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The impact of oil price and COVID-19 pandemic on clean energy stocks: an empirical approach using ARDL

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Abstract

Purpose – Over the last decade, investments in green energy companies have witnessed noticeable growth rates. However, the glacial pace of the world economic restoration due to COVID-19 pandemic placed a high degree of uncertainty over this market. Therefore, this study investigates the short- and long-term relationships between COVID-19 new cases and WilderHill New Energy Global Innovation Index (NEX) using daily data over the period from January 23, 2020 to February 1, 2023.

Design/methodology/approach – The authors utilize an autoregressive distributed lag bounds testing estimation technique.

Findings – The results show a significant positive impact of COVID-19 new cases on the returns of NEX index in the short run, whereas it has a significant negative impact in the long run. It is also found that the S&P Global Clean Energy Index has a significant positive impact on the returns of NEX index. Although oil has an influential effect on stock returns, the results show insignificant impact.

Practical implications – Governments have the chance to flip this trend by including investment in green energy in their economic growth stimulation policies. Governments should highlight the fundamental advantages of investing in this type of energy such as creating job vacancies while reducing emissions and promoting innovation.

Originality/value – First, as far as the authors are aware, the authors are the first to examine the effect of oil prices on clean energy stocks during COVID-19. Second, the authors contribute to studies on the relationship between oil prices and renewable energy. Third, the authors add to the emerging strand of literature on the impact of COVID-19 on various sectors of the economy. Fourth, the findings of the paper can add to the growing literature on sustainable development goals, in specific the papers related to energy sustainability.

Keywords Renewable energy, Corporate sustainability, COVID-19, ADRL, WilderHill New Energy Global Innovation Index

Paper type Research paper

1. Introduction

On March 11, 2020, the World Health Organization (WHO) announced that coronavirus (COVID-19) had become a pandemic. Initially, when the novel virus originated in China in December 2019, it was not anticipated to become so quickly widespread across the globe, disrupting almost all sectors of the economy. Experts indicate that this health crisis has had a subordinate effect equivalent to that of the Second World War. The accompanying decline in

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oil prices has made the effect of the pandemic even worse. The oil price crash was driven from both demand and supply sides. It was initiated by the price war between Saudi Arabia and Russia, followed by the decrease in demand due to lockdowns and production disruptions, as well as the shortage and expense of storage spaces. There has been a drop in the demand for oil by about one-third, which is about 30 million barrels per day, due to the pandemic (Nawaz, 2020). Brent oil's price dropped from \$68.9 on January 6, 2020 to \$25.57 by the end of April 2020. The decline in crude Brent oil has been lower than that in West Texas Intermediate (WTI), due to its storage and transportation means, as it can be transported through pipelines and stored using floating storage. Meanwhile, WTI witnessed a large daily drop in US crude of about 30% on April 20, 2020, mainly due to the storage spaces reaching maximum capacity. The pandemic has ended the longest US bull cycle in history (Nawaz, 2020). On the other side, there have been significant initiatives worldwide toward an alternative source to oil, namely renewable energy.

This paper investigates the long-run and short-run impacts of daily new cases of COVID-19 and the oil price return on the WilderHill New Energy Global Innovation Index (NEX) and the Morgan Stanley Capital International world index using data over the period from January 23, 2020 to February 1, 2023. The importance of renewable energy has increased with the sustainable development goals (SDGs) agenda of the United Nations which involves the emphasis on this issue in SDG 7. Countries across the globe have started to get committed to increase the share of renewables in the global energy consumption by the end of 2030. Based on the International Renewable Energy Agency report, global renewable energy capacity increased by 176 GW in 2019. Wind and solar energies represent the main contributors, making up about 90% of the increase in the use of renewables (Hosseini, 2020). Crude oil and renewables tend to be substitutes when the volatility in crude oil increases, the demand shifts to renewables (Kyritsis & Serletis, 2019). However, there are several concerns at present, as 70% of the newly installed wind capacity in 2019 was in countries such as China, the US, the UK, India and Spain that have been suffering badly from COVID-19. One of the issues brought up by COVID-19 is whether it has affected the components of sustainability such as transitions to clean energy. This study investigates the short- and long-term relationships between COVID-19 new cases and WilderHill New Energy Global Innovation Index (NEX) using daily data over the period from January 23, 2020 to February 1, 2023.

One of the apparent effects of the pandemic has been the spillover to the financial markets, which reflects the conditions of the economy. A decline in stock markets worldwide has been documented. However, the level of decline depends on the stage of the pandemic in that market (Ashraf, 2020). For instance, the S&P 500 declined by 13%, the FTSE 100 by 24% and the NIKKEI by 15% during the period from the beginning of January to the beginning of May 2020 (GCC-STAT, 2020).

We utilize autoregressive distributed lag (ARDL) bounds testing estimation technique, Gregory and Hansen's (1996) cointegration test and nonlinear ARDL approach to capture the short-run and long-run relationships between clean energy investment and oil price movements due to the COVID-19 outbreak. The findings of the bound tests and the Gregory–Hansen test indicate that all the variables are cointegrated in the long run. The findings show a significant positive impact of COVID-19 new cases on the returns of NEX index in the short run, whereas it has a significant negative impact in the long run. The positive impact in the short run can be justified by the role of the investors' recognition of clean energy as an alternative source of investment to escape the nongreen stocks which are reflected in the NEX, which features companies that direct their innovative technologies toward the utilization of clean and low-carbon energy. Whereas, the negative impact of COVID-19 new cases on the returns of NEX index in the long run might be due to the disruption in global supply chain which causes a drop in the clean energy investments. It is also found that the S&P Global Clean Energy Index (SPGCE) has a significant positive impact on the returns of NEX index.

Our paper contributes to existing literature in several ways. First, as far as we are aware, we are the first to examine the effect of oil prices on clean energy stocks during COVID-19. Second, we contribute to studies on the relationship between oil prices and renewable energy (Kyritsis & Serletis, 2019; Albuquerque, Koskinen, & Zhang, 2019, Albuquerque, Koskinen, Yang, & Zhang, 2020). Third, we add to the emerging strand of literature on the impact of COVID-19 on various sectors of the economy (Topcu & Gulal, 2020; Zhang, Hu, & Ji, 2020; Ashraf, 2020; Ozili & Arun, 2020). Fourth, the findings of the paper can add to the growing literature on SDGs, in specific the papers related to energy sustainability such as Murshed and Tanha (2021) and Murshed, Khan, and Rahman (2022).

The rest of the paper proceeds as follows. We review the literature in Section 2. We discuss our data in Section 3. We explain our methodology in Section 4. We present and discuss our results in Section 5. We conclude in Section 6.

2. Literature review

Theoretically, there are no models to explain the relationship between the prices of oil and clean energy stocks. However, many empirical studies have been conducted to test this relationship. The first to study the relationship were Henriques and Sadorsky (2008). Using a vector autoregressive (VAR) model, they show that the variations in the prices of clean energy stocks are positively and significantly affected by shocks in technology. However, oil price shocks do not have any statistically significant effect on the stock prices of alternative energy companies. Similar results are found by Sadorsky (2012), who estimates a set of GARCH (Generalized auroregressive conditional heteroskedasticity) models to analyze the volatility spillovers between oil prices and prices of clean energy and technology stocks. The author finds that prices of clean energy stocks correlate more highly with technology stock prices than with oil prices. In contrast, using a similar approach to that used by Henriques and Sadorsky (2008) to analyze the data from three clean energy indices, Kumar, Managi, and Matsuda (2012) find that the fluctuations in clean energy stock prices are captured by past movements in oil prices. In a similar study, Managi and Okimoto (2013) extend the study of Henriques and Sadorsky (2008) into the Markov-switching framework. They demonstrate a significant and positive effect of oil prices on clean energy stock prices after a structural break in late 2007.

Broadstock, Cao, and Zhang (2012) consider the application of time-varying conditional correlation and asset pricing models to examine the effect of international oil prices on the returns of clean energy stocks in China. Considering the structural instability, the study shows a stronger relation following the 2008 financial crisis, indicating that investors in the Chinese stock market, especially in energy-related stocks, become more sensitive to the shocks in the international crude oil market after the crisis.

Bondia, Ghosh, and Kanjilal (2016) use a cointegration model to investigate the relationship between oil and renewable energy stock prices in the long term. They find that clean energy stock prices are influenced by oil prices in the short run, but not in the long run. However, Reboredo, Rivera-Castro, and Ugolini (2017) use wavelet analysis and show that the linkages are weak in the short run but become stronger in the long run. Recently, Fu, Chen, Sharif, and Razi (2022) investigate the relationship between clean energy stock, financial stress and price volatility of oil, natural gas and gold. The empirical results of the study show that clean energy stock performance is significantly negatively impacted by oil and gold prices, both in the short and long terms. In contrast, clean energy stock performance is positively impacted by natural gas only in the long term, with no discernible short-term effects. The effect of the stock markets for renewable energy on the markets for oil, coal and gas is also examined by Jiang, Wang, Lie, and Mo (2021). Their findings show a general positive dependency, to variable degrees, across different quantiles and the various types of fuels. Their reliance appears to be weak in the gas market, but is rather strong when the oil and coal markets are bullish or bearish.

He *et al.* (2021) examine the effect of the returns on clean energy stocks on the price of gold and oil in the US and European economies. The results over the long-term show that renewable energy stocks in the US and Europe are favorably impacted by oil price variations in higher and extremely higher quantiles (when the market is bullish). This positive relationship, however, is found across all quantiles over the short term. Furthermore, Yahya, Kanjilal, Dutta, Salah Uddin, and Ghosh (2021) analyze the levels, means and error variances of the nonlinear price transmission mechanisms between the clean energy stock and the price of crude oil. The results show a nonlinear price transmission channel between the two asset classes. They also find that the clean energy index emerges as the primary factor influencing the price of crude oil.

Kocaarslan and Soytas (2019) examine whether the oil price to clean energy stock price relationship is asymmetric or not. Using a nonlinear autoregressive distributed lag (NARDL) model, they find significant asymmetric effects among the variables of interest. They also suggest that the effects of changes in the oil prices on clean energy stock prices fluctuate considerably in the short and long run. More specifically, they show 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. However, in the long run, the increased oil price has a negative effect on clean energy stock prices and this effect is asymmetric.

Ahmad (2017) investigates the directional spillover between crude oil prices and stock prices of technology and clean energy companies and finds that technology stocks can explain the return and volatility spillovers of renewable energy stocks and crude oil prices. Furthermore, the study shows that technology and clean energy indices are the dominant emitters of return and volatility spillovers to the crude oil prices.

Dutta (2017) builds on the relationship between oil prices and alternative energy stock prices by assessing whether the crude oil volatility index (OVX) plays a role in explaining the variance of alternative energy stock returns. In doing so, the author uses the information content of the OVX, an indicator of oil price uncertainty, and finds that clean energy stock returns are highly sensitive to OVX shocks.

Pham (2019) contributes to the knowledge of the oil price to clean energy stock price relationship by examining it across different sub-sectors of the clean energy market and finds that the relationship varies largely across these sub-sectors. The study also shows that oil is a good hedging instrument for the clean energy sectors when making international portfolios.

Kyritsis and Serletis (2019) adopt a bivariate structural VAR model, modified to accommodate GARCH-in-mean errors, to study the effects of oil price shocks, as well as those of uncertainty about oil prices, on the returns of clean energy stocks. They find that oil price uncertainty has no statistically significant effect on stock returns, and that the relationship between oil prices and stock returns is symmetric. In a recent study, however, Dawar, Dutta, Bouri, and Saeed (2021) provide strong evidence of the declining dependence of clean energy stock returns on crude oil returns using weekly data covering crude oil prices (WTI market) and three clean energy stock indices (the WilderHill Energy Index, MAC Global Solar Energy Index and SPGCE). They further examine the asymmetrical impacts of oil returns on clean energy stock returns under various market conditions, and they show that negative oil returns have a big impact during bearish episodes but little impact during bullish ones.

To address the impacts of different exogenous oil price structural shocks on clean energy stocks, Zhang, Cai, and Yang (2020) apply wavelet-based quantile-on-quantile and Granger causality-in-quantiles methods and show that the effects of different exogenous oil price structural shocks on clean energy stocks vary across quantiles and investment horizons. More specifically, the impacts of oil supply shocks on clean energy in the short term and long term are strong. In addition, in the middle term, the impacts of the aggregate oil demand shock are relatively positive in the higher and lower quantiles of clean energy stocks. In the long run, the impact of the oil-specific demand shock on stocks is asymmetric in higher quantiles of clean energy stocks.

Based on the nonparametric causality-in-quantiles test, Hammoudeh, Mokni, Ben-Salha, and Ajmi (2021) investigate the relationships between the returns and volatility of oil prices and five clean energy stock indexes. The results show that during normal market conditions, oil returns drive renewable stock index returns, but this is not the case during severe market conditions. Furthermore, under all market conditions, none of the five renewable energy stock returns have any predictive power for oil returns. Moreover, the results imply that there were no meaningful causal relationships between the oil price and the stocks of renewable energy during the COVID-19 epidemic period. The causal association prior to COVID-19, nevertheless, was close to what was reported for the whole time.

Recently, using Granger predictability in distribution and quantile impulse response analysis, Çevik *et al.* (2023) examine the relationship between clean energy stock and oil market returns. The findings show that the predictions of the clean energy stock returns for the oil prices depend on the market conditions, i.e. whether the market is bullish or bearish. Our paper differs from Çevik *et al.* (2023) as we focus only on the COVID-19 era and we utilize different methodology. More specifically, we utilize ARDL bounds testing to investigate the short- and long-term relationships between COVID-19 new cases and WilderHill New Energy Global Innovation Index (NEX).

3. Data

This paper employs daily closing prices of WilderHill New Energy Global Innovation Index (NEX) over the period from January 23 to February 1, 2023. NEX is the first and leading global index for clean, alternative and renewable energy. It comprises companies from all over the world which aim their innovative technologies at the production and use of cleaner energy, conservation, effectiveness and improving renewable energy in general. Moreover, it includes companies which apply low-carbon methods that aim at climate change alleviation and reducing emissions compared to fossil fuel use (Henriques & Sadorsky, 2008).

The SPGCE is also used. SPGCE consists of 100 global clean energy-related businesses from developed and emerging markets. It aims to track companies that focus on producing energy from different renewable sources such as wind, solar, hydro and biomass sources as well as companies that provide clean technology.

The change in oil prices has a large impact on the cost of producing goods or providing services as it has no direct substitute as a factor of production. Therefore, the increase in oil prices might negatively affect cash flow and accordingly harm the stock market performance. When zooming at the renewable energy stock prices, it is expected to have a direct relationship with the oil market as rising oil prices may stimulate investors toward investment in other nonfossil-based energy sources. This paper examines the impact of oil price on the renewable energy sector using the nearest WTI crude oil futures contract.

In the eras of high financial market uncertainties such as the one created by COVID-19 pandemic, investors' risk aversion increases as they become more concerned about any incurred investment losses (Cui *et al.*, 2023). To measure the intensity of COVID-19 pandemic, the number of global new cases is used.

Several studies have proved the significant impact of the short-term interest rate on stock price movements, including Sadorsky (2001) andKumar, Managi, and Matsuda (2012). Therefore, this paper employs the yield on three-month US treasury bills.

For all the prices and indices, the logarithmic returns are calculated as $100 \times \ln(P_t/P_{t-1})$. The stock market indices are exported from Yahoo Finance, the oil price futures contracts are extracted from the Energy Information Administration and the number of new cases of COVID-19 are obtained from the WHO.

Table 1 shows the descriptive statistics of all the variables. In Table 2, the correlation matrix was calculated for the dependent and independent factors used in the model. It can be

Variable	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
WTI ($ per barrel)	63.128	23.632	−37.630	123.700	0.420	3.165
NEX (US dollar)	368.911	100.975	155.910	626.130	0.214	2.530
SPGCE (US dollar)	1653.967	396.998	675.315	2720.790	−0.340	3.276
NCOVID19 (case)	885109.8	1011530	100	1.11e+07	4.213	30.584
INT (%)	0.909	1.416	−0.046	4.695	1.558	3.972

Note(s): This table shows the descriptive statistics of all the variables. WTI is the West Texas Intermediate crude oil futures contract. NEX is the WilderHill New Energy Global Innovation Index. SPGCE is the S&P Global Clean Energy Index. NCOVID19 is the global new cases of COVID-19. INT is the three-month treasury yield
Source(s): Table by authors

Table 1.
Descriptive statistics

	NEX	WTI	SPGCE	NCOVID19	INT
NEX	1				
WTI	−0.4256	1			
SPGCE	0.9273	−0.5617	1		
NCOVID19	0.1671	−0.4415	0.2064	1	
INT	−0.3368	0.1355	−0.0031	−0.0669	1

Note(s): This table reports the correlation coefficients between the variables. NEX is the natural logarithm of the WilderHill New Energy Global Innovation Index. WTI is the natural logarithm of the West Texas Intermediate crude oil futures contract. SPGCE is the natural logarithm of the S&P Global Clean Energy Index. NCOVID19 is the natural logarithm of the global new cases of COVID-19. INT is the natural logarithm of the three-month treasury yield
Source(s): Table by authors

Table 2.
Correlation matrix

noticed that there is a high correlation between the dependent variable NEX and the independent variable SPGCE with correlation coefficient of 0.9273. This shows that the movement in NEX is highly explained by this factor. The multicollinearity issue between the other independent variables (WTI, SPGCE) can be controlled by applying the ARDL model (Al-Mulali, Solarin, & Ozturk, 2016). Figure 1 shows line graphs of all the variables.

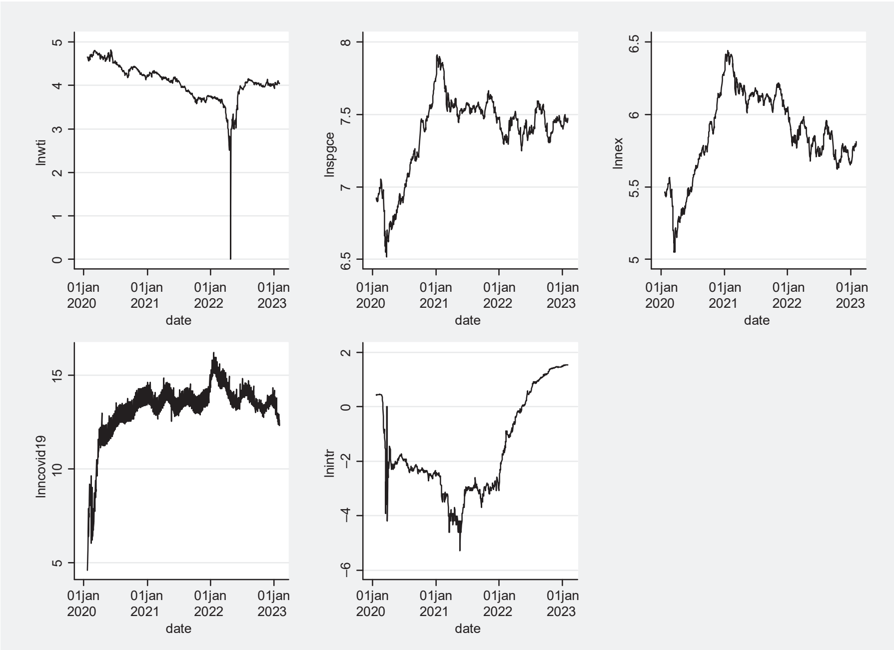
4. Model and methodology

4.1 ARDL model

To test for the existence of a long-run relationship among the suggested time series variables, the literature suggests several methods, including Engle and Granger (1987), Phillips and Hansen (1990), Johansen (1988, 1991) and Johansen and Juselius (1990) tests. However, all these methods require the use of variables from the same integration level, i.e. I(1). To overcome this problem, Pesaran (1997) established a rigorous approach named the ARDL model, which moves from the general to the specific and uses a sufficient number of lags that aim to capture the specifications of the data generation process. This approach can include variables that are integrated of different levels, either I (0) or I(1), or even fractionally cointegrated.

Since the aim of this study is to examine the short- and long-run relationships between clean energy investment and oil price movements due to COVID-19 outbreak, the natural log model can be presented as follows:

$$ln(NEX)_t = \mu_0 + \mu_1\, ln(COVID19)_t + \mu_2\, lnWTI_t + \mu_3\, ln\, SPGCE + \mu_4\, lnINT_t + \varepsilon_t \quad (1)$$



Source(s): Figure by authors

Figure 1. Line graph of the variables

where ε_t is the regression error term and the intercept of the model is given by μ_0. The coefficients $\mu_1, \mu_2\mu_3, and\ \mu_4$ represent, respectively, the impacts of new COVID-19 cases, fluctuations in the crude oil prices (WTI), the SPGCE and the interest rate (INT) on WilderHill new energy global innovation stocks (NEX). Looking at the endogeneity problem, ARDL is mostly free of residual correlation, which not only minimizes the problem of endogeneity but also removes the problems associated with serial correlation as claimed by Pesaran and Shin (1998). In addition, the ECM (Error correction model) that aims to capture both short- and long-term equilibrium features can be derived from the ARDL by a simple linear transformation.

4.2 Methodology

To check the integration level of all the variables, Dickey and Fuller (1979), Phillips and Perron (1988) and Zivot and Andrews (2002) unit root tests are employed. After the level of integration of the suggested variables has been confirmed, ARDL bound testing is applied to confirm the existence of a long-run relationship among the variables. This can be done by comparing the critical values of F-statistics with the calculated F-value. Ouattara (2004) reports that the bounds test is based on the assumption that the variables are I(0) or I(1) so, in the presence of I(2) variables, the computed F-statistics provided by Pesaran, Shin, and Smith (2001) become invalid. In addition, Tursoy and Faisal (2018) note that, although the model can include variables with different integration levels, the dependent variable in the model should be I (1). Similarly, other diagnostic tests are applied to detect serial correlation, heteroscedasticity and conflict to normality. If the calculated value of the F-statistic is more than the upper limit of the critical values, the null hypothesis of no cointegration is rejected. Otherwise, the null hypothesis cannot be rejected if the F-statistic value is below the critical lower bound. Accordingly, the F-test for joint significance can be represented by H0: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = 0$ in Equation (1), while the alternative is that at least one μ is not equal to 0. Moreover, Gregory and Hansen's (1996) test is used to check for the cointegration with regime shifts.

Once a cointegration relationship has been established, the above equation is estimated to capture the long-run dynamics, and the optimal lag length for each case is selected using the Akaiki information criterion (AIC). The estimated value of μ_0 measures the long-run effect on investment in new energy global innovation (NEX) in the suggested model. Once the above equation has been estimated, the residuals can be used as an approximation of the error correction term (ECT), which indicates the speed of adjustment, that is, how quickly the variables return to the long-run equilibrium after a shock. The ECM is formulated as follows:

$$\Delta In(NEX)_t = \delta_0 + \sum_{h=1}^{n} \delta_{1h}\Delta In(NEX)_{t-1} + \sum_{i=1}^{n} \delta_{1i}\Delta InCOVID19_{t-i} + \sum_{k=0}^{q} \delta_{1k}\Delta InWTI_{t-k} + \sum_{j=0}^{d} \delta_{2j}\Delta lnSPGCE_{t-j} + \sum_{l=0}^{b} \delta_{3l}\Delta InINT_{t-l} + \theta ECT + \varepsilon_t \tag{2}$$

In addition to ARDL estimation technique, NARDL that is proposed by Shin, Yu, and Greenwood-Nimmo (2014) is used as a robustness check as it reports the long-run and short-run asymmetries.

5. Results and discussion

Table 3 shows the results of the unit root tests of all the variables. The variables are tested at level and first difference to check their level of integration. All the variables become stationary when first differenced, i.e. I (1), except for the oil price series (WTI) and the new cases of COVID-19 (NCOVID19) which are stationary at level, i.e. I (0).

We proceed with the bound test to investigate whether or not a long-run relationship exists among WilderHill new energy global innovation, oil price, global new cases of COVID-19, S&P global clean energy and the interest rate. Table 4 reports the results of the Pesaran, Shin, and Smith (2001) cointegration test.

The optimum lag length, selected based on the AIC, is shown in the second row of Table 4. More importantly, the calculated F-statistic (5.395) exceeds the upper limit of the critical

Table 3. Unit root test results

Variable	Levels ADF	Levels PP	Levels Zivot–Andrews	Returns ADF	Returns PP	Returns Zivot–Andrews
WTI	−4.826***	−3.400**	−6.101*** (1)	−41.747***	−52.044***	−19.105*** (1)
SPGCE	−1.731	−1.802	−3.353 (1)	−24.933***	−25.024***	−12.210*** (1)
NEX	−1.494	−1.609	−3.058 (1)	−23.181***	−23.306***	−11.901*** (1)
NCOVID19	−7.449***	−6.561**	−4.408 (1)	−46.615***	−64.625***	−13.351*** (1)
INTR	−1.747	−0.810	−4.276 (1)	−32.217***	−37.859***	−15.474*** (1)

Note(s): This table reports the results of unit root tests for all the variables. WTI is the natural logarithm of the West Texas Intermediate crude oil futures contract. NEX is the natural logarithm of the WilderHill New Energy Global Innovation Index. SPGCE is the natural logarithm of the S&P Global Clean Energy Index. NCOVID19 is the natural logarithm of the global new cases of COVID-19. INT is the natural logarithm of the three-month treasury yield. ADF represents the Augmented Dickey and Fuller (1979), PP the Phillips and Perron (1988) and Zivot and Andrews' (2002) unit root tests. *** and ** indicate statistical significance of 1 and 5%, respectively
Source(s): Table by authors

Model	NEX = f (NCOVID19, WTI, SPGCE, INT)					
Optimal lag length (AIC)	(4, 1, 0, 1, 0)					
F-statistic (bound test)	5.395*					
	10%		5%		1%	
Critical *F*-value	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
	2.45	3.52	2.86	4.01	3.25	5.06

Gregory and Hansen's test for cointegration with regime shifts

	Test statistics	Breakpoint	Date	Asymptotic critical values 1%	5%	10%
ADF	−5.61**	619	619	−6.05	−5.56	−5.31
Zt	−6.30***	137	137	−6.05	−5.56	−5.31
Za	−97.16***	137	137	−70.18	−59.40	−54.38

Note(s): This table reports the results of the cointegration test. NEX, which is the natural logarithm of the WilderHill New Energy Global Innovation Index, is regressed on the natural logarithm of the global new cases of COVID-19 (NCOVID19), the natural logarithm of the West Texas Intermediate crude oil price (WTI), the natural logarithm of the S&P Global Clean Energy Index (SPGCE) and the three-month treasury yield (INT). * represents significance at 1%. The lag length is selected using the Akaike Information Criteria (AIC). To compare the statistics of the F-values, lower and upper limits, I (0) and I (1), of Pesaran *et al.* (2001) critical values, are used
Source(s): Table by authors

Table 4. Cointegration results (1)

values and thus prompts a rejection of the null hypothesis of no cointegration. Accordingly, WilderHill new energy global innovation index, oil price, global new cases of COVID-19, the SPGCE and the interest rate are revealed to move together in the long term. Moreover, the results of Gregory and Hansen's (1996) test for cointegration with regime shifts show that the variables are cointegrated. The results are shown in the lower part of Table 4.

Table 5 shows the results for both the short- and long-run coefficients. The upper section of the table shows that the interest rate and new COVID-19 cases have negative impact on WilderHill new energy global innovation index in the long run. The negative impact of COVID-19 cases might be due to the disruption in global supply chain which causes a drop in the clean energy investments (Eroğlu, 2021). Selmi, Bouoiyour, Hammoudeh, Errami, and Wohar (2021) state that shutting down government offices and energy agencies to contain the spread of COVID-19 caused a delay in the accomplishment of renewable energy projects. One of the International Energy Agency IEA reports states that the world energy investments are expected to increase. However, this upward trend is hit by number of barriers including high borrowing costs, flat household incomes and lower business confidence [1]. The negative effect of the three-month interest rate yield is in line with that of Henriques and Sadorsky (2008) who found a negative and significant impact on the stock prices of alternative energy companies. Surprisingly, the oil price returns have no significant impact on WilderHill new energy global innovation index which is going in line with the results of Inchauspe, Ripple, and Trück (2015) who found that the impact of oil price returns is significantly lower despite its effective effect since 2007. Regarding the impact of S&P clean energy on WilderHill new energy global innovation index, the results show a highly significant positive effect. This result matches that of Sadorsky (2012), Managi and Okimoto (2013) and Henriques and Sadorsky (2008). This suggests that the investors consider the high performance in clean energy as an indicator of a good performance in the innovative technologies that focus on clean energy, renewables and efficiency.

$NEX = f\,(NCOVID19, WTI, SPGCE, INT)$	Variable	Coefficient	Std. Error
Long-run estimates	$NCOVID_t$	−0.017**	0.007
	WTI_t	0.005	0.022
	$SPGCE_t$	0.998***	0.033
	INT_t	−0.058***	0.004
Short-run estimates	ΔNEX_{t-1}	0.081***	0.013
	ΔNEX_{t-2}	−0.012	0.013
	ΔNEX_{t-2}	0.028**	0.013
	$\Delta NCOVID_t$	0.001**	0.0004
	$\Delta SPGCE_t$	0.851***	0.014
	Constant	−0.054***	0.013
	ECT_{t-1}	−0.039***	0.008

Note(s): This table reports the results obtained from the ARDL estimation. NEX, which is the natural logarithm of the WilderHill New Energy Global Innovation Index, is regressed on the natural logarithm of global new cases of COVID-19 (NCOVID19), the natural logarithm of the West Texas Intermediate crude oil price (WTI), the natural logarithm of the S&P Global Clean Energy Index (SPGCE) and the three-month treasury yield (INT). *, ** and *** represent the 10, 5 and 1% levels of significance, respectively
Source(s): Table by authors

Table 5.
ARDL results (1)

Looking at the lower section of Table 5 which presents the short-run results, the estimated coefficients of the lagged returns of NEX have a positive impact on the contemporaneous returns. In addition, the returns of the SPGCE have the same impact on NEX in the short run. On the contrary to its impact in the long run, the change in COVID-19 cases has a positive impact on the returns of WilderHill new energy global innovation index in the short run. This result is in line with that of Wan, Xue, Linnenluecke, Tian, and Shan (2021) who found a positive impact of the pandemic on the clean energy stocks. They justified their results by highlighting the role of the investors' recognition of clean energy as an alternative source of investment. Another explanation is presented by Albuquerque, Koskinen, Yang, and Zhang (2020), who find that firms with high environmental and social ratings earned an extra daily return of 0.45% in the period from February 24 to March 17, 2020 compared to those with low environmental and social ratings. Albuquerque, Koskinen, and Zhang (2019) present a model for firms that invest in environmental and social policies as a strategy to differentiate their products. They conclude that this investment leads to higher customer loyalty and lower price elasticity for their products.

The last row of Table 5 shows the ECT that appears to be negative (as expected) and statistically significant at 1% level. It demonstrates that, if there is any deviation in the model, the short-run variation will be adjusted by 3.9% within the first year.

Since ARDL assumptions are built on residuals' independency and normality, the estimation has been followed by several diagnostic tests that aim at examining the residual against the autocorrelation and heteroscedasticity. Model specification is also investigated. To do so, tests of Durbin–Watson and Breusch–Godfrey for autocorrelation in residuals are applied, while the heteroskedasticity is examined by applying the Lagrange multiplier test for autoregressive conditional heteroscedasticity (ARCH). In addition, Ramsey's RESET test has been used to investigate if there is any misspecification in the model.

Table 6 shows that the estimated model explains 88% of the variation in NEX. In addition, it reports the results obtained from using Breusch–Godfrey test that aims at testing the presence of serial correlation in the model. As the p-value of Breusch–Godfrey test (0.8709) is more than the significance level of 0.05, there is no evidence of serial correlation in the model. With respect to Ramsey's RESET test which examines the existence of any misspecification in the model, it is clear that the model is properly specified because the p-value (0.2452) is more than the significance level (5%). In another word, the results obtained from all the diagnostic tests prove that there is no serial correlation in the residuals. Moreover, the variance of the errors is constant (homoscedastic).

In order to check the robustness of the obtained results, the same model is estimated without including the oil price returns. The cointegration results, ARDL results and the diagnostic tests are shown in Tables 7–9, respectively. The results obtained using this model are the same as that obtained when including oil price returns.

Another way to check the robustness of the results is done using the NARDL estimation approach (Shin *et al.*, 2014). Table 10 shows the results of the NARDL estimation. The obtained results are comparable with the ARDL bound test approach. The middle part of the table shows the long-run increasing and decreasing effects of the variables on the return of NEX index. When the SPGCE increases by 1%, NEX index increases by 1.059% and when the SPGCE decreases by 1%, NEX index decreases by 1.040%. When the three months yield (INT) increases by 1%, NEX index decreases by 0.035% whereas when INT decreases by 1%, NEX index increases by 0.040%. However, the overall results show no asymmetry effect in the long run or in the short run. This can be seen in the third part of Table 10 which shows F-statistics of the long-run and short-run asymmetry effects. Figure 2 shows the cumulative impact of all the variables on NEX index.

6. Conclusion

The beginning of the year 2020 was a remarkable period for the stock markets. It started with steady prices for the world stock market, followed by a sharp drop in prices as the Dow Jones

Test	Coefficient	Results
R^2	0.8838	
Adjusted R^2	0.8822	
Durbin–Watson statistics	2.0088	No first-order autocorrelation
Heteroscedasticity Test: ARCH	2.373 (0.1234)	No problem in heteroscedasticity
Breusch–Godfrey Serial Correlation LM Test	0.026 (0.8709)	No serial correlation
Ramsey RESET test	1.39 (0.2452)	Model has no omitted variables

Source(s): Table by authors

Table 6. Diagnostic tests

Model	NEX = f (NCOVID19, SPGCE, INT)					
Optimal lag length (AIC)	(4, 1, 1, 1, 0)					
F-statistic (bound test)	6.738*					
	10%		5%		1%	
Critical F-value	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
	2.72	3.77	3.23	4.35	4.29	5.61

Note(s): This table reports the results of the cointegration test. NEX, which is the natural logarithm of the WilderHill New Energy Global Innovation Index, is regressed on the natural logarithm of the global new cases of COVID-19 (NCOVID19), the natural logarithm of the S&P Global Clean Energy Index (SPGCE) and the three-month treasury yield. * represents significance at 1%. The lag length is selected using the Akaike Information Criteria (AIC). To compare the statistics of the F-values, lower and upper limits, I (0) and I (1), of Pesaran *et al.* (2001) critical values, are used
Source(s): Table by authors

Table 7. Cointegration results (2)

$NEX = f(NCOVID19, SPGCE, INT)$	Variable	Coefficient	Std. Error
Long-run estimates	$NCOVID_t$	−0.018**	0.008
	$SPGCE_t$	0.997***	0.032
	INT_t	−0.058***	0.004
Short-run estimates	ΔNEX_{t-1}	0.081***	0.013
	ΔNEX_{t-2}	−0.011	0.013
	ΔNEX_{t-2}	0.028**	0.013
	$\Delta NCOVID_t$	0.001**	0.0004
	$\Delta SPGCE_t$	0.851***	0.014
	Constant	−0.054***	0.013
	ECT_{t-1}	−0.040***	0.008

Note(s): This table reports the results obtained from the ARDL estimation. NEX, which is the natural logarithm of the WilderHill New Energy Global Innovation Index, is regressed on the natural logarithm of global new cases of COVID-19 (NCOVID19), the natural logarithm of the S&P Global Clean Energy Index (SPGCE) and the three-month treasury yield. *, ** and *** represent the 10, 5 and 1% levels of significance, respectively
Source(s): Table by authors

Table 8.
ARDL results (2)

Test	Coefficient	Results
R^2	0.8838	
Adjusted R^2	0.8824	
Durbin–Watson statistics	2.0086	No first-order autocorrelation
Heteroscedasticity Test: ARCH	2.403 (0.1211)	No problem in heteroscedasticity
Breusch–Godfrey Serial Correlation LM Test	0.025 (0.8733)	No serial correlation
Ramsey RESET test	1.40 (0.2430)	Model has no omitted variables

Source(s): Table by authors

Table 9.
Diagnostic tests

Industrial Average had its biggest one-day point decline in history on March 15, 2020. This sharp drop in prices was the result of investors' concern about the spread of the coronavirus in the US. This paper employs this episode to examine the long-run and short-run impacts of daily new COVID-19 cases and the oil price return on the WilderHill New Energy Global Innovation Index (NEX). This is done using daily data from January 23, 2020 to February 1, 2023 with the employment of ARDL bounds testing estimation technique, Gregory and Hansen's (1996) cointegration test and nonlinear ARDL approach.

The results of both, the bound tests and Gregory–Hansen test show that all the variables are cointegrated in the long run. The findings show a significant positive impact of COVID-19 new cases on the returns of NEX index in the short run, whereas it has a significant negative impact in the long run. On one hand, the positive impact in the short run can be justified by the role of the investors' recognition of clean energy as an alternative source of investment to escape the nongreen stocks. This is reflected in the NEX, which features companies that direct their innovative technologies toward the utilization of clean and low-carbon energy. On the other hand, the negative impact of COVID-19 new cases on the returns of NEX index in the long run might be due to the disruption in global supply chain which causes a drop in the clean energy investments (Eroğlu, 2021). Selmi *et al.* (2021) state that shutting down government agencies and energy agencies to contain the spread of COVID-19 caused a delay in the accomplishment of renewable energy projects. It is also found that the SPGCE has a significant positive impact on the returns of NEX index. Although oil has an influential effect

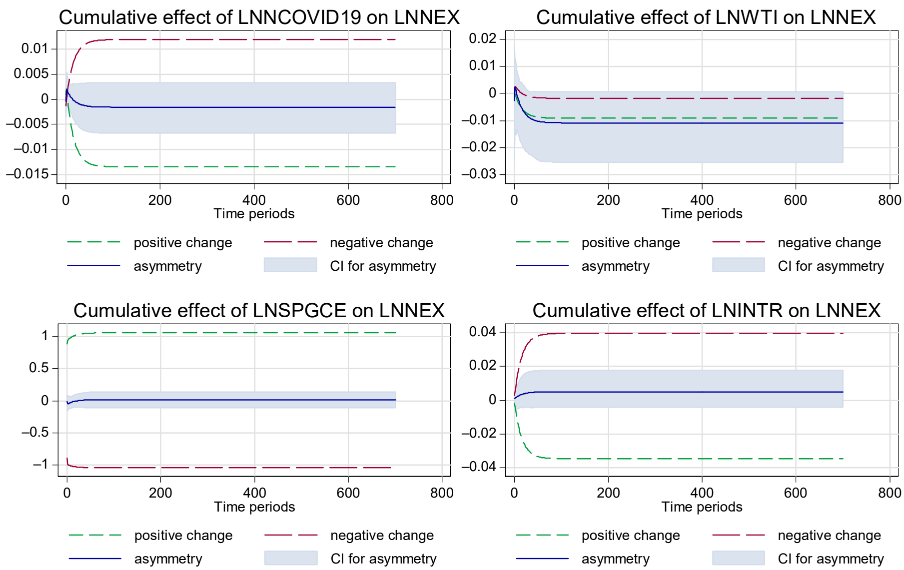
Cointegration test statistics		t-statistics F-statistics			−5.0869*** 3.9564**	
	Long-run effect [+]			Long-run effect [−]		
Variables	Coefficient	F-stat	Prob.	Coefficient	F-stat	Prob.
NCOVID	0.013	2.821	0.093	0.012	2.818	0.094
WTI	−0.009	0.09092	0.763	−0.002	0.003088	0.956
SPGCE	1.059	328.2	0.000	−1.040	482.5	0.000
INT	−0.035	13.12	0.000	0.040	29	0.000

	Long-run asymmetry		Short-run asymmetry	
	F-stat	Prob.	F-stat	Prob.
NCOVID	0.3291	0.566	1.354	0.245
WTI	1.86	0.173	0.229	0.632
SPGCE	0.06886	0.793	0.8068	0.369
INT	0.7876	0.375	0.0666	0.796

Diagnostics tests	
White noise test	54.35 (0.0646)
Heteroskedasticity test	0.03825 (0.8449)
Ramsey RESET test	1.463 (0.2233)

Source(s): Table by authors

Table 10. Asymmetry statistics (NARDL estimation)



Note(s): 95% bootstrap CI is based on 100 replications

Source(s): Figure by authors

Figure 2. Cumulative effect of the different variables on NEX index

on stock returns, the results show insignificant impact. This result matches that of Inchauspe, Ripple, and Trück (2015) who found that the impact of oil price returns is significantly lower despite its effective effect since 2007.

The findings of this study have various implications as for instance that it is recommended for governments have the chance to flip the negative impact of COVID-19 by including investment in green energy in their economic growth stimulation policies. Governments should highlight the fundamental advantages of investing in this type of energy such as creating job vacancies while reducing emissions and promoting innovation. Furthermore, the results can be utilized to aid policymakers in their efforts to achieve SDG7 that focuses on ensuring access to affordable, reliable, sustainable and modern energy for all by the year 2030 and overall achieving energy sustainability. Furthermore, companies are recommended to direct their innovative technologies toward the utilization of clean and low-carbon energy. It is also recommended that public awareness campaigns to be held to further promote the green energy investments.

The main aim of this paper is to find the impact of oil price and COVID-19 pandemic on WilderHill New Energy Global Innovation Index (NEX). However, other measures of clean and renewable energy might be examined, too. Therefore, future studies may consider looking at the impact of these variables on other renewable stocks such as the European Renewable Energy Total Return (ERIX) and NYSE Arca Technology 100 Index to compare the results and have a more comprehensive picture.

Note

1. https://www.iea.org/reports/world-energy-investment-2022/overview-and-key-findings

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