Energy Economics 148 (2025) 108592

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Common volatility in clean energy stocks

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A R T I C L E   I N F O

JEL classification:
C32
C58
G10
Q25
Q30
Q40

Keywords:
Clean energy
Renewable energy
Sustainable finance
COVOL
Common volatility
Geopolitical risks

A B S T R A C T

This study investigates common volatility (COVOL) within the clean energy sector, motivated by the sector's growing importance and its susceptibility to external shocks. For this purpose, we use the COVOL measure developed by Engle and Campos-Martins (2023) to explore sector-wide and sub-sector common volatility, in a range of sub-sectors including renewable energy, energy storage, energy conversion, power conservation, and greener utilities. Our analysis highlights the major events that significantly impact the volatility of clean energy stocks. These include global economic disruptions, geopolitical tension, policy changes and climate-related events. Other key findings reveal the heterogeneous association of sub-sectors' COVOL to different economic and financial factors, alongside superior explanatory power of COVOL on clean energy risk and return compared to alternative news-based uncertainty measures. These insights emphasize the importance for investors to integrate thorough risk management strategies and for policymakers to create a stable, supportive environment for the clean energy market. The study's implications extend to enhancing sector resilience and informing strategic investment and policy decisions, contributing to the sustainable growth of clean energy amidst global economic and environmental uncertainties.

1. Introduction

In recent years, the clean energy sector has become a fundamental component of sustainable development, attracting growing interest from investors, policymakers, and researchers.[2] The shift towards clean energy sources, spurred by the global imperative to address climate change and improve energy security, has notably amplified the sector's significance in the global economy. A recent report published by the International Energy Agency (IEA) noted that the sector's contribution accounted for 10% of global GDP growth in 2023.[3] Additionally, clean energy investments reached $1.8 trillion in 2023, representing an increase of 50% compared to 2019.[4] According to FTSE Russel, the global green sector had a market capitalization of USD 7.2 trillion in 2021, representing 7% of the worldwide stock market capitalization.[5] The surge in interest in clean sector investments underscores its crucial role in mobilizing funds for sustainable initiatives that support the shift to a low-carbon or net-zero emissions economy.

The clean energy sector has gained significant importance in the financial market due to its crucial role in combating climate change and driving sustainable economic growth. Global initiatives to reduce carbon emissions have led to substantial investments in clean energy source. For instance, according to International Energy Agency, the total global investment in clean energy is expected to double the

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[1] The authors wish to thank Yvonne Fang for her research assistance in this project.

[2] Clean energy is defined as energy source that is environmentally friendly in terms of emissions. Clean energy is the broad term that encompasses green energy. Green energy refers to renewable sources that come from naturally recurring processes and are continuously replenished. In turn, renewable energy is primarily concerned with the sustainability of the source; however not all renewable energy is necessarily green or clean. See, https://be-cis.com/green-vs-renewable-vs-clean-energy-differences/.

[3] See, https://www.iea.org/commentaries/clean-energy-is-boosting-economic-growth.

[4] See, https://www.iea.org/reports/clean-energy-market-monitor-march-2024.

[5] https://content.ftserussell.com/sites/default/files/investing in the green economy 2022 final 8.pdf.

https://doi.org/10.1016/j.eneco.2025.108592
Received 30 May 2024; Received in revised form 1 May 2025; Accepted 5 May 2025
Available online 29 May 2025

investment in fossil energy, reaching USD 2 trillion.[6] This surge in investment underscores the sector's potential but also highlights the need to understand the risks associated with such rapid growth.

Therefore, it is of utmost importance for risk managers and policymakers to systematically understand which shocks, and to what extent they collectively affect the volatility of the sector. Types of shocks are diverse such as economic, environmental, geopolitical, societal, and technological. Besides, their intensity and frequency can vary across years and across types (Engle and Campos-Martins, 2023).[7] For example, policy changes can significantly alter market dynamics, technological breakthroughs can disrupt existing industries, and geopolitical conflicts can affect supply chains and investment flows.

Moreover, the clean energy sector is interconnected with global financial markets, meaning that shocks in one area can have ripple effects worldwide. This interconnectedness amplifies the importance of having robust risk assessment tools. Thus, practitioners and policymakers need a broad measure of risk that captures the impacts of all shocks and identifies which has the greatest effect on asset volatility at any given time. Engle and Campos-Martins (2023) propose a measure that can satisfy this condition, namely Common Volatility (COVOL, hereafter).

In this paper, we conduct an analysis of the COVOL of the clean energy stock sector. Our primary objective is to identify significant events that have influenced the sector's volatility over time. Additionally, we aim to explore potential differences in COVOLs across sub-sectors within the clean energy industry. Furthermore, we investigate whether understanding COVOL can improve the prediction of risk and return for clean energy stocks. What are the key drivers of volatility in the clean energy sector, and how do these drivers impact asset returns? Additionally, is there a common volatility factor that influences all stocks within the sector, and if so, how does this factor affect individual stock volatility? Lastly, how do different sub-sectors within the clean energy market vary in their volatility patterns, and what are the implications for risk management and investment strategies?

COVOL quantifies the impact of concurrent shocks on all assets within the system, thus gauging the overall impact of shocks in the sample. Based solely on the individual asset prices, the estimation of COVOL is more likely to reflect what actually happened in the market compared to other news-based uncertainty measures, with a notion that asset prices fully reflect the impact of all relevant news on predictions of the future cashflows. Other uncertainty measures based on text mining such as economic policy uncertainty or geopolitical risk may only capture one type of shocks. Further, Engle and Campos-Martins (2023) argue that the news-based measures may only reflect "what people are worried might happen or already did happen". In their comparative analyses using data of global equity markets, Engle and Campos-Martins (2023) finds that the COVOL measure contains more relevant information that can help improve the predictions of the asset's return compared to other news-based uncertainty measures.

As clean energy investments have become increasingly important in financial markets, the literature on the subject has rapidly expanded, dividing into three major strands. The first strand examines the impact of green assets, including investments in clean energy sources, on corporate strategy and organizational performance (e.g., Heinkel et al., 2001; Gianfrate and Peri, 2019; Tang and Zhang, 2020; Lin and Su, 2022; among others). The second strand explores the interlinkages between clean energy assets and other asset classes, as well as the spillover effects among clean energy assets themselves (e.g., Lundgren et al., 2018; Reboredo et al., 2020; Reboredo and Ugolini, 2020; Pham, 2021; Saeed et al., 2021; Elsayed et al., 2022; Dogan et al., 2022; Mensi et al., 2022). The third strand investigates the financial attributes of clean energy assets, such as return, liquidity, and volatility, along with their drivers (e.g., Hachenberg and Schiereck, 2018; Febi et al., 2018; Kocaarslan and Soytas, 2021; Naeem and Karim, 2021; Nguyen et al., 2021; Liang et al., 2022; Pham and Nguyen, 2022; Pham et al., 2022; among others). Our study addresses a research gap within the third strand of literature on the clean energy stock sector. While previous research has mostly examined the sector-level volatility or considered one type of shocks (e.g., climate-related or economic events), little is known on co-movement of volatility among individual stocks driven by common volatility shocks as well as single stock exposure to those shocks. This knowledges is crucial for several reasons. First, it can provide deeper insights into the risk management strategies, especially in terms of portfolio diversification with detail factor loadings of portfolio's components to hedge against any type of major events shaking the whole clean energy sector. Second, it helps investors identify systemic risks and the potential for contagion within the sector, enhancing investment decision-making. Lastly, analyzing volatility co-movements can inform policy-making, particularly in areas related to financial stability and the promotion of sustainable investments. This approach addresses a critical gap in the existing literature, emphasizing the need for taking into account impact of common volatility shocks resulting from any types of event to manage risks of the portfolio more effectively and more thoroughly.

To explore the unresolved questions surrounding the volatility of the clean energy sector, our study adopts the advanced methodology developed by Engle and Campos-Martins (2023) for estimating a time-varying COVOL. This methodology is applied to a comprehensive dataset comprising daily prices of 68 stocks from the Wilder Hill Clean Energy Index spanning from January 2010 to January 2024. The Engle and Campos-Martins model conceptualizes COVOL as a common risk factor reflecting synchronized price movements across the sector. Our analysis identifies key events that have significantly influenced the sector's common volatility shocks, including the COVID-19 pandemic peak in 2020, the aftermath of Donald Trump's presidential inauguration in early 2017, the global stock and energy markets downturn in 2015, and during the Climate Change Conference (COP 27) in 2022. These findings highlight the sensitivity of the clean energy sector to both global economic shifts and significant political and environmental events, underscoring the importance of understanding these dynamics for risk management and investment strategy formulation. Given the estimated common volatility factor of the sector, our study provides a comprehensive factor loading analysis, offering insights into how individual stocks within the sector respond to systematic volatility. We find that that within the clean energy sector, companies have varied sensitivities to common volatility shocks.

Building on our investigation of the overarching COVOL within the clean energy sector, we further delved into the COVOL of specific sub-sectors. Our study segmented the clean energy sector into five categories including renewable energy generation, energy storage, energy conversion, power conservation, and greener utilities. Our findings reveal distinct volatility patterns across different sub-sectors, which suggest varied responses to both sector-specific and macroeconomic influences. For instance, the energy storage sub-sector exhibited less volatility during political events but showed significant sensitivity to technological advancements and regulatory changes. Conversely, the renewable energy generation sub-sector demonstrated high volatility during global economic downturns and policy announcements related to climate change, underscoring its vulnerability to external economic and environmental factors.

As the common volatility of clean energy sector is time-varying, our study further investigates the impacts of several global and sectoral factors on its dynamics. Using a comprehensive lists of potential drivers, our analysis highlights the inverse relationship between oil

[6] See, https://www.iea.org/data-and-statistics/charts/global-investment-in-clean-energy-and-fossil-fuels-2015-2024.

[7] Annual World Economic Forum survey highlighted that extreme weather was the top risk in terms of likelihood between 2019 and 2021, while weapons of mass destruction, climate action, and infectious diseases were top risk in terms of impact in 2019, 2020, and 2021, respectively.

Table 1
The largest estimated common volatility — All clean energy stocks.

A. Largest common volatility

Date	f_t^{σ}	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
3/16/2020	29.88	−0.24	−15.64	−14.63	−10.04	−12.77	COVID-19
3/18/2020	20.92	0.43	−13.59	−15.50	−27.99	−5.32	COVID-19
2/7/2017	16.12	0.01	−1.06	−1.43	−1.60	0.02	Aftermath of Trump's presidential inauguration
10/23/2015	15.35	−0.17	0.67	−0.23	−1.73	1.10	Global equity selloff following Chinese crash
8/9/2011	14.82	0.22	8.16	4.96	−2.50	4.63	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
3/13/2020	13.79	0.24	3.10	8.83	0.73	8.88	COVID-19
5/10/2010	12.75	−0.08	6.55	4.18	2.23	4.30	Severe flood in US Southeast, causing 1.9 billion damage
11/10/2022	11.62	0.09	9.60	2.20	0.74	5.40	COP 27
3/9/2020	11.26	−0.36	−12.41	−22.49	−28.22	−7.90	COVID-19
9/21/2020	10.99	0.12	−1.18	−3.37	−4.48	−1.16	Higest land and ocean surface temperature for September 2020 in the 141-year record
3/12/2020	10.20	−0.35	−14.45	−13.32	−4.59	−9.99	COVID-19
4/6/2020	10.09	0.70	7.74	5.16	−8.31	6.80	COVID-19
8/8/2011	9.46	−0.32	−10.27	−8.89	−6.63	−6.90	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
10/25/2011	9.26	0.26	−4.15	−2.11	2.06	−2.02	European sovereign debt crisis
10/22/2014	8.37	−0.60	−3.13	−1.91	−2.80	−0.73	Oil price crash 2014–2015
6/28/2021	8.34	1.09	4.23	−3.44	−1.55	0.23	All-time heat records in western North America
3/19/2020	8.32	0.43	5.65	6.58	21.36	0.47	COVID-19
4/1/2020	7.94	−0.25	−7.35	−5.08	−0.83	−4.51	COVID-19
2/7/2022	7.75	−0.40	−0.31	1.27	−1.08	−0.37	Russian-Ukraine tension
12/26/2018	7.66	−0.12	5.65	6.04	8.32	4.84	DOW's biggest single-day point gain ever

B. Estimated factor loadings

LZM (0.31)	ATLX (0.27)	SES (0.23)	NRGV (0.22)	FSR (0.2)	FREY (0.2)
AMPS (0.19)	OPAL (0.18)	FSLR (0.18)	SLDP (0.17)	SPWR (0.16)	CSIQ (0.16)
STEM (0.16)	JKS (0.16)	NVTS (0.15)	JOBY (0.15)	GGR (0.15)	SEDG (0.14)
WOLF (0.13)	CHPT (0.13)	QS (0.13)	SHLS (0.12)	RUN (0.12)	BE (0.12)
AEIS (0.11)	FCEL (0.11)	OLED (0.11)	ALB (0.11)	LEV (0.1)	ITRI (0.1)
ARRY (0.1)	ENPH (0.09)	BELFB (0.09)	GWH (0.09)	SOL (0.08)	MAXN (0.08)
PWR (0.08)	FLNC (0.08)	AMSC (0.08)	BLDP (0.08)	ACHR (0.08)	GEVO (0.08)
AMRC (0.08)	ESE (0.07)	TPIC (0.07)	NIO (0.07)	MYRG (0.07)	PLUG (0.07)
BLNK (0.07)	PLPC (0.07)	ORA (0.06)	BEPC (0.06)	MP (0.06)	ENVX (0.06)
EVGO (0.06)	RNW (0.06)	TSLA (0.06)	THRM (0.06)	PSNY (0.06)	EOSE (0.06)
PLL (0.05)	SQM (0.04)	NAAS (0.04)	RIVN (0.02)	WBX (0.01)	AMPX (0.01)
LAC (0.00)	XPEV (0.00)				

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^{σ} denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

market volatility and common volatility of the clean energy sector, indicating that increased oil market volatility leads to reduced volatility in the clean energy sector. Sub-sectoral investigation further unveils heterogeneous effects from media climate concerns and term spreads on COVOL across sub-sectors. Notably, energy storage and conversion are particularly sensitive to climate discourse, suggesting a strong alignment with technological and policy dynamics. Additionally, the term spread between 10- and 2-year Treasury bonds shows divergent effects, indicating different economic expectations across sub-sectors, which underscores the need for tailored risk management strategies reflecting the unique characteristics and sensitivities within the clean energy market.

Our study makes several significant contributions to the literature on clean energy sector. First, our research significantly advances the field of green finance by being the first to quantify the COVOL within the sector, employing an innovative methodology formulated by Engle and Campos-Martins (2023). This methodological approach enables us to capture the collective responses of individual stocks to external shocks, offering a groundbreaking perspective on the dynamic interactions within the sector. Applying this advanced statistical framework to measure the time-varying common volatility helps gauge overall sector risk and hence our study brings clarity to the volatility interactions that shape the financial landscape of the clean energy stock sector. This marks a crucial development in the literature strand that explores the investment attributes of clean energy stocks (Henriques and Sadorsky, 2008; Kocaarslan and Soytas, 2019; Wen et al., 2014; Wang et al., 2022; Kocaarslan and Soytas, 2021; among others).

Second, this research elucidates the drivers of sector-wide common volatility, offering insights into the underlying factors that influence market movements within the clean energy industry. By identifying and analyzing these drivers, our study helps clarify how media attention to climate change, and fluctuations in oil prices impact the sector's volatility. This contribution is crucial for developing robust financial strategies and risk management practices that can mitigate adverse effects while capitalizing on favorable conditions.

Third, our analysis extends beyond the general sector to explore COVOL within specific sub-sectors of the clean energy market. In this direction, our analysis enriches the growing literature on sub-sector analysis of clean energy stocks (Pham, 2019; Kuang, 2021; Li et al., 2023; Chen et al., 2022). This detailed examination allows us to discern unique volatility characteristics and risk profiles associated with different areas such as renewable energy generation, energy storage, and energy conversion. By segmenting the analysis, we provide stakeholders with nuanced insights that are essential for targeted investment and policy decisions, enhancing the granularity of risk assessment in the clean energy sector.

Fourth, our research makes a significant contribution by quantifying company-specific exposures to COVOL risk, a critical aspect often overlooked in the existing literature. This comprehensive analysis enables us to identify the most vulnerable companies within the clean energy sector to common volatility shocks and to evaluate how these shocks affect their financial performance. Such precise mapping of risk exposure at the company level is essential for investors aiming to optimize their portfolios, allowing them to strategically balance high-risk and stable investments in line with their risk tolerance and investment goals (Antonakakis et al., 2018; Maitra et al., 2021; Pham et al., 2023). Furthermore, this detailed risk assessment provides policymakers with the necessary insights to develop targeted support measures, thereby strengthening the resilience and sustainability of the clean energy market.

Lastly, our analysis makes a significant contribution to the asset pricing literature by demonstrating the substantial explanatory power of Common Volatility (COVOL) in predicting the risk and return of clean energy assets. Our findings indicate that COVOL effectively captures the systemic risks inherent in the clean energy sector, providing a more comprehensive understanding of volatility dynamics compared to traditional uncertainty measures. This evidence aligns with the findings of Engle and Campos-Martins (2023), who highlighted the importance of common volatility in global equity markets. By extending their methodology to the clean energy context, our study underscores the versatility and robustness of COVOL as a critical metric for asset pricing. This advancement not only enhances theoretical frameworks within asset pricing but also offers practical implications for investors seeking to optimize portfolio management and for policymakers aiming to develop informed regulatory policies. Consequently, our research provides valuable insights that bridge the gap between asset pricing theory and the practical realities of the clean energy market, facilitating more effective investment strategies and policy interventions.

Overall, our study offers profound implications for both investors and policymakers by highlighting the importance of understanding and managing common volatility in the clean energy sector. For investors, the insights provided can guide more informed decisions regarding asset allocation and risk assessment. For policymakers, understanding the dynamics of COVOL can aid in crafting policies that promote stability in the clean energy market, thus supporting long-term investment in sustainable energy solutions. These contributions significantly advance the field's understanding of financial risks in clean energy, supporting the sector's growth and its critical role in the global transition to sustainable energy.

The structure of the paper is outlined as follows. Section 2 briefly reviews the relevant literature. Section 3 presents the modeling framework used to estimate the COVOL within the clean energy sector. Section 4 details the data sample and discusses the estimation results of COVOL. Section 5 explores the dynamics of COVOL, examining its underlying drivers as well as its explanatory power on asset's return. This section also discusses the policy and practical implications of our findings. Section 6 offers concluding remarks.

2. Literature review

Our study contributes to the clean energy finance literature by focusing on the financial dynamics and risk management of investments in the clean energy stock sector. Therefore, in this section, we will review the related literature to contextualize our research within this field.

The transition from using fossil energy to using clean energy has recently attracted the interest of many researchers. Earlier research has focused on examining and analyzing the relationship between fossil energy and clean energy markets (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Reboredo and Ugolini, 2018; Wen et al., 2014; Reboredo et al., 2017; among others). Henriques and Sadorsky (2008) apply a vector autoregression model and find that technology stock prices have a larger impact on clean energy stock prices than oil prices. Using multivariate GARCH models, Sadorsky (2012) further documents that clean energy stocks are more correlated with technology stocks than with oil prices. In addition, Kumar et al. (2012) investigate the interdependence between oil prices, renewable energy stock prices, and carbon prices. They find that changes in renewable energy stock index are correlated with variations in interest rates, technology stock prices, and past oil prices. Employing an asymmetric GARCH model, Wen et al. (2014) reveal that the correlation between Chinese clean energy stocks and fossil fuel stocks is significant and asymmetric and clean energy stocks are more speculative and riskier. Reboredo et al. (2017) quantify the co-movement between renewable energy stocks and oil prices using the wavelet decomposition method, showing a weak dependence between renewable energy stock prices and oil in the short run but a stronger linkage in the long run.

The more recent development in the literature on clean energy can be branched into three distinct strands. The first examines how investments in clean projects, including clean energy investments, influence corporate strategies and organizational performance. Gianfrate and Peri (2019) find that green bonds can reduce European issuers' debt costs by about 0.2 percent. Tang and Zhang (2020) reveal that green bond issuances increase the issuing firm's stock price and liquidity due to heightened institutional ownership. Flammer (2021) shows that green bond announcements receive positive investor responses, especially for first-time issuers. In China, Su and Lin (2022) note that green bonds have a lower bid–ask spread compared to traditional bonds, while Tan et al. (2022) document a positive impact on the return on equity for issuers of green bonds.

The second strand explores the interdependence among clean energy investments and between clean and conventional financial assets. The literature on the interconnectedness between clean energy stocks and other financial markets shows intricate relationships with significant spillovers from traditional bond and stock markets to green bonds. Studies by Reboredo et al. (2020) and Ferrer et al. (2021) indicate that these spillovers are primarily short-term but can vary in intensity, often influenced by broader economic factors like the US dollar and oil volatility. Research such as that conducted by Saeed et al. (2021) explores the behavior under extreme market conditions, finding that connections between clean and conventional energy investments strengthen, particularly when influenced by macroeconomic variables. Furthermore, Naeem et al. (2023) explore regional specifics within the Gulf Cooperation Council, noting minimal correlations with GCC stocks but stronger connections with markets in the UAE, Qatar, and Saudi Arabia. Other noteworthy studies that explore the co-movement of clean energy sector with dirty energy sources include Farid et al. (2023), Maghyereh et al. (2019), and Alkathery et al. (2023). Other studies focus on the spillover effects between clean energy investments with other green assets. For instance, Pham (2021) investigates the frequency connectedness and cross-quantile dependence between clean energy stocks, green building stocks, green building stocks, and transportation stocks, and green bonds, finding limited spillover effects. Using a time-varying copula model, Liu et al. (2021) reveal a positive relationship in both average and tail connectedness between clean energy stocks and green bonds. Chatziantoniou et al. (2022) introduce a quantile frequency connectedness approach to explore return spillover effects across clean energy, green bonds, and sustainable investments markets, revealing that green bonds and clean energy markets are net receivers of return shocks, while sustainable investments are net transmitters. Dogan et al. (2022) assess the interconnectedness between renewables energy sources and other green assets using the TVP-VAR framework, identifying moderate levels of connectedness with renewable energy sources predominantly acting as net transmitters of volatility shocks. Pham et al. (2024) explore the impact of the climate policy uncertainty index on the return spillovers among green energy stocks using GARCH-MIDAS model and document a negative effect.

The third strand focuses on the investment attributes of clean energy stocks and their determinants. Research show that factors like oil prices, interest rates, and technology stock performance significantly influence price movements of clean energy stocks (Kocaarslan and Soytas, 2019; Pham, 2019), with the sector showing varied responses to these drivers across different sub-sectors. Wang et al. (2022) also note that global economic conditions impact the volatility of clean energy stocks. Notably, fluctuations in the value of the US dollar and macroeconomic uncertainties can exacerbate the volatility of clean energy stocks (Kocaarslan and Soytas, 2021; Shahbaz et al., 2021). In addition, research by Ahmad et al. (2018) and Dutta et al. (2020) highlights the effectiveness of VIX and commodity volatilities as hedging tools against the inherent risks in clean energy equities.

Despite considerable research in the clean energy sector, important questions about its volatility persist. One critical aspect that has not been fully investigated is whether a common volatility factor affects all stocks within the sector. The identification of such a factor is essential for comprehending the systemic risks and operational dynamics that collectively impact these investments. Moreover, it is essential to examine what drives this common volatility — are market-wide economic conditions, climate policy risks or global financial risks contributing to these dynamics? Additionally, understanding how different firms within the sector vary in their exposure to this common volatility factor is vital. This analysis could unveil the susceptibility of individual companies to sector-wide shocks, which is essential for investors looking to mitigate risks and for policymakers striving to stabilize the market. This analysis not only deepens the understanding of financial behaviors within clean energy stock sector but also aids in crafting more robust financial and regulatory strategies tailored to the unique characteristics of the clean energy sector.

3. COVOL methodology

Let $\boldsymbol{r}_t$ be the vector of clean energy excess returns $\boldsymbol{r}_t = \left(r_{1,t}, \dots, r_{N,t}\right)'$ where $r_{i,t} = \tilde{r}_{i,t} - r_{f,t}.\tilde{r}_{i,t}$ is the observed return and $r_{f,t}$ is the risk-free return, $i = 1, \dots, N$.

The first step of the common volatility calculation involves a factor model with $\mathrm{AR}(1) - \mathrm{GARCH}(1,1)$ errors for each time series $i = 1, \dots, N$, of excess returns as follows:

$$r_{i,t} = c_i + \delta_i r_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{f}_t + u_{i,t} \tag{1}$$

$$u_{i,t} = \sqrt{h_{i,t}} e_{i,t} \tag{2}$$

$$h_{i,t} = \omega_i + \alpha_{i,1} u_{i,t-1}^2 + \beta_{i,1} h_{i,t-1} \tag{3}$$

where i, t denotes the stocks and time period. $c_i, \delta_i, \boldsymbol{\beta}_i, \omega_i, \alpha_{i,1}, \beta_{i,1}$ are parameters to be estimated ($\left|\delta_i\right| < 1; \omega_i > 0; \alpha_{i,1} > 0; \beta_{i,1} \geq 0; \alpha_{i,1} + \beta_{i,1} < 1$). $\boldsymbol{f}_t$ is a vector of factors and $u_{i,t}$ is the error term with variance–covariance matrix $h_{i,t}$. $e_{i,t}$ is the standardized residuals. Our factor vector $\boldsymbol{f}_t$ includes the three Fama–French factors (Excess market returns, Small-Minus-Big (SMB), and High-Minus-Low (HML)) and the excess returns on the WTI crude oil continuous futures. The Fama–French factors capture the common risk factors in equity markets, while WTI returns capture oil price shocks, a significant determinant of clean energy stock returns.

Let $\boldsymbol{e}_t = \left(e_{1,t}, \dots, e_{N,t}\right)'$ be a vector of the standardized residuals. Engle and Campos-Martins (2023) argue that even though the standardized residuals have unit variance and zero covariance, their squared term or absolute values are likely to be correlated in the cross-section. Thus, the comovement of volatilities is most likely caused by the positive correlation between shocks to those volatilities, since volatility is partly predictable. Let the variance shock to stock i be:

$$\phi_{i,t}^{\sigma} \equiv \frac{u_{i,t}^2 - h_{i,t}}{h_{it}} = e_{i,t}^2 - 1 \tag{4}$$

$\phi_{i,t}^{\sigma}$ is the proportional difference between the squared idiosyncrasy ($e_{i,t}^2$) and its expectation (1). If many clean energy stocks have larger squared idiosyncrasies than usual at the same time, this can be viewed as a common volatility shock to the entire clean energy sector.[8] Let f_t^{σ} be the variance (latent) factor that captures the common volatility in the clean energy sector: $f_t^{\sigma} > 0; E[f_t^{\sigma}] = 1$. Using this, we can further decompose the standardized residuals as follows:

$$e_{i,t} = \sqrt{g\left(s_i, f_t^{\sigma}\right)} \epsilon_{i,t} \tag{5}$$

$$g\left(s_i, f_t^{\sigma}\right) \equiv s_i\left(f_t^{\sigma} - 1\right) + 1 \tag{6}$$

where $\epsilon_{i,t} \sim \mathrm{IIN}(0,1)$ i.e., independently and identically normally distributed with zero mean and unit variance, $i = 1, \dots, N$. Additionally, $\epsilon_t = \left(\epsilon_{1,t}, \dots, \epsilon_{\mathrm{N},t}\right)'$ is independent of f_t^{σ}. s_i is the factor loading for stock i. The estimation of f_t^{σ} and s_i is conducted using maximum likelihood.[9]

Let ρ_{e^2} be the equicorrelation of the squared standardized residuals. The test statistics for the existence of a common volatility among the stocks is given as follows:

$$\xi_{e^2} = \frac{\sqrt{\frac{NT}{(N-1)/2}} \sum_{i>j,j=1}^{N} \sum_{t=1}^{T} \left(e_{it}^2 - 1\right)\left(e_{jt}^2 - 1\right)}{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(e_{it}^2 - 1\right)^2} \tag{7}$$

ξ_{e^2} has a standard normal distribution under the null hypothesis of no common volatility among the stocks ($\rho_{e^2} = 0$).

3.1. Drivers of common volatility in the clean energy sector

Next, we explore how the common volatility of clean energy sector and sub-sectors is related to various climate and financial risks. Specifically, we estimate the following model:

$$(f_t^{\sigma} - 1) = \alpha_1 * CLM\_FIN\_Risk_t + \alpha_2 * X_t + \epsilon_t \tag{8}$$

where f_t^{σ} denotes a $N-$dimensional vector of common volatility (COVOL) of clean energy sector and sub-sectors. Thus, our dependent variable $(f_t^{\sigma} - 1)$ is the normalized COVOL measures around their means (=1, by construction), therefore, no constant is added to the regressions. $CLM\_FIN\_Risk_t$ is a $N \times Ri$ vector of climate and financial risks, where Ri is the number of risk factors. X_t denotes a $N \times C$ vector of C control variables, which capture the changes in macroeconomic and financial conditions. Specifically, we include the following variables in $CLM\_FIN\_Risk_t$: (1) the logged climate change concern indexes of Ardia et al. (2020) (a proxy for climate risks), (2) the logged CBOE Crude Oil Volatility Index (OVX, a proxy for the oil market volatility), (3) the logged CBOE Volatility Index (VIX, a proxy for the stock market volatility), and (4) the logged CBOE Energy Sector ETF Volatility Index (VXXLE, a proxy for the energy market volatility).[10] Additionally, X_t includes: (1) the returns on the S&P 500; (2) the returns on the USD indexes; (3) the first-differenced term spread between the 10-year and 2-year U.S. Treasury Bills; and (4) a dummy variable for the COVID-19 financial crisis period.[11][12] Note that the VXXLE series were discontinued in early February 2022, therefore, we are not controlling for other crises after 2022 such as the Ukraine-Russia war.[13] ϵ_t denotes the standard errors. Our choice of the explanatory variables in Eq. (8) is motivated by the empirical literature on clean energy stock behaviors. Specifically:

[8] These common events are associated with geopolitical news that are related to the clean energy sector (for example, climate change policy).

[9] We use the GEOVOL package in R to estimate f_t^{σ} and s_i. Following Engle and Campos-Martins (2023), f_t^{σ} is normalized to have a mean of 1, and the maximum number of iterations for the MLE estimation is 150.

[10] Thus, $Ri = 4$ and $CLM\_FIN\_Risk_t$ is a $N \times 4$ matrix of climate and financial risks.

[11] We define this period to be from March 1, 2020 to April 30, 2020.

[12] Thus, $C = 4$ and X_t is a $N \times 4$ matrix of macroeconomic and financial conditions.

[13] All dependent and independent variables used in these regressions are stationary, according to the Augmented Dickey–Fuller and the Phillips–Perron unit root tests. The results of these tests are available upon request.

1. *Climate risks:* The media climate change concern index reflects the extent of media concerns about climate change. An increase in climate change concerns causes a shift in investor preferences towards sustainable investments such as clean energy stocks, which change the risk spillover patterns in energy markets (Narayan, 2024; Pham et al., 2024; Bouri et al., 2023; Cepni et al., 2023; Fahmy, 2022).
2. *Oil market volatility:* An increase in oil price volatility (proxied by an increase in the OVX index) influence investors' perception of risks in the crude oil market, which is considered a substitute for clean energy. Previous studies document a significant effect of oil market volatility on clean energy stock behavior (Ahmad, 2017; Ahmad et al., 2018; Dutta, 2017).
3. *Stock market volatility:* Stock market volatility (proxied by the VIX index) represents the level of uncertainty in the broader equity markets. Given that clean energy stocks are a subset of the overall equity market, it is expected that stock market volatility influence the risk transmission in clean energy markets (Saeed et al., 2021; Ding et al., 2023).
4. *Energy market volatility:* The VXXLE index captures the volatility in energy equity investments. Akyildirim et al. (2022) show that an increase in energy equity market volatility is associated with higher spillovers across energy investments. Dutta et al. (2020) document that an increase in the VXXLE increases the realized volatility of clean energy ETFs.
5. *S&P 500 returns:* The S&P 500 returns capture the performance of the U.S. stock market. As clean energy stock is a sub-sector of the broad stock market, the level of common risks within the clean energy market is expected to be influenced by the S&P 500 returns (Yousaf et al., 2022).
6. *USD index returns:* A stronger USD influences the liquidity and riskiness of clean energy investments, thereby affecting the risk transmissions among clean energy (Kocaarslan and Soytas, 2021).
7. *Term spread:* The term spread between the 10-year and 2-year Treasury bonds is a measure of long-term economic trends and stability, which have been shown to significantly influence the clean energy market (Kocaarslan and Soytas, 2019, 2021).
8. *COVID-19 financial crisis:* Finally, the COVID-19 financial crisis has been shown to increase the risk spillovers in a wide range of markets, including the clean energy and sustainable investment sector (Baker et al., 2020; Le et al., 2023; Ghosh et al., 2023; Jia and Dong, 2024).

To account for the fact that our dependent variable is estimated, we employ the Estimated Dependent Variable (EDV) model of Lewis and Linzer (2005) to estimate Eq. (8). Under this approach, the standard errors are augmented to account for uncertainty in the estimation of the estimated dependent variable, and the coefficients are estimated using Feasible Generalized Least Squares (FGLS).

4. Data and COVOL estimation

In this paper, we employ daily closing prices of 68 clean energy stocks from the WilderHill Clean Energy Index, spanning from January 2010 to January 2024. The data is source from the database Thomson Reuters Datastream. This comprehensive dataset, detailed in Table A.1 in the Appendix A, includes ticker symbols, sub-sector classifications, and business descriptions, representing a wide cross-section of the US clean energy market. Despite being an unbalanced panel due to varying equity launch dates, our methodology accommodates these differences, ensuring accurate COVOL estimations at each time point using all available data.[14] By converting prices to log-returns and adjusting for the risk-free rate, we obtain the stocks' excess returns, with summary statistics and diagnostics detailed in Table A.2 in Appendix A.

To measure the common volatility of the clean energy sector, we estimate the AR(1)-GARCH(1,1) model specified by Eqs. (1), (2), and (3), for each time series of excess returns. Eq. (1) is considered factor model, in which, excess returns is regressed against the four factors as described in Section 3. In addition, each factor model includes a lagged dependent variable given the time dependence observed in the first moment of data. Given the strong evidence for the presence of ARCH effects, we estimate a GARCH (1,1) model for the second moment. The averaged correlation of the standardized residuals from the factor models, 0.07098, which is (slightly) positive. For the test statistics and p-values from the AR(1) and ARCH (1) tests by individual stock, see Table A.2 in Appendix A.

For the sake of saving space, we only present the averaged estimated standardized residuals and volatilities across all stocks in the sample. The averaged estimated residuals are shown in Fig. 1. The daily cross-sectional mean standardized residual is given by averaging the daily standardized residuals of the individual stocks. Fig. 2 show the cross-sectional mean clean energy conditional volatilities, model and computed as the square root of the cross-sectional mean variance obtained from the GARCH (1,1). For comparison, we also show the logged values of the CBOE SP 500 Implied Volatility Index (VIX) (Fig. 2a) and of the CBOE Crude Oil Volatility Index (OVX) (Fig. 2b). The correlations between cross-sectional mean clean energy sector conditional volatility and that of SP 500 index and WTI oil futures are 0.1269 and 0.1828. It is noteworthy despite some correlations, these comparisons highlight the distinct volatility characteristics of the clean energy sector, which motivates our endeavour to measure the sector's common volatility metric.

After estimating the factor pricing models, the volatility standardized residuals from AR(1)-GARCH(1,1) model are saved for each of 68 clean energy stocks. Before estimating the clean energy common volatility, we test the null hypothesis of no common variance shocks as explained in Eq. (7). For this sample, the estimated correlation among the squared standardized residuals is $\hat{\rho}_{e^2} = 0.0250$, and the test statistic is $\hat{\xi}_{e^2} = 43.285$, with a p-value of 0. Thus, the null hypothesis of no common variance shocks is strongly rejected, so we can proceed to estimate the common volatility of the clean energy sector using the standardized residuals of 68 clean energy stocks.

5. Empirical results and implications

5.1. Time-varying sectorwide COVOL and extreme values

The COVOL is estimated as described in Section 4.1. We set the maximum number of iterations to be 150 in the calculation of the COVOL. All of our COVOL estimations converge in less than 105 iterations. To evaluate the goodness-of-fit of the model, we calculate the test statistic in Eqs. (7) using $\hat{\epsilon}_{it}^2 = \frac{\hat{e}_{it}^2}{g(\hat{s}_i, \hat{f}_t^{\sigma})}$. The empirical correlation $\hat{\rho}_{\epsilon^2} = 0.0005$, and the test statistic is $\hat{\xi}_{\epsilon^2} = -2.8264$, with a p-value of 0.9976. Thus, by removing the common volatility, we find no evidence that the resulting squared standardized residuals are positively correlated, which supports the decomposition in Eqs. (5)–(6). This also indicates that the global common volatility factor f_t^{σ} is able to capture volatility co-movements in the clean energy stock market. The 20 largest estimates of common volatility in clean energy sector measured by f_t^{σ} are shown in Table 1 Panel A. Table 1 also display the cross-sectional mean renewable winsorized excess returns ($\bar{r}_t$), the

[14] We follow Campos-Martins and Hendry (2024) to address the unbalanced panels. Specifically, at each point in time, we estimate the global common factors based on all available observations in that cross section. The Monte Carlo simulation analysis in Engle and Campos-Martins (2023) shows that the GEOVOL algorithm works well even for cross-sections with the number of stocks is as small as 2.

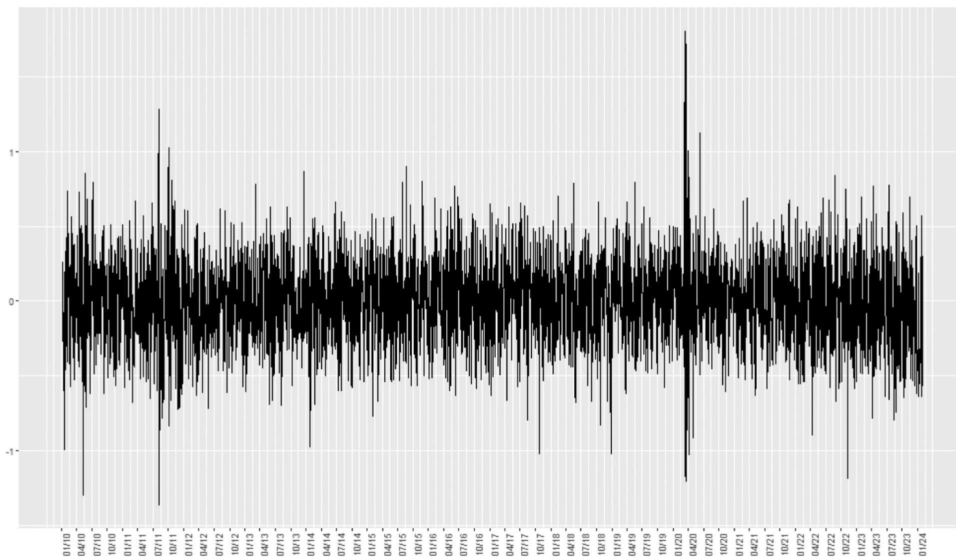


Fig. 1. Cross-sectional mean clean energy residuals.
The figure presents the cross-sectional mean clean energy standardized residuals, which are obtained from the GARCH(1,1) model for each series.

returns on the Invesco WilderHill Clean Energy ETF (r_t^{PBW}), the SPDR energy sector fund (r_t^{XLE}), the WTI crude oil futures (r_t^{WTI}), and the SP 500 index (r_t^{SP500}). There are several intriguing observations standing out from the table. First, the results indicate that several spikes in clean energy sector's COVOL happened during the global COVID-19 breakout, characterized by highly volatile stock or/and energy markets. For instance, the highest value of the sector COVOL (29.88) was on 3/16/2020, at the onset of the COVID-19 pandemic when the major US stock index SP 500 tumbled by more than 12.5 percent. Similarly, the spike of the COVOL on 3/18/2020 was matched with the exceptional decline in oil price of nearly 28 percent. These results are consistent with Shaikh (2022) and Corbet et al. (2020), who document a significant impact of the COVID-19 pandemic on the clean energy sector and heightened volatility spillovers between the clean energy stocks and crude oil during the early stage of the pandemic. In addition, when the sector experienced significant fluctuations, especially negative ones, clean energy stocks were particularly vulnerable to common volatility shocks. This is evidenced by various extreme values of the index, which coincide with substantial variations of the Invesco WilderHill Clean Energy ETF returns.

Furthermore, the interplay between COVOL spikes and climate-related events also offers insights into the sector's risk profile. For instance, the high COVOL values on dates like 8/8/2011 and 8/9/2011 during record warm summers across several U.S. states might have increased concerns from investors on climate changes, leading to heightened common shocks to clean energy stocks. Additionally, the COVOL spike observed on 6/28/2021, following a devastating heatwave in North America, underscores the sector's sensitivity to extreme weather events, which can disrupt operations and affect asset performance. The spike on 11/10/2022, during COP 27, further indicates how global climate policy discussions can introduce uncertainty into the market, affecting the clean energy sector's common volatility. This finding is in line with Sadorsky (2022), who reveals that policy uncertainty intensifies the systematic of clean energy stocks. These patterns illustrate the interconnectedness of climate risk, policy decisions, and market behavior, highlighting the need for investors to consider environmental and climate risks when evaluating clean energy investments.

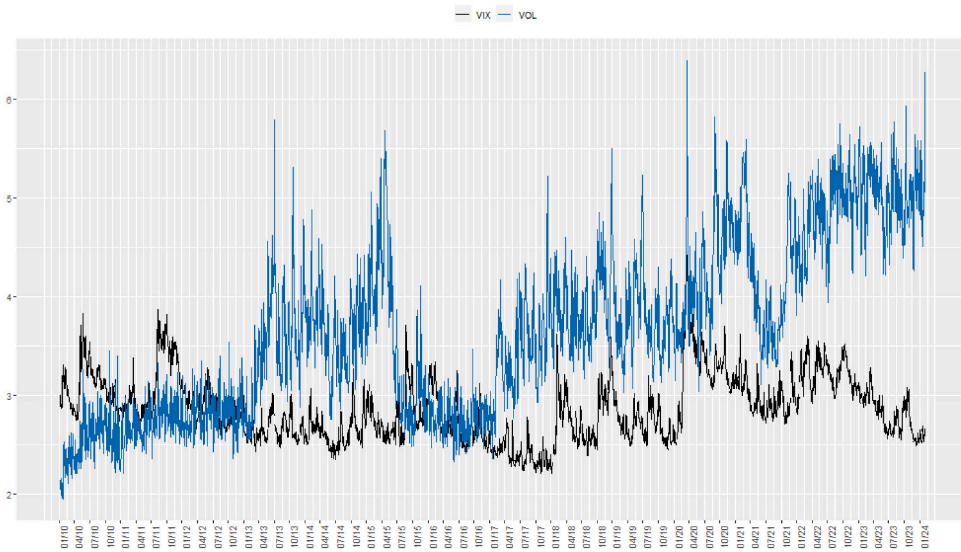
In Table 1 Panel B, we further present the estimated clean energy stocks loadings in descending order of magnitude showing the proportional impact of COVOL on each stock's variance. It is noteworthy that there is substantial heterogeneity in the individual stock factor loadings with the highest and lowest loadings ranging from 0.31 (LZM) and 0.00 (XPEV). The substantial heterogeneity in the individual stock factor loadings, as highlighted in the clean energy sector analysis, underscores the varied responses of companies to sector-wide volatility shocks. Stocks like LZM (Lifezone Metals), ATLX (Atlas Lithium), and SES (SES AI Corp) showing the largest factor loadings are highly sensitive to such shocks, suggesting their stock prices may exhibit more pronounced fluctuations in response to sector-wide changes. This heightened sensitivity could be attributed to their specific business models, market positions, or the nature of their involvement in the clean energy sector. For instance, companies heavily invested in pioneering technologies or those with less diversified operations might be more susceptible to shifts in investor sentiment or regulatory changes affecting the sector.

Conversely, the minimal impact of common volatility shocks on companies like AMPX (Amprius Technologies), LAC (Lithium Americas), and XPEV (Xpeng) indicates a lower sensitivity to sector-wide trends. This could reflect more stable operational bases, diversified investment strategies, or business models less reliant on the variables driving sector-wide volatility. For investors, understanding these dynamics is crucial for portfolio diversification and risk management. It suggests that a mix of stocks with varying sensitivities to common volatility shocks could balance potential risks and rewards.

Moreover, these findings emphasize the importance of in-depth analysis for investors considering clean energy stocks. Identifying companies with higher loadings could pinpoint higher-risk investments, potentially offering higher returns but requiring careful monitoring for signs of sector-wide distress. Similarly, stocks with lower sensitivity to common volatility might provide more stability, serving as a hedge against sector-specific risks in a diversified portfolio. Overall, the disparity in factor loadings among clean energy stocks not only highlights the sector's complexity but also its potential for strategic investment planning. Investors and fund managers can leverage this information to tailor their investment approaches, aligning them with their risk tolerance and investment goals while contributing to the transition to a more sustainable energy future.

In Fig. 3, we further display the monthly averaged estimated clean energy sector common volatility (COVOL). It is observable that the COVOL experienced substantial variations over time, fluctuating between 0.5 and 6. These variations indicate the time-varying nature of COVOL, emphasizing that the common risk factor to clean energy sector varies with the sector's sensitivity to changes in macroeconomic conditions, renewable energy policy shifts, or sector developments. Furthermore, major spikes in COVOL can often be traced to pivotal

(a) Conditional volatilities vs. VIX



(b) Conditional volatilities vs. OVX

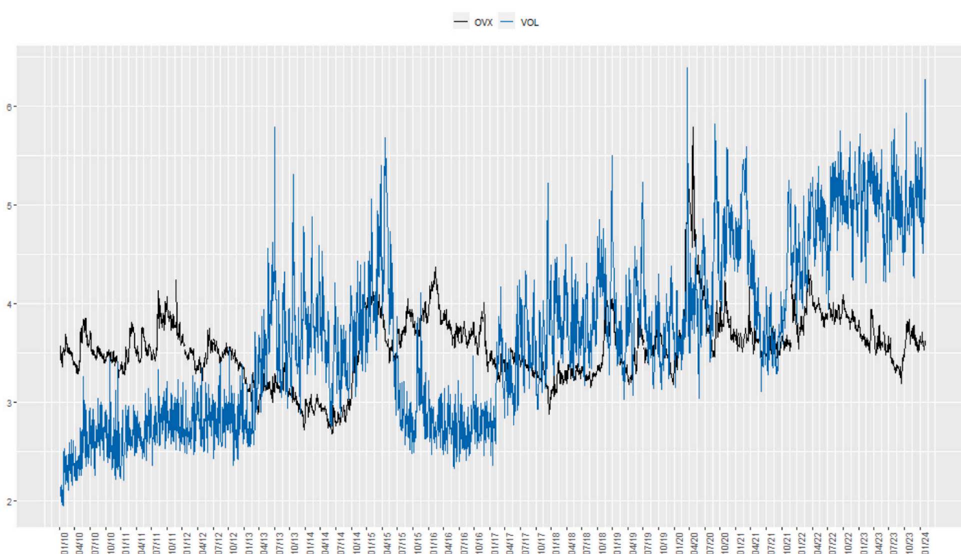


Fig. 2. Cross-sectional mean clean energy conditional volatilities.
The blue line presents the cross-sectional mean clean energy conditional volatilities, which are obtained from the GARCH(1,1) model for each series. The black line presents the logged values of the CBOE Volatility index (VIX) (Fig. 2(a)), and of the CBOE Crude Oil Volatility Index (OVX) (Fig. 2(b)).

events in global economy or financial markets. For instance, a notable surge in COVOL during the early months of 2020 coincides with the onset of the COVID-19 pandemic, which causes substantial volatility across global financial markets and led to unprecedented volatility in energy prices (Szczygielski et al., 2022). The COVID-19 pandemic had a profound impact on global energy demand and investment trends, accelerating the transition towards clean energy. The implementation of travel restrictions and lockdowns led to a considerable reduction in energy needs as industrial activities slowed down, causing a significant drop in oil prices. For instance, the price of oil plummeted to a two-decade low in April 2020 due to the pandemic's impact on demand and a price war between major oil producers.

Simultaneously, these conditions facilitated a rise in clean energy investments, as evidenced by the increase in additions of renewable energy sources like wind and solar PV at the fastest rate in two decades, despite economic downturns. The Paris-based International Energy Agency's "World Energy Outlook 2020" report indicated that while investment in fossil fuels declined, investment in renewable projects was projected to rise. This trend reflects a broader shift in the global energy mix, with renewables set to meet a significant portion of energy demand growth over the coming decade. The growth of renewable energy investments is also supported by the rise in sustainable financial instruments, such as green bonds. In 2020, despite the overall fall in energy investment, sustainable bond issuance increased, with projections for green bonds alone reaching significant totals by year-end. This surge in sustainable financing, contributed by both developed and emerging markets, indicates a growing commitment to green energy projects and sustainability-focused financial strategies.

The spike in COVOL during July and August 2011 can be attributed to the European sovereign debt crisis, which was a major financial event affecting global markets during this time. The crisis was characterized by high government debt and institutional failures in several European countries, sparked by Greece's debt reaching almost twice the

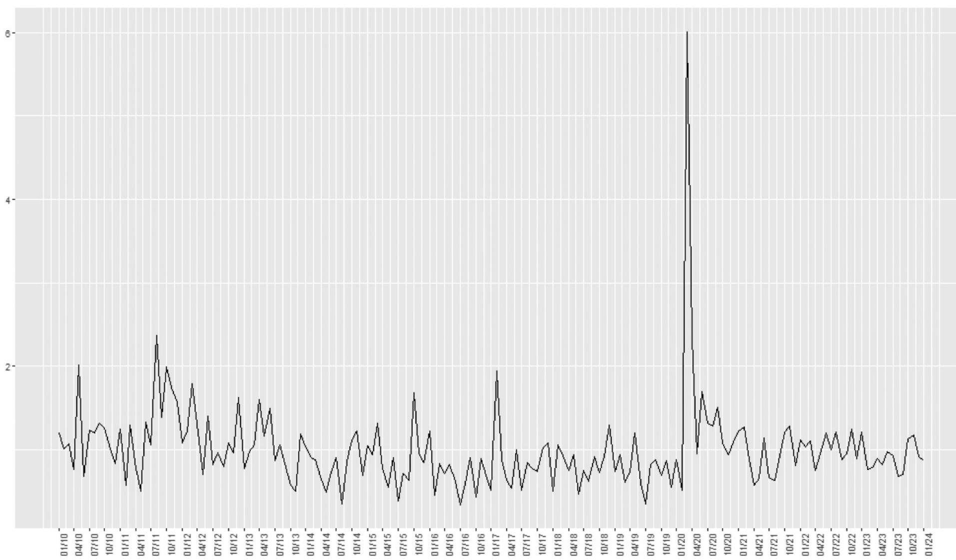


Fig. 3. The monthly common volatility — All clean energy stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for all clean energy stocks.

Eurozone limit set at 60 percent of GDP. This triggered a cascade of financial instability across the European Union, with subsequent bailouts requested by countries like Ireland, Portugal, Cyprus, and Spain to begin economic recovery. The crisis had significant implications for the global economy, including the energy markets. During periods of financial distress, investments in different sectors, including clean energy, may be affected as investors react to changing risk assessments and seek to reallocate funds. Uncertainty in European economies could have led to broader market volatility, influencing the energy sector, as it is often sensitive to economic cycles and policy changes (Ferrer et al., 2018). The heightened risk aversion during such crises typically increases the cost of borrowing and impacts investment in sectors perceived as riskier, which at times can include clean energy.

5.2. Sub-sector COVOL

In this subsection, we provide more insights into the COVOL of clean energy sector by examining the sub-sector COVOL. Kuang (2021) documented significant heterogeneities in risk and return profiles across different clean energy stock sub-sectors. We categorize clean energy stocks into five sub-sectors, including renewable energy generation (11 companies), energy storage (18 companies), energy conversion (15 companies), power conservation (18 companies) and greener utilities (6 companies). This examination is important for at least two reasons. First, sub-sector analysis allows for a more nuanced understanding of risk within the clean energy sector. By partitioning the sector into various sub-sectors, we can discern specific risks and performance drivers unique to each area. For example, renewable energy generation companies may have different volatility profiles compared to those in energy storage, given their distinct operational challenges and market dynamics. Likewise, companies focused on energy conversion and greener utilities may experience unique factors affecting their common volatility due to varying regulatory environments and technological developments. Second, an in-depth look at sub-sector COVOL provides insights into the interplay of technological innovations, policy changes, and market forces within the renewable energy industry. Technological breakthroughs in energy storage or conversion, for instance, could significantly alter the investment landscape, potentially leading to a reallocation of capital within the sector and affecting the common volatility accordingly. Meanwhile, shifts in public policy towards greener utilities could impact these companies differently compared to those in energy generation, further justifying the need for sub-sector examination.

To estimate the sub-sector COVOL, we separate the AR(1)-GARCH (1,1) standardized residuals $e_{i,t}$ into sub-samples which correspond to the five sub-sectors described above. Then for each sub-sample, we repeat the empirical procedure discussed in Section 5.1. The resulting COVOL estimated for each sub-sample represent the common volatility in the sub-sectors. Note that while the sector-wide COVOLs capture the common variance shocks among all 68 clean energy stocks, the sub-sector COVOLs capture the common variance shocks for the relevant sub-samples of these 68 stocks. As stocks within the same sub-sectors are more closely related to one another, the sub-sector COVOLs further capture the dynamics within the sub-sectors, which may have not been captured by the sector-wide COVOL. Additionally, the sub-sector COVOL also capture the idiosyncrasies in the common volatility among different clean energy sub-sectors. This is useful in identifying the sub-sector COVOL that matters the most in predicting clean energy sector-wide risks and returns, as we will further illustrate in Section 5.3.

Before we proceed with the sub-sector COVOL estimation, we verify that common volatility exists across all AR(1)-GARCH(1,1) residuals in each sub-sector and report the results in Panel A of Table A.3. The null hypothesis of no common variance shocks is strongly rejected across all sub-sectors. Next, after estimating the sub-sector COVOL, we evaluate the goodness-of-fit of the COVOL decomposition by calculating the test statistic in Eq. (7) using $\hat{\epsilon}_{it}^2 = \frac{\hat{e}_{it}^2}{g(\hat{s}_i, \hat{f}_t^{\sigma})}$ for each sub-sector. As shown in Panel B of Table A.3, we fail to reject the null hypothesis of no common volatility across all sub-sectors after the COVOL decomposition. This supports the decomposition in Eqs. (5)–(6) for the sub-sectors and indicates that the common volatility factor f_t^{σ} is useful in capturing the volatility co-movements in the clean energy sub-sectors.

Similar to the sector wide analysis, for each sub-sector, we present each sub-sector's 20 largest COVOL values and the loading factors of constituent companies. The outcomes, which include the highest common volatility values and corresponding company loadings, are systematically cataloged in Tables 2 to 6. Each table is dedicated to one of the four sub-sectors: Table 2 for Renewable Energy Generation, Table 3 for Energy Storage, Table 4 for Energy Conversion, Table 5 for Power Conservation, and Table 6 for Greener Utilities. This structured approach provides an organized view of the sub-sector-specific common volatility metrics, facilitating comparative analysis and strategic assessment within the renewable energy industry.

In Tables 2 through 6, Panel A delineates the most substantial common volatility (COVOL) estimates across clean energy sub-sectors, juxtaposed with mean winsorized excess returns and returns on key

Table 2
The largest estimated common volatility — Renewable energy generation sector.

A. Largest common volatility

Date	f_t^σ	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
3/13/2020	14.93	0.24	3.10	8.83	0.73	8.88	COVID-19
11/16/2021	10.29	−0.32	0.08	0.15	−0.15	0.39	COP 26
4/6/2020	10.16	0.70	7.74	5.16	−8.31	6.80	COVID-19
3/18/2020	9.69	0.43	−13.59	−15.50	−27.99	−5.32	COVID-19
3/28/2011	9.58	0.41	0.48	−0.24	−1.36	−0.28	Fukushima Daiichi nuclear disaster
3/16/2020	8.68	−0.24	−15.64	−14.63	−10.04	−12.77	COVID-19
10/22/2014	8.28	−0.60	−3.13	−1.91	−2.80	−0.73	Oil price crash 2014–2015
10/20/2011	8.11	−0.16	0.35	0.78	−0.95	0.45	US stock seffoff following European sovereign debt crisis
3/19/2020	8.00	0.43	5.65	6.58	21.36	0.47	COVID-19
12/2/2021	7.36	−0.28	−0.09	2.87	1.41	1.41	COVID-19 (first case of omicron in the US)
12/5/2013	7.18	−0.92	−0.80	−0.34	0.19	−0.43	COP 19
11/17/2011	6.83	−0.91	−2.70	−2.31	−3.74	−1.69	European sovereign debt crisis
10/31/2022	6.60	1.24	1.90	0.84	−1.57	−0.75	Stock market volatility due to inflationary concerns
12/7/2010	6.51	−0.57	−0.39	−0.38	−0.77	0.05	COP 16
1/27/2011	6.51	0.43	0.19	−0.59	−1.95	0.22	Coolest January in the US since 1994
1/23/2014	6.48	−1.75	−2.48	−1.14	0.61	−0.89	Extreme weather worldwide
1/12/2015	6.42	−0.93	−1.60	−2.92	−4.85	−0.81	Oil price crash 2014–2015
8/10/2012	6.25	0.59	0.71	0.18	−0.53	0.22	Drought disaster in the US
4/20/2020	6.18	−0.87	−2.46	−3.17	0.00	−1.80	COVID-19
6/19/2013	6.11	−1.07	−0.93	−0.92	−0.20	−1.39	European Commission meeting for climate and energy policies in Brussels

B. Estimated factor loadings

CSIQ (0.42)	FSLR (0.4)	JKS (0.38)	OPAL (0.34)	AMPS (0.34)	ARRY (0.34)
TPIC(0.24)	MAXN(0.22)	SOL(0.19)	ORA(0.13)	GEVO(0.11)	

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^σ denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

financial indices such as the Invesco WilderHill Clean Energy ETF, the SPDR Energy Sector fund, WTI crude oil futures, and the SP 500 index. These observations yield several insights. Most pronounced is the clustering of extreme COVOL values in the renewable energy generation, energy conversion and power conservation sub-sectors during the COVID-19 pandemic, mirroring the sector-wide COVOL profile. Intriguingly, the peak COVOL readings in the energy conversion and power conservation sub-sectors coincide precisely with the sector-wide apexes, suggesting synchronous volatility shocks across these domains during critical periods such as the initial COVID-19 outbreak. This concurrence highlights the role of the pandemic in precipitating synchronized volatility within the clean energy sector, particularly accentuating the vulnerability of sub-sectors such as energy conversion and power conservation. The correlation between these spikes and global market tremors underscores the intrinsic link between clean energy investments and broader economic stability.

Unlike other clean energy sub-sectors, which showed peaks in common volatility (COVOL) closely aligned with the COVID-19 pandemic, the energy storage and greener utilities sectors diverged significantly in the timing of their highest COVOL events. Remarkably, the energy storage sector did not experience any of its extreme COVOL values during the pandemic. In the case of the greener utilities sector, only two major COVOL events coincided with this period. Instead, the most significant COVOL spikes for both energy storage and greener utilities were concentrated between 2010 and 2012. This timeframe was marked by several pivotal global events impacting equity, energy, and renewable markets, such as the European debt crisis, the Arab Spring, the Fukushima Daiichi nuclear disaster, and the climate change negotiations culminating in the Durban Platform for Enhanced Action, all occurring within these years. Notably, the extreme COVOL values for these sub-sectors were not primarily influenced by significant fluctuations in the broader energy market (e.g., crude oil prices) or the stock market (e.g., SP 500 returns). This stands in contrast to other sub-sectors, where extreme COVOL events were more closely linked to major market movements.

This differentiation suggests that these sub-sectors are influenced by distinct sub-industry dynamics or events, which is consistent with findings of Kuang (2021) and Pham (2019). The energy storage sub-sector, pivotal for enabling the integration of intermittent clean energy sources like solar and wind into the grid, might experience volatility spikes tied to technological deployments, regulatory changes, or shifts in supply chain dynamics. The spike in energy storage COVOL in 2015–2016 can be explained by the substantial jump in the deployment of energy storage technologies during this period, compared to the previous period.[15] This period also observes several legislative changes that influence the deployment of energy storage technologies. For example, the PJM's frequency regulations, which target grid frequency stability, require the need to quickly ramp up or down electricity supply into the grid. This further emphasize the roles of advanced storage technologies.[16] A bipartisan Battery Storage Caucus was also proposed during this period, which aims to support the development of storage technology in the U.S. Such events can significantly impact investor perceptions and market valuations independent of broader economic trends. Similarly, the greener utilities sub-sector, encompassing companies involved in the transmission and distribution of clean energy, might see its volatility shaped by policy announcements, shifts in consumer demand for clean energy, or changes in infrastructure investment priorities. These factors can lead to volatility patterns that diverge from those observed in the clean energy sector at large during the pandemic. This divergence underscores the nuanced nature of the clean energy market and highlights the importance of sub-sector-specific analyses. Investors

[15] Please see the Energy Information Administration (EIA)'s battery storage report for details: https://www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery_storage_2021.pdf.

[16] Please see https://kleinmanenergy.upenn.edu/research/publications/energy-storage-in-pjm-exploring-frequency-regulation-market-transformation/ for an overview of the regulations.

Table 3
The largest estimated common volatility — Energy storage sector.

A. Largest common volatility

Date	f_t^{σ}	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
2/7/2017	54.94	0.01	−1.06	−1.43	−1.60	0.02	Aftermath of Trump's presidential inauguration
10/23/2015	48.56	−0.17	0.67	−0.23	−1.73	1.10	Global equity selloff following Chinese crash
5/10/2010	15.40	−0.08	6.55	4.18	2.23	4.30	High stock market volatility following 2010 Flash Crash
3/14/2011	14.68	−1.05	0.70	0.54	0.03	−0.61	Fukushima Daiichi nuclear disaster
3/2/2010	13.93	0.76	0.73	0.83	1.24	0.23	Heavy snowstorms in the US
9/21/2012	13.33	0.28	−0.53	0.11	1.10	−0.01	Third warmest September on record
11/16/2015	12.90	0.31	2.17	3.28	2.42	1.48	COP 21
12/15/2010	12.37	−0.76	−0.39	−0.55	0.38	−0.51	Aftermath of Obama's presidential election
6/28/2021	12.17	1.09	4.23	−3.44	−1.55	0.23	All-time heat records in western North America
7/16/2010	12.15	−0.99	−3.05	−2.41	−0.80	−2.92	Stock market volatility due to economic concerns
9/19/2016	11.86	0.41	1.64	−0.06	0.63	0.00	Second highest global land and ocean surfaces for September in the 137-year record
11/30/2010	11.59	−0.95	−2.16	−0.35	−1.91	−0.61	COP 16
1/28/2011	10.92	−1.31	−2.76	−0.43	4.23	−1.80	European sovereign debt crisis
9/7/2011	10.89	0.13	3.36	3.60	3.79	2.82	European sovereign debt crisis
1/26/2010	10.80	0.23	−0.49	−0.64	−0.73	−0.42	Second warmest worldwide ocean surface temperature for January
7/13/2021	10.79	−1.55	−2.72	−0.76	1.54	−0.35	Earth's warmest month in recorded history
5/6/2011	10.71	1.08	0.92	0.44	−2.66	0.38	European sovereign debt crisis
8/9/2011	10.38	0.22	8.16	4.96	−2.50	4.63	Arab Spring
10/18/2012	10.32	−1.09	−1.22	−0.01	−0.02	−0.24	Widespread dust storm in the US
11/29/2016	9.50	−0.48	−1.89	−1.23	−4.01	0.13	Paris Agreement came into force

B. Estimated factor loadings

ATLX (0.52)	SLDP (0.36)	SES (0.33)	ALB (0.32)	FREY (0.31)	PLL (0.27)
QS (0.27)	LEV (0.2)	GWH (0.18)	SQM (0.18)	NIO (0.12)	TSLA (0.12)
FLNC (0.1)	AMPX (0.08)	ENVX (0.05)	RIVN (0.04)	LAC (0)	XPEV (0)

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^{σ} denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

and analysts should consider the unique drivers of volatility within each sub-sector to make informed decisions and develop robust investment strategies that account for the distinct risks and opportunities presented by the energy storage and greener utilities markets.

The analysis of factor loadings across different clean energy sub-sectors, as detailed in Panel B of Tables 2 to 6, reveals the varying degrees of sensitivity individual companies have to common volatility shocks within their respective sub-sectors. This sensitivity indicates how sub-sector common volatility innovations might impact these companies. In the renewable energy generation sub-sector, Canadian Solar (CSIQ) and First Solar (FSLR) emerge as the most affected by sub-sector-specific volatility, indicating a higher risk profile in response to subsector-wide shocks. Conversely, Ormat (ORA) and Gevo (GEVO) show the least sensitivity, suggesting a more stable performance during turbulent times (Table 2, Panel B). The energy storage sub-sector sees Atlas Lithium (ATLX) and Solid Power (SLDP) as the most vulnerable to common volatility shocks, highlighting their potential risk exposure to sudden changes in market dynamics. On the other end, Lithium Americas (LAC) and Xpeng (XPEV) demonstrate lower susceptibility, indicating relative resilience (Table 3, Panel B).

For the energy conversion sub-sector, Lifezone Metals (LZM) and Plug Power (PLUG) are identified as the most impacted by common volatility shocks. This suggests that these companies' valuations are more sensitive to sector-specific risks. ESCO Technologies (ESE) and Gentherm (THRM), however, face the least impact, which could reflect their operational stability or diversified risk management strategies (Table 4, Panel B). In the power conservation sub-sector, Fisker (FRS) and Gogoro (GGR) bear the brunt of sub-sector volatility shocks, potentially making their financial performance more unpredictable during periods of sector-wide stress. Polestar (PSNY) and NaaS Technology (NAAS), however, exhibit minimal sensitivity, indicating a possible buffer against such shocks (Table 5, Panel B). Finally, within the greener utilities sub-sector, Sun Power (SPWR) and Sunrun (RUN) are the most significantly affected by common volatility shocks, underscoring their higher exposure to sector-specific challenges. Stem (STEM) and Brookfield Renewable (BEPC), however, show the least sensitivity, which may point to their strategic positioning or effective risk mitigation practices (Table 6, Panel B).

These findings not only highlight the differential impact of common volatility shocks across companies within the same sub-sectors but also suggest potential strategic considerations for investors and managers. Companies with lower sensitivity to these sub-sector common shocks might offer more stability and lower risk in volatile markets, while those with higher sensitivity might require closer monitoring and proactive risk management strategies.

To further illustrate the heterogeneity in the common volatility across sectors, we present the pairwise correlation matrix among the sector-wide and subsector COVOL in Table A.4. The result shows that the coefficient of correlations between the sector-wide COVOL and individual sub-sector COVOL range between 0.36 and 0.60, indicating a moderately positive relationship. Furthermore, the coefficients of correlation among the individual sub-sector COVOLs much smaller (typically less than 0.20). This indicates that clean energy stocks in the same sub-sector have distinguishing common volatility patterns, compared to stocks in the broader clean energy market.

Next, we compare the variance in the firm-level factor loadings across sub-sectors. Specifically, we calculate the variance ratio tests of

Table 4
The largest estimated common volatility — Energy conversion sector.

A. Largest common volatility

Date	f_t^{σ}	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
3/16/2020	24.42	−0.24	−15.64	−14.63	−10.04	−12.77	COVID19
3/18/2020	15.96	0.43	−13.59	−15.50	−27.99	−5.32	COVID19
2/7/2022	15.11	−0.40	−0.31	1.27	−1.08	−0.37	Russia-Ukraine tension
8/8/2011	11.96	−0.32	−10.27	−8.89	−6.63	−6.90	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
1/3/2012	10.11	1.10	3.30	2.74	4.09	1.54	US stock market rally on positive economic data of China and India
3/9/2020	9.42	−0.36	−12.41	−22.49	−28.22	−7.90	COVID19
8/4/2011	9.22	−0.09	−8.54	−7.10	−5.94	−4.90	European sovereign debt crisis
9/9/2021	8.82	0.26	0.87	0.21	−1.69	−0.46	COVID19
3/12/2020	8.81	−0.35	−14.45	−13.32	−4.59	−9.99	COVID19
8/9/2011	8.54	0.22	8.16	4.96	−2.50	4.63	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
9/10/2010	8.30	−0.64	−0.22	1.03	2.92	0.49	Oil rally following OPEC data
1/25/2022	8.02	−1.29	−2.43	3.81	2.71	−1.22	Russia-Ukraine tension
11/29/2023	7.92	0.80	3.20	−0.75	1.88	−0.09	COP 28
4/1/2020	7.54	−0.25	−7.35	−5.08	−0.83	−4.51	COVID19
4/30/2020	7.31	−0.93	−3.60	−2.24	22.39	−0.93	COVID19
1/3/2022	7.26	0.79	2.13	3.05	1.15	0.64	Russia-Ukraine tension
3/7/2022	7.26	0.42	1.97	1.46	3.17	−3.00	Russia-Ukraine tension
11/28/2011	7.22	0.82	4.28	3.68	1.48	2.88	COP 17
3/19/2020	7.22	0.43	5.65	6.58	21.36	0.47	COVID19
4/6/2020	7.18	0.70	7.74	5.16	−8.31	6.80	COVID19

B. Estimated factor loadings

LZM (0.45)	PLUG (0.38)	FCEL (0.32)	BE (0.31)	NRGV (0.3)	BLDP (0.27)
ACHR (0.25)	ENPH (0.22)	JOBY (0.21)	SEDG (0.2)	BELFB (0.19)	MP (0.16)
AEIS (0.13)	ESE (0.12)	THRM (0.09)			

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^{σ} denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

the sub-sector factor loadings presented in Panel B of tables 2–6 and present the results in Table A.5. The number in each cell indicates the variance ratio between the factor loadings' variance of the row sub-sector and that of the column sub-sector. The p-value of the variance ratio tests are in the parentheses. Looking at the table, we can conclude that the renewable energy subsector has the smallest factor loading variance, indicating that firm-level exposure to common volatility in the renewable energy subsector is more homogeneous compared to other subsectors. The ranking in the factor loading variance in the other subsectors (in descending orders) is as follows: (1) Energy Conversion; (2) Greener Utilities; (3) Energy Storage; (4) Power Conservation. However, the p-values of the variance ratio tests indicate that the difference in factor loading variances among these subsectors are statistically insignificant. Note that while the renewable energy sub-sector has relatively smaller exposure heterogeneity among firms, we still observe substantial variations in the renewable energy factor loadings, which range from 0.11 to 0.4. As the factor loadings measure the individual firms' exposure to common volatility, comparing the factor loading variances between sub-sectors allows us to identify the sectors with the largest (smallest) firm-level exposure heterogeneity. Larger variances in firm-level factor loadings imply that firms respond more differently to common volatility, which indicates larger hedging and diversification opportunity within a particular sub-sector.

The examination of how common volatility (COVOL) within clean energy sub-sectors fluctuates over time provides deeper insights into the dynamics of sub-sector common volatility shocks. Through analyzing the monthly averages of COVOL, presented from Figs. 4 to 8 for each specific sub-sector, we uncover distinct temporal patterns that reveal the intricate ways external events and sector-specific developments influence market behavior. Across the majority of clean energy sub-sectors, the apex of monthly averaged COVOL is observed in March 2020, a testament to the profound impact of the COVID-19 pandemic on global financial and energy markets. This convergence points to the widespread effect of such systemic external shocks, leading to increased volatility across various sectors of clean energy. Contrastingly, the energy storage sector displays a unique pattern of volatility peaks, notably in late 2015 and late 2016. These periods coincide with significant global climate policy developments, including the negotiations leading up to and the enactment of the Paris Agreement. This divergence suggests that policy and regulatory milestones, especially those related to climate change, exert a considerable influence on the energy storage sector, underscoring its pivotal role in the transition towards low-carbon energy solutions.

Overall, the empirical findings delineate the distinctive volatility landscapes across clean energy sub-sectors, illustrating the profound impact of global events like the COVID-19 pandemic on market volatility. Sector-specific analyses, particularly around factor loadings, offer critical insights into individual companies' vulnerability to common volatility shocks. The divergence in volatility patterns between sub-sectors such as energy storage and greener utilities highlights the influence of policy and technological developments. Temporal analysis further underscores the sector's responsiveness to external shocks over time. Ultimately, these insights emphasize the necessity of nuanced, sub-sector-specific strategies for navigating the complexities of the clean energy market.

5.3. Determinants of clean energy COVOL

Given the time-varying nature of COVOL highlighted in Sections 5.1 and 5.2, this section delves into how various global uncertainty factors influence the common volatility within the clean energy sector. To this end, we employ the Estimated Dependent Variable (EDV) model to estimate Eq. (8), which accounts for the uncertainty in the estimation of the dependent variable (COVOL). The corresponding regression results presented in Table 7 offer valuable insights into the determinants of common volatility (COVOL) across the clean energy sector and its sub-sectors. The table suggests that the common volatility (COVOL)

Table 5
The largest estimated common volatility — Power conservation sector.

A. Largest common volatility

Date	f_t^{σ}	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
3/16/2020	24.27	−0.24	−15.64	−14.63	−10.04	−12.77	COVID19
9/21/2020	16.95	0.12	−1.18	−3.37	−4.48	−1.16	COVID19
3/18/2020	11.42	0.43	−13.59	−15.50	−27.99	−5.32	COVID19
3/12/2020	10.26	−0.35	−14.45	−13.32	−4.59	−9.99	COVID19
12/19/2018	9.25	−1.21	−1.95	−1.18	2.05	−1.55	High stock market volatility due to Fed's rate hike concern
12/28/2016	9.01	−1.00	−1.59	−1.09	0.30	−0.84	Aftermath of Trump's presidential election
8/9/2011	8.94	0.22	8.16	4.96	−2.50	4.63	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
2/12/2018	8.82	1.34	1.60	1.62	0.15	1.38	High stock market volatility due to Fed's rate hike concern
6/24/2011	8.72	−0.12	−0.57	−1.91	0.15	−1.18	European sovereign debt crisis
11/10/2022	8.70	0.09	9.60	2.20	0.74	5.40	Stock rally following easing inflation concern
1/29/2020	8.41	−0.77	−0.46	−1.05	−0.28	−0.09	COVID19
11/28/2011	7.92	0.82	4.28	3.68	1.48	2.88	COP 17
2/29/2012	7.80	−0.55	−3.41	−1.14	0.49	−0.47	N/A
5/10/2010	7.17	−0.08	6.55	4.18	2.23	4.30	High stock market volatility following 2010 Flash Crash
6/14/2011	6.77	−0.35	2.30	2.11	2.11	1.25	European sovereign debt crisis
5/30/2013	6.74	0.95	1.26	−0.23	0.51	0.37	Third warmest May over global land and ocean surfaces on record
6/16/2022	6.72	−0.35	−6.70	−5.80	1.96	−3.31	2022 US bear stock market
2/7/2019	6.65	−0.75	−1.48	−2.24	−2.57	−0.94	US-China tradewar
3/3/2016	6.61	0.76	−0.72	1.50	−0.26	0.35	Highest March temperature on record
6/14/2010	6.59	0.39	0.93	−0.52	1.80	−0.18	Record-warm temperature in several US cities

B. Estimated factor loadings

FSR (0.40)	GGR (0.40)	CHPT (0.34)	ITRI (0.33)	AMRC (0.32)	WOLF (0.31)
WBX (0.24)	BLNK (0.22)	NVTS (0.2)	OLED (0.17)	PWR (0.16)	EVGO (0.15)
MYRG (0.13)	AMSC (0.11)	PLPC (0.11)	SHLS (0.07)	PSNY (0.06)	NAAS (0.01)

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^{σ} denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

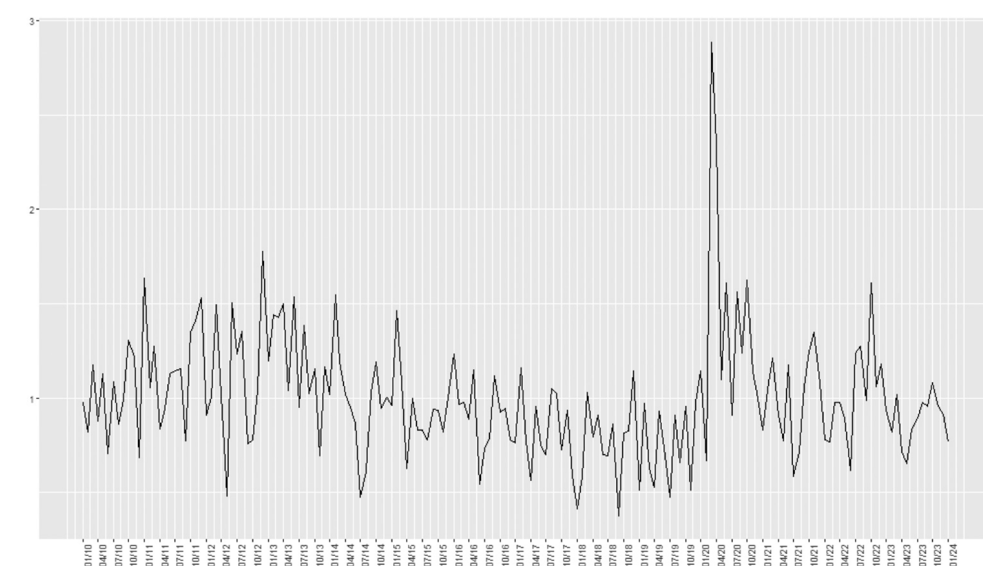


Fig. 4. The monthly common volatility — Renewable energy generation stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for all renewable energy generations stocks.

increases significantly during the COVID-19 financial crisis, as the coefficients on the COVID dummy variables are positive and statistically significant across the table.

Column (1) of Table 7 investigates the determinants of sector-wide COVOL. First, the media climate change concern (MCCC) index exhibits a negative and statistically significant relationship with the common volatility of clean energy stocks. One potential explanation is that as concerns about climate change increases, investments in clean energy technologies become increasingly diverse (for example, across different types of technologies, geographical regions, etc.). This contributes to

Table 6
The largest estimated common volatility — Greener utilities sector.

A. Largest common volatility							
Date	f_t^{σ}	$\bar{r}_t$	r_t^{PBW}	r_t^{XLE}	r_t^{WTI}	r_t^{SP500}	Event
5/20/2010	14.92	−0.44	−4.63	−4.57	−2.70	−3.98	High stock market volatility following 2010 Flash Crash
3/18/2020	12.05	0.43	−13.59	−15.50	−27.99	−5.32	COVID19
2/25/2011	11.43	0.67	0.74	1.58	0.61	1.05	European sovereign debt crisis
8/9/2011	10.19	0.22	8.16	4.96	−2.50	4.63	Warmest summer on record across Texas, Oklahoma, New Mexico, and Lousiana
7/13/2012	9.69	0.63	0.95	1.74	1.18	1.64	European sovereign debt crisis
1/4/2011	9.00	0.19	0.19	−0.86	−2.40	−0.13	Aftermath of Obaham's presidential election
12/30/2013	8.80	0.47	1.57	−0.72	−1.03	−0.02	Third highest global land and ocean surface temperature on record
3/10/2010	8.71	0.68	0.81	0.87	0.73	0.45	N/A
7/17/2018	8.53	−0.75	−0.16	−0.40	0.03	0.40	US-China tradewar
3/12/2012	8.51	−0.50	−1.25	−0.55	−0.99	0.02	European sovereign debt crisis
7/1/2010	8.40	0.36	0.60	−0.36	−3.61	−0.32	Europe's most extreme heatwave since 2003
12/14/2017	8.39	0.32	0.44	−0.36	0.77	−0.41	Fed's rate hike
10/22/2013	8.35	0.60	1.03	0.55	−1.44	0.57	N/A
3/16/2020	8.25	−0.24	−15.64	−14.63	−10.04	−12.77	COVID19
3/7/2013	8.22	−0.16	0.00	0.51	1.24	0.18	N/A
11/10/2022	8.09	0.09	9.60	2.20	0.74	5.40	COP 27
10/2/2012	8.03	−0.25	−0.24	0.18	−0.64	0.09	N/A
1/3/2017	7.97	1.08	0.81	1.12	2.62	0.85	High oil volatility on OPEC data
2/11/2011	7.96	1.04	1.28	−0.01	−1.33	0.55	European sovereign debt crisis
11/29/2011	7.89	−0.20	−1.34	1.42	1.60	0.22	COP 17

B. Estimated factor loadings					
SPWR (0.58)	RUN (0.5)	EOSE (0.4)	RNW (0.33)	STEM (0.33)	BEPC (0.17)

Panel A of the table presents the dates with the largest common volatility and the values of the returns on the same day. f_t^{σ} denotes the common volatility. $\bar{r}_t$ denotes the cross-sectional mean renewable energy winsorized excess returns. r_t^{PBW}, r_t^{XLE}, r_t^{WTI} and r_t^{SP500} denote the returns on the Invesco WilderHill Clean Energy ETF, the SPDR energy sector fund, the WTI-crude oil future price, and the S&P 500. Panel B lists the stock tickers and their factor loadings (in parentheses). A description of each stock is in the Appendix A. All dates are of m/d/yyyy formats.

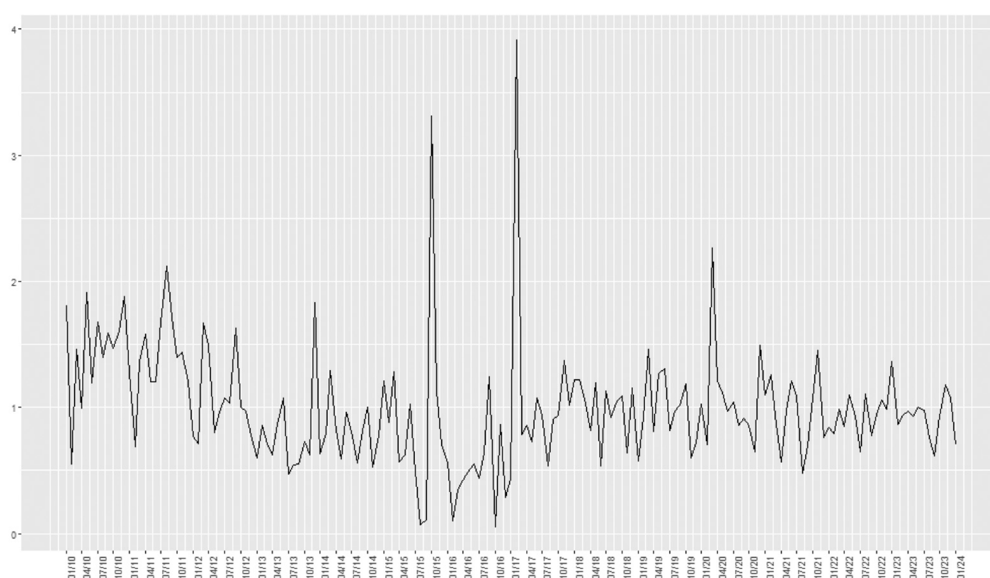


Fig. 5. The monthly common volatility — Energy storage stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for energy storage stocks.

lowering the sector-wide common volatility in the clean energy stock market. Second, the CBOE oil volatility index (OVX) exhibits a significant and negative relationship (−0.165), implying that rising oil volatility dampens the common volatility of clean energy stocks. This relationship suggests that investors may view clean energy investments as a hedge against oil market fluctuations, mitigating their exposure to oil price shocks. This result aligns with Niu (2021), Umar et al. (2022), and Ferrer et al. (2018) who find that there is a weak or even uncorrelated relationship between clean energy stocks and oil price. Third, the USD index exhibits a positive relationship with clean energy common volatility. This finding is in line with the evidence by Kocaarslan and Soytas (2021), who document an increase in clean energy stock volatility when the USD appreciates. This is because an increase in the USD value reduces the liquidity of riskier assets such as clean energy stocks, thereby increasing the risk premia of clean energy stocks. We complement these findings by highlighting the clean energy sub-sectors that are most sensitive to USD movements. Fourth, the term spread (Term10Y2Y) exhibits a positive effect on clean energy stock common volatility. A potential reason is that a widening term spread is observed during recessionary periods (Kocaarslan and Soytas, 2021). Additionally, this indicate that raising financing costs experienced by

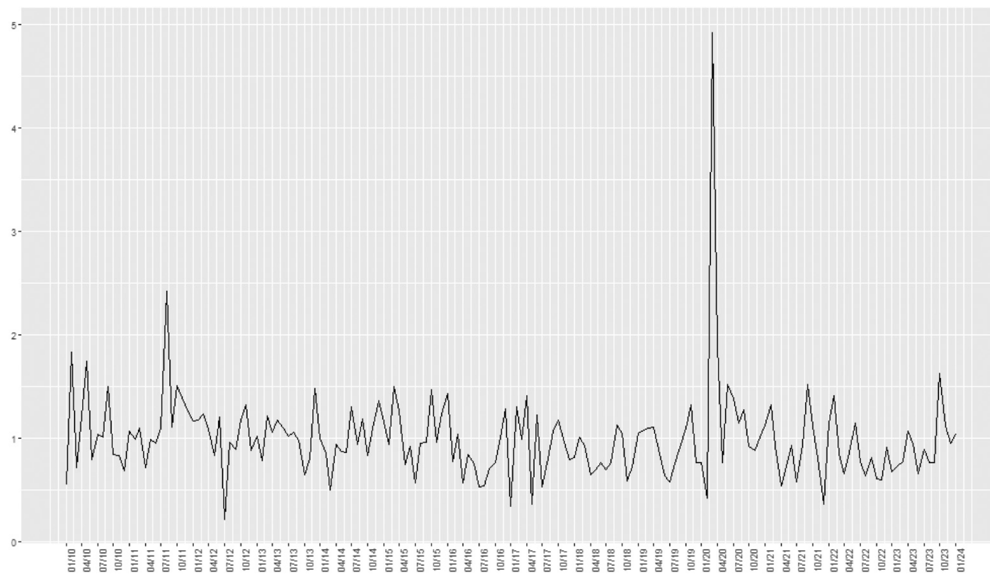


Fig. 6. The monthly common volatility — Energy conversion stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for energy conversion stocks.

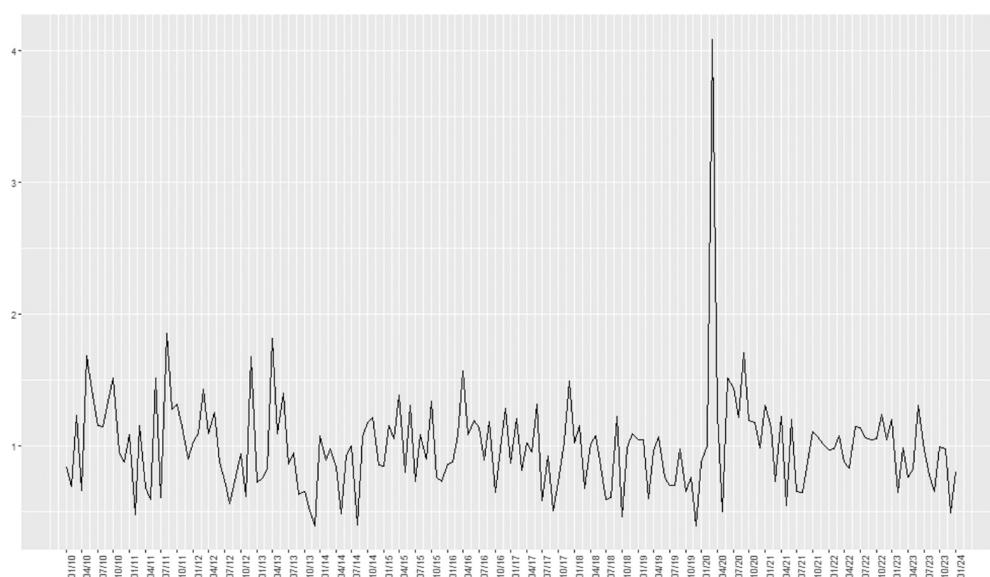


Fig. 7. The monthly common volatility — Power conservation stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for power conservation stocks.

financial institutions could intensify the volatility of this stock sub-sector through the negative effects on its liquidity. Finally, other factors such as the VIX, VXXLE, and S&P 500 index (SP500) exhibit statistically insignificant effects on clean energy COVOL. Overall, the empirical results in Column (1) point to the clean energy sector's significant ties with macroeconomic and financial market uncertainties. Notably, as clean energy COVOL exhibit either a negative or statistically insignificant relationship with most of the independent variables in column (1), our results implies the resilience of the clean energy stock market to macroeconomic and financial fluctuations.

Expanding the analysis to sub-sector-specific COVOL impacts reveals both similarities and nuanced differences across sub-sectors. First, the renewable energy and power sector exhibits a negative and statistically significant relationship with the MCCC index. In contrast, the energy conversion and utilities sectors exhibit a negative but statistically insignificant relationship with the MCCC index, while the storage sector shows a positive and statistically insignificant relationship with the MCCC index. These results suggest a divergence in how climate change concerns impact volatility across sub-sectors.

The implied volatility of the crude oil futures measured by OVX exerts a markedly negative influence on the common volatility of all sub-sectors, as evidenced in Columns (2)–(6). This indicates that increases in oil market volatility significantly reduce common volatility shocks in most clean energy sub-sectors. These consistent results implies broader sectoral resilience or counter-cyclicality to oil market fluctuations.

The VIX and VXXLE indices, representing broader market and energy sector volatilities, respectively, have relatively consistent impacts across sub-sectors. Notably, the VXXLE index exhibits a positive relationship with COVOL in all sub-sectors. Note that this relationship is statistically significant for the renewable energy, power conservation, and greener utilities sector, while it is statistically insignificant for other sectors. Also, the coefficient of the stock market volatility, VIX, is statistically insignificant for all sub-sectors, except the greener utilities

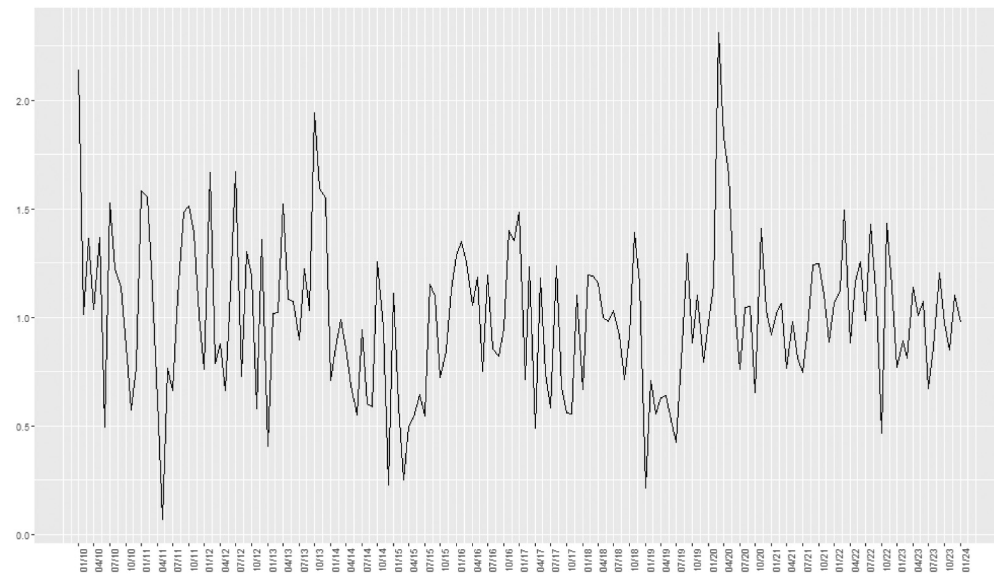


Fig. 8. The monthly common volatility — Greener utilities stocks.
The figure presents the monthly common volatility estimated from the empirical model in Section 3 for greener utilities stocks.

Table 7
Determinants of clean energy common volatilities.

Sector	Dependent variable: Normalized common volatility ($f_t^{\sigma}-1$)					
	(1) All	(2) RE	(3) Storage	(4) Conversion	(5) Power	(6) Utilities
MCCC	−0.187**	−0.127*	0.054	−0.014	−0.190***	−0.055
	(0.087)	(0.067)	(0.068)	(0.072)	(0.073)	(0.052)
OVX	−0.165**	−0.291***	−0.166***	−0.204***	−0.191***	−0.229***
	(0.082)	(0.065)	(0.063)	(0.069)	(0.070)	(0.049)
VIX	0.158	−0.054	0.008	0.048	−0.187	−0.286***
	(0.143)	(0.109)	(0.112)	(0.120)	(0.119)	(0.090)
VXXLE	−0.008	0.251**	0.024	0.065	0.296**	0.323***
	(0.152)	(0.123)	(0.115)	(0.133)	(0.128)	(0.094)
SP500	−3.344	1.650	−4.930***	−1.988	−1.980	−3.555***
	(2.340)	(1.763)	(1.761)	(1.978)	(1.900)	(1.326)
USD	14.684**	−3.533	−0.260	0.311	12.871**	−2.974
	(7.186)	(5.346)	(5.952)	(5.850)	(5.807)	(4.205)
Term10Y2Y	1.187*	−0.221	−0.419	0.661	0.719	0.242
	(0.637)	(0.479)	(0.483)	(0.529)	(0.513)	(0.387)
COVID	0.860***	0.684***	0.733***	0.580***	0.241*	0.340***
	(0.173)	(0.148)	(0.139)	(0.148)	(0.132)	(0.106)
Num.Obs.	2616	2616	2616	2616	2616	2616
R2	0.075	0.241	0.250	0.171	0.156	0.482
R2 Adj.	0.072	0.238	0.247	0.168	0.153	0.480
AIC	9464.9	11 417.5	17 752.2	10 730.2	10 825.2	14 047.9
BIC	9517.7	11 470.3	17 805.0	10 783.0	10 878.0	14 100.8
Log.Lik.	−4723.454	−5699.746	−8867.102	−5356.092	−5403.596	−7014.965
RMSE	1.64	1.42	2.16	1.54	1.48	1.59

The table presents the regression results on the determinants of clean energy common volatilities. The dependent variable is the **normalized** common volatility ($f_t^{\sigma}-1$) for all clean energy stocks (column (1)), the renewable energy generation sector (column (2)), the energy storage sector (column (3)), the energy conversion sector (column (4)), the power conservation sector (column (5)), and the greener utilities sector (column (6)). The independent variables include the logged media climate change concerns (MCCC), the logged CBOE oil volatility index (OVX), the logged CBOE volatility index (VIX), the logged CBOE energy sector volatility index (VXXLE), the returns on the S&P 500 (SP500), the returns on the USD index (USD), and the first-differenced term spread between the 10- and 2-year Treasury bonds. All models include a dummy for the COVID-19 financial crisis. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The estimation follows the estimated dependent variable (EDV) model of Lewis and Linzer (2005), to account for the fact that the dependent variable is estimated.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sector. Moreover, the stock market returns, proxied by returns on the S&P 500 index, reveal an insignificant effect on the COVOL across sub-sectors, with the notable exception of a significant negative impact of S&P 500 returns on the greener utilities and energy storage sub-sectors. This implies that positive stock market performance may reduce common volatility shocks among greener utilities and energy storage stocks, hinting at a unique market perception towards this sub-sector. The negative coefficient of S&P 500 in Columns (3) and (6) may signal that investor sentiment towards energy storage and greener utilities improves during periods of overall economic growth, as reflected by rising stock market returns. Such positive market conditions could lead to increased investment and stability within the energy storage and greener utilities sector, contrasting with its behavior under other economic circumstances.

Concerning the impact of the USD dollar index, the regression results across model specifications consistently show a lack of statistical

Table 8
The PBW volatility shocks regressed on different risk measures.

	Dependent variable: $\phi_{PBW,t}$			
	(1)	(2)	(3)	(4)
$COVOL^2_{All}$	0.0103***			0.0102***
	(3.89)			(3.92)
EPU		0.0430		0.0395
		(1.16)		(1.02)
$GPRD$			−0.0277	−0.0217
			(−0.61)	(−0.47)
Constant	−0.0356	0.0111	0.0111	−0.0249
	(−1.64)	(0.48)	(0.48)	(−1.14)
N	3603	3539	3539	3539
Adj. R-Square	0.02720	0.00002	−0.00020	0.02670

The table presents the regression results of the volatility shocks on the Invesco WilderHill Clean Energy ETF, ($\phi_{PBW,t} = e^2_{PBW,t} - 1$, where $e_{PBW,t}$ denotes the standardized residuals of the PBW). The PBW index aims to mirror the performance of the WilderHill ECO Index. The independent variable in Columns (1), (2), (3) are the squared Renewable Energy Common Volatility ($COVOL^2_{All}$), the log-differenced Economic Policy Uncertainty (EPU), and the log-differenced Geopolitical Risk Index ($GPRD$) respectively. Column (4) includes all three variables as the independent variables. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics and statistical significance are determined based on the Newey–West standard errors, which accounts for heteroskedasticity and autocorrelation in the data.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9
The PBW returns regressed on different risk measures.

	Dependent variable: $R_{PBW,t}$			
	(1)	(2)	(3)	(4)
$COVOL^2_{All}$	−0.0140***			−0.0141***
	(−2.83)			(−2.83)
EPU		0.0167		0.0230
		(0.24)		(0.32)
$GPRD$			−0.00704	−0.0184
			(−0.08)	(−0.22)
Constant	0.0328	−0.0166	−0.0166	0.0329
	(0.77)	(−0.43)	(−0.43)	(0.77)
N	3542	3542	3542	3542
Adj. R-Square	0.0166	−0.000267	−0.000281	0.0161

The table presents the regression results of the returns on the Invesco WilderHill Clean Energy ETF, ($R_{PBW,t}$, calculated by log-differencing the daily closing prices of the ETF). The PBW index aims to mirror the performance of the WilderHill ECO Index. The independent variable in Columns (1), (2), (3) are the squared Renewable Energy Common Volatility ($COVOL^2_{All}$), the log-differenced Economic Policy Uncertainty (EPU), and the log-differenced Geopolitical Risk Index ($GPRD$) respectively. Column (4) includes all three variables as the independent variables. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics and statistical significance are determined based on the Newey–West standard errors, which accounts for heteroskedasticity and autocorrelation in the data.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

significance, with the exception of the power conservation sector. These results suggest that most of the sensitivity to USD exchange rate in the clean energy stock market is concentrated among power conservation stocks, while the common volatility shocks of other sub-sectors are independent from the strengthening or weakening of the US dollar. Such a finding implies a degree of resilience or detachment of the clean energy sector from the direct financial implications of currency movements. This insight is crucial for investors and policymakers, as it highlights the need to look beyond currency effects when assessing the risk and stability of investments in the clean energy sector, focusing instead on intrinsic industry drivers and other macroeconomic drivers. Lastly, the term spread between 10- and 2-year Treasury bonds (Term10Y2Y) shows a statistically insignificant effects on the sub-sector common volatility. Combining with the results in column (1), this indicates that clean energy sub-sector common volatility contains unique information about each sub-sector, compared to the overall sector-wide common volatility measures.

Table 10
Validation tests with sub-sector common volatilities.

Dependent variable:	$\phi_{PBW,t}$		$R_{PBW,t}$	
	(1)	(2)	(3)	(4)
$COVOL^2_{RE}$	0.0153***	0.0149***	0.00968	0.00966
	(4.35)	(4.22)	(1.52)	(1.52)
$COVOL^2_{Storage}$	0.00007	0.00007	0.00008	0.00008
	(0.43)	(0.40)	(0.23)	(0.25)
$COVOL^2_{Conversion}$	0.00844***	0.00845***	−0.0170**	−0.0170**
	(2.66)	(2.69)	(−2.18)	(−2.17)
$COVOL^2_{Power}$	0.000988	0.000895	−0.0100*	−0.0101*
	(0.29)	(0.27)	(−1.68)	(−1.69)
$COVOL^2_{Utilities}$	0.0136***	0.0133***	−0.00282	−0.00286
	(4.15)	(4.07)	(−0.40)	(−0.40)
EPU		0.0325		0.0167
		(0.86)		(0.23)
$GPRD$		−0.0195		−0.0243
		(−0.43)		(−0.30)
Constant	−0.113***	−0.102***	0.0478	0.0480
	(−4.89)	(−4.43)	(0.97)	(0.98)
N	3603	3539	3542	3542
Adj. R-Square	0.0397	0.0381	0.0216	0.0211

The table presents the regression results of the PBW's volatility shocks ($\phi_{PBW,t}$) (columns (1)-(2)) and returns ($R_{PBW,t}$) (columns (3)-(4)) on the squared renewable energy sectoral common volatilities ($COVOL^2_{RE}, COVOL^2_{Storage}, COVOL^2_{Conversion}, COVOL^2_{Power}, COVOL^2_{Utilities}$). Columns (1) and (3) do not include the log-differenced economic policy uncertainty and the geopolitical risk indexes, while columns (2) and (4) include these two additional variables. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t statistics and statistical significance are determined based on the Newey–West standard errors, which accounts for heteroskedasticity and autocorrelation in the data.

In summary, the analysis of determinants of COVOL across the clean energy sector and its sub-sectors reveals a complex landscape where oil uncertainty emerges as a consistent driver of common volatility. However, the impact of other determinants such as media climate change concerns, stock market volatility, broader energy market dynamics, and term spreads vary significantly, highlighting the unique sensitivities and resilience factors within each sub-sector. This variance underscores the importance of tailoring risk management and investment strategies to the specific characteristics and external influences affecting each sub-sector of the clean energy market.

5.4. COVOL's explanatory power

Following similar approach presented in Engle and Campos-Martins (2023), this section explores the explanatory power of the COVOL on the clean energy assets' risk and return in a comparison with other popular news-based uncertainty indices, including the Economic Policy Uncertainty (EPU) and the Geopolitical Risk Index (GPRD) constructed for the United States. Data of both measures are collected from the website https://www.policyuncertainty.com/. We conduct analyses at both sector-wide and sub-sector level.[17] Tables 8 and 9 reports the explanatory power of COVOL on assets' risk and return at the sector-wide level, respectively. Meanwhile, Table 10 presents the results for the sub-sector levels.

Similar to Engle and Campos-Martins (2023) we proxy risk of clean energy sector as the squared standardized residuals of the Invesco WilderHill Clean Energy ETF (PBW), $\phi_{PBW,t} = e^2_{PBW,t} - 1$, where $e^2_{PBW,t} = \frac{R^2_{PBW,t}}{\hat{\sigma}^2_{PBW,t}}$. $R_{PBW,t}$ denotes the return of PBW, calcualted as log-difference of the daily closing prices of PBW, and $\hat{\sigma}^2_{PBW,t}$ is the

[17] We run the analyses using the daily data and monthly data aggregated from daily data, respectively. Both approaches generate consistent results. We, therefore, only report the estimation results using the daily data to conserve space.

conditional variance of PBW obtained from GARCH(1,1) model. It is worth noting that the PBW index aims to mirror the performance of the WilderHill ECO index.

As seen, we consistently find that COVOL measure deliver superior explanatory power compared to the two other considered news-based uncertainty measures for both clean assets' risk and return, highlighted by their corresponding estimates are consistently significant at 1% level. However, not all sub-sectors contribute equally to the predictive power of COVOL. Our decomposition analyses show that, the explanatory power of the COVOL on clean energy assets' risk are mainly driven by the renewable energy, conversion and utilities sub-sectors. Meanwhile, largest contributor to the predictive power of COVOL on clean energy asset return are conversion and power sub-sectors.[18]

6. Implications of the study

Our paper is the first to measure and investigate the common volatility shocks to the clean energy sector, providing valuable insights into the common risks faced by companies in this fast-growing sector. These insights have several important implications for investors and policymakers.

First, the examination of time-varying sector-wide common volatility (COVOL) and its pronounced spikes during significant global events, such as the COVID-19 pandemic and climate-related incidents, offers pivotal insights for both the investment community and policy makers within the clean energy domain. In the current environment characterized by supply chain disruptions, heightened energy security concerns, and inflationary pressures, understanding these volatility patterns is crucial. This nuanced understanding facilitates the development of tailored strategies aimed at mitigating risk and capitalizing on the sector's growth potential.

For investors, the observed correlation between COVOL spikes and external economic and environmental variables underscores the imperative of integrating a broad spectrum of risk factors, including current macroeconomic conditions and geopolitical risks, into their analytical frameworks. A refined diversification strategy that acknowledges these variables can safeguard portfolios against unforeseen volatility, enhancing stability and potential returns. Specifically, investments in sub-sectors or assets less sensitive to supply chain disruptions or geopolitical tensions may offer a hedge against broader sector-wide fluctuations.

From a policy perspective, the findings advocate for the implementation of robust support mechanisms designed to bolster the clean energy sector amid current challenges. Policies aimed at accelerating renewable energy deployment, doubling the rate of energy intensity improvements, and further electrification of end-uses are essential. This includes enhancing support for renewable capacity expansion, doubling the rate of energy intensity improvements, and promoting further electrification of end-users.[19] Integrating comprehensive risk assessments that consider current geopolitical dynamics and environmental challenges into energy policy formulation and infrastructure planning emerges as a critical strategy. Delivering the needed infrastructure depends on expediting planning and permitting processes, as a net-zero emissions energy system requires more and varied infrastructure, including expanded transmission and distribution grids, CO2 pipelines, and new hydrogen infrastructure.

Second, the heterogeneity in COVOL responses across clean energy sub-sectors to various macroeconomic, policy, and environmental stimuli highlights the necessity for a differentiated approach in investment and policy-making processes. Investors are encouraged to leverage current insights into the unique risk profiles and performance drivers of each sub-sector, such as the rapid advancements in battery storage technologies or the emerging hydrogen economy, optimizing investment decisions and portfolio construction for risk-adjusted returns. For instance, investors can consider investments in energy efficiency technologies, companies involved in electrification of end-uses, and emerging technologies such as hydrogen and carbon capture, utilization, and storage (CCUS). This strategy not only aligns investments with individual risk tolerances but also capitalizes on the growth trajectories of different sub-sectors within the clean energy landscape, especially in light of recent technological breakthroughs and policy support. Policy measures tailored to the distinct needs and challenges of each clean energy sub-sector can more effectively nurture growth and mitigate risk. For instance, providing targeted incentives for emerging technologies like green hydrogen or supporting the expansion of battery manufacturing to address current supply chain constraints can foster sub-sector development. Such an approach requires a granular understanding of sub-sector dynamics and a commitment to addressing specific vulnerabilities through targeted support and regulatory measures. Moreover, the differential impact of economic indicators, such as the term spread between 10- and 2-year Treasury bonds, on various sub-sectors illuminates the intricate relationship between macroeconomic conditions and clean energy investments. For investors, this insight offers a valuable tool for anticipating sub-sector performance amid the current economic climate characterized by inflationary pressures and changing interest rates. Policymakers, in turn, must consider the implications of economic policies on the clean energy sector, striving for measures that promote stability and sustainable growth in the present economic environment.

Third, our consistent finding that oil market volatility (OVX) reduces common volatility (COVOL) across the clean energy sector and most sub-sectors carries significant practical and policy implications. For investors, this inverse relationship underscores the value of clean energy investments as a hedge against oil market fluctuations, especially in the current context of heightened oil price volatility due to geopolitical tensions like the Russia-Ukraine conflict or Middle-East tension. Incorporating clean energy assets into portfolios could offer a stabilizing effect during periods of heightened oil market instability, thus reducing overall portfolio risk. Moreover, a diversified investment strategy, with a mix of sub-sectors exhibiting varying degrees of sensitivity to OVX, could further enhance resilience against oil price shocks. Policymakers, on the other hand, can leverage these insights to foster a more stable energy transition by encouraging investment in clean energy assets amid current energy security concerns, thereby reducing dependence on volatile oil markets. By promoting incentives and subsidies that bolster the clean energy sector's role as a risk mitigation tool, governments can attract more private capital into clean energy, which would help reduce dependence on volatile oil markets. Furthermore, policies that support the development of clean energy infrastructure could strengthen its competitive position, ensuring a smoother shift away from oil-based energy sources, ultimately fostering a more secure and diversified energy landscape.

Fourth, our analysis delves into company-level data, identifying which companies are most vulnerable to sector-wide common volatility (COVOL) shocks. This granular examination reveals significant heterogeneity in how individual companies within the clean energy sector respond to external volatility drivers, with some companies exhibiting higher sensitivity to COVOL shocks than others. This variance

[18] To further elaborate on the usefulness of considering the sub-sector COVOL, in a robustness check, we add the sector-wide COVOL as one of the control variables for Table 10. The idea is to check whether an inclusion of sector-wide COVOL can absorb the effects of subsector COVOL. The results show that the coefficients on the sub-sector COVOLs are still statistically significant, especially the renewable energy (RE) and greener utilities (Utilities) sector. Since the inclusion of the sector-wide COVOL cannot absorb all sub-sector effects, there is unique factors within the subsector that matter. This echoes the need to investigate clean energy COVOL at subsector level. These results are not reported in the paper, but are available upon request.

[19] See, Net Zero Roadmap: A Global Pathway to Keep the 1.5 °C Goal in Reach by International Energy Agency, https://www.iea.org/reports/net-zero-roadmap-a-global-pathway-to-keep-the-15-0c-goal-in-reach.

Table A.1
Clean energy stock list.
Source: WilderHill.

Company	Ticker	Sector	Description
Archer Aviation	ACHR	Energy Conversion	Electrifying aircraft, vertical takeoff & landing
Advanced Energy	AEIS	Energy Conversion	Power conditioning: inverters, thin film deposition
Albermarle	ALB	Energy Storage	Lithium, specialty materials in batteries for energy storage
Altus Power	AMPS	Renewable Energy Harvesting	Large utility-scale & rooftop solar PV, community solar
Amprius Technologies	AMPX	Energy Storage	Silicon anode batteries, greater energy density
Ameresco	AMRC	Power Delivery & Conservation	Energy saving efficiencies, net zero CO2, decarbonization
American Superconductor	AMSC	Power Delivery & Conservation	Wind, grid conditioning; superconductors
Array Technologies	ARRY	Renewable Energy Harvesting	Solar, tracker mounts follow sun through the day
Atlas Lithium	ATLX	Energy Storage	Lithium, battery metals nickel, rare earths, graphite
Bloom Energy	BE	Energy Conversion	Stationary fuel cells, not-yet cleanest/renewable fuels
Bel Fuse	BELFB	Energy Conversion	Transformers, power supplies, circuit protection, AC/DC
Brookfield Renewable	BEPC	Greener Utilities	Renewables hydro, wind, solar; energy storage
Ballard Power	BLDP	Energy Conversion	Mid-size fuel cells; PEM such as in transportation
Blink Charging	BLNK	Power Delivery & Conservation	EV Charging, among bigger EV charging networks
Chargepoint	CHPT	Power Delivery & Conservation	EV Charging, global including for fleets and businesses
Canadian Solar	CSIQ	Renewable Energy Harvesting	Solar, vertically integrated solar manufacturer, China
Enphase	ENPH	Energy Conversion	Microinverters, also energy storage systems and software
Enovix	ENVX	Energy Storage	Silicon-anodes, 3D for improving new lithium-ion batteries
Eos	EOSE	Greener Utilities	Zinc batteries, 100% discharging, longer-life, not-li-ion on grid
ESCO Technologies	ESE	Energy Conversion	Power management, shielding, controls, testing
EVgo	EVGO	Power Delivery & Conservation	EV Charging, DC fast-charging Networks, renewable power
FuelCell Energy	FCEL	Energy Conversion	Stationary fuel cells, distributed power generation
Fluence	FLNC	Energy Storage	Battery storage, for renewables and digital applications
Freyr	FREY	Energy Storage	Greener batteries, after IRA it has moved from Nordics to US
First Solar	FSLR	Renewable Energy Harvesting	Thin film solar, CdTe low-cost alternate to polysilicon
Fisker	FSR	Power Delivery & Conservation	EV crossover SUV, is assembled by contract manufacturer
Gevo	GEVO	Cleaner Fuels	Biofuels, lower-carbon liquid fuels from renewable sources
Gogoro	GGR	Power Delivery & Conservation	Electric scooters, swappable battery stations, Taiwan-based
ESS Tech	GWH	Energy Storage	Iron flow batteries, longer duration is non-lithium storage
Itron	ITRI	Power Delivery & Conservation	Meters, utility energy monitoring, measurement & management
JinkoSolar	JKS	Renewable Energy Harvesting	Solar, wafers through solar modules, China-based OEM
Joby Aviation	JOBY	Energy Conversion	Electric aircraft, cleaner, more energy efficient
Lithium Americas	LAC	Energy Storage	Lithium, deposits in the State of Nevada in US
Lion Electric	LEV	Energy Storage	Urban electric trucks, buses, vans; vehicle to grid storage
Lifezone Metals	LZM	Energy Conversion	Low-carbon battery metals, Nickel no smelting
Maxeon	MAXN	Renewable Energy Harvesting	Solar, efficient PV panel manufacturer after spinoff
MP Materials	MP	Energy Conversion	Rare Earths, domestic US source Neodymium, NdPr
MYR Group	MYRG	Power Delivery & Conservation	Grid transmission, distribution aids solar & wind farms
NaaS Technology	NAAS	Power Delivery & Conservation	EV charging, energy storage balancing wind, China
NIO Inc	NIO	Energy Storage	EVs, China-based startup premium vehicles, battery as a service
Energy Vault	NRGV	Energy Conversion	Gravity energy storage; can repurpose old wind blades
Navitas Semiconductor	NVTS	Power Delivery & Conservation	Gallium Nitride GaN fast charging EVs
Universal Display	OLED	Power Delivery & Conservation	Organic light emitting diodes, efficient displays
Opal Fuels	OPAL	Cleaner Fuels	Renewable natural gas RNG, CH4 from landfills, dairies
Ormat	ORA	Renewable Energy Harvesting	Geothermal, also in areas of recovering heat energy
Piedmont Lithium	PLL	Energy Storage	Lithium, US domestic source battery-grade lithium
Preformed Line Products	PLPC	Power Delivery & Conservation	Grid products and transmission OEM, solar
Plug Power	PLUG	Energy Conversion	Small fuel cells, for eg forklifts; drop in replacements
Polestar	PSNY	Power Delivery & Conservation	Electric vehicles pure play, global, and is based in Sweden
Quanta Services	PWR	Power Delivery & Conservation	Infrastructure, modernizes grid & power transmission
Quantumscape	QS	Energy Storage	Battery, solid state lithium-metal energy dense fast charge
Rivian	RIVN	Energy Storage	Electric vehicles, trucks and commercial fleets, charging
ReNew Energy	RNW	Greener Utilities	India renewables, among largest there in solar & wind
Sunrun	RUN	Greener Utilities	Residential solar systems, PPA, lease or purchase rooftop PV
SolarEdge Technologies	SEDG	Energy Conversion	Inverters, solar optimizers, inverters
SES AI Corp	SES	Energy Storage	Li-metal anode battery, may be safer, faster-charging
Shoals	SHLS	Power Delivery & Conservation	Solar, for electric balance of system, wiring, combiners
Solid Power	SLDP	Energy Storage	Solid electrolyte battery, Earth-abundant materials
Emeren	SOL	Renewable Energy Harvesting	Solar development, Europe, US, plus China, global pipeline
SunPower	SPWR	Greener Utilities	Solar system provider, storage and distributed generation
Chemical & Mining of Chile	SQM	Energy Storage	Lithium, large producer in energy storage
Stem	STEM	Greener Utilities	Microgrids, smart new energy storage via machine learning
Gentherm	THRM	Energy Conversion	Thermoelectrics, heat energy, battery management
TPI Composites	TPIC	Renewable Energy Harvesting	Wind Blades; also light-weighting transportation
Tesla	TSLA	Energy Storage	Electric vehicles, pure-play across EVs, advanced energy storage
Wallbox	WBX	Power Delivery & Conservation	EV Charging, allows bi-directional vehicle to grid, V2G
Wolfspeed	WOLF	Power Delivery & Conservation	Electrifying power, Silicon Carbide SiC, converters
Xpeng	XPEV	Energy Storage	Electric vehicles, advanced mobility, swappable batteries, China

in vulnerability underscores the importance of nuanced investment strategies and targeted policy support. The identification of companies with higher vulnerability to COVOL shocks is instrumental for portfolio management. Investors should consider this variability when constructing their portfolios, possibly favoring companies with lower COVOL sensitivity to enhance portfolio resilience. Furthermore, investors could employ dynamic asset allocation strategies that adjust to the changing risk profiles of these companies, thereby optimizing risk-adjusted returns over time. The findings highlight the need for differentiated policy support within the clean energy sector. Recognizing that certain

Table A.2
Summary statistics of the excess returns.

Ticker	Mean	Max	Min	SD	Skewness	Kurtosis	JB	ADF	Q	Q2
ACHR	−0.2696	5.2318	−5.8604	2.3601	−0.08159	2.6498*	4.963	−15.3542*	140.0*	283.0*
AEIS	0.0781	2.9363	−3.0186	1.3610	−0.03389	2.3552*	63.2*	−36.3777*	229.0*	98.0*
ALB	0.0838	2.7162	−2.6251	1.1787	−0.02013	2.4914*	39.1*	−35.3865*	306.7*	458.3*
AMPS	−0.1198	4.5678	−4.4755	1.9313	−0.04506	2.8793	0.7273	−15.8804*	125.2*	713.7*
AMPX	−0.6228	6.8978	−8.2398	3.2291	−0.1199	2.5773	3.405	−11.1228*	43.17	54.0*
AMRC	0.0220	3.5239	−3.4988	1.5654	0.03617	2.4217*	49.0*	−34.6476*	273.3*	280.3*
AMSC	−0.1598	4.7253	−4.8414	2.1972	0.07463	2.3436*	68.1*	−35.6840*	256.3*	164.1*
ARRY	−0.1351	5.4392	−5.5324	2.5861	0.06317	2.2586*	19.9*	−17.5397*	85.3*	59.6*
ATLX	−0.6707	11.7783	−13.4196	5.2415	−0.0910*	3.0252	3.932	−31.8397*	220.4*	1709.4*
BE	−0.1754	6.2499	−5.9196	2.8581	0.1059	2.3143*	30.3*	−22.7490*	119.8*	58.7*
BELFB	−0.0034	3.4678	−3.5140	1.6200	0.006347	2.3382*	65.8*	−35.2769*	278.2*	195.4*
BEPC	−0.0696	2.5613	−2.6028	1.2102	0.1102	2.2651*	22.1*	−16.7151*	150.2*	59.3*
BLDP	−0.0901	4.6957	−4.4758	2.0937	0.1069*	2.3583*	68.7*	−37.1277*	234.7*	156.5*
BLNK	−0.2999	7.7558	−7.7709	3.4704	0.06635	2.4209*	52.8*	−34.6121*	259.2*	212.9*
CHPT	−0.3616	6.0210	−5.9153	2.5215	0.0677	2.9295	1.082	−20.9289*	98.5*	692.1*
CSIQ	−0.0144	4.4608	−4.4137	2.0118	0.06652	2.3564*	64.9*	−37.4473*	256.1*	113.9*
ENPH	0.0680	5.5052	−5.3043	2.4969	0.02136	2.3061*	61.0*	−33.4329*	236.6*	120.9*
ENVX	−0.0184	6.3376	−5.9459	2.9236	0.1000	2.2200*	21.3*	−16.6999*	66.6*	40.38
EOSE	−0.3616	8.4348	−7.7704	3.6122	0.2266*	2.5669*	15.4*	−16.9267*	131.5*	238.0*
ESE	0.0174	1.9181	−1.8919	0.8829	−0.02108	2.3055*	72.7*	−34.8379*	344.1*	158.1*
EVGO	−0.4375	6.0719	−5.9886	2.8635	0.1510	2.2472*	22.4*	−16.4236*	83.2*	51.1*
FCEL	−0.3197	5.6280	−5.8449	2.6551	0.0867*	2.3348*	71.0*	−34.2761*	320.2*	236.3*
FLNC	−0.2254	6.7991	−6.9710	3.2642	0.08604	2.2795*	13.2*	−14.5962*	85.2*	38.03
FREY	−0.2101	4.3140	−4.7221	1.9416	−0.1129	2.7618	4.66	−17.1384*	238.3*	1479.3*
FSLR	0.0037	3.5175	−3.5330	1.5780	−0.03597	2.4173*	51.8*	−35.9497*	259.7*	215.4*
FSR	−0.3512	4.4848	−5.5308	2.0337	−0.2155*	3.1532	11.9*	−20.6943*	174.4*	1600.3*
GEVO	−0.4856	6.3282	−6.5527	2.9030	0.0859*	2.4305*	49.0*	−27.8364*	279.8*	170.0*
GGR	−0.3332	3.6542	−4.3319	1.4654	−0.3595*	3.6911*	31.1*	−11.3527*	166.8*	1174.4*
GWH	−0.5020	6.1952	−7.0710	2.7147	−0.1165	2.8648	2.455	−16.3501*	197.1*	900.3*
ITRI	0.0074	2.3329	−2.4000	1.0814	−0.05336	2.3935*	56.9*	−35.0310*	355.9*	201.0*
JKS	−0.0323	5.3762	−5.4160	2.5069	0.0009791	2.2562*	81.0*	−35.2696*	280.0*	177.8*
JOBY	−0.2231	4.9500	−5.2590	2.1906	−0.04486	2.7070	3.235	−17.9040*	79.7*	159.0*
LAC	−0.4106	5.8841	−6.0634	2.6105	0.07339	2.5279*	13.9*	−21.3034*	113.0*	112.0*
LEV	−0.3582	4.8048	−5.1882	2.4213	0.08802	2.2164*	22.8*	−16.8211*	95.5*	80.8*
LZM	−0.0623	2.7078	−4.0190	0.9434	−0.9250*	7.5824*	554.5*	−8.4551*	518.3*	1598.8*
MAXN	−0.2959	6.9936	−7.2480	3.4223	0.01347	2.2179*	22.4*	−18.3472*	65.7*	43.9*
MP	−0.0907	5.0845	−4.7185	2.2916	0.08061	2.2765*	21.2*	−18.4784*	87.4*	41.97
MYRG	0.0515	2.6524	−2.5139	1.1979	0.03802	2.3004*	74.4*	−35.7396*	268.9*	232.7*
NAAS	−0.4806	5.2318	−6.1920	2.4838	−0.07054	2.5056*	17.7*	−22.6167*	168.7*	133.4*
NIO	−0.2256	6.0445	−6.0533	2.8751	0.08505	2.3091*	29.0*	−22.2176*	136.8*	46.6*
NRGV	−0.3184	6.4300	−7.1770	2.7722	−0.0342	3.0631	0.2634	−13.6144*	122.5*	1096.2*
NVTS	−0.0399	5.6482	−5.6286	2.4715	−0.0007886	2.6448*	4.063	−15.0136*	155.1*	593.1*
OLED	0.0333	3.5603	−3.3720	1.5656	0.03389	2.4708*	42.7*	−37.9047*	199.1*	131.5*
OPAL	−0.1907	2.8114	−3.5103	1.1149	−0.4353*	3.8618*	43.2*	−14.3801*	163.1*	779.8*
ORA	0.0342	2.0819	−2.1631	0.9784	−0.1230*	2.3235*	77.9*	−35.4656*	305.1*	153.7*
PLL	−0.0999	5.3926	−5.3142	2.5465	0.06802	2.2214*	41.5*	−22.0925*	245.4*	117.4*
PLPC	0.0092	2.9034	−2.7178	1.2984	0.06508	2.3355*	68.9*	−37.0231*	224.2*	193.1*
PLUG	−0.1529	5.7387	−5.5028	2.5153	0.1213*	2.4226*	58.9*	−35.9147*	264.8*	228.2*
PSNY	−0.2227	4.0304	−4.7942	1.9672	−0.04045	2.6630*	3.479	−12.7231*	204.1*	455.4*
PWR	0.0903	2.1546	−2.0293	0.9664	−0.01968	2.3333*	67.0*	−36.6741*	267.6*	143.9*
QS	−0.2571	6.6561	−6.5671	3.0623	0.08747	2.3684*	15.9*	−17.5441*	93.7*	56.8*
RIVN	−0.4112	5.7076	−6.3697	2.8571	0.02814	2.3288*	10.8*	−13.6777*	69.2*	41.57
RNW	−0.0922	3.6906	−3.5878	1.6045	0.06879	2.4856*	9.1*	−15.2804*	154.7*	182.1*
RUN	0.0064	5.1827	−5.1862	2.3865	−0.04119	2.3290*	41.4*	−26.9771*	212.2*	285.8*
SEDG	0.0812	4.2500	−4.1041	1.9471	−0.003207	2.3569*	39.1*	−28.8394*	203.0*	153.3*
SES	−0.3535	5.3726	−6.5017	2.3709	−0.2664*	3.0279	8.9*	−15.8771*	143.1*	653.9*
SHLS	−0.1713	5.4649	−5.6083	2.5818	0.0669	2.3199*	15.4*	−17.7263*	38.7	73.7*
SLDP	−0.3056	5.6543	−6.2730	2.6904	−0.07116	2.4471*	9.4*	−14.2387*	121.0*	195.5*
SOL	−0.2551	5.2922	−5.2843	2.4462	0.1172*	2.3060*	80.6*	−36.3766*	255.5*	153.9*

(*continued on next page*)

companies are more susceptible to volatility shocks, targeted measures, such as fiscal incentives or financial support programs, could be implemented to bolster the resilience of these vulnerable entities. Additionally, policies aimed at enhancing sector-wide transparency and predictability, such as clear regulatory frameworks and consistent policy signals, can indirectly benefit these companies by stabilizing the broader market environment. In addition, governments can provide targeted support to companies in clean energy sector that are more susceptible to volatility shocks, such as fiscal incentives or financial support program, to bolster their resilience.

Lastly, our analysis of the explanatory power of COVOL reveals its superior explanatory power compared to other news-based uncertainty measures, such as the Economic Policy Uncertainty (EPU) and Geopolitical Risk Index (GPRD). Our findings show that COVOL significantly influences both the risk and return of clean energy assets at the sector-wide level, providing investors and policymakers with crucial insights. For investors, understanding the influence of COVOL on sector-wide return and volatility amid current uncertainties can enhance their portfolio management strategies. By closely monitoring and predicting COVOL trends, they can better anticipate market volatility and adjust their asset allocations to minimize risk exposure. For policymakers, recognizing the predictive value of COVOL can guide the development of more effective regulations and support mechanisms tailored to the clean energy sector's unique volatility profile. Crafting policies that

Table A.2 (*continued*).

Ticker	Mean	Max	Min	SD	Skewness	Kurtosis	JB	ADF	Q	Q2
SPWR	−0.0542	4.5676	−4.8224	2.1758	0.007371	2.2942*	74.9*	−35.4903*	314.5*	206.4*
SQM	0.0313	2.8528	−2.6838	1.2868	0.01195	2.3286*	67.8*	−35.1522*	383.5*	240.7*
STEM	−0.2931	6.8262	−7.3245	3.3418	0.02631	2.3507*	15.0*	−17.6410*	101.9*	96.8*
THRM	0.0744	2.8999	−2.7555	1.3056	−0.02298	2.2973*	74.5*	−36.0488*	241.4*	138.3*
TPIC	−0.1141	4.5236	−4.8700	2.1158	−0.02767	2.4151*	27.7*	−25.0982*	292.7*	313.6*
TSLA	0.0972	3.8538	−3.7388	1.7079	0.007117	2.3935*	53.4*	−35.1689*	287.1*	104.9*
WBX	−0.4060	5.2039	−6.1433	2.5459	−0.09901	2.6210*	5.454	−14.3149*	135.9*	487.3*
WOLF	0.0265	3.3545	−3.6295	1.5712	−0.1306*	2.3828*	67.4*	−34.8294*	396.2*	272.7*
XPEV	−0.3823	6.6434	−6.1972	2.9686	0.1412	2.2465*	23.6*	−17.2820*	100.1*	42.01

The table presents the summary statistics of the stock excess returns (%). JB stands for the Jarque–Bera test statistics of normality. ADF stands for the test statistics of the Augmented Dickey–Fuller unit root test. Q and Q2 stand for the Ljung–Box test on returns and their squared terms.* denotes significance at the 5% level.

stabilize market conditions, such as transparent subsidy structures and consistent regulatory frameworks, and clear policy signals in the current policy environment, will help mitigate the systematic risk of the sector identified through COVOL.

7. Conclusion

This paper aims to quantify and analyze the common volatility (COVOL) in the clean energy sector, providing a comprehensive overview of how sector-wide and sub-sector common volatility shocks evolved over time. Through an innovative empirical approach, we have identified significant spikes in COVOL linked to global economic disruptions, such as the COVID-19 pandemic, as well as climate-related events and policy shifts. Our analysis extends to the examination of COVOL of five distinct sub-sectors, uncovering substantial heterogeneity in responses to these volatility drivers.

Our key findings highlight the significant impact of oil uncertainty on COVOL within the clean energy sector, emphasizing the sector's susceptibility to changes in the oil market. Additionally, our company-level analysis highlights the varied vulnerability of firms within the sector to common volatility shocks, with implications for investors and policymakers alike. These insights contribute to a deeper understanding of the renewable energy market's dynamics, offering valuable perspectives for managing investment risks and formulating supportive policies.

The contributions of this paper are multifaceted. Firstly, it advances the academic literature on financial volatility by introducing a sector-specific analysis of COVOL within the renewable energy market. Secondly, it offers practical insights for investors seeking to navigate the volatility of this burgeoning sector, emphasizing the importance of diversified portfolios and dynamic investment strategies. Thirdly, the findings provide a solid empirical foundation for policymakers to develop targeted measures that enhance sector resilience and encourage sustainable growth.

Future research in this area could explore several avenues. Expanding the dataset to include a broader range of companies and sub-sectors, as well as extending the timeframe of the analysis, could provide more nuanced insights into the long-term trends and drivers of COVOL in the clean energy sector. Additionally, examining the impact of emerging technologies and market innovations on sector volatility could offer forward-looking perspectives on investment and policy strategies. Finally, comparative analyses between the clean energy sector and other sectors could highlight unique challenges and opportunities for managing volatility in a transitioning energy market.

In conclusion, this paper sheds light on the complex interplay between global events, policy environments, and market dynamics in shaping the volatility of the clean energy sector. By elucidating the factors contributing to COVOL and their implications for the sector, our study paves the way for more informed investment decisions and effective policy interventions, contributing to the resilience and growth of renewable energy as a key component of the global energy mix.

Table A.3
Test of the squared standardized residuals decomposition.

Sector	Correlation ($\hat{\rho}_{e^2}$)	Test statistic ($\hat{\xi}_{e^2}$)	*p*-value
Panel A: Before COVOL decomposition			
All clean energy	0.0250	43.29	0.00
Renewable energy generation	0.0415	12.28	0.00
Energy storage	0.0237	5.39	0.00
Energy conversion	0.0349	15.33	0.00
Power conservation	0.0193	11.89	0.00
Greener utilities	0.0340	6.01	0.00
Panel B: After COVOL decomposition			
All clean energy	0.0005	−2.83	1.00
Renewable energy generation	−0.0715	−22.07	1.00
Energy storage	−0.0287	−16.27	1.00
Energy conversion	−0.0526	−22.20	1.00
Power conservation	−0.0392	−22.13	1.00
Greener utilities	−0.1562	−28.27	1.00

Table A.4
Pairwise correlation matrix among sub-sector COVOLs.

	All	RE	Storage	Conversion	Power	Utilities
All	1.0000					
RE	0.5206	1.0000				
Storage	0.4566	0.0492	1.0000			
Conversion	0.5902	0.1507	0.0835	1.0000		
Power	0.6020	0.1507	0.0939	0.2604	1.0000	
Utilities	0.3688	0.1675	0.0769	0.1210	0.1230	1.0000

Note: All, RE, Storage, Conversion, Power, Utilities stand for all clean energy stocks, the renewable energy generation sector, the energy storage sector, the energy conversion sector, the power conservation sector, and the greener utilities sector respectively. All coefficients of correlation are statistically significant at the 1% level.

CRediT authorship contribution statement

Linh Pham: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Son Pham:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Hung Do:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Emawtee Bissoondoyal-Bheenick:** Writing – review & editing, Writing – original draft, Data curation. **Robert Brooks:** Writing – review & editing, Writing – original draft.

Appendix A

See Tables A.1–A.5.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108592.

Table A.5
Variance ratio tests of the sub-sector factor loadings.

	Renewable energy	Energy storage	Energy conversion	Power conservation
Energy storage	3.169 (0.004)			
Energy conversion	5.281 (0.000)	1.667 (0.414)		
Power conservation	2.577 (0.010)	0.814 (0.704)	0.488 (0.181)	
Greener utilities	3.671 (0.000)	1.159 (0.837)	0.695 (0.461)	1.424 (0.510)

Note: The number in each cell indicates the variance ratio between the factor loadings' variance of the row sub-sector and that of the column sub-sector. The *p*-value of the variance ratio tests are in the parentheses.

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