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Geopolitical risk and renewable energy asset prices: Implications for sustainable development

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ABSTRACT

This study intends to investigate the impact of geopolitical uncertainty, proxied by the geopolitical risk (GPR) index, on the volatility of renewable energy exchange traded funds (ETFs). Employing a two-state Markov regime switching model reveals that an upturn in the GPR index increases (reduces) the likelihood of being in the low (high) volatility regime. This finding could be attributed to the fact that when the geopolitical risk increases, users of crude oil, which is highly sensitive to such risk, tend to consider clean energy as a substitute for traditional energy sources. This causes a growth in the equity prices of new energy firms, further leading to a drop in the levels of volatility. Additionally, the results of generalized autoregressive conditional heteroscedasticity (GARCH) models also confirm that higher GPR implies lower risk for these green assets. The outcomes have implications to policymakers and investors participating in clean energy markets.

1. Introduction

Over the past few years, demand for renewable energies has increased substantially due to growing concerns about climate change. Accordingly, investments in international clean energy markets have also experienced an ascending trend. For example, a recent study by Bloomberg New Energy Finance documents that global investment in transitional energy has reached $755 billion in 2021. The study also indicates that in order to achieve climate neutrality, investment in this sector would reach over $2 trillion between 2022 and 2025, and about $4.1 trillion during the period 2026–2030.[1] Hence, investments in renewable energies will need to triple in the coming years with a view to reducing net carbon emissions to zero.

Given that clean energy markets appear to be a relatively new class of assets to invest in, they could be highly volatile in nature [1]. Therefore, precise estimates of time-varying volatility are of paramount importance to market participants for understanding the risk of investor portfolio consisting of clean energy assets. Hence, it is crucial to identify the factors that drive the volatility of this emerging asset class.

To this end, the present study aims to investigate whether geopolitical risk (henceforth, GPR) can predict the uncertainty linked to clean energy asset returns. In doing so, we contribute to the literature in several aspects. First, based on our knowledge, it is among the preliminary studies to examine whether clean energy assets react to geopolitical uncertainty. Given that oil price variations are affected by geopolitical risk through the supply and demand channels [2,3], GPR may exert a significant impact on clean energy assets from the intuition that oil and renewable energy prices are highly covariant [4]. In particular, geopolitical risk may affect clean energy assets via at least four channels. First, when increasing geopolitical risk has a positive effect on crude oil prices, traditional energy sources could be replaced by renewable energies [5]. This in turn improves the operating situations of new energy firms and their stock performance [6]. Second, investors' expectations for future oil supply and demand changes could influence their perspective about alternative energy industry, which is further reflected in their investment decisions [7]. Thus, variations in geopolitical risk may impact the clean energy asset returns through investor sentiment. Third, the transition to renewable energy leads to greater energy self-sufficiency and reduces geopolitical conflicts. Thus, increasing geopolitical risk will certainly encourage policy makers and investors to shift towards clean energies, which would have a positive effect on the renewable energy asset class. Fourth, rising geopolitical risk often causes higher uncertainty leading to an immediate disruption of economic

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[1] This information is sourced from https://assets.bbhub.io/professional/sites/24/Energy-Transition-Investment-Trends-Exec-Summary-2022.pdf.

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activities, which is further reflected in financial markets including stocks, exchange rates and commodities [8–10]. Due to a close connection with these financial markets, clean energy assets also become susceptible to geopolitical risk.

Second, we employ the Markov regime switching (MRS) approach to study the impact of GPR on the probability of being in the low and high volatility regimes for different clean energy assets. Note that a number of studies find that GPR has a positive effect on global crude oil price, leading to a drop in its volatility levels [11,12]. Given that oil prices and clean energy asset returns are positively correlated [13–16], it could be postulated that GPR would also exert a negative impact on the volatility of clean energy asset class. Assuming this indicates that when geopolitical uncertainty increases, the likelihood of remaining in the low (high) volatility state tends to increase (decrease). Hence, by focusing on the low (high) volatility state, we are able to examine how changes in the geopolitical risk levels impact the volatility of the clean energy asset class when stock markets are relatively calm (volatile). Doing so thus allows us to examine whether GPR drives the regime transition for clean energy asset returns.

Third, we extend the discussion on the role of geopolitical risk in financial markets. More specifically, our study adds to the limited literature on the GPR-stock association at sector levels. Investigating such linkage is important given that there may be industry specific responses to shocks emanating from geopolitical conflicts. Since the magnitude of these responses may vary among the sectors, proper knowledge on how geopolitical risk impacts the volatility of clean energy asset class could be useful for developing appropriate hedging strategies to mitigate such risk. Hence, the information contained in our empirical results could provide insight into means of building accurate stock-valuation models and accurate forecasts of the volatility of these assets.

It is worth noting that contrasting to the existing literature [6,17–19] focusing on clean energy asset class, we utilize the information on renewable energy exchange traded funds (ETFs) instead of using renewable energy stock indexes. Considering these ETFs is beneficial given that unlike equities, they are not sensitive to non-synchronous trading issues. As documented by Lo and MacKinlay [20], such issues may lead to spurious estimates when conducting market efficiency tests. Besides, these assets are particularly liquid and behave like a stock [21].

The empirical results might be useful for current and future investors in new energy companies. As growing concerns about environmental sustainability shift investors towards eco-friendly businesses, this research could attract those shareholders willing to decarbonize their portfolios by holding renewable energy assets. Moreover, socially responsible investments have ecological influences that assure a certain degree of sustainability. Therefore, our investigation is particularly important for eco-friendly investors who require sound knowledge on how to diversify the risk associated with their portfolios [22]. The findings of this study thus help such investors in detecting potential risk linked to green portfolios and gaining superior risk-adjusted returns. In sum, this strand of research offers stylized facts about socially responsible investments which market participants could consider when including clean energy assets in their portfolios to moderate climate related risk.

2. Literature review

We now provide a brief review of prior studies that deal with new energy equity markets. This literature can be divided into two segments. The first strand of literature investigates the price spillover linkage between dirty and clean energy assets. Important contributions in this segment include Henriques and Sadorsky [13] Broadstock et al. [14], Reboredo et al. [15], Dawar et al. [16], Managi and Okimoto [23], Bondia et al. [24], among others. Henriques and Sadorsky [13], for instance, adopt a vector autoregression (VAR) process to explore whether clean energy stock prices react to oil price and technology stock price shocks. The authors show a significant connection amongst these markets. Using an asset pricing model, Broadstock et al. [14] find that the linkage between oil and Chinese clean energy stocks appears to be strong during the turmoil periods. The study also demonstrates a positive association between these variables implying that an upturn in oil prices would encourage investments in alternative energy firms. Moreover, Bondia et al. [24] also provide evidence of price spillover effects between clean and dirty energy assets. Employing the Granger causality method, the study shows that oil prices seem to rule the stock prices of renewable energy firms. Applying a continuous wavelet approach, Reboredo et al. [15] document a robust long-term relationship between oil and clean energy stocks, albeit such linkage is found to be fragile in the short run. A recent study by Saeed et al. [25] provides empirical evidence on the return spillovers between clean and dirty energy assets in lower and upper quantiles. More recently, Dawar et al. [16] reveal that clean energy asset prices respond differently to new information on West Texas Intermediate (WTI) oil prices under diverse market conditions.

The second line of literature examines the volatility linkage between commodity prices and new energy asset returns. Sadorsky [26], for example, finds volatility cross effects between fossil fuel and green stocks. Methodologically, the study considers a number of multivariate GARCH models and concludes that clean energy assets are a good hedge for portfolios comprising oil or dirty assets. Using the time-varying copula approach, Reboredo [27] shows that oil price volatility significantly contributes around 30% to downside and upside risk of new energy firms. Ahmad [28] uses the directional spillover method, proposed by Diebold and Yilmaz [29], to document that technology and renewable energy stocks are the dominant emitters of volatility spillovers to the US crude oil market. Besides, Dutta [17] shows that crude oil implied volatility (hereafter, OVX) exerts a significant impact on the realized volatility of alternative energy stocks. A similar study by Ahmad et al. [1] finds gold and OVX as a good hedge for clean energy equities. Dutta et al. [30] document similar findings as well. Furthermore, Bouri et al. [31] show that crude oil along with gold appear to be safe-haven assets for new energy firms amid the turmoil periods. In addition, Xia et al. [32] demonstrate that fossil energy–related products such as oil, gas, coal, electricity and carbon emit volatility to clean energy assets. More recently, Yahya et al. [33] combine a two-regime threshold vector error correction model with the DCC-GARCH process to document a long-term volatility linkage between oil and clean energy assets.

3. Materials and methods

3.1. Data

The daily GPR data, recently created by Caldara and Iacoviello [34], are retrieved from http://www.policyuncertainty.com. Next, we collect the information on clean energy ETFs from Thomson Reuters DataStream database. Three different ETFs are studied in our research: Invesco WilderHill Clean Energy ETF (henceforth, PBW), Invesco Global Clean Energy ETF (henceforth, PBD) and Invesco Solar Energy ETF (henceforth, TAN). All these indexes allow investors to have an exposure to clean energy investments. Our sample covers the period from April 15, 2008 to March 10, 2020, yielding 2997 daily data points. The starting point of our sample is dictated by the availability of the clean energy data. It is also noteworthy that the daily GPR data are not available after March 10, 2020.

Fig. 1 depicts the time-series plots of different indexes considered in this research. As exhibited in this graph, we identify a substantial fall in the clean energy asset prices during the current COVID-19 pandemic period. At the same time, the geopolitical risk has also increased significantly.

We report the summary statistics in Table 1. Negative mean returns are observed for all the ETFs with TAN being more volatile than the rest. Besides, none of the time series including GPR satisfies the normality assumption. Finally, the augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests confirm that the return indexes along with GPR are stationary.

Table 1
Descriptive statistics of clean energy ETFs and GPR.

Index	PBW	PBD	TAN	GPR
Mean	−0.0372	−0.0212	−0.0687	109.56
Standard deviation	2.095	1.828	2.8546	85.51
Skewness	−0.4747	−0.6818	−0.3886	2.6107
Kurtosis	9.356	13.52	10.07	18.05
Jarque-Bera test	5155.12***	14056.45***	6312.43***	31700.67
ADF test	−51.93***	−55.43***	−50.97***	−11.33***
PP test	−51.88***	−55.42***	−50.87***	−42.40***

Notes: This table presents the descriptive statistics for different ETFs and GPR index. We consider the log-returns for these ETFS, while the GPR data are at levels. ***p < 0.01, **p < 0.05, *p < 0.10.

3.2. Empirical method

This paper employs a two-step methodology. Step I involves estimating a two-state Markov regime switching regression approach to generate the state probabilities. While doing so, we consider the information on crude oil volatility index (OVX) as a covariate. Many recent papers conclude that renewable energy equities respond significantly to the changes in the level of oil market volatility [17–19]. Uddin et al. [19], for instance, show that when analyzing the dependence structure between renewable energy and other asset classes, it is crucial to control for the effect of OVX. Next, step II consists of regressing the probabilities of remaining in the low (high) volatility regime on the GPR data. Our purpose is to observe how changes in GPR index affect the risk linked to new energy assets when the volatility levels are low. We frame the MRS regression model as follows:

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

where, $R_{i,t}$ denotes the logarithmic difference for the i-th 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 time period t, the transmission probability from regime 1 to regime m at time period $t+1$ is dependent on the regime at time period t entirely. 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 our empirical analysis, we consider two regimes in order to obtain the estimates for low and high volatility states. Following Uddin et al. [19], we also use the regime classification measure (RCM) for evaluating 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 our MRS process appears to be a good-fitting model if the RCM statistic is close to 0.

Next, we propose the following regression model to investigate the impact of GPR on the volatility of clean energy ETFs:

$$\mathrm{asin}\sqrt{p_t} = \lambda_0 + \sum_{i=0}^{n} \lambda_i \log(GPR)_{t-i} + \varepsilon_t \tag{4}$$

where, p_t indicates the filtered probability of lying in the low (high) volatility regime at time t. The asin (arcsine function) is used to transform the probabilities so that they can be used in a linear regression model [35].

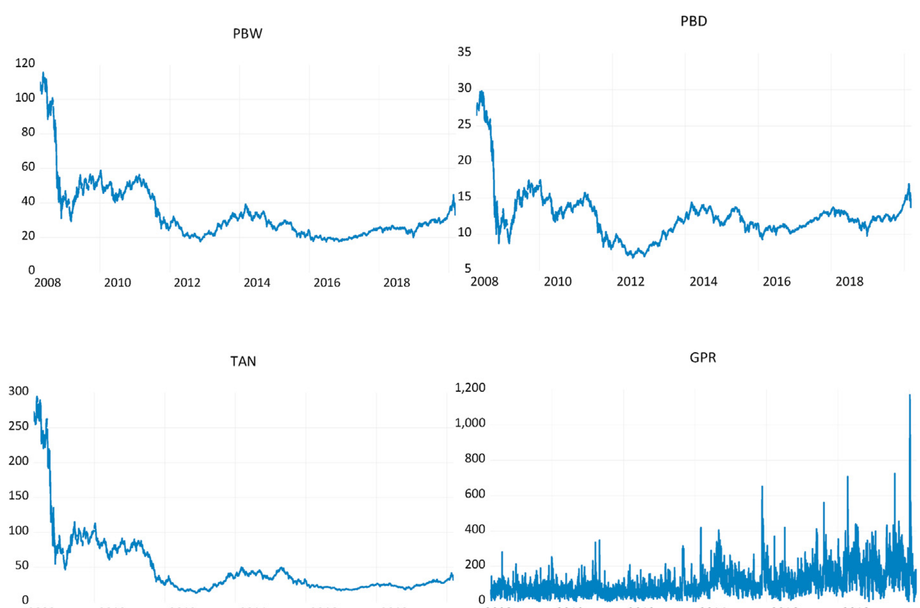

Fig. 1. Time series of clean energy ETFs and GPR.

4. Empirical findings

The results of our MRS model, presented in Table 2, demonstrate that all the new energy ETFs react negatively to OVX shocks. Hence, when oil market is highly volatile, a fall is witnessed in clean energy asset returns. This result is not startling, since an upward swing in energy market uncertainty tends to induce a drop in the level of energy prices, which further causes the prices of clean energy assets, close substitutes of oil assets, to decline [19]. We also report statistically significant results for all the sigma coefficients, which would suggest a swapping between the low and high volatility regimes.

In addition, for all the ETF indexes, the RCM statistic indicates that the regime switching approach can be considered to be a good-fitting model. Figs. 2 and 3 demonstrating the filtered probabilities of remaining in low and high volatility regimes also reveal a strong switching pattern for each of the clean energy assets. Note that for PBW index, regime 2 remains the high volatility state, while regime 1 being the high volatility state for other 2 indexes as evidenced by the sigma values.

Table 3 displays the findings of Equation (4) for the low volatility state. We report that λ_i, measuring the effect of geopolitical uncertainty, appears to be statically significant for each clean energy ETF. Hence, we empirically show that new energy ETFs are sensitive to geopolitical risk. More importantly, the impact is positive indicating that with an increase in the GPR index, the likelihood of remaining in the low volatility state seems to be increasing.

Next, the findings of Table 4 are consistent with those shown in Table 3. We now observe that the impact of GPR is negative revealing an inverse association between the regime probabilities and geopolitical risk. Therefore, when there is an upsurge in the GPR index, the likelihood of remaining in the high volatility state decreases. This finding could be attributed to the fact that when the geopolitical risk increases, users of crude oil, which is highly sensitive to such risk, tend to consider clean energies as a substitute for traditional energy sources. This causes a growth in the equity prices of new energy firms, further leading to a drop in the levels of volatility.

Moreover, it is evident from Tables 3 and 4 that the lagged values of GPR are statistically significant. For instance, in Table 4, we find significant values up to lag 7 when looking at the results for the PBW index. A possible explanation for this finding is that investors might react to information at different points in time, or have difficulty in evaluating the effect of GPR on the returns and act with a delay.

In sum, our findings confirm that green assets react to geopolitical risk significantly and thus the GPR index has emerged as an important factor affecting the investment decisions. In other words, we document that GPR can predict the uncertainty associated with clean energy stock returns.

5. Additional tests

This section studies the effect of GPR on the conditional volatility of clean energy assets. Such inspections will further verify our previous finding that increasing GPR has a negative effect on the volatility levels of new energy ETFs. That is, we aim to investigate if higher GPR implies lower risk for these green assets.

To serve this purpose, we estimate both symmetric and asymmetric generalized autoregressive conditional heteroscedasticity (GARCH) models. We first define the mean equation as follows:

$$R_t = \pi + \varphi R_{t-1} + \varepsilon_t \tag{5}$$

where, R_t denotes the logarithmic returns for a specific ETF index at time t. The residual term ε_t is assumed to follow the normal or Student's t distribution. Notably, the AR(1) process has been selected based on the values of Akaike information criterion (AIC) and Bayesian information criterion (BIC) criteria.

Regarding the conditional variance equation, we consider an extended GARCH (1,1) model, defined as:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \theta \Delta GPR_{t-1} \tag{6}$$

with ω, α and β being the parameters of GARCH (1,1) process. In addition, h_t^2 refers to the conditional variance and ε_{t-1}^2 represents the effect of news or shocks. Note that $(\alpha + \beta)$ captures the volatility persistence for ETF returns.

Next, we consider estimating an asymmetric version of GARCH model. In particular, we employ an extended GJR-GARCH process which is given by:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta\varepsilon_{t-1}^2 S_{t-1} + \beta h_{t-1}^2 + \theta \Delta GPR_{t-1} \tag{7}$$

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 $\alpha + \beta + 1/2\,\delta$.

The results of our GARCH analyses are reported in Tables 5 and 6. In both exhibits, we find that the impact of GPR on the conditional volatility is significant and negative as indicated by the corresponding parameter θ. Thus, both symmetric and asymmetric

Table 2
Estimates of MRS approach.

Panel A: Estimated coefficients

Index	State	Constant	AR(1)	OVX shocks	Sigma	χ^2 test
PBW	S1	0.0226 (0.0293)	0.0704*** (0.0194)	−0.2710*** (0.0162)	0.9739*** (0.0214)	204.03**
	S2	−0.3872** (0.1969)	- 0.0014 (0.0475)	−0.2872*** (0.0458)	3.6933*** (0.0469)	
PBD	S1	−0.3042* (0.1716)	−0.0611 (0.0450)	−0.2411*** (0.0332)	3.4541*** (0.0405)	315.53***
	S2	0.0282 (0.0222)	0.0242 (0.0201)	−0.2464*** (0.0156)	0.2538*** (0.0196)	
TAN	S1	−0.1872 (0.1964)	0.0457 (0.0396)	0.3250*** (0.0591)	4.2568*** (0.0497)	195.22***
	S2	−0.0272 (0.0405)	0.0723*** (0.0215)	−0.2937*** (0.0234)	1.5893*** (0.0263)	

Panel B: Transition probabilities and expected durations

Index	P11	P12	P21	P22	DU1	DU2	RCM
PBW	0.9952	0.0048	0.0294	0.9706	210.07	34.06	17.52
PBD	0.9706	0.0294	0.0056	0.9944	33.96	178.86	19.01
TAN	0.9388	0.0612	0.0171	0.9829	16.32	58.63	18.41

Notes: This table displays the estimates of our MRS model provided in equations (1)–(3). Values in parentheses indicate standard errors.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

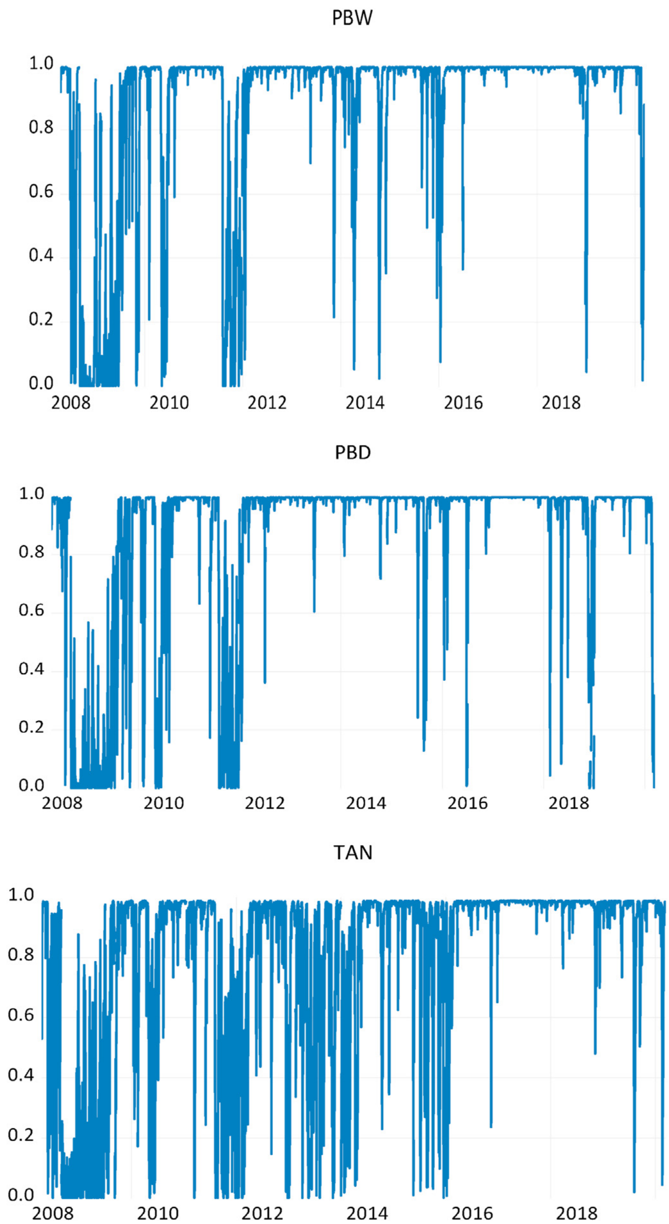

Fig. 2. Filtered probabilities for low volatility regime. Note: The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the PBW, PBD and TAN indexes. The X-axis indicates the timeline,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

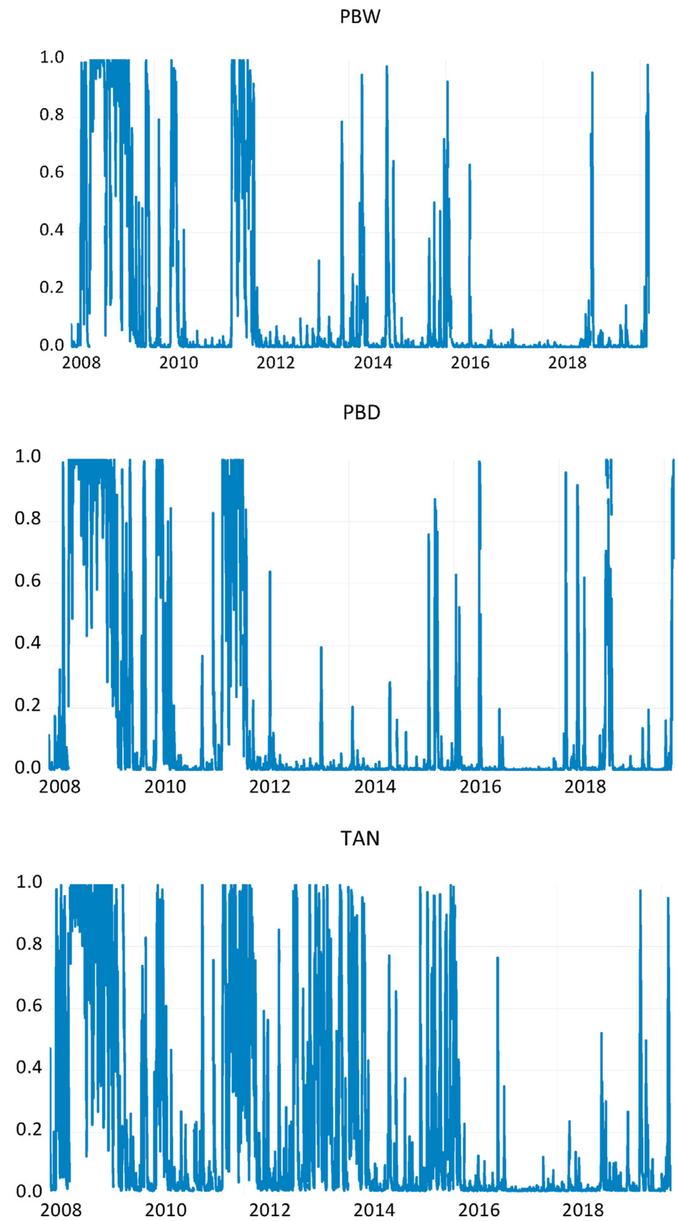

Fig. 3. Filtered probabilities for high volatility regime. Note: The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the high volatility states for the PBW, PBD and TAN indexes. The X-axis indicates the timeline,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

GARCH specifications conclude the same. Such inverse relations demonstrate that when an increment is observed in geopolitical risk index, the volatility of these ETFs seems declining.

6. Discussion

A number of studies [28,30,36] have examined the effects of crude oil price uncertainty, metal price uncertainty and climate policy uncertainty on the volatility levels of clean energy assets. However, whether these assets react to geopolitical uncertainty remains under-studied. This is surprising given that geopolitical conflicts trigger environmental pollution, which could be reduced with the transition to alternative energies [6]. Thus, with the increase in geopolitical uncertainty in recent years, many countries have invested more in renewables. Such initiatives are also reflected in the asset prices of clean energy companies.

It is also worth noting that oil and clean energy markets are close substitutes. As oil price variations are highly sensitive to geopolitical turmoil [11,12], clean energy prices, which exhibit similar dynamics like traditional energy prices, might react significantly to the rise and fall in geopolitical risk. This would cause the asset prices of alternative energy firms to be varying in response to

Table 3
Impact of geopolitical risk (Low volatility state).

	Estimate	Standard error	Decision
Panel A: PBW			
Constant	0.3465	0.0547	***
$\log(GPR)_{t-1}$	0.5257	0.0119	***
$\log(GPR)_{t-2}$	0.4635	0.0123	***
$\log(GPR)_{t-3}$	0.0367	0.0124	***
$\log(GPR)_{t-4}$	0.0385	0.0122	***
$\log(GPR)_{t-5}$	0.0410	0.0118	***
F-statistic	62.16		***
Adj. R^2 (%)	9.62		
Panel B: PBD			
Constant	0.1818	0.0609	***
$\log(GPR)_{t-1}$	0.0488	0.0130	***
$\log(GPR)_{t-2}$	0.0398	0.0134	***
$\log(GPR)_{t-3}$	0.0327	0.0136	**
$\log(GPR)_{t-4}$	0.0388	0.0135	***
$\log(GPR)_{t-5}$	0.0423	0.0133	***
$\log(GPR)_{t-6}$	0.0452	0.0129	***
F-statistic	55.43		***
Adj. R^2 (%)	10.27		
Panel C: TAN			
Constant	0.0642	0.0593	Insignificant
$\log(GPR)_{t-1}$	0.0363	0.0123	***
$\log(GPR)_{t-2}$	0.0259	0.0127	**
$\log(GPR)_{t-3}$	0.0255	0.0129	**
$\log(GPR)_{t-4}$	0.0363	0.0129	**
$\log(GPR)_{t-5}$	0.0402	0.0129	***
$\log(GPR)_{t-6}$	0.0303	0.0128	**
$\log(GPR)_{t-7}$	0.0444	0.0127	***
$\log(GPR)_{t-8}$	0.0508	0.0124	***
F-statistic	54.45		***
Adj. R^2 (%)	13.15		

Notes: In this Table, estimates of Equation (4) are presented. We select the number of lags based on the values of Akaike information criterion (AIC) and Bayesian information criterion (BIC).
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 4
Impact of geopolitical risk (High volatility state).

	Estimate	Standard error	Decision
Panel A: PBW			
Constant	1.2774	0.0570	***
$\log(GPR)_{t-1}$	−0.0459	0.0120	***
$\log(GPR)_{t-2}$	−0.0388	0.0124	***
$\log(GPR)_{t-3}$	−0.0314	0.0125	**
$\log(GPR)_{t-4}$	−0.0304	0.0126	**
$\log(GPR)_{t-5}$	−0.0271	0.0125	**
$\log(GPR)_{t-6}$	−0.0272	0.0123	**
$\log(GPR)_{t-7}$	−0.0261	0.0119	**
F-statistic	45.93		***
Adj. R^2 (%)	10.01		
Panel B: PBD			
Constant	1.2890	0.0582	***
$\log(GPR)_{t-1}$	−0.0606	0.0129	***
$\log(GPR)_{t-2}$	−0.0519	0.0133	***
$\log(GPR)_{t-3}$	−0.0509	0.0133	***
$\log(GPR)_{t-4}$	−0.0617	0.0138	***
F-statistic	75.09		***
Adj. R^2 (%)	9.28		
Panel C: TAN			
Constant	1.5878	0.0586	***
$\log(GPR)_{t-1}$	−0.0397	0.0123	***
$\log(GPR)_{t-2}$	−0.0260	0.0128	**
$\log(GPR)_{t-3}$	−0.0311	0.0129	**
$\log(GPR)_{t-4}$	−0.0359	0.0129	***
$\log(GPR)_{t-5}$	−0.0477	0.0128	***
$\log(GPR)_{t-6}$	−0.04382	0.0127	***
$\log(GPR)_{t-7}$	−0.0473	0.0122	***
F-statistic	59.41		***
Adj. R^2 (%)	12.58		

Notes: In this Table, estimates of Equation (4) are presented. We select the number of lags based on the values of Akaike information criterion (AIC) and Bayesian information criterion (BIC).
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 5
GARCH estimates.

Parameters ↓	Error distribution is normal		Error distribution is Student's *t*	
	Estimates	Standard error	Estimates	Standard error
ω	0.049***	0.010	0.049***	0.014
α	0.080***	0.007	0.082***	0.010
β	0.907***	0.008	0.906***	0.011
θ	−0.001**	0.0005	−0.001**	0.0005
Persistence	0.987		0.988	
Log-likelihood	−5875.63		−5850.30	
AIC	3.927		3.911	
BIC	3.931		3.925	

Notes: θ measures the effect of GPR. The persistence of volatility amounts to $\alpha + \beta$.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

the fluctuation in GPR index. Moreover, several recent studies [8,10] also argue that increasing geopolitical risk leads to higher uncertainty which could be harsh to the systematic development of national economy, further being reflected in traditional financial markets such as stocks and oil. The clean energy asset market could receive similar shocks from geopolitical uncertainty as it maintains a high correlation with other asset classes including equities and commodities. Furthermore, it is also expected that both investor sentiment and trading decisions are significantly influenced by the changes in the level of geopolitical risk which might drive the volatility of clean energy asset class. Hence, geopolitical risk might play a crucial role in understanding the volatility dynamics of clean energy asset class.

To this end, our study joins the literature on clean energy asset markets by documenting a negative association between geopolitical risk and the volatility of clean energy assets. As discussed earlier, the significant linkage between these variables could be attributed to the high correlations between oil and new energy markets, rapid transition to renewable energy, investors' enthusaism for renewables and financial market integration. Given that geopolitical risk has emerged as a key determinant of clean energy asset returns, market participants could use its information content to predict the volatility of renewable energy firms. Hence, along with other uncertainty measures (e.g., climate policy uncertainty, equity and commodity market volatility indexes), geopolitical risk also deserves more attention from investors, researchers and policymakers.

In sum, our study suggests that policymakers and investors participating in alternative energy markets should pay considerable attention to the impact of geopolitical risk on this new asset class when forecasting future volatility, assessing portfolio risk and making appropriate hedging decisions. Understanding the performance of green assets is of utmost importance to ethical investors

Table 6
GJR-GARCH estimates.

Parameters ↓	Error distribution is normal		Error distribution is Student's t	
	Estimates	Standard error	Estimates	Standard error
ω	0.061***	0.010	0.061***	0.014
α	0.036***	0.009	0.035***	0.012
β	0.908***	0.008	0.905***	0.011
γ	0.072***	0.011	0.079***	0.017
θ	−0.0009**	0.0004	−0.001**	0.0005
Persistence	0.9800		0.9795	
Log-likelihood	−5862.89		−5839.39	
AIC	3.919		3.904	
BIC	3.933		3.920	

Notes: θ measures the effect of GPR. The persistence of volatility amounts to.$\alpha + \beta + \frac{1}{2}\gamma$.
***p < 0.01, **p < 0.05, *p < 0.10.

given that these companies produce ecological goods and provide climate-friendly services [37–39]. Besides, proper knowledge on the risk linked to clean energy asset class is essential for socially responsible investors as they focus not only on the environmental performance of a firm but also consider its financial performance. Therefore, our results offer key implications to both investors and policymakers.

7. Conclusions

Earlier studies find that oil price volatilities are sensitive to geopolitical uncertainty. However, the effect of such risk on the volatility of renewable energy assets, which exhibit similar dynamics like the oil assets, is yet to be explored. This paper intends to fill this gap by examining the effect of geopolitical uncertainty, measured by the geopolitical risk (GPR) index, on the volatility levels of renewable energy exchange traded funds.

Methodologically, we employ the Markov regime switching process and different forms of GARCH models to serve our purpose. Looking at the filtered probabilities obtained from the MRS regressions, we find that an upturn in the GPR index increases (reduces) the likelihood of being in the low (high) volatility regime. This result suggests that when GPR mounts, consumers of crude oil would shift towards clean energies in order to replace traditional energy sources which are highly susceptible to geopolitical conflicts. Such transition may cause a significant increment in the asset prices of new energy firms, further leading to a drop in the levels of volatility. Additionally, the results of GARCH models also reveal an inverse relationship between GPR and the volatility of clean energy asset class. Therefore, when an upsurge is observed in the geopolitical risk index, the volatility of these clean energy ETFs seems declining. In other words, higher GPR implies lower risk for these green assets.

The findings of this paper offer several important policy implications. First, as increasing geopolitical risk is found to exert a positive effect on clean energy asset prices, policymakers are likely to promote the usage of renewable energy sources with the increment of geopolitical conflicts. One could thus expect that rising geopolitical uncertainty encourages the future developments of new energy technologies, which would in turn decrease the dependence on traditional energy sources such as fossil fuels. In addition, the transition to renewable energy also leads to greater energy self-sufficiency and reduces the adverse impacts of climate change. It is, therefore, important to pay more attention to understand how the association between geopolitical risk and clean energy markets evolves over time. Second, investors could utilize the information content of geopolitical risk to predict the volatility of clean energy asset class more precisely. Our results are thus important for market participants while finding more efficient ratios for portfolio optimization, hedging and risk management. In sum, along with the economic policy uncertainty and crude oil volatility, geopolitical risk can also be used as a supplement for making proper asset-allocation decisions and gaining better portfolio diversification benefits.

CRediT authorship contribution statement

Anupam Dutta: Conceptualization, Validation, Formal analysis, Writing – original draft. **Probal Dutta:** Writing – review & editing, Final Revision, Project administration.

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.

Table A1
Acronyms

Acronym	Meaning
AIC	Akaike information criteria
ADF	Augmented Dickey-Fuller
BIC	Bayesian information criteria
DCC-GARCH	Dynamic conditional correlation - generalized autoregressive conditional heteroskedasticity
ETF	Exchange traded fund
GARCH	Generalized autoregressive conditional heteroskedasticity
GPR	Geopolitical risk
GJR	Glosten, Jagannathan, Runkle
MRS	Markov regime switching
OVX	Oil Implied Volatility index
PBD	Invesco Global Clean Energy ETF
PBW	Invesco WilderHill Clean Energy ETF
PP	Phillips-Perron
RCM	Regime classification measure
TAN	Invesco Solar Energy ETF
VAR	Vector autoregressive
WTI	West Texas Intermediate

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