lags of the dependent and the independent variables. The error correction term (*ECT*) measures the speed at which variables re-adjust from short run shocks to revert back to long run relationship.

4. Empirical results

4.1 The base-line ARDL model

We manoeuvre through the standard vector autoregressive (VAR) model to determine the maximum lags to include in the ARDL estimation for each variable. This is done via the lag selection criteria option available under the standard VAR. The summary of the maximum lag lengths for the VAR model and each variable are presented in Table 5 below.

Table 5 shows that the optimal lag length for the standard VAR model is 6. Similarly, the table reports the optimal lag length of the dependent variable (lnCEI) as 6 and the highest maximum lag length amongst the independent variables as also 6 (lnCEE's lag length). We, therefore, input 6 in the EVIEWS ARDL equation estimation option for both the dependent variable and the regressors to estimate our underlying ARDL model. The summary of the estimated results for the selected ARDL model is presented in Table 6. The model exhibits very impressive goodness of fit with an adjusted R-squared of 99.98% and an overall model F-statistic significant at below 1% alpha level.

It is evident from the results presented in Table 6 that our model is free from serial correlation. A careful observation of Figure 2 will show that CUSUMSQ graph is not as perfectly stable as the CUSUM graph, but most of the time it remains within the 5% upper and lower bounds. Thus, whenever the CUSSUMSQ strays off and appears on or slightly beyond the boundary, it quickly returns back inside. CUSUMSQs with similar behaviour were reported by previous studies. For instance, Rahman and Kashem (2017) report a similar CUSUMSQ plot which is slightly outside the 5% bounds for a brief while. Similarly, two of the CUSUMSQs reported by Ozturk and Acaravci (2011) are at some points slightly outside the 5% boundaries. However, both studies concluded that their models were in general stable, because their CUSUMSQs were only slightly outside the 5% lines and that all other relevant tests confirm the stability of their ARDL models. Therefore, similar to these studies, except for the slight instability portrayed by the CUSUMSQ, all other relevant tests for stability including Ramsey Reset test, CUSUM test and recursive coefficients (see, Appendix VIII) confirm the coefficients and dynamic stabilities of our ARDL model.

Tables 5. Maximum lags for the variables.

Variable	Lag length
The VAR model	6
ln*CEI*	6
ln*OPR*	2
ln*HUB*	3
GPI	2
ln*CEF*	5
ln*CEE*	6
ln*VTD*	2

Lag selection method: Akaike Information Criterion (AIC).

Table 6 Summary of the ARDL Model

Model selected: *ARDL (2, 2, 0, 0, 1, 2, 1)*		
Goodness of fit and diagnostic tests		
Adjusted R-squared		99.98%
Model F-statistic		469.11**
Breusch-Godfrey Serial Correlation LM Test:		
	F-statistic - 1 lag	0.044
	F-statistic - 2 lags	0.069
Heteroskedasticity Tests:		
	White	0.654
	ARCH$^{\psi}$	2.3332**
Ramsey RESET Test		2.043
CUSUM (see, Figure 2)		Stabl
CUSUMSQ (see, Figure 2)		Stabl

Selected Model: *ARDL(2, 2, 0, 0, 1, 2, 1*); Model selection method: AIC; ***significant @ 1%, **significant @ 5%, *significant @ 10%; $^{\psi}$White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Figure 2 Line graphs

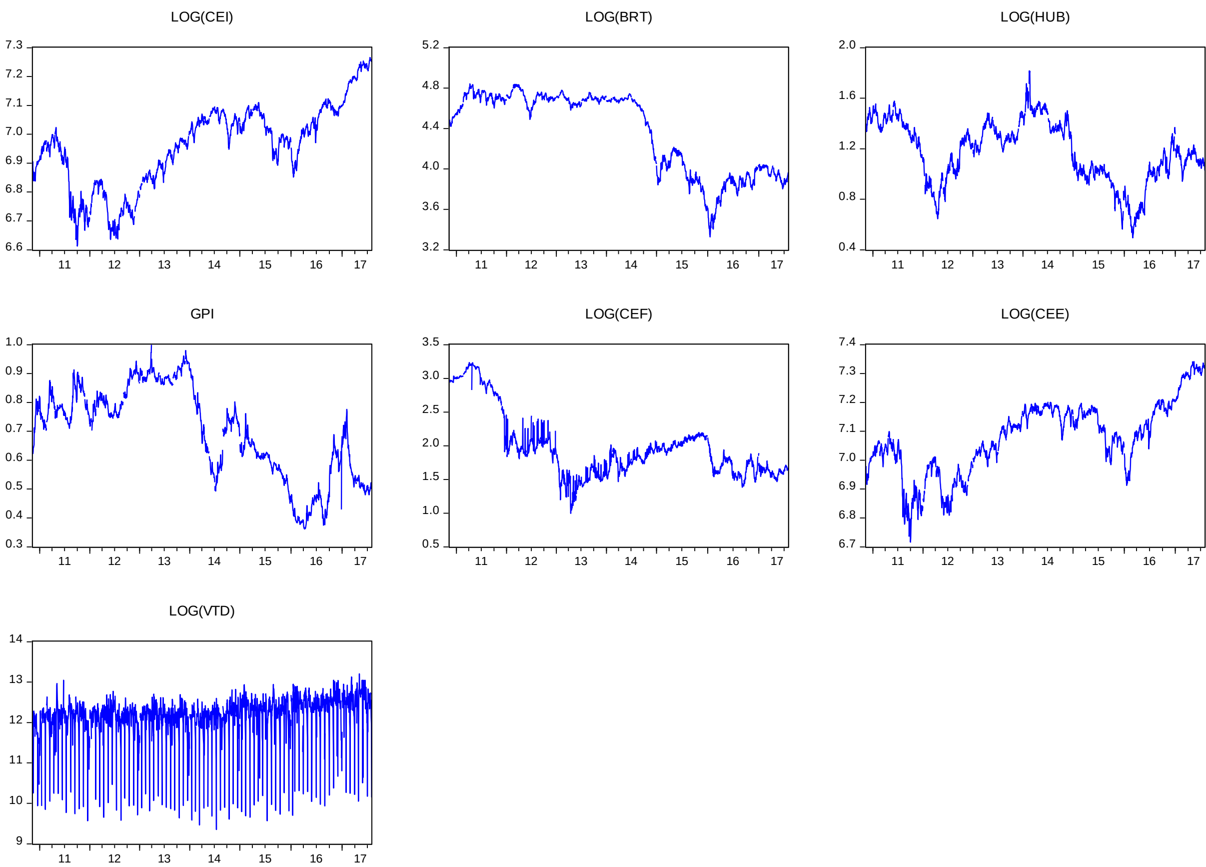
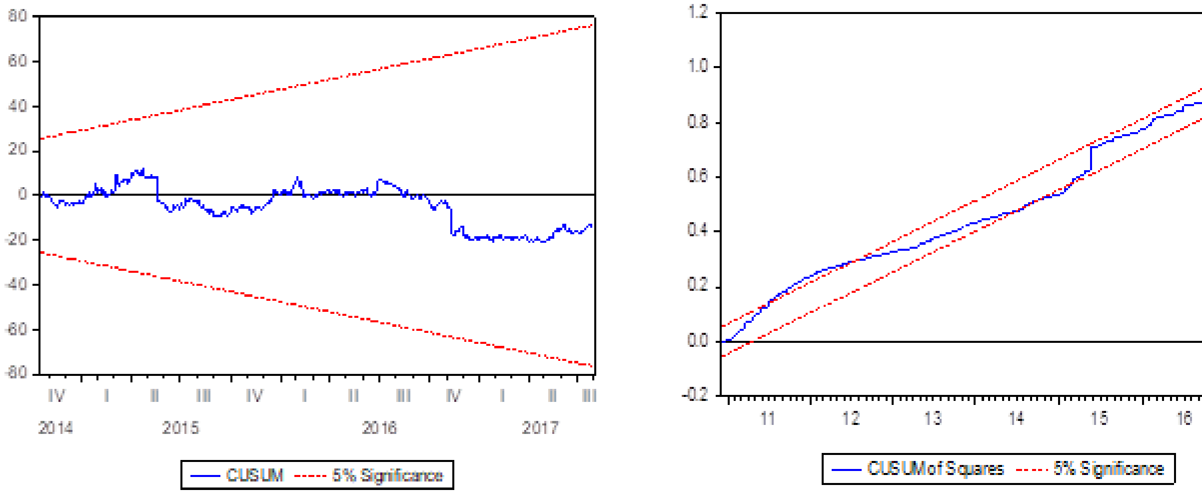


Figure 3: CUSUM and CUSUMSQ



The insignificance of the Ramsey RESET test statistic is an indication that no important variable has been omitted and that the model is correctly specified. We report two tests for heteroskedasticity with White test showing evidence of heteroskedasticity while the ARCH test statistic appears significant at 5% showing evidence of non-constant variance. For this reason, we estimate our baseline ARDL model while invoking heteroskedasticity consistent standard errors (Figure 3).

4.2 Bounds cointegration test

In this section, we present two bounds cointegration tests to establish whether the dependent variable, *ln(CEI)*, is having a long run cointegrating relationship with any of the independent variables in the model. The first bounds test is a joint F-test on the lagged level of the dependent and the independent variables (Pesaran et al., 2001; McNown et al., 2018). The second test is a t-test on the coefficient of the lagged level of the dependent variable only.

The results reported in Table 7 test the null hypothesis $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0$ against the alternative hypothesis $H_1: \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq \lambda_7 \neq 0$. Since the joint F-statistic exceeds the upper critical value at 1% level of significance, we therefore reject the null hypothesis of 'no level relationship' and conclude that CEI has a significant level relationship with at least one of the regressors.

To test the significance of the coefficient on the lagged level of the dependent variable, we present the result of bounds t-test in Table 7. The t-statistic tests the null hypothesis $H_0: \lambda_1 = 0$ against the alternative hypothesis $H_0: \lambda_1 \neq 0$. As the t-statistic falls outside the upper bound at 1% level of significance, we rejection the 'no level relationship' null hypothesis. This reinforces the bounds F-test result and we, therefore, conclude that *ln(CEI)* is cointegrated with at least one regressor in the model.

5. The long run relationship

Following the rejection of the 'no level relationship' null hypothesis by both the joint F-test and t-test, we establish the existence of cointegration relationship between ln(CEI) and, at least, one of the independent variables in our model. This econometric evidence informs our estimation of the long run level relationships between ln(CEI) and the rest of the independent variables as presented in Table 8.

Table 7: Joint F-test on the lagged levels of all variables

	Value	Signif.	*I(0)*	*I(1)*
F-statistic	4.7139***	10%	2.12	3.23
Number of variables	6	5%	2.45	3.61
		1%	3.15	4.43

***significant @ 1%, **significant @ 5%, *significant @ 10%

Table 8 t-bounds test on the lagged level of the dependent variable.

	Value	Signif.	I(0)	I(1)
t-statistic	-5.7545***	10%	-2.57	-4.04
Number of variables	1	5%	-2.86	-4.38
		1%	-3.43	-4.99

***significant @ 1%, **significant @ 5%, *significant @ 10%

The results in the table show that all the independent variables are individually significantly associated with ln(CEI). Thus, the coefficients of Henry Hub Natural gas price (HUB), carbon emission futures (CEF) and clean energy efficiency (CEE) are individually positive and statistically significant.

6. The short run dynamics

The short run model is an error correction model which presents the dynamic relationship between the dependent and the independent variables in an ARDL regression. It estimates the first difference stationery relationship between the dependent and the independent variables. Unlike the long run level model, it includes the lags of the dependent and independent variables.

Results in Table 10 present the relationships between all the independent variables which appear in the main ARDL model at one or more lags. Thus, lnHUB and GPI which appear at 0 lag in the underlying ARDL are excluded from the error correction model. Therefore, only lnOPR, lnCEF and lnCEE appear in the results of the short-run error correction model in Table 10. Evidently, the coefficients of all the three variables are positive and statistically significant.

Table 9 Long run relationships

Variable	Coefficient	Std. Error
ln(OPR)	-0.0633***	0.0203
ln(HUB)	0.0525**	0.0225
GPI	-0.0924**	0.0442
ln(CEF)	0.0282**	0.0109
ln(CEE)	1.1077***	0.0513
ln(VTD)	-0.0171**	0.0085

***significant @ 1%, **significant @ 5%, *significant @ 10%

Conversely, however, the coefficients of oil price *(OPR)*, gas price index *(GPI)* and volume of clean energy stock traded *(VTD)* are negative and individually statistically significant.

Table 10 Short run dynamics

Variable	Coefficient	Std. Error
Δ*ln(CEI(-1))*	0.0984***	0.0237
Δ*ln(OPR)*	0.0085***	0.0029
Δ*ln(OPR(-1))*	0.0049*	0.0029
Δ*ln(CEF)*	0.0021***	0.0007
Δ*ln(CEE)*	0.8684***	0.0048
Δ*ln(CEE(-1))*	-0.0679***	0.0211
Δ*ln(VTD)*	-0.000115	0.0001
BRK1	0.000149	0.0003
BRK2	0.000155	0.0007
ECT(-1)	-0.0146***	0.0025
Constant	-0.0066***	0.0011
Adjusted R-squared		95.72%

***significant @ 1%, **significant @ 5%, *significant @ 10%

4.5 Error-correction-based Granger causality

Granger causality tests the pair of null hypotheses that x_t does not cause y_t and y_t does not cause x_t through a pair of equations (Rahman and Kashem, 2017). However, Odhiambo (2009) contends that the conventional Granger causality test may not be appropriate in an ARDL environment and recommends the use of error-correction-based Granger causality test. Therefore, following Odhiambo (2007, 2009) and Narayan and Smyth (2008), we use the Granger causality approach that incorporates the error-correction term into each equation in the pair. However, we only estimate and report pair-wise Granger causality between *ln(CEI)* and *ln(CEF)*, and between *ln(CEI)* and *ln(CEE)*, as we only encounter evidence of cointegration in these two cases (see, Odhiambo, 2009 Rahman and Kashem, 2017). In this regard, the two relevant pairs of error-correction-based Granger causality equations are presented as follows.

Ln(CEI) and ln(CEF)

$$ln(CEI)_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, ln(CEI)_{t-i} + \sum_{i=0}^{q} \alpha_{2i}\, ln(CEF)_{t-i} + \varphi ECT_{t-1} + \epsilon_t \qquad (6)$$

$$ln(CEF)_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i}\, ln(CEF)_{t-i} + \sum_{i=0}^{q} \beta_{2i}\, ln(CEI)_{t-i} + \varphi ECT_{t-1} + \varepsilon_t \qquad (7)$$

ln(CEI) and *ln(CEE)*

$$ln(CEI)_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1i}\, ln(CEI)_{t-i} + \sum_{i=0}^{q} \gamma_{2i}\, ln(CEE)_{t-i} + \varphi ECT_{t-1} + \epsilon_t \qquad (8)$$

$$ln(CEE)_t = \theta_0 + \sum_{i=1}^{p} \theta_{1i}\, ln(CEE)_{t-i} + \sum_{i=0}^{q} \theta_{2i}\, ln(CEI)_{t-i} + \varphi ECT_{t-1} + \varepsilon_t \qquad (9)$$

Table 11 presents the results of the pair-wise Granger causality for the two cointegrated cases specified above.

Table 11 Pair-wise error-correction-based Granger causality

	Short-run *F*-stat (Prob.)	Long-run *t*-stat on ECT_{t-1} (Prob.)	Joint-strong *F*-stat (Prob.)
Dependent variable: Δln*CEI*			
Independent variables: (with causality running to Δln*CEI*).		−3.0938*** (0.0020)	
ECT_{t-1}			
Δln*OPR*	1.7945 (0.1665)		4.568*** (0.0034)
Δln*HUB*	0.3460 (0.7076)		3.3599** (0.0181)
Δ*GIP*	0.5397 (0.5830)		3.5038** (0.0149)
Δln*CEF*	5.8005*** (0.0031)		3.5672*** (0.0005)
Δln*(CEE)*	178.9*** (0.0000)		303.3*** (0.0000)
Dependent variables: Δln*CEE*			
Independent variables (with causality running to Δln*CEE*).		−4.0874*** (0.0000)	
ECT_{t-1}			
Δln*CEI*	122.2*** (0.0000)		255.80*** (0.0000)

***significant @ 1%, **significant @ 5%, *significant @ 10%

Table 11 presents the types of causalities (short-run, long-run and joint-strong) usually estimated within the framework of ARDL. The results of the three variations of the error-correction-based Granger causality tests in Table 11 show that long-run causality flows jointly and individually from OPR, HUB, GPI, CEF and CEE to CEI. It is also evident from the table that there is a short-run causality running from CEF and CEE to CEI. Thus, apart from CEF and CEE, none of the regressors Granger causes CEI in the short run. Furthermore, there is a causal flow running from CEI back to CEE and this implies bidirectional causality between CEE and CEI in both the short and the long run.

5 Discussion of results

The theoretical framework we have designed and used in this study by integrating energy security elements into the context of NCT, is particularly unique. The framework advocates that oil and natural gas prices, energy efficiency and carbon price individually and jointly explain the substitution between conventional and clean energy sources. Our study particularly argues that this is evident in changes in clean energy stock performance.

We document a significant relationship between oil price and clean energy stock price in both the short run and the long run. In the short run, the stationary oil price at first difference and its first lag are significantly positively related to clean energy stock price. Consistent with NCT, this implies a close substitution between the two variables. As our result fails to establish a causation between them, the substitution in the short run could flow from either energy source. This means that an increase in oil price may lead to a substitution away from oil to clean energy leading to an increase in clean energy stock price. The reverse may hold true with the price increase originating from clean energy stocks. Conversely, however, our long run level model reveals a significant positive relationship between the two variables with no definite causal flow from either variable. This is consistent with the finding reported by Bondia et al. (2016). The possible explanation that could be offered here is that the transition going-on from oil to clean energy sources might be one of the key reasons for the recent crash in oil price. Thus, as clean energy is substituted for oil, it is expected that, on the longer term, the stock performance of clean energy will increase and the price of oil will fall. This result is particularly consistent with the finding documented by Kocaarslan and Soytas (2019), especially in relation to variation in the nature of the relationship from short to long run.

Two measures of natural gas price, namely *HUB* and *GPI*, are used in this study. As the price from Henry Hub market is starkly different from the prices in NBP, TTF and ZEE, we include HUB as a separate gas price in our ARDL model. However, because prices in NBP, TTF and ZEE are highly similar in terms of behaviour and structure, we integrate them to form a simple composite price index (*GIP*). Incidentally, both variables are excluded from the error correction model because they are included in the main ARDL model at 0 lags. Therefore, we only encounter the variables featuring in the long run model with *HUB* exhibiting a significant positive relationship with *CEI*, and *GPI* a significant negative one. No evidence of causality is found in both cases. The positive relationship between *HUB* and *CEI* implies that in the US substitution away from natural gas to clean energy sources takes place over the long run as the price of natural gas increases leading to a better clean energy stocks performance. The reverse may hold true as the price of natural gas in the region falls. However, the significant negative relationship between *GPI* and *CEI* suggests that in Europe moving away from the consumption of natural gas by transitioning over to clean energy sources raises clean energy stock price and lower the prices of natural gas in the three markets. This finding is closely related to the significant positive association between *CEF* and *CEI* discussed in the next paragraph.

Carbon emission futures is cointegrated with *CEI*; it is significantly positively associated with *CEI* in both the short and the long run and is Granger caused by, and in turn, Granger causes *CEI*. This result suggests that progress in attaining environmental sustainability raises the price of carbon emission futures and this in turn propels transition to clean energy sources and a boost in clean energy stock price. We expect that the reverse holds true. This finding is also closely linked to the long run significant negative relationship between clean energy stock price on the one hand, and *OPR* and *GPI*, on the other hand. Thus, *CEF* is one of the major factors that stimulates increases in clean energy stock price which in turn drives down the price of oil as well natural gas prices in the European markets. This finding is inconsistent with the result of insignificant relationship reported by Kumar et al. (2012).

The variable, energy efficiency, is included to play a dual role in this study. Its first role is to proxy for energy efficiency as an important element of energy security. In this regard, *CEE* is significantly positively associated with *CEI* in both the short run and the long run. In addition, the two variables are cointegrated and the causal flow between them is bidirectional. This implies that as an important element of energy security, *CEE* drives substituting clean energy for fossil fuels and in so doing leads to a rise in the price of clean energy stocks. The second role of energy efficiency variable is to serve as a control for the high-level similarity between clean energy stocks and technology companies' stocks. In this regard, and consistent with the previous literature (see, Henrique and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013), the short and the long run positive relationship between *CEE* and *CEI* implies that investors consider clean energy companies as high technology companies, and therefore, treat their stocks as such.

6 Conclusion and policy implications

We develop and use a theoretical framework that integrates concerns for energy security into the context of NCT. Three important elements of energy security (fossil fuel prices, energy efficiency and environmental sustainability) are shown to stir-up substitution between fossil fuels and clean energy sources. The result of this stimulation manifests as changes in the price of clean energy stock. Unlike hydrocarbon energy sources, clean energy sources do not have specific market within which their prices could be ascertained. Therefore, clean energy stock quotations or indices existing within stock markets are the only means through which we may observe the reflection of the changes in clean energy values. Consequently, we use ARDL which accounts for structural breaks to investigate the relationship between the five variables representing the three elements of energy security and clean energy stock price.

Firstly, we document that the five variables representing the three elements of energy security significantly jointly explain variations in clean energy stock price. However, relationships with clean energy stock price at individual level vary across the five variables. Carbon emission future and energy efficiency emerged as the most important elements of energy security which explain variations in clean energy price in both the short and the long run. This implies that individuals, companies and governments take environmental sustainability and energy efficiency very seriously in their pursuit of energy security and the way in which they substitute clean energy for oil and gas or vice versa. Secondly, on the link between oil price and clean energy stock price, the relationship appears positive and explains energy substitution which could be in favour of either energy source. However, this positive relation re-adjusts back to a negative relationship in the long run indicating a significant transition away from oil to clean energy sources. Thirdly, we establish that natural gas prices in the three European market are related with CEI differently compared to the way natural gas price in the US gas market is related with CEI. In the US, a rise in the Henry Hub natural gas price stimulates changes in substitution between natural gas energy and clean energy sources thereby driving changes in the clean energy stock price. However, in Europe, including the UK, it is the transitioning to clean energy sources, induced by progress in environmental sustainability, that drives up the price of clean energy stock price which in turn forces down natural gas prices in NBP, TTF and ZEE markets. The fall in prices in the three markets, in turn, signals a rise in clean energy stock price.

Finally, we end the conclusion by outlining three important implications of our findings. Firstly, our findings suggest that elements of energy security, most especially carbon emission and energy efficiency, are important drivers of the on-going energy transition from conventional to clean energy sources. This means that provision of clean and efficient energy in ensuring the environ- mental well-being of the planet, earth, is considered important both at present and in the future. Secondly, when formulating energy policies which incorporate energy security concerns, governments should carefully consider and stimulate the elements of energy security that are relevant to their respective economies. This is because our study has shown that the variables representing the elements of energy security are important stimulators of the on-going transition to cleaner energy sources. Furthermore, this facilitates the realisation of energy policy objectives; for example, achieving environmental sustainability, encouraging investments in clean energy stocks or hedging against fossil fuel prices volatility. Thirdly, when formulating strategies for the flotation of their stocks in any stock market, clean energy companies should carefully consider the joint and individual effects of oil price, relevant gas prices, carbon price and energy efficiency on clean energy stock prices. For, it is evident that these variables operationalise the behaviour of the key elements of energy security as they affect clean energy stock price. This becomes pertinent with investors' increasing ethical consciousness of the need for corporations to demonstrate sustainable practices and behaviours. This signifies the need for corporations listed on international capital markets to incorporate United Nation's sustainable development goals into their missions and operations.

Notes

1. The themes include availability, infrastructure, prices, societal effect, environment, governance and efficiency (see, Ang, Choong, and Ng 2015).
2. These are indexes whose computations are based on market capitalizations.
3. On this note, McNown, Sam, and Goh (2018, 10) state that 'One of the objectives of this study is to evaluate the performances of the ARDL bounds test when the weakly exogenous regressors assumption is violated. Based on Monte Carlo simulation evidence presented here, it is found that the tests underlying the PSS ARDL bounds testing approach are not affected by the violation of this assumption'.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data used in this paper were obtained from the following sources:

(i) Clean Energy Stock Price (CEI): Daily data on this variable were collected from Nasdaq Global Indexes (NASDAQ OMX Green Economy Family). https://indexes.nasdaqomx.com/Index/History/GRNCLNFO.

(ii) Clean Energy Efficiency (CEE): Daily data on this variable were collected from Nasdaq Global Indexes (NASDAQ OMX Green Economy Family): https://indexes.nasdaqomx.com/Index/History/GRNENEF

(iii) Brent (OPR): Daily data on this variable were collected from investing.com – https://www.investing.com/ commodities/brent-oil-historical-data

(iv) Carbon Emission Futures (CEF): Data obtained from investing.com – https://www.investing.com/ commodities/carbon-emissions-historical-data

(v) Henry Hub Natural Gas price (HHUB): Daily data for HUB price were collected from the US Energy Infor- mation Administration (EIA). https://www.eia.gov/dnav/ng/hist/rngwhhdD.htm

(vi) Gas Price Index (GPI). Daily data on NBP, ZEE and TTF prices were collected from Energy Market Price: https://www.energymarketprice.com/?act=ps&pid=80&prid=4.

(vii) Volume of clean energy stock traded (VTD): Daily data on this variable were collected from Nasdaq Global Indexes (NASDAQ OMX Green Economy Family). https://indexes.nasdaqomx.com/Index/History/ GRNCLNFO.

References

Abdo, H., and Kouhy, R. (2016). "Readings in the UK energy security." *Energy Sources, Part B: Economics, Planning, and Policy, 11*(1): 18-25.

Ang, Beng Wah, Wei Lim Choong, and Tsan Sheng Ng. (2015). "Energy security: Definitions, dimensions and indexes." *Renewable and sustainable energy reviews,* 42: 1077-1093.

Barbier, E. B. (2019). "The concept of natural capital." *Oxford Review of Economic Policy, 35*(1): 14- 36.

Blum, H., and Legey, L. F. (2012). "The challenging economics of energy security: Ensuring energy benefits in support to sustainable development." *Energy Economics, 34*(6): 1982-1989.

Bondia, R., Ghosh, S., and Kanjilal, K. (2016). "International crude oil prices and the stock prices of clean energy and technology companies: evidence from non-linear cointegration tests with unknown structural breaks." *Energy, 101*: 558-565.

Costanza, R., and Daly, H. E. (1992). "Natural capital and sustainable development." *Conservation biology, 6*(1): 37-46.

De Jong, C., and Schneider, S. (2009). "Cointegration between gas and power spot prices." *The Journal of Energy Markets, 2*(3): 27.

Diebold, F. X., and Kilian, L. (2000). "Unit-root tests are useful for selecting forecasting models." *Journal of Business & Economic Statistics, 18*(3): 265-273.

Dutta, A. (2017). "Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index." *Journal of Cleaner Production, 164*: 1157-1166.

Ekins, P., Simon, S., Deutsch, L., Folke, C., and De Groot, R. (2003). "A framework for the practical application of the concepts of critical natural capital and strong sustainability." *Ecological economics, 44*(2-3): 165-185.

Fenichel, E. P., and Hashida, Y. (2019). "Choices and the value of natural capital." *Oxford Review of Economic Policy, 35*(1): 120-137.

Galinis, A., Martišauskas, L., Jääskeläinen, J., Olkkonen, V., Syri, S., Avgerinopoulos, G., and Lekavičius, V. (2020). Implications of carbon price paths on energy security in four Baltic region countries. *Energy Strategy Reviews, 30*: 100509.

Gasser, P. (2020). "A review on energy security indices to compare country performances." *Energy Policy, 139*: 111339.

Hassan, A. (2019a). "Do renewable energy incentive policies improve the performance of energy f irms?" Evidence from OECD countries." *OPEC Energy Review, 43*(2): 168-192.

Hassan, A. (2019b). "Verbal tones in sustainability assurance statements." *Sustainability Accounting, Management and Policy Journal,* 10(3): 427-450.

Henriques, I., and Sadorsky, P. (2008). "Oil prices and the stock prices of alternative energy companies." *Energy Economics, 30*(3): 998-1010.

Kan, S. (2016). "Energy Security in Saudi Arabia: Challenges, Threats and Solutions". PhD thesis. Nottingham Trent University.

Kocaarslan, B., and Soytas, U. (2019). "Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar)." *Energy Economics, 84*: 104502.

Kornafel, M., and Telega, I. (2020). "Dynamics of natural capital in neoclassical growth model." *International Journal of Sustainable Economy, 12*(1): 1-24.

Kumar, S., Managi, S., and Matsuda, A. (2012). "Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis." *Energy Economics, 34*(1): 215-226.

Kyritsis, E., and Serletis, A. (2019). “Oil prices and the renewable energy sector. *The Energy Journal*, *40*(The New Era of Energy Transition).
Lucas, J. N. V., Francés, G. E., and González, E. S. M. (2016). “Energy security and renewable energy deployment in the EU: Liaisons Dangereuses or Virtuous Circle?” *Renewable and sustainable energy reviews*, *62*: 1032-1046.
Managi, S., and Okimoto, T. (2013). “Does the price of oil interact with clean energy prices in the stock market?” *Japan and the World Economy*, *27*: 1-9.
Marques, A. C., Fuinhas, J. A., and Menegaki, A. N. (2016). “Renewable vs non-renewable electricity and the industrial production nexus: Evidence from an ARDL bounds test approach for Greece.” *Renewable energy*, *96*, 645-655.
Matsumoto, K. I., Doumpos, M., and Andriosopoulos, K. (2018). “Historical energy security performance in EU countries.” *Renewable and Sustainable Energy Reviews*, *82*: 1737-1748.
McNown, R., Sam, C. Y., and Goh, S. K. (2018). “Bootstrapping the autoregressive distributed lag test for cointegration.” *Applied Economics*, *50*(13): 1509-1521.
Murthy, V. N., and Okunade, A. A. (2016). “Determinants of US health expenditure: Evidence from autoregressive distributed lag (ARDL) approach to cointegration.” *Economic Modelling*, *59*: 67-73.
Narayan, P. K. (2004). “Fiji's tourism demand: the ARDL approach to cointegration.” *Tourism Economics*, *10*(2): 193-206.
Narayan, P. K., and Smyth, R. (2008). “Energy consumption and real GDP in G7 countries: new evidence from panel cointegration with structural breaks.” *Energy Economics*, *30*(5): 2331-2341.
Odhiambo, N. M. (2007). “Supply-leading versus demand-following hypothesis: Empirical evidence from three SSA countries.” *African Development Review*, *19*(2): 257-280.
Odhiambo, N. M. (2009). “Energy consumption and economic growth nexus in Tanzania: An ARDL bounds testing approach.” *Energy policy*, *37*(2), 617-622.
Pearce, D. (1988). “Economics, equity and sustainable development.” *Futures*, *20*(6): 598-605.
Perron, P., and Vogelsang, T. J. (1992). “Nonstationarity and level shifts with an application to purchasing power parity.” *Journal of business & economic statistics*, *10*(3): 301-320.
Pesaran, M. H., Shin, Y., and Smith, R. J. (2001). “Bounds testing approaches to the analysis of level relationships.” *Journal of applied econometrics*, *16*(3): 289-326.
Pham, L. (2019). “Do all clean energy stocks respond homogeneously to oil price?” *Energy Economics*, *81*: 355-379.
Rahman, M. M., and Kashem, M. A. (2017). “Carbon emissions, energy consumption and industrial growth in Bangladesh: Empirical evidence from ARDL cointegration and Granger causality analysis.” *Energy Policy*, *110*: 600-608.
Reboredo, J. C., and Ugolini, A. (2018). “The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach.” *Energy Economics*, *76*: 136-152.
Sadorsky, P. (2012). “Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies.” *Energy economics*, *34*(1): 248-255.
Shao, L., and Zhang, H. (2020). “The impact of oil price on the clean energy metal prices: A multi-scale perspective.” *Resources Policy*, *68*: 101730.
Solow, R. M. (1974). Intergenerational equity and exhaustible resources. *The review of economic studies*, *41*, 29-45.

Song, Y., Ji, Q., Du, Y. J., and Geng, J. B. (2019). "The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets." *Energy Economics*, *84*, 104564.
Sun, C., Ding, D., Fang, X., Zhang, H., and Li, J. (2019). "How do fossil energy prices affect the stock prices of new energy companies? Evidence from Divisia energy price index in China's market." *Energy*, *169*: 637-645.
Sun, C., Zhang, F., and Xu, M. (2017). "Investigation of pollution haven hypothesis for China: an ARDL approach with breakpoint unit root tests." *Journal of cleaner production*, *161*: 153-164.
Tursoy, T., and Faisal, F. (2018). "The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration." *Resources Policy*, *55*: 49-54.
van Geldrop, J., and Withagen, C. (2000). "Natural capital and sustainability." *Ecological Economics*, *32*(3): 445-455.
Waziri, B. Z., Hassan, A., and Kouhy, R. (2018). "The effect of transitioning to renewable energy consumption on the Nigerian oil and gas exports." *International Journal of Energy Sector Management*, 12(4): 507-524.
Winzer, C. (2012). "Conceptualizing energy security." *Energy policy*, *46*: 36-48.
Xia, T., Ji, Q., Zhang, D., and Han, J. (2019). "Asymmetric and extreme influence of energy price changes on renewable energy stock performance." *Journal of Cleaner Production*, *241*: 118338.
Yergin, D. (2006). "Ensuring energy security." *Foreign affairs*, 69-82.
Zhang, H., Cai, G., and Yang, D. (2020). "The impact of oil price shocks on clean energy stocks: Fresh evidence from multi-scale perspective." *Energy*, *196*: 117099.

Appendices

Appendix 1. Alternative estimation method – Generalised Method of Moments (GMM)

Dependent variable: ln*CEI*
Method: Generalised Method of Moments Date: 10/23/2020 Time: 18:14
Sample (adjusted): 11/11/2010–7/31/2017
Included observations: 1709 after adjustments
Sequential 1-step weighting matrix & coefficient iteration
Estimation weighting matrix: HAC (Bartlett kernel, Newey-West fixed bandwidth = 8.0)Standard errors & covariance computed using estimation weighting matrix
Convergence achieved after 12 iterations
Instrument specification: $\ln CEI_{t-1}$ $\ln OPR_{t-1}$ $\ln HUB_{t-1}$ GPI_{t-1} $\ln CEF_{t-1}$ $\ln CEE_{t-1}$ $\ln VTD_{t-1}$
Constant added to instrument list

Lagged dependent variable & regressors added to instrument list

Lagged dependent variable & regressors added to instrument list

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
ln*OPR*	−0.054983	0.021531	−2.553641	0.0107
ln*HUB*	0.085571	0.019800	4.321819	0.0000
GPI	−0.178193	0.053018	−3.360981	0.0008
ln*CEF*	0.042050	0.008904	4.722398	0.0000

ln*CEE*	1.007477	0.007522	133.9295	0.0000
ln*VTD*	0.000732	0.000376	1.945307	0.0519
AR(1)	0.960418	0.006915	138.8973	0.0000
R-squared	0.998748	Mean dependent var		6.957266
Adjusted *R*-squared	0.998743	S.D. dependent var		0.143714
S.E. of regression	0.005095	Sum squared resid		0.044177
Durbin-Watson stat	2.238261	*J*-statistic		4.318795
Instrument rank	8	Prob(*J*-statistic)		0.037694
Inverted AR Roots		0.96		

We estimate the GMM model to further check the robustness of our ARDL long-run results and the models are highly similar in terms of signs and significance.