Impact of energy sector volatility on clean energy assets

Author(s): Dutta, Anupam; Bouri, Elie; Saeed, Tareq; Vo, Xuan Vinh

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Abstract

We study the effect of uncertainty in energy sector firms on clean energy exchange traded funds (ETFs). In doing so, we use the information on energy sector implied volatility index (VXXLE) to reflect the risk or uncertainty of energy sector firms. Unlike the existing literature that mainly employs linear models to study the association between clean energy and financial markets, we apply Markov regime switching models to uncover how clean energy ETFs react to volatility shocks in the energy sector market during high and low volatility regimes. Our findings reveal a negative effect, suggesting that when implied volatility levels are high for energy sector firms a drop is likely to be observed in clean energy asset returns. The results also show evidence of an asymmetric effect. During the high volatility regime, the association between energy sector volatilities and clean energy ETFs holds stronger compared to the low volatility regime. We further document that changes in the levels of VXXLE substantially impact the realized volatility of these ETFs. Our findings offer significant implications to investors and policymakers.

Keywords: Energy sector volatility; Clean energy ETFs; Markov regime switching; Risk transmission

1. Introduction

In recent years, investments in the global clean energy industry have experienced an upward trend. In 2018, for example, investing in this sector amounts to \$332.1 billion. In fact, investments in renewable energies have been over \$300 billion for the last five years in a row. During this decade (2010-2018), \$2.6 trillion have been spent in world alternative energy sector, more than treble the amount spent in the past decade. More specifically, China has invested \$758 billion over the past 10 years followed by the U.S. (\$356 billion) and Japan (\$202 billion). Moreover, during this period, Europe as a whole has invested \$698 billion[1].

Considering the significance of renewable energy market as a new asset class, the literature on the global clean energy sector is growing. Sadorsky (2012) documents a positive association between oil returns and clean energy equity returns and evidence of significant volatility transmissions. Using a panel data regression, Kumar et al. (2012) show that clean energy equities are sensitive to energy price fluctuations. Reboredo (2015) finds that the association between crude oil prices and clean energy prices tends to vary over time. Bondia et al. (2016) provide evidence of a unidirectional linkage between oil and clean energy indices, mainly running from commodity prices to equity prices. Employing wavelets, Reboredo et al. (2017) conclude that the association between oil and alternative energy stocks holds stronger in the long-term. In addition, Ahmad (2017) concludes that oil and clean energy assets are positively correlated, suggesting that higher oil prices would lead to an upturn in the return of clean energy stocks. Dutta et al. (2018) demonstrates that the risk of clean energy equities could be diversified using the information contents of the European Union emission trading prices. Recently, Bouri et al. (2019) report that important commodities such as oil and precious metals act as safe-haven assets

[1] Source: Bloomberg NEF

for alternative energy markets during bearish periods. Dutta (2019) shows that uncertainty in silver market, which is used in the photovoltaic system for generating solar energy, has a significant negative impact on the solar energy firms' equity prices. Xia et al. (2019) find that fluctuations in electricity, oil and coal prices lead to a substantial change in renewable energy equity returns. Additionally, Kocaarslan and Soytas (2019) document that the US dollar appreciation plays a major role in the time-dependent association between oil and renewable energy assets. Song et al. (2019) show that the renewable energy stock market is closely related to the crude oil market. Sun et al. (2019), however, reveal that oil prices account for only a small part of stock price fluctuations of new energy companies. Besides, Maghyereh et al. (2019) combines wavelet with multivariate GARCH model to evidence a bidirectional volatility transmission relationship between oil and clean energy stock markets. More recently, Saeed et al. (2020), using the DCC-GARCH process, find that clean energy stocks can hedge oil price risk. Besides, Dutta et al. (2020) report that green assets are found to be more susceptible to oil market volatility rather than to oil price fluctuations. Liu and Hamori (2020) also document that oil market sends volatility to the US and European renewable energy stock markets. In addition, Troster et al. (2020) provide empirical evidence that GARCH and GAS (Generalized Autoregressive Score) approaches appear to be optimal for modeling clean energy stock returns. Using the cross-quantilogram correlation approach, Yahya et al. (2020) shows that clean energy stock indexes are influenced by the fluctuations in nonferrous metal prices.

Note that limited studies utilize the information content of oil volatility index (OVX) to assess whether crude oil volatility affects the clean energy equity returns. Dutta (2017), for example, finds that the OVX and the realized volatility of clean energy equities move in tandem. Furthermore, Ahmad et al. (2018) indicate that the OVX and clean energy equity indices are inversely related, suggesting that the ability of the OVX diversify the risk of clean energy stock markets.

Alongside this background, the aim of this paper is to assess the impact of energy sector uncertainty on clean energy exchange-traded funds (ETFs). To serve our purpose, we consider the information on energy sector implied volatility index (henceforth, VXXLE), published by Chicago Board Options Exchange (CBOE), to proxy for the energy sector risk. Although VXXLE can be viewed as a superior measure for tracking the risk associated with energy sector companies, it does not receive much attention in academic studies. Only few studies examine the behavior of this implied volatility index. López (2018) finds that the VXXLE experiences a drop in response to US macroeconomic news and events related to OPEC meetings. Recently, Nikkinen and Rothovius (2019) argue that the VXXLE can be decomposed into two components related to OVX and VIX, with 55% and 45% weights respectively.

Our contributions are as follows. Firstly, we are the first to assess the effect of the VXXLE on the stock market performance of clean energy firms. Given that clean energy assets can be highly volatile (Ahmad et al., 2018), it is important for economic actors to understand the dynamics and sources of such risks so that appropriate decisions regarding portfolio construction and risk management can be taken. Notably, the use of VXXLE could be informational, as this volatility index characterizes a forward-looking measure of uncertainty in the stock prices of energy sector companies following the VIX (López, 2018). Note that investors holding assets in clean energy equity market closely follow the stock prices of fossil fuel companies given that these equities are generally viewed as competing assets. Wen et al. (2014) also document that stock prices of renewable energy firms are driven by the positive or negative news stemming from energy sector stock market. In particular, investors may worry that once positive news about fossil fuel stocks emerges, the investment funds will largely switch from the new energy stocks to the fossil fuel stocks, thus dampening their returns. Now, as VXXLE captures market uncertainty about the energy companies' returns over the next 30 days, one can postulate that the information on VXXLE has predictive power for the stock prices of clean energy companies.

Hence, our analyses have important implications to market participants who are keen to predict energy firms' future uncertainty.

Secondly, contrasting to the existing literature, we make use of clean energy ETFs instead of clean energy equities. Doing so is advantageous as these ETFs are extremely liquid and easily traded like a stock (Krause and Tse, 2013). Besides, ETFs are free from the non-synchronous trading issues related to stock index data. Lo and MacKinlay (1990), for example, argue that avoiding the non-synchronous trading problems can lead to more robust results related to market efficiency tests.

Thirdly, we use the Markov regime switching (MRS) model to study the effect of VXXLE on clean energy ETFs. The existing studies focusing on the association between green investments and other financial assets mostly employ linear models (e.g., ordinary least squares (OLS) regression), albeit the linkage amongst financial markets is prone to recurrent changes as a consequence of economic shocks, terrorist attacks, natural disasters[2]. Therefore, the fixed parameter assumption of least squares method is too restrictive, and hence the applied model

[2] Only a couple of studies (Managi and Okimoto, 2013; Dutta et al., 2020) employ regime switching models to investigate the linkage between clean energy or green assets and other financial markets. Managi and Okimoto, for instance, employ the regime switching process to detect the possibility of a structural change by analyzing smoothed probabilities. The authors find regime shifting behavior after 2007 which in turn impacts the linkage between oil and clean energy stock markets. The work of Dutta et al. (2020) also adopts the MRS model and indicates a swapping between different regimes implying that there exist high and low volatility states for green assets.

could be misspecified. To this end, adopting the MRS regression is beneficial given that its specification allows the estimated coefficients to swing across a distinct number of states (Uddin et al., 2018). By employing the MRS regression, we can explore how clean energy assets react to energy market shocks during high and low volatility states.

For the rest of the paper, the next section describes the dataset. Section 3 outlines the econometric models. Results are analyzed in Section 4. Section 5 discusses the findings. Section 6 concludes.

2. Data

Three different clean energy ETFs are considered in this study: Invesco WilderHill Clean Energy ETF (henceforth, PBW), Invesco Global Clean Energy ETF (henceforth, PBD) and iShares Global Clean Energy ETF (henceforth, ICLN). PBW allows investors to have an exposure to clean energy investments. PBD offers a global perspective in the exposure to the clean energy index. ICLN offers a way to invest in companies comprising various sub-sectors related to wind and solar energy sources. In addition, we use the VXXLE index, computed by the CBOE. The data on VXXLE and various clean energy ETFs are extracted from DataStream. They are daily, covering the period March 16, 2011 - December 31, 2018, yielding 2,034 daily observations. Fig.1 exhibits the time-series evolution of all indexes, where a significant drop is observed in energy sector asset prices during the period 2014-2016 during which the crude oil market experiences a downturn due to the oversupply of crude oil.

The empirical analyses are conducted with daily log returns. Table 1 shows that all clean energy assets experience negative returns during the sample period. The VXXLE shows a higher volatility than the clean energy indexes. All return series exhibit nonzero skewness with kurtosis exceeding 3, suggesting non-normality in the return distributions. This suggestion is validated using the Jarque-Bera test.

We employ the Augmented Dickey-Fuller (ADF) and Phillips-Pearson (PP) tests to examine if the data used are stationary. The results, shown in Table 2a, confirm the rejection of the null hypothesis of non-stationarity for all the return series. Moreover, given the non-normality of the return distributions, we apply the RALS-LM unit root test as well. These findings are presented in Table 2b, which further confirm that the return indexes are stationary.

Table 3 exhibits the unconditional correlations among the return series. The correlations amongst the clean energy ETFs appear to be positive, whereas each of these indexes is negatively related to VXXLE. Such an inverse relationship implies that portfolio risk can be reduced by holding assets in these markets.

3. Methodology

3.1. Markov regime switching (MRS) approach

The MRS model receives enormous attention in the finance literature (e.g., Balcilar and Ozdemir, 2013; Balcilar et al., 2015; Uddin et al., 2018; Basher et al., 2016). For example, Uddin et al. (2018) argue that financial time-series are nonlinear in nature and therefore, it is important to use econometric models which take into account the asymmetric association amongst the financial time-series. To this end, employing the MRS model is beneficial, as it is able to capture such asymmetry and allows the parameters to shift between various regimes. Accordingly, our MRS model has the following form:

(1) $$R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{i,t-1} + \gamma_{i,r_t} \Delta VXXLE_t + u_{i,t}$$

In Equation 1, $R_{i,t}$ is the log return for *i*-th clean energy ETF index at time *t*, r_t refers to a discrete regime variable, α_{i,r_t} is the regime-dependent intercept and β_{i,r_t} and γ_{i,r_t} are regime-dependent slope coefficients. At the current period *t*, the diffusion probability from regime 1 to regime *m* at the next period *t* + 1 is dependent on the regime at the current period *t* entirely.

(2) $$p_{jk} = \Pr(r_{t+1} = k | r_t = \mathrm{j}), p_{jk} \geq 0, \sum_{k=1}^{M} p_{jk} = 1$$

To evaluate the regime-dependent parameters, Equation (1) is estimated in two regimes. Our objective is to examine whether for the high volatility regime the association between energy sector volatilities and clean energy ETFs holds stronger compared to the low volatility regime. Moreover, following previous studies (Ang and Bekaert, 2002; Uddin et al., 2018), we consider estimating the regime classification measure (RCM) to gauge the accuracy of the MRS approach:

(3) $$RCM(r) = 100r^2(1/T)\sum_{t=1}^{T}\prod_{i=1}^{r}\hat{\mathrm{p}}_{i,t}$$

The RCM statistics ranges from 0 to 100, where 0 implies that the MRS model classifies the regimes precisely, while 100 indicates that the model fails to do so.

3.2. Test of asymmetric effects

We further examine the existence of asymmetric relations between VXXLE and clean energy ETFs, which is crucial as asset prices often behave asymmetrically to the changes in market uncertainty (Dutta et al., 2020). The information on the presence of a symmetric association will allow the clean energy firms to properly gauge the risk emanating from energy sector, while managing such risk could be difficult when the impact of the VXXLE is nonlinear. Besides, due to the fact increases and decreases in the VXXLE might cause cyclical fluctuations in clean energy business, exploring the asymmetric impact of such shocks on clean energy assets is of paramount importance.

For the inspection of the asymmetric relationship, the following mean equation is estimated:

$$R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{1i,r_t} \Delta VXXLE_t^{+} + \gamma_{2i,r_t} \Delta VXXLE_t^{-} + u_{i,t} \quad (4)$$

In the above equation, $\Delta VXXLE_t^{+} = \max(\Delta VXXLE_t, 0)$ and $\Delta VXXLE_t^{-} = \min(\Delta VXXLE_t, 0)$ refer to positive and negative energy volatility shock. To examine the presence of asymmetric associations, it suffices to test $H_0\colon \gamma_1 = \gamma_2$.

4. Results

4.1. Results of MRS regression

Panel A of Table 4 presents the estimates of the MRS regression, whereas Panel B of Table 4 shows the transition probabilities and expected durations. A number of notable findings can emerge. First, VXXLE has a negative impact on the clean energy ETFs under study. Thus, when volatility levels are high for energy sector companies, a drop is likely to be observed in clean energy ETFs. Such finding is expected given that an upsurge in energy sector volatility leads to a fall in crude oil prices, which in turn leads to a decline in the prices of clean energy ETFs (Dutta, 2017). Another possible reason could be that there usually exists an inverse association between implied volatilities and stock returns. In fact, a strand of literature confirms this result. Badshah (2012), for example, documents a negative association between stock returns and changes in the implied volatility index for the US, Germany and the UK markets. Additionally, Basher and Sadorsky (2016) show that the VIX index is negatively related to emerging market stock indices.

In line with previous literature, we also show that risk and return are inversely related for energy sectors.

Second, the sigma coefficient, which presents the magnitude of volatility measured by standard deviation for each regime, is higher for regime 1 compared to regime 2. This finding implies that regime 1 (regime 2) is the high (low) volatility regime. Moreover, all the sigma coefficients are statistically significant, implying a switch between high and low volatility regimes. We further note that the effect of VXXLE is higher in regime 1 than in regime 2. Therefore, for the high volatility regime the association between energy sector volatilities and clean energy ETFs holds stronger compared to the low volatility regime.

Third, the DU1 and DU2 statistics representing the expected durations for occupying a specific regime, suggests that the PBW index, in comparison to other series, has higher probabilities of being in a particular state. Additionally, based on the smoothed probability for all the clean energy ETFs, both regimes seem to be highly persistent as the values of $p_{11}$and p_{22} are close to 1 in most of the cases.

Fourth, the RCM values indicate that the MRS regression fits well for each of the clean energy ETFs under study. Figures 2 and 3 depict smooth probabilities of belonging in high and low volatility regimes. Consistent with the RCM statistics reported in Table 4, a strong switching pattern between the regimes is observed for all the clean energy assets. In particular, we notice that during the beginning of our sample period (i.e., March, 2011) the probability of being in the high volatility state is very high (close to 1) for all the ETFs (see Fig.2). Fig.3 also demonstrates that during the same period the probability for being in the low volatility state remains very low. One would expect that global energy market becomes highly uncertain in March, 2011 due to the

Libyan war, which in turn causes the stock prices to fall. Moreover, there is a high probability for being in the high volatility regime throughout the year 2015 (see Fig.2), when energy market experiences a downturn due to the oversupply of crude oil. This finding is also confirmed by Fig.3, where we observe a low probability for being in the low volatility regime.

Overall, the findings suggest that the energy sector implied volatility exerts a negative impact on clean energy assets. Our results are consistent with Dutta (2019) who shows that oil and metal volatility indexes have negative effects on solar energy stock returns. Ahmad et al. (2018) also conclude that the OVX and clean energy equities are inversely related. One possible reason behind this inverse linkage between risk and return is that price decreases could raise portfolio adjustment cost of risk-averse agents more than price increases (Ji and Fan, 2016).

4.2. Test of asymmetric effects

The findings of our asymmetric analysis, reported in Table 5, mimic those presented in Table 4. For example, the influence of VXXLE on clean energy ETFs remains negative suggesting that when energy sector volatility decreases, clean energy assets experience an increase in their prices. An upturn in energy sector volatility, on the other hand, will result in a decrease in the prices of clean energy assets. It is noteworthy that for the asymmetric analyses, regime 2 appears to be the high volatility state for all the indexes under study. We also note that for all these indexes, both negative and positive volatility shocks have significant effects on the clean energy assets.

Furthermore, the results of the asymmetric tests ($H_0: \gamma_1 = \gamma_2$) are shown in Table 5. On the basis of this test, it can be concluded that the effect of VXXLE is found to be asymmetric (with few exceptions). Hence, changes (upward and downward shifts) in energy sector volatility exert a diverse effect on the prices of clean energy ETFs.

The nonlinear association between the sectors under study has dynamic implications to researchers and policymakers. For instance, such connections would encourage academics and risk managers to adopt nonlinear models instead of linear models. Furthermore, companies operating in new energy segments should also take a dynamic approach in hedging the risk of the clean energy sector. Furthermore, the asymmetric impact of the energy sector volatility on clean energy assets should be considered in model-based specification.

4.3. Subsample analysis

This section scrutinizes the effect of crisis periods on the relationship between energy sector uncertainty and clean energy assets. To reach this goal, we conduct subsample analyses to examine whether renewable energy assets react differently under diverse market circumstances. Specifically, we consider the period December 2014 - March 2016, which covers the oil market downturn during which the oversupply of crude oil has adversely affected crude oil prices.

The results of our subsample investigation are given in Table 6. They confirm the significant negative effect of VXXLE on clean energy ETFs. Regime 1 still remains the high volatility state, except for the PBD index. However, unlike in the full period analyses, the effect of VXXLE is higher in regime 2 than in regime 1 for PBW and ICLN indexes. Therefore, for the low volatility regime, the aforesaid linkage gets stronger now. Giot (2005) also shows that during the sub-period analyses, the risk return relationship tends to be tightening in a low-volatility trading environment. One possible reason could be that options traders respond aggressively to decreases in process during low-volatility periods by bidding up implied volatility, whereas options traders hesitate to do the same in continued high-volatility periods.

4.4. Robustness checking

To verify whether the findings presented in Table 4 are robust, we employ two alternative measures of volatility used in previous studies (Maghyereh et al., 2016). The first alternative measure is the realized volatility (RV) proxied by the squared returns of another energy sector ETF index, namely the XLE[3]. The second alternative measure is the conditional volatility based on GARCH models. Given that squared returns appear to be a noisy measure of volatility, we estimate an AR(1)-GARCH(1,1) model for the XLE index. The results of the robustness analyses are shown in Tables 7-8. They confirm an asymmetric association between energy sector volatility shocks and clean energy ETFs.

Overall, our findings are robust given that they remain vastly consistent irrespective of the sample sizes and the different measures used.

4.5. Additional analyses

Previous studies provide empirical evidence that clean energy assets are sensitive to the fluctuations in oil and technology stock prices (Sadorsky, 2012; Kumar et al., 2012; Managi and Okimoto, 2013; Bondia et al., 2016; Bouri et al., 2019; Kocaarslan and Soytas, 2019; Song et al., 2019). Sadorsky, for instance, argues that as investors view alternative energy companies as similar to other high technology companies, clean energy asset returns are substantially influenced by the changes in technology stock prices. Recently, Song et al. (2019) show that clean energy stocks are highly sensitive to oil price shocks.

[3] XLE data are extracted from the DataStream.

Another stand of literature shows that crude oil volatility index (OVX) also exerts a significant impact on clean energy stock indexes (Dutta, 2017; Ahmad et al., 2018). These studies evidence that crude oil volatility and clean energy stock price volatility are positively correlated. In this section, we examine the impact of VXXLE on clean energy assets after controlling for the effects of WTI oil prices, OVX and technology stock prices proxied by the NYSE Arca Technology Index (PSE).

Note that since WTI, OVX and PSE indexes are highly correlated with the VXXLE, orthogonalized returns on these indexes are considered. To this end, a two-step procedure is adopted. In the first step, the returns on WTI/OVX/PSE are regressed on the VXXLE to gauge its effect on these indexes. In the second step, the residuals are estimated and incorporated into the MRS model along with the VXXLE in three separate analyses.

The results of these additional analyses are reported in Tables 9-11, where several interesting outcomes are observed. First, the impact of VXXLE is still significant in each of the cases considered. Second, the technology stock prices have a positive influence on the clean energy asset returns and more importantly, the magnitude of this impact is higher than that of the VXXLE (see Table 9). Third, although the effect of WTI oil prices is significant in majority of the cases, the VXXLE impacts more than the oil prices as evidenced by the size of this effect (see Table 10). Fourth, the impact of OVX appears to be insignificant in most of the cases suggesting that the VXXLE captures the variations in clean energy ETFs more than the crude oil price volatility (see Table 11). This last finding contradicts with those reported by Dutta (2017) and Ahmad et al. (2018) who show that clean energy indexes react significantly to OVX shocks. The most likely explanation could be that we employ a non-linear framework, while the papers cited above adopt a linear model. Given that financial time series are usually non-linear in nature, adopting non-linear specifications could be misleading (Behmiri and Manera, 2015). Although Dutta (2017) conducts some non-linear or asymmetric analyses by examining whether positive or negative oil shocks matter for clean energy assets, his approach is essentially linear. Hence this research emphasizes the need to employ a non-linear framework to precisely detect the association among the variable under study.

Overall, our analysis concludes that the information on VXXLE is more important compared to traditional oil prices or oil market volatility when predicting the returns of clean energy ETFS. Besides, in addition to the VXXLE, technology stock prices also play a major role in determining the movements in clean energy asset prices.

4.6. Risk transmission relationship

So far, we have investigated whether energy sector uncertainty indexes (VXXLE and OVX) impact the first-order moment (i.e., mean return) of the clean energy ETFs. It is, however, important for investors and policymakers to understand the risk transmission relationship between these markets given that what matter for both market participants and policymakers are not market price variations per se, but their unpredictability and the resultant risks for producers, traders, consumers, and government agents. We, therefore, examine the effect of VXXLE and OVX on the realized volatility (RV) of clean energy assets. For comparison purpose, the United States Oil Fund or USO ETF index is also considered. In addition, the effect of technology stock price volatility (RV_PSE) is measured as well. Note that the RV of each index is proxied by squared returns. To serve our purpose, we estimate the following models:

(5) $RV_t = \delta_0 + \delta_1 RV_{t-1} + \epsilon_t$ (Baseline RV model)

(6) $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 \Delta VXXLE_t + \epsilon_t$ (RV-VXXLE model)

(7) $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 \Delta OVX_t + \epsilon_t$ (RV-OVX model)

(8) $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 RV\_PSE_t + \epsilon_t$ (RV-PSE model)

where, RV_t denotes the realized volatility of PBW/PBD/ICLN/USO index at time *t*.

The estimates of models 5-8 are presented in Table 12. These findings evidence that the information contents of VXXLE, OVX and RV_PSE play a pivotal role in explaining the variance of different ETFs under consideration. For example, in case of PBW index, the R^2 statistics amount to 5.2%, 10.7%, 8.5% and 37.2% for the baseline, RV-VXXLE, RV-OVX and RV-PSE models, respectively. Hence, VXXLE, OVX and RV_PSE provide additional information beyond what is contained in the historical volatilities of these ETFs. We further observe that RV_PSE affects the volatility of clean energy ETFs more than VXXLE or OVX implying that clean energy assets are mainly sensitive to the changes in RV_PSE. However, for the USO index, the impact of OVX is higher than the others. We thus report that energy sector ETF and clean energy ETFs react differently to the changes in OVX, VXXLE and RV_PSE. The possible explanation is that while the price of oil is the primary driver of how the stock prices of fossil fuel companies are perceived, clean energy asset prices are more influenced by technology stock prices rather than crude oil volatility. This finding indicates that market participants view investments in clean energy stocks as being more closely related to general movements in the technology sector rather than fluctuations in the oil prices. Therefore, for the clean energy assets, crude oil volatility shocks are not as important as shocks to technology stock price volatility. The findings of Table 12 further show that VXXLE has better predictive power than OVX. One would expect that as fossil fuel and clean energy stocks are generally viewed as competing assets, stock prices of renewable energy firms are affected by both positive and negative news stemming from the energy sector stock market (Wen et al., 2014). Hence, VXXLE, which captures the market uncertainty for the energy sector stocks over the next 30 days, generates more accurate volatility forecasts than does the crude oil VIX.

5. Discussion

It is well documented that studying the risk-return link for the global clean energy equity markets is important, because proper knowledge on the linkage between an asset and its volatility (risk) is a fundamental issue in understanding the financial market uncertainty. Many studies have used realized volatility (RV) to measure the market risk, while another strand of literature shows that implied volatility indexes such as the VIX performs better than other historical measures (e.g., RV) in predicting stock market uncertainty (Kambouroudis and McMillan, 2016)[4]. The literature on risk-return nexus is growing because holding VIX derivatives has been shown to help in hedging the risk associated with stock prices. Nevertheless, existing empirical works have not paid considerable attention to this relation for clean energy equities. Few exceptions include Ahmad et al. (2018) and Dutta et al. (2020) who document that commodity volatility indices such as oil VIX, gold VIX and silver VIX can diversify the risk of clean energy assets.

Throughout this paper, we extend this scarce literature by using the information content of VXXLE in predicting the prices of clean energy assets. Our results indicate that the relationship between VXXLE and clean energy ETFs is asymmetric showing that negative returns lead to higher volatility than do positive returns of the same size. This finding is comparable to previous

[4] One possible explanation is that VIX reflects the forward-looking measure of uncertainty. Mencia and Sentana (2013), for example, argue that the VIX is of paramount importance to investors on a daily basis for decisions related to trading. Besides, given that VIX contains market expectations, this measure appears as a useful instrument for predicting market risk. Overall, the information on VIX reflects the risk and return patterns.

studies on US equities. For example, Mencia and Sentana (2013) claim that investors trade options on the underlying assets in order to buy protection during the crisis periods, which increases the value of VIX indexes.

Moreover, our empirical investigation also shows that clean energy assets are sensitive to the changes in technology stock prices as well, while oil price volatility does not matter much for these ETFs. This finding reveals that oil price is not the main driver of clean energy assets as market participants might view these firms as similar to other high technology companies. On the whole, technology stock prices along with the VXXLE index play a crucial role in determining the movements in clean energy asset prices. Therefore, investors holding assets in renewable energy markets should closely observe the fluctuations in technology stock prices and energy sector volatility index.

6. Conclusions

In this study, we examine the impact of energy sector volatility on clean energy ETFs. Unlike previous studies that mainly employ linear models to study the dynamics of association between clean energy and other asset classes, we apply the Markov regime switching regression. Notably, we use the energy sector implied volatility index (VXXLE) to measure the risk or uncertainty of energy sector firms. Our findings reveal that VXXLE has a negative impact on various clean energy ETFs, suggesting that when volatility levels are high for energy sector companies, a drop is likely to be observed in clean energy ETFs. Further analyses indicate an asymmetric association. We also show that for the high volatility regime, the association between energy sector volatilities and renewable energy ETFs gets stronger compared to the low volatility regime. In addition, the results demonstrate that changes in the levels of VXXLE substantially impact the realized volatility of these ETFs.

Our analyses offer significant implications to investors and policymakers. The findings of this study could receive special attention from current and future investors in clean energy sectors. Given that rising worries about energy security and climate change shift market participants towards ethical investments, our results might help investors aiming at decarbonizing their portfolios by including more clean energy equities. In fact, our findings could help investors to understand the risk associated with clean energy assets and assist them in their quest to hedge their portfolio risk. Given that energy sector volatility and alternative energy firms' asset returns are inversely associated, investors and risk managers can consider the potential diversification of the downside risk of clean energy markets using the VXXLE. For policymakers, our findings are important in the sense that an upward trend in energy sector volatility does not encourage incentives to investment in the clean energy industry, while a downward trend could lift clean energy investments without the need for specific support from energy policies.

Our analyses offer scope for future research as well. For example, future studies can examine whether energy market uncertainty could impact clean energy sub-sectors. In addition, time-varying correlations among implied volatilities and various sub-sectors of the clean energy equity markets could also be explored to make inferences regarding portfolio implications. Such analyses might be useful for understanding the portfolio and risk management at a disaggregated level.

References

Ahmad, W., Sadorsky, P., Sharma, A., 2018. Optimal hedge ratios for clean energy equities. Economic Modelling 72, 278-295.

Ahmad, W., 2017. On the dynamic dependence and investment performance of crude oil and clean energy stocks. Research in International Business and Finance 42, 376-389.

Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. Review of Financial Studies, 15 (4), 1137–1187.

Badshah, I.U., 2012. Quantile regression analysis of the asymmetric return-volatility relation. Journal of Futures Markets, 33, 235-265.

Behmiri, N.B. and Manera, M. 2015. The role of outliers and oil price shocks on volatility of metal prices. Resour. Policy 46, 139–150.

Balcilar, M., Hammoudeh, S., Asaba, N.A.F., 2015. A regime-dependent assessment of the information transmission dynamics between oil prices, precious metal prices and exchange rates. International Review of Economics & Finance, 40, 72–89.

Balcilar, M., Ozdemir, Z.A., 2013. The causal nexus between oil prices and equity market in the US: a regime switching model. Energy Economics 39, 271–282.

Basher, S.A., Sadorsky, P., 2016. Hedging emerging stock prices with oil, gold, VIX, and bonds: a comparison between DCC, ADCC, and GO-GARCH. Energy Economics 54, 235-247.

Basher, S.A., Haug, A.A., Sadorsky, P., 2016. The impact of oil shocks on exchange rates: a Markov-switching approach. Energy Economics 54, 11–23.

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

Bouri, E., Jalkh, N., Dutta, A., Uddin, G. S., 2019. Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. Energy, 178, 544-553.

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

Dutta, A., Bouri, E., Noor, M. H., 2018. Return and volatility linkages between CO2 emission and clean energy stock prices. Energy, 164, 803-810.

Dutta, A., 2019. Impact of silver price uncertainty on solar energy firms. Journal of Cleaner Production, 225, 1044-1051.

Dutta, A., Bouri, E. Roubaud, D., 2018. Nonlinear Relationships amongst the Implied Volatilities of Crude Oil and Precious Metals. Resources Policy, 61, 473-478.

Dutta, A., Bouri, E., Das, D. Roubaud, D., 2020. Assessment and Optimization of Clean Energy Equity Risks and Commodity Price Volatility Indexes: Implications for Sustainability. Journal of Cleaner Production, 243, 118669.

Dutta, A., Jana, R.K. and Das, D. (2020). Do Green Investments React to Oil Price Shocks? Implications for Sustainable Development. Journal of Cleaner Production, 266: 121956.

Giot, P., 2005. Relationships Between Implied Volatility Indexes and Stock Index Returns, Journal of Portfolio Management, 26, 12-17.

Ji, Q., Fan, Y., 2016. Modelling the joint dynamics of oil prices and investor fear gauge. Research in International Business and Finance, 37, 242-251.

Kambouroudis D.S., McMillan D.G., 2016. Does VIX or volume improve GARCH volatility forecasts? Applied Economics, 48,1-19.

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

Krause, T., Tse, Y., 2013. Volatility and return spillovers in Canadian and U.S. industry ETFs, International Review of Economics & Finance 25, 244–259.

Kumar, S., Managi, S., Matsuda, A., 2012. Stocks prices of clean energy firms, oil and carbon markets: a vector autoregressive analysis. Energy Economics 34, 215-226.

Liu, T. and Hamori, S. (2020). Spillovers to Renewable Energy Stocks in the US and Europe: Are They Different? Energies 13(12): 3162.

Lo, A. W., MacKinlay, A.C., 1990. An econometric analysis of nonsynchronous trading. Journal of Econometrics, 45(1–2), 181–211

Lopez R. 2018. The behaviour of energy-related volatility indices around scheduled news announcements: implications for variance swap investments. Energy Economics, 72: 356–64.

Maghyereh, A. I., Awartani, B., Bouri, E., 2016. The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Economics, 57, 78-93.

Managi, S., Okimoto, T., 2013. Does the price of oil interact with clean energy prices in the stock market? Jpn. World Econ. 27, 1–9.

Mencia, J., Sentana, E., 2012. Valuation of VIX derivatives. Journal of Financial Economics, 108, 367-391.

Meng, M., Im, K.S., Lee, J., Tieslau, M.A., 2014. More powerful LM unit root tests with nonnormal errors. In: Sickles, R.C., Horrace, W.C. (Eds.), Festschrift in Honor of Peter Schmidt. Springer, New York, pp. 343–357.

Nikkinen, J., Timo R., 2019. Energy sector uncertainty decomposition: A new approach based on implied volatilities. Applied Energy, 248: 141-148.

Reboredo, J.C., 2015. Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics 48, 32-45.

Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A. 2017. Wavelet-based test of comovement and causality between oil and renewable energy stock prices. Energy Economics 61, 241-252.

Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics 34, 248-255.

Saeed, T., Bouri, E. and Vo, X.V. (2020). Hedging Strategies of Green Assets against Dirty Energy Assets, Energies 13(12): 3141.

Song, Y., Ji, Q., Du, Y.-J., and Geng, J.-B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. Energy Econ. 84:104564.

Sun, C.; Ding, D.; Fang, X.; Zhang, H.; Li, J. How do fossil energy prices affect the stock prices of new energy companies? Evidence from Divisia energy price index in China's market. Energy 2019, 169, 637–645.

Troster V., Shahbaz M., Macedo D.N. (2020) Optimal Forecast Models for Clean Energy Stock Returns. In: Shahbaz M., Balsalobre-Lorente D. (eds) Econometrics of Green Energy Handbook. Springer, Cham.

Uddin, G.S., Rahman, M.L., Shahzad, S.J.H., Rehman, M.U., 2018. Supply and demand driven oil price changes and their non-linear impact on precious metal returns: a Markov regime switching approach, Energy Economics 73, 108–121.

Wen, X., Guo, Y., Wei, Y., Huang, D., 2014. How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Econ. 41, 63–75.

Xia, T., Ji, Q., Zhang, D., Hans, J., 2019. Asymmetric and extreme influence of energy price changes on renewable energy stock performance. Journal of Cleaner Prodction, 118338.

Yahya, M., Ghosh, S., Kanjilal, K., Dutta, A. and Uddin, G.S. (2020). Evaluation of cross-quantile dependence and causality between nonferrous metals and clean energy indexes. Energy, 202: 117777.

Table 1: Descriptive statistics

Index ↓	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera test
PBW	-0.0182	0.715	-0.277	5.567	584.07***
PBD	-0.0069	0.582	-0.377	7.101	1472.69***
ICLN	-0.0158	0.637	-0.336	5.901	751.08***
VXXLE	0.0004	1.511	0.951	12.371	7745.54***

Notes: This table reports the descriptive statistics of different indexes under study. For clean energy ETFs we consider the logarithmic differences, while for the VXXLE we use simple differences. *** indicates statistical significance at 1% level.

Table 2a: Results of unit root tests

Index ↓	ADF Tests		PP Tests	
	Level	1st Difference	Level	1st Difference
PBW	-3.75*** (.00)	-26.67*** (.00)	-3.52*** (.00)	-42.87*** (.00)
PBD	-2.12 (.24)	-29.89*** (.00)	-2.14 (.62)	-45.38*** (.00)
ICLN	-3.88*** (.00)	-26.53*** (.00)	-3.59*** (.61)	-45.17*** (.00)
VXXLE	-4.74*** (.00)	-24.17*** (.00)	-4.22*** (.75)	-49.60*** (.00)

Notes: *p*-values are given in parentheses. *** indicates statistical significance at 1% levels.

Table 2b: Results of RALS-LM unit root tests

	Test statistic	$\hat{\rho}^2$	$\hat{T}_B$		$\hat{k}$
PBW	12.26***	0.259	2011	2012	2
PBD	5.89***	0.914	2011	-	5
ICLN	6.02***	0.787	2011	-	1
ΔVXXLE	6.88***	0.558	2011	-	0

Notes: This table shows the findings of RALS-LM unit root test. $\hat{k}$ indicates the optimal number of lags selected using a general to specific procedure is represented by, while $\hat{T}_B$ denotes the location of structural breaks. The corresponding critical values for $\rho^2 = 0.1, \ldots, 0.9$ can be found in Meng et al. (2014). The test-statistics for RALS-LM unit root tests appear to be invariant to the location of breaks. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 3: Correlation matrix

	PBW	PBD	ICLN	VXXLE
PBW	1			
PBD	0.8130***	1		
ICLN	0.7677***	0.8198***	1	
VXXLE	-0.6162***	-0.6383***	-0.5989***	1

Notes: This Table exhibits the unconditional correlations among different indexes. *** indicates statistical significance at 1% levels.

Table 4: Results of Markov regime switching model

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	VXXLE shock	Sigma	χ^2 test
PBW	S1	-0.031	0.025	-0.301***	0.733***	177.51***
		(0.28)	(0.40)	(0.00)	(0.00)	
	S2	-0.009	0.073**	-0.276***	0.445***	
		(0.51)	(0.03)	(0.00)	(0.00)	
PBD	S1	0.010	0.034	-0.257***	0.755***	178.02***
		(0.27)	(0.11)	(0.00)	(0.00)	
	S2	-0.114**	-0.108**	-0.234***	0.357***	
		(0.02)	(0.03)	(0.00)	(0.00)	
ICLN	S1	0.042**	0.016	-0.319***	0.577***	116.39***
		(0.03)	(0.44)	(0.00)	(0.00)	
	S2	0.015	-0.059*	-0.150***	0.375***	
		(0.35)	(0.09)	(0.00)	(0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9835	0.0165	0.0093	0.9907	60.71	107.91	21.82
PBD	0.9811	0.0189	0.0977	0.9023	52.91	10.24	21.93
ICLN	0.9833	0.0167	0.0118	0.9812	60.15	53.14	22.41

Notes: The results are based on the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{i,r_t} \Delta VXXLE_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 5: Results of asymmetric effects

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	VXXLE Shock (+)	VXXLE Shock (-)	Sigma	$H_0: \gamma_1 = \gamma_2$
PBW	S1	0.023	0.068***	-0.309***	0.232***	0.440***	-1.87*
		(0.30)	(0.00)	(.00)	(0.00)	(0.00)	
	S2	-0.009	0.019	-0.317***	0.281***	0.734***	-0.85
		(0.82)	(0.52)	(.00)	(0.00)	(0.00)	
PBD	S1	0.043***	0.028	-0.258***	0.190***	0.361***	-2.88***
		(0.00)	(0.20)	(.00)	(0.00)	(0.00)	
	S2	-0.043	-0.126**	-0.298***	0.210***	0.771***	-1.14
		(0.56)	(0.03)	(.00)	(0.00)	(0.00)	
ICLN	S1	-0.055	0.016	-0.213***	0.206***	0.364***	2.45**
		(0.25)	(0.73)	(.00)	(0.00)	(0.00)	
	S2	0.047**	-0.026	-0.324***	0.238***	0. 741***	-3.77***
		(0.02)	(0.38)	(.00)	(0.00)	(0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU1	RCM	χ^2 test
PBW	0.9897	0.0103	0.0189	0.9811	97.45	52.97	21.87	157.88***
PBD	0.9842	0.0158	0.0939	0.9061	63.45	10.85	22.01	145.82***
ICLN	0.6312	0.3688	0.1599	0.8401	2.71	6.25	24.51	222.86***

Notes The results are based on the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{1i,r_t} \Delta VXXLE_t^+ + \gamma_{2i,r_t} \Delta VXXLE_t^- + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t* and $\Delta VXXLE_t^+ = \max(\Delta VXXLE_t, 0)$, $\Delta VXXLE_t^- = \min(\Delta VXXLE_t, 0)$. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. In addition, the asymmetric impact ($H_0: \gamma_1 = \gamma_2$) is investigated by applying student's *t*-test. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 6: Subsample analyses

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	VXXLE shock	Sigma	χ^2 test
PBW	S1	-0.034 (0.41)	0.036 (0.49)	-0.234*** (0.00)	0.657*** (0.00)	53.52***
	S2	-0.060* (0.06)	0.032 (0.56)	-0.427*** (0.00)	0.375*** (0.00)	
PBD	S1	0.003 (0.92)	-0.004 (0.95)	-0.099*** (0.00)	0.286*** (0.00)	5.74**
	S2	-0.029 (0.29)	-0.005 (0.91)	-0.342*** (0.00)	0.386*** (0.00)	
ICLN	S1	-0.076 (0.28)	0.016 (0.89)	-0.168*** (0.00)	0.704*** (0.00)	35.75***
	S2	0.018 (0.60)	-0.019 (0.77)	-0.311*** (0.00)	0.343*** (0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9800	0.0200	0.0256	0.9744	50.11	39.12	25.02
PBD	0.6293	0.3703	0.2010	0.7990	2.69	4.97	24.89
ICLN	0.3235	0.6765	0.3763	0.6237	1.48	2.66	26.61

Notes: The subsample analyses are based on the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{i,r_t} \Delta VXXLE_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 7: Robustness test based on realized volatility

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	Realized volatility	Sigma	χ^2 test
PBW	S1	0.110*** (0.00)	-0.068** (0.04)	-0.506*** (0.00)	0.677*** (0.00)	45.11***
	S2	-0.100*** (0.00)	0.162*** (0.00)	-0.361*** (0.00)	0.432*** (0.00)	
PBD	S1	0.053*** (0.00)	-0.008 (0.79)	-0.488*** (0.00)	0.594*** (0.00)	106.46***
	S2	-0.058** (0.03)	-0.018** (0.60)	-0.307*** (0.00)	0.319*** (0.00)	
ICLN	S1	-0.062** (0.03)	0.028 (0.44)	-0.275*** (0.00)	0.683*** (0.00)	164.11***
	S2	0.043** (0.04)	-0.023 (0.43)	-0.511*** (0.00)	0.343*** (0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.4694	0.5306	0.4229	0.5771	1.88	2.36	27.11
PBD	0.6888	0.3112	0.3102	0.6898	3.21	3.23	27.87
ICLN	0.7022	0.2978	0.3415	0.6585	3.35	2.93	28.64

Notes: This Table provides results of the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{i,r_t} RV_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t* and RV_t is the realized volatility of XLE index at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 8: Robustness test based on GARCH volatility

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	GARCH volatility	Sigma	χ^2 test
PBW	S1	0.019 (0.24)	0.043 (0.18)	-0.814** (0.04)	0.952*** (0.00)	296.82***
	S2	-0.076** (0.04)	0.063* (0.08)	-0.645* (0.08)	0.492*** (0.00)	
PBD	S1	-0.096** (0.02)	-0.017 (0.69)	-0.798** (0.04)	0.895*** (0.00)	449.94***
	S2	-0.033*** (0.00)	-0.002 (0.96)	-0.749** (0.03)	0.381*** (0.00)	
ICLN	S1	-0.119** (0.04)	0.033 (0.55)	0.744 (0.16)	0.942 (0.24)	257.79***
	S2	0.006 (0.62)	-0.007 (0.81)	-0.646** (0.04)	0.486*** (0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9820	0.0180	0.0271	0.9729	55.70	36.94	26.84
PBD	0.9486	0.0514	0.0213	0.9787	19.44	46.97	27.08
ICLN	0.9379	0.0621	0.0138	0.9862	16.10	72.35	27.96

Notes: This table presents the results from a Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t}R_{t-1} + \gamma_{i,r_t}CV_t + u_{i,t}$, where $R_{i,t}$ refers to the return for green assets at time *t* and CV_t is the conditional volatility of XLE index at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * denote significance of results at 1%, 5% and 10% levels respectively.

Table 9: Impact of VXXLE after controlling for technology stock price shocks

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	PSE-100	VXXLE	Sigma	χ^2 test
PBW	S1	-0.065	0.032	0.968***	-0.300***	1.377***	162.95***
		(0.23)	(0.17)	(0.00)	(0.00)	(0.00)	
	S2	-0.027	0.061***	0.862***	-0.131***	0.852***	
		(0.31)	(0.00)	(0.00)	(0.00)	(0.00)	
PBD	S1	0.003	0.011	0.821***	-0.199***	0.683***	206.49***
		(0.86)	(0.43)	(0.00)	(0.00)	(0.00)	
	S2	-0.146	-0.070	0.463***	-0.240***	1.521***	
		(0.15)	(0.17)	(0.00)	(0.00)	(0.00)	
ICLN	S1	0.009	0.019	0.700***	-0.133***	0.491***	129.91***
		(0.73)	(0.47)	(0.00)	(0.00)	(0.00)	
	S2	-0.145**	0.007	0.623***	-0.400***	0.587***	
		(0.04)	(0.43)	(0.00)	(0.00)	(0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9853	0.0147	0.0086	0.9914	68.26	116.70	19.02
PBD	0.9863	0.0137	0.0761	0.9239	72.90	13.14	22.34
ICLN	0.9692	0.0308	0.0737	0.9263	32.45	13.57	21.99

Notes: This Table provides results of the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t}R_{t-1} + \gamma_{i,r_t}\Delta VXXLE_t + \varphi_{i,r_t}RPSE_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t* and $RPSE_t$ is the return of PSE index at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 10: Impact of VXXLE after controlling for oil price shocks

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	WTI	VXXLE	Sigma	χ^2 test
PBW	S1	-0.030	0.068***	0.091***	-0.470***	1.061***	132.70***
		(0.33)	(0.00)	(0.00)	(0.00)	(0.00)	
	S2	-0.056	0.029	0.014	-0.811***	1.632***	
		(0.40)	(0.32)	(0.70)	(0.00)	(0.00)	
PBD	S1	0.124***	-0.011	0.031	-0.200***	0.631***	122.53***
		(0.00)	(0.80)	(0.11)	(0.00)	(0.00)	
	S2	-0.083**	-0.003	0.038**	-0.679***	1.094***	
		(0.02)	(0.86)	(0.02)	(0.00)	(0.00)	
ICLN	S1	0.028	-0.069	0.049**	-0.339***	0.886***	109.57***
		(0.46)	(0.14)	(0.04)	(0.00)	(0.00)	
	S2	-0.098*	0.015	0.071***	-0.667***	1.336***	
		(0.06)	(0.51)	(0.00)	(0.00)	(0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9951	0.0049	0.0095	0.9905	203.36	105.59	23.35
PBD	0.9431	0.0569	0.0295	0.9705	17.58	33.88	26.45
ICLN	0.9846	0.0154	0.0127	0.9873	65.04	78.46	24.79

Notes: This Table provides results of the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{i,r_t} \Delta VXXLE_t + \varphi_{i,r_t} RWTI_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time *t* and $RWTI_t$ is the return of WTI oil index at time *t*. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 11: Impact of VXXLE after controlling for oil volatility (OVX) shocks

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	OVX	VXXLE	Sigma	χ^2 test
PBW	S1	-0.023 (0.46)	0.074*** (0.00)	0.034 (0.46)	-0.638*** (0.00)	1.051** (0.03)	155.16***
	S2	-0.064 (0.35)	0.015 (0.59)	-0.083** (0.02)	-0.654*** (0.00)	1.665*** (0.00)	
PBD	S1	-0.260** (0.03)	-0.089* (0.07)	-0.043 (0.22)	-0.509*** (0.00)	1.733*** (0.00)	173.72***
	S2	0.024 (0.28)	0.035* (0.09)	-0.010 (0.62)	-0.583*** (0.00)	0.843*** (0.00)	
ICLN	S1	0.022 (0.53)	-0.075** (0.04)	0.014 (0.51)	-0.363*** (0.00)	0.886*** (0.00)	128.91***
	S2	-0.089** (0.04)	0.013 (0.56)	-0.034 (0.22)	-0.685*** (0.00)	1.336*** (0.00)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9933	0.0067	0.0123	0.9876	150.23	81.25	20.74
PBD	0.9196	0.0804	0.0156	0.9844	12.44	63.95	22.67
ICLN	0.9878	0.0122	0.0101	0.9899	81.65	99.03	24.65

Notes: This Table provides results of the Markov regime switching (MRS) model of this form: $R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{t-1} + \gamma_{i,r_t} \Delta VXXLE_t + \varphi_{i,r_t} \Delta OVX_t + u_{i,t}$, where $R_{i,t}$ refers to the return for clean energy assets at time t and ΔOVX_t is the first-order difference of OVX at time t. There are two panels in this Table: Panel A includes the estimates of MRS process and Panel B displays the transition probabilities and expected durations. In addition, RCM is the regime classification measure. The transition probabilities are reported as Pij. The expected duration of being in state i is reported as DUi, i.e., DU1 for state 1 and DU2 for state 2. The χ^2 test is performed to examine whether the state variances are equal. *p*-values are given in parentheses. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels respectively.

Table 12: Risk transmission relationship

	PBW	PBD	ICLN	USO
Panel A: $RV_t = \delta_0 + \delta_1 RV_{t-1} + \epsilon_t$				
Constant	2.15***	1.44***	1.81***	3.01***
RV_{t-1}	0.22***	0.21***	0.18***	0.20***
R^2	5.2%	4.6%	3.3%	4.1%
F-statistic	109.05***	94.71***	68.55***	84.53***
Panel B: $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 \Delta VXXLE_t + \epsilon_t$				
Constant	2.11***	1.42***	1.80***	2.98***
RV_{t-1}	0.24***	0.23***	0.19***	0.21***
$\Delta VXXLE_t$	0.90***	0.71***	0.73***	0.83***
R^2	10.7%	10.5%	8.6%	6.7%
F-statistic	117.75***	114.88***	92.04***	70.77***
Panel C: $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 \Delta OVX_t + \epsilon_t$				
Constant	2.15***	1.44***	1.82***	2.96***
RV_{t-1}	0.23***	0.22***	0.18***	0.22***
ΔOVX_t	0.54***	0.37***	0.39***	1.25***
R^2	8.5%	7.3%	5.8%	13.9%
F-statistic	91.20***	76.96***	60.89***	158.01***
Panel D: $RV_t = \delta_0 + \delta_1 RV_{t-1} + \delta_2 RV\_PSE_t + \epsilon_t$				
Constant	1.08***	0.56***	0.96***	2.51***
RV_{t-1}	0.14***	0.09***	0.10***	0.19***
RV_PSE_t	1.11***	0.93***	0.88***	0.45***
R^2	37.2%	41.8%	32.5%	7.1%
F-statistic	579.24***	701.72***	470.62***	75.25***

Notes: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

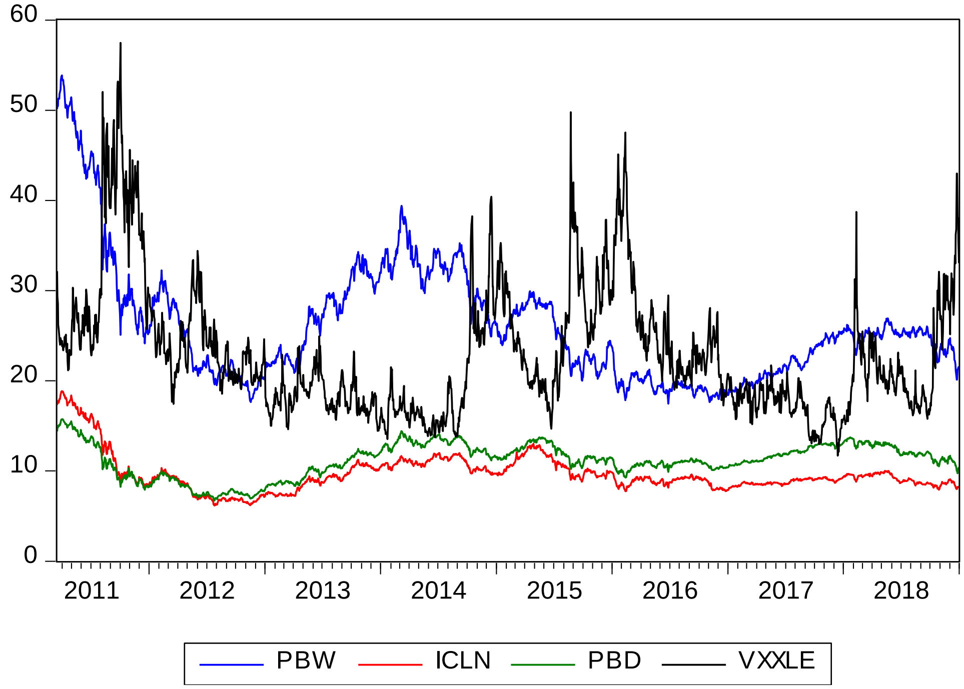

Fig. 1: Time-series plot of different indexes studied

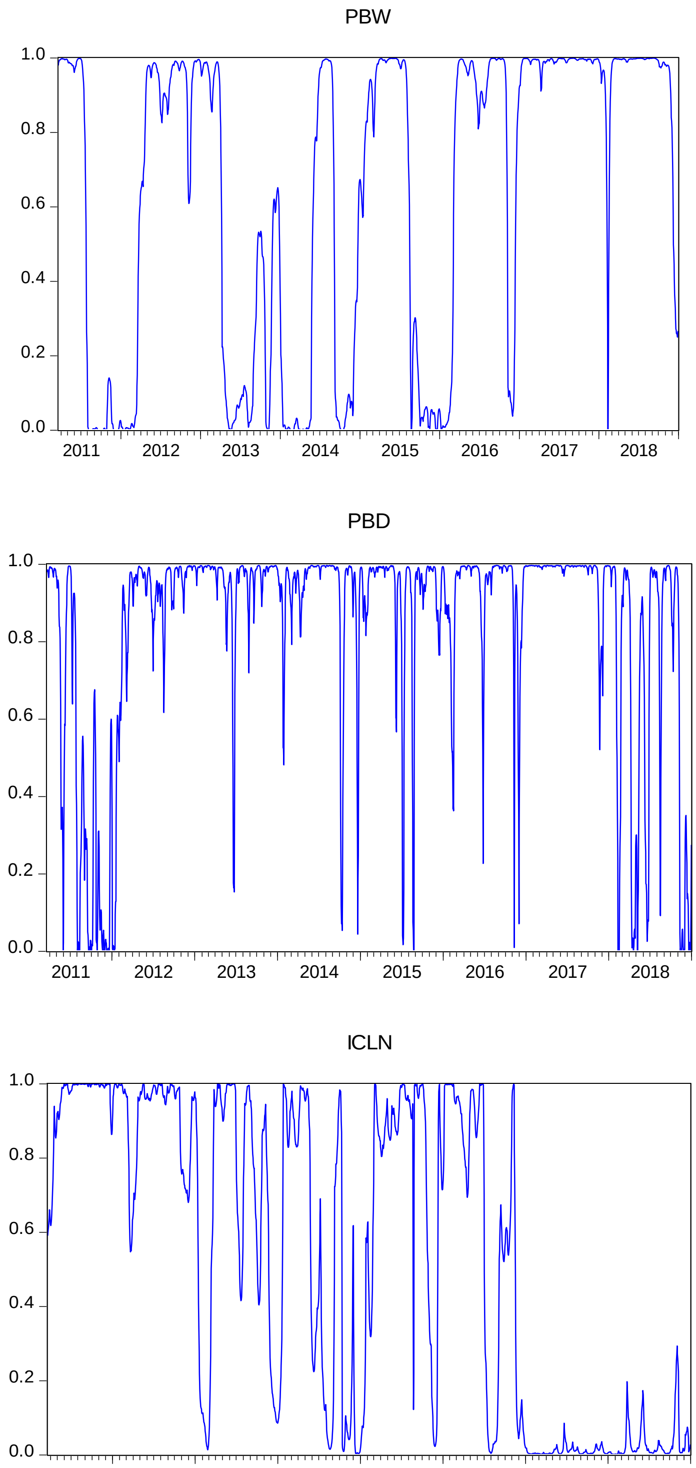

Fig. 2: Smoothed probabilities for being in high volatility states for different clean energy ETFs

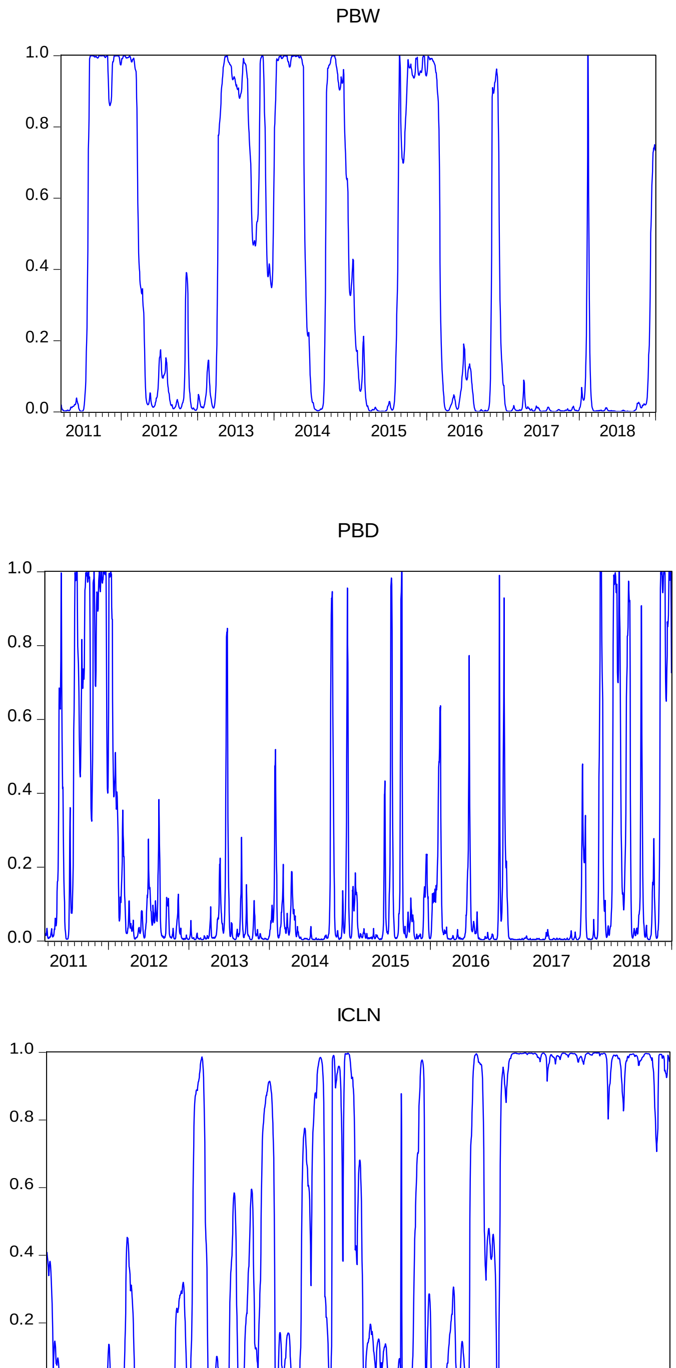

Fig. 3: Smoothed probabilities for being in low volatility states for different clean energy ETFs