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Hedging potentials of green investments against climate and oil market risks

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Received 24 April 2022
Revised 16 November 2022
Accepted 14 March 2023

Abstract

Purpose – This study aims to examine the ability of clean energy stocks to provide cover for investors against market risks related to climate change and disturbances in the oil market.

Design/methodology/approach – The study adopts the feasible quasi generalized least squares technique to estimate a predictive model based on Westerlund and Narayan's (2015) approach to evaluating the hedging effectiveness of clean energy stocks. The out-of-sample forecast evaluations of the oil risk-based and climate risk-based clean energy predictive models are explored using Clark and West's model (2007) and a modified Diebold & Mariano forecast evaluation test for nested and non-nested models, respectively.

Findings – The study finds ample evidence that clean energy stocks may hedge against oil market risks. This result is robust to alternative measures of oil risk and holds when applied to data from the COVID-19 pandemic. In contrast, the hedging effectiveness of clean energy against climate risks is limited to 4 of the 6 clean energy indices and restricted to climate risk measured with climate policy uncertainty.

Originality/value – The study contributes to the literature by providing extensive analysis of hedging effectiveness of several clean energy indices (global, the United States (US), Europe and Asia) and sectoral clean energy indices (solar and wind) against oil market and climate risks using various measures of oil risk (WTI (West Texas intermediate) and Brent volatility) and climate risk (climate policy uncertainty and energy and environmental regulation) as predictors. It also conducts forecast evaluations of the clean energy predictive models for nested and non-nested models.

Keywords Clean energy stocks, Oil risk, Climate risk, Hedging, Forecast evaluation

Paper type Research paper

JEL Classification — C51, C58, G15, Q29

The authors appreciate the comments received from reviewers and participants at the Fulbright Review of Economics and Policy workshop on Green Finance and Sustainable Recovery post-COVID-19 Pandemic (August 11, 2022).

Funding: This work was funded by Fulbright University Vietnam.

Declaration of conflicts of interest: The authors declare that there are no conflicts of interest.

Credit authorship contribution statement: Idris A. Adediran: conceptualization, introduction, methodology, estimation, results, reading and editing. Raymond Swaray: conceptualization, data gathering, reading and editing. Aminat O. Orekoya: Introduction and literature review. Balikis A. Kabir: Estimation, discussion of findings and conclusion.

Fulbright Review of Economics and Policy
Vol. 3 No. 1, 2023
pp. 49-73
Emerald Publishing Limited
e-ISSN: 2635-0181
p-ISSN: 2635-0173
DOI 10.1108/FREP-04-2022-0030

1. Introduction

The effects of global warming and climate change have become more apparent over the past decade. Floods, heat waves and wildfires are rising in Europe (especially France, Spain, Greece, Portugal and Spain), Asia and North Africa (Bohringer Cantner, Costard, Kramkowski, Gatzen, & Pietsch, 2020; Meier, Elliott, & Strobl, 2023). Researchers have been able to attribute the rise in natural disasters to global warming and climate change (see Wang, Jiang, & Lang, 2017 and relevant papers cited therein). Therefore, it is imperative to engage market-based approaches such as investments in green assets as well as pursuance of green growth policies. These efforts aim to ensure that a large portion of the energy demand is met through renewable sources to reduce greenhouse gas emissions and ultimately address climate change challenges (Sinha, Sengupta, & Alvarado, 2020; Bohringer *et al.*, 2020). Besides, the international financial environment is increasingly facing higher market risks especially due to several factors including crude oil price fluctuations, policy uncertainties and the COVID-19 pandemic, among others (see Salisu, Ogbonna, Oloko, & Adediran, 2021; Boubaker, Goodell, Pandey, & Kumari, 2022; Boungou & Yatié, 2022; Salisu, Tchankam, & Adediran, 2022 and relevant papers cited therein). For example, the oil shock of April 2020, which occurred during the height of the COVID-19 pandemic, may have contributed to instability in the oil market, which has become more volatile, particularly with respect to price (see Salisu, Oloko, & Adediran, 2021). We look at oil price volatility more closely in this paper. This study, therefore, highlights the need to search for investments to protect investors against market risks, which has become increasingly heightened, especially in the COVID-19 era, coupled with the need to maintain responsible investments that promote a green economy. Hence, this study explores whether clean energy stocks can function as hedges against identified financial risks.

This paper explores if clean energy stocks, as relevant proxies for green investment, possess hedging and diversification potentials that can benefit investors in financial markets (which range from stock markets, bond markets, currency markets and commodity markets) against oil market specific risks and market risks that relate to regulations regarding global warming and climate change. In other words, we demonstrate how clean energy stocks could effectively hedge oil market and climate risks. This is motivated by evidence of recurring impacts of oil price shocks on global financial investors (Apergis & Miller, 2009; Salisu & Adediran, 2020) as well as the impact of regulatory policy framework against greenhouse emissions and climate change (Reboredo, 2018). The present study is therefore motivated to demonstrate that clean energy stock markets may be an attractive, emerging alternative class of assets for environmentally responsible investors seeking to decarbonize their investments (Dutta, Jana, & Das, 2020; Braga, Semmler, & Grass, 2021; Cepni, Demirer, & Rognone, 2022).

Both climate and crude oil market risks are related to the environment (Saeed, Bouri, & Vo, 2020; Kabir, Rahman, Rahman, & Anwar, 2021), hence, they are relevant to the global drive for promotion of green technology and sustainable development goals (Kocaarslan & Soytas, 2021). Crude oil is a major fossil fuel, taken with other hydrocarbons, contribute more than 70% of global carbon emissions (Balcılar, Demirer, Hammoudeh, & Nguyen, 2015), hence, responsible investment focused on decarbonization and combating climate change favour an analysis of this nature that could show clean energy stocks as viable investment options for portfolio diversification, in the midst of rising oil market risks and against climate risks faced by investors.

This study contributes to the literature in two ways. First, our analysis of hedging effectiveness of clean stocks is based on aggregate clean energy indices (global, the United States (US), Europe and Asian markets) and sectoral clean energy indices (Wind & Solar) in order to cover various international markets and asset classes (Table 1). Second, we conduct an impact analysis for the hedging effectiveness as well as the forecast evaluation analysis. We further analyse the hedging effectiveness across the full sample and COVID-19 sample period, given the motivation around the pandemic as a source of financial market risk (see Salisu, Ogbonna, *et al.*, 2021). Our study differs from

	Description	Sample	Frequency
Clean energy assets			
Global	Wilder Hill new energy global (NEX)	7/9/2012 - 7/11/2022	Daily
Europe	NQ OMX clean energy Europe	11/29/2010 - 7/11/2022	Daily
US	NQ OMX clean energy US	11/29/2010 - 7/11/2022	Daily
Asia	NQ OMX clean energy Asia	11/29/2010 - 7/11/2022	Daily
Solar	NASDAQ OMX solar (GRNSOLAR)	10/15/2010 - 7/11/2022	Daily
Wind	ISE global wind energy TR (GWETR)	2/7/2017 - 7/11/2022	Daily
Oil risks			
WTI	West Texas intermediate oil price realised volatility	10/15/2010 - 7/11/2022	Daily
Brent	Brent crude oil price realized volatility	10/15/2010 - 7/11/2022	Daily
Climate risks			
CPU	Climate policy uncertainty (Gavriilidis, 2021)	10/1/2010 - 12/1/2021	Monthly
EER	Energy and environmental regulation (Baker *et al.*, 2020)	10/1/2010 - 12/1/2021	Monthly

Source(s): Table by authors

Table 1.
Data description

Kuang (2021), which examines the safe haven property of clean energy stocks compared to "dirty" energy stocks and shows that clean energy stocks may provide diversification benefits. Our study differs from Kuang (2021) in that the latter considers the hedging potentials of the clean energy stocks in the face of specific market risks [1]. Further, our disaggregated analysis of the hedging effectiveness of sectoral clean energy stocks makes it different from Pham (2019), which is limited to the nexus between oil prices and clean energy stocks.

We take the predictability analysis further to explore the out-of-sample forecasting of the clean energy stock returns based on the measures of climate and oil risks as the predictor series. We adopt a method that fits the behaviours of the variables in the model in terms of persistent regressor series, endogeneity bias due to the bivariate model and conditional heteroscedasticity in the series (see Sharma, 2021 for step-by-step application of the Westerlund and Narayan (2012, 2015) method). We obtain robust results that indicate the potential of clean energy stocks in shielding against oil market risks. Our results also show that clean energy stocks are limited to hedging against climate risks. Hence, we show that promoting these types of assets may help combat climate change while also being a financially-smart investment choice.

We present a brief literature review in Section 2 followed by the detailed methodology for the predictability and forecast evaluations in Section 3. Section 4 discusses some preliminary results and the main findings, while Section 5 completes the study and provides a conclusion.

2. Literature review

This study is rooted in the modern theory of optimal asset selection put forward by Markowitz (1952) where the expected returns and risks of assets are the key components of portfolio selection; hence, risk management is at the core of portfolio management. The theory of portfolio choice for which Harry Markowitz received the 1990 Nobel Prize in Economic Sciences can be used to explain how households allocate their financial assets to reduce risk in times of uncertainty [2]. Financial assets can serve as hedges, safe havens or diversifiers (Baur & Lucey, 2010). A hedge is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio over time. A diversifier is positively correlated with other assets or portfolios while safe havens are assets that function as hedge assets during market crises. The distinction between hedges and safe havens is that the latter can help investors manage extreme market turmoil, that is, they can provide diversification benefits for investors against systemic risks that cut across most financial markets such as the Global Financial Crisis of 2007–2008 or the COVID-19 pandemic. The former category, which we address in this study, can help provide cover for investors with their ability to deliver positive returns in the face of specific market risks (in our case, oil and climate risks). In other words, if the clean energy stocks are able to perform a hedging role, they would, by implication, be negatively correlated with traditional assets.

Empirical analysis of the hedging ability of different assets is not new, for example, precious metals have been considered (Yaya, Tumala, & Udomboso, 2016; Kumar, 2017; Salisu, Vo, & Lawal, 2021), as well as agricultural commodities (Hernandez, Shahzad, Uddin, & Kang, 2018) and stocks (Lin, Zhou, Jiang, & Ou, 2021; Živkov, Manić, Đurašković, & Gajić-Glamočlija, 2022). Hedging roles of some assets have been conducted against oil shocks due to the latter's high volatility (Maitra, Guhathakurta, & Kang, 2021). The bulk of the relevant literature has been limited to the analysis of the nexus between oil market fundamentals and clean energy stocks (see, for example, Henriques & Sardosky, 2008; Managi & Okimoto, 2013; Reboredo & Ugolini, 2018) without recourse to the hedging role of the latter. The studies of Sardosky (2012), Dutta (2017), Ahmad, Sardosky, and Sharma (2018), and Dutta, Bouri, Das, and Roubaud (2021) examine the volatility spillovers between clean energy stocks and some other assets, including oil. The studies report some significant relationships on which the present study can stand to check if the clean stocks can hedge oil risk.

Climate risk has also become popular in the finance literature since climate change has been found to affect financial markets (Oloko, Adediran, & Fadiya, 2022). Another dimension to the importance of climate risk is the significant impact of climate policy uncertainty on investment (Ren, Shi, & Jin, 2022; Bouri, Iqbal, & Klein, 2022). This study contributes to a growing body of research on the diversification potential of green investments. It situates among studies examining whether green assets offer protection against specific or general market risks (see Dutta *et al.*, 2020; Reboredo & Ugolini, 2020). The important gap the present study fills is to put forward evidence on the possible hedging benefits of clean energy assets against climate change and oil market risks. This idea is important in the current times when the call for decarbonization, green growth and investment inform policy direction under international agreements such as the United Nations Framework Convention on Climate Change.

3. Methodology and data

This study uses a predictive model to identify if clean energy assets (each considered individually as predict and) provide any hedging benefit against market specific risks associated with climate change or the crude oil market (whose proxies are also considered individually as the predictor). The modelling framework follows the specification developed in Westerlund and Narayan (2012, 2015) to simultaneously account for any conditional heteroskedasticity, persistence (unit root properties) and endogeneity bias the clean energy indices may have (see Sharma, 2021). The empirical models are as follows:

$$clean_t = \alpha^{clm} + \beta^{*clm} clm_{t-1} + \phi^{clm}\left(clm_t - \rho^{clm} clm_{t-1}\right) + \varepsilon_t^{clm} \tag{1}$$

$$clean_t = \alpha^{oil} + \beta^{*oil} oil_{t-1} + \phi^{oil}\left(oil_t - \rho^{oil} oil_{t-1}\right) + \varepsilon_t^{oil} \tag{2}$$

where $clean_t$ represents the clean energy stock returns of the six alternative clean energy indices (global, Europe, US, Asia and sectoral (solar and wind)); the models are defined for the regressors such that: *clm* represents the climate risk based model and *oil* is the oil risk based model; α^{clm} and α^{oil} are the constant terms of the respective models, β^{*clm} and β^{*oil} are the bias-adjusted beta (slope) coefficients of the respective models that indicate the hedging effectiveness of the clean energy assets, and ε_t^{clm} and ε_t^{oil} are the error terms of the two classes of models.

Since the clean energy returns series exhibit conditional heteroscedasticity (given that they are high frequency financial series), the error terms, therefore, mirror the autoregressive conditional heteroscedasticity (ARCH) model:

$$\sigma^2_{\varepsilon^{clm},t} = \varpi_t^{clm} + \sum\nolimits_{i=1}^{k} \varpi_i^{clm} \varepsilon_{t-i}^{(clm)2} \tag{3a}$$

$$\sigma^2_{\varepsilon^{oil},t} = \varpi_t^{oil} + \sum\nolimits_{i=1}^{k} \varpi_i^{oil} \varepsilon_{t-i}^{(oil)2} \tag{3b}$$

The bias-adjusted generalized least squares estimator is suitable. We checked this by pre-weighting the series with the quantity: $1\Big/\sqrt{\sigma^2_{\varepsilon,t}}$. The bias-adjusted Beta (subsequently referred to as the Beta-adjusted coefficient) is derived from the following formula:

$$\beta^{*clm} = \beta^{clm} - \phi^{clm}\left(\rho^{clm} - 1\right) \tag{4a}$$

$$\beta^{*oil} = \beta^{oil} - \phi^{oil}\left(\rho^{oil} - 1\right) \tag{4b}$$

To demonstrate the hedging effectiveness of the clean energy assets, we specify two criteria as follows: (1) no hedge ($\beta^{*clm} \leq 0$ and $\beta^{*oil} \leq 0$) and (2) hedge ($\beta^{*clm} > 0$ and $\beta^{*oil} > 0$) (see Arnold & Auer, 2015; Salisu & Adediran, 2020). "No hedge" is obtained when the Beta-adjusted coefficient is less than zero (or negative) in which case the returns of the clean energy assets fall with the risk levels examined. On the other hand, clean energy stocks would possess hedging potential when the coefficient is greater than zero (i.e., positive). In the case of "hedge," the clean energy returns increase in the face of higher climate and oil market risks.

In addition, we explore the out-of-sample forecast evaluation of the clean energy asset models. The forecast evaluation exercise is extensive where we compare the forecast accuracies of nested models and non-nested models. For the nested models, the historical average (HA) is the benchmark, which serves as the basis for comparing the oil risk and climate risk predictive based models. Our model uses the technique for forecast evaluation set forth by Clark and West (2007) to test the difference between the HA and the risk-based predictive models. The rejection of the null hypothesis of Clark and West test indicates the better performance of the preferred models (climate risk-based models and oil risk-based models). The Clark and West test statistic is obtained from the following estimations:

$$\widehat{f}^{\,clm}_{t+h} = c^{clm} + \zeta^{clm} \tag{5a}$$

$$\widehat{f}^{\,oil}_{t+h} = c^{oil} + \zeta^{oil} \tag{5b}$$

where the out-of-sample forecasts are defined as: $\widehat{f}^{\,clm}_{t+h} = M\widehat{S}E_{ha} - (M\widehat{S}E_{clm} - adj_{clm})$, $\widehat{f}^{\,oil}_{t+h} = M\widehat{S}E_{ha} - (M\widehat{S}E_{oil} - adj_{oil})$, the quantities with subscript *ha* are observed from the HA model, h is the out-of-sample forecast horizon, the mean squared errors of the respective predictive models are defined as follows: $M\widehat{S}E_{ha} = P^{-1}\sum(u_{t+h} - \widehat{u}_{ha,t+h})^2$, $M\widehat{S}E_{clm} = P^{-1}\sum(u_{t+h} - \widehat{u}_{clm,t+h})^2$, $M\widehat{S}E_{oil} = P^{-1}\sum(u_{t+h} - \widehat{u}_{oil,t+h})^2$, $adj_{clm} = P^{-1}\sum(\widehat{u}_{ha,t+h} - \widehat{u}_{clm,t+h})^2$, $adj_{oil} = P^{-1}\sum(\widehat{u}_{ha,t+h} - \widehat{u}_{oil,t+h})^2$, and P represents the number of predictions for computing the average sum of squares. For the forecast evaluation using the Clark and West test, the coefficients of Eq. 5a and 5b (c^{clm}& c^{oil}) are statistically significant. The statistical significance of the coefficients indicates the better performance of the "favored" climate- and oil risk-based models.

For the non-nested models where we compare the two oil risk-based models and the two climate risk-based models, we examine the out-of-sample forecast analysis using the modified Diebold and Mariano forecast evaluation test (see Harvey, Leybourne, & Newbold, 1997). The test works by comparing the forecast errors of the competing models in the following specification:

$$MDM = \left(\sqrt{T + 1 - 2h + T^{-1}h(h-1)/T}\right)DM \tag{6}$$

Where MDM is the modified Diebold and Mariano test statistic (Harvey *et al.*, 1997) and DM is the conventional Diebold and Mariano test statistic (Diebold & Mariano, 1995) defined as:

$$DM = diff^{*} \Big/ \sqrt{V(diff)/T} \sim N(0,1) \tag{7}$$

where T is the sample size, $diff = l(\varepsilon_{brent}) - l(\varepsilon_{wti})$ [or $diff = l(\varepsilon_{EER}) - l(\varepsilon_{CPU})$], $l(\varepsilon_{brent})$ is the loss function of the model with Brent price realized volatility as the predictor, $l(\varepsilon_{wti})$ is the loss function of the model with West Texas intermediate (WTI) price realized volatility as the predictor, $l(\varepsilon_{EER})$ is the loss function of the model with the energy and environmental regulation (EER) index as the predictor, $l(\varepsilon_{CPU})$ is the loss function of the model with climate policy uncertainty as the predictor, and $diff^{*}$ and $V(diff)$ are the mean and variance of the loss differentials, respectively.

The null hypothesis for the MDM test is $E(diff) = 0$, which contrasts with the alternative, $E(diff) < 0$ which suggests that the models with WTI (CPU (climate policy uncertainty)) outperform those with Brent (EER). The reverse becomes the case if $E(diff) > 0$, whereas there is no difference in the forecast performance if $E(diff) = 0$ is obtained. We conduct the out-of-sample forecast evaluation for the daily data frequency (involving oil risk) using a 75:25 data split and produce 10-, 30-, 60- and 120-day forecasts. For the monthly data frequency involving climate risks, we also conduct the forecast evaluation using a 75:25 data split and produce forecasts monthly for the next 4 months.

The study, therefore, analyses both daily and monthly data; the analysis of climate risk is conducted with monthly data frequency, while that of oil risk is conducted with daily data frequency to preserve the data generating process [3]. This is a way to circumvent the limitation of monthly climate risk data. We obtain daily prices of clean energy stock indices from Bloomberg terminals and compute the return series as follows: $r_t = 100 * (\log p_t - \log p_{t-1})$; where r_t is the return series calculated as the log differences in the price series (p_t).

The climate risk is principally measured with climate policy uncertainty data (Gavriilidis, 2021) [4], and for robustness, we alternatively measure the climate risk with the equity market volatility tracker: EER dataset (Baker, Bloom, Davis, & Terry, 2020) [5]. Both of these climate risk data are only available on a monthly basis. We also measure oil market risk in two ways to obtain robust findings using two crude oil price benchmarks, the daily Brent and West Texas Intermediate crude oil indices. Hence, we measure oil market risk by obtaining the realized volatility from the indexes using:

$$RVol_t = \sqrt{\sum_{i=1}^{22} r_{it}^2} \tag{8}$$

where $RVol_t$ is the realized volatility series, and r_t^2 is the squared returns summed across 22 trading days in a month. The oil prices for computing the oil market realized volatility are obtained in daily frequency from the US energy information administration [6].

4. Discussion of findings

4.1 Preliminaries

We explore the behaviour of the series used for this study using graphical representations and various statistical tools to reveal more information about the possible association between the regressors and regressands. The movements of the proxies used for climate risks and oil market risks are represented by Figure 1, while Figures 2 and 3 present the line graphs of clean energy assets and the proxies of oil market and climate risks, respectively. Figure 1 (shown on the left) shows that the climate risk proxies behave in a similar but not identical fashion. The graph reveals that the two indexes started with perfect co-movement in 2010, however, the energy and environmental index had its highest value (risk level) recorded in mid-2013 while that the highest recorded CPU value was in 2018. This might be because the instruments used to measure the two are different, which will be an advantage when it comes to checking the robustness of our results. The oil market risks, WTI and Brent volatilities, on the other hand, perfectly co-move with each other, Figure 1 (shown on the right) shows no significant difference in the movement of Brent and WTI oil volatility which would mean that these two proxies should lead to similar results in the model estimation stage.

The graphs in Figure 2 show that though clean energy returns revolve around a mean of zero, there is a notable higher volatility in the return series at the points where oil risks are very high (especially during the COVID-19 pandemic period). This shows that there might be a significant relationship between oil risk and the clean energy returns. Figure 3 presents the trends of the clean energy returns against climate policy uncertainty and the energy and environmental policy index. These graphical analyses fail to show any clear insights on the direction of relationship to expect between the variables. However, the correlation analyses conducted in the second panel of Table 2 are much clearer and suggest that the clean energy stock returns are positively related to the oil risk measures and climate policy uncertainty but appear to be negatively associated with EER index. We subject these to further scrutiny in the main analysis.

To complement the graphical representations of the series, additional statistics for point estimates are used. The point estimates include mean, standard deviation, skewness and kurtosis. The series was further analysed to check for persistence, conditional heteroscedasticity and endogeneity. The results are presented in Tables 2 and 3 for the regressor and regressand series, respectively. Results in Table 2 compares the CPU index (average, 134) with that of EER index (average, 0.327) with the former also having larger standard deviation (95) (higher volatility) than the latter (0.267). Although the graphs did not reveal the difference between the Brent and WTI volatility series, the results in Table 2 show that WTI oil risk has a slightly greater average (4.39) compared to Brent crude (4.06) and the standard deviation also affirms that WTI is more volatile (4.267) than Brent crude (3.699). The skewness for both the climate and oil risks indexes are positive reflecting a possible long right tail and the kurtosis shows that they are leptokurtic. Furthermore, the table reveals that the climate policy uncertainty index is persistent while the energy and environmental policy index is not, however, both oil risk proxies show evidence of persistence. The oil risk proxies exhibit an ARCH effect across lags 1, 5 and 10 while the climate risk proxies display no ARCH effect.

Table 3 reveals the averages of the clean energy returns and, as expected, the global clean energy returns have the highest mean of 0.04 among the markets and Asia index record the lowest average returns (0.006). The global index also displays the lowest standard deviation figures (1.33) while Asia has the highest (1.46). When it comes to the two energy sources, the solar index has a higher mean (0.051) and standard deviation (2.119) compared with the wind index (mean, 0.037 and standard deviation, 1.217). Negative skewness is recorded for all the clean energy return series, which indicates a possible long left tail with a kurtosis value greater than 3, which would mean the series does not follow a normal distribution. Finally, the null hypotheses of no persistence, no conditional heteroscedasticity and no endogeneity bias

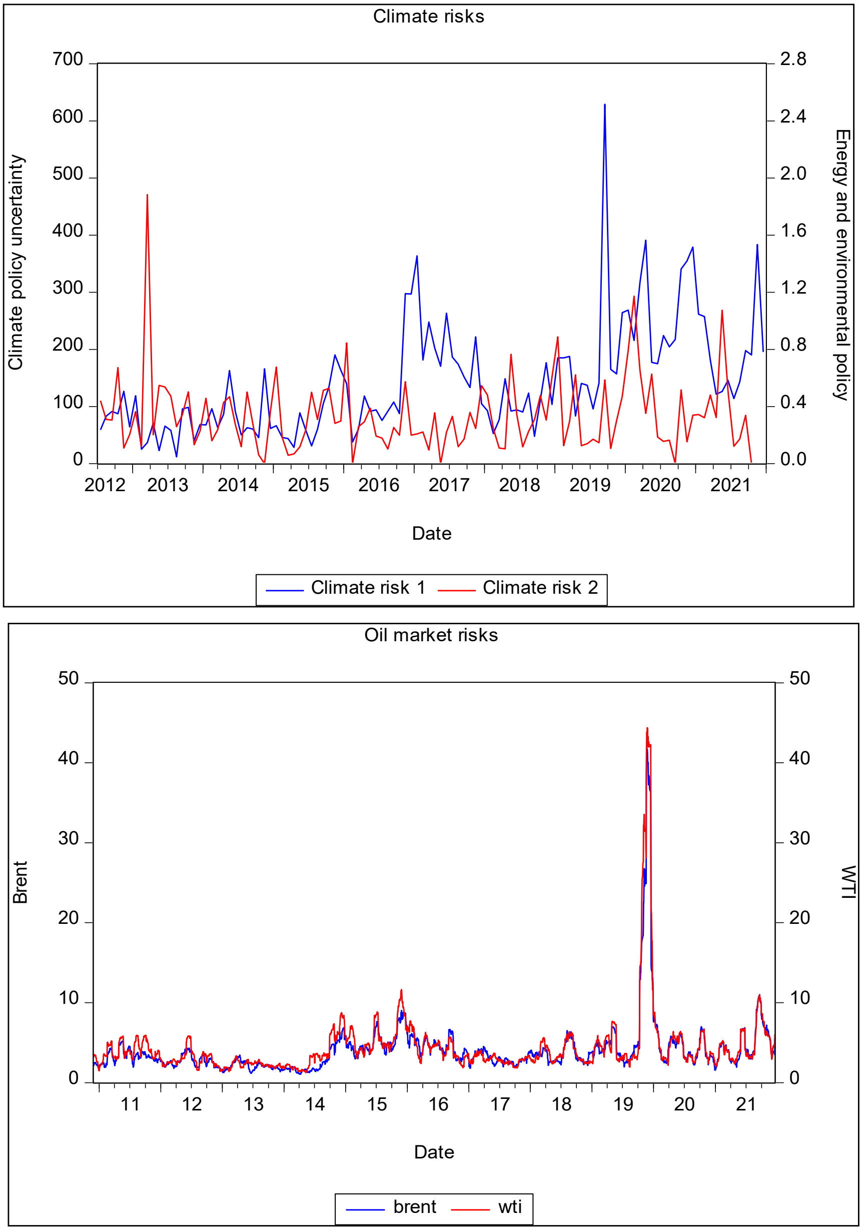
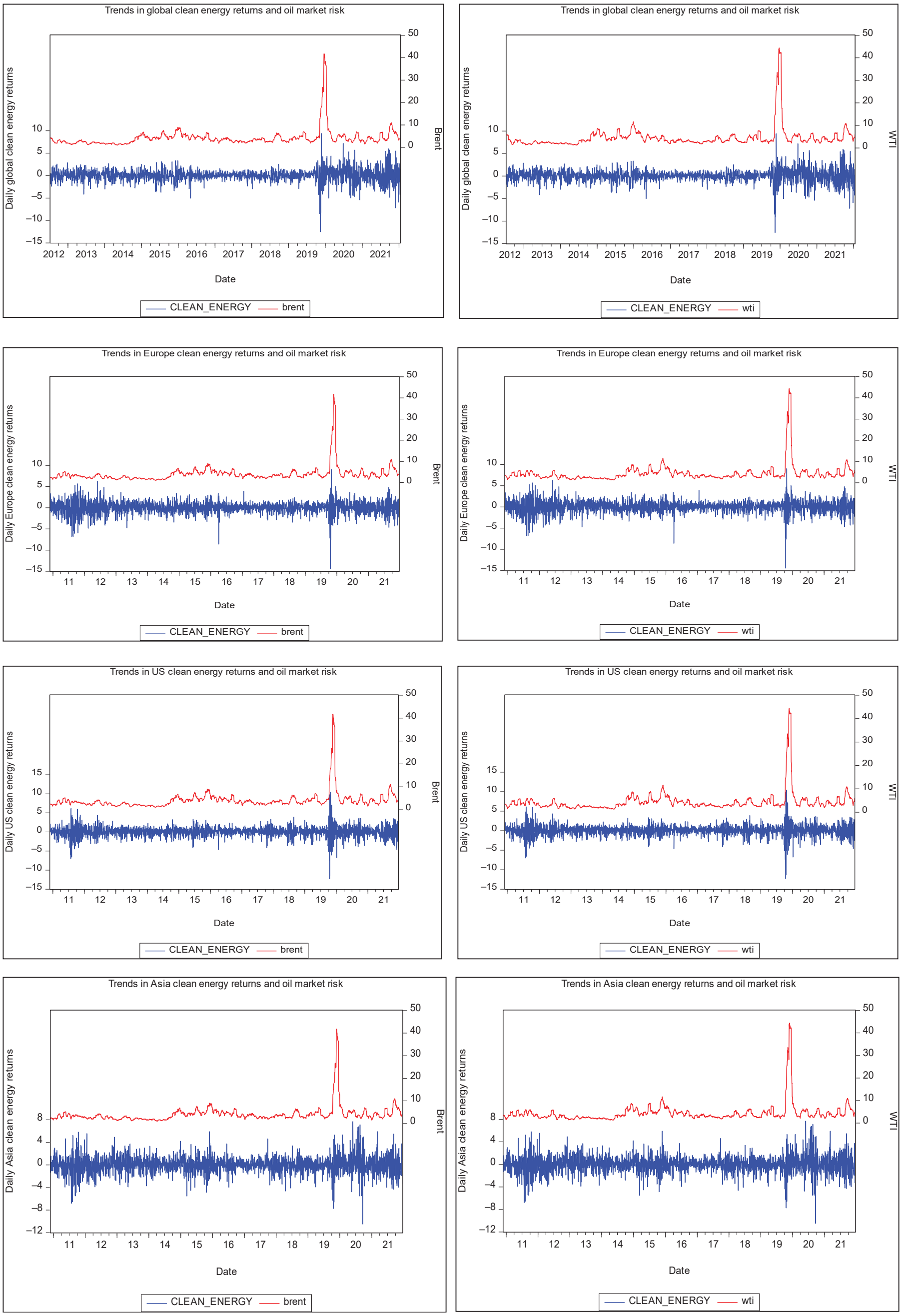


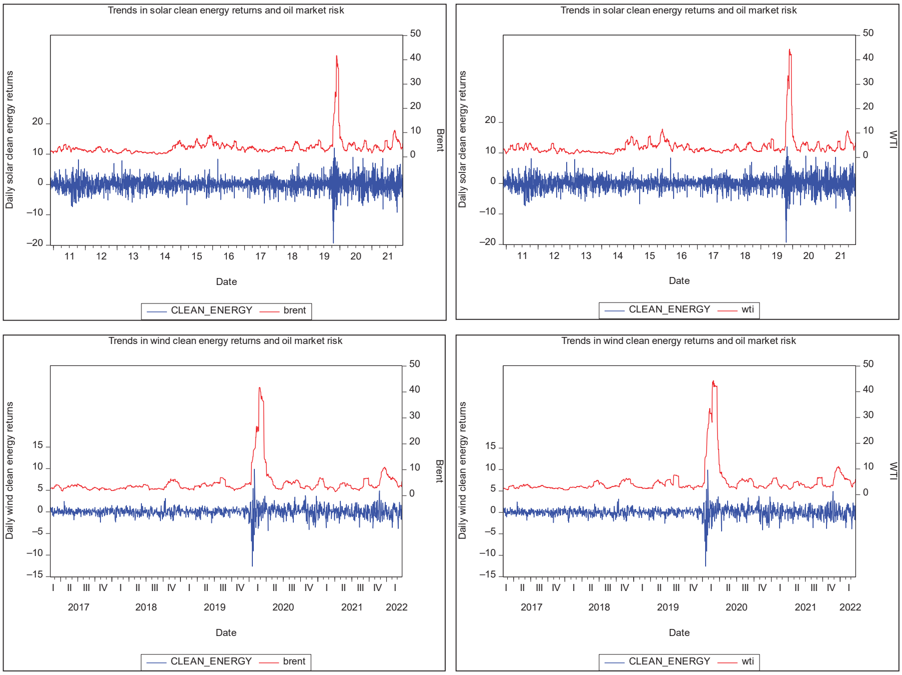
Figure 1.
Trends in climate and oil market risks

Note(s): The figure on the left shows two measures of climate risk data, CPU (climate risk 1) and EER (climate risk 2). The figure on the right is the graphical plot of the two measures of oil risk data; Brent crude oil price volatility and WTI crude oil price volatility
Source(s): Figure by authors



(continued)

Figure 2.
Clean energy returns and oil market risks



Note(s): The figures here present the graphical plots of each of the clean energy price returns and oil market risks. The plots of clean energy returns and volatility of Brent price are displayed on the left while the plots of clean energy returns and volatility of WTI price are on the right. The rows are arranged for the 'Global', 'Europe', 'US', Asia', 'Solar', and 'Wind' clean energy indices respectively

Source(s): Figure by authors

Figure 2

are all rejected for the clean energy returns series. These checks demonstrate that the Westerlund and Narayan (2012, 2015) model is suitable when used in this context.

4.2 Main results

This section focuses on the contributions of our paper, which studied the hedging potentials of aggregate and sectoral clean energy stocks against climate and oil market risks; and the use of alternative approaches to analyse the out-of-sample forecasting evaluation of the clean energy predictive models for nested and non-nested models. The preliminary analysis of the clean energy stock indices (the regressands) and the measures of climate & oil risks (the predictor series) validate our predictive model, which was based on Westerlund and Narayan (2012, 2015) but also included a feasible quasi generalized least squares (FQGLS) technique. The FQGLS technique of analysis which is designed for return predictability is the most appropriate model to use since the dependent variable (clean energy stocks) was presented in terms of returns (see Salisu, Adediran, Omoke, & Tchankam, 2023). Further corroborating evidences are shown in the preliminary results in Tables 2 and 3 which confirm the presence of persistence and conditional heteroscedasticity in the series as well as possible endogeneity bias in the relationship being examined.

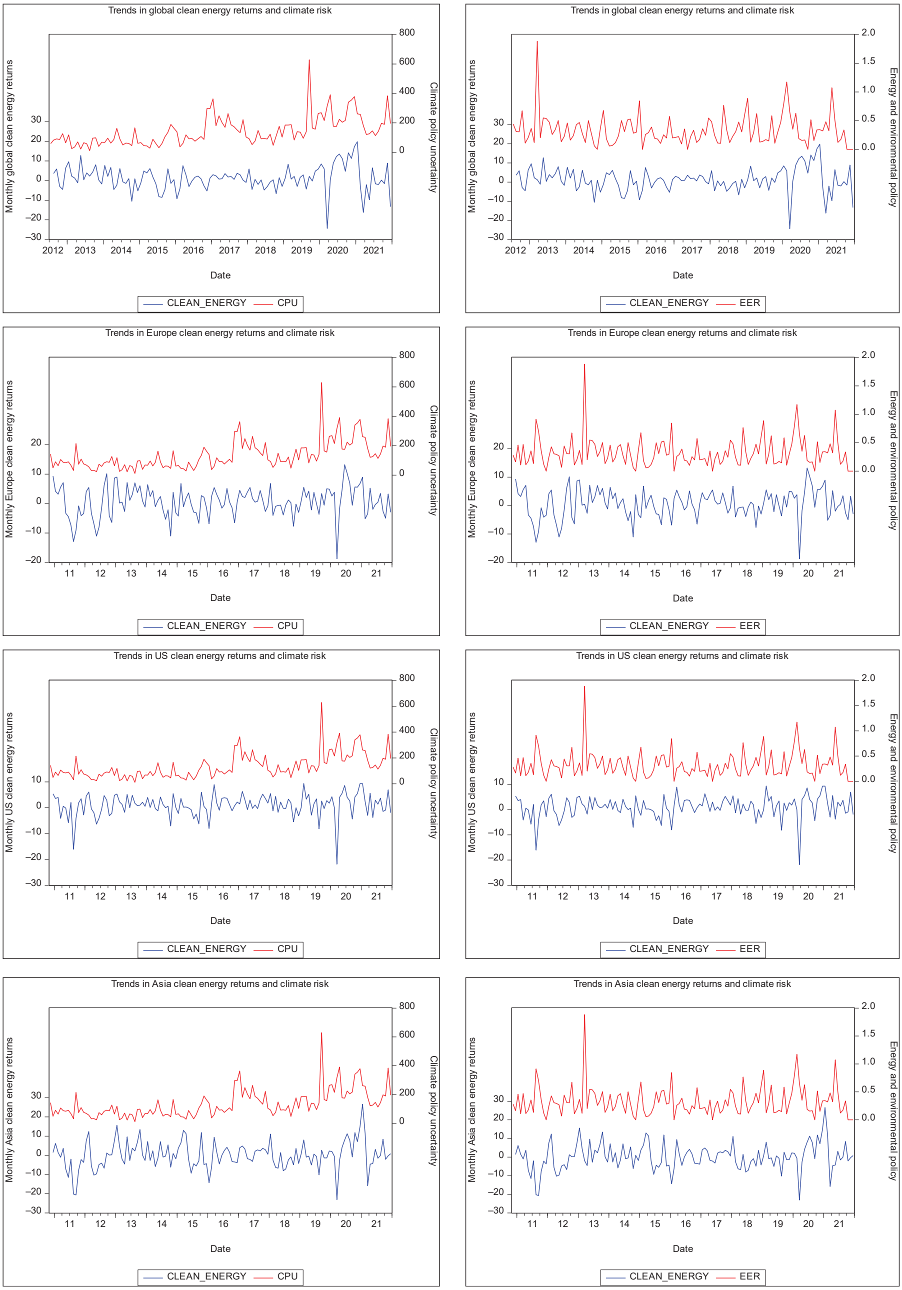


Figure 3.
Clean energy returns and climate risks

(*continued*)

Note(s): The figures here present the graphical plots of each of the clean energy price returns and climate risks. The plots of clean energy returns and CPU index are on the left column while the plots of clean energy returns and EER index are on the right column. The rows are arranged for the ‘Global’, ‘Europe’, ‘US’, Asia’, ‘Solar’, and ‘Wind’ clean energy indices respectively

Source(s): Figure by authors

Figure 3

First, we explored the hedging role and effectiveness of clean investments across different markets (global index, Europe index, US index and Asia index) and across renewable energy sources (solar and wind energy indices). We presented the results in Table 4. The upper panel of Table 4 details the results of the hedging effectiveness of clean energy assets where oil market risks (Brent and WTI crude price volatilities) are the predictors. The lower panel of Table 4 documents the results when the climate risk measures (EER and CPU) are the predictors [7]. Recall that the hedging effectiveness of the clean assets is explored on the basis of the following criteria: (1) no hedge ($\beta^{*clm} \leq 0$ and $\beta^{*oil} \leq 0$) and (2) hedge ($\beta^{*clm} > 0$ and $\beta^{*oil} > 0$) (see Arnold & Auer, 2015; Salisu & Adediran, 2020).

The results extensively show widespread evidence (11 out of 12 cases) [8] of hedging against oil market risks for all the classes of clean energy assets. This aligns with Saeed *et al.*’s (2020) finding that clean energy assets are more effective as hedges compared to dirty energy assets. Moreover, the Beta-adjusted coefficients are positive and statistically different from zero, indicating that investment in clean energy stocks could benefit financial investors who wish to mitigate oil market risks. Further results conducted using data from the COVID-19 pandemic period (2020 - 2022) are presented in Table 5. They reveal positive and significant Beta-adjusted coefficients across the board, thereby indicating that clean energy stocks possess hedging powers even during times of economic and world turbulence such as the

Statistic	Climate risk (1)	Climate risk (2)	Oil risk (1)	Oil risk (2)
Mean	133.520	0.327	4.056	4.392
Std. Dev	94.766	0.261	3.699	4.267
Skewness	1.830	2.224	6.563	6.382
Kurtosis	8.099	11.945	57.246	51.922
Persistence	0.576***	0.075	0.991***	0.992***
	(0.072)	(0.088)	(0.003)	(0.002)
ARCH(1)	0.358	0.003	71566.70***	85591.69***
	[0.551]	[0.956]	[0.000]	[0.000]
ARCH(5)	0.129	0.076	16711.60***	18781.21***
	[0.985]	[0.996]	[0.000]	[0.000]
ARCH(10)	0.557	0.101	8723.71***	9626.31***
	[0.845]	[0.999]	[0.000]	[0.000]
Correlation analysis				
Global	0.1758	−0.0745	0.0213	0.0255
Europe	0.1101	−0.1276	0.0143	0.0145
US	0.1241	−0.2016	0.0199	0.0227
Asia	0.1242	−0.1230	0.0107	0.0098
Solar	0.1783	−0.1252	0.0183	0.0168
Wind	0.1448	−0.0968	0.0151	0.0208

Note(s): Climate risk 1 (CPU) is climate policy uncertainty (Gavriilidis, 2021), Climate risk 2 (EER) is equity market volatility: EER (Baker *et al.*, 2020), Oil risk 1 is the realized volatility from the Brent crude oil price, Oil risk 2 is the realized volatility from the WTI crude oil price. ARCH is the test for conditional heteroscedasticity conducted with ten (10) lags. The null hypotheses for persistence and ARCH tests are no persistence and no ARCH effects, respectively. "***" indicates statistical significance at the 1% significance level. Values in "()" are standard errors while those in "[]" are probability values
Source(s): Table by authors

Table 2.
Further preliminary analysis

Statistics	Global	Europe	US	Asia	Solar	Wind
Mean	0.040	0.017	0.036	0.006	0.051	0.037
Std. Dev	1.331	1.375	1.343	1.461	2.119	1.217
Skewness	−0.595	−0.715	−0.488	−0.220	−0.442	−0.949
Kurtosis	11.449	10.333	12.109	6.875	8.695	18.937
Persistence	0.189***	0.043**	−0.095***	0.148***	0.012	0.099***
	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.027)
ARCH(1)	0.019***	57.209***	796.93***	74.35***	183.35***	88.205***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH(5)	123.33***	83.688***	297.79***	61.129***	171.26***	96.543***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH(10)	67.991***	56.229***	185.01***	39.181	93.055***	51.934***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Endogeneity	−0.258***	−0.265***	−0.201***	−0.257***	−0.452***	−0.256***
	(0.049)	(0.051)	(0.049)	(0.054)	(0.078)	(0.047)

Note(s): The regressand series are the 'Global', 'Europe', 'US', Asia', 'Solar' and 'Wind' clean energy indices, respectively. ARCH is the test for conditional heteroscedasticity conducted with ten (10) lags. The null hypotheses for persistence, ARCH and endogeneity tests are "no persistence", "no ARCH effects" and "no endogeneity bias" respectively. "**" and "***" indicates statistical significance at the 5% and 1% significance levels. Values in "()" are standard errors while those in "[]" are probability values
Source(s): Table by authors

Table 3.
Preliminary analysis [Regressand series]

Table 4.
Hedging role of clean energy assets

	Oil market risks											
	Global		Europe		US		Asia		Solar		Wind	
Oil risks	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*
α^{oil}	0.035***	0.046***	0.029***	0.022***	0.078***	0.068***	0.006	−0.009**	0.008	0.049***	0.028***	0.030***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.007)	(0.008)	(0.004)	(0.004)
β^{*oil}	0.010***	0.006***	0.008***	0.010***	0.001	0.003**	0.006***	0.010***	0.020***	0.005***	0.011***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Hedging role?	Hedge	Hedge	Hedge	Hedge	No hedge	Hedge	Hedge	Hedge	Hedge	Hedge	Hedge	Hedge

	Climate risks											
	Global		Europe		US		Asia		Solar		Wind	
Climate risks	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*
α^{clm}	2.035***	0.363	2.955***	0.5820**	3.178***	−0.22***	3.001***	−1.34***	5.589***	−1.01***	2.142***	−0.490
	(0.066)	(0.493)	(0.185)	(0.285)	(0.311)	(0.052)	(0.286)	(0.182)	(0.379)	(0.201)	(0.227)	(1.098)
β^{*clm}	−2.04***	0.001	−6.02***	0.006***	−4.89***	0.013***	−7.21***	0.015***	−7.06***	0.017***	−5.24***	0.008
	(0.595)	(0.002)	(0.711)	(0.001)	(0.797)	(0.0003)	(0.920)	(0.001)	(1.439)	(0.001)	(0.892)	(0.005)
Hedging role?	No hedge	No hedge	No hedge	Hedge	No hedge	Hedge	No hedge	Hedge	No hedge	Hedge	No hedge	No hedge

Note(s): This table presents the predictability results that indicate the hedging effectiveness of disaggregated clean energy assets against oil and climate risks. α^{oil} and β^{*oil} are the constant and Beta-adjusted coefficient of the models with oil market risk series (realized volatility of WTI and Brent prices) as the predictors. α^{clm} and β^{*clm} are the constant and Beta-adjusted coefficient of the models where the two climate risk series (CPU and EER) are the regressors. The hedging role is informed by the Beta-adjusted coefficients. $\beta^* \leq 0$ indicates 'no hedge' and $\beta^* > 0$ indicates 'hedge'. "**" and "***" indicates statistical significance at the 5% and 1% significance levels
Source(s): Table by authors

	Global	Europe	US	Asia	Solar	Wind
Oil market risks (WTI)						
α^{oil}	0.114***	−0.001	0.020*	0.037***	0.206***	0.050***
	(0.017)	(0.015)	(0.011)	(0.005)	(0.019)	(0.005)
$\beta{*}^{oil}$	0.015***	0.016***	0.013***	0.008***	0.006***	0.011***
	(0.003)	(0.002)	(0.004)	(0.0009)	(0.003)	(0.0009)
Hedging role?	Hedge	Hedge	Hedge	Hedge	Hedge	Hedge
Oil market risks (Brent)						
α^{oil}	0.121***	−0.012**	0.033**	0.038***	0.146***	0.043***
	(0.006)	(0.002)	(0.016)	(0.003)	(0.020)	(0.004)
$\beta{*}^{oil}$	0.010***	0.014***	0.009**	0.008***	0.017***	0.009***
	(0.001)	(0.0003)	(0.004)	(0.0005)	(0.006)	(0.0004)
Hedging role?	Hedge	Hedge	Hedge	Hedge	Hedge	Hedge

Note(s): This table presents the predictability results that indicate the hedging effectiveness of disaggregated clean energy assets against oil and climate risks. α^{oil} and $\beta{*}^{oil}$ are the constant and Beta-adjusted coefficient of the models with oil market risk series (realized volatility of WTI and Brent prices) as the predictors. α^{clm} and $\beta{*}^{clm}$ are the constant and Beta-adjusted coefficient of the models where the two climate risk series (climate policy uncertainty and EER) are the regressors. The hedging role is informed by the Beta-adjusted coefficients. $\beta* \leq 0$ indicates 'no hedge', $\beta* > 0$ indicates 'hedge'. "**" and "***" indicates statistical significance at the 5% and 1% significance levels. The analysis is limited to oil risk given that the monthly data for climate risks is too small (about 25 observations)
Source(s): Table by authors

Table 5.
COVID-19 analysis

COVID pandemic. This appears, without a doubt, to prove the hedging effectiveness of the assets and, as such, investors can rest assured that these environmentally responsible investments serve as an effective risk management strategy.

On the other hand, the results of the analysis of hedging effectiveness when it comes to climate risk are not as prevalent as that of the results of oil risks. These results align with the findings of Pham (2019) but differ from what Cepni *et al.* (2022) found given that our study, unlike Cepni *et al.* (2022), considers more heterogeneous global indices. In all six indices considered, the clean energies fail to hedge against climate risks when the latter is measured by EER index. This is indicated by the results of the predictive models with EER as the predictor where the Beta-adjusted coefficients are negative and strongly statistically significant at 1% significance level. Our results indicate that the major clean energy indices of Europe, the US and Asia (and solar index) provide refuge for investors against climate risks. In these cases, the adjusted Beta coefficients are positive and statistically significant at the 1% significant level. The two other cases (global clean energy index and wind index) where we report "no hedge" still exhibit positive but statistically insignificant coefficients. Thus, the evidence shows clean energy stocks have a high potential of hedging against oil risks and climate risks.

We evaluate the forecasting powers of the four predictors (Brent price volatility, WTI price volatility, EER and CPU) across the various models for clean energy stocks. We conduct the out-of-sample forecast evaluation for two categories of models – nested and non-nested models – and therefore adopt two model evaluation tests, (1) the Clark and West test and (2) the modified Diebold & Mariano (MDM) test [9]. The evaluation of nested models involved comparing the HA model with each of the oil risk-based and climate risk-based predictive models (HA versus Brent, HA versus WTI, HA versus EER and HA versus CPU). The evaluation of non-nested models included a comparison between the two oil risk-based models (Brent versus WTI) and a comparison between the two climate risk-based models (EER versus CPU). The criteria for evaluating the performance of the models is the statistical significance of the Clark and West (CW) statistic. In our model, this statistic indicated that the preferred model was superior. Meanwhile, the negative and MDM statistics were negative and statistically significant, which further supports the use of WTI volatility and CPU as better proxies of oil price risk and climate risk, respectively (see Narayan & Sharma, 2015; Salisu, Ogbonna, & Adediran, 2020; Sharma, 2021; Salisu, Vo, & Lawal, 2021; Salisu, Ogbonna *et al.*, 2021; Salisu, Gupta, & Pierdzioch, 2022; Salisu, Tchankam *et al.*, 2022).

The results in the upper part of Table 6 appear to suggest equality in the forecast performances of the HA model and the Brent volatility based models. This is adjudged principally by the statistical insignificance of the CW tests. On the other hand, a sizeable number of the CW statistics in the lower panel of Table 6 are statistically significant, which suggests that the predictive models including WTI volatility outperform the HA model.

Table 6. Out-of-sample forecast evaluation of oil risk models [Nested models]

Historical average (HA) versus Brent												
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*
h = 10	0.919	0.919	1.278	1.278	1.147	1.147	1.297	1.297	1.760	1.760	1.187	1.175
h = 30	0.921	0.921	1.275	1.274	1.146	1.146	1.295	1.294	1.757	1.758	1.186	1.174
h = 60	1.048	1.042	1.270	1.270	1.143	1.143	1.289	1.288	1.757	1.758	1.191	1.180
h = 120	1.114	1.104	1.258	1.257	1.134	1.134	1.280	1.279	1.751	1.751	1.180	1.169
CW	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*	*HA*	*Brent*
h = 10	0.001		0.003		−0.001		0.004		0.002		0.039***	
	(0.002)		(0.002)		(0.001)		(0.003)		(0.004)		(0.014)	
h = 30	0.001		0.003		−0.001		0.004		0.002		0.039***	
	(0.001)		(0.002)		(0.001)		(0.003)		(0.004)		(0.013)	
h = 60	0.014		0.004		−0.001		0.004		0.002		0.038***	
	(0.009)		(0.002)		(0.001)		(0.002)		(0.004)		(0.013)	
h = 120	0.033***		0.003		−0.001		0.004		0.001		0.036***	
	(0.012)		(0.002)		(0.001)		(0.002)		(0.004)		(0.012)	

Historical average (HA) versus WTI												
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*
h = 10	0.919	0.917	1.278	1.276	1.147	1.145	1.297	1.296	1.760	1.759	1.187	1.166
h = 30	0.921	0.919	1.275	1.272	1.146	1.144	1.295	1.293	1.757	1.756	1.186	1.166
h = 60	1.048	1.037	1.270	1.268	1.143	1.141	1.289	1.287	1.757	1.757	1.191	1.172
h = 120	1.114	1.100	1.258	1.255	1.134	1.132	1.280	1.278	1.751	1.750	1.180	1.162
CW	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*	*HA*	*WTI*
h = 10	0.006**		0.009**		0.006**		0.007**		0.009		0.070***	
	(0.003)		(0.004)		(0.002)		(0.003)		(0.007)		(0.024)	
h = 30	0.006**		0.010**		0.006**		0.007**		0.010		0.069***	
	(0.003)		(0.004)		(0.002)		(0.003)		(0.007)		(0.024)	
h = 60	0.026*		0.010**		0.005**		0.007**		0.009		0.067***	
	(0.014)		(0.004)		(0.002)		(0.003)		(0.007)		(0.023)	
h = 120	0.046***		0.010**		0.005**		0.007**		0.009		0.063***	
	(0.017)		(0.004)		(0.002)		(0.003)		(0.007)		(0.022)	

Note(s): This table presents the results for the forecast evaluation of the oil risk based models where either the realized volatility of WTI or Brent price serve as the predictor. The forecast evaluation analysis compares the oil risk-based models with the HA model given that we are dealing with the return series of the clean energy prices. The oil risk-based models and HA model are "nested" since the latter can be seen as a subset of the former, hence the choice of Clark and West as the forecast evaluation test. The rejection of the null hypothesis of the Clark and West test indicates the better performance of the preferred models. "*", "**" and "***" indicates statistical significance at the 10%, 5% and 1% significance levels
Source(s): Table by authors

Table 7. Out-of-sample forecast evaluation of climate risk model [Nested models]

Historical average (HA) versus CPU												
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*
h = 1	4.372	4.387	4.634	4.681	3.758	3.727	6.353	6.417	8.103	7.778	5.444	5.335
h = 2	4.386	4.394	4.624	4.662	3.743	3.725	6.325	6.396	8.070	7.746	5.477	5.355
h = 3	5.070	5.057	4.915	5.056	4.316	4.372	6.671	6.801	8.472	8.190	5.424	5.304
h = 4	5.042	5.030	4.934	5.054	4.305	4.352	6.647	6.797	8.436	8.162	5.379	5.257
CW	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*	*HA*	*CPU*
h = 1		0.205		0.480		1.372**		0.632		9.248***		1.751
		(0.325)		(0.665)		(0.594)		(0.978)		(3.288)		(1.164)
h = 2		0.272		0.577		1.310**		0.591		9.205***		1.886
		(0.328)		(0.666)		(0.592)		(0.970)		(3.259)		(1.149)
h = 3		0.468		−0.859		0.695		−0.233		8.745***		1.848
		(0.380)		(0.936)		(0.850)		(1.267)		(3.268)		(1.127)
h = 4		0.463		−0.189		0.827		−0.409		8.605***		1.858
		(0.375)		(0.934)		(0.853)		(1.268)		(3.236)		(1.106)

Historical average (HA) versus EER												
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*
h = 1	4.372	4.373	4.634	4.631	3.758	3.785	6.353	6.338	8.102	8.234	5.444	5.421
h = 2	4.386	4.393	4.624	4.655	3.743	3.771	6.325	6.316	8.070	8.218	5.477	5.394
h = 3	5.070	5.072	4.951	4.880	4.316	4.227	6.671	6.539	8.472	8.502	5.424	5.360
h = 4	5.042	5.045	4.934	4.861	4.305	4.220	6.647	6.512	8.436	8.465	5.379	5.312
CW	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*	*HA*	*EER*
h = 1	1.116		1.336		0.645		2.028		0.090		2.039	
	(0.901)		(0.919)		(0.621)		(1.873)		(2.374)		(3.279)	
h = 2	1.051		1.118		0.707		2.675		−0.083		2.835	
	(0.893)		(0.936)		(0.618)		(1.857)		(2.359)		(3.311)	
h = 3	1.080		2.177		1.722		3.845		1.953		2.766	
	(0.884)		(1.408)		(1.185)		(2.559)		(3.101)		(3.248)	
h = 4	1.069		2.184		1.682		3.870		1.959		2.757	
	(0.874)		(1.395)		(1.175)		(2.536)		(3.073)		(3.186)	

Note(s): This table presents the results for the forecast evaluation of the climate risk-based models where either the CPU or EER serve as the predictor. The forecast evaluation analysis compares the climate risk-based models with the HA model given that we are dealing with the return series of the clean energy prices. The climate risk-based models and HA model are "nested" since the latter can be seen as a subset of the former, hence the choice of Clark and West as the forecast evaluation test. The rejection of the null hypothesis of CW test indicates the better performance of the preferred models. "*", "**" and "***" indicates statistical significance at the 10%, 5% and 1% significance levels
Source(s): Table by authors

Table 8.
Out-of-sample forecast evaluation [Non-nested models]

	Oil risks (brent versus WTI)											
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*
h = 10	0.919	0.917	1.278	1.276	1.148	1.145	1.297	1.296	1.761	1.759	1.175	1.167
h = 30	0.922	0.920	1.274	1.272	1.147	1.145	1.295	1.294	1.758	1.757	1.175	1.166
h = 60	1.042	1,038	1.270	1.268	1.144	1.142	1.288	1.287	1.758	1.757	1.180	1.173
h = 120	1.104	1.100	1.258	1.255	1.135	1.133	1.279	1.278	1.752	1.750	1.170	1.162
MDM	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*	*Brent*	*WTI*
h = 10	−1.252		−1.211		−1.748**		−0.715		−0.659		−1.541*	
h = 30	−1.329*		−1.219		−1.766**		−0.709		−0.662		−1.512*	
h = 60	−1.424*		−1.178		−1.609*		−0.634		−0.527		−1.435*	
h = 120	−1.062		−1.206		−1.579*		−0.824		−0.529		−1.352*	

	Climate risk (EER versus CPU)											
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*
h = 1	4.373	4.387	4.631	4.681	3.785	3.727	6.338	6.417	8.234	7.778	5.421	5.335
h = 2	4.393	4.394	4.655	4.662	3.771	3.725	6.316	6.396	8.218	7.746	5.394	5.355
h = 3	5.072	5.057	4.880	5.056	4.227	4.372	6.539	6.801	8.502	8.190	5.360	5.304
h = 4	5.045	5.030	4.861	5.054	4.220	4.352	6.512	6.797	8.465	8.162	5.312	5.257
MDM	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*	*EER*	*CPU*
h = 1	0.134		0.470		−0.398		0.444		−1.515*		−0.213	
h = 2	0.005		0.057		−0.276		0.386		−1.360		−0.056	
h = 3	−0.072		0.505		0.371		0.603		−0.578		−0.043	
h = 4	−0.084		0.121		0.074		0.143		−0.122		−0.395	

Note(s): This table presents the results for the forecast evaluation of the oil risk-based models where either the realized volatility of WTI or Brent price serve as the predictor in the upper panel and the climate risk-based models where either the CPU or EER serve as the predictor in the lower panel. The forecast evaluation analysis compares each of the two oil risk-based models and the two climate risk-based models. The climate risk-based models and oil risk-based models are "non-nested" since for instance the model with Brent price volatility as the predictor cannot be seen as a subset of the model with WTI price volatility. Likewise, the models with CPU and EER are also non-nested, hence the choice of MDM forecast evaluation test. Negative and statistical significance of the MDM test indicates the better performance of the preferred models over the benchmark models. In both cases, the models with WTI are specified as the preferred of the oil risk models whereas the models with CPU are specified as the preferred of the two climate risk models. "*", "**" and "***" indicates statistical significance at the 10%, 5% and 1% significance levels
Source(s): Table by authors

An implication of this finding is that the inclusion of WTI improves the predictability of the various clean energy stocks and that WTI may be a better proxy for the global crude oil price. This finding is in line with a group of other studies such as Narayan (2020), Azimli (2020), and Adediran, Yinusa, and Lakhani (2021) that have argued that the West Texas intermediate is a better proxy of crude oil price for studies related to hedging.

Similar conclusions can be obtained from Table 7 where the model containing EER fail to outperform the HA benchmark model in any of the cases whereas the forecast evaluation results show some cases where the CPU-based models beat the benchmark model. The foregoing results obtained from out-of-sample forecast evaluations strengthen the in-sample predictability results. In addition to evaluating the hedging effectiveness, we submit that CPU is the better measure of climate risk than EER. These conclusions are also partly corroborated by the results of the model evaluations of non-nested models in Table 8 where we compare Brent versus WTI and EER versus CPU. Given that the models with WTI and CPU are the "preferred" models of the analysis, the largely negative (although scantily statistically significant) MDM statistics also suggest that WTI price realized volatility (as measure of oil market risk) predict clean energy stocks better than the Brent price realized volatility.

5. Conclusion

This study examines the ability of clean energy stocks to hedge oil market and climate risks. This study demonstrates that green assets not only support decarbonization projects and combat climate change, they can also be an attractive diversification option for investors. Among the contributions of this study to the growing literature is the analysis of global and regional clean energy indices (global, US, Europe and Asia) and sectoral indices (solar and wind) for robust results. We also conduct forecasting analysis of the clean energy stocks with various measures of oil risks (WTI and Brent crude volatility) and climate risks (CPU and EER) as predictors. The pre-test analyses conducted on the variables justify the choice of Westerlund and Narayan (2012, 2015) method to analyse the nexus between clean energy indices and either of oil risk and climate risk. In addition to the foregoing impact analyses, we conduct forecasting analyses with alternative forecast evaluation techniques.

The outcome shows that clean energy stocks can effectively hedge oil market risk, as 11 out of 12 cases in our study demonstrate. The only exception is the US where hedging against oil risk does not occur These results are corroborated with additional results obtained from the COVID-19 sample period where all the clean energy stocks demonstrate significant hedging power against oil market risks. This could mean that investing in clean energy stocks can help investors reduce the risks from the oil market. However, the results associated with climate risks reveal that clean energy assets cannot entirely hedge climate risk given that one of the climate risk proxies, EER, could not be hedged with any of the clean energy assets from any of the markets included in this study. The results improved with the consideration of climate policy uncertainty as shown by the results where the clean energy indices of Europe, US, Asia as well as the solar index are shown to be capable of protecting investors against climate risk. Further analysis carried out to test the forecasting ability of the predictors shows that WTI performs better than Brent as a global crude price proxy. Also, CPU is found to be a better climate risk proxy compared to EER.

Since the results of this study suggests the hedging ability of clean energy stocks for oil market risk, we therefore recommend that global financial investors should further tap into this opportunity which will not only mitigate the oil market financial risks to their portfolios but also reduce the devastating effects of excessive use of crude oil on the environment. Investors can shift attention to the clean energy indices considered in this study not only as a profitable investment choice for evading market risks but also as an environmentally responsible investment for promoting decarbonization which can combat climate change.

The limited ability of clean energy assets to successfully hedge climate risk proxies call for more comprehensive climate regulatory policies across countries to reduce the risks associated with dealing with green technology and clean investments. Future researchers could build on this study by evaluating the economic significance of the findings of the nexus between clean energy assets and climate and oil risks. Other prospective researchers could make relevant contributions by developing a text-based climate risk index with a daily frequency to circumvent the data limitation encountered by the present study in terms of the available monthly climate risk measures.

Notes

1. The literature review makes clear distinction between hedging and safe haven properties vis-à-vis diversification benefits of assets.
2. See details on the Nobel Prize in Economic Sciences for the year 1990 here: https://www.nobelprize.org/prizes/economic-sciences/1990/press-release/.
3. The details of the data are provided in Table 1.
4. See https://www.policyuncertainty.com/climate_uncertainty.html.
5. See https://fred.stlouisfed.org/series/EMVENRGYENVREG
6. See https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm
7. In addition to the CPU & EER indices, we also use the temperature anomaly data published by the National Aeronautics and Space Administration (https://data.giss.nasa.gov/gistemp/) (see Oloko *et al.*, 2022 for justification for its use as a measure of risk associated with climate change). The results are presented in the appendix of this paper (see Tables A1 and A2) and are similar to those of the EER.
8. The only exception where the various clean investments fail to provide cover against one of the oil risks is the US clean energy index against Brent volatility where the coefficient is positive but not statistically significant.
9. We also report the root mean square errors (RMSE) for the estimated models. The rule of thumb for evaluating the statistic is that the lower the RMSE, the better the model performance.

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Appendix

	Global	Europe	US	Asia	Solar	Wind
α^{clm}	5.0216***	4.2175**	−2.1038***	3.3167***	2.3219**	4.2501
	(0.4430)	(1.8169)	(0.3395)	(0.0891)	(1.0308)	(2.6122)
β^{*clm}	−4.2793***	−4.2177**	4.6775***	−3.2976***	0.5319	−4.2796
	(0.6975)	(1.9095)	(0.5248)	(0.1609)	(1.1828)	(2.9614)
Hedging role?	No hedge	No hedge	*Hedge*	No hedge	No hedge	No hedge

Note(s): The table presents the predictability results that indicate the hedging effectiveness of disaggregated clean energy assets against climate risk measured with risk associated with climate change (temperature anomaly). α^{oil} and β^{*oil} are the constant and Beta-adjusted coefficient of the models with temperature anomaly as the predictor. The hedging role is informed by the Beta-adjusted coefficients. $\beta^* \leq 0$ indicates 'no hedge', $\beta^* > 0$ indicates 'hedge'. "**" and "***" indicates statistical significance at 5% and 1% significance levels
Source(s): Table by authors

Table A1.
Hedging role of clean energy assets against temperature anomaly

Table A2. Out-of-sample forecast evaluation temperature anomaly [Temp]

	Historical average versus temp											
	Global		Europe		US		Asia		Solar		Wind	
RMSE	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*
$h = 10$	4.3722	4.3759	4.6343	4.7417	3.7588	3.8755	6.3538	6.4534	8.1023	8.1480	5.4552	5.4948
$h = 30$	4.3867	4.3990	4.6240	4.7380	3.7439	3.8699	6.3255	6.4243	8.0702	8.1147	5.4831	5.5117
$h = 60$	5.0701	5.0584	4.9515	5.0386	4.3164	4.5499	6.6715	6.7287	8.4728	8.5299	5.4303	5.4614
$h = 120$	5.0428	5.0312	4.9345	5.0194	4.3053	4.5301	6.6474	6.7015	8.4365	8.4941	5.3843	5.4097
CW	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*	*HA*	*Temp*
$h = 10$	1.3772		−0.1459		0.2770		−0.5527		−0.6728**		2.2345	
	(1.2032)		(0.9112)		(0.8014)		(1.1066)		(0.3349)		(2.3695)	
$h = 30$	1.2904		−0.2045		0.2302		−0.5399		−0.6497*		2.3054	
	(1.1930)		(0.9048)		(0.7955)		(1.0966)		(0.3327)		(2.3236)	
$h = 60$	1.5045		−0.0116		−0.8591		−0.0413		−0.8990**		2.2491	
	(1.1993)		(0.9172)		(1.3184)		(1.1957)		(0.4134)		(2.2792)	
$h = 120$	1.4879		0.0074		−0.7429		0.0040		−0.9028**		2.3088	
	(1.1864)		(0.9093)		(1.3118)		(1.1859)		(0.4097)		(2.2366)	

Note(s): The table presents the results for the forecast evaluation of the climate risk based models where temperature anomaly serves as the predictor. The forecast evaluation analysis compares the climate risk-based models with the HA model given that we are dealing with the returns series of the clean energy prices. The climate risk-based models and HA model are "nested" since the latter can be seen as a subset of the former, hence the choice of Clark and West (CW) as the forecast evaluation test. The rejection of the null hypothesis of CW test indicates the better performance of the preferred model (climate risk-based models). "*", "**" and "***" indicates statistical significance at 10%, 5% and 1% significance levels
Source(s): Table by authors