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The energy transition: The behavior of renewable energy stock during the times of energy security uncertainty

Philip Igeland [a], Leon Schroeder [a], Muhammad Yahya [b,*], Yarema Okhrin [c], Gazi Salah Uddin [a]

[a] *Department of Management and Engineering, Linköping University, Linköping, Sweden*
[b] *School of Economics and Business, Norwegian University of Life Sciences, Ås, Norway*
[c] *Department of Statistics, Faculty of Business and Economics, University of Augsburg, Germany*

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ABSTRACT

The global energy sector is experiencing a transition towards renewable energy primarily driven by issues related to climate change and energy security. In this paper, we investigate the impact of uncertainties and potential drivers connected to energy security on the volatilities and returns of renewable energy stocks. Further, we examine how uncertainty and potential drivers connected to energy security affect the volatilities and returns of renewable energy stocks. By applying the MS-GARCH (1,1) and MS-GJR-GARCH (1,1) approach we calculate the Value at Risk (VaR) and Conditional Value-at Risk (CVaR). In addition, we estimate a fixed effects model to determine the impact of the uncertainty variables on the estimated conditional volatility and returns. Our findings indicate that economic policy uncertainty (EPU) positively impacts the returns of renewable stocks, attributing to an increased engagement towards a renewable transition. However, the prices of crucial green metals were found to have a negative impact on renewable stocks suggesting that the transition to renewable energy might impose implications regarding energy security if not managed correctly. The findings of this study have important implications for policymakers, market participants, and governmental agencies in devising a roadmap to promote the transition process to renewable energy sources.

1. Introduction

During the coming decades, the global energy sector is expected to transition from fossil fuel-based energy sources to renewable sources [1]. The shift can largely be attributed to the beliefs in the renewable's potential to mitigate the growing fears of climate change and concerns regarding energy security [2]. The International Energy Agency (IEA) emphasizes that significant investments in the sector are required to achieve the net-zero emission goal of the Paris Agreement [3]. Concerns regarding energy security currently stem from fluctuating energy prices, the implications of energy dependency and the long-term availability of the energy sources [4,5]. Therefore, this study aims to examine the effects of uncertainties, including Economic Policy Uncertainty (EPU), WTI crude oil price, Geopolitical risk (GPR), Russia-Ukraine conflict in 2014 (RC), and Climate Policy Uncertainty (CPU), on the returns and volatilities of energy firms.

Energy security concerns related to fossil fuels, such as oil and gas, are primarily driven by issues surrounding energy availability, geopolitical uncertainty, affordability, price volatility, and import dependency of fossil fuels (Alqahtani et al., n.d.; [6–8]). These concerns reduce confidence in traditional energy sources and increase desire to adopt renewable energy that can provide stable, affordable domestic supply. By investing in renewable sources like solar, wind, and biofuels, countries aim to reduce reliance on imported fuels and exposure to global oil and gas price shocks. This enhances energy security by diversifying energy mix and increasing control over domestic resources [9–11]. Expanding renewable generation from domestic resources enhances energy self-sufficiency and stability.

Over the last decade, the investment in the renewable energy sector increased considerably. Fig. 1 provides an overview of the development of annual financial commitments in the renewable energy sector [12]. It is apparent that between 2013 and 2018, onshore wind and solar PV established their dominance, attracting, 29% and 46%, respectively, of global renewable energy investments [12]. Even though the transition toward renewable energy has started to gain momentum, fossil-based fuel still maintains its place as one of the most important commodities

* Corresponding author.
E-mail addresses: phiig866@student.liu.se (P. Igeland), leosc058@student.liu.se (L. Schroeder), muhammad.yahya@nmbu.no (M. Yahya), yarema.okhrin@uni-a.de (Y. Okhrin), gazi.salah.uddin@liu.se (G.S. Uddin).

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and macro indicators [7].

Over the recent years, the world has experienced significant oil price fluctuations caused by events such as the global COVID-19 pandemic and periods of heightened economic policy uncertainty and geopolitical risk [7,13,14]. Recently Russian aggression has added further thrust to turmoil and uncertainty in energy markets. As one of the largest exporters of oil and natural gas to global markets, many European countries are heavily dependent on Russia for their energy supply, giving Russia an asymmetric advantage that can be exploited in antagonistic actions [11,15]. These types of destabilizing events have proven a valuable lesson regarding the consequences of energy dependency and deteriorated the state of energy security by threatening both the availability and affordability of energy [4,5]. To improve the energy security, countries have begun to diversify their energy sources, speeding up the transition to renewable energy [10,15]. However, there are concerns that the shift towards renewable energy simply relocates the autonomy from oil and gas producing countries to those supplying the materials required by alternative energy sources [16].

Renewable energy technology is often heavily dependent on critical metals and minerals. The production and processing of these commodities are geographically less diversified than fossil fuels. For example, the cobalt and rare earth metals market is dominated by counties such as China and The Democratic Republic of Congo whose production constitutes 70% of the global output [17]. The concentration of mineral supplies indicates that the renewable energy sector's ability to reduce energy dependency might be limited. Further, achieving the net-zero goals of the Paris Agreement would require six times more metal inputs by 2050 compared to today [18]. However, the current and projected mining extraction is not enough to supply the required amounts of metals needed for the transition consistent with the goals of the Paris Agreement. The increased extraction and production are feared to give rise to environmental and social issues, creating a higher exposure to climate risk [17]. The acceleration and importance of critical metals might therefore also have implications regarding the renewable energy sector's ability to improve energy security through providing long term viable energy sources and mitigating the effects of climate change.

Based on these findings, we can conclude that the traditional energy sector is currently encountering issues related to energy security and that renewable energy is currently viewed as the best solution. In this regard, we add to the existing literature by investigating the impact of energy security uncertainties on the renewable energy sector. This will enable us to provide a comprehensive insight regarding the fundamental drivers of the renewable energy sector. These findings will facilitate the policymakers and governmental agencies in devising a roadmap to encourage investments into the renewable energy sector. This is crucial as with a better understanding of the risks associated with the renewable sector, governments can pursue supportive policies during times of heightened uncertainty and implement measures aimed at strengthening the sector's resistance against these risks. We intend to achieve this by examining the impact of news-based uncertainty, oil prices, critical green metals and uncertainty events on renewable energy stocks.

To answer our research questions, we employ Markov Switching (MS)-GARCH (1,1) type framework to estimate the conditional volatility and the Conditional Value at Risk (CVaR) to compare the different characteristics of the stocks. Employment of MS-GARCH is justifiable as the energy market is characterized by several periods of rising and falling trends. Additionally, we estimate a fixed effects model incorporating uncertainties and several drivers to examine their impact on the renewable energy stocks and traditional energy stocks. This is crucial to provide a comprehensive overview of the drivers impacting both energy sectors and to differentiate the drivers of traditional energy from the renewable energy stocks.

This paper makes several key contributions to the literature on uncertainties and energy stocks. First, we provide new firm-level evidence while past studies have focused on market indices. Second, we examine the impact of under-researched uncertainties including geopolitical risk, climate policy uncertainty, and green metal prices. Third, we differentiate between drivers of renewable energy versus traditional energy stocks. Fourth, we employ Markov-switching GARCH models to analyze risk characteristics of individual renewable firms. Finally, we discuss implications of green metal dependence for the energy transition.

Our findings from the MS-GARCH framework indicate that the unconditional uncertainty is significantly high over both regimes suggesting extreme volatility patterns. Furthermore, we report heterogeneous and asymmetric volatility behavior as the unrest in the energy markets and the geopolitical uncertainty contribute significantly to the overall volatility. Regarding key drivers of energy markets, our findings suggest that the news-based uncertainties are found to have a larger influence on renewable stocks compared to oil prices. Contrary to previous research, we found that EPU positively impact on the returns, possibly marking a shift where the renewable energy stocks are seen to benefit from heightened economic policy uncertainty. Lastly, green

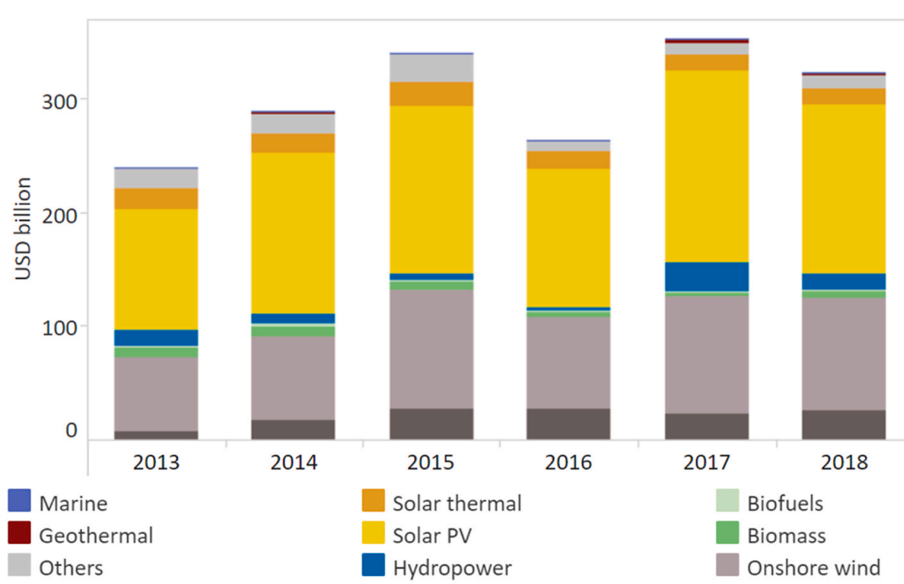


Fig. 1. Renewable energy investment.
Source: IRENA [12]. Notes. The Y-axis shows the annual investments in USD billions of dollars for the respective renewable energy subsectors.

metal prices are found to decrease the returns implying that new challenges regarding energy dependency and sustainability might arise due to the transition. Our findings suggest that the policymakers should provide financial incentives, like tax credits, to ensure adequate mining and processing capacity for key renewable energy metals including lithium and cobalt. Investors and firms should monitor potential metal supply constraints using tools such as the World Bank's Climate-Smart Mining Facility (World Bank, 2020).

The rest of the paper is structured as follows: section 2 provides an overview of literature, section 3 presents the data, section 4 provides the methodological framework, section 5 provides an results and discussion, and section 6 concludes.

2. Literature review

The effects of climate change on the overall aggregate economic activity seem to be negative, but there exist indications that the renewable energy sector might be affected differently. The sector has been assigned a crucial role in combating climate change by enabling a transition from the traditional fossil-fuel based energy sector through the Paris Agreement in 2015 [19]. The research of Sadorsky [20] found that increasing GHG emissions was one of the major drivers of renewable energy consumption in G7 countries. Menyah & Wolde-Rufael [21] found further evidence supporting this possible relationship in their study focusing on the US market. The linkage between GHG emissions and renewable energy uses also proved to hold when extending the sample size to more newly industrialized countries [22]. A relevant note is that all the above-mentioned studies stressed the importance of policy implications aiming at environmental sustainability as a determining factor for the link between GHG emissions and renewable energy utilization.

Regarding a possible connection between climate change and investment in the renewable energy sector, the existing literature proposes that a relationship might be found under certain circumstances. However, the connection seems to be country dependent. For example, Chen et al. [9] argued that the effect of GHG and climate change on investment in renewable energy vary significantly between countries with different levels of renewable energy investment. The authors demonstrated that in countries with existing renewable energy infrastructure, the investments in the renewables increased with increasing levels of GHG.

Based on these findings, it is evident that climate change brings new risks and uncertainties into the economic sphere that needs to be taken into consideration. Despite significant increase in investments to accelerate the transition process, scarce literature examines the climate risk as a global externality [23]. Several studies concluded the negative impact of EPU on the renewable energy consumption and stock returns of these firms (see e.g., Ref. [24–26]). The impact of EPU is suggested to mainly be transmitted through the uncertainty of inflation [26]. Further, Kocaarslan & Soytas [27] argued that EPU may function as a mediator of volatility between reserve currency and renewable energy stocks. These studies stressed the regulatory stability and consistency, especially regarding green policies, are beneficial for the renewable energy sector.

Regarding geopolitical risk (GPR), Yang et al. [28] showed that there are significant and dynamic risk spillovers from GPR to renewable energy stock markets. The effects were not found to be explicit positive or negative. However, oil and stock market uncertainties were found to be more informative than GPR. Su et al. [8] reported similar findings and added that energy security, trade disputes, conflicts over intellectual property rights and competition over rare earth metals encourage a transition from the traditional energy sources. A relevant note is that the studies, in this regard, stressed the importance of policy implementation aiming at environmental sustainability as a determining factor for the link between GHG emissions and renewable energy use [21,22]. In addition, investment in renewable energy has been found to increase with rising GHG for countries with already high levels of renewable energy use while no relationship can be found for countries with low levels [9]. Little, if any, research regarding the impact of green metal prices on the volatilities and returns of renewable energy stock has been conducted. However, most previous studies regarding crucial metals have proven the scarcity and importance of the commodities to the renewable energy sector [17,29].

The COVID-19 pandemic resulted in one of the biggest international crises this century, where the global demand for energy usage rapidly changed [6]. The event demonstrated the importance of energy security, particularly during uncertain periods [30]. Hemrit & Benlagha [31] studied the impact of global pandemic uncertainty on the renewable energy sector and report fared relatively well during the period. In addition, the authors argued that the acceleration in the transition of renewable energy is the increased uncertainty of investments in fossil fuels. Wan et al. [32] examined the difference in investors' market attention between fossil fuels and renewable energy during and after the pandemic and report that renewable energy had an advantage, performing better than fossil fuels firms and being the only one obtaining a positive effect on the investors' market attention.

In summary, the impact of uncertainties like geopolitical risk, climate policy, and green metal prices on renewable stocks remains understudied, particularly at the firm level. Furthermore, few studies have differentiated between drivers of renewable energy versus traditional energy stocks. Therefore, this study aims to address these gaps by examining the effects of multiple uncertainties including economic policy uncertainty, geopolitical risk, climate policy events, and green metal prices on the volatilities and returns of renewable energy firms. Additionally, it compares the drivers of renewable stocks to those of traditional energy stocks. The findings will facilitate policymakers, investors, and agencies in strengthening the renewable energy sector against risks and promoting the transition from traditional fossil fuel-based sources.

3. Data and summary statistics

In this study, we use daily observations of 24 renewable energy companies and their corresponding indexes representing benchmarks for the renewable energy groups between the period March 2012 to March 2022. The number of observations differs as the companies are listed on various stock exchanges with different trading days. The sample period is selected to cover the oil price shock during 2015 and 2016, annexation of Crimea, the COVID-19 crisis, to capture the effects and transition of climate change and include the current Russo-Ukraine war, events that are likely to affect energy security. All the data is retrieved from Refinitiv Eikon DataStream. For the selected renewable energy firms, we utilize the WilderHill Clean Energy Index (ECO) as a benchmark. The ECO index uses a modified equal dollar weighted method and includes companies that are active within clean energy or contribute to the advancement of the clean energy sector and is widely used in previous research (see e.g., Ref. [33,34]).

The renewable energy companies are chosen based on Reuters [35]. The companies on their list were qualified as global energy leaders based on probabilistic programming techniques analyzing the firm's strengths regarding the following dimensions: management and investor confidence, legal compliance, financial performance, innovation, risk and resilience, people and social responsibility, reputation, and environmental impact [35]. The companies were selected from the top 25 renewable energy subsector list. Based on data unavailability, we excluded one company resulting in 24 renewable energy companies.[1]

Fig. 2 illustrates the log and the logarithmic difference of the daily close price for the ten selected renewable energy companies and the ECO

[1] For the sake of brevity, we chose to present the graphs for some of the firms. The comprehensive graphs for all the firms can be obtained from the corresponding author upon request.

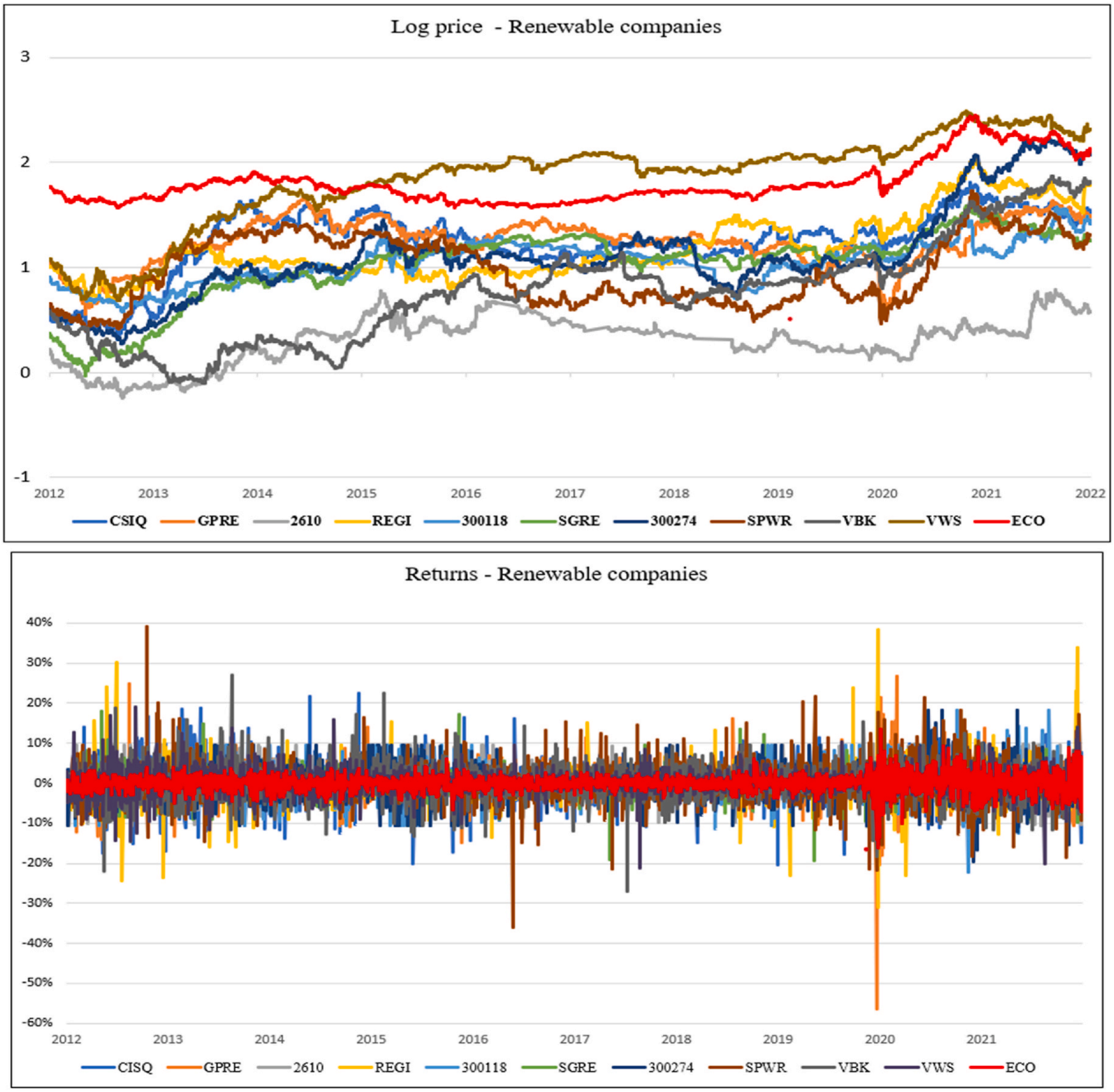


Fig. 2. Log Price - Renewable Energy Stock
Notes: We present the daily log price of the selected renewable companies. The data is retrieved from Refinitiv.

index for benchmark comparison. Majority of the renewable company stock prices seem to move in a resembling pattern to each other and have a similar performance to the benchmark during the sample period. Downturns can be observed during 2012–2013 and at the start of 2020. However, the recovery seems to have been relatively quick, especially after the drop in 2020 connected to the pandemic, where we see a sharp increase in the growth of the renewable stock values. In terms of returns, we observe signs of volatility clustering for all returns indicating that GARCH-type models could be useful when modeling the volatility of the returns. We can further see that the returns of the renewable energy firms follow a similar pattern with periods of higher volatility during 2012–2014, during the peak of the COVID-19 crisis in 2020 and a possibly a spike at the start of the Russia-Ukraine war. Meanwhile, the period between 2014 and 2020 seems to be characterized by more tranquility. This further suggests that the conditional variance is time-varying, deeming a regime-switching model appropriate. The similarities in the volatility patterns could indicate that the renewable firms react uniformly to shocks.

3.1. Descriptive statistics

Table 1 provides the descriptive statistics of the daily returns for the firms and the benchmarks. The returns of Green Plains Inc are extremely negatively skewed (−1.236) and have a high kurtosis value (30.226) indicating that negative returns and extreme events have been prevalent for the company. Renewable Energy Group Inc on the other hand shows positively skewed returns (0.597) and a high kurtosis value (19.643), indicating a tendency for positive returns and extreme conditions. In terms of skewness and kurtosis, more than half of the firms exhibits negative skewness indicating an increased tendency to attain negative return while the value of excess kurtosis is larger than 4 for all the firms exhibiting leptokurtic distribution of return series. Similar findings are observed for the case of ECO. The Jarque-Bera statistic advocates the non-Gaussian pattern and rejects the null of normality for all returns. Engle [36] test for autoregressive conditional heteroscedasticity (ARCH) rejects the null-hypothesis of homoscedasticity at the 1% significance level for all returns, implying the presence of ARCH effect. The ADF test of Dickey & Fuller [37] rejects the null-hypothesis of stationarity at the 1% significance level. Lastly, the Ljung-Box test (Q2) with 12 lags

Table 1
Descriptive statistics.

Series	Mean	SD	Min	Max	Skew	KURT	JB	ARCH	$Q^2(12)$	ADF	n
ECO Wilderhill	0.03	2.0	−16.23	13.40	−0.42	9.11	0.00***	674.5***	56.4***	11.9***	2516
Alto Ingredients	−0.06	5.715	−41.5	50.3	0.99	12.8	0.00***	133.6***	20.0*	−12.4***	2413
Canadian Solar Inc	0.066	3.917	−23.2	22.5	−0.07	7.2	0.00***	61.2***	11.1	−12.5***	2413
CropEnergies AG	0.021	2.5	−20.2	13.7	−0.43	8.8	0.00***	64.9***	37.2***	−13.2***	2467
First Solar Inc	0.029	3.267	−20.7	37.5	0.70	14.5	0.00***	16.9	11.4	−12.6***	2413
GCL	−0.015	4.065	−29.7	30.6	0.54	11.2	0.00***	68.5	37.8***	−11.1***	2198
Global PVQ SE	−0.022	10.089	−51.2	91.6	0.82	12.9	0.00***	368.7***	293.7***	−13.1***	2469
Green Plains Inc	0.029	3.672	−56.5	26.7	−1.24	30.2	0.00***	162.6***	46.4***	−13.2***	2413
GTE	−0.029	3.744	−34.1	34.6	0.97	18.4	0.00***	169.4***	12.9	−13.4***	2340
HTF	0.343	4.252	−63.4	24.6	−3.99	75.2	0.00***	6.8***	6	−7.1***	728
Inox Wind Ltd	−0.112	3.346	−19.0	18.2	0.53	7.9	0.00***	56.1***	26.3***	−12.3***	1622
JAST	0.028	3.319	−10.6	9.8	0.16	4.8	0.00***	291.2***	31.7***	−11.8***	2089
Motech Industries Ltd	−0.036	2.862	−10.5	9.5	0.27	5.3	0.00***	230.1***	33.1***	−11.8***	2356
REG	0.073	3.712	−30.9	38.4	0.60	19.6	0.00***	156.7***	20.9*	−13.1***	2412
Risen Energy Co Ltd	0.028	3.505	−22.3	18.2	−0.02	6.1	0.00***	209.6***	6.3	−12.0***	2201
SAAE	−0.002	3.054	−10.6	9.6	−0.15	5.7	0.00***	471.3***	25.4*	−13.4***	2152
SGR	0.075	2.757	−19.4	18.1	−0.04	9.0	0.00***	69.0***	15	−13.4***	2507
SolarWorld AG	−0.285	10.265	−150.8	61.9	−0.96	31.6	0.00***	103.8***	215.4***	−14.7***	2328
Sunedison Inc	−0.444	8.952	−79.3	96.9	−0.60	32.4	0.00***	114.3***	50.9***	−10.9***	1395
SPS	0.111	3.649	−19.5	18.2	0.05	5.2	0.00***	156.7***	14.6	−12.1***	2317
SunPower Corp	0.034	4.33	−36.0	39.2	0.22	10.6	0.00***	40.3***	8.7	−12.9***	2413
TPI Composites Inc	0.018	3.897	−29.4	29.3	−0.56	12.8	0.00***	113.0***	14	−10.7***	1365
VERBIO	0.091	3.531	−27.1	26.9	−0.07	8.8	0.00***	45.8***	12.4	−12.5***	2465
VWS	0.102	2.818	−21.2	19.2	−0.06	9.4	0.00***	101.0***	15.1	−13.3***	2415
XEM	0.042	3.086	−10.6	9.6	−0.04	4.9	0.00***	308.9***	38.8***	−13.0***	2270

Notes. GCL (GCL-Poly Energy Holdings Ltd), GTE (Guodian Technology & Environment Group Corp Ltd), HTF (Hanergy Thin Film Power Group Ltd), JAST (Jiangsu Akcome Sience & Technology Co Ltd), SAAE (Shanghai Aerospace Automobile Electromechanical Co Ltd), SGR (Siemens Gamesa Renewable Energy SA), REG (Renewable Energy Group Inc), SPS (Sungrow Power Supply Co Ltd), VERBIO (VERBIO Vereinigte BioEnergie AG), VWS (Vestas Wind Systems A/S), XEM (Xiangtan Electric Manufacturing Co Ltd).

indicates the presence of autocorrelation in majority of renewable firms.

4. Methodology

To examine the underlying research questions, we first utilize Markov-Switching GARCH models to estimate the risk profiles of renewable stocks based on daily price data. We further employ fixed effects panel models to evaluate the impact of uncertainties on the volatilities and returns of renewable and traditional energy firms. Indices representing green metal prices are created through principal component analysis and included in the models.

We employ Markov-switching GARCH models to estimate the time-varying volatility and risk metrics for individual renewable energy firms. These models allow us to capture stylized facts such as volatility clustering, leverage effects, and structural breaks which are commonly exhibited in stock return data [38]. This flexibility in capturing turbulent periods and structural changes makes MS-GARCH better suited than regular GARCH models for our sample period, which includes events like the annexation of Crimea, COVID-19 crisis, and the current Russia-Ukraine war. Following Ardia et al. [38], we implement the two state Bayesian Markov-switching GARCH approach. By using the Bayesian estimation, we can integrate parameter uncertainty and obtain predictive distributions. This provides new insight into the risk characteristics and potential losses faced by renewable energy companies based on their daily stock price movements. It is well-documented that numerous financial assets are characterized by structural breaks therefore it is important to utilize a framework that allows us to capture these properties [38]. Furthermore, the MS-GARCH type frameworks are superior in capturing the stylized facts embedded in the returns data as it integrates parameter uncertainty via the Bayesian approach improves estimations [38]. We select the best-suited framework based on deviance information criterion (DIC) from various specifications (MS-GARCH(m,n), MS-GJR-GARCH(m,n), and MS-EGARCH(m,n)) and distributions (Student-t and skewed Student-t). In order to quantify the risk for the firms, we conduct two in sample risk assessment metrics, Value at Risk (VaR) and Conditional Value at Risk (CVaR). The estimated time-varying conditional volatility is then used in the research model to examine the effects of the different uncertainties on the renewable stock volatilities. Below, we provide a brief overview of the employed framework.[2]

4.1. MS-GARCH(1,1) type models

Ardia et al. [38] argues for the utilization of a Bayesian approach as an estimation method for the MS-GARCH since procedures such as Markov chain Monte Carlo (MCMC) integrate parameter uncertainty into risk forecasts via the predictive distribution. Further, the joint posterior distribution of the model parameters can be explored by MCMC. Following Ardia et al. [38], we describe the general MS-GARCH framework as:

$$r_t \mid (s_t = k, \varphi_{t-1}) \sim D(0, h_{k,t}, \xi_k) \quad 1$$

where $D(0, h_{k,t}, \xi_k)$ represents the continuous distribution with a zero mean, time-varying variance $h_{k,t}$, and additional asymmetric parameters gathered in the vector ξ_k. The unobservable variable s_t, defined on the discrete space $\{1, \dots, K\}$, is assumed to evolve with regards to a latent first-order ergodic homogenous Markov chain with transition probability matrix $P \equiv \{p_{i,j}\}_{i,j=1}^{K}$, where $p_{i,j} \equiv P[s_t = j | s_{t-1} = i]$. φ_{t-1} is the information set of all observations up to time $t-1$.

With the specification of $D(\bullet)$ in Eq (1), $h_{k,t}$ can be described as $E[r_t^2 | s_t = k, \varphi_{t-1}] = h_{k,t}$. Here $h_{k,t}$ is the variance of r_t conditional on the realization of s_t and the information set φ_{t-1}, where the conditional variances follow different GARCH processes for each regime $k = 1, \dots, K$. Further, given the regime $s_t = k$ then $h_{k,t} \equiv h(r_{t-1}, h_{k,t-1}, \theta_k)$ where $h_{k,t}$ is a function of past conditional variance ($h_{k,t-1}$), past returns (r_{t-1}) and regime-dependent parameters (θ_k) [38,39]. The GJR-GARCH can therefore be specified in MS-GJR-GARCH form as:

[2] We refer the interested readers to Ardia et al. [38,56] for a comprehensive overview of the employed framework.

$$h_{k,t} = \alpha_{0,k} + \alpha_{1,k}\varepsilon_{t-1}^2 + \alpha_{2,k}1(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 + \beta_k h_{k,t-1} \quad 2$$

4.2. Bayesian and MCMC estimation

GARCH and MS-GARCH models have usually been estimated through a frequentist approach [39]. However, utilization of a Bayesian approach is advantageous as it allows the joint posterior distribution of the model parameters to be explored by using Markov chain Monte Carlo (MCMC) procedures and the parameter uncertainty is naturally integrated into the risk forecasts via the predictive distribution [38]. Following Ardia et al. [38], we can define the likelihood function as:

$$L(\psi|\varphi_T) \equiv \Pi_{t=1}^T f(y_t|\psi,\varphi_{t-1}) \quad 3$$

The Bayesian estimation method uses a combination of the likelihood function in Eq (3) and a prior $f(\psi)$ to establish the posterior distribution's kernel $f(\psi|\varphi_T)$. Following Ardia et al. [38], we can calculate $f(\psi)f(\Omega)$ from independent diffuse priors:

$$\begin{gathered} L(\Omega) = f(\xi_1,\theta_1)f(\xi_2,\theta_2)\ldots f(\xi_K,\theta_K)f(P)1(\bar{h}_1 < \bar{h}_2 < \ldots < \bar{h}_K), \\ f(\xi_k,\theta_k) \propto f(\xi_k)f(\theta_k)1((\xi_k,\theta_k) \in COVSC_k)(k=1,2,\ldots,K) \\ f(\theta_k) \propto f_N(\theta_k; 0, 1000\times I)1(\theta_k > 0)(k=1,2,\ldots,K) \\ f(\xi_k) \propto f_N(\xi_k; 0, 1000\times I)1(\xi_{k,1} > 0, \xi_{k,2} > 2)(k=1,2,\ldots,K) \\ f(P) \propto \Pi_{i=1}^K \left(\Pi_{j=1}^K p_{i,j}\right)1(0 < p_{i,j} < 1) \end{gathered} \quad 4$$

Here $f_N(\bullet;\mu,\Sigma)$ is the density of a multivariate normal with a covariance matrix Σ and vector of means μ. **0** denotes a vector of zeros while **I** denote an identity matrix of appropriate sizes. $\bar{h}_k \equiv \bar{h}_k(\xi_k,\theta_k)$ represents the unconditional variance in regime k while $COVSC_k$ is the covariance-stationary condition in regime k as described by Trottier & Ardia [40]. The asymmetry parameter is $\xi_{k,1}$ while $\xi_{k,2}$ is the tail parameter of the skewed Student-t distribution in regime k. Further, by assuming that the K rows are independent and follow a Dirichlet prior with all hyper-parameters equal to two we obtain the prior density for the transition matrix. Since the posterior is of an unknown form, simulation techniques are used to approximate it. Following Ardia et al. [38], we use MCMC simulations that are generated through the adaptive random-walk Metropolis sampler of Vihola [41] to approximate the posterior distribution. This is done by using 5000 burn-in draws and then building a posterior sample of 1000 with the next 10 000 draws, only keeping every 10th draw to diminish autocorrelation in the chain.

4.3. VaR and CVaR estimations

The VaR metric is a commonly used financial risk measurement, measuring the amount and probability of potential losses of instruments. The VaR is often complemented by CVaR introduced by Artzner et al. [42], which is a metric that emphasizes more on the tail risk and extreme potential losses. The two metrics together facilitate the analysis of the connected risks and provide a basis for risk evaluation. Following Olofsson et al. [43], we express the VaR as:

$$VaR\tau\ t \equiv inf\ \{rt \in \mathbb{R}|F(rt|F\ t-1) = \tau\} = F-1\ (\tau|F\ t-1) \quad 5$$

The CVaR (or Expected Shortfall) measures the potential loss, lower than its VaR in t at the τ, and is often used as a complement to VaR. Further, calculating CVaR allows for a more extensive risk analysis and gives greater insight into the risk from an investor's perspective. Following Olofsson et al. [43], we define the CVaR as:

$$CVaR\tau\ t \equiv E\ (\ r_t \Big| r_t \le VaR\tau\ t, F\ t-1\ ) = 1\ \tau \int VaR\tau\ t - \infty z f(z|F\ t-1)dz \quad 6$$

5. Empirical results and discussion

In this section, we present the model selection process for the returns of the firms and analyze the estimation outputs of the MS-GARCH(1,1) type models. In addition, we provide a comprehensive overview of the VaR and CVaR for each of the firm in our model. Finally, we examine various drivers of renewable energy firms by utilizing a fixed effects panel model.

5.1. MS-GARCH models

The estimates from the MS-GARCH(1,1) framework for the renewable energy firms are presented in Table 2.[3] Following Spiegelhalter et al. [44], we have advocated the utilization of the deviance information criterion (DIC) as a goodness-of-fit measurement for Bayesian estimations. Therefore, we have opted to proceed with the model achieving the lowest DIC value in our model selection process. We ensure that all specified and fitted models have succeeded in removing heteroscedasticity and autocorrelation in the residuals by performing the Ljung-Box and ARCH test on the residuals.[4] Based on the DIC values, the best-fitted specification is MS-GJR-GARCH(1,1) form for most of the cases using the skewed Student-t distribution. However, six of the returns series are best fitted with the standard MS-GARCH(1,1) suggesting that the leverage effect is not as prevalent for these firms. Although it is important to note that the benchmark for the renewable firms (ECO) is best fitted by an MS-GJR-GARCH indicating that the returns of the renewable energy market, in general, is affected by the leverage effect. Below, we present some of the key findings from the best-suited MS-GARCH type frameworks.

All the renewable firms except VERIBO (VBK.DE) and Siemens Gamesa (SGRE) report differences between the estimated $\alpha_{0,1}$, $\alpha_{0,2}$, although the majority are relatively small, implying existence of structural breaks in the returns of varying degrees for these return series. Alternatively, this implies asymmetric impact on the return series, indicating bad news contributes significantly more to the volatility than the positive news of equal magnitude. The leverage effect is larger in regime I than in regime II for Siemens Gamesa (SGRE) and Vestas Wind Systems (VWS) indicating the effect of bad news will have a greater on impact volatility in the first regime, meanwhile the opposite is true for Green Plains Inc (GPRE) and Risen Energy (300118.SZ).

The β_1 coefficient is larger than β_2 for all the underlying firms except Siemens Gamesa (SGRE), SunPower Corp (SPWR), VERIBO (VBK.DE) and Vestas Wind Systems (VWS) indicating a tendency of higher inertia in regime I than regime II for these companies. This suggest that the variance memory decays slower in the first regime, implying past volatility assists in predicting future volatility to a greater degree in regime I. Further, the $\alpha_{1,1}$ coefficient is smaller than the $\alpha_{1,2}$ for seven of the renewable firms, showing that the positive relation between past and current variance is larger in the second regime than in the first. This also indicates that the larger the shock to the variance the higher the volatility will be in both regimes, however, the effect of the shock will be larger in the second regime for these companies. Lastly, the annualized unconditional volatility is higher in regime II for all firms, implying higher uncertainty prevailing in the second regime.

To conclude, the first regime is characterized by low unconditional volatility for all the firms. For Siemens Gamesa (SGRE) and Vestas Wind Systems (VWS), there is a strong reaction to past negative returns while the reaction is weak or non-existent for the rest of the returns. In addition, there is low persistency of the volatility process for Siemens Gamesa (SGRE), SunPower Corp (SPWR), VERIBO (VBK.DE) and Vestas Wind Systems (VWS) while its high for the rest, characterizing the first regime as calm market condition for these firms. Meanwhile, the results

[3] We have also fitted the MS-GARCH framework for the oil and gas firms. For the sake of brevity, we chose not to report these estimates. However, these results can be obtained from the corresponding author upon request.

[4] For the sake of brevity, we chose not to present these results in the manuscript. However, these results can be obtained from the corresponding author upon request.

Table 2
MS-GARCH model estimates.

	ALTO	CSQI	CE2.DE	FSLR	3800.HK	QCE	GPRE	1296.HK	0566.HK	INOX	002610.SZ	VBK.DE	VWS.CO	600416.SS
Regime 1 (k = 1)														
$\alpha_{0,1}$	−0.302***	0.000	0.000	0.000	0.000	–	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	–	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha_{1,1}$	0.140***	0.019***	0.037***	0.286***	0.041***	–	0.041***	0.168***	0.000	0.043***	0.050***	0.012***	0.289***	0.019***
	-(0.002)	-(0.001)	(0.000)	-(0.003)	-(0.001)	–	-(0.002)	-(0.002)	(0.000)	-(0.003)	(0.000)	(0.000)	-(0.005)	-(0.001)
$\alpha_{2,1}$	−0.042***	–	–	–	0.001***	–	0.106***	–	0.000	0.091***	–	–	0.206***	0.036***
	-(0.001)	–	–	–	(0.000)	–	-(0.004)	–	(0.000)	-(0.003)	–	–	-(0.003)	-(0.001)
β_1	0.957***	0.974***	0.944***	0.386***	0.938***	–	0.864***	0.639***	0.000	0.628***	0.930***	0.164***	0.524***	0.884***
	(0.000)	-(0.002)	-(0.001)	-(0.005)	-(0.002)	–	-(0.006)	-(0.002)	(0.000)	-(0.007)	(0.000)	-(0.003)	-(0.008)	-(0.004)
Dof(ν)	16.075***	4.151***	2.761***	98.200***	9.661***	–	27.999***	4.109***	2.103***	28.007***	6.348***	93.932***	31.646***	7.554***
	-(0.001)	–	-(0.001)	–	-(0.002)	–	(0.002)	-(0.001)	–	-(0.023)	-(0.001)	–	-(0.004)	–
Skewness (η)	1.125***	–	1.000***	–	1.146***	–	0.969***	1.087***	–	1.550***	1.063***	–	0.887***	–
	-(0.001)	–	-(0.001)	–	-(0.002)	–	(0.002)	-(0.001)	–	-(0.023)	-(0.001)	–	-(0.004)	–
$p_{1,1}$	0.957***	0.973***	0.854***	0.003***	0.966***	–	0.885***	0.827***	0.261***	0.811***	0.957***	0.655***	0.637***	0.996***
	(0.000)	-(0.001)	-(0.001)	-(0.001)	-(0.001)	–	-(0.002)	-(0.006)	-(0.001)	-(0.006)	-(0.001)	-(0.003)	-(0.004)	(0.000)
UV_1	0.477	0.665	0.183	0.309	0.455	–	0.513	0.522	0.003	0.504	0.236	0.136	0.821	0.475
State probability	0.770	0.915	0.461	0.221	0.680	–	0.639	0.844	0.172	0.498	0.840	0.135	0.398	0.716
Regime 2 (k = 2)														
$\alpha_{0,2}$	−0.296***	0.003	0.000	0.000	0.000	–	0.000	0.003***	0.000	0.000	0.000	0.000	0.000	0.000
	-(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	–	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha_{1,2}$	0.164***	0.191***	0.130***	0.038***	0.048***	–	0.180***	0.675***	0.327***	0.080***	0.042***	0.084***	0.082***	0.158***
	-(0.002)	-(0.005)	-(0.001)	(0.000)	-(0.001)	–	-(0.003)	-(0.010)	-(0.003)	-(0.004)	-(0.001)	-(0.001)	-(0.005)	-(0.002)
$\alpha_{2,2}$	0.065***	–	–	–	0.001	–	0.475***	–	0.006***	0.048***	–	–	0.073***	0.045***
	-(0.001)	–	–	–	(0.000)	–	-(0.008)	–	-(0.001)	-(0.002)	–	–	-(0.003)	-(0.001)
β_2	0.933***	0.337***	0.726***	0.958***	0.732***	–	0.478***	0.003***	0.541***	0.738***	0.869***	0.838***	0.871***	0.625***
	(0.000)	-(0.006)	-(0.002)	-(0.001)	-(0.004)	–	-(0.006)	(0.000)	-(0.003)	(0.007)	-(0.001)	-(0.002)	-(0.007)	-(0.004)
$p_{2,1}$	0.144***	0.295***	0.125***	0.283***	0.072***	–	0.203***	0.937***	0.154***	0.188***	0.227***	0.054***	0.240***	0.009***
	(0.000)	-(0.005)	-(0.001)	-(0.003)	-(0.001)	–	-(0.003)	-(0.002)	-(0.001)	-(0.004)	-(0.003)	-(0.001)	-(0.004)	(0.000)
UV_2	1.885	1.362	0.482	0.983	0.671	–	0.725	1.586	0.854	0.742	1.056	0.694	0.945	0.647
State probability	0.231	0.085	0.539	0.779	0.320	–	0.361	0.156	0.828	0.502	0.160	0.865	0.602	0.284

	6244.TWO	REGI	300118.SZ	600151.SS	SGRE	SWVK	SUNED	300274.SZ	SPWR	TPIC	ECO
Regime 1 (k=1)											
$\alpha_{0,1}$	0.000	0.000	0.000	−0.291***	0.000	0.000	0.002***	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	-(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha_{1,1}$	0.033***	0.012***	0.032***	0.098***	0.006***	0.000	0.124***	0.051***	0.003***	0.051***	0.020***
	-(0.001)	(0.000)	(0.000)	-(0.001)	(0.000)	(0.000)	-(0.003)	-(0.001)	(0.000)	-(0.001)	(-0.000)
$\alpha_{2,1}$	0.000	–	0.000***	0.019***	0.217***	–	0.006***	–	–	0.077***	0.051***
	(0.000)	–	(0.000)	-(0.001)	-(0.004)	–	-(0.001)	–	–	-(0.001)	(-0.001)
β_1	0.917***	0.982***	0.961***	0.964***	0.857***	0.000	0.075***	0.936***	0.865***	0.869***	0.932***
	-(0.001)	(0.000)	(0.000)	(0.000)	-(0.003)	(0.000)	-(0.006)	-(0.003)	-(0.002)	-(0.002)	(-0.001)
Dof(ν)	38.020***	63.756***	4.159***	8.180***	34.091***	2.102***	39.976***	6.464***	4.932***	9.997***	16.461***
	-(1.272)	-(0.867)	-(0.023)	-(0.039)	-(0.761)	(0.000)	-(0.896)	-(0.071)	-(0.042)	-(0.325)	(-0.2087)
Skewness (η)	1.124***	0.989***	0.997***	1.014***	0.993***	–	0.656***	–	0.850***	0.965***	0.825***
	-(0.001)	-(0.002)	-(0.001)	-(0.001)	-(0.003)	–	-(0.016)	–	-(0.004)	-(0.002)	(-0.001)
$p_{1,1}$	0.836***	0.895***	0.990***	0.963***	0.803***	0.527***	0.909***	0.921***	0.896***	0.806***	0.9968***
	-(0.002)	-(0.003)	(0.000)	(0.000)	-(0.005)	-(0.001)	-(0.002)	-(0.003)	-(0.001)	-(0.005)	(-0.001)
UV_1	0.201	0.269	0.385	0.280	0.346	0.003	0.802	0.464	0.310	0.319	0.2433
State probability	0.729	0.539	0.691	0.819	0.368	0.114	0.196	0.907	0.125	0.725	0.803
Regime 2 (k=2)											
$\alpha_{0,2}$	0.000	0.001***	0.001***	−0.968***	0.000	0.005***	0.000	0.001	0.000	0.002	0.000***
	(0.000)	(0.000)	(0.000)	-(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\alpha_{1,2}$	0.105***	0.538***	0.027***	0.267***	0.021***	0.889***	0.072***	0.225***	0.032***	0.089***	0.000***
	-(0.001)	-(0.004)	(0.000)	-(0.003)	-(0.001)	-(0.001)	-(0.002)	-(0.005)	(0.000)	-(0.001)	(0.000)

(*continued on next page*)

Table 2 (*continued*)

	6244.TWO	REGI	300118.SZ	600151.SS	SGRE	SWVK	SUNED	300274.SZ	SPWR	TPIC	ECO
$\alpha_{2,2}$	0.023***	–	0.254***	−0.037***	0.077***	–	0.114***	–	–	0.010***	0.114***
	-(0.001)	–	-(0.003)	-(0.002)	-(0.004)	–	-(0.002)	–	–	-(0.001)	(-0.001)
β_2	0.816***	0.323***	0.446***	0.821***	0.923***	0.000	0.819***	0.379***	0.957***	0.572***	0.876***
	-(0.002)	-(0.004)	-(0.005)	-(0.001)	-(0.004)	(0.000)	-(0.006)	-(0.007)	(0.000)	-(0.004)	(-0.001)
$p_{2,1}$	0.441***	0.124***	0.023***	0.170***	0.115***	0.061***	0.022***	0.769***	0.015***	0.512***	0.013***
	-(0.003)	-(0.003)	(0.000)	(0.000)	-(0.003)	(0.000)	-(0.001)	-(0.005)	(0.000)	-(0.004)	(-0.001)
UV_2	1.040	0.897	0.833	1.104	0.909	1.858	1.058	1.022	0.826	1.023	0.611
State probability	0.271	0.461	0.309	0.181	0.633	0.886	0.804	0.093	0.875	0.275	0.198

Note: We report the mean and the standard error of the mean in parenthesis of MS-GARCH (1,1) type model estimates with two regimes for the renewable energy stock returns. Dof(v) is the tail parameter and skewness(η) the skewed student's t distribution. UVk is the annualized unconditional volatility for regime k, and p_{kj} the probability of being in regime based on former regime. State probability is the mean of the probability of being in a state k. ***, **, * denotes significance at 1%, 5% and 10% level. Alto Ingredients (ALTO), Canadian Solar Inc (CSIQ), CropEnergies AG (CE2.DE), First Solar Inc (FSLR), GCL-Poly Energy Holdings Ltd (3800.HK), Global PVQ SE (QCE.HM), Green Plains Inc (GPRE), Guodian Technology & Environment Group Corp Ltd (1296.HK), Hanergy Thin Film Power Group Ltd (0566.HK), Inox Wind Ltd (INOXWINDS.NS), Jiangsu Akcome Sience & Technology Co Ltd (002610.SZ), Motech Industries Ltd (6244.TWO), Renewable Energy Group Inc (REGI), Risen Energy Co Ltd (300118.SZ), Shanghai Aerospace Automobile Electromechanical Co Ltd (600151.SS), Siemens Gamesa Renewable Energy SA (SGRE.MC), SolarWorld AG (SWVK.SG), Sunedison Inc (SUNED), Sungrow Power Supply Co Ltd (300274.SZ), SunPower Corp (SPWR), TPI Composites Inc (TPIC), VERBIO Vereinigte BioEnergie AG (VBK.DE), Vestas Wind Systems A/S (VWS.CO), Xiangtan Electric Manufacturing Co Ltd (600416.SS).

are inconclusive for the other firms and the benchmark since they either got a strong persistence of the volatility process or a weak reaction to past negative returns in regime I. Interestingly, the state probability of being in regime II is higher than the probability of being in regime I for Gamesa (SGRE), Vestas Wind Systems (VWS), VERIBO (VBK.DE) and SunPower Corp (SPWR) suggesting that turbulent market conditions are more common than calm for these returns during the examined period. Further, the switching probability $p_{2,1}$ is relatively low for these firms indicating that the returns are unlikely to switch from regime II to regime I. This may indicate that the governmental agencies and financial actors' ability and willingness to invest in the development of renewable activities are limited or reduced during times of heightened economic turbulence while calmer economic conditions are likely to increase the attractiveness of the renewable sector. Furthermore, the renewable energy sector is in a development phase, implying that the renewable firms are exposed to a high degree of idiosyncratic uncertainty. Therefore, the more frequent spikes that are hard to attribute to specific events might be explained by more firm specific factors.

Overall, our finding regarding the risk and return characteristics of renewable stocks are largely unfazed by oil price aligns with Inchauspe et al. [45], who argue renewable stock volatility is better explained by technology stocks than oil prices. The lack of oil price impact could signify renewable energy provides a robust hedge against fossil fuel uncertainty [1], encouraging further adoption.

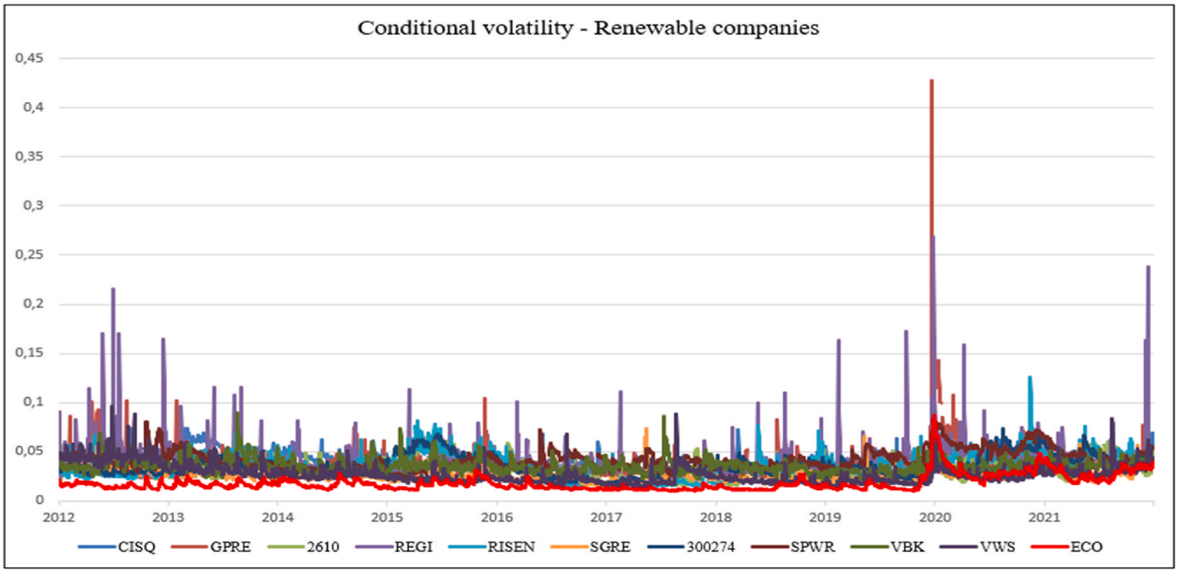
5.2. Conditional volatility

In this section, we provide a brief overview of the conditional volatility estimates from the MS-GARCH type frameworks. Fig. 3 illustrates the development of conditional volatility for the renewable energy sector and traditional energy sector. In general, the conditional volatilities are varying over time with several periods of rising and falling trends. It is noteworthy that the in the conditional volatility for all the returns is apparent in the beginning of 2020, attributed to the economic slowdown with the outbreak of COVID-19 crisis. Towards the end of subsample, we observe another spike which can be attributed to the Russian invasion of Ukraine on February 24, 2022. The higher tendency of non-uniformity among the renewable firms might be explained by the greater diversity among the firms making it more likely that an event affects each firm differently, attributing to the idiosyncratic factors impacting these firms [46–48].

Unlike renewable energy sector, the traditional energy sector, is characterized by significantly low overall variation. However, it is also apparent that the economic uncertainty positively contributing to the conditional volatilities of the firms in this sector. Between 2014 and 2016, we observe the turbulence for the traditional energy returns, which is a period characterized by Crimea dispute as well as uncertainties and war in the Middle East. Similar to the firms in renewable energy sector, the outbreak of COVID-19 leads to a significant increase in the uncertainties of the firms. However, the invasion of Ukraine by Russia leads to a significantly positive increase in overall uncertainty in the traditional energy sector. This may be attributed to the sanctions imposed on Russian oil & gas by the US and the EU, leading to an overall increase in uncertainty for these firms. As Russia is one of the largest producers of oil & gas globally, such sanctions result in a disequilibrium in the market prices and hence the overall uncertainty of the traditional energy sector.

5.2.1. Value at Risk (VaR) and Conditional Value at Risk (CvaR)

In this section, we present and analyze the summary statistics of Value at Risk (VaR) and Conditional Value at Risk (CvaR) in Tables 3 and 4, respectively, based on 1% and 5% threshold level. The time-varying VaR and CVaR for some key renewables and traditional energy companies are presented in Figs. 3 and 4, respectively. Regarding VaR, our findings indicate that the within sector dynamics follows a similar pattern. The renewable returns display losses ranging from a maximum



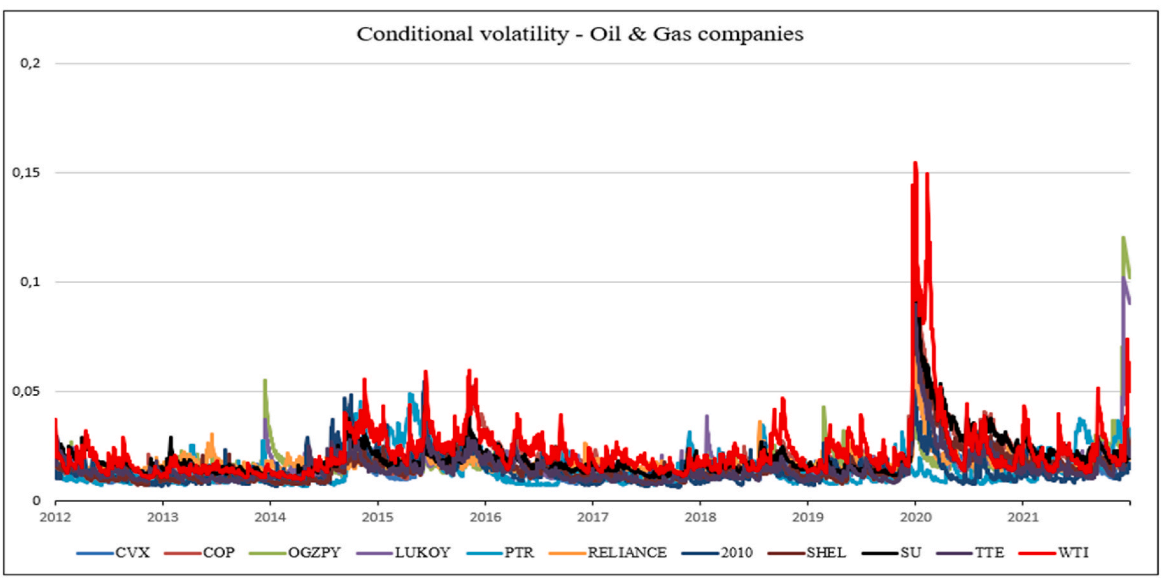


Fig. 3. Conditional volatility - Renewable stock returns
Note: We present the daily conditional volatility of the selected renewable energy companies. The data is retrieved from Refinitiv. Note: We present the daily conditional volatility of the selected oil & gas companies. The data is retrieved from Refinitiv.

value between −1.98% and −3.46% to a minimum value between −9.42% and −20.55% with a mean value around −4.21% to −6.49% in the 5% confidence interval, with exception of Green Plains (GPRE) which exhibit a minimum value of −0.578. The VaR for the oil and gas returns also demonstrate similar losses within traditional energy group displaying a maximum range between −0.93% and 2.05%, a minimum range of −7.20% to −18.35% and a mean value of between −2.08% and −3.17%. In terms of CVaR, the renewable returns display a range of the maximum value from −3.20% to −5.60%, a minimum value range of −11.27% to −26.33% and a mean value of around −6.07% to −9.40%, excluding Green Plains (GPRE). The difference in the CVaR results between the groups is more evident, where the change of the renewable returns was larger, suggesting that the renewables are more sensitive than fossil fuel return in worst case scenarios (see Fig. 5).

In terms of time-varying VaR and CVaR, we observe a higher frequency of deeper drops for the for the renewable returns. The large drops in the traditional energy returns mostly coincide with events such as the Crimean conflict in 2014 and its aftermath in the 2014–2016 period, the covid-19 pandemic and the Russo-Ukrainian war of 2022. Meanwhile, the frequent renewable drops seem more randomly scattered, strengthening the indications that the renewable energy sector is still in the development phase and idiosyncratic characteristics of the firms largely derives the variations in the sector.

Overall, the MS-GARCH(1,1), conditional volatility, VaR and CVaR, indicate that the renewable energy firms exhibit higher uncertainty than the traditional energy firms. This is in-line with previous research which showed renewable energy firms to have market beta values around 2 while oil firms exhibited market beta values of around 0.7 (see e.g., Ref. [20,33,46,49]). The riskier attribute needs to be taken into consideration by investors when making investment decisions as well as

Table 3
VaR results.

Threshold level	5%				1%			
	Mean	Max	Min	S.D.	Mean	Max	Min	S.D.
Renewable								
CSQI	−0.0610	−0.0346	−0.1289	0.0138	−0.1092	−0.0671	−0.2134	0.0214
GPRE	−0.0537	−0.0324	−0.4094	0.0233	−0.0844	−0.0523	−0.5480	0.0363
002610.SZ	−0.0494	−0.0198	−0.0942	0.0117	−0.0819	−0.0450	−0.1259	0.0201
REGI	−0.0597	−0.0289	−0.2055	0.0159	−0.0882	−0.0542	−0.3030	0.0271
300118.SZ	−0.0554	−0.0215	−0.1798	0.0207	−0.0923	−0.0401	−0.2360	0.0289
SGRE	−0.0418	−0.0217	−0.1152	0.0109	−0.0724	−0.0433	−0.1769	0.0168
300274.SZ	−0.0568	−0.0229	−0.1126	0.0162	−0.0935	−0.0518	−0.1730	0.0230
SPWR	−0.0649	−0.0375	−0.1239	0.0147	−0.1106	−0.0660	−0.2062	0.0243
VBK.DE	−0.0544	−0.0327	−0.1300	0.0109	−0.0965	−0.0633	−0.2138	0.0182
VWS.CO	−0.0421	−0.0221	−0.1442	0.0148	−0.0715	−0.0377	−0.2105	0.0252
Oil & gas								
CVX	−0.0244	0.0130	−0.1524	0.0135	−0.0394	−0.0213	−0.2225	0.0208
COP	−0.0317	−0.0133	−0.1691	0.0177	−0.0491	−0.0211	−0.2458	0.0266
OGZPY	−0.0246	−0.0164	−0.1634	0.0075	−0.0408	−0.0261	−0.2493	0.0131
LUKOY	−0.0256	−0.0142	−0.1657	0.0108	−0.0425	−0.0252	−0.2410	0.0174
PTR	−0.0208	−0.0093	−0.0720	0.0122	−0.0366	−0.0170	−0.1030	0.0191
RELIANCE	−0.0267	−0.0205	−0.0943	0.0064	−0.0430	−0.0337	−0.1349	0.0100
2010.SR	−0.0210	−0.0087	−0.0742	0.0092	−0.0373	−0.0200	−0.1051	0.0146
SHEL	−0.0248	−0.0116	−0.1374	0.0132	−0.0403	−0.0187	−0.1922	0.0206
SU	−0.0316	−0.0167	−0.1835	0.0154	−0.0519	−0.0278	−0.2414	0.0246
TTE	−0.0251	−0.0122	−0.1265	0.0117	−0.0403	−0.0200	−0.1749	0.0180

Note: We present mean, max, min and standard deviation statistics of daily Value at Risk (VaR) estimations at 5% and 1% levels.

Table 4
CVaR results.

Threshold level	5%				1%			
	Mean	Max	Min	S.D.	Mean	Max	Min	S.D.
Renewable								
CSQI	−0.0909	−0.0556	−0.1786	0.0181	−0.1427	−0.0958	−0.2416	0.0230
GPRE	−0.0763	−0.0451	−0.4925	0.0311	−0.1100	−0.0703	−0.5784	0.0439
002610.SZ	−0.0688	−0.0352	−0.1127	0.0186	−0.0991	−0.0681	−0.1338	0.0169
REGI	−0.0762	−0.0469	−0.2633	0.0217	−0.1281	−0.0860	−0.3209	0.0295
300118.SZ	−0.0784	−0.0334	−0.2130	0.0254	−0.1177	−0.0569	−0.2451	0.0310
SGRE	−0.0613	−0.0358	−0.1505	0.0142	−0.0967	−0.0619	−0.1950	0.0184
300274.SZ	−0.0794	−0.0399	−0.1476	0.0201	−0.1176	−0.0762	−0.1960	0.0248
SPWR	−0.0940	0.0560	−0.1745	0.0206	−0.1466	−0.0901	−0.2606	0.0302
VBK.DE	−0.0812	−0.0522	−0.1793	0.0152	−0.1300	−0.0892	−0.2487	0.0216
VWS.CO	−0.0607	−0.0320	−0.1833	0.0208	−0.0936	−0.0511	−0.2253	0.0294
Oil & gas								
CVX	−0.0337	−0.0176	−0.1926	0.0179	−0.0499	−0.0275	−0.2426	0.0244
COP	−0.0425	−0.0177	−0.2144	0.0231	−0.0607	−0.0289	−0.2733	0.0307
OGZPY	−0.0349	−0.0223	−0.2136	0.0110	−0.0544	−0.0341	−0.2781	0.0168
LUKOY	−0.0366	−0.0212	−0.2097	0.0147	−0.0575	−0.0370	−0.2586	0.0209
PTR	−0.0308	−0.0146	−0.0903	0.0160	−0.0490	−0.0254	−0.1107	0.0207
RELIANCE	−0.0371	−0.0287	−0.1184	0.0085	−0.0555	−0.0442	−0.1459	0.0114
2010.SR	−0.0312	−0.0158	−0.0924	0.0123	−0.0493	−0.0285	−0.1126	0.0165
SHEL	−0.0345	−0.0159	−0.1694	0.0176	−0.0516	−0.0242	−0.2009	0.0244
SU	−0.0445	−0.0236	−0.2181	0.0209	−0.0674	−0.0358	−0.2524	0.0295
TTE	−0.0345	−0.0169	−0.1552	0.1555	−0.0509	−0.0257	−0.1871	0.0211

Note: We present mean, max, min and standard deviation statistics of daily Conditional Value at Risk (CVaR) estimations at 5% and 1% levels.

governments and institutions encouraging the transition to renewable energy.

5.3. Research model

To evaluate the potential drivers of renewable energy firms, we employ WTI crude oil price, economic policy uncertainty, geopolitical risk, climate policy uncertainty, Russo-Ukrainian conflicts, the Covid-19 pandemic, and green metals as explanatory variables in a panel regression. The Climate policy uncertainty index (CPU) by Gavriilidis [50] was used to construct a dummy variable expressing important events from the index. The Economic policy uncertainty index (EPU) developed by Baker et al. [51] is utilized as a global uncertainty proxy. The daily Geopolitical Risk (GPR) index developed by Caldara & Iacoviello [52] is used to examine the effect of geopolitical tension on the returns of the companies. PCA1 and PCA2 are green metal variables created through a principal component analysis and transformed into an index. The metals included were selected due to their importance in the renewable energy sector [17]. The Covid-19 dummy variable covers the market crash following the pandemic outbreak, and the Russian conflict (RC) variable was created to cover important news and dates connected to the conflict. We utilize fixed effects panel data models to estimate the impact of different uncertainty measures on the volatilities and returns of energy stocks. The panel structure with firm fixed effects allows us to control for unobserved heterogeneity across renewable firms (Greene, 2004). This approach allows the inclusion of under-researched uncertainty factors like green metal prices alongside more commonly studied drivers. To analyze the impact of these potential drivers and

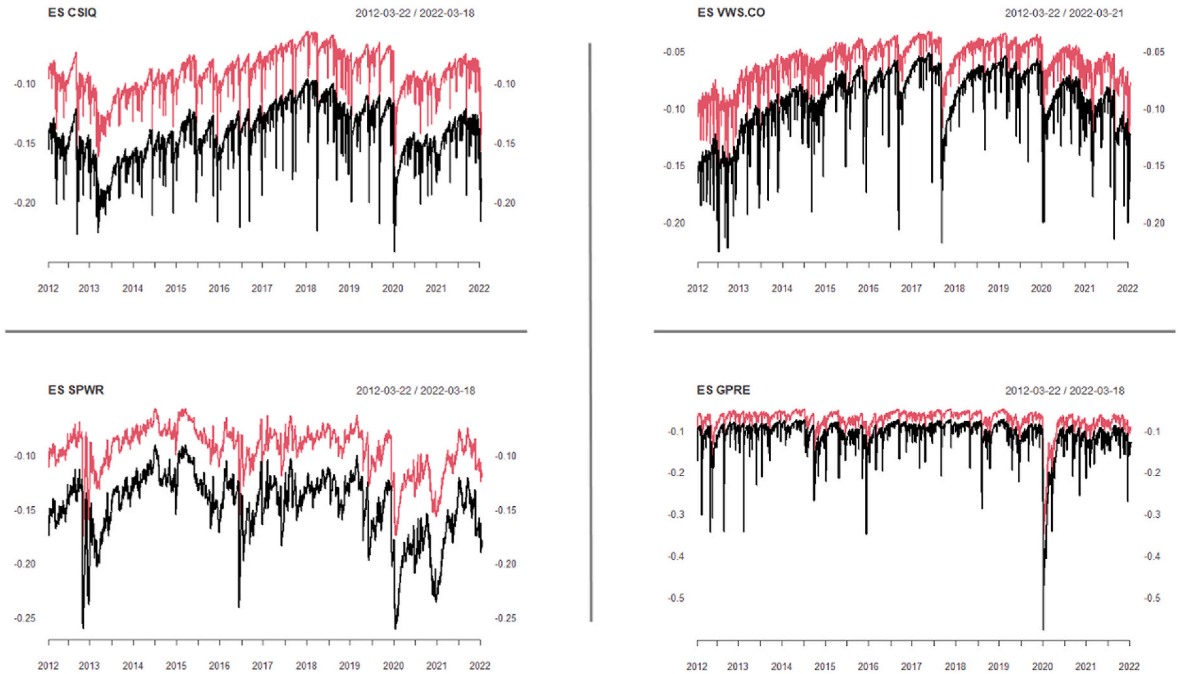


Fig. 4. CVaR (ES) Renewable returns
Note: This figure illustrates the in sample CvaR of Canadian Solar (CSIQ), Vestas Wind Systems (VWS.CO), SunPower Corp (SPWR) and Green Plains (GPRE). The red line indicates the 5% confidence level while the black line indicates the 1%.

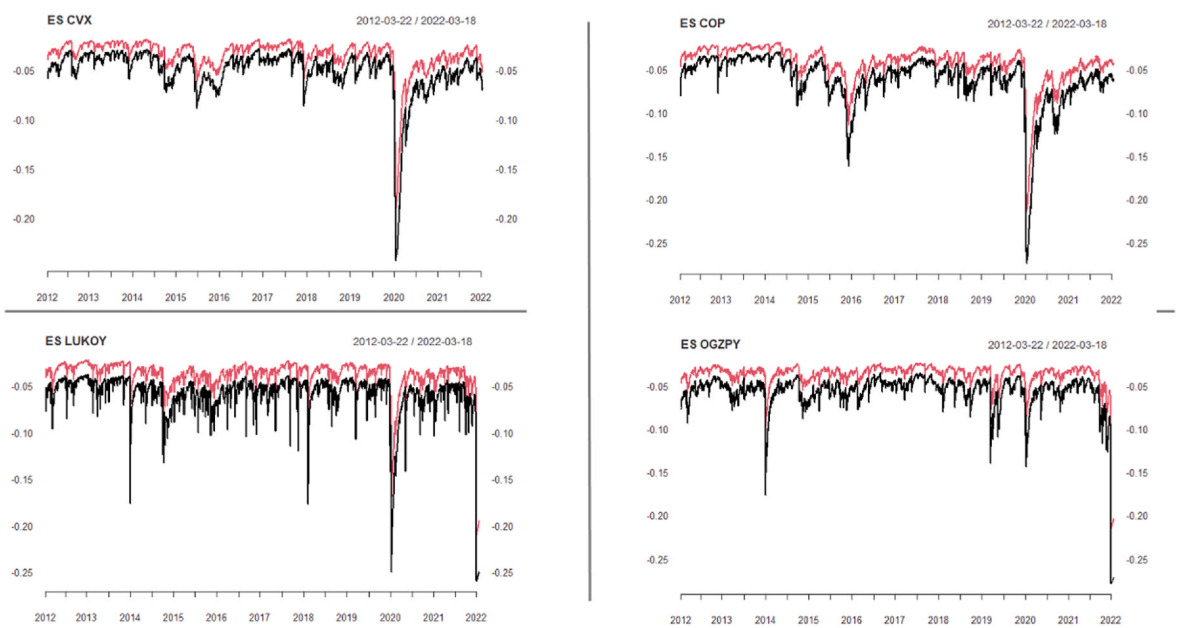


Fig. 5. CVaR (ES) Oil & Gas Return
Note: This figure illustrates the in sample CvaR of Chevron Corp (CVX), ConocoPhillips (COP), NK Lukoil (LUKOY) and Gazprom (OGZPY). The red line indicates the 5% confidence level while the black line indicates the 1%.

uncertainties related to energy security, we utilized a fixed effect panel models specified as follows:

$$VOL_{i,t} = \beta_0 + \beta_1 WTI_{i,t} + \beta_2 EPU_{i,t} + \beta_3 GPR_{i,t} + \beta_4 RC_{i,t} + \beta_5 C19_{i,t} + \beta_6 CPU_{i,t} + \alpha_i + \varepsilon_{i,t}, \quad (7)$$

$$RET_{i,t} = \beta_0 + \beta_1 WTI_{i,t} + \beta_2 EPU_{i,t} + \beta_3 GPR_{i,t} + \beta_4 RC_{i,t} + \beta_5 C19_{i,t} + \beta_6 CPU_{i,t} + \alpha_i + \varepsilon_{i,t}. \quad (8)$$

where, $VOL_{i,t}$ *and* $RET_{i,t}$, is the conditional volatility and returns, respectively, for the company *i* on day *t* extracted from the MS-GARCH (1,1) type models, $WTI_{i,t}$ corresponds to the logged daily WTI price, $EPU_{i,t}$ and $GPR_{i,t}$ are the daily logged values of the economic policy uncertainty and geopolitical risk uncertainty indices, respectively. $RC_{i,t}$ is a dummy variable representing the 2014 Crimea conflict and the current Russo-Ukraine war, $C19_{i,t}$, is a dummy accounting for the 2020 COVID-19 stock market crash and $CPU_{i,t}$ is a dummy that marks events associated with climate policy uncertainty. α_i represents the entry-specific intercepts that capture heterogeneities across firms while $\varepsilon_{i,t}$ is an error term. Further, we conduct two additional regressions, one where WTI is replaced with WTI100 and another where it is replaced by WTI50 to examine whether relatively high or low oil threshold prices have an impact on the volatilities or returns. The $WTI100_{i,t}$ and $WTI50_{i,t}$ are dummies representing when the WTI prices exceed 100 USD and when it is below 50 USD, respectively.

Further, we are also interested in examining the effects of green metal prices on the volatility and returns of the renewable energy stocks, resulting in the following fixed effects models:

$$VOL_{i,t} = \beta_0 + \beta_1 PCA1_{i,t} + \beta_2 PCA2_{i,t} + \beta_3 EPU_{i,t} + \beta_4 GPR_{i,t} + \beta_5 RC_{i,t} + \beta_6 C19_{i,t} + \beta_7 CPU_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{9}$$

$$RET_{i,t} = \beta_0 + \beta_1 PCA1_{i,t} + \beta_2 PCA2_{i,t} + \beta_3 EPU_{i,t} + \beta_4 GPR_{i,t} + \beta_5 RC_{i,t} + \beta_6 C19_{i,t} + \beta_7 CPU_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{10}$$

here, we replace the WTI variables with $PCA1_{i,t}$ and $PCA2_{i,t}$ that represents the first two components of a principal component analysis (PCA). We utilize PCA to consolidate the prices of 8 critical green metals into unified indices representing the overall variation in these metal prices. To construct the indices, we gathered the daily prices of aluminum, copper, nickel, platinum, lithium, zinc, silicon, and cobalt. The daily prices of the commodities were then logged to remove size and currency differences before performing a PCA. We found the first two components to be sufficient since they together explain around 83% of the total variation and were the only components to have an eigenvalue above 1. $PCA1_{i,t}$ is characterized by putting the least emphasis on platinum while the weights of the other metals are relatively equally distributed, with aluminum and zinc having the highest. $PCA2_{i,t}$ on the other hand, emphasizes more on lithium, zinc and cobalt. Since all regressions showed signs of heteroscedasticity and autocorrelation, we used robust Arellano standard errors in an effort to mitigate these effects and thereby improve the reliability of the estimations.

Table 5 reports the summarized results of the fixed effects regression frameworks. Our findings indicate that EPU has a positive and significant effect on the volatilities indicating that an increase in EPU increases the volatility of the firms. Further, the effect of EPU on the returns is also positive suggesting that the renewable firms have benefitted from increased EPU during the period. This is in contrast with previous research concluding that EPU increases the volatility and decreases the returns of the renewable stocks (see e.g., Ref. [24–26]). The difference is primarily attributed to the fact that the earlier studies utilize broader renewable energy indices, thereby providing a more macroeconomic perspective, while ours gives more of a microeconomic insight. However, it is important to note that these studies stressed the fact that regulatory stability and consistency regarding green policies are beneficial for the renewable energy sector. Therefore, there is a possibility that our finding of a positive relationship between EPU and renewable energy returns marks a shift where the implemented beneficial policies have altered the risk perception of the sector. Further, the renewable energy stocks might be perceived as more attractive during times of increased EPU compared to other energy sources due to the increasing attention to climate change since the traditional sources have a more unforeseeable future and are more likely to suffer from new regulations. Overall, the positive EPU coefficient contradicts some previous studies which found heightened policy uncertainty decreases renewable stock returns [24,26]. This reversal may indicate renewable firms are now perceived as a "safe haven" for investment amid uncertain conditions given rising climate concerns and fossil fuel risks [23], signifying a shift in investor preferences.

GPR has a negative and significant relationship with the stock volatilities implying that an increase in the geopolitical risk decreases the volatility of the stocks while the effect on the stock returns is positive. This indicates that heightened geopolitical risk has been beneficial for the renewable energy sector during the examined period. Previous research regarding the sign of the effect of GPR on the returns and volatility of renewable energy stock has been inconclusive with both positive and negative relationships being found (see e.g., Ref. [8,28]). Nonetheless, Su et al. [8] have argued that GPR related issues such as trade disputes and conflicts might encourage the transition to renewable energy due to its contribution to reducing energy dependence. Further, Rodríguez-Fernández et al. [10] and Stulberg [11] have reported that the energy security of the EU to be vulnerable due to its dependence on Russia for its supply. The positive effect of GPR on the returns of the

Table 5
Summarized results from the fixed effects models.

Model	Fixed effects - WTI			Fixed effects – Green metals	
	Fixed effects – Robust standard errors: Arellano				
Variables	*RET*	*VOL*	*Variables*	*RET*	*VOL*
EPU	0.00197297***	0.00292577***	EPU	0.0021082***	0.00269281***
	(0.00065879)	(0.00079133)		(0.00064286)	(0.00080283)
GPR	0.00141609***	−0.00222723***	GPR	0.0017488***	−0.00128051***
	(0.00046313)	(0.00032580)		(0.00041911)	(0.00026594)
RC	0.00133134	0.00553008***	RC	0.0019655	0.00445388***
	(0.00143197)	(0.00116286)		(0.0014493)	(0.00124796)
C-19	−0.01403127***	0.01743275***	C-19	−0.014380***	0.01873012***
	(0.00348715)	(0.00584690)		(0.0035673)	(0.00601115)
CPU	−0.00070106	−0.00080416	CPU	−0.00075523	−0.00051915
	(0.00097068)	(0.00067911)		(0.00096323)	(0.00064742)
WTI	−0.00034554	0.00122046	PCA1	−0.00039774***	−0.00014241
	(0.00062580)	(0.00190026)		(0.000055198)	(0.00018160)
[WTI50]	0.00123244***	[0.00054029]	PCA2	−0.00023881**	−0.00148407***
	(0.00037245)	(0.00092075)		(0.00011185)	(0.00035786)
[WTI100]	−0.00050464	[0.00149966]			
	(0.00060319)	(0.00119026)			
Observations	24082	24083	Observations	24486	24487
R^2 – Adj	0.0023449	0.084574	R^2 – Adj	0.0028255	0.1252

Note: We present the summarized results from the estimated fixed effects models using Arellano robust standard errors. Estimated standard errors in parenthesis. [WTI50] and [WTI100] indicates that the variables have been regressed separately from each other and WTI in order to avoid multicollinearity. ***,**,* denotes significance at 1%, 5% and 10%. RET = returns, VOL = conditional volatilities.

renewable firms might therefore be a result of an increased incentive towards diversification of energy sources during periods of high geopolitical tension, such as the Russian conflict, which seem to have proven beneficial to the renewable energy firms.

Considering the results of EPU and GPR, it is indicative that the positive effects of the transition towards renewable energy dominates the potential negative effects of heightened news-based uncertainty. Even so, it is important to highlight the importance of continued beneficial policies aimed toward the renewable sector for the relationship to hold.

However, although there are indications that the pursuit of energy security has had a positive impact on the renewable stock, our findings suggest that new challenges might arise. The green metal variable PCA2 has a negative effect on the stock volatilities and returns suggesting that an increase in green metal prices, especially lithium, zinc and cobalt, decreases the return and volatility of the renewable energy stocks. The other green metal variable PCA1 shows no significant effect on the volatilities of renewable energy stocks however a negative and significant effect on the returns. These results imply that the returns of the renewable firms suffer from increased metal prices, likely due to their dependency on these commodities for production. The importance of green metals might have implications for the effort to diversify the energy sources to decrease energy dependency. By reasoning along the lines of Hache [16], there is a possibility that the energy dependency could shift from oil-producing countries to countries rich in green metals. This shift may occur as the transition to renewable energy sources increases. Green metals could then be used by producing countries as a political leverage, like the current geopolitical importance of crude oil [8]. Furthermore, metals critical to the renewable energy sector are found to be scarce and less geographically diversified compared to fossil fuels [17]. For instance, in the Russia-Ukraine war of 2022, the EU is putting in an increased effort to reduce its dependency on Russian energy since the dependence limits the countries' ability to respond to Russian aggression. However, Russia is an important producer of the metals necessary to produce renewable energy such as nickel and cobalt [17]. Hence the efficiency of reducing energy dependency by increasing the share of renewable energy might be limited. Furthermore, although the previous findings regarding GPR indicated that geopolitical events, such as wars, have a positive impact on the returns of the renewable stocks it is likely that wars affecting the producers of green metals will impose negative consequences on the sector. Therefore, it is apparent that policies aimed at diversifying the sources and strengthening international relations with producing countries are important to secure the supply of critical metals and ensure the transition efficiency in reducing energy dependency.

The importance of green metals might also have implications regarding the transition's effectiveness in mitigating climate change and its long-term viability. Current and projected mining extraction is not enough to supply the required amounts of metals needed for the transition consistent with the Paris Agreement. The increased extraction and production are also feared to give rise to environmental and social issues if not managed properly [17]. This indicates that although the relationship between the stock volatilities and return with CPU currently is insignificant the influence of climate risk might increase with the growing extraction of critical metals. Policies and regulations aimed at ensuring the long-term availability of the commodities and that the extraction is conducted in a sustainable way are therefore vital for the sector's success in mitigating the effects of climate change. Overall, our findings suggest that rising green metal prices reduce renewable stock returns aligns with the view that mineral resource dependence may create new energy security and sustainability challenges [16]. As the transition accelerates, scarcity and concentrated supply of key metals could enable producer countries to exert political leverage as with fossil fuels [8].

The relationship between the stock volatility of the renewable firms and the oil price (WTI) is found to be insignificant, indicating that the oil price does not affect the volatility of these firms. Likewise, the WTI100 and WTI50 dummy variables are insignificant which means that oil prices above 100 USD or below 50 USD have no impact on the volatility of the renewable stocks. These findings indicate that a relationship between the oil price and the volatilities of the renewable energy stocks is weak or non-existent during the period. Previous findings regarding the relationship are rather inconclusive. Some studies argue that the impact of oil prices on renewable energy stock volatility is small and better explained by technology stocks (see e.g., Ref. [33,45]). While others argue for a stronger relationship that might be time or geographically dependent (see e.g., Ref. [53–55]). It is noteworthy that WTI50 variable shows a significant and positive relationship between oil prices below 50 USD and the returns of the renewable energy stocks. The research regarding the relationship between oil price and renewable energy returns originally started from the hypothesis of a substitution effect where high oil prices would lead to higher utilization of alternative energy sources [33]. Contrary to the substitution effect hypothesis, the WTI50 variable suggests that low oil prices increase the returns of the renewable energy stocks. This might be caused by renewable energy stocks appearing more attractive to investors during times of depressed oil prices when the traditional energy sector is likely to suffer. The fact that our results indicate that the risk and returns of the renewable energy stocks are largely unfazed by oil price while extremely low prices increase the returns suggests that these firms could be seen as an attractive investment during periods of turbulence in the oil market.

Lastly, the C-19 variable which serves as a proxy for the stock market crash has a positive impact on the volatilities while the effect on the returns is negative. This is probably explained by the economic slowdown during the period and that the stock markets, in general, fell into bearish phase. The RC variable which indicates the effect of the Crimean crisis in 2014 and the current Russo-Ukraine war has increased the volatility of the renewable energy stocks, however, it had no effect on the stock returns. The impact on volatility might be a result of general heightened uncertainty on the stock market during the periods of conflict considering that there is no effect on the returns of the stocks and the previous results regarding GPR and WTI.

6. Conclusion and policy implications

The renewable energy sector exhibits significant potential to mitigate climate change and improve energy security, catalyzing its rapid growth. However, this transition brings uncertainties that necessitate examining renewable firms' risk-return profile and drivers. Our analysis reveals important characteristics of these renewable energy firms. Renewable energy stocks exhibit higher uncertainty compared to conventional counterparts, highlighting their riskier nature during this pioneering phase. However, contrary to expectations, increased uncertainty boosted returns, conferring potential "safe haven" appeal amid pressing energy security concerns and mounting unease over fossil fuel longevity. Nevertheless, dependence on scarce green metals for renewable technologies dampens returns, threatening to undermine energy transition goals if supplies tighten.

Our findings have several important implications for policymakers and market participants. The positive interconnectedness between economic policy uncertainty (EPU) and renewable energy stock returns suggests a shift in investor behavior, where renewable energy is increasingly perceived as a stable investment during periods of economic turmoil. This trend offers policymakers an opportunity to encourage investment in renewables as part of economic stabilization strategies, such as implementing financial incentives like tax credits, and establishing favorable regulatory frameworks to support renewable energy development. Simultaneously, the negative impact of green metal prices on these stocks highlights a significant dependency, suggesting the necessity for strategies to mitigate uncertainties associated with commodity price fluctuations. This includes diversifying supply sources, investing in recycling technologies, and potentially developing risk mitigation tools like loan guarantees or insurance products specifically for renewable energy investments. These strategies are essential considerations for market participants seeking to mitigate investment risks in the renewable sector, ensuring a more robust and resilient energy market in the face of economic uncertainties.

Moreover, our findings reveal that renewable energy stocks are becoming increasingly attractive investment options during periods of heightened geopolitical tension, demonstrating their potential role in enhancing energy independence. This trend offers a strategic direction for policymakers to actively promote renewable energy to reduce reliance on traditional energy sources, especially during geopolitical crises. Such promotion could include developing targeted public awareness campaigns and providing strategic funding for renewable energy projects that enhance national energy security. For investors, this indicates the potential of renewable energy stocks as hedges against geopolitical risks. Furthermore, the decoupling of renewable energy stocks from oil price volatility highlights their stability as investments, making them particularly appealing in volatile markets. This observation suggests that investors might consider increasing their allocation to renewable energy in their portfolios, especially during periods of oil market instability. Overall, these findings underscore the necessity for a holistic approach in renewable energy policy and investment strategies. Policymakers and market participants should consider the evolving global economic landscape and the intricate dynamics of the energy market, incorporating factors like geopolitical stability, energy diversification, and market resilience in their strategic planning.

Further research could therefore be conducted on how to solve or mitigate the challenges that arise due to the dependency on green metals. It could also be interesting to investigate possible hedging opportunities caused by the low influence of other energy prices and the positive effects of traditional fuel energy risk. Further, this study examined the overall global renewable energy sector. Further research could investigate whether the relationships between uncertainty and renewable investment differ across countries and regions. Analyzing geographic variations would provide additional insights into the transition. Additionally, future work could employ instrumental variable methods and formal exogeneity testing to allow for stronger causal inferences related to the interconnectedness conclusions. Examining endogeneity would further validate the empirical findings and predictive relationships identified in this analysis.

Data availability statement

The data that support the findings of this study are available from Refinitiv Eikon DataStream, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of Refinitiv Eikon DataStream.

CRediT authorship contribution statement

Philip Igeland: Writing – original draft, Visualization, Methodology, Software, Formal analysis. **Leon Schroeder:** Data curation, Writing – original draft. **Muhammad Yahya:** Visualization, Investigation, Writing – original draft, Writing – review & editing. **Yarema Okhrin:** Supervision, Writing – review & editing, Methodology, Validation. **Gazi Salah Uddin:** Supervision, Software, Validation, Writing – review & editing, Writing – original draft, Resources.

Declaration of competing interest

We confirm that this research received no external financial or non-financial support and that there's no financial/personal interest or belief that could affect their objectivity, and that there is no competing interest for any of the authors.

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