Assessment and Optimization of Clean Energy Equity Risks and Commodity Price Volatility Indexes: Implications for Sustainability

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Assessment and Optimization of Clean Energy Equity Risks and Commodity Price Volatility Indexes: Implications for Sustainability

Abstract

Although clean energy equities have emerged as a new asset class for market participants, especially environmentally concerned investors, existing and previous studies pay very little attention to how equity investors in clean energy markets can reduce their downside risk. The authors of this paper address this void by considering the roles of the commodity market volatility indexes of crude oil, gold and silver. Using the dynamic conditional correlation model, the results show that commodity volatilities and clean energy equity prices move in opposite directions. Based on the hedging effectiveness, each of the three volatility indexes performs as an effective tool for reducing the risk of clean energy equity indexes. Meanwhile, the implied volatility index of crude oil is the most effective tool, followed by that of gold and silver. The application of an asymmetric model confirms the main findings. The findings extend the limited understanding on how to hedge the downside risk of clean energy stock indices, and provide useful implications to market participants on the ability of implied volatility indexes of major commodities to hedge that risk.

Keywords: Clean energy equities; Commodity market volatility; Time-varying correlations; Hedging effectiveness

1. Introduction

Recent years have seen a rapid development of the renewable energy industry (Kazemilari et al., 2017). Related investments in this sector have witnessed a substantial uptrend over the last few years, growing from $47 billion in 2004 to $279.8 in 2017[1]. This significant expansion was mainly driven by the adverse impact of conventional energy sources on global climate change, and thus the willingness of governments to cope with deteriorating environmental conditions[2]. Given this rapid expansion of the renewable energy business, clean energy stocks have emerged as a new asset class for market participants, especially environmentally concerned investors. Accordingly, scholars are becoming interested in investigating the association between clean energy and other asset classes. However, previous studies pay very little attention to how investors holding equity assets in clean energy markets can reduce their downside risk. This is surprising given investments in clean energy stocks have positive environmental and socio-economic impacts that potentially help ensuring a certain degree of sustainability. Furthermore, clean energy equities seem highly volatile, which makes proper knowledge of how to hedge their risks crucial for gaining portfolio diversification benefits (Ahmad et al., 2018) and thereby for the stability of investments in clean energy stocks.

In this paper, the authors extend this scant literature by investigating whether commodity market volatility indexes, namely crude oil implied volatility index (OVX), gold volatility index (GVZ)

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[1] http://www.iberglobal.com/files/2018/renewable_trends.pdf

[2] For example, Reboredo et al. (2017) contend that alternative energies receive considerable attention as they emit less carbon than traditional energy sources. Chiu et al. (2016) indicate that the usage of renewable fuels has increased with a view to reducing GHG emissions and moderating the negative effect of volatile energy prices. Dutta (2019) argues that concerns about energy security and climate changes are the main reasons behind the significant growth of the clean energy industry.

and silver volatility index (VXSLV), can diversify the risk associated with clean energy equity indexes.

From an econometric perspective, the correlation analysis employed in this paper is based on a bivariate DCC-GARCH model (Engle, 2002), which estimates the correlation matrix directly by utilizing the standardized residuals which reduces the number of parameters to be estimated. Compared to other various multivariate GARCH specifications, the empirical superiority of DCC-GARCH models is demonstrated (see, among others, Sadorsky 2014). Hedging effectiveness is assessed along the lines of Basher and Sadorsky (2016).

The findings arising from this analysis would help market participants to understand the role of crude oil or precious metal implied volatilities in hedging the risk linked to clean energy stock indexes. Furthermore, investors might utilize the information provided in the implied volatility indexes of major commodities to predict clean energy stock market returns. In addition, policymakers can build on the findings of this paper to articulate policies seeking to avoid the contagion risk stemming from volatile commodity markets. The findings of this paper could also be useful to academics who are engaged in research involving asset pricing models, with the enhancement of the latter being dependent on a better understanding of the relationships across assets and markets.

2. Related studies

The global energy transition to a low carbon planet aims to achieve a sustainable future for the planet and a reliable and sustainable access to modern energy services. Accordingly, the emergence of clean energy investments helps in advancing environmental and economical sustainability. Numerous studies focus on energy efficiency, hybrid renewable energy systems, and cleaner sustainability (Shezan and Das, 2017)[3].

A growing strand of research considers the clean energy stocks and their relationships with other asset classes[4]. However, previous research exploring the connection amongst commodity markets and renewable energy stocks is scarce. Sadorsky (2012a) finds that an upsurge in oil prices increases the risk associated with clean energy equities. Kumar et al. (2012) document that stock prices of renewable energy firms are sensitive to oil price shocks. Employing a copula approach, Reboredo (2015) shows that the dependence between oil and clean energy stock prices evolves over time. Additionally, Bondia et al. (2016) indicate a short-term linkage between oil and renewable energy equity markets and, more importantly, show that the Granger-causality runs from commodity to stock markets. Using continuous and discrete wavelets, Reboredo et al. (2017) indicate that although the short-run relationship between energy prices and clean energy equities appears to be weak, such a relationship seems strong in the long run. Ahmad (2017) finds that oil prices and renewable energy stock returns move in the same direction, implying that an upturn in energy prices leads to an increase in the stock prices of alternative energy firms.

Another strand of literature uses the information content of the OVX to explore whether energy market uncertainty has any impact on clean energy stock indexes. Dutta (2017) finds a positive association between the levels of oil price volatility and the realized volatility of renewable energy stocks. Ahmad et al. (2018) show that OVX and clean energy equities are negatively correlated, and hence the inclusion of OVX in a portfolio of clean energy equities reduces the risk associated with the alternative energy markets. However, the association between precious metals (e.g., gold and silver) and renewable energy stocks remains understudied. Ahmad et al. (2018) examines the

[3] Related studies include Shezan et al. (2016) and Shezan et al. (2018).
[4] Table A1 exhibits an extensive literature review of existing studies focusing on clean energy stock markets.

role of gold in reducing the volatility of clean energy portfolios. They show that gold fails to minimize such risk, which is surprising given that this precious metal is frequently used to hedge equity market risks (Junttila et al., 2018). More recently, Bouri et al. (2019) focus on the roles of gold and crude oil prices and document similar findings. Basher and Sadorsky (2016), however, claim that precious metals are no longer effective in moderating the risk linked to stock prices. A similar finding is documented by Cunado et al. (2019). This is based on the rationale that the upward correlation between gold and equity markets tends to lessen the attractiveness of investments in precious metals as hedging instruments.

In this paper, unlike the standing literature, the authors examine whether oil and precious metal (gold and silver) volatility indexes can hedge clean energy stock market risk. Given that implied volatility indexes such as the US VIX usually have a negative link with stock market indexes, one can wonder whether commodity market volatility indexes could be used as effective hedging tools against clean energy equity risks[5].

The contributions of the paper are two-fold. Firstly, the analyses in this study complement the outcome of Ahmad et al. (2018), which is the only study found in the existing literature that examines whether a commodity implied volatility index (i.e., OVX) can be used as a hedging tool for clean energy equities. This current paper differs from Ahmad et al. (2018) in that it uses, besides the OVX, two potential hedging tools from the commodity markets, namely the gold and silver implied volatility indexes (i.e., gold volatility index (GVZ) and silver volatility index (VXSLV)). This current paper uses the information on gold volatility as this precious metal is frequently used to hedge equity market risks. In addition, the silver implied volatility is considered,

[5] Basher and Sadorsky (2016) also argue that different VIX indexes, which have a negative connection with stock prices, could diminish the risk associated with equity markets.

as silver represents a precious metal that is massively consumed in the photovoltaic (PV) process in order to produce solar energy. Secondly, this current paper estimates the time-varying correlations between commodity implied volatility indexes and clean energy stock prices. Note that the unconditional correlations cannot capture the dynamics of the aforementioned linkage as they ignore the time-varying fluctuations of the correlation structure. Exploring the connection between commodity and clean energy markets in a time-varying environment would help us to observe how the said association evolves over time.

3. Data and preliminary analyses

3.1. Data

The daily dataset covers the period March 16, 2011 to December 31, 2018, yielding 2,034 daily common observations. The commencement of the sample period is dictated by the availability of the implied volatility index of silver. All the information is collected from DataStream. The indexes covered in this study include three implied volatility indexes from strategic commodities and three clean energy stock indexes. The former indexes are the oil volatility index (OVX), the gold volatility index (GVZ) and the silver volatility index (VXSLV). Each of these indexes was constructed by the Chicago Board of Options Exchange (CBOE) in order to measure the market's expectation of 30-day volatility. They were computed according to the VIX methodology applied to the US options markets. The clean energy stock indexes include Wilder Hill Clean Energy (ECO), S&P Global Clean Energy (SPGCE), and MAC global solar energy stock (MAC). Traded on the American Stock Exchange, ECO is an equal-dollar-weighted index, tracking clean energy equity prices. At present, it constitutes 40 renewable energy firms. SPGCE provides liquid and tradable exposure to 30 global renewable energy companies. In fact, it is a modified capitalization-weighted index consisting of a diversified mix of companies from clean energy production, clean energy equipment, and technology. Finally, MAC is traded on the New York Stock Exchange ARCA, and consists of a wide range of firms such as solar power equipment producers, and suppliers of materials or services to solar equipment producers.

3.2. Preliminary analyses

Summary statistics of the data series are given in Table 1. It is evident from these statistics that the mean return of each of the three clean energy stock indexes is negative. MAC has the highest standard deviation among the stock indexes. In addition, ECO and SPGCE are negatively skewed, while the MAC is positively skewed. All the clean energy stock indexes have leptokurtic return, which points to a departure from normality.

Table 1: Summary statistics of the daily series - Levels

	Mean	SD	Skewness	Kurtosis	JB statistics
ECO	-0.0174	0.7127	-0.2733	5.61	604.41***
SPGCE	-0.0156	0.5487	-0.3803	6.64	1175.22***
MAC	-0.0316	1.0082	0.0767	5.94	736.32***
OVX	0.0040	2.0999	0.9304	14.42	11350.10***
GVZ	-0.0070	2.2781	1.0154	9.97	4469.57***
VXSLV	-0.0159	2.0307	1.7826	17.89	19872.47***

Notes: This table reports the summary statistics for daily series. SD: Standard Deviation. JB: Jarque-Bera. *** indicates statistical significance at 1% level.

These results are also confirmed by the Jarque-Bera statistics. Moreover, amongst the volatility indexes, GVZ has the highest amount of volatility followed by OVX and VXSLV. Additionally, none of the implied volatility series satisfies the normality assumption.

Table 2 shows the results of the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The null hypothesis for these tests is that the series under study is not stationary. Results show that each of the six series under study is stationary even at levels.

Table 2: Results of standard stationarity tests

	ADF Test		PP Test	
	Levels	Logarithmic differences	Levels	Logarithmic differences
ECO	-3.65 (.00)***	-42.73 (.00)***	-3..41 (.02)**	-42.72 (.00)***
SPGCE	-3.90 (.00)***	-37.83 (.00)***	-3.66 (.00)***	-37.84 (.00)***
MAC	-3.94 (.00)***	-41.67 (.00)***	-3.82 (.00)***	-41.69 (.00)***
OVX	-3.44 (.00)***	-28.92 (.00)***	-3.15 (.02)**	-49.59 (.00)***
GVZ	-4.84 (.00)***	-48.12 (.00)***	-4.22 (.00)***	-54.98 (.00)***
VXSLV	-4.01 (.00)***	-47.90 (.00)***	-3.32 (.02)**	-55.14 (.00)***

Notes: This table presents the results for the ADF and PP tests. p-values are given in parentheses. *** and ** denote statistical significance at 1% and 5% levels.

It is noteworthy that the results of the traditional stationary tests could be misleading when the data used have structural breaks (Perron, 1989). Accordingly, an ADF test taking structural changes into account is applied, and the results are reported in Table 3. The results indicate that once the structural breaks are taken into account, the ECO and OVX indexes are no longer stationary at levels. All the indexes, however, become stationary after taking the logarithmic differences. Accordingly, the empirical analyses are conducted with the log differences of the six series (ECO, SPGCE, MAC, OVX, GVZ, and VXSLV).

Table 3: ADF test accounting for structural breaks

	Levels	Logarithmic differences
ECO	-4.18 (.11)	43.33 (.00)***
SPGCE	-5.11 (.00)***	38.44 (.00)***
MAC	-5.32 (.08)***	42.28 (.00)***
OVX	-4.03 (.14)	29.53 (.00)***
GVZ	-6.28 (.00)***	48.52 (.00)***
VXSLV	-6.08 (.00)***	37.50 (.00)***

Notes: This table presents the results of ADF stationarity test after accounting for structural breaks. *p*-values are given in parentheses. *** denotes statistical significance at 1% level.

4. Econometric methodology

This study applies the bivariate DCC-GARCH process of Engle (2002). In fact, the empirical superiority of DCC-GARCH models over other multivariate GARCH models is documented in prior studies (Sadorsky, 2012b)[6]. The DCC-GARCH process estimates the correlation matrix directly by utilizing the standardized residuals which reduces the number of parameters to be estimated. This notable process is suitable to study time-varying correlations and make inferences regarding the hedging effectiveness (Sadorsky, 2012b). A robustness analysis is also applied based on an asymmetric DCC-GARCH (ADCC-GARCH) process.

The mean equation of the bivariate process is given by:

$$r_t = L + \tau r_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = H_t^{1/2} \eta_t \tag{2}$$

where r_t is a matrix of logarithmic differences for the commodity implied volatility and clean energy stock indexes, L designates a matrix of fixed parameters, τ is a matrix of coefficients gauging the influence of own-lagged and cross mean transmission, ε_t indicates the noise term, η_t is a matrix of *iid* innovations. Moreover, $H_t^{1/2}$ refers to the matrix of conditional volatilities. The covariance matrix is expressed as:

$$H_t = D_t R_t D_t \tag{3}$$

where $D_t = diag(\sqrt{h_t^s}, \sqrt{h_t^c})$ is a diagonal of time-varying standard deviations, and h_t^s and h_t^c are the conditional volatilities of clean energy stock and commodity markets, respectively. They are defined as:

[6] The authors of this paper have decided not to use other multivariate GARCH models such as VAR-AGRCH or BEKK as they might be subject to the so-called "curse of dimensionality" resulting from the increase in the number of covariance terms, which makes the estimation of the covariance matrix very difficult.

$$h_t^s = d_s^2 + b_{11}^2 h_{t-1}^s + b_{21}^2 h_{t-1}^c + a_{11}^2 \varepsilon_{s,t-1}^2 + a_{21}^2 \varepsilon_{c,t-1}^2 \tag{4}$$

$$h_t^c = d_c^2 + b_{12}^2 h_{t-1}^s + b_{22}^2 h_{t-1}^c + a_{12}^2 \varepsilon_{s,t-1}^2 + a_{22}^2 \varepsilon_{c,t-1}^2 \tag{5}$$

R_t is the conditional correlation matrix of the standardized returns ε_t. It is expressed as:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{6}$$

As for Q_t,it is the time-varying conditional correlation of residuals as given by:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \xi_{t-1} \xi_{t-1}' + \theta_2 Q_{t-1} \tag{7}$$

where θ_1 and θ_2 are non-negative scalar parameters such that $\theta_1 + \theta_2 < 1$ for the model to be stationary, and Q_0 refers to the matrix of unconditional correlations for the standardized noise ξ_t. The parameters of the DCC-GARCH models are estimated via the quasi-maximum likelihood estimation technique. Further details regarding the estimation of the dynamic conditional correlations are given in Engle (2002).

5. Empirical Results

5.1. Time-varying correlations

The time-varying correlations obtained from the DCC-GARCH process are discussed in this subsection. Table 4 shows the descriptive statistics for the pairwise time-varying correlations, while Figures 1-3 plot the time-varying correlations. Looking at the numbers presented in Table 4, it appears that the mean correlation is negative suggesting that commodity volatilities and clean equity returns move in opposite directions. That is, a decrease in clean energy stock returns is associated with an upsurge in crude oil or metal price volatility. Accordingly, during a downturn in the market of clean energy stocks, a long position in any of the implied volatility indexes generates profits useful to offset the losses of investments in clean energy stocks.

Table 4: Summary statistics of time-varying correlations

	Mean	Standard Deviation	Maximum	Minimum
ECO/OVX	-0.338	0.137	-0.902	0.089
ECO/GVZ	-0.268	0.128	-0.835	0.181
ECO/VXSLV	-0.234	0.139	-0.747	0.207
SPGCE/OVX	-0.269	0.175	-0.889	0.311
SPGCE/GVZ	-0.268	0.124	-0.725	0.608
SPGCE/VXSLV	-0.210	0.094	-0.700	0.449
MAC/OVX	-0.271	0.111	-0.646	0.218
MAC/GVZ	-0.269	0.118	-0.716	0.618
MAC/VXSLV	-0.189	0.119	-0.600	0.333

Notes: This table presents the summary statistics for the time-varying correlations between commodity VIXs and clean energy stocks.

Figures 1-3 demonstrate that these correlations tend to vary over time and, hence, they are not constant. Moreover, such time-varying correlations are observed in both positive and negative regions indicating a time-dependent connection between these markets. To sum up, these findings suggest that clean energy stock price risks can be diversified if investors include both renewable energy assets and commodity volatility indexes in their portfolios.

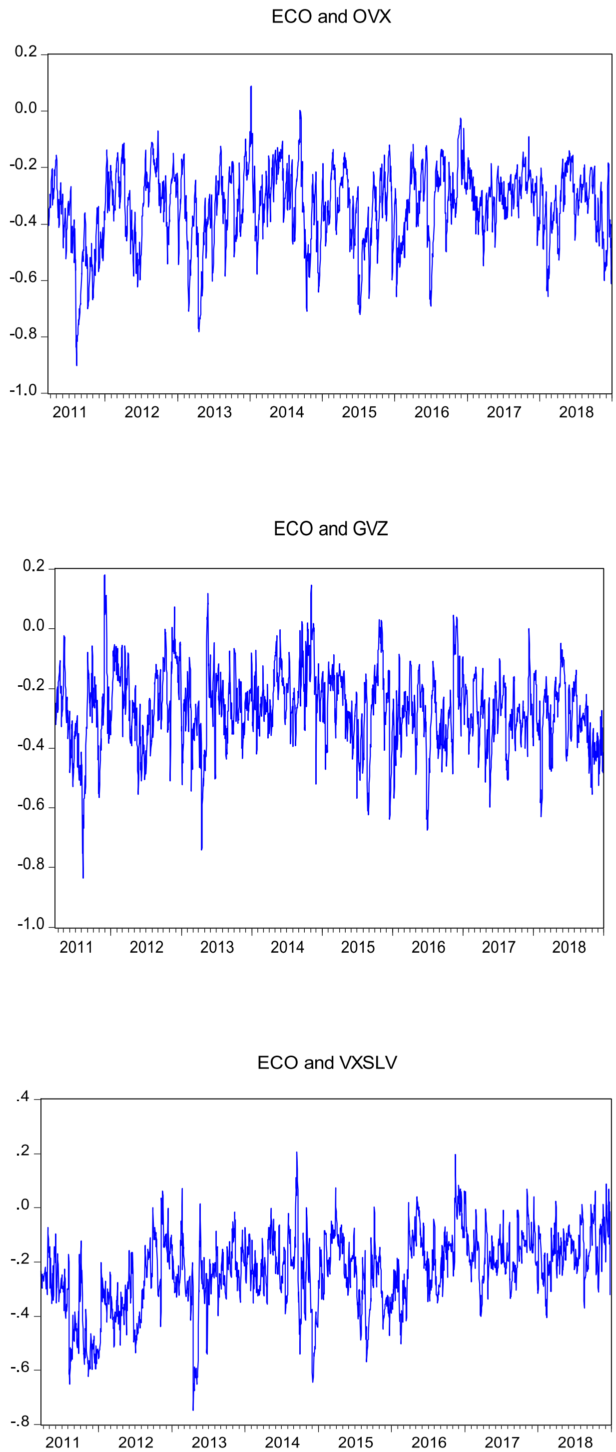

Fig. 1: Time-varying correlations between ECO and commodity VIX indexes

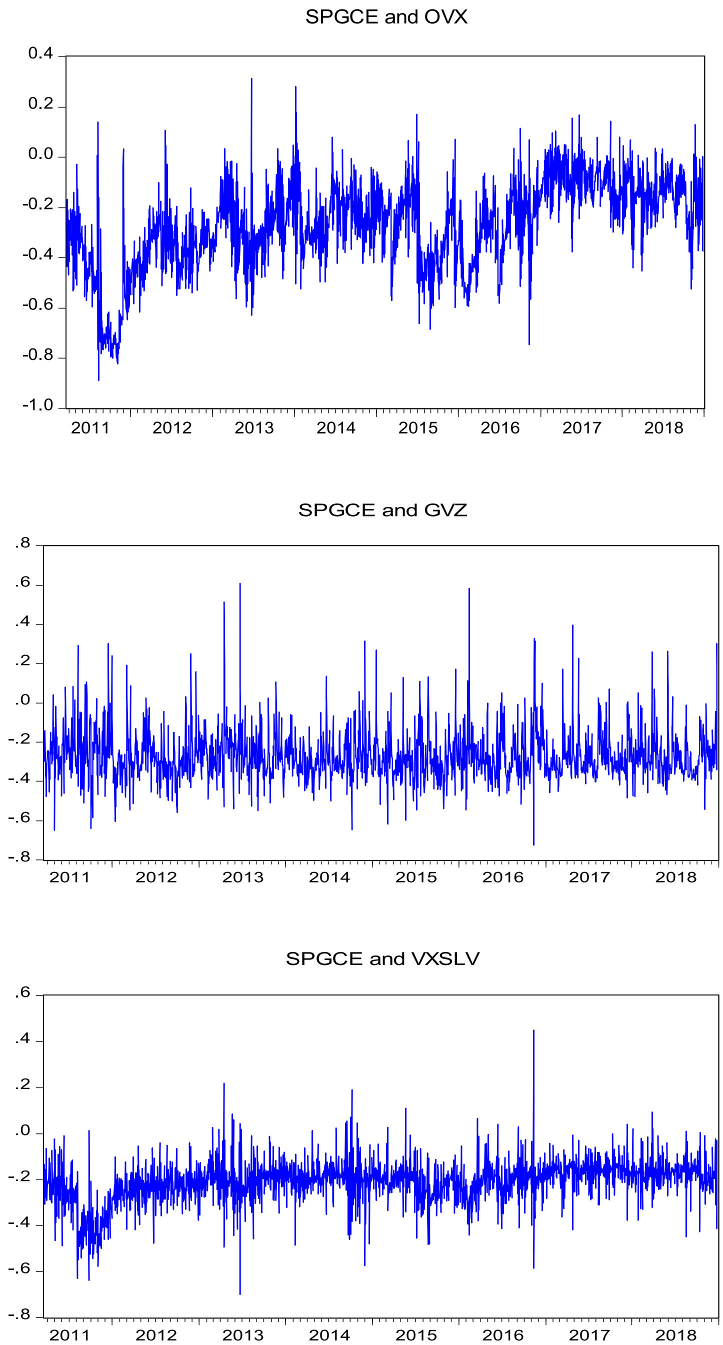

Fig. 2: Time-varying correlations between SPGCE and commodity VIX indexes

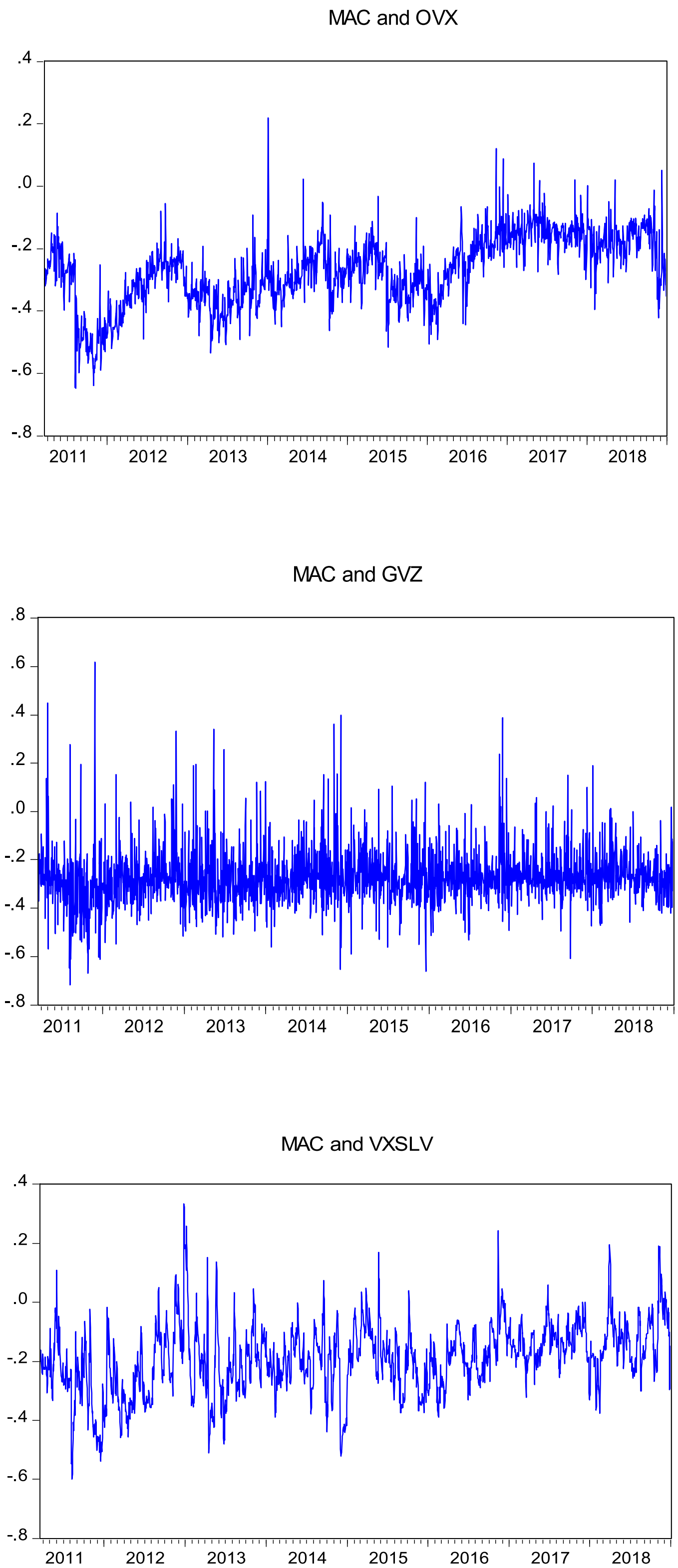

Fig. 3: Time-varying correlations between MAC and commodity VIX indexes

5.2. Hedging effectiveness

This subsection focuses on the effective role of commodity volatility indexes in hedging the downside risk of clean energy stock indexes. More specifically, it explores whether combining commodity volatility indexes and renewable energy equities in a portfolio reduces the risk of the resultant portfolio. The hedging effectiveness (HE) is defined as[7]:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{8}$$

where $Var_{unhedged}$ designates the variation in returns for clean energy equities, while Var_{hedged} is the variation in returns for the commodity-equity portfolio defined as:

$$Var_{hedged} = (\omega_t^{cs})^2 h_t^c + (1 - (\omega_t^{cs})^2) h_t^s + 2\omega_t^{cs}(1 - \omega_t^{cs}) h_t^{cs} \tag{9}$$

where h_t^s and h_t^c are given respectively in Equations 4 and 5, h_t^{cs} is the conditional covariance between the commodity and equity indices, and ω_t^{cs} refers to the optimal weight of commodity volatility indexes in a portfolio comprising stock and commodity volatility indexes at time *t*:

$$\omega_t^{cs} = \frac{h_t^c - h_t^{cs}}{h_t^c - 2h_t^{cs} + h_t^s} \tag{10}$$

Note that a higher HE results in better portfolio risk reduction, signifying that the selected investment policy should produce superior risk-adjusted returns.

[7] See Ku, Chen, and Chen (2007) for more details.

Table 5: Hedging effectiveness obtained from DCC-GARCH estimates

	$Var_{unhedged}$	Var_{hedged}	HE (%)
Panel A: ECO index			
ECO/OVX	0.50	0.38	24%
ECO/GVZ	0.50	0.32	36%
ECO/VXSLV	0.50	0.35	30%
Panel B: SPGCE index			
SPGCE/OVX	0.30	0.21	30%
SPGCE/GVZ	0.30	0.22	27%
SPGCE/VXSLV	0.30	0.22	27%
Panel B: MAC index			
MAC/OVX	1.02	0.61	40%
MAC/GVZ	1.02	0.71	30%
MAC/VXSLV	1.02	0.70	31%

Notes: $Var_{unhedged}$ is the variance of the returns on the portfolio of stocks and Var_{hedged} refers to the variance of returns of the commodity-stock portfolio. Hedging effectiveness (HE).

The results obtained from equation (8) are presented in Table 5, shown in three panels (Panel A for ECO index; Panel B for SPGCE index; Panel C for MAC index). These results suggest that investors holding assets in renewable energy stock markets should include the implied volatility index of crude oil or precious metals in their portfolios for hedging clean energy equity risks. This is because a significant amount of risk reduction is observed when such portfolios are formed. For both SPGCE and MAC indexes, the HE associated to OVX is substantially higher than that associated with GVZ and VXSLV. Specifically, the risk for the OVX-stock portfolio is reduced by 30% and 40% for SPGCE and MAC, respectively. However, the risk for the GVZ-stock and VXSLV-stock portfolios is reduced by around 27% and 31%, respectively. These results suggest that OVX frequently appears to be the most suitable asset to hedge the risks of clean energy stock indexes. For the ECO index, GVZ is the best asset for hedging renewable energy stock indexes, followed by VXSLV and OVX. To be specific, the risk for the GVZ-stock portfolio is reduced by 36%. For OVX and VXSLV, the risk reduction is 24% and 30% respectively. Note that Ahmad et al. (2018) also document that OVX is among the best assets to hedge clean energy equities. The analysis in this paper, however, differs from this earlier research in several aspects. First, Ahmad et al. (2018) have not considered the application of precious metal volatility indexes in hedging clean energy equities. Second, they use only the ECO index to track clean energy stock prices, while this current paper conducts a more comprehensive research by including SPGCE and MAC indexes in the empirical analyses. Third, this current paper shows that for the ECO index, both GVZ and VXSLV are hedging instruments, and they perform better than the OVX. Overall, the findings of this paper confirm the effective role of oil and precious metal volatility indexes in hedging clean energy stocks. It is worth mentioning that these results are also supported by those reported in Table 4, which shows that the average correlations between commodity implied volatility indexes and clean energy stock market returns are negative. Such negative correlations typically indicate more portfolio risk reduction.

5.3. Robustness test

For testing the robustness of the findings, the ADCC-GARCH process is employed. This asymmetric specification is adopted as financial time-series are often non-linear in nature. In the ADCC-GARCH model, h_t^s and h_t^c are defined as:

$$h_t^s = d_s^2 + b_{11}^2 h_{t-1}^s + b_{21}^2 h_{t-1}^c + a_{11}^2 A(\varepsilon_{s,t-1})^2 + a_{21}^2 A(\varepsilon_{c,t-1})^2 + B[(\varepsilon_{s,t-1}) \times ((\varepsilon_{s,t-1}) < 0)]$$

(11)

$$h_t^c = d_c^2 + b_{12}^2 h_{t-1}^s + b_{22}^2 h_{t-1}^c + a_{12}^2 A(\varepsilon_{s,t-1})^2 + a_{22}^2 A(\varepsilon_{c,t-1})^2 + B[(\varepsilon_{c,t-1}) \times ((\varepsilon_{c,t-1}) < 0)]$$

(12)

where, $A(\varepsilon_{s,t-1})^2$ and $B[(\varepsilon_{s,t-1}) \times ((\varepsilon_{s,t-1}) < 0)]$ along with $A(\varepsilon_{c,t-1})^2$ and $B[(\varepsilon_{c,t-1}) \times ((\varepsilon_{c,t-1}) < 0)]$ respectively specify the connection between one market volatility and own past positive (negative) returns.

Table 6: Hedging effectiveness obtained from ADCC-GARCH estimates

	$Var_{unhedged}$	Var_{hedged}	HE (%)
Panel A: ECO index			
ECO/OVX	0.50	0.38	24%
ECO/GVZ	0.50	0.34	32%
ECO/VXSLV	0.50	0.36	28%
Panel B: SPGCE index			
SPGCE/OVX	0.30	0.23	23%
SPGCE/GVZ	0.30	0.21	30%
SPGCE/VXSLV	0.30	0.23	23%
Panel B: MAC index			
MAC/OVX	1.02	0.63	38%
MAC/GVZ	1.02	0.71	30%
MAC/VXSLV	1.02	0.67	34%

See notes to Table 5.

Table 6 presents the findings from the analyses based on the ADCC-GARCH model. The findings mimic those shown in Table 5. That is, commodity market volatility indexes act as hedging tools against clean energy stock market risks. The only discrepancy is that for the SPGCE index, GVZ now outperforms other volatility indexes. In summary, the overall findings are generally robust as they do not alter much depending on the specification of the DCC-GARCH models used.

6. Discussion and implications for sustainable development

While previous studies examine how clean energy stocks interact with other assets regarding return correlations and volatility spillovers, what is lacking, however, is a complete understanding of how investors in clean energy stocks can hedge their investments. (see Table A1). Sadorsky (2012b), for instance, shows that oil can be used to hedge the risk associated with clean energy equities. Bouri et al. (2019), however, argue that oil is no longer a good hedge for clean energy stock markets. Additionally, Dutta et al. (2018) find that the EU allowance market is an effective tool for hedging the downside risk clean energy equities. Ahmad et al. (2018), on the other hand, demonstrate that the US equity VIX and oil volatility index act as a more effective hedge for clean energy equities compared to oil, gold and allowance markets. Therefore, the findings of previous studies are somewhat mixed and hence how to hedge clean energy assets merits further investigation.

The present study aims to explore the possibilities of hedging an investment in clean energy stocks with the implied volatility indexes of oil, gold and silver markets. Since earlier studies evidence that traditional assets such as oil and gold no longer act as an active hedging instrument for renewable energy stocks, this empirical work, therefore, investigates the hedging effectiveness of the abovementioned VIX indexes. Given that different VIX indexes have a negative linkage with stock prices (Basher and Sadorsky, 2016), the application of commodity market VIX series could thus diversify the risk associated with clean energy equity markets.

Using the dynamic conditional correlation model, the results show that commodity volatilities and clean energy equity prices move in opposite directions. Based on the hedging effectiveness, each of the three volatility indexes performs as an effective tool for reducing the risk of clean energy equity indexes. Hence the findings of this empirical investigation confirm the superiority of implied volatility indexes over the traditional assets like oil, gold and silver when hedging the downside risk of clean energy equity markets. These results are partially consistent with those reported by Ahmad et al. (2018) who show that implied volatility indexes are the best assets to hedge clean energy equities. Unlike Ahmad et al. (2018), we examine the role of gold and silver volatility series in diversifying the risk associated with clean energy equity markets. This is an important contribution considering that gold is frequently used to hedge equity market risks and silver represents a precious metal that is heavily utilized in the photovoltaic process for the purpose of generating solar energy[8].

The main takeaway from this research is that OVX provides the most effective hedge for clean energy stock prices followed by gold and silver volatility indexes. Therefore, from a hedging perspective, alternative energy assets are more closely affected by oil price volatility than precious metal volatilities. This finding can be explained in light of the positive association between crude oil and clean energy stocks (e.g., Sadorsky, 2012b), which has its root in the fact that clean energy is regarded as a substitute to the dirty energy such as crude oil. Accordingly, and given that crude

[8] Dutta (2019) also argues that it is important to observe if including precious metal in portfolios of alternative energy stocks could successfully diversify the portfolio risk.

oil prices and the oil implied volatility index generally move in opposite directions[9], the implied volatility of crude oil prices exhibit a more (consistent) negative correlation with clean energy stock indices than the volatility of metals, which makes the implied volatility of crude oil to provide more diversification benefits and thereby to act as a more effective hedging tool. In light of the above rationale, lower crude oil prices reduce the attractiveness and economic viability of investment in clean energy projects, which leads to a halt in the development of clean energy and thus to adverse impacts on the stock price of clean energy firms. Therefore, when crude oil price declines, the price of clean energy stocks declines also, whereas the implied volatility of crude oil increases, implying an ability of the oil implied volatility index to hedge the downside risk of clean energy stock indices.

To sum up, commodity market volatility indexes emerge as an effective instrument for hedging clean energy equities. This is a new finding as earlier studies have not explored the potential role of commodity market volatility series in hedging clean energy stocks.

These results have important implications for market participants given that there is already a growing movement among pension funds, university endowments and mutual funds toward divesting from fossil fuels. In addition, growing concerns about energy security and climate change also inspire financial institutions invest in alternative energy sectors. The findings are therefore encouraging for investors who aim to decarbonize their equity portfolio and swap oil stocks for clean energy stocks.

An understanding of how investors holding assets in clean energy sectors can hedge their investment is essential for risk management. Knowledge of stock and commodity price interaction

[9] There is also empirical evidence that the US VIX is inversely related to the US equity index, the S&P 500 (Ait-Sahalia et al., 2013).

is also helpful for portfolio managers looking to receive diversification benefits and investment protection against downside risk. Since clean energy equities represent a relatively new class of assets to invest in, and these assets can be very volatile, a complete understanding of how risk in clean energy equities can be diversified is of paramount importance. Such knowledge could play a pivotal role in outlining sustainable business strategies and designing optimal portfolios.

As mentioned earlier, investments in clean energy stocks have positive environmental and socio-economic impacts that potentially help ensuring a certain degree of sustainability. Hence it is important to consider the application of modern portfolio theory with a view to gaining proper knowledge in stock market strategies. The current research provides important implications for institutional investors who fail to identify the clean energy market risk via proper financial modeling.

7. Conclusion

Investing in the renewable energy sector has increased significantly over the last decade. Given this, clean energy stocks have emerged as a new asset class for market participants. Numerous studies examine the association between clean energy and other asset classes. However, to date investigating how investors holding assets in clean energy stock markets can hedge their investments receives very little attention from academia. In order to extend this scarce literature, this paper aims to investigate whether commodity market volatility indexes can be used as hedging instruments against the downside risk of clean energy stock indexes. Specifically, crude oil, gold and silver volatility indexes have been considered in this empirical analysis along with three clean energy stock indexes. Methodologically, the DCC-GARCH model is applied to study time varying conditional correlation and the hedging effectiveness is assessed.

The major findings of this investigation are summarized as follows. First, each of the three volatility indexes is negatively related to clean energy stock indices, suggesting the ability of volatility indices to act as an effective tool for hedging clean energy stock indexes. More practically, a decrease in the returns of clean energy stock indexes can be offset by an upsurge in the implied volatility of crude oil or precious metals (gold and silver). The application of the asymmetric DCC-GARCH model also confirms this finding. Second, among the implied volatility series, the implied volatility of crude oil is the best hedging tool, followed by that of gold and silver. Third, the pairwise correlations are time-dependent and hence are not constants. Furthermore, the mean correlation is negative suggesting that commodity volatilities and equity prices move in opposite directions. Taken together, it is concluded that clean energy stock price risks can be diversified if investors include both renewable energy assets and commodity volatility indexes in their portfolios.

Some important implications emerge from the findings as proper knowledge of time-varying correlations amongst the studied commodity markets and clean energy stock indexes would help market participants to understand the role of crude oil or precious metal implied volatilities in hedging the risk linked to clean energy stock indexes. Furthermore, investors might utilize the information provided in the implied volatility indexes of major commodities to predict clean energy stock market returns. In addition, policymakers can build on the empirical findings to articulate policies seeking to avoid the contagion risk stemming from volatile commodity markets. The findings could also be useful to academics who are engaged in research involving asset pricing models, with the enhancement of the latter being dependent on a better understanding of the relationships across assets and markets. Additionally, the findings could serve scholars in their attempt to understand the market returns associated with clean energy companies.

Future studies can further consider the portfolio implications by studying the conditional tail-risk between commodity implied volatility indexes and clean energy equity indices, while accounting for regime switching (Ji et al., 2018). Another interesting research avenue is studying the portfolio implications in the time-frequency space.

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Table A1: Summary of existing literature on clean energy stock markets

Reference	Econometric models used	Variables	Data frequency	Time period	Major Findings
Henriques and Sadorsky (2008)	VAR model	Oil, technology and renewable energy stock prices	Weekly	January 3, 2001 to May 30, 2007	Both oil and technology stock prices affect the clean energy equities.
Broadstock et al. (2012)	BEKK approach	Brent oil and Chinese energy sector stock markets	Weekly	January 7, 2000 to May 27, 2011	Oil prices have significant impacts on clean energy firms.
Kumar et al. (2012)	VAR model	Oil prices and different global clean energy stock indexes	Weekly	April 22, 2005 to November 26, 2008	Oil and stock prices have a positive linkage.
Sadorsky (2012a)	CAPM model	Oil and clean energy stock prices	Yearly	2001-2007	An upsurge in oil prices increases the risk associated with clean energy equities.

Sadorsky (2012b)	BEKK and DCC models	Oil, technology and clean energy stock prices	Daily	January 1, 2001 to December 31, 2010	Oil can be used to hedge the risk associated with clean energy equities.
Managi and Okimoto (2013)	Markov switching VAR model	Oil, technology and renewable energy stock prices	Weekly		A positive relationship between oil prices and clean energy stock prices is reported.
Wen et al. (2014)	Asymmetric BEKK model	Chinese clean energy and fossil fuel companies	Daily	August 30, 2006 to September 11, 2012	There is a significant volatility spillover between the variables.
Reboredo (2015)	Copula approach	Oil and clean energy stock prices	Daily	December 30, 2005 to December 12, 2013	The dependence between oil and clean energy stock prices evolves over time
Bondia et al. (2016)	Cointegration approach	Oil and clean energy stock prices	Weekly	January 3, 2003 to June 5, 2015	Causality runs from oil to clean energy stocks.

Reboredo et al. (2017)	Wavelet coherence approach	Oil and clean energy stock prices	Daily	January 1, 2006 to March 16, 2015	Oil prices have a long-term impact on clean energy stock prices.
Ahmad (2017)	Directional spillover method and VARMA-GARCH approach	Oil and clean energy stock prices	Daily	May 2, 2005 to April 30, 2015	An upturn in energy prices leads to an increase in the stock prices of alternative energy firms
Dutta (2017)	Range-based volatility measures	OVX and clean energy stock prices	Daily	May 10, 2007 to June 30, 2016	Clean energy stock market returns are highly sensitive to OVX shocks.
Dutta et al. (2018)	VAR-GARCH and DCC-GARCH models	Carbon emission and clean energy stock prices	Daily	July 1, 2009 to December 31, 2017	Emission market is an effective tool for hedging the risk associated with clean energy equities.

Ahmad et al. (2018)	DCC-GARCH and GO-GARCH models	VIX, OVX, gold VIX, bond and clean energy stock prices	Daily	March 3, 2008 to October 31, 2017	VIX is the best asset to hedge clean energy equities followed by OVX.
Reboredo and Ugolini (2019)	Multivariate vine-copula dependence approach	US and EU Energy prices and clean energy stock returns	Daily	January 2, 2009 to September 1, 2016	Oil and electricity prices are major contributors to the dynamics of clean energy stock returns.
Bouri et al. (2019)	Copula approach	Oil, gold and clean energy stock prices	Daily	November 21, 2003 to March 30, 2018	Neither crude oil nor gold is more than a weak safe-haven asset for clean energy stocks.
Dutta (2019)	GARCH-jump approach	Silver VIX and solar energy stocks	Daily, weekly	March 16, 2011 to December 31, 2017	Solar energy stock market returns are highly sensitive to silver price risk.