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Climate risk and green investments: New evidence

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A R T I C L E I N F O

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A B S T R A C T

The academic literature on green energy equity markets has increased extensively over the last decade due to growing concerns about climate change and the substantial flow of investments into alternative energy markets. This study contributes by investigating the effect of climate risk on the return and volatility of green energy assets. This is one of the first papers to assess such effects using the recently developed climate policy uncertainty index as an indicator of climate risk. In particular, we seek to answer the following research questions. Firstly, does rising climate risk lead to a significant increase in green energy asset returns? Secondly, does climate risk affect the volatility of green energy assets negatively? Employing various models, we provide statistical evidence in favour of our hypotheses. Rising climate risk seems to encourage investment in alternative energy, which leads to an upward demand for green energy, which in turn increases the prices of green energy investments and decreases their volatility levels. Our analysis further shows that when climate risk increases, the correlation between crude oil and green energy returns decreases. Furthermore, green energy assets are more effective than gold for hedging oil market risk, without ignoring the hedging ability of technology stock investment.

1. Introduction

The academic literature on green energy investments has grown extensively over the last decade, attracting ample attention among academics, for several reasons. Firstly, investments in this sector are increasing significantly[1] and hence, clean energy stocks have emerged as an important asset class [1]. Secondly, research into the field of sustainable finance is also developing quickly due to growing concerns about climate change and its potential impact on economic and social welfare.[2] Thirdly, eco-friendly and socially responsible investors intend to participate in green energy sectors in order to possess low carbon portfolios [5]. Fourthly, whether green energy stocks can hedge traditional and non-traditional asset classes is of paramount interest to investors and policymakers.

In this study, we add to the existing literature on green energy assets by investigating the effect of climate risk on the return and volatility of green energy assets. In doing so, we contribute in two major ways. Firstly, we use the recently published climate policy uncertainty (CPU) index as a proxy for climate risk. The CPU index, developed by Ref. [6]; is a news-based measure of climate uncertainty. Its use is beneficial for exploring the association under study as CPU is constructed based on keywords such as “uncertainty”, “uncertain”, “carbon dioxide”, “climate”, “climate risk”, “greenhouse gas emissions”, “greenhouse”, “CO2”, “emissions”, “global warming”, “climate change”, “green energy”, “renewable energy”, “environmental”, “regulation”, “legislation”, “White House”, “Congress”, “EPA”, “law”, “policy” etc. While earlier studies [7,8] mainly use information on the EU-ETS (European Union emission trading system) allowance prices to study the impact of environmental risk on clean energy assets, we are among the first to employ this new indicator of climate risk in the context of the return and volatility of clean energy firms. Recently [9], consider climate risk while focusing on the relative performance of green over brown energy assets, without considering regime switching models, conditional correlations, and hedging analysis or crude oil and technology stocks.

Secondly, we examine the impact of climate risk on the dynamic

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[1] Over the decade 2010–2019, for example, over $2.8 trillion have been disbursed in the global clean energy industry, more than three times that expended during the period 2000–2009.

[2] There are also studies on central banks and environmental policy objectives (e.g. Ref. [2] and banking policies under a changing financial conditions [3]. Furthermore [4], find evidence that receiving adaptation funding negatively affects CO2 emissions.

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Acronym	Meaning
AIC	Akaike information criteria
BIC	Bayesian information criteria
CPU	Climate policy uncertainty
DCC-GARCH	Dynamic conditional correlation - generalized autoregressive conditional heteroskedasticity
ETF	Exchange traded fund
EUA	European Union Allowances
EU-ETS	European Union - emission trading system
GARCH	Generalized autoregressive conditional heteroskedasticity
GJR	Glosten, Jagannathan, Runkle
GFC	Global financial crisis
MRS	Markov regime switching
NYSE	New York Stock Exchange
OVX	Oil Implied Volatility
PBD	Invesco Global Clean Energy ETF
PBW	Invesco WilderHill Clean Energy ETF
QR	Quantile regression
SPDR	Standard & Poor's depository receipt
RCM	Regime classification measure
VAR	Vector autoregressive
VXXLE	Energy Sector ETF Volatility index
WTI	West Texas Intermediate
XNTK	SPDR NYSE Technology ETF

correlations between clean energy assets and strategic commodities (e.g. crude oil and gold) as well as technology stocks. Crude oil always plays a crucial role in green energy industries given that traditional energy prices and clean energy prices are intertwined [10]. Therefore, clean energy asset prices seem to be driven by oil price variations. For example, when oil prices go up, demand for clean energies increases, which leads to higher stock prices of alternative energy firms [11]. The information on gold, on the other hand, is used to examine whether gold acts as an effective hedging instrument during periods of high climate uncertainty. While the recent literature [1,12,13] documents that gold is no longer a hedge for clean energy stocks, our objective is to scrutinize whether this precious metal can minimize the risk linked to the clean energy asset class in the presence of high climate risk. Hence, given the substantial increase in climate risk over the past years, our analysis could be useful for eco-friendly investors who seek to hold low-carbon portfolios. Notably, when climate risk is high, socially responsible investors, caring about environmental concerns and the adverse effects of climate change, tend to increase their investments in cleaner energy, which potentially leads to an increase in the price of clean energy investments. Previous studies (e.g. Refs. [14,15], provide evidence that clean energy firms are highly correlated with technology firms, as the two groups share common features. Notably, innovations offered by technology companies are crucial for technological development and support the invention and progress of clean energy companies.

It is also worth mentioning that, in contrast to earlier studies [10,16–18], we use data on green energy exchange traded funds (ETFs) instead of renewable energy equity indexes. The same is true for the technology stock ETF. Taking the information on ETFs into account could be useful given that ETFs, unlike stock indexes, are less sensitive to non-synchronous trading issues. As indicated by Ref. [19]; such issues may lead to spurious estimates when executing market efficiency tests. In addition, ETF assets are particularly liquid and behave similarly to stock [20].

The main objective of this research is to examine whether climate risk exerts a positive impact on clean energy asset returns. That is, we investigate whether rising climate risk leads to a growth in clean energy asset prices. When climate risk increases, there might be a desire to shift towards alternative energies rather than fossil fuels. This causes the demand for renewable energies to grow, which is reflected in higher stock prices of clean energy firms, leading to the first hypothesis:

H1. : Climate risk affects clean energy asset returns positively.

Moreover, as the return of an asset is inversely related to its volatility, one would expect that higher climate risk implies lower risk for clean energy assets. Accordingly, we formulate the hypothesis:

H2. : Climate risk has a negative impact on the volatility levels of clean energy ETFs.

To test the above hypotheses, we employ the Markov regime switching (MRS) regression model and the generalized autoregressive conditional heteroskedasticity (GARCH) process. While each of these approaches is used extensively in previous literature, we adopt them for several reasons. Firstly, using the MRS regressions, we are able to examine the impact of climate risk on clean energy stock returns under low and high volatility regimes. Such inspections are crucial, since the effect of climate risk may regime-dependent. Hence, our analyses could have important implications for market participants during high and low volatility periods. Secondly, employing the GARCH model, we observe how the conditional volatility of clean energy equities reacts to changes in the levels of climate risk. To serve this purpose, we insert the CPU index into the GARCH equation as an exogenous variable.

Moreover, while studying how the dynamic associations between clean energy ETFs and each of crude oil, gold, and technology ETF react to climate risk, we calculate the time-varying correlations between clean energy ETFs and oil/gold/technology ETF using the dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) process, then regress these correlations on the climate risk index employing the quantile regression model.

The findings, in brief, support our hypotheses, implying that clean energy ETFs react significantly to climate risk. More specifically, higher climate risk implies higher returns for the green energy assets under consideration and, therefore, a significant drop is observed in the levels of volatility for green energy assets. We further extend the analysis to make inferences regarding portfolio management. Examining the impact of climate risk on a portfolio comprising clean energy ETFs and strategic commodities and technology stock investments, we find that, with an upsurge in climate risk, the correlation between oil (gold) futures prices and clean energy asset returns decreases (increases). It seems that during periods of high climate risk, both gold and clean energy asset prices experience a significant increment, while crude oil futures prices tend to decline substantially. These results simply suggest that amid phases of high climate risk, investors participating in crude oil markets might hedge the potential risk by including green assets in the portfolio. In fact, our portfolio analysis confirms that when climate risk increases, green assets are more effective than gold and technology investments in hedging oil market risk.

This paper proceeds as follows. The following section consists of a brief review of the relevant literature. Section 3 describes the data and outlines the methods employed. The results are presented in Section 4. We conclude in Section 5.

2. A brief review of the relevant literature

This section briefly reviews the existing literature on clean energy stock markets. We divide the standing literature into two segments. The first examines the price transmission association between brown and green/clean energy assets. Major contributions in this strand include [15,21–25]; among others. [21]; for example, employ a vector

Table 1
Summary statistics of data.

	PBW	PBD	XNTK	CPU	WTI	Gold
Mean	−0.0855	0.0596	1.0052	128.88	−0.4539	0.4281
Std.Dev	10.0359	8.7861	6.6774	87.1999	12.2002	3.6300
Skewness	−0.5175	−0.9605	−1.3593	2.0534	−0.8652	0.0662
Kurtosis	5.79	7.11	8.38	9.81	10.00	3.21
Jarque-Bera	57.00***	132.16***	233.82***	406.00***	333.96***	0.40
ADF	−10.61***	−9.88***	−11.73***	−3.24**	−8.28***	−9.67***
PP	−10.82***	−9.98***	−11.74***	−7.01***	−8.45***	−9.63***

Notes: This table reports the summary statistics of monthly data. PBW (Invesco WilderHill Clean Energy ETF). PBD (Invesco Global Clean Energy ETF). XNTK (SPDR NYSE Technology ETF). CPU (Climate Policy Uncertainty). WTI (West Texas Intermediate Crude oil futures prices). Except for CPU which is in levels, PBW, PBD, XNTK, WTI, and Gold are logarithmic returns. ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron). ***p $<$ 0.01, **p $<$ 0.05.

autoregression (VAR) method to study whether renewable energy stock prices respond to oil price and technology stock price shocks. The results suggest significant links among these markets. Adopting an asset pricing model [22], demonstrate that the connection between oil and Chinese new energy stocks varies over time and appears to be stronger after mid-2008, which corresponds to the global financial crisis (GFC) period. The findings reveal a positive linkage between these variables, indicating that an upsurge in energy prices would promote investment in renewable energy companies [24]. also find price transmission relationships between clean and dirty energy assets. Applying the Granger causality approach, they document that crude oil prices Granger cause the stock prices of alternative energy firms in the short run. Using a continuous wavelet approach [15], report a strong long-run association between oil and clean energy stocks, though the connection seems to weaken in the short run [26]. consider return spillover and its determinants between green and brown energy assets, using a tail dependency approach. They show time-varying spillovers between green and brown energy assets in lower and upper quantiles, which exhibits an asymmetric effect. They further highlight the important role of macroeconomic conditions, US dollar index, and crude oil market uncertainty [25]. indicate that the relationship between renewable energy equity returns and West Texas Intermediate (WTI) oil prices differs under different market states. More recently [9], show that climate policy uncertainty matters to the relative performance of green energy over brown energy assets without paying attention to regime switching models and the dynamic conditional correlations and hedging implications. Furthermore, they overlook crude oil as a source of brown energy and technology stock investments which reflect the performance of tech firms providing necessary innovation for a smooth transition to a low-carbon future.

Another strand of literature explores the risk transmission relationship between commodity and clean energy markets.[3] [14]; for example, documents a significant volatility linkage between fossil fuel and green stocks. In particular, the author employs a series of multivariate GARCH specifications and infers that the renewable energy asset class appears to be a good hedge for portfolios comprising dirty assets [30]. considers a time-varying copula approach and concludes that crude oil volatility significantly contributes nearly 30% to downside and upside risk of clean energy firms [31]. adopts the directional spillover approach developed by Ref. [32]; and finds that technology and clean energy equities are the dominant emitters of volatility spillovers to the US crude oil market [16]. documents that the crude oil implied volatility (OVX) index has a positive effect on the realized volatility of alternative energy stocks [1]. show that both gold and OVX act as good hedges for the renewable energy asset class [33]. conclude the same. Additionally [12], report that crude oil as well as gold appear to be safe-haven assets for clean energy companies during turbulent phases [34]. report that crude oil, gas, coal, electricity and carbon emit volatility to renewable energy stocks [5]. find that the Energy Sector ETF Volatility (VXXLE) index sends volatility to clean energy ETFs. A recent study by Ref. [35] employs a two-regime threshold vector error correction model combined with the DCC-GARCH process to assess the association between oil and clean energy assets, showing a long-term volatility linkage between these markets.

3. Methodology

3.1. Data

The data on the climate policy uncertainty index (CPU[4]) are retrieved from http://www.policyuncertainty.com. The data on clean energy ETFs are taken from the DataStream database. We study two different clean energy ETFs in this empirical work: Invesco WilderHill Clean Energy ETF (henceforth, PBW) and Invesco Global Clean Energy ETF (henceforth, PBD). Each of these ETFs allows market participants to have exposure to renewable energy investments. For comparison purposes, we use information on SPDR NYSE Technology ETF (XNTK), which reflects the performance of the NYSE technology index comprising 35 leading US-listed technology-related companies. A proxy for the performance of tech companies is included because previous studies (e.g. Refs. [14,15], argue that clean energy firms are highly correlated with technology firms as the two groups share common features. We also use WTI crude oil and gold futures prices in our analysis, and the data are collected from the DataStream database. The data sample covers the period from May 2008 to March 2021, yielding 155 monthly data points. The initial date of our sample is dictated by the availability of renewable energy equity prices. Note that the CPU data are available only on a monthly basis, and therefore we consider monthly observations for the ETFs and strategic commodities (WTI and gold).

Table 1 gives the summary statistics of the data and the results of the unit root tests. The data on CPU is used in its level form (i.e., without transformation) because it is stationary at levels, whereas we use logarithmic returns for the rest (i.e., PBW, PBD, XNTK, WTI, and Gold) computed as the natural logarithm of two consecutive monthly prices. Of the two clean energy ETFs, PBW appears to be more volatile than PBD, while XNTK is less volatile than the clean energy asset class. As expected, gold is less volatile than crude oil. Among these indexes, only

[3] On a related front [27], examine the investment efficiency of the new energy industry in China and show evidence of a low level of efficiency [28]. use a multivariate GARCH model and find a significant volatility spillover effect between European Union Allowances (EUA) and certified emissions reduction markets that differs across the various phases of the EU-ETS. On another front [29], consider the economics of crude oil, biofuel and food commodities.

[4] Notably, CPU exclusively reflects news about climate policy uncertainty and thus disregards news related to natural disasters. Furthermore, given the construction of CPU, it is not expected for increasing interest in or coverage of climate issues to lead to an increase in the CPU measure [6]. claims that the CPU index can be used as an additional tool to capture climate policy uncertainty at the macro level.

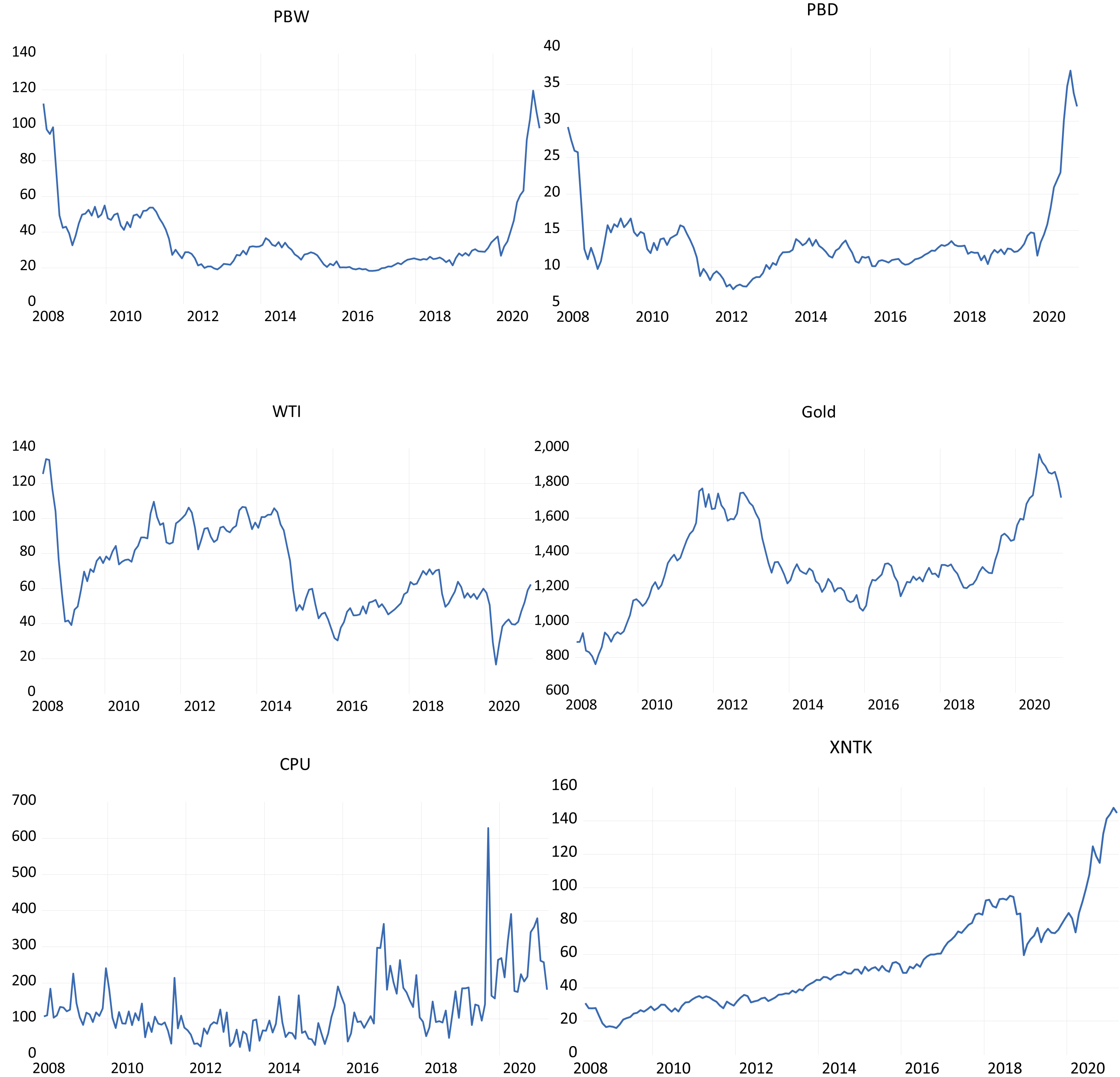

Fig. 1. **a**Level series of various indexes. Note: This figure shows the prices for the various ETFs and commodities, and the CPU index. The X-axis indicates the timeline, while the Y-axis shows the asset prices/climate risk values. **b**: Return series for various ETFs and commodities. Note: This figure shows the logarithmic returns for the various ETFs and commodities. The X-axis indicates the timeline, while the Y-axis shows the asset prices/climate risk values.

gold returns are positively skewed. Interestingly, the Jarque-Bera test suggests that the gold data satisfy the normality assumption, though other indexes do not follow a normal distribution. Finally, the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests provide statistical evidence that the return series of the five indexes as well as the CPU index are stationary.

Fig. 1a shows all the price indexes along with the CPU index. We observe that clean energy ETFs experience a large downturn around the 2008 global financial crisis and a relatively smaller downturn during the peak of the COVID-19 pandemic in February–March 2020. Crude oil prices decline sharply during the 2008 global financial crisis, the period 2015–2016 during which Saudi Arabia and Russia engaged in an oil price war, and the pandemic.[5] Interestingly, clean energy ETFs and the technology ETF see a large growth after the peak period of the COVID-19 pandemic. Gold prices mainly increase in the period after the 2008 global financial crisis and during most of the pandemic period. The CPU index exhibits several spikes in recent years. Fig. 1b plots the return

[5] Both the GFC and COVID-19 outbreaks periods had adversely affected economic and market conditions and thus equity prices, irrespective of climate risks. Therefore, these two crisis events might have an impact on our overall results, which necessitates a subsample analysis to capture and isolate their potential impact.

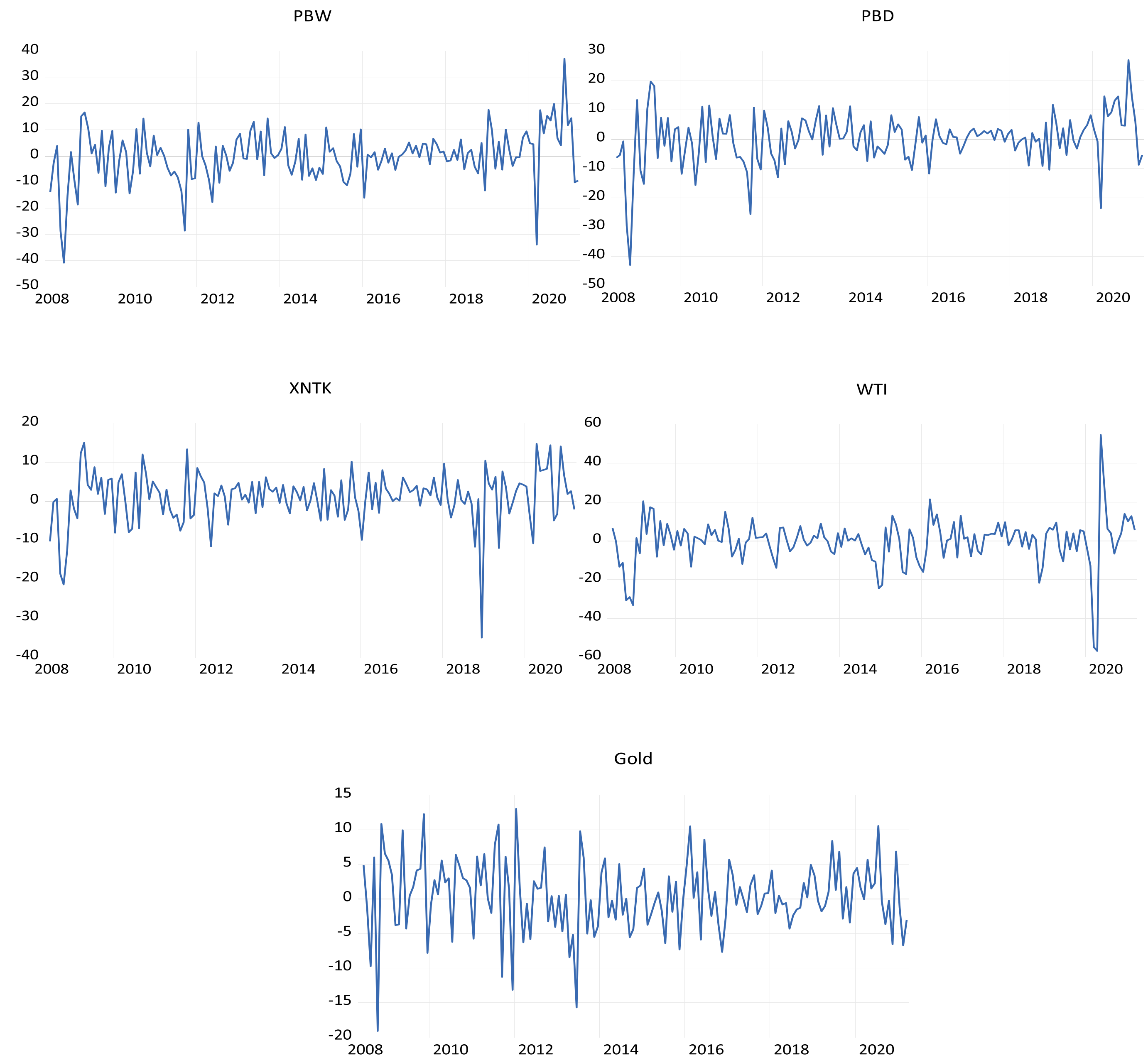

Fig. 1. (*continued*).

series of PBW, PBD, XNTK, WTI, and Gold, showing large fluctuations around the pandemic period.

3.2. Markov regime switching (MRS) model

As mentioned, the purpose of adopting the MRS approach is to examine the effect of climate risk on the returns of clean energy ETFs while the model parameters to switch between different volatility regimes (e.g. low and high volatility regimes). While numerous studies have employed the MRS model over the years, it continues to receive considerable attention among academics due to its attractive features [36];[49]; [37,38]. The model is defined as:

$$R_{i,t} = \alpha_{i,r_t} + \beta_{i,r_t} R_{i,t-1} + \gamma_{i,r_t} CPU_{t-1} + u_{i,t} \tag{1}$$

where, $R_{i,t}$ indicates the logarithmic returns for the i-th ETF index at time t, r_t refers to a discrete regime variable, α_{i,r_t} denotes the regime-dependent intercept, and β_{i,r_t} and γ_{i,r_t} are regime-dependent slope coefficients. From time period t, the transmission probability from regime 1 to regime m at time period $t+1$ is entirely dependent on the regime at time period t. In addition, the transition probabilities are given as:

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

In this study, we consider two regimes in order to obtain the parameters estimates for low and high volatility regimes. In line with [37]; we employ the regime classification measure (RCM) to evaluate the accuracy of our regime switching process:

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

The above statistic lies between 0 and 100. Note that the MRS specification appears to be a good-fitting model if the RCM statistic is

Table 2
Estimates of MRS approach.

Index	State	Constant	AR (1)	CPU	Sigma	χ^2 test
Panel A: Estimated coefficients						
PBW	S1	−3.5372**	0.1188	0.0272**	10.6685***(1.0696)	71.39***
		(1.7470)	(0.0921)	(0.0114)		
	S2	−2.2304*	-0.1815	0.0202***	2.9591***	
		(1.2289)	(0.1636)	(0.0074)	(1.1485)	
PBD	S1	−10.4126**	0.2901*	0.0586**	12.4298***	32.79***
		(5.2177)	(0.1576)	(0.0262)	(1.1447)	
	S2	0.1614	0.1438	0.0032	4.6286***	
		(1.0410)	(0.1012)	(0.0070)	(1.0919)	
XNTK	S1	−4.4536	0.1514	0.0295*	8.9352***	50.36***
		(3.2121)	(0.1785)	(0.0177)	(1.1228)	
	S2	1.5699**	−0.2169***	0.0058	3.3201***	
		(0.7077)	(0.0840)	(0.0045)	(1.1371)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9911	0.0089	0.0433	0.9567	112.23	23.11	16.91
PBD	0.9297	0.0703	0.0305	0.9695	14.22	32.83	17.66
XNTK	0.8538	0.1462	0.0940	0.9060	6.84	10.63	19.02

Notes: This table displays the estimates of the MRS approach. Values in parentheses indicate standard errors.
***p < 0.01, **p < 0.05, *p < 0.10.

close to 0 or low.

3.3. GARCH process

Based on the Akaike and Bayesian information criteria (i.e., AIC and BIC), we choose the GJR-GARCH process (Glosten, Jagannathan and Runkle, 1993) to study the impact of climate risk on the volatility of green energy ETFs. Given that clean energy assets are highly sensitive to crude oil volatility [1,16,25], we control for the effect of OVX. The extended GJR-GARCH process is thus given by:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta\varepsilon_{t-1}^2 S_{t-1} + \beta h_{t-1}^2 + \vartheta OVX_{t-1} + \theta CPU_{t-1} \tag{4}$$

where, S_{t-1} denotes a dichotomous variable that equals 1 when ε_{t-1} is negative and 0 otherwise. The persistence of volatility amounts to$\alpha + \beta + \frac{1}{2}\delta$.

3.4. DCC-GARCH approach and quantile regression

In order to estimate the time-varying correlations between clean energy ETFs and strategic commodities,[6] we employ the DCC-GARCH process:

$$R_t = M + \tau R_{t-1} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = H_t^{1/2}\eta_t \tag{6}$$

where R_t denotes the matrix of logarithmic returns for the various indexes used, M indicates the matrix of fixed parameters, τ refers to the matrix of coefficients assessing the effect of own-lagged and cross mean transmission, ε_t indicates the noise term, η_t denotes the matrix of *iid* innovations. Moreover, $H_t^{1/2}$ is the matrix of conditional volatilities, which is further decomposed as:

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag\left(\sqrt{h_t^i}, \sqrt{h_t^j}\right) \tag{8}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{9}$$

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1\xi_{t-1}\xi_{t-1}^{'} + \theta_2 Q_{t-1} \tag{10}$$

In equation (8), h_t^i and h_t^j define the conditional volatilities of technology/clean energy ETFs and oil/gold, respectively. We define h_t^i and h_t^j as:

$$h_t^i = d_i^2 + b_{11}^2 h_{t-1}^i + b_{21}^2 h_{t-1}^j + a_{11}^2\varepsilon_{i,t-1}^2 + a_{21}^2\varepsilon_{j,t-1}^2 \tag{11}$$

$$h_t^j = d_j^2 + b_{12}^2 h_{t-1}^i + b_{22}^2 h_{t-1}^j + a_{12}^2\varepsilon_{i,t-1}^2 + a_{22}^2\varepsilon_{j,t-1}^2 \tag{12}$$

In equation (10), Q_t denotes the time-varying conditional correlation of residuals, 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 indicates the matrix of unconditional correlations for the standardized noise ξ_t. Then the pairwise dynamic conditional correlation is given by:

$$\rho_t = \frac{h_t^{ij}}{\left(\sqrt{h_t^i}\sqrt{h_t^j}\right)} \tag{13}$$

where, h_t^{ij} represents the conditional covariance between the clean energy ETFs and crude oil/gold/technology ETF. Note that we adopt the quasi-maximum likelihood estimation technique to estimate the parameters of the DCC-GARCH process.[7]

Next, to explore the impact of climate risk on the dynamic conditional correlations under diverse market conditions, we employ the quantile regression (QR) approach.[8]

We frame this process as:

$$Q_{\rho_t}(\tau|\rho_{t-1}, \mathrm{CPU}_{t-1}) = \varphi(\tau) + \lambda(\tau)\rho_{t-1} + \theta(\tau)\mathrm{CPU}_{t-1} \tag{14}$$

Following [40]; $Q_{\rho_t}(\tau|\rho_{t-1}, \mathrm{CPU}_{t-1})$ signifies the τ conditional quantile of ρ_t, the dynamic conditional correlations at time *t*. Meanwhile, $\varphi(\tau)$ measures the unobserved impact in the quantile model.

Now, for a given τ, the following equation is estimated by minimizing the weighted absolute deviation:

$$arg \min_{\varphi(\tau),\lambda(\tau)+\theta(\tau)} \sum_{t=1}^{T} \varphi_\tau(\rho_t - \varphi(\tau) - \lambda(\tau)\rho_{t-1} - \theta(\tau)\mathrm{CPU}_{t-1}) \tag{15}$$

[6] we also consider technology ETF.

[7] The estimated coefficients of the DCC-GARCH model are not reported here. They are available on request from the authors.

[8] Several other studies such as [25,39] use QR.

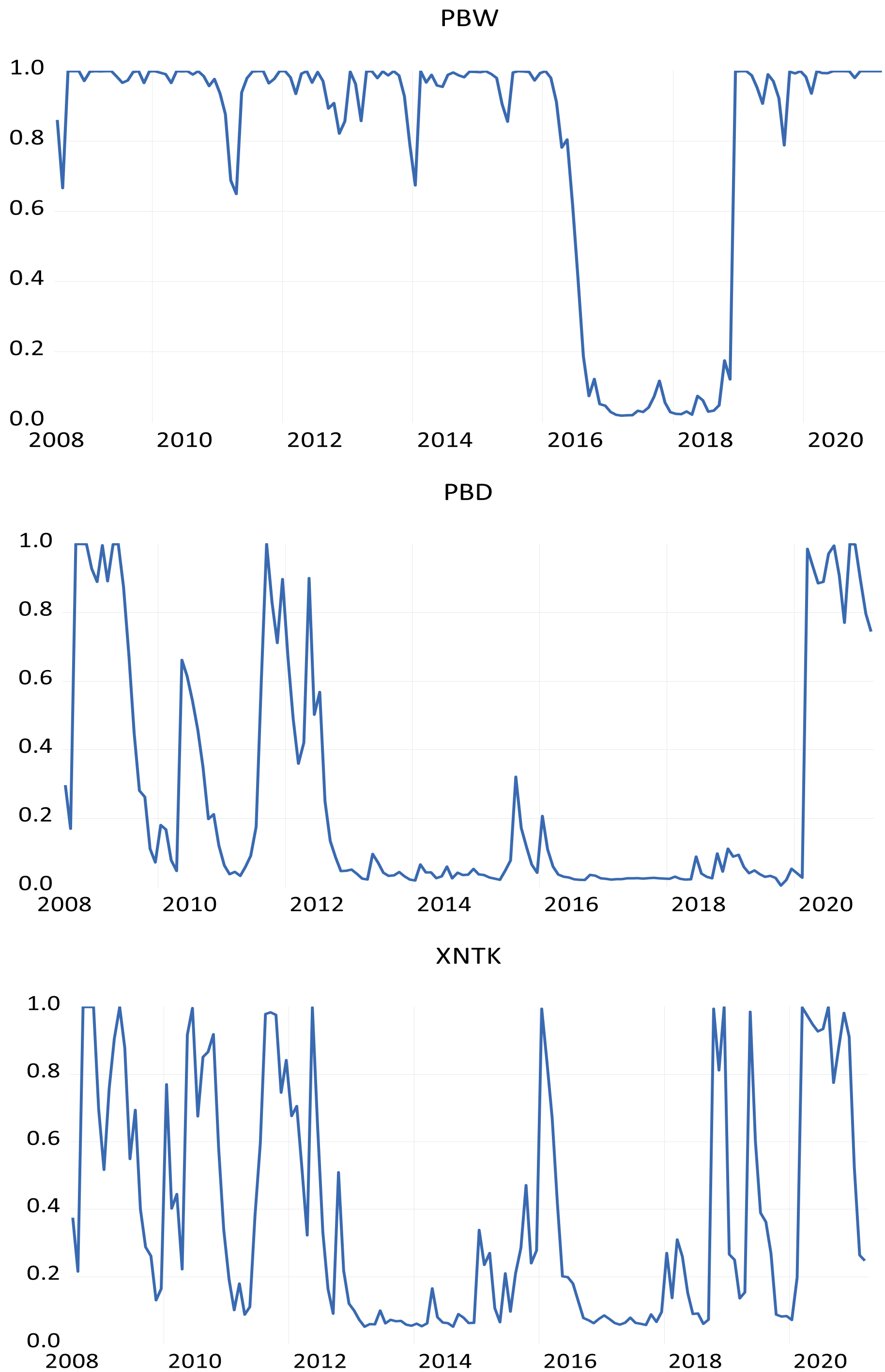

Fig. 2. Filtered probabilities for high volatility regime. Note: The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the high volatility states for the PBW, PBD and XNTK indexes. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities.

where, $\varphi_\tau(u) = u(\tau - I(u < 0))$ and I (•) refers to the indication function.

For a positive and statistically significant $\theta(\tau)$, we conclude that an upturn in the CPU index causes an increase in the correlation level. For a negative $\theta(\tau)$, on the other hand, we report a reverse association between them.

Several quantiles ($\tau = 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95$) are considered in our estimation process. Lower quantiles (i.e., 0.05, 0.10, 0.25) imply low correlation regimes, while higher quantiles (i.e., 0.75, 0.90, 0.95) indicate high correlation regimes.

4. Results and discussion

4.1. CPU and ETFs returns: Estimates of the Markov regime switching (MRS) model

The estimates of the MRS approach, shown in Table 2, reveal that the impact of climate risk (i.e., the CPU index) on the returns of clean energy ETFs is significant at the 1% level. More importantly, each of these ETFs reacts positively to climate risk. These findings thus support our first hypothesis implying that, with an increase in climate risk there would be

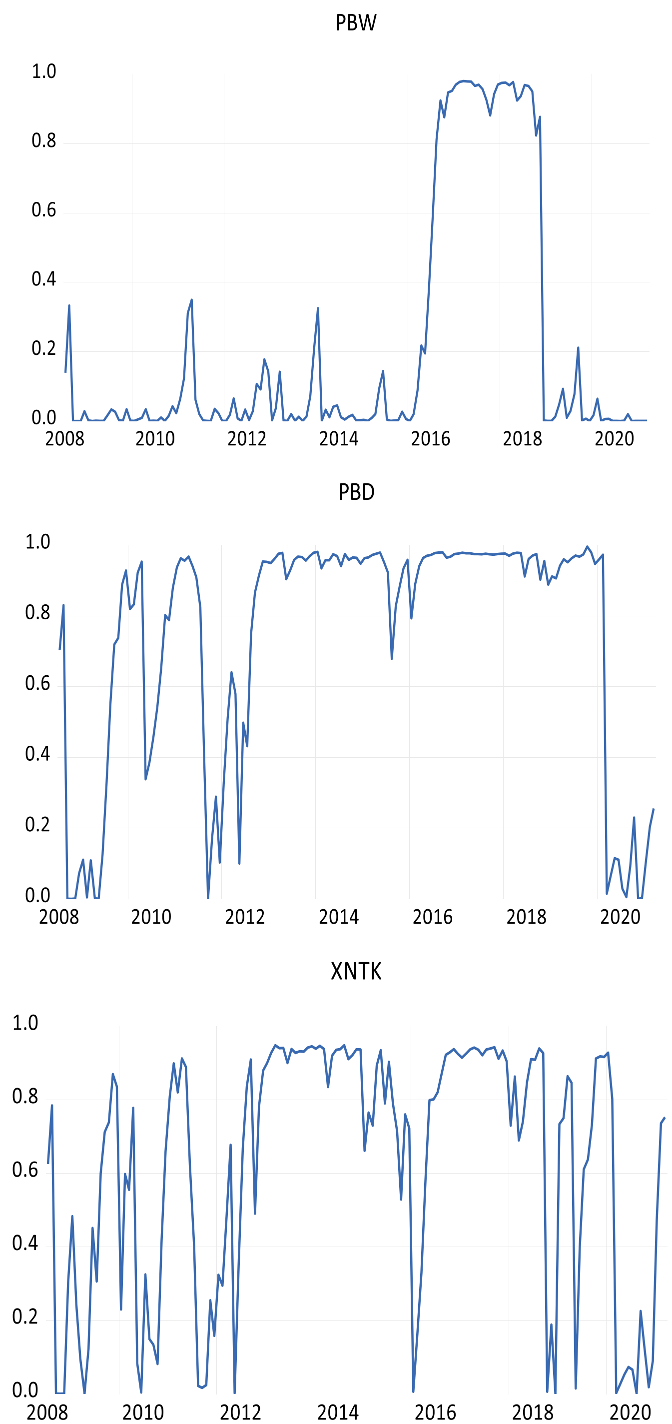

Fig. 3. Filtered probabilities for low volatility regime. Note: The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the PBW, PBD and XNTK indexes. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities.

an upsurge in the price of clean energy investments. Our results could be attributed to an increasing demand for clean energies during periods of high climate risk, which leads to a growth in the security prices of alternative energy companies. For comparison, we consider the technology ETF (XNTK), and find that the impact of climate risk is significant at the 10% level.

It is noteworthy that for all indexes, regime 1 appears to be the high volatility regime, while regime 2 is the low volatility regime. We report that the effect of CPU is significant in both volatility regimes for the PBW index, while the same coefficient is significant only in the high volatility regime for the PBD index. In case of the XNTK index, like the PBD index, we find a significant result only in the high volatility regime. Furthermore, we provide statistical evidence that all the sigma coefficients are significant at the 1% level, suggesting a swapping between the low and high volatility states. In addition, the RCM statistic implies that the MRS regression can be considered a good-fitting model in each case. Figs. 2 and 3 plot the filtered probabilities of remaining in the low and high volatility states, and indicate a clear switching pattern for all assets.

Table 3
Estimates of GJR-GARCH process.

Index →	PBW	PBD	XNTK
ω	22.0996*	7.3465***	3.0089*
α	0.1080	0.0955	0.1471***
β	0.0168	0.6176***	0.6094***
γ	0.2351	0.1328	0.2744***
ϑ	0.0378***	0.0094***	0.0091**
θ	−0.1202***	−0.0682***	−0.0342**
Log-likelihood	−538.86	−512.00	−471.66
AIC	7.161	6.810	6.283
BIC	7.339	6.989	6.461

Notes: ϑ and θ measure the effects of OVX and CPU, respectively. ***p < 0.01, **p < 0.05, *p < 0.10.

4.2. *CPU and ETFs volatility: Estimates of GJR-GARCH process*

Table 3 displays the results of the GJR-GARCH model. We find that CPU has a negative impact on the volatility of the two clean energy ETFs under study. Therefore, when climate risk increases, we observe a downturn in the risk levels of these green investments. These findings support our second hypothesis, implying that the volatility of clean energy assets is inversely related to the level of climate risk. The results reported in Table 3 also hold for the XNTK index. In addition, OVX exerts a positive impact on each of these ETFs, which suggests that rising crude oil volatility is associated with an upturn in the risk levels of these assets. The findings of [16,25] confirm that OVX positively affects the volatility of clean energy assets.

4.3. *Time-varying dynamic conditional correlations*

Figs. 4 and 5 show the time-varying dynamic correlations between strategic commodities and clean energy/technology ETFs. We report several interesting findings. For example, during the periods of the 2008 global financial crisis, European sovereign debt crisis, and 2014 oil market crisis, the correlations between crude oil and green ETFs remain mostly positive. The same is observed for the correlations between crude oil and technology ETF. However, such correlations turn out to be negative during the ongoing pandemic. It seems that in the earlier stage of the COVID-19 crises, during which WTI prices decline significantly, both green and technology assets can be considered a good hedge for crude oil market risk.[9] Looking at Fig. 5, we note a different scenario for the correlations between gold and green ETFs. During all crisis periods, such correlations remain negative, implying that gold is a good hedge for green assets during periods of turmoil. However, inspecting the correlations between gold and technology ETF, a positive association emerges throughout the sample period, except for the 2008 financial crisis era. Hence, gold can be regarded as a good hedge for the

[9] Clean energy assets possibly benefit from fiscal policies adopted by governments, especially US governments, during the GFC and pandemic periods. These include fiscal incentives for research and development, and support for new infrastructure investment projects.

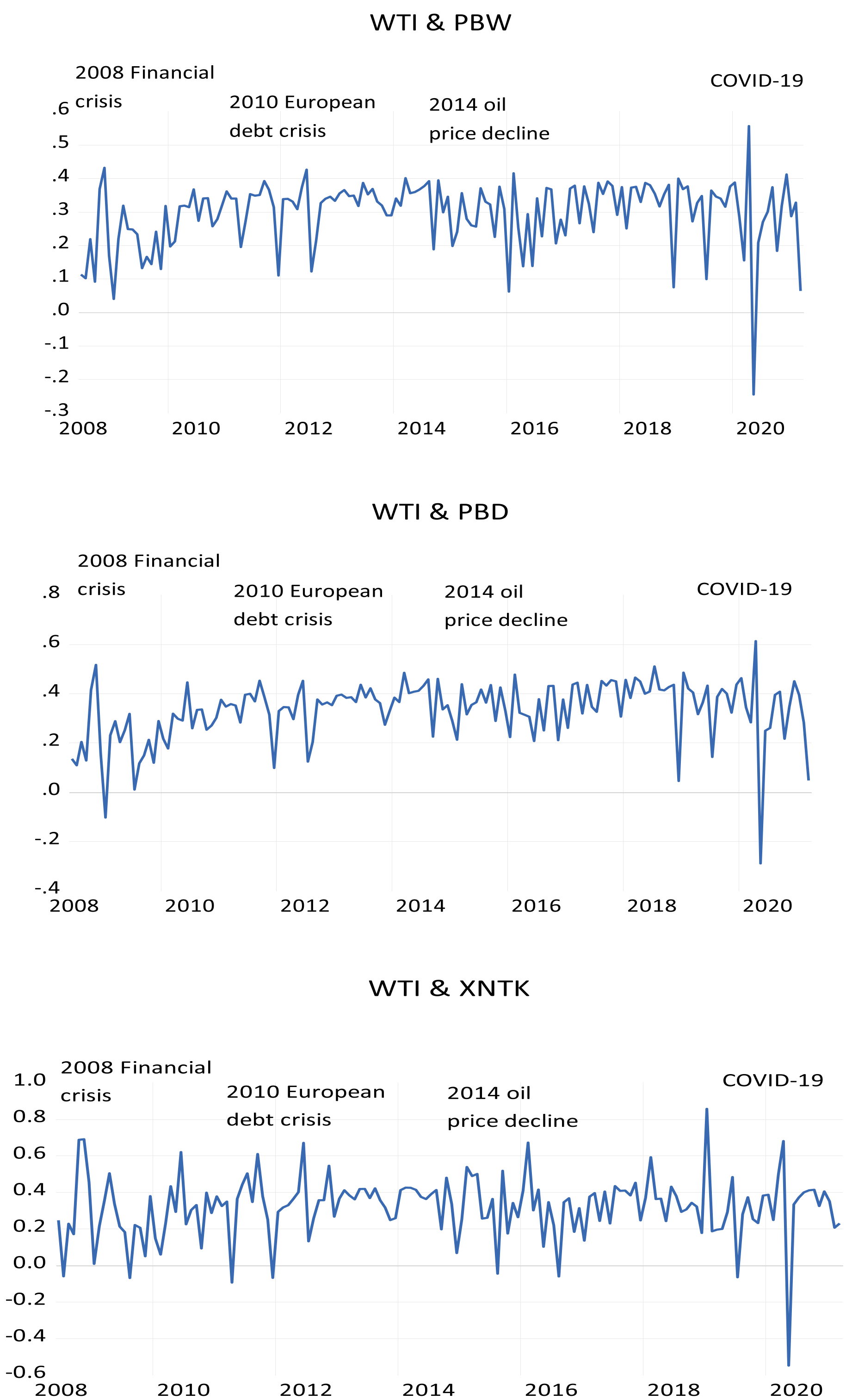

Fig. 4. Time-varying conditional correlations between oil and green energy/technology ETFs. Note: The time-varying conditional correlations are derived from the bivariate DCC-GARCH process. The correlations measure how the associations between oil and the various ETFs evolve over time. The correlations are observed in both positive and negative regions indicating a time-dependent connection between these markets. The X-axis indicates the timeline, while the Y-axis shows the correlations.

technology stock sector in the global financial crisis period only[10].

Now, we examine how these correlations react to climate risk using the estimates of quantile regression, as shown in Tables 4 and 5. The findings in Table 4 reveal that CPU has a negative impact on the correlations between oil and green/technology assets. Thus, when climate risk increases, the aforesaid correlations tend to decline. Notably, the result is significant only at extreme lower quantiles, indicating that when correlations are low they seem to decrease further with an upsurge in climate risk. This finding makes sense given that, when climate risk is high, there is a tendency to invest more in clean energy or technology

[10] We plot the dynamic time-varying correlations between green and technology ETFs in Appendix Fig. A1. As expected, we observe high positive correlations throughout the sample period confirming that technology sector assets would not be a good hedge for green assets [14,15]. Such high positive associations could be attributable to the fact that investors view alternative energy companies as similar to other high technology companies.

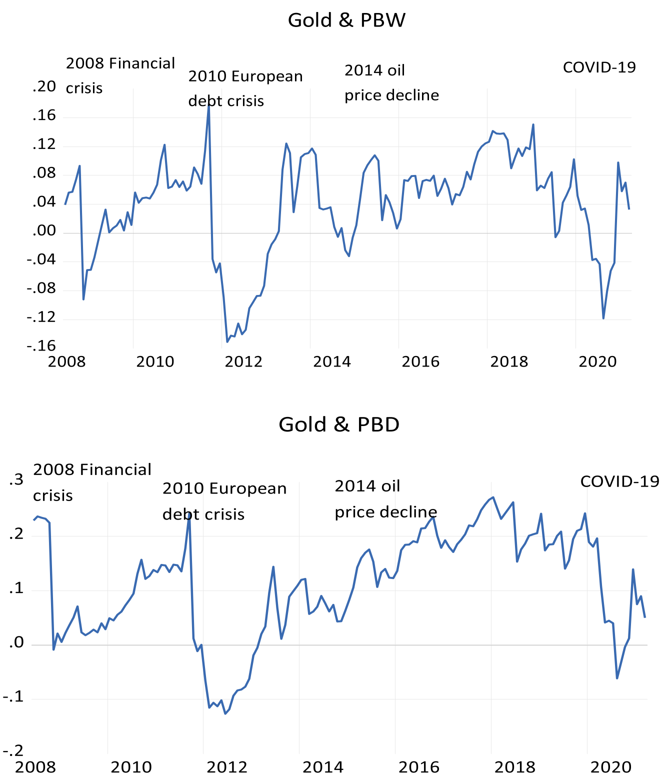

Fig. 5. Time-varying conditional correlations between gold and green energy/technology ETFs. Note: The time-varying conditional correlations are derived from the bivariate DCC-GARCH process. The correlations measure how the associations between gold and the various ETFs evolve over time. The correlations are observed in both positive and negative regions indicating a time-dependent connection between these markets. The X-axis indicates the timeline, while the Y-axis shows the correlations.

sectors as oil prices experience a significant drop. In such cases, thus, oil and clean energy/technology assets move in the opposite direction. The implication of these findings is that investors holding assets in crude oil sectors may use clean energy/technology assets in order to hedge the portfolio risk during phases of high climate risk.

From Table 5 we observe that climate risk has a positive impact on the correlation between gold and PBW. Similar results are found for PBD, except at the upper quantile of 0.95 where the impact appears to be negative. Accordingly, when the correlations between gold and PBD are extremely high, there could be a drop due to the increase in climate risk. Panel C shows no significant impact of CPU on the correlations between gold and technology ETF.[11]

Overall, these results indicate that when climate risk tends to increase, gold prices are also high and hence we note a significant growth in the correlations between this precious metal and green energy ETFs. Hence, during periods of high climate risk, gold may not be a good hedge for the clean energy asset class, although the issue of hedging effectiveness is examined in more detail in the next section. It is also stimulating to consider whether green energy ETFs or technology ETF can be used to hedge the risk of the crude oil market which sees a substantial drop in its price levels amid phases of high climate uncertainty. We address this in the following section.

4.4. Portfolio implications: Climate risk, hedge ratios, and hedging effectiveness

To give more insight into the portfolio and hedging implications, we empirically compare the hedging performance of clean energy ETFs, gold, and technology ETF against the crude oil market during periods of low and high climate risk. In doing so, we consider three portfolios: (1) WTI and green ETF; (2) WTI and technology ETF; and (3) WTI and gold. Our objective is to examine which of green ETF, technology ETF, and gold is most effective in hedging oil market risk.

In line with [41]; we estimate the hedge ratios (β_t) as:

Table 4
Impact of CPU on the correlations between oil and green energy/technology ETFs.

Quantiles→	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Panel A: PBW							
Constant	0.2440***	0.1746	0.2288***	0.2871***	0.3620***	0.3995***	0.4101***
ρ_{t-1}	0.0769	0.1876	0.1531	0.1865**	0.0034	−0.0688	−0.0774
CPU_{t-1}	−0.0013***	−0.0006	−0.0001	−0.0002	0.00002	0.0001	0.0001
Panel B: PBD							
Constant	0.0261	0.0309	0.1040**	0.1317***	0.2038***	0.3360***	0.4442***
ρ_{t-1}	0.7004***	0.6640***	0.6102***	0.6235***	0.6101***	0.3776***	0.2525***
CPU_{t-1}	−0.0009***	−0.0003	−0.0002	−0.00002	−0.000004	0.00002	−0.0001
Panel C: XNTK							
Constant	0.2879***	0.3463*	0.2713***	0.3628***	0.3982***	0.5206***	0.5542***
ρ_{t-1}	−0.2419	−0.1713	−0.0086	0.0175	0.0793	0.0549	0.2745***
CPU_{t-1}	−0.0017**	−0.0013	−0.0002	−0.0002	−0.0001	−0.0004	−0.0004

Notes: This table presents the QR results for the oil-ETF linkage. ***$p < 0.01$, **$p < 0.05$.

[11] As suggested by one anonymous reviewer, the beginning of our full sample period spanning from May 2008 to March 2021 overlaps with the global financial crisis of 2008, whereas its ending overlaps with the COVID-19 pandemic. Both of these crisis periods had adversely affected economic and market conditions and thus equity prices, irrespective of climate risks. Therefore, these two crisis events might have an impact on our overall results, which necessitates a subsample analysis to capture and isolate their potential impact. In fact, we tried to conduct subsample analyses but failed to provide robust and reliable results due to the small size of our subsample period, which comprises 155 monthly observations. This issue is left for future research.

Table 5
Impact of CPU on the correlations between gold and green energy/technology ETFs.

Quantiles→	Q (0.05)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.95)
Panel A: PBW							
Constant	−0.1181***	−0.1042***	−0.0371***	0.0160	0.0378**	0.1216***	0.1592***
ρ_{t-1}	0.4838***	0.3610***	0.4122***	0.3143***	0.2465***	0.5152***	0.6107***
CPU_{t-1}	−0.00001	0.0002***	0.0001**	0.00002	0.0001	0.00007	0.00005
Panel B: PBD							
Constant	−0.1059***	−0.0701**	−0.0037	0.0339***	0.0613***	0.2155***	0.3961***
ρ_{t-1}	0.5209***	0.4267***	0.3818***	0.4223***	0.4579***	0.1841	0.1787
CPU_{t-1}	0.00003	0.0002***	0.0001**	0.00009	0.0002**	0.00002	−0.0005***
Panel C: XNTK							
Constant	0.0010	0.0015	0.0051**	0.0044***	0.0067***	0.0083***	0.0081***
ρ_{t-1}	0.6258***	0.7385***	0.8066***	0.9483***	0.9684***	0.9758***	0.9830***
CPU_{t-1}	0.000001	−0.000009	−0.00001	−0.0000003	−0.000001	−0.0000001	0.000003

Notes: This table presents the QR results for the gold-ETF linkage. ***p < 0.01, **p < 0.05.

Table 6
Optimal hedge ratios.

	Low climate risk regime	High climate risk regime
WTI/gold	0.1679	0.2767
WTI/PBW	0.2213	0.2571
WTI/PBD	0.2053	0.2403
WTI/XNTK	0.2183	0.2891

Notes: Low climate risk regimes refer to periods when CPU is less than its mean value and high climate risk regimes indicate phases when CPU exceeds its mean value.

Table 7
Hedging effectiveness.

	Low climate risk regime	High climate risk regime
WTI/gold	21.02%	16.88%
WTI/PBW	17.69%	19.31%
WTI/PBD	18.93%	21.09%
WTI/XNTK	18.11%	15.82%

Notes: Low climate risk regimes refer to periods when CPU is less than its mean value and high climate risk regimes indicate phases when CPU exceeds its mean value.

$$\beta_t = \frac{h_t^{xy}}{h_t^{y}} \tag{16}$$

where, h_t^{xy} indicates the covariance between WTI and each of gold, clean energy ETF, and technology ETF at time t and h_t^y denotes the variance of gold/ETF at time t. As suggested by Ref. [42]; portfolios with lower hedge ratios have better hedging effectiveness.

Note that we compute the hedge ratios for both low and high climate risk regimes. Low climate risk regimes refer to periods when CPU is less than its mean value whereas high climate risk regimes indicate phases when CPU exceeds its mean value.

The hedge ratios, presented in Table 6, reveal that when climate risk is low, a \$100 long position in WTI can be hedged with a \$16.79 short position in gold, \$22.13 short position in PBW, \$20.53 short position in PBD, and \$21.83 short position in XNTK. During the phase of high climate risk, the hedge ratios are much higher, suggesting that a larger short position in gold (\$27.67) is needed to hedge a \$100 long position in WTI. For PBW, PBD, and XNTK, it is \$25.71, \$24.03, and \$28.91, respectively. Hence, when climate risk tends to increase, investors participating in the crude oil market seeking to hedge their potential downside risk, need to take a shorter position in gold, green energy, or technology stocks.

Next, we calculate the hedge effectiveness (HE), which gives an indication of the percentage of the variance eliminated by the hedge:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{17}$$

where $Var_{unhedged}$ denotes the variance of the unhedged portfolio including only WTI. Furthermore, Var_{hedged} denotes the variance of the hedged portfolio comprising WTI and the other asset (gold, PBW, PBD, or XNTK). It is defined as:

$$Var_{hedged} = \left(\omega_t^{xy}\right)^2 h_t^x + \left(1 - \omega_t^{xy}\right)^2 h_t^y + 2\omega_t^{xy}\left(1 - \omega_t^{xy}\right) h_t^{xy} \tag{18}$$

where h_t^x and h_t^y are the conditional volatilities of WTI and the other asset (gold, PBW, PBD, or XNTK); h_t^{xy} indicates the covariance between WTI and each of gold, PBW, PBD, and XNTK, and ω_t^{xy} is the optimal weight of WTI in the portfolio comprising WTI and the other asset. ω_t^{xy} is given by:

$$\omega_t^{xy} = \frac{h_t^x - h_t^{xy}}{h_t^x - 2h_t^{xy} + h_t^y} \tag{19}$$

Note that if HE is equal to 1, a perfect hedge situation emerges. However, if HE is equal to 0, there is a lack of hedging effectiveness.

The estimated results, displayed in Table 7, show evidence on the effectiveness of hedging. Notably, during the phase of high climate risk, the percentage of variance reduced by hedging WTI with green ETFs is the highest (21.09 for PBD and 19.31% for PBW), followed by WTI/gold and WTI/technology ETF. These results highlight the valuable role of green energy investments to hedge the downside risk of brown energy prices such as crude oil prices, which nicely complement the findings of [9].

5. Conclusion

In this paper, we examine the impact of climate risk on the security prices of clean energy firms, providing the first evidence based on the recently developed climate policy uncertainty index as an indicator of climate risk. Using the Markov regime switching regression and asymmetric GARCH models, we provide evidence that the effect of climate risk is positive on the returns of green energy assets but negative on their volatility. It seems that rising climate risk encourages investors and policymakers to shift towards alternative energy sectors, which leads to an upward demand for renewable energies. Consequently, the prices of clean energy investments tend to go up, initiating a significant drop in its volatility levels. Our analysis further shows that, with an upsurge in climate risk, the correlation between oil (gold) prices and clean energy returns decreases (increases). During periods of high climate risk, both gold and clean energy asset prices experience a significant increment, while crude oil prices tend to decline substantially. We also find that when climate risk increases, green energy assets are more effective than gold and technology stocks for hedging crude oil market risk. However, we should not disregard the role of technology stocks in hedging the risk of crude oil in low and high phases of climate risk.

Our results have key implications for socially responsible investors who participate in alternative energy markets in order to maintain eco-efficiency portfolios. Given that green and ethical investments have ecological influences that assure a certain degree of sustainability [33, 35,43], this study is of particular interest to eco-friendly investors who require precise information for making proper asset allocation decisions when investing in green energy sectors based on high and low values of climate risk. Overall, the results offer stylized facts about eco-friendly investments, which enhance our knowledge of how to deal with environment-related risk and uncertainty while considering various hedging instruments.

Given the possible limitations of measuring climate change uncertainty, such as the inability to measure natural disasters, and the possibility of professional investors viewing it differently, especially in light of the emergence of other climate-based measures, it would be interesting to conduct more research comparing the hedging ability of CPU to other related measures. Furthermore, the beginning and ending of our sample period overlap with the GFC of 2008 and the COVID-19 pandemic, respectively. Under such extreme events, economic and market conditions deteriorated and shaped equity prices, irrespective of climate risks. It is therefore relevant and important to assess the potential impact of these two crisis events on the overall results. However, this issue is left for future research.

Credit author statement

Anupam Dutta: Conceptualization; Validation; Analysis; Writing - original draft, **Elie Bouri**: Writing; Editing; Final Revision; Project administration, **Timo Rothovius**: Writing; Editing; Final Revision; Supervision, **Gazi Salah Uddin**: Writing; Analysis; Final Revision; Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

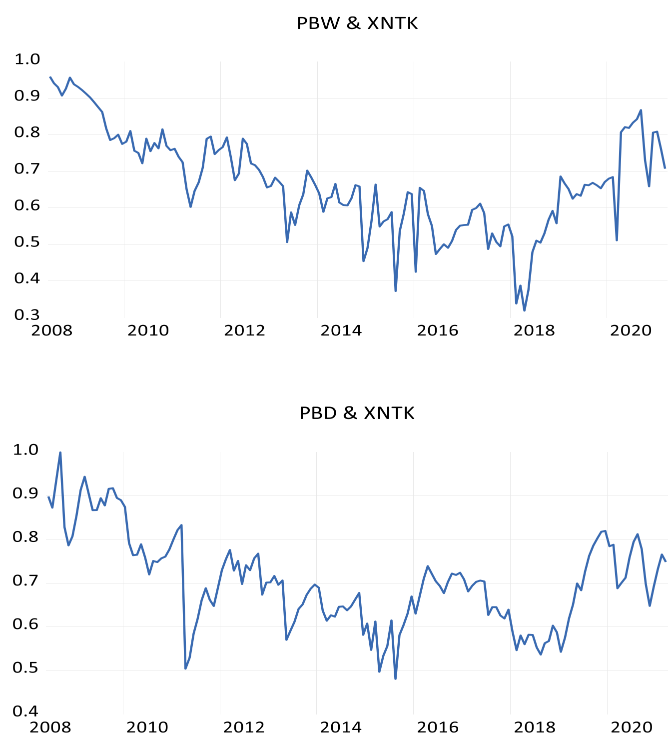

Fig. A1. Time-varying conditional correlations between green and technology ETFs.
Note: The time-varying conditional correlations are derived from the bivariate DCC-GARCH process. The correlations measure how the associations between green and technology ETFs evolve over time. The X-axis indicates the timeline, while the Y-axis shows the correlations. .

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