International Review of Economics and Finance 111 (2026) 105811

Contents lists available at ScienceDirect

International Review of Economics and Finance

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

Rare earth elements in the clean energy transition: Hedge effectiveness and safe haven properties

Maruf Yakubu Ahmed, Anupam Dutta *, Timo Rothovius

School of Accounting and Finance, University of Vaasa, Vaasa, Finland

A R T I C L E I N F O

Handling Editor: Dr. Shweta Sharma

Keywords:
Rare earth elements
Clean energy stocks
Hedge and safe haven
Hedging effectiveness

A B S T R A C T

This study investigates the dynamic relationship between rare earth elements (REEs) and clean energy stocks, focusing on their association with geopolitical and economic stress, and the escalating demand for clean energy solutions from January 2015 to May 2024. We assess whether REEs are a hedge and/or safe haven asset for the clean energy market and analyze their time-varying hedging effectiveness and hedge ratios. Our analysis suggests a strong non-linear correlation between the markets examined. REEs exhibit a strong positive correlation with clean energy stocks under normal conditions, but this relationship weakens during extreme market volatility. However, REEs show a significant positive correlation with the wind subsector during certain extreme market shocks. This suggests that REEs do not function as a hedge for the clean energy market and do not demonstrate safe haven behavior, especially for the wind subsector during turbulent times. REEs exhibit weak hedging effectiveness, particularly during the United States-China trade tensions, but perform better during the COVID-19 pandemic and other crises. Comparatively, REEs outperform Bitcoin but underperform gold in hedging effectiveness across all subsamples and the full sample analysis. The hedge ratios for REEs vary across subsamples and peak for gold and Bitcoin during the COVID-19 pandemic and the Russia-Ukraine war. Our empirical evidence underscores the vulnerabilities and investment risks of REEs in the clean energy transition. This study provides novel insight for investors and policymakers navigating the complexities of the global energy transition.

1. Introduction

This paper examines the evolving relationship between rare earth elements (REEs) and clean energy stocks, emphasizing their association with geopolitical and economic crises, and the escalating demand for clean energy technologies. REEs are critical minerals that play an indispensable role in the production of clean energy solutions, including wind turbines, electric vehicles, solar panels, hydrogen storage, and energy-efficient lighting (see Apergis & Apergis, 2017; Binnemans et al., 2013; Hanif et al., 2023; Henriques & Sadorsky, 2023). With global energy demand forecasted to rise by 30% by 2030, the pressing need to address climate change externalities has accelerated the transition to renewable energy sources, intensifying the demand for REEs (IEA, 2023). However, their availability remains a significant challenge, as China maintains near-monopolistic control of global REE mining and refining (Bergougui et al., 2025; IEA, 2023a; Proelss et al., 2020). This heavy geographical concentration heightens supply chain vulnerabilities, exacerbated by geopolitical risks and natural disasters, challenging the clean energy transition (Madaleno et al., 2023).

* Corresponding author.
E-mail addresses: maruf.ahmed@uwasa.fi (M.Y. Ahmed), adutta@uwasa.fi (A. Dutta), tr@uwasa.fi (T. Rothovius).

https://doi.org/10.1016/j.iref.2026.105811
Received 28 December 2025; Received in revised form 31 August 2026; Accepted 3 September 2026
Available online 4 September 2026

Clean energy stocks are relatively new investment assets known to carry a high level of volatility (Dutta, 2017). This market has shown remarkable growth and has consistently outperformed the S&P 500 and MSCI Global index in recent years (Wu et al., 2026; Yahya et al., 2020), coinciding with a notable shift as institutional investors increasingly divest from traditional energy sectors (Doğan et al., 2024; Yahya et al., 2020). In 2023, clean energy investment inflows surged by 24%, outpacing the 15% increase in fossil fuel investments (IEA, 2023b; Soto et al., 2026). The International Energy Agency (IEA) reports that of the USD 2.8 trillion invested in the energy sector in 2023, approximately USD 1.7 trillion was directed towards clean energy sectors (IEA, 2023b). This rise in investment has driven both demand and price for critical energy transition minerals, doubling their market size to ~USD 320 billion over the past five years (IEA, 2023a). The IEA Sustainable Development Scenario estimates that by 2040, clean energy technologies will account for 40% more REE demand compared to current levels (IEA, 2021). The global energy sector is steadily transitioning toward renewable energy sources (Dutta et al., 2025; Grandell et al., 2016; Xu et al., 2026), a trend mirrored in the transportation sector, where electric vehicles (EVs) accounted for ~18% of all cars sold in 2023 (Doğan et al., 2025; IEA, 2021b). The interaction between REEs and the clean energy market plays a fundamental role in the transition to net-zero emissions by 2050.

The motivation for this study is further underscored by the increasing frequency of geopolitical and economic stress that disrupts REE supply chains. For instance, China's 2010 restriction of REE exports to Japan, prompted by territorial disputes, triggered a global price surge and exposed the fragility of REE supply chains (see Habib et al., 2016; IEA, 2023; Smith Stegen, 2015). Similarly, China imposed export restrictions on selected REEs in 2018-2019 as a retaliatory measure against the United States' ban on Huawei (Baskaran & Schwartz, 2024). The COVID-19 pandemic has likewise demonstrated how geopolitical risks can amplify and disrupt clean energy investment (IEA, 2021). The IEA's clean energy transition risk assessment estimates that China's 77% share of REE refining by 2030 will pose greater geopolitical risks and increased price volatility compared to other critical minerals (IEA, 2021a; Lin et al., 2024).

Despite the growing literature on the clean energy market and the pivotal role of REEs in the shift from fossil fuels to green energy sources, their association with geopolitical instability and financial market dynamics remains underexplored. Previous studies have investigated REEs' connectedness with renewable energy (see Chen et al., 2020; Ding et al., 2022; Madaleno et al., 2023; Song et al., 2021; Zhou et al., 2022) and their relationship with geopolitical instability (see Fan et al., 2023; Hu et al., 2023; Li et al., 2023). For instance, Hau et al. (2022) highlight the correlation between REEs and trade policy uncertainty in China and the United States, while Farina and Anctil (2022) examine the impact of China's policies on REEs and the price sensitivity of the renewable energy market. Furthermore, other studies reveal the correlation between geopolitical instability and renewable energy (see Acheampong et al., 2023; Alsagr & Van Hemmen, 2021; Dutta & Dutta, 2022; Overland, 2019), and Cai and Wu (2021) demonstrate a time-varying correlation between geopolitical risks and green energy consumption. This research deepens our understanding of the dynamic relationship between REEs and clean energy stocks, particularly in terms of their hedge and safe haven properties during periods of market stress.

The research conducted in this paper is firmly rooted in established frameworks, including Modern Portfolio Theory (MPT) and Behavioral Finance, which guide the selection of analytical tools and the interpretation of findings. MPT underscores the importance of diversification to mitigate risks and assess asset interconnectedness through statistical techniques such as correlation and copulas (Markowitz, 1952; Sklar, 1959). For REEs to function as an effective hedge against clean energy stocks, they must demonstrate low or negative correlation properties under normal market conditions. However, MPT recognizes that correlations are not constant, as they shift across different market regimes and often increase significantly during periods of crisis. This time-varying nature of correlations is essential for assessing REEs' hedging properties under varying geopolitical and economic environments. In contrast, Behavioral Finance highlights investors' psychology and decision-making during extreme market volatility (Shefrin, 2001). Cognitive biases such as herding and loss aversion can intensify volatility and undermine the effectiveness of hedging strategies (Kahneman & Tversky, 1984; Shleifer & Summers, 1990). These biases are particularly pertinent to the REEs market, where geopolitical and economic crises, and speculative behavior can be associated with irrational price swings and unstable correlation with clean energy stocks. By integrating MPT and Behavioral Finance, our study constructs a robust theoretical framework for assessing the hedging and safe haven properties of REEs. While the former provides a foundation for the quantitative analysis of correlations and hedging effectiveness, the latter offers an explanation for the deviations observed during periods of market stress. These combined theories enable us to evaluate not only REEs' risk-mitigating capabilities but also to understand the underlying reasons why their effectiveness fluctuates across different market conditions.

The paper addresses key questions to bridge the gap in understanding the function of REEs: Do REEs function as a hedge and/or safe haven for the clean energy market during periods of uncertainty? Prior studies such as Baldi et al. (2014) and Ding et al. (2022) have explored the correlation between REEs and the clean energy market but have not explicitly tested the risk-mitigating properties under extreme geopolitical and economic uncertainty. This research question aims to fill this gap by examining whether REEs provide protection during both normal (hedge) and adverse conditions (safe haven), using quantile regression (Baur & McDermott, 2010) and a dynamic conditional correlation (DCC-GARCH Student-t copula) model. While the former model was employed to assess the hedge/safe haven properties of REEs under different market conditions (normal, bearish and extreme volatility) due to its robustness to outliers, the latter model allows us to capture the regime-dependent relationships between REEs and clean energy stocks evolving over time. Additionally, how does REEs' time-varying hedging effectiveness compare to gold (GLD) and Bitcoin (BTC)? A plethora of studies have well documented the hedging/safe haven properties of GLD and BTC against market volatility (see Baur & Lucey, 2010; Baur & McDermott, 2010; Hussain Shahzad et al., 2020). However, the performance of REEs relative to these assets remains unexplored. This question seeks to compare the dynamic hedging effectiveness (HE)/optimal hedging ratio (HR) of REEs with GLD and BTC, providing insights into their relative utility as risk management tools during crises (e.g., U.S.-China trade war, COVID-19 pandemic, Russia-Ukraine war). The HE metric quantifies the reduction in portfolio variance achieved by including a hedging asset, while HR determines the optimal weight of the hedging asset in the portfolio. These metrics provide a clear comparison of the effectiveness of REEs, GLD, and BTC in providing the highest risk reduction for clean energy portfolios under varying geopolitical and economic conditions. Thus, HE and HR are relevant for portfolio investment strategies. For instance, during a period of low HE, the diversification benefit of REEs declines, often prompting investors to increase their allocation to cash holdings as a defensive measure.

Our study offers important contributions to the existing literature. First, theoretically, it explicitly distinguishes between the hedging, safe haven, hedging effectiveness, and optimal hedging ratio properties of REEs in the context of clean energy markets. This distinction is achieved by integrating advanced econometric techniques, including a quantile-based approach and the DCC-GARCH Student-t copula framework, which capture the non-linear and time-varying relationships between REEs and clean energy stocks. This methodological approach allows for a detailed assessment of how the HE and HR of REEs fluctuate across normal, bearish, and extreme market conditions, addressing a critical gap in the literature. Second, we evaluate the hedging performance of REEs against multiple clean energy indices during major geopolitical and economic crises, specifically before and during the United States-China trade tensions, the COVID-19 pandemic, and the Russia-Ukraine war. This regime-specific analysis provides deeper insights into the risk-mitigating potential of REEs under different turbulence conditions. Third, we compare REEs' hedging performance against two well-established hedge and safe haven assets (GLD and BTC). This comparative analysis provides actionable insights into portfolio diversification strategies by clarifying the context-dependent and limited role of REEs in risk management, while reaffirming GLD's dominance as a conventional safe haven asset.

Our empirical findings show that REEs exhibit a strong positive correlation across all the clean energy sectors (ECO, SPGCLE, GRNWIND, KEVP, GRNSOLAR) under normal market conditions. The regression analysis reveals an insignificant correlation between REEs and clean energy stocks during extreme market turbulence, except for the wind energy subsector, which exhibits a significant positive correlation. Overall, the findings suggest that REEs do not function as a hedge and demonstrate no safe haven behavior across all the clean energy stocks. These co-movements are intuitive and align logically with the fundamental input-output relationship between REEs and clean energy technologies. This relationship creates a positive correlation between their performance, which inherently undermines the hedging or safe haven properties of REEs. Additionally, China's near-monopolistic control of the REE market and the resulting lack of transparency further weaken REEs' effectiveness as reliable hedge and safe-haven assets. These findings reinforce the conventional expectation stemming from the strong input-output relationship between REEs and clean energy technologies.

To address the issue of REEs' association with geopolitical events due to the geographical concentration of production and economic uncertainty, and to better capture dynamic non-linear relationships, this study employs the DCC-GARCH Student-t copula framework. This approach enables the assessment of time-varying hedge effectiveness (HE) and optimal hedge ratio (HR). We compare the time-varying HE and HR of REE, GLD, and BTC across four distinct subsample periods: Subsample I (January 2015 to March 2018) pre-United States-China trade tension; Subsample II (March 2018 to March 2020), United States-China trade war; Subsample III (March 2020 to February 2023), COVID-19 pandemic; Subsample IV (February 2023 to May 2024), Russia-Ukraine war. These findings underscore the capacity of REEs, GLD, and BTC to serve as a hedge asset against the time-varying portfolio variance of clean energy stocks. The evidence shows the HE of GLD consistently outperforms both REEs and BTC across all subsample scenarios. This superior performance may be associated with GLD's financial detachment from clean energy technologies and its traditional role as a trusted store of value. BTC exhibited its strongest hedging performance during the COVID-19 pandemic but fell short compared to the HE achieved by both GLD and REEs during the same period and across other subsamples. This relatively weaker performance may be attributed to BTC's highly speculative nature and limited widespread acceptance, which undermine its consistency and effectiveness as a stable hedge compared to GLD and REEs.

Notably, the HE of REEs dropped sharply during the United States-China trade tensions but surged significantly during the COVID-19 pandemic and the Russia-Ukraine war, while remaining relatively stable in the pre-United States-China trade tension period. The sharp decline appears linked to China's near-monopolistic control over REE production and its strategic use of export controls as a retaliatory measure in geopolitical disputes. Conversely, the increase during the crisis periods may be related to the strong input-output relationship between REEs and clean energy technologies, which generates a positive correlation that eliminates the negative correlation necessary for effective hedging. These patterns suggest that geopolitical events are associated with heterogeneous hedging properties of REEs. Overall, evidence from the full sample confirms GLD's superiority as the most reliable hedging asset. REEs, despite their geopolitical sensitivity, outperformed BTC across most clean energy indices. The optimal HR is generally high for both GLD and BTC during the pandemic periods, whereas it varies in most cases for REEs.

The remainder of this study is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the dataset and model estimation procedures. Section 4 presents the empirical results and discusses the estimated models. Section 5 provides additional evidence on time-varying correlations, hedge effectiveness, and hedge ratios. Section 6 includes a discussion on the contributions and implications of this study, while Section 7 concludes the paper.

2. Literature

2.1. The relationship between rare earth and clean energy stocks

The interconnectedness between REEs and clean energy solutions reveals mixed findings. Fluctuations in the price of REEs significantly impact the clean energy market (Baldi et al., 2014; Ding et al., 2022). Using the Diebold and Yilmaz framework, Zheng et al. (2021) find that connectedness between REEs and renewable energy indicates moderate volatility spillover, while Song et al. (2021) show REEs to be a receiver of dynamic returns and volatility shocks during the COVID-19 period. The empirical results find a significant dynamic correlation between REEs and the new energy market, reflecting their critical role in clean energy technologies (Chen et al., 2020). The spillover effect between REEs and the renewable energy market reveals a complex relationship, driven by new policy initiatives and economic fundamentals (Ding et al., 2022). Madaleno et al. (2023) demonstrate that REEs act as a net receiver of spillovers, contingent on market conditions, time horizons, and quantiles, particularly in the short run. In brief, critical metals are mainly a net receiver of spillovers. Bouri et al. (2021) examine the dynamic return and volatility connectedness between the REE stock index and major sector indices, including clean energy. The study finds that connectedness strengthened significantly during 2010-2012 and the COVID-19 pandemic. REEs consistently served as a net receiver of shocks, whereas the clean energy sector shifted from serving as a net receiver of shocks before the pandemic to a net transmitter during the crisis.

2.2. Geopolitical risks on rare earth and clean energy

Geopolitical factors significantly expose the supply chain vulnerability of REEs. China's monopolistic position in the mining and refining sectors amplifies concerns about potential supply chain disruption resulting from trade restrictions and political tensions (Farina & Anctil, 2022; Li et al., 2023). Given REEs' critical role not only in clean energy production but also in various critical industries, their supply chain is vulnerable to shocks and risks (Opare et al., 2021; Proelss et al., 2020). The vulnerability of REEs extends beyond physical disruptions to encompass dynamic societal and geopolitical factors, speculative markets, export embargoes, and environmental regulations (see Aziman et al., 2023; Hu et al., 2023). For instance, United States-China trade tensions increase market uncertainty in both the renewable energy sector and the REEs market (Bouri et al., 2021; Calderon et al., 2020). Farina and Anctil (2022) demonstrate that China's REE policies exerted a significant effect on price sensitivity in the renewable energy market. The relationship between REE prices and trade policy uncertainty is negative and positive in China and the United States, respectively (Hau et al., 2022). Empirical evidence shows positive correlations between geopolitical risks and the price of imported REEs, while gross import values are inversely related (Fan et al., 2023). The study reveals that political risks have a significant influence on time and frequency spillovers between REEs and green energy, particularly in short-term dynamic connectedness (Zhou et al., 2022).

The relationship between geopolitical risks and renewable energy consumption has been explored in recent literature. Acheampong et al. (2023) find that heightened geopolitical risks can negatively impact the effectiveness of renewable energy in mitigating emissions, highlighting a complex interplay between geopolitical instability and energy transitions. In contrast, Alsagr and Van Hemmen (2021) find evidence of a significant positive effect of geopolitical risks on clean energy consumption patterns in emerging markets, indicating that geopolitical tensions can sometimes accelerate the adoption of renewable energy as a strategic alternative to fossil fuels. The time-varying connectedness between geopolitical instability and renewable energy consumption indicates the potential alleviation of geopolitical tension, with renewable energy sources serving as a strategic alternative to fossil fuels (Cai & Wu, 2021). This finding is consistent with the study that shows a rise in renewable energy consumption can offset reliance on fossil fuels, thereby reducing geopolitical instability associated with energy insecurity (Overland, 2019). Furthermore, evidence from the study suggests that when geopolitical risks increase, crude oil prices tend to rise due to supply chain disruption and market sensitivity, which often encourages investors and consumers to explore alternative energy sources such as clean energy technologies (Dutta & Dutta, 2022). Geopolitical tension can simultaneously stimulate investment in clean energy technologies while deterring it due to instability (IEA, 2021).

3. Data and methodology

3.1. Data

To evaluate the risk profile of REEs, clean energy assets, geopolitical and economic events, we utilized daily data from January 2015 to May 2024, excluding non-trading days for the purpose of uniformity. The sample period selected was based on the availability of data. Our dataset consists of the Vaneck Rare Earth Strategic Metals ETF (REMX), the largest and most liquid ETF tracking the REE sector as a proxy for the REEs market. Although REMX is an equity-based instrument rather than direct commodity price index, it is widely accepted as a proxy for REE market in both academic and industry research (Bouri et al., 2021; Dutta et al., 2025; Henriques & Sadorsky, 2023). REMX composition consists of companies directly engaged in mining, refining and distribution of REEs and strategic metals. These companies must generate at least 50% revenue from the REEs. For the broader clean energy market, we utilize the WilderHill Clean Energy Index (ECO) and the S&P Global Clean Energy Index (SPGCLE), both globally recognized benchmark indices. To capture the specific value chain within the clean energy sector, we include three subsector indices: the NASDAQ OMX Wind Index (GRNWIND), the Kensho Electric Vehicle Index (KEVP), and the NASDAQ OMX Solar Index (GRNSOLAR) as proxies for the wind energy, clean mobility, and solar energy sectors, respectively. Geopolitical risk (GPR) represents a proxy for geopolitical instability to contextualize periods of market stress for REEs driven by global instability, trade tensions, and uncertainty, based on the index developed by Caldara and Iacoviello (2022). For comparative analysis, we incorporate the S&P Gold Index (GLD) and Bitcoin (BTC), widely studied for their hedging and safe haven properties in the clean energy market (Elie et al., 2019; Gustafsson et al., 2022). Additionally, to address the discrepancy in trading calendars between BTC and other assets, the dataset was synchronized by retaining only observations corresponding to common business days across all series.

All price data for REMX, ECO, SPGCLE, KEVP, and GLD were retrieved from the Refinitiv DataStream database. In addition, the wind and solar indices (GRNWIND and GRNSOLAR) along with the BTC price index were obtained from Investing.com (Investing, 2024), while the daily GPR data were sourced from the Economic Policy Uncertainty database (EPU, 2024). We define daily returns as the logarithmic difference in prices for all series between time t and $t-1$ as $R_{i,t} = \ln\left(P_{i,t}\right)$ - $\ln\left(P_{i,t-1}\right)$, except for the GPR index, which is used in its raw form.

Fig. 1 depicts the price series of clean energy indices in our sample. Interestingly, we identify a slight upward trend in the various clean energy stock indices from 2015 to 2019, followed by a drastic decline during the COVID-19 pandemic crisis in early 2020, before experiencing a significant peak and a moderate decline towards the end of the sample period. The price of REMX, shown in Fig. 2, trends downwards from 2018, hitting its lowest point during the COVID-19 crisis, followed by a high peak and a decline towards the end of the sample. GLD's price exhibits an increasingly upward trend throughout the period, whereas BTC's price displays a volatile upward trend (Fig. 3).

Fig. 4 illustrates the return time series for REMX, BTC, GLD, and the clean energy indices across the sample period, indicating volatility clustering, mean reversion, and stationarity of the series. These characteristics show consistent volatility patterns and a tendency for the returns to revert to their mean over time.

The summary statistics showing the characteristics of the return series of clean energy stock indices are shown in Panel A, Table 1. It can be observed that GRNSOLAR has the highest average returns, followed by GRNWIND, SPGCLE, and KEVP, over the sample period. Clean energy return series exhibit a mean value close to the median, suggesting the absence of large asymmetries in the data distributions. ECO displays the highest standard deviation, making it the most volatile return series, whereas SPGCLE is the least volatile, with the lowest standard deviation. ECO shows positive skewness, while the other return series have negative skewness; positive (negative) skewness implies a higher likelihood of large positive (negative) returns without a correspondingly frequent likelihood of large negative (positive) returns. All return series demonstrate excess kurtosis (i.e., a leptokurtic distribution), implying heavier tails than normal distributions. Additionally, the Jarque-Bera test statistics indicate that all sampled return series reject the null hypothesis of normal distribution at p-value < 0.01. Both the Phillips-Perron (PP) test and the Augmented Dickey-Fuller (ADF) test reject the null hypothesis of a unit root for all return series at p-value < 0.01. We examine the dependence structure among all the sampled variables using different copulas to capture their joint behavior. The Student-t copula emerges as the best fit, exhibiting the lowest Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and a goodness-of-fit p-value > 0.05, highlighting its superior capability to capture the dependence structure of the data series.

Panel B of Table 1 presents the descriptive statistics for the REMX, BTC, GLD, and GPR sampled series. BTC exhibits the highest average returns, significantly higher than REMX and GLD returns, but this comes with the highest standard deviation, underscoring its status as a volatile asset.

Table 2 presents the correlation among the sampled series of clean energy stock indices, REMX, BTC, GLD, and GPR. We find that REEs (REMX) exhibit a moderately positive correlation with the clean energy stocks, with the highest being KEVP and the lowest GRNWIND. REMX exhibits an insignificant correlation with GPR, while BTC and GLD exhibit a near-zero negative correlation with GPR, suggesting they can be used for hedging during normal conditions (Baur & Lucey, 2010).

3.2. Methodology

We examine the hedge and safe haven properties of REEs (REMX), assuming that REE price changes are influenced by fluctuations in the clean energy stock market. We utilize the framework of Baur and Lucey (2010) and Baur and McDermott (2010), which established the foundational definitions and empirical frameworks for analyzing hedge and safe-haven assets.

3.2.1. Hedge

A hedge asset is, on average, uncorrelated or negatively correlated with another asset or portfolio. Unlike a safe haven, a hedge does not inherently reduce losses during market uncertainty, as it may exhibit positive correlation under such conditions while maintaining a negative correlation under regular market conditions.

3.2.2. Safe haven

A safe haven asset, on average, exhibits zero or negative correlation with another asset or portfolio, particularly during periods of severe market stress or uncertainty. The defining characteristic of a safe haven lies in its capacity to sustain a non-positive correlation

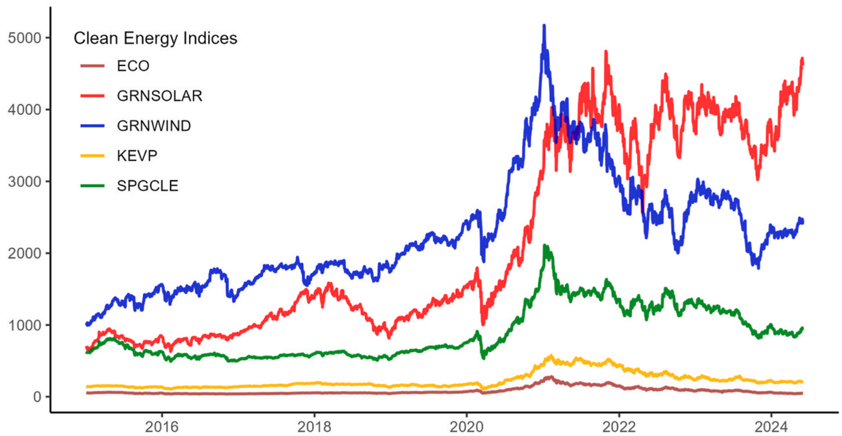

Fig. 1. Clean energy price indices.

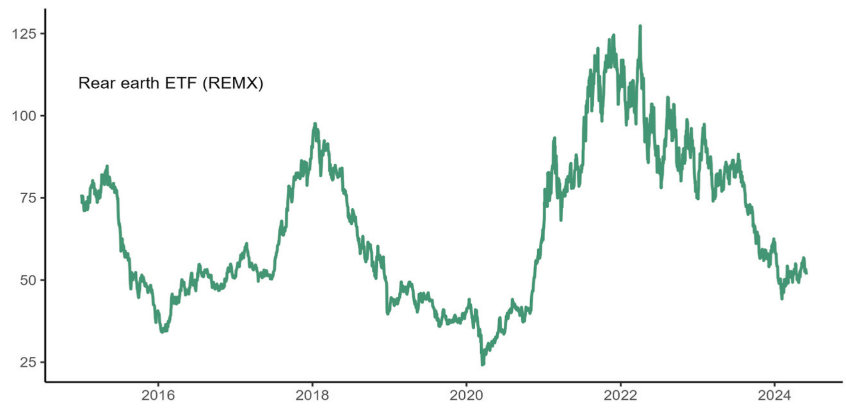

Fig. 2. Rare earth element ETF price.

Fig. 3. Bitcoin and gold price.

in adverse market conditions. Such an asset does not need to maintain a consistent correlation (positive or negative) across normal, bearish, or bullish markets, but it must offer protection during adverse market conditions. When a safe haven asset exhibits negative correlation during turmoil, it offsets investor losses by increasing in value as other assets or the portfolio decreases in value. Consequently, a safe haven is not expected to offer return protection during stable market conditions.

This definition of hedge and safe haven, as proposed by Baur and Lucey (2010) and Baur and McDermott (2010), is grounded in MPT and behavioral finance. It emphasizes the importance of assets exhibiting low or negative correlations in optimizing the risk-return trade-off (Markowitz, 1952; Shefrin, 2001). However, some studies have underscored the limitations of static approaches and the need for time-varying, regime-dependent analysis of hedging and safe haven effectiveness (Anas et al., 2025). Kroner and Sultan (1993) introduced the beta hedge model as an alternative framework that computes an optimal risk-minimizing hedge ratio by incorporating time-varying correlation and long-term cointegration among assets typically overlooked by conventional hedging models. Basher and Sadorsky (2024) demonstrate that the hedging properties of energy commodities are regime-dependent and influenced by supply shocks, policy changes, and macroeconomic trends. Conlon et al. (2020) and Anas et al. (2025) highlight the critical role of liquidity and market depth in determining safe haven status, as illiquid assets often fail to provide reliable protection during crises. Building upon these insights, our study extends the literature by accounting for the unique characteristics of REEs as strategic commodities. We incorporate the time-varying and regime-dependent nature of REEs' behavior through the DCC-GARCH Student-t copula framework. This approach is designed to capture time-varying non-linear dependencies, thereby providing a robust foundation for evaluating REEs’ role in risk management within clean energy portfolios.

Accordingly, we employ the econometric approach of Baur and McDermott (2010) to assess the safe haven properties of REEs. We assume that REE prices are influenced by changes in the clean energy stock market, with these relationships varying under specific or extreme market conditions. Our proposed model regresses REE price returns against five clean energy stock indices (ECO, SPGCLE,

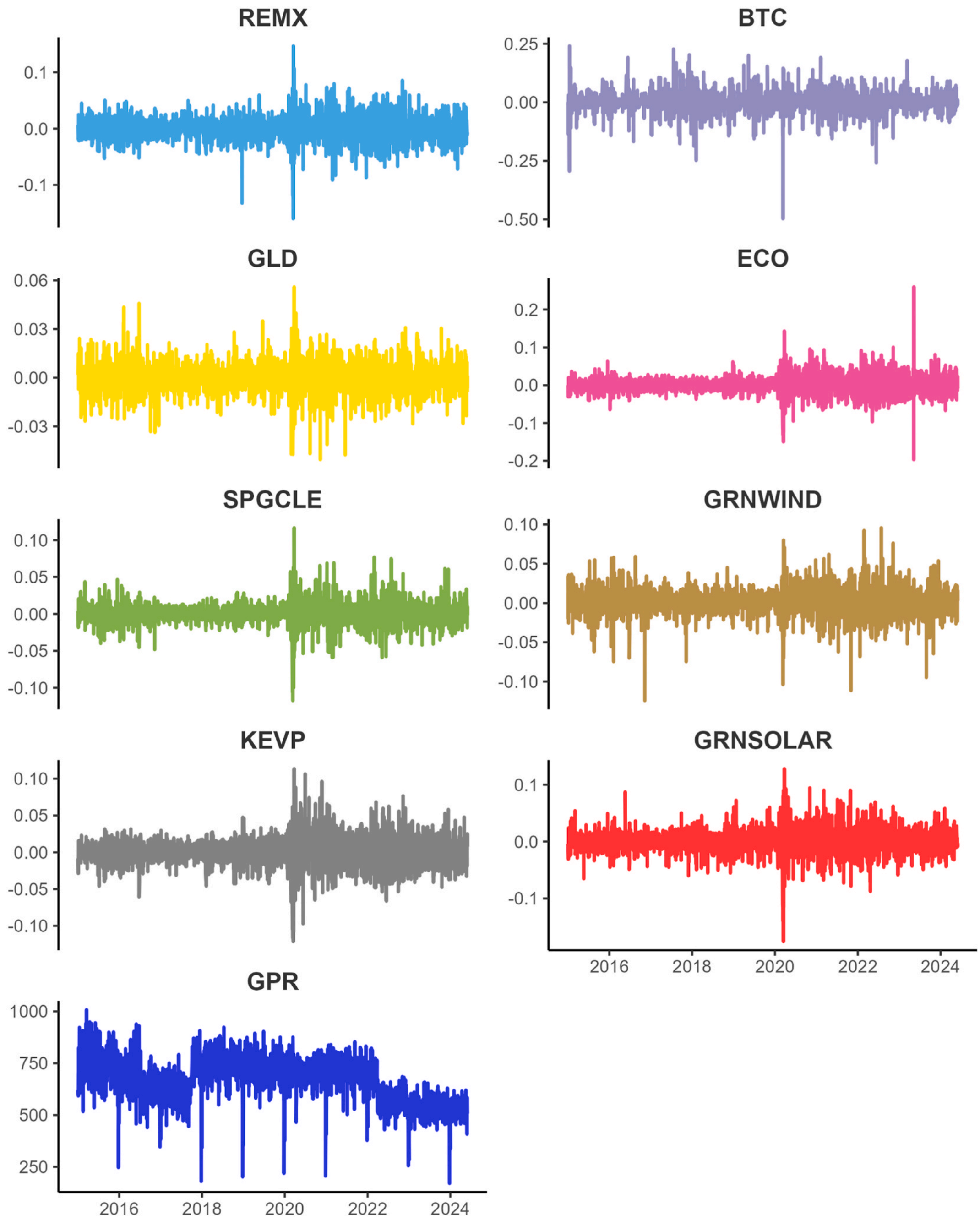

Fig. 4. The return series for clean energy stock indices, REMX, BTC, GLD, and GPR
Note: All return series are transformed using natural logarithms, except for GPR.

GRNWIND, KEVP, and GRNSOLAR) over the sample period from January 2015 to May 2024. The regression specification to test the hypothesis is specified as follows:

$$r_{REE,t} = \alpha + \beta_t r_{index,t} + \varepsilon_t \tag{1}$$

$$\beta_t = p_0 + p_1 D\left(r_{index} q_{q10}\right) + p_2 D\left(r_{index} q_{q5}\right) + p_3 D\left(r_{index} q_{q1}\right) \tag{2}$$

$$D\left(r_{index} q_x\right) = \begin{cases} 1 \textit{ if } r_{index,t} < r_{index} q_x \\ 0 \textit{ if } r_{index,t} \geq r_{index} q_x \end{cases} \tag{3}$$

Table 1
Descriptive statistics.

Panel A: Clean energy indices					
	ECO	SPGCLE	GRNWIND	KVEP	GRNSOLAR
Mean	0.0002	0.0003	0.0005	0.0003	0.0010
Median	0.0000	0.0002	0.0004	0.0002	0.0008
Maximum	0.2601	0.1166	0.0959	0.1135	0.1281
Minimum	−0.1970	−0.1175	−0.1244	−0.1213	−0.1758
Std. Dev.	0.0236	0.0152	0.0169	0.0191	0.0210
Skewness	0.2919	−0.1200	−0.2421	−0.0561	−0.2449
Kurtosis	13.8396	10.3370	8.2502	7.1434	8.5682
J-B test	12059***	5515***	2845***	1758***	3197***
PP test	−47.89***	−41.13***	−43.47***	−45.90***	−46.12***
ADF test	−47.88***	−41.11***	−43.48***	−45.87***	−46.15***
Copula type	**Gaussian**	**Gumble**	**Student t**	**Clayton**	**Frank**
AIC	−7903.45	−3845.5	−8912.53	−4140.42	−3824.47
BIC	−7816.36	−3839.7	−8819.63	−4134.62	−3818.66
GOF p-value	0.033	0.004	0.095	0.005	0.004
Observations	2456	2456	2456	2456	2456

Panel B: Rare earth ETF (REMX), Bitcoin (BTC), Gold (GLD) and Geopolitical risk (GPR)				
	REMX	BTC	GLD	GPR
Mean	0.0001	0.0022	0.0003	670.92
Median	0.0000	0.0019	0.0001	682.00
Maximum	0.1468	0.2408	0.0560	1008.00
Minimum	−0.1599	−0.4973	−0.0506	170.00
Std. Dev.	0.0215	0.0439	0.0090	107.51
Skewness	−0.1159	−0.8018	−0.0877	−0.3560
Kurtosis	6.8939	14.2566	7.1411	3.3333
J-B test	1557***	13230***	1758***	63***
PP test	−45.84***	−51.79***	−44.18***	−15.97***
ADF test	−45.89***	−51.48***	−44.19***	−16.26***
Observations	2456	2456	2456	2456

Notes: *** denote the rejection of the null hypothesis at 1% significant level.

Table 2
Correlation matrix.

	REMX	BTC	GLD	ECO	SPGCLE	GRNWIND	KVEP	GRNSOLAR
REMX	1							
BTC	0.21	1						
GLD	0.14	0.08	1					
ECO	0.59	0.21	0.07	1				
SPGCLE	0.57	0.21	0.13	0.79	1			
GRNWIND	0.26	0.05	0.03	0.29	0.40	1		
KVEP	0.61	0.21	0.02	0.84	0.70	0.26	1	
GRNSOLAR	0.28	0.09	0.03	0.40	0.42	0.37	0.38	1

$$h_t = \delta + \omega\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{4}$$

Eq. (1) where $r_{REE,t}$ represents the logarithmic return of the REE price at time t, $r_{index,t}$ denotes the return of a clean energy stock index at time t; the parameters α and β_t are to be estimated, and ε_t denotes the error term. The parameter β_t is modelled by Eq. (2), where the coefficients to estimate are p_0, p_1, p_2, and p_3. A significant deviation of any estimated coefficients p_1, p_2, and p_3 in Eq. (2) from zero suggests the presence of a non-linear correlation between the returns of REEs and clean energy stocks. Based on the definitions of hedge and safe haven outlined earlier, the estimates of Eq. (2) model are interpreted as follows: if p_1, p_2, and p_3 are non-positive, REEs act as a weaker safe haven for the specified clean energy sector; if p_1, p_2, and p_3 are negative and statistically significant, REEs serve as a strong safe haven; if the estimate of $p_0 = 0$ and the sum of other parameters (p_1, p_2, and p_3) does not exceed p_0 positively, REEs are considered a weak hedge; if the p_0 is negative and the combined effect of p_1, p_2, and p_3 does not offset it positively, REEs are considered a strong hedge for the clean energy stock returns. Eq. (3) defines the dummy variable denoted by D, which capture extreme clean energy stock market movements at the 10%, 5%, and 1% quantiles of the return distribution, identifying periods of extreme market uncertainty when investors typically seek safe haven assets. Finally, Eq. (4) specifies a GARCH (1,1) model to estimate the error term and account for heteroscedasticity. This framework allows us to robustly test the hedge and safe haven properties of REEs across diverse market conditions.

4. Empirical results

In this section, we report the estimated coefficients from the regression model defined in Eqs. (1)–(4). Table 3 presents the estimated results for p_0 and the total effects under extreme market stress. Specifically, the sum of p_0 and p_1 captures the effect at the 10% quantile, the sum of p_0, p_1, and p_2 represents the effect at the 5% quantile, and the sum of all the coefficient estimates (p_0, p_1, p_2 and p_3) indicates the effect at the 1% quantile. A statistically significant zero (negative) coefficient estimate in extreme market conditions (0.10, 0.05, or 0.01 quantiles) indicates that REEs act as a weak (strong) safe haven asset.

Our analysis uncovers evidence of a non-linear relationship between REEs and each clean energy stock index.

Table 3 reveals evidence of significant positive correlation between REEs and all clean energy subsectors on average. However, under extreme market conditions, the evidence indicates weak non-linearity for most subsectors. The non-linearity is least pronounced, or weakest, for ECO, SPGCLE, KEVP, and GRNSOLAR, whereas it is moderate for GRNWIND. In the hedge column of Table 3, we observe a highly significant positive correlation between REEs and ECO, SPGCLE, GRNWIND, KEVP, and GRNSOLAR. Since coefficients in the hedge column are not negative or equal to zero, REEs do not function as a hedge for clean energy stocks under normal market conditions. REEs are critical inputs in clean energy technologies, creating a positive correlation between REE prices and clean energy stock performance. This input-output relationship explains why REEs cannot serve as a hedge, as their prices are driven by the same industrial factors that influence the clean energy market under normal market conditions. According to the IEA (2023) report, the rapid adoption of clean energy solutions has tightened the REE market, heightening energy security concerns and price volatility as supply struggles to meet burgeoning demand. These factors have decreased REEs' ability to effectively hedge clean energy stocks. These results are consistent with Baldi et al. (2014) and Ding et al. (2022), who find that the rising price of REEs negatively impacts clean energy stock performance. In contrast, our findings contradict Juan C and Andrea's (2020) suggestion that, under normal market conditions, REEs can serve as a hedge for the clean energy market.

From Table 3, the results when investigating the safe haven properties during period of extreme market conditions (quantile 10%, 5% and 1%), where zero (negative) coefficients indicate that REEs are a weak (strong) safe haven. The results show that REEs do not serve as a safe haven for ECO, SPGCLE, GRNWIND, KEVP and GRNSOLAR. For instance, coefficients (p_1, p_2, and p_3) for ECO are non-negative and statistically insignificant across all quantiles, indicating that REEs do not act as a strong safe haven asset. Similarly, the corresponding coefficients for GRNWIND are not consistently non-positive and statistically insignificant, indicating that REEs fail to qualify as a weak safe haven asset.

However, an intuitive divergence is observed with GRNWIND, where REEs exhibit a strong positive relationship with GRNWIND during a bearish market shock at the 5% quantile. This strong association is noteworthy, highlighting the wind energy subsector as the largest demand source of REEs within the clean energy market (IEA, 2021). The significant demand for REEs in wind turbine technology stems from their essential role in the manufacturing of permanent magnets (Baskaran & Schwartz, 2024). REEs' role as inputs to clean energy technologies limits their ability to serve as safe havens, making them poor candidates for capital preservation during crises. Additionally, these findings align with the report suggesting that the market transparency of REEs remains limited, as its opacity complicates the strategic hedging or safe haven roles, investment decisions, and risk assessment needed for stable supply and proactive policies (IEA, 2021a). Furthermore, REE prices are linked to supply chain constraints and geopolitical instability exposure due to China's near-monopoly control in mining and refining (Madaleno et al., 2023). Our findings are consistent with studies that identify a significant correlation between REEs and renewable energy in extreme market conditions (see Apergis & Apergis, 2017; Juan C & Andrea, 2020; Song et al., 2021).

5. Dynamic conditional correlation-student-t-copula and hedging effectiveness

Copula frameworks offer a versatile and robust approach to modelling the interconnectedness between variables, especially in financial and commodity markets. We employ a DCC-Student-t copula to capture extreme nonlinear tail dependence, a prevalent feature of financial and commodity returns. According to Sklar (1959), the copula functions as a general technique to construct joint univariate or multivariate distributions. According to the theorem, the joint distribution function in a copula framework can be expressed as:

$$F_X(x_1, x_2, \ldots.., x_N) = C(u_1, u_2, \ldots.., u_N) \tag{5}$$

where $u_1 = F_X(x_1)$, $u_2 = F_X(x_2)$ and $u_N = F_X(x_N)$ denote the univariate distribution functions for variable X_1 ,X_2,X_N, and $F_X(x_1, x_2, \ldots$

Table 3
Results for the hedge and safe haven analysis.

REMX	Hedge	Safe haven quantiles		
		0.1	0.05	0.01
ECO	0.494***	0.998	−1.021	−0.272
SPGCLE	0.790***	0.385	0.103	−0.117
GRNWIND	0.341***	−2.279	2.775**	−0.506
KEVP	0.652***	−0.261	0.163	−0.262
GRNSOLAR	0.242***	−0.749	0.787	0.877

Notes: **, and *** denote significance at the 5% and 1% levels, respectively.

$.., x_N)$ is the joint distribution function. For the bivariate case, the Student-t copula is specified as:

$$C_{v,\mathscr{R}}(u_1, u_2) = t_{v,\mathscr{R}}\left(t_v^{-1}(u_1), t_v^{-1}(u_2)\right) \tag{6}$$

where $\mathscr{R}$ is the time-invariant correlation matrix, and v denotes the degrees of freedom (DoF). We extend the Student-t copula from the bivariate to the multivariate case:

$$C_{v,\mathscr{R}}(u_1, \ldots, u_N) = t_{v,\mathscr{R}}\left(t_v^{-1}(u_1), \ldots, t_v^{-1}(u_N)\right) = t_v^{-1}, \mathscr{R} \prod_{i=1}^{N} t_v^{-1}(x_i) \quad (7)$$

Here, t_v^{-1} represents the inverse of the univariate Student-t distribution, with the v capturing symmetric tail dependence in the multivariate setting, and $t_{v,\mathscr{R}}$ denotes the multivariate Student-t distribution. To incorporate time-varying dynamics, we replace the constant correlation matrix $\mathscr{R}$ with the DCC matrix proposed by Engle (2002). The resulting DCC-GARCH equation is specified as:

$$r_t = L + Ar_{t-1} + \varepsilon_t \tag{8}$$

$$\varepsilon_t = H_t^{1/2} z_t \tag{9}$$

where r_t is a matrix of logarithmic returns, L denotes a matrix of constant parameters, A represents a matrix of coefficients capturing lagged returns and shocks, ε_t denotes the residual term, whereas z_t is a matrix of *iid* innovations and H_t represents the conditional variance-covariance matrix. The matrix H_t is further decomposed as:

$$H_t = V_t \Omega_t D_t \tag{10}$$

$$V_t = diag\left(\sqrt{v_t^c}, \sqrt{v_t^r}\right) \tag{11}$$

$$\Omega_t = diag(\hat{Q}_t)^{-1/2} Q_t diag(\hat{Q}_t)^{-1/2} \tag{12}$$

$$Q_t = (1 - \alpha - \beta)Q + \alpha(u_{t-1}u_{t-1}) + \beta Q_{t-1} \tag{13}$$

In eq. (11), v_t^c and v_t^r denote the conditional volatility of the clean energy stock indices and the REEs/Bitcoin/gold markets, respectively. In Eq. (13), Q_t represents the time-varying conditional correlation matrix of ε_t, α and β are non-negative scalars ensuring model stationarity by satisfying $\alpha + \beta < 1$, and Q is the unconditional correlation matrix for the standardized residuals. The pairwise dynamic conditional correlation is expressed as:

$$\rho_t = \frac{v_t^{cr}}{\left(\sqrt{v_t^c}\ \sqrt{v_t^r}\right)} \tag{14}$$

In eq. (14), ρ_t and v_t^{cr} are the time-varying correlation and conditional covariance between clean energy stocks and REEs/Bitcoin/gold, respectively. The DCC-GARCH framework is estimated using the quasi-maximum likelihood (QML) method, paired with the Student-t copula for optimal fit.

Following the methodology of Ku et al. (2007) and Gustafsson et al. (2022), we compute the hedging effectiveness (HE), which measures the reduction in variance of hedged portfolios compared to unhedged portfolios consisting of clean energy stock indices and REEs/Bitcoin/gold, expressed as:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{15}$$

where $Var_{unhedged}$ represents the variance of unhedged portfolios consisting only of clean energy stock indices, whereas Var_{hedged} denotes the variance of the combined portfolio, incorporating both clean energy stocks and REEs/Bitcoin/gold. A higher *HE* value suggests superior risk reduction and improved hedging efficiency. The variance of the Var_{hedged} is defined as:

$$Var_{hedged} = (\omega_t^{cr})^2 v_t^c + \left(1 - (\omega_t^{cr})^2\right) v_t^r + 2\omega_t^{cr}\left(1 - \omega_t^{cr}\right) v_t^{cr} \tag{16}$$

where ω_t^{cr} represents the optimal weight of clean energy stocks in the combined portfolio (hedge portfolio), calculated as follows:

$$\omega_t^{cr} = \frac{v_t^c - v_t^{cr}}{v_t^c - 2v_t^{cr} + v_t^r} \tag{17}$$

Figs. 5 and 6, A1, and A2 illustrate the time-varying conditional correlation between the clean energy indices and REEs/GPR/GLD/BTC. As shown in Fig. 5, REEs exhibit a persistent positive correlation with all the clean energy indices over time. This correlation is particularly strong and consistent between REEs and the broad clean energy indices (ECO and SPGCLE), reflecting significant integration of both markets. Surprisingly, the correlation between REEs and GRNSOLAR declines significantly post-2020, likely due to supply chain disruption during the COVID-19 pandemic. The correlation between REEs and KEVP exhibits an upward trend post-2020,

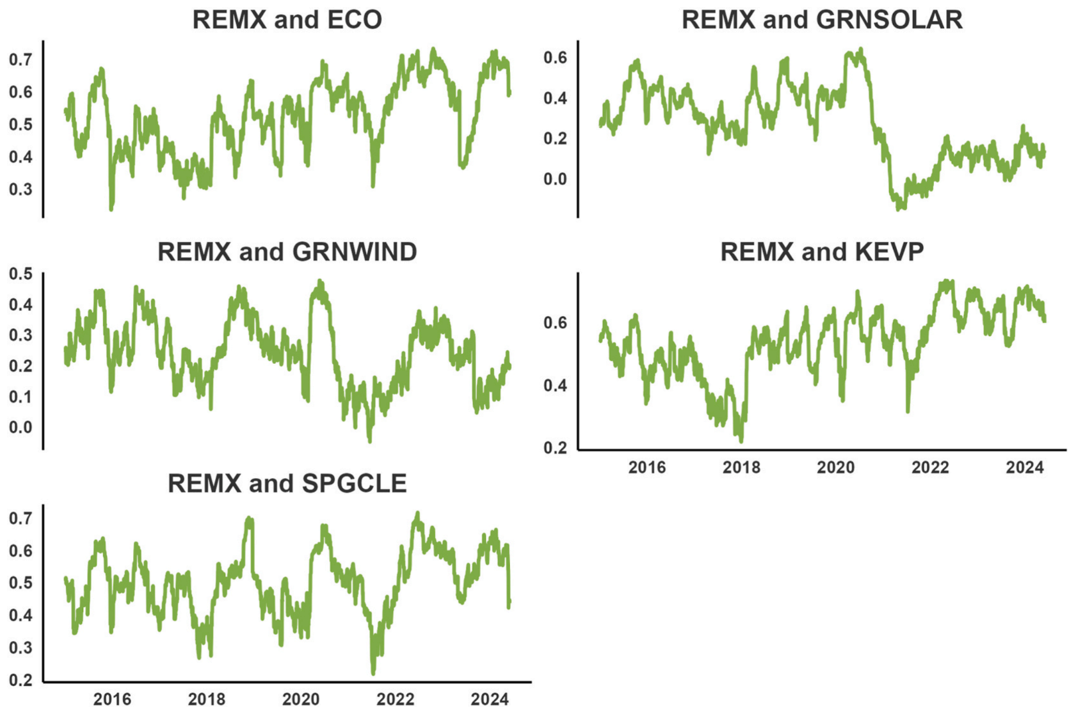

Fig. 5. DCC correlation between rare earth elements and clean energy indices.

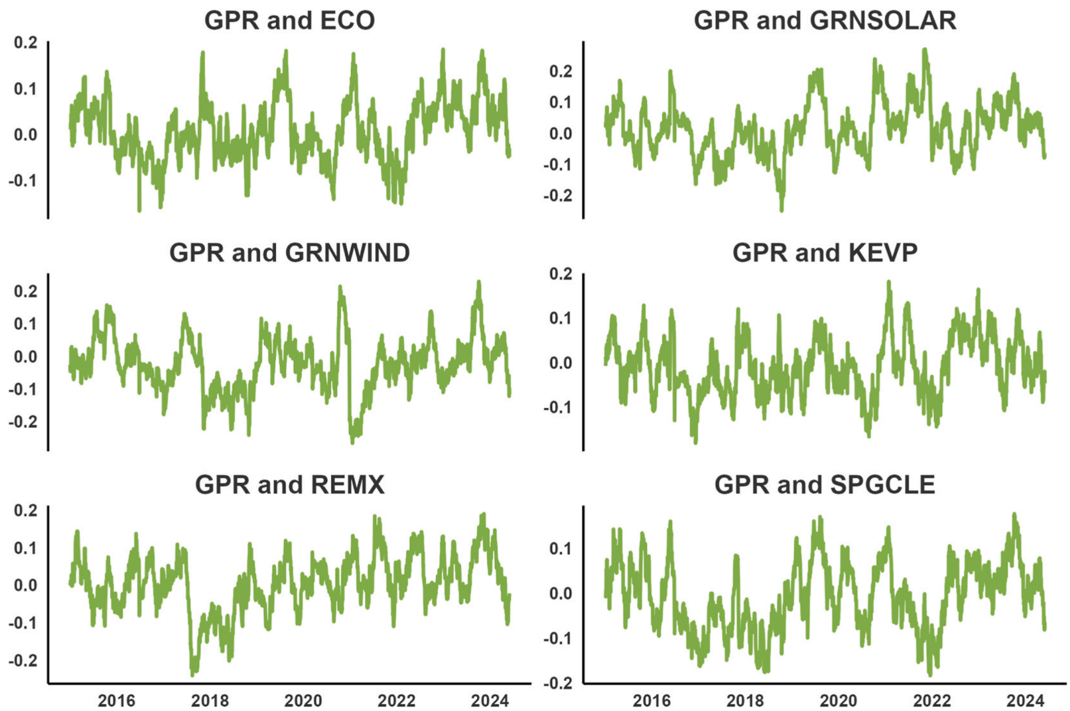

Fig. 6. DCC correlation between geopolitical risks, clean energy stocks, and rare earth elements.

aligning with the global adoption of EVs, particularly in developed countries (IEA, 2021). The correlation between REEs and GRNWIND fluctuates over time more than the other indices. Generally, we observe some short periods of sharp decline in correlation, but it remains positive, notably during geopolitical instability and supply chain shocks, such as the United States-China trade tensions (2018-2019) and the COVID-19 pandemic (2020-2021). Overall, the trend remains strong and positive, implying that REEs are neither a hedge nor a safe haven asset for the sustainable energy market under adverse conditions.

Fig. 6 depicts the correlation between GPR and the clean energy indices (ECO, SPGCLE, GRNWIND, GRNSOLAR, KEVP) and REEs. The correlation between GPR and sustainable energy indices appears relatively weak over time. Unlike the commodity market, the clean energy market shows less sensitivity to GPR, with no persistent trend of positive or negative correlation. Similar evidence of weak correlation is observed between GPR and REEs. However, an upward trend is observed from 2018 to 2022, aligning with the United States-China trade tensions and the COVID-19 period. These patterns suggest that GPR does not maintain a strong linear relationship with either REEs or clean energy stocks. Instead, its impact is non-linear and context-dependent, varying across different geopolitical events. Fig. A1 reveals a relatively weak correlation between GLD and all the clean energy indices throughout the sampling period. However, we observe an upward trend in correlation from 2020 to 2022, coinciding with the COVID-19 pandemic. This suggests that gold's status as a reliable hedge or safe haven weakens during crises. Gold exhibits a slight positive correlation with GPR over time, consistent with gold's historical reputation as a safe haven asset during periods of geopolitical instability. From Fig. A2, unlike gold, we observe a moderate correlation between BTC and all the clean energy indices, particularly post-2020 during the COVID-19 period. This correlation surge coincides with the cryptocurrency bull run of 2020-2021.

Table 4 presents the hedging effectiveness (HE) measured across distinct subsamples using Eq. (15).

To robustly capture the time-varying hedging effectiveness of REEs for clean energy stocks, we divided the sample period from January 2015 to May 2024 into four subsamples, each corresponding to distinct geopolitical and economic events (Caldara & Iacoviello, 2022). It is noteworthy that the divisions are not arbitrary but justified by major global events that significantly influence the REE supply chain, the clean energy market, and investor sentiment. Subsample I (January 1st, 2015, to March 21st, 2018): this period encompasses the adoption of the Paris Agreement in 2015, which significantly accelerated global investment in the clean energy market (UNFCCC, 2015). It includes key geopolitical events such as the Paris terrorist attack and the Iran nuclear deal. During this phase, REE prices exhibit steady growth, due to China's consistent export quotas and the lack of major geopolitical disruptions, prior to the escalation of United States-China trade tensions in the middle of 2018. Subsample II (March 22nd, 2018, to March 10th, 2020): this period covers the escalation of United States-China trade tensions, including the announcement of strong actions against China's unfair trade (USTR, 2018), imposition of tariffs and restrictions on REE exports (Baskaran & Schwartz, 2024). These developments generated considerable price spikes and market uncertainty during the first Trump administration. However, toward the end of 2019, tensions temporarily eased following the signing of the Phase One United States-China trade deal (USTR.GOV, 2019), just before the COVID-19 pandemic. Subsample III (March 11th, 2020, to February 23rd, 2023): this period is characterized by the COVID-19 declaration as a global pandemic by World Health Organization (WHO, 2020), which disrupted the clean energy market and global supply chains, including REE mining and refining. Subsample IV (February 24th, 2023, to May 31st, 2024): this period covers the Russia-Ukraine war (UN, 2022), which disrupted global energy markets, and the post-COVID period.

The results in Table 4 reveal findings regarding the HE of REEs, GLD, and BTC against clean energy stocks across different subsamples. First, in Subsample I, GLD and REEs outperform BTC during the adoption of the Paris Agreement, and geopolitical risk events such as the Paris terrorist attack and the Iran nuclear deal. GLD emerges as the most effective hedging asset, with the highest (lowest) HE of 77% (57%), respectively. REEs exhibit a moderate HE, generally between 10% and 33%, outperforming BTC in most indices. BTC demonstrates the lowest HE, ranging from 9% to 15%, reflecting its speculative nature and limited acceptance as a store of value. This period precedes major geopolitical instability and may serve as a useful benchmark for assessing HE under normal market conditions. The superior performance of GLD's HE aligns with its traditional role as a safe haven asset during stable periods, while the moderate HE

Table 4
Hedging effectiveness (HE) in percentages (%).

	Hedging effectiveness			
	Subsample I	Subsample II	Subsample III	Subsample IV
Panel A: REMX				
ECO	17.758	12.910	36.344	39.763
SPGCLE	6.065	2.715	10.934	4.613
GRNWIND	31.066	16.852	26.704	26.748
KEVP	9.856	11.612	25.270	15.260
GRNSOLAR	33.768	28.115	47.010	38.092
Panel B: BTC				
ECO	11.956	12.193	21.573	20.790
SPGCLE	8.703	4.438	7.436	4.766
GRNWIND	15.821	8.373	13.647	14.784
KEVP	8.863	10.843	19.560	7.691
GRNSOLAR	13.958	18.497	20.857	21.904
Panel C: GLD				
ECO	72.455	76.565	86.757	90.048
SPGCLE	56.824	57.832	70.491	68.650
GRNWIND	73.668	70.815	73.500	76.674
KEVP	68.584	77.411	83.327	83.226
GRNSOLAR	77.411	84.580	84.996	81.522

Note: This table displays the HE estimates. Subsample I spans from January 2015 to March 2018 (Paris Climate Agreement, Paris terrorist attack and Iran nuclear deal); Subsample II covers March 2018 to March 2020 (the United States-China trade tension); Subsample III covers March 2020 to February 2023 (COVID period); Subsample IV covers February 2023 to May 2024 (Russia-Ukraine war, post-COVID period).

of REEs reflects their strategic importance as inputs in clean energy technologies, with limited but present hedging potential. Our findings are consistent with Baur and Lucey (2010), who find GLD to be effective as a hedge during normal market conditions, and with Bouri et al. (2020), who reveal that gold outperforms Bitcoin as a hedging asset. Second, in Subsample II, REEs experience a significant decline of ~36% on average in HE, while GLD continues to maintain a dominant HE. The HE of BTC remains low, with minimal changes. The decline in REEs' HE likely stems from the United States-China trade war's disruption of REE supply chains, which increased price volatility and undermined REEs' hedging role. China's near-monopolistic control of global REE production and its export restrictions exacerbated the supply chain risks (IEA, 2021a; Proelss et al., 2020). This finding aligns with studies that show supply shocks (e.g., trade restrictions) reduce REEs' effectiveness as a hedge, as uncertainty increases price volatility (Bouri et al., 2021; Calderon et al., 2020).

Third, in Subsample III, both REEs and BTC experience a sharp increase in HE, while GLD shows a moderate improvement as an effective hedge asset. The COVID-19 pandemic accelerated the pre-existing shift towards clean energy investment as part of economic recovery programs, boosting the demand for REEs (Basher & Sadorsky, 2024; IEA, 2021). For instance, the European Union Green Deal (EGD) stimulated clean energy markets, indirectly increasing REE demand. This policy-driven demand partially offset the supply chain disruptions caused by COVID-19 pandemic lockdowns (EEB, 2024). BTC's HE surged by ~35% on average across the clean energy indices, reflecting significant improvement during the COVID-19 period. This rise may be linked to Bitcoin's perceived role as a hedge against fiat currency devaluation, inflation fears driven by large-scale monetary stimulus, and economic uncertainty (Shahzad et al., 2020). However, its effectiveness remains inconsistent over the long term due to its speculative nature and limited widespread acceptance, which hampers its reliability as a stable hedge compared to gold. Our results align with prior studies demonstrating BTC's inability to serve as a reliable shelter during the pandemic due to its heightened volatility (Chemkha et al., 2021). However, they contradict Bouri et al. (2020), who indicate the superiority of BTC over both gold and other commodities in terms of hedging benefits in tail dependency (e.g., COVID-19 crisis).

Fourth, in Subsample IV, GLD sustains a higher HE than both REEs and BTC in the post-COVID-19 pandemic period. Following market turbulence, the HE of REEs slightly declines on average but remains significantly higher compared to Subsamples I and II, while BTC experiences a moderate decline on average. The Russia-Ukraine war disrupted global energy markets, increasing the demand for clean energy alternatives while simultaneously straining the volatile REE supply chains. In this context, GLD reinforces its role as the traditional hedging tool under uncertain conditions, exhibiting HE superior to both REEs and BTC during all the subsample periods. The financial detachment of GLD from clean energy technologies, along with limited herding behavior among its investors, allows it to serve as an effective hedge (Baur & Lucey, 2010; Forbes & Rigobon, 2002). In contrast, the role of REEs as critical inputs in clean energy production creates shared risk exposure, while BTC's speculative nature limits its reliability as an effective hedging instrument. Evidence from prior studies shows that GLD outperforms BTC in hedging effectiveness across several stock indices (Hussain Shahzad et al., 2020). However, our finding contradicts the Gustafsson et al. (2022) study, which suggests that BTC outperforms GLD in hedging effectiveness during the COVID pandemic.

Our findings highlight that geopolitical and economic events are heterogeneous in the magnitude of their influence on REEs' hedging properties. This suggests that the role of geopolitical instability is non-linear and context-dependent, varying across different subsample regimes and geopolitical events. Notably, we observe that the HE of REEs was relatively stable during Subsample I but increased significantly during Subsamples III and IV. These latter periods are characterized by major crises (e.g., COVID-19 pandemic, Russia-Ukraine war), which drove a surge in demand for clean energy technologies and, consequently, for REEs. This pattern underscores the strong input-output relationship between REEs and clean energy technologies. This finding aligns with previous studies arguing that increased geopolitical instability will prompt energy-importing countries to pivot towards green energy sources to secure their domestic energy security (Cai & Wu, 2021; Dutta & Dutta, 2022). Conversely, REEs show evidence of weak HE during the Subsample II (United States-China trade war) period. This finding may be associated with China's near-monopolistic control over REE production and its use of export restrictions as a retaliatory measure against United States trade policy (Baskaran & Schwartz, 2024). These insights offer valuable information to investors seeking to diversify clean energy portfolios using REEs. Investors can optimize their allocations by adjusting REE exposure based on prevailing geopolitical risks, for instance, by reducing holdings during periods of heightened United States-China trade tensions. Nevertheless, GLD remains the superior hedging asset for clean energy portfolios across various geopolitical conditions. Accordingly, investors may prioritize GLD over REEs when seeking effective hedging instruments.

The results from Table 5 show the full sample HE for REE, BTC, and GLD across the portfolio of clean energy indices. GLD consistently exhibits the highest HE across all the clean energy indices, ranging from 63% (SPGCLE) to 82% (GRNSOLAR). This aligns with this study's finding in Table 4 that GLD outperforms REEs and BTC in all subsamples, reinforcing its role as a traditional hedge asset. REEs show moderate effectiveness overall, with the lowest (highest) HE of 6% (36%), respectively. This variability reflects REEs'

Table 5
Analysis of full sample hedging effectiveness in percentage (%).

Hedging effectiveness			
	REMX	BTC	GLD
ECO	25.701	15.094	80.535
SPGCLE	5.678	5.992	62.730
GRNWIND	26.326	13.559	73.760
KEVP	14.416	9.763	77.028
GRNSOLAR	35.567	18.257	81.596

inconsistent hedging properties, likely due to their positive correlation with clean energy stocks and sensitivity to supply chain disruption, as shown in Fig. 5 and Table 4, respectively. BTC exhibits the lowest HE across all indices, ranging from 6% (SPGCLE) to 18% (GRNSOLAR). These findings reveal that BTC exhibits temporary hedging capabilities during specific crisis periods such as the COVID-19 pandemic, where HE peaked at ~81% on average across indices. Evidence from Table 5 underscores GLD's superiority as a traditional hedging asset, while highlighting REEs as a better hedge asset compared to BTC.

Furthermore, we examine the optimal hedging ratios for the assets, following the approach proposed by Junttila et al. (2018), expressed as:

$$\beta_t^* = \frac{v_t^{cr}}{v_t^r} \tag{18}$$

where β_t^* denotes the optimal hedging ratio (HR) of the portfolio. Fig. 7, A3, and A4 illustrate the hedging ratio plot for REEs-, BTC-, and GLD-clean energy pairs, respectively, across the subsamples. The results indicate that HR varies over time across all the clean energy pairs. Notably, the optimal HR for REEs/BTC/GLD increases significantly during crises, particularly the COVID-19 pandemic, highlighting the heightened financial and economic uncertainty. While the HR for the REEs-clean energy indices pairs exhibits variation across subsamples, those of the BTC- and GLD-clean energy indices pairs remain consistent in most periods. For instance, to minimize the risk of a two-asset portfolio, a long \$1 position in the clean energy stock can be hedged with a β_t^* dollar short position in REEs/BTC/GLD. Empirical evidence suggests that the higher the HR, the more expensive the hedge, and a lower HR implies a cheaper hedge (López Cabrera & Schulz, 2016).

The HR trend shown in Fig. 7, A3, and A4 reveals that the majority of the clean energy stocks' hedge coverage was generally cheaper before the COVID pandemic compared to during and post-pandemic periods. These findings are consistent with prior studies, which indicate a higher hedging ratio during crisis periods due to heightened economic and financial uncertainty (Chemkha et al., 2021; Gustafsson et al., 2022b). Furthermore, as depicted in Fig. 7, the REEs-GRNWIND and REEs-GRNSOLAR pairs in particular exhibit high HR during the Paris terrorist attack, the Iran nuclear deal, and the COVID-19, underscoring the influence of geopolitical instability and economic stress on hedging dynamics.

6. Robustness analysis

In this section, we conduct several robustness tests. Tables 6 and 7 report the results of these tests. First, we consider several subsample analyses, as shown in Table 6. For example, we split the sample based on the COVID-19 pandemic and the Russia-Ukraine war. Second, we use several energy transition metal price indexes (e.g., copper, cobalt, and nickel) to check the robustness of our analysis.[1] Table 7 displays these results.

6.1. Subsample analysis

In Table 6, REEs' HE increases post-COVID across all clean energy indices, mirroring the sharp rise observed during Subsample III (the COVID-19 period) in Table 4. This consistency confirms that the improvement in REEs' hedging performance is primarily driven by the pandemic-induced surge in demand for clean energy technologies, particularly the solar, wind, and EV sectors. Additionally, the HE of REEs during the periods before and during the Russia-Ukraine war, reported in Table 6, aligns closely with the findings of Subsample IV in Table 4, where REEs' HE remains relatively stable but high. In summary, these results reinforce the robustness of REEs as context-dependent hedging assets.

6.2. Alternative energy metal indices

Table 7 presents the robustness results of the HE for energy transition metals, using copper, nickel, and cobalt as benchmarks. When compared with the results for REEs in Table 4, all energy metals exhibit a consistent surge in HE during the COVID-19 pandemic (Subsample III), reflecting a market-wide response to clean energy demand shocks and heightened volatility. This similarity validates the observed HE patterns for REEs. However, REEs display distinct behavior due to their unique geopolitical sensitivity, as evidenced by a sharp decline in HE during the United States-China trade war (Subsample II), a period in which copper, nickel, and cobalt maintained relatively stable or even improved hedging performance, underscoring REEs' unique vulnerability to geopolitical supply chain disruptions. This divergence confirms that REEs' sensitivity to China's monopolistic control over production is a distinct risk factor not shared by other energy metals. Notably, cobalt exhibits consistently superior and stable HE across all subsamples compared to REEs, copper, and nickel. This may be attributed to cobalt's strong and deeply embedded demand in high-growth sectors such as EV batteries. Overall, these robustness checks reinforce the core findings of the study while underscoring the nuanced and context-dependent nature of REEs as a hedge asset, performing well under demand-driven shocks but remaining vulnerable to supply-chain geopolitical disruptions compared to more stable alternatives such as cobalt.

[1] The data on metal prices were retrieved from Refinitiv DataStream Database.

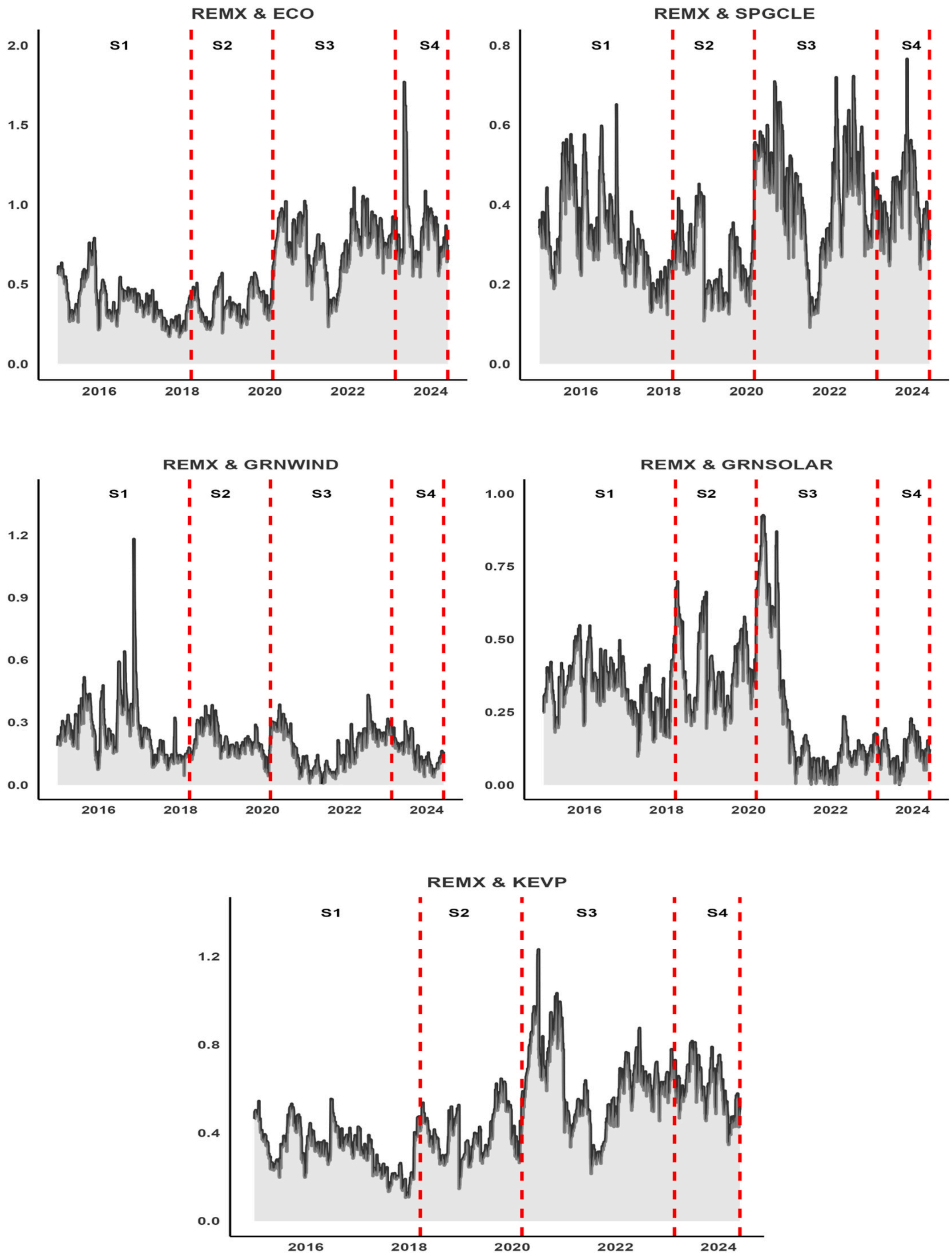

Fig. 7. DCC time-varying optimal hedging ratio for rare earth elements and clean energy indices pairs
Note: This table displays the HE estimates. Subsample I spans from January 2015 to March 2018 (Paris Climate Agreement, Paris terrorist attack and Iran nuclear deal); Subsample II covers March 2018 to March 2020 (the United States-China trade tension); Subsample III covers March 2020 to February 2023 (COVID period); Subsample IV covers February 2023 to May 2024 (Russia-Ukraine war, post-COVID period).

6.3. Gaussian Copula DCC-GARCH

The Gaussian Copula DCC-GARCH result presented in Table 8 provide additional robustness to our study. The comparison between the Gaussian Copula and Student-t DCC-GARCH estimates shows a remarkable consistency in the pattern of HE, despite the difference

Table 6
Analysis of REMX hedging effectiveness in percentage (%).

	Hedging effectiveness			
	Pre-COVID	Post-COVID	Pre-Russia & Ukraine war	Russia & Ukraine war
ECO	15.662	38.012	21.225	39.790
SPGCLE	4.433	7.199	6.079	4.401
GRNWIND	25.891	26.861	26.151	26.876
KEVP	10.043	19.777	14.137	15.290
GRNSOLAR	30.014	42.380	34.689	38.336

Note: This table displays the HE estimates for the REMX index. The Pre-COVID period spans from January 2015 to March 2020; the Post-COVID period spans from March 2020 to May 2024; the pre-Russia-Ukraine war period runs from January 2015 to February 2023; the ongoing Russia-Ukraine war spans from February 2023 to May 2024.

Table 7
Analysis of alternative energy metals hedging effectiveness in percentage (%).

	Hedging effectiveness			
	Subsample I	Subsample II	Subsample III	Subsample IV
Panel A: Copper				
ECO	44.427	51.093	75.763	80.381
SPGCLE	28.632	26.754	54.271	47.587
GRNWIND	49.039	45.771	58.131	61.276
KEVP	35.713	48.888	68.047	67.331
GRNSOLAR	52.483	65.580	75.809	68.891
Panel B: Nickel				
ECO	22.569	24.935	62.939	57.395
SPGCLE	10.775	9.765	37.734	24.793
GRNWIND	27.741	24.199	42.855	36.884
KEVP	16.660	23.916	54.008	40.924
GRNSOLAR	29.606	39.606	63.903	44.212
Panel C: Cobalt				
ECO	71.342	68.708	92.471	94.804
SPGCLE	65.073	60.404	88.204	91.261
GRNWIND	74.453	65.694	89.627	92.256
KEVP	66.978	68.371	90.842	92.984
GRNSOLAR	74.414	73.350	91.536	92.775

Note: This table displays the HE estimates. Subsample I spans from January 2015 to March 2018 (Paris Climate Agreement, Paris terrorist attack and Iran nuclear deal); Subsample II covers March 2018 to March 2020 (the United States-China trade tension); Subsample III covers March 2020 to February 2023 (COVID period); Subsample IV covers February 2023 to May 2024 (Russia-Ukraine war, post-COVID period).

in the distribution of assumptions underlying each framework. The Student-t copula, which accounts for tail dependence and fat-tailed distributions, recorded slightly higher HE values, particularly during extreme market events such as COVID-19 pandemic. In contrast, the Gaussian copula, which assumes normality and linear dependence, generates lower absolute HE values but preserves the same relative rankings and contextual trends. For instance, both copula specifications confirm that cobalt consistently outperforms REE (REMX), copper, and nickel as a hedging asset, and REE's HE sharply rises during demand-driven crises (e.g. COVID-19 pandemic) while declining during supply-side disruptions (e.g. U.S.- China trade war). The minor difference in HE absolute value highlights the relevance of tail dependence in extreme market conditions but the preservation of the core patterns validates that our findings are primarily driven by market dynamics such as input-output relationship between REE (REMX) and clean energy and its geopolitical association rather than by the choice of copula specification.

7. Discussion

The motivation for this research stems from the growing importance of REEs in the global clean energy transition. REEs are critical inputs for technologies such as wind turbines, electric vehicles, and renewable energy infrastructure, causing their demand to rise rapidly as countries pursue decarbonization goals. At the same time, REE markets are highly exposed to geopolitical instability, particularly because production and processing are concentrated in a few countries and are vulnerable to trade disputes, supply chain disruptions, and international conflicts. Given these characteristics, investors and policymakers need to understand whether REEs can serve as a hedge or safe haven against risks in clean energy investments. This study addresses that gap by examining how REEs and clean energy stocks interact under both normal and crisis conditions.

This strand of empirical research is crucial given that it challenges the common assumption that assets closely linked to the clean energy transition automatically provide diversification benefits for clean energy investors. The findings reveal a strong positive relationship between REEs and clean energy stocks during normal market conditions, meaning that they tend to move together rather than offset each other's risks. Furthermore, the relationship changes during periods of extreme market stress, indicating complex and

Table 8
Analysis of energy metals hedging effectiveness in percentage (%).

	Hedging effectiveness			
	Subsample I	Subsample II	Subsample III	Subsample IV
Panel A: REMX				
ECO	17.054	11.080	35.767	37.862
SPGCLE	5.890	2.172	10.611	4.738
GRNWIND	29.567	14.867	25.563	26.352
KEVP	9.540	9.274	23.214	14.633
GRNSOLAR	30.299	30.883	43.738	35.225
Panel A: Copper				
ECO	45.454	49.663	77.663	78.671
SPGCLE	30.126	25.545	57.188	48.953
GRNWIND	50.377	45.021	60.905	61.000
KEVP	34.723	46.501	69.504	66.000
GRNSOLAR	52.897	63.341	76.551	67.087
Panel B: Nickel				
ECO	22.734	26.539	62.282	54.448
SPGCLE	11.736	11.156	37.674	23.246
GRNWIND	27.494	25.226	42.309	33.885
KEVP	16.877	25.060	52.514	37.762
GRNSOLAR	30.162	39.860	61.756	40.525
Panel C: Cobalt				
ECO	48.013	45.024	81.248	81.863
SPGCLE	36.415	27.172	64.792	58.351
GRNWIND	51.998	36.505	68.725	65.901
KEVP	40.953	43.763	75.541	70.904
GRNSOLAR	54.362	53.718	77.408	70.714

Note: This table displays the HE estimates. Subsample I spans from January 2015 to March 2018 (Paris Climate Agreement, Paris terrorist attack and Iran nuclear deal); Subsample II covers March 2018 to March 2020 (the United States-China trade tension); Subsample III covers March 2020 to February 2023 (COVID period); Subsample IV covers February 2023 to May 2024 (Russia-Ukraine war, post-COVID period).

non-linear market dynamics. By comparing REEs with traditional and alternative hedging assets such as gold and Bitcoin, the research provides a clearer understanding of their relative effectiveness in risk management. The results show that REEs generally perform worse than gold and only outperform Bitcoin, suggesting that their role as a protective investment asset is limited despite their strategic importance in the energy transition.

The implications of the study are significant for both investors and policymakers. For investors, the results suggest that holding REEs alongside clean energy stocks may not provide the expected protection during market downturns, particularly because REEs do not consistently behave as a hedge or safe haven asset. This highlights the need for more diversified risk-management strategies and greater reliance on proven hedging instruments such as gold. For policymakers, the findings underscore the vulnerabilities of the clean energy supply chain and the investment risks associated with dependence on critical minerals. The research therefore supports efforts to diversify REE supply sources, strengthen supply chain resilience, and reduce geopolitical dependencies. More broadly, the study contributes to understanding how commodity markets and sustainable finance interact, providing valuable insights for managing risks during the global transition to clean energy.

8. Conclusion

The global shift towards sustainable energy has fueled unprecedented demand for REEs, which are vital for producing clean energy solutions. This clean energy transition, critical to achieving net-zero emissions by 2050, requires an uninterrupted supply chain for REEs. However, China's near-monopolistic control of REE supply introduces significant risks from geopolitical tensions, trade restrictions, and natural disasters. Against this backdrop, we examine the risk profile of REEs by analyzing their dynamic correlation with the clean energy market and their association with geopolitical risks over the period from January 2015 to May 2024. This paper investigates whether REEs function as a hedge and/or safe haven for clean energy assets. Additionally, we compare the time-varying HE and HR of REEs, GLD, and BTC across four distinct subsample periods.

Our findings reveal a significant non-linear correlation between the returns of REEs and clean energy stock returns on average. REEs exhibit a strong positive correlation across all clean energy indices (ECO, SPGCLE, GRNWIND, KEVP, GRNSOLAR). However, regression estimates reveal that these relationships are generally insignificant during extreme market shocks across most indices. REEs exhibit a strong positive correlation with the wind energy subsector (GRNWIND) during extreme market shocks, highlighting the wind energy subsector's role as the largest demand source for REEs within the clean energy market. Our empirical results show that REEs do not function as a consistent hedge or safe haven for the clean energy market. These findings are intuitive and align logically with the fundamental input-output relationship between REEs and clean energy technologies. This relationship creates a positive correlation between their performance, which inherently undermines the hedging or safe haven properties of REEs. Additionally, China's near-monopolistic control of the REE market and the resulting lack of transparency further weaken their effectiveness as reliable hedge and safe-haven assets.

To address the issue of REEs' association with geopolitical instability due to the geographical concentration of production, and to better capture dynamic non-linear relationships, this study employs the DCC-GARCH Student-t copula framework. This approach enables the assessment of time-varying hedge effectiveness (HE) and optimal hedge ratio (HR). This evidence highlights the ability of REEs, GLD, and BTC to act as an effective hedge against the time-varying portfolio variance of clean energy stocks during periods of geopolitical and economic uncertainty. The evidence shows the HE of GLD consistently outperforms both REEs and BTC across all subsample scenarios. This superior performance may be associated with GLD's financial detachment from clean energy technologies and its traditional role as a trusted store of value. During crises, investors tend to prioritize liquidity and proven safe haven assets (e.g., gold), while avoiding relatively illiquid commodities linked to industrial production, which often fail to provide reliable capital preservation. BTC exhibited its strongest hedging performance during the COVID-19 pandemic but fell short compared to the HE achieved by both GLD and REEs during the same period and across other subsamples. This relatively weaker performance may be attributed to BTC's highly speculative nature and limited widespread acceptance, which undermine its consistency and effectiveness as a stable hedge compared to GLD and REEs.

Notably, the HE of REEs dropped sharply during the United States-China trade tensions but surged significantly during the COVID-19 pandemic and the Russia-Ukraine war, while remaining relatively stable in the pre-United States-China trade tension period. The sharp decline appears linked to China's near-monopolistic control over REE production and its strategic use of export controls as a retaliatory measure in geopolitical disputes. Conversely, the increase during the crisis periods may be related to the strong input-output relationship between REEs and clean energy technologies, which generates a positive correlation that eliminates the negative correlation necessary for effective hedging. These patterns suggest that geopolitical tensions are associated with heterogeneous hedging properties of REEs. This underscores the role of geopolitical instability on REE and clean energy markets through multiple channels, including supply chain disruption, trade tensions, and increased uncertainty, with effects that are distinctly non-linear and context-dependent.

Overall, evidence from the full sample confirms GLD's superiority as the most reliable hedging asset. REEs, despite their geopolitical sensitivity, outperformed BTC across most clean energy indices. The optimal HR is generally high for both GLD and BTC during the pandemic periods, whereas it varies in most cases for REEs.

Amid growing geopolitical tensions and heightened uncertainty, our findings provide critical insights for investors and policymakers. For investors, understanding the context-dependent hedging properties of REEs can inform portfolio diversification strategies, particularly for institutional investors exposed to clean energy and critical mineral markets. For instance, since the findings reveal REEs to be effective hedges only during specific crises, such as the COVID-19 pandemic, and ineffective during others, such as the United States-China trade war, investors may adjust their portfolio allocation dynamically to compensate for this exposure. For policymakers, those in energy-importing countries such as the European Union and Japan, who face supply-chain vulnerabilities due to China's dominance in REE production (IEA, 2021a), may respond strategically by diversifying investment in alternative REE sources (Australia and Myanmar) or recycling programs to reduce this dependency. Countries may build strategic reserve stockpiles of REEs to mitigate extreme price volatility during geopolitical tensions and strengthen multilateral agreements through the World Trade Organization (WTO) to prevent the weaponization of REE exports.

The challenges of this study include the lack of publicly available information on REE stocks, as many are not traded publicly, the limited number of renewable energy stock options, and the difficulty of isolating specific subsectors. We acknowledge the use of REMX ETF as a proxy for REE commodity price may capture broader equity-market risks. This potential limitation is address through our robustness checks that employ other energy metals (copper, nickel and cobalt). However, future studies can employ alternative REE proxy or construct a new index that directly tracks REE commodity price. Additionally, future research could examine the sensitivity of critical minerals and clean energy to a United States-China trade war index instead of relying on a broader geopolitical risks index. Alternative methodologies such as rolling window VaR and CVaR could be employed to investigate the hedging and safe haven characteristics of REEs. Furthermore, future research could expand the analysis to various clean energy subsectors and their respective critical mineral value chains.

CRediT authorship contribution statement

Maruf Yakubu Ahmed: Conceptualization, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Anupam Dutta:** Formal analysis, Resources, Supervision, Writing – original draft, Writing – review & editing. **Timo Rothovius:** Conceptualization, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interests

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

Acknowledgements

Maruf Yakubu Ahmed gratefully acknowledges the generous financial support provided by Liikesivistysrahasto (Grant# 240069).

Appendix A

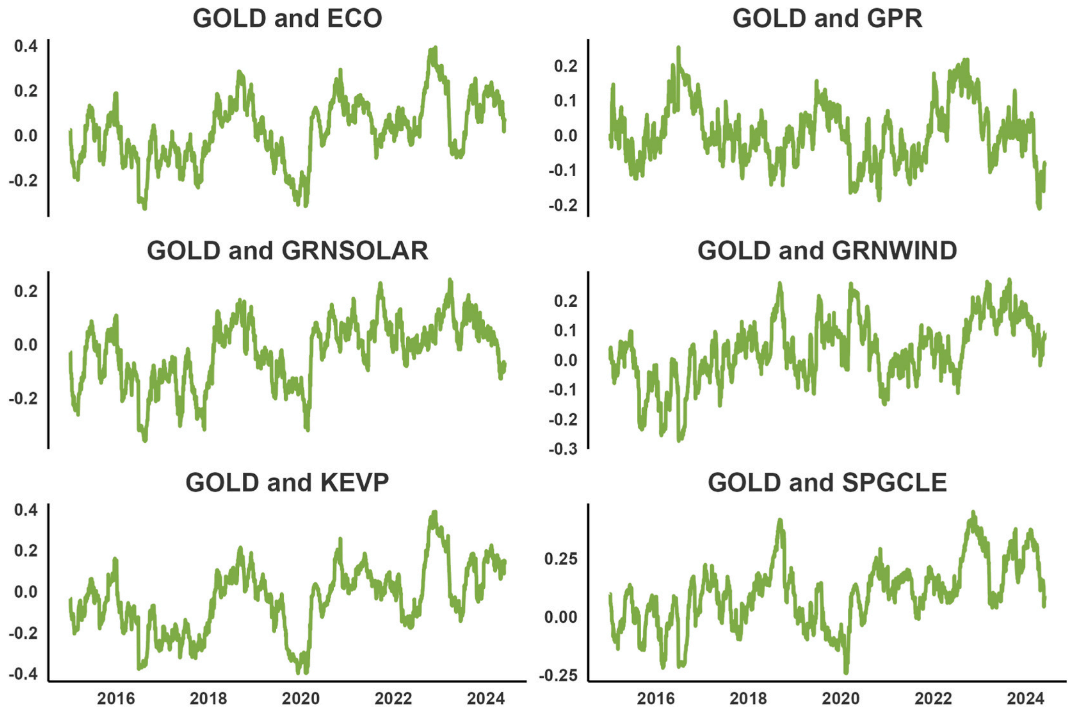

Fig. A1. DCC correlation between gold, clean energy stocks, and geopolitical risks

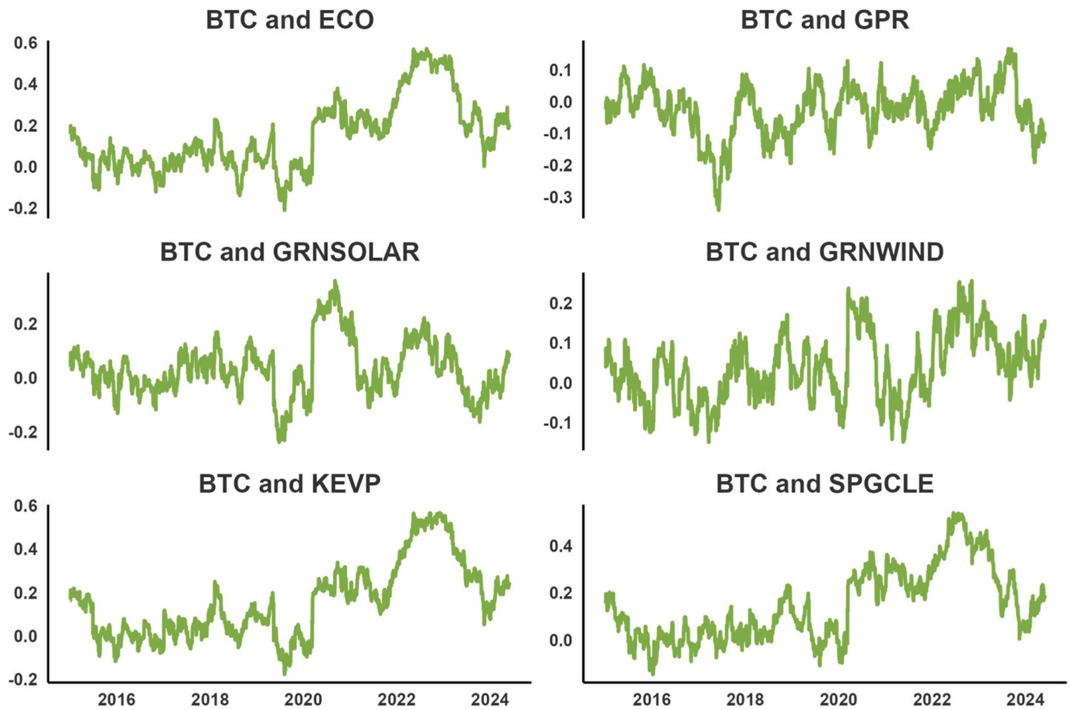

Fig. A2. DCC correlation between Bitcoin, clean energy stocks, and geopolitical risks

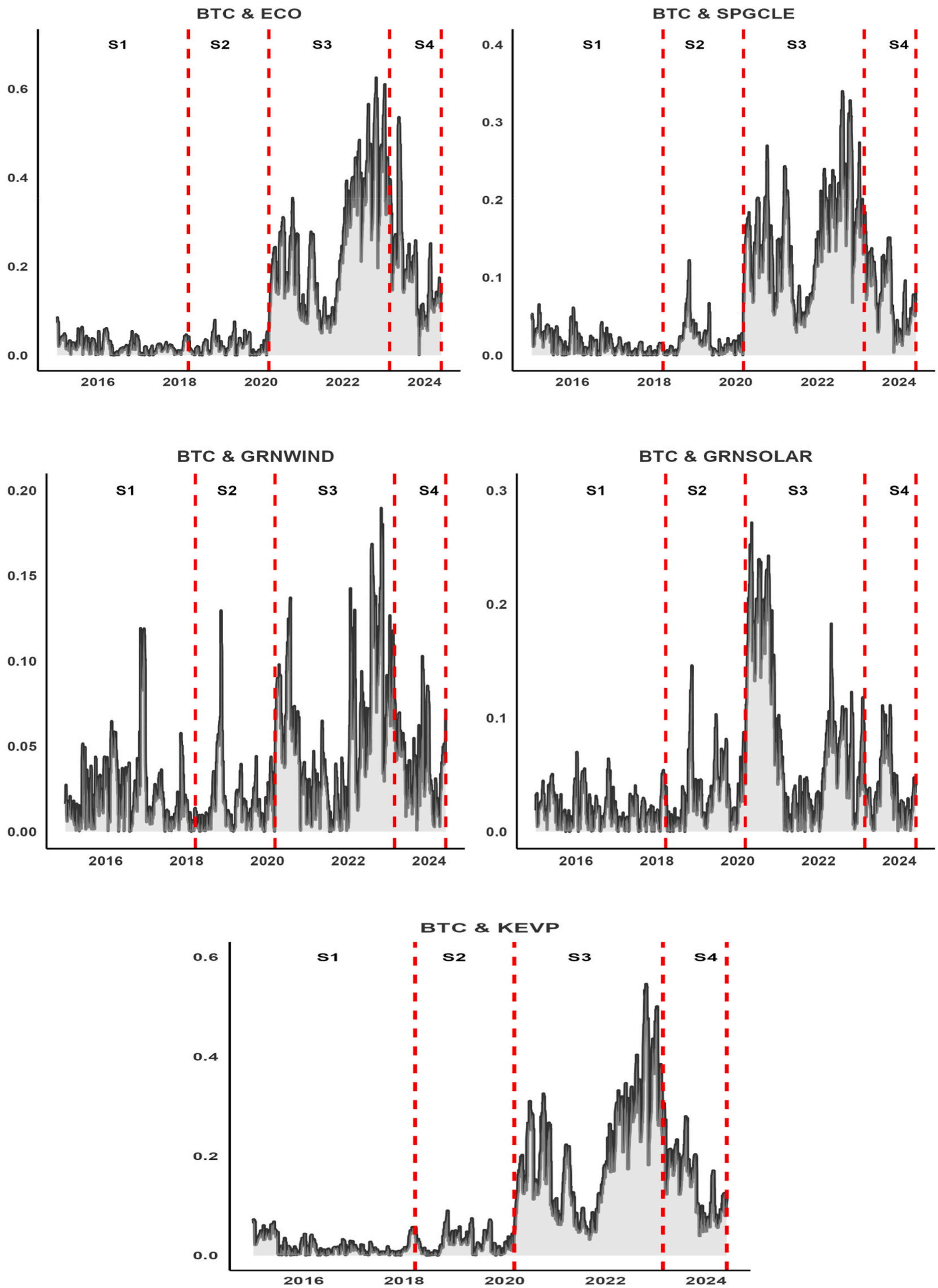

Fig. A3. DCC time-varying optimal hedging ratio for Bitcoin and clean energy indices pairs

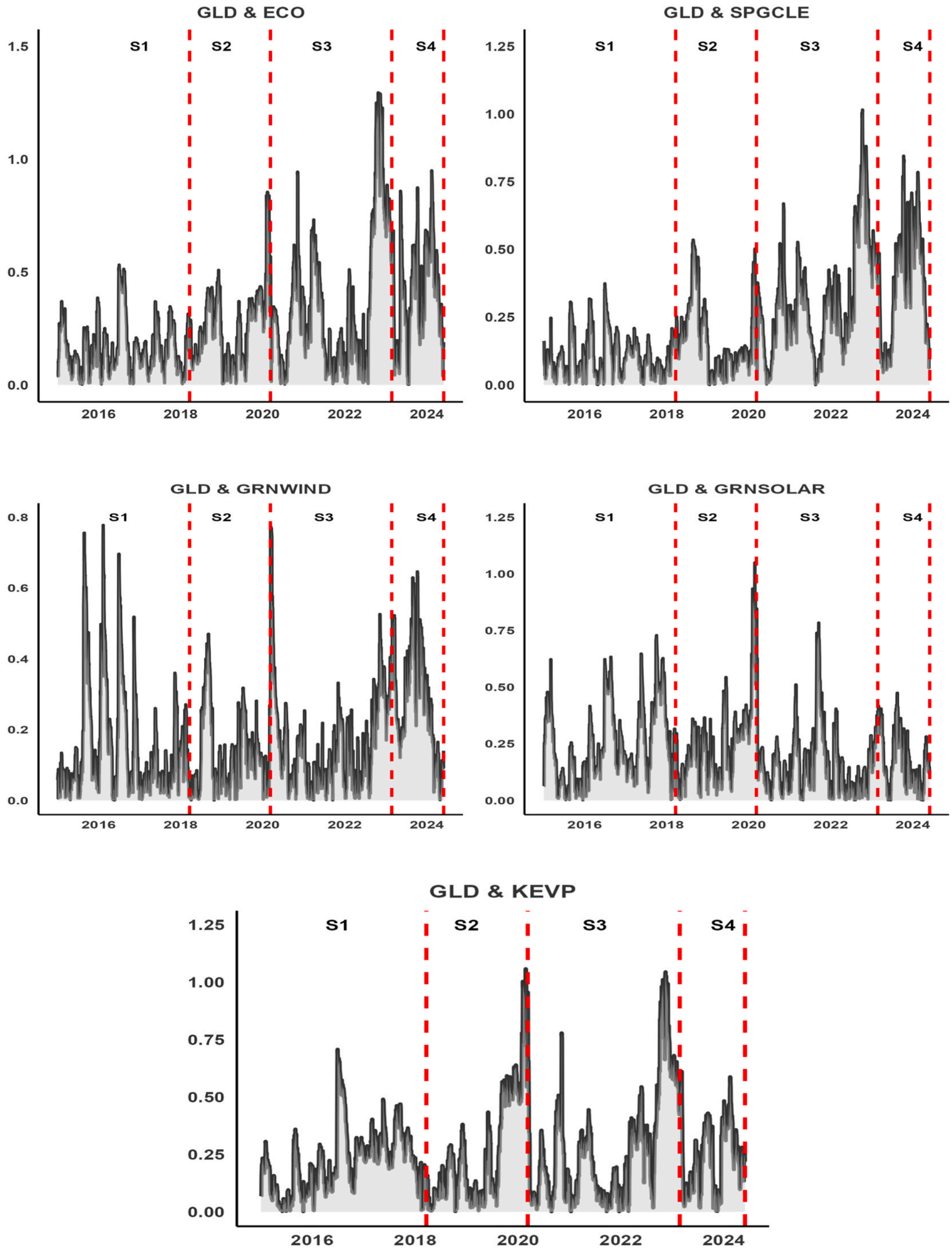

Fig. A4. DCC time-varying optimal hedging ratio for gold and clean energy indices pairs

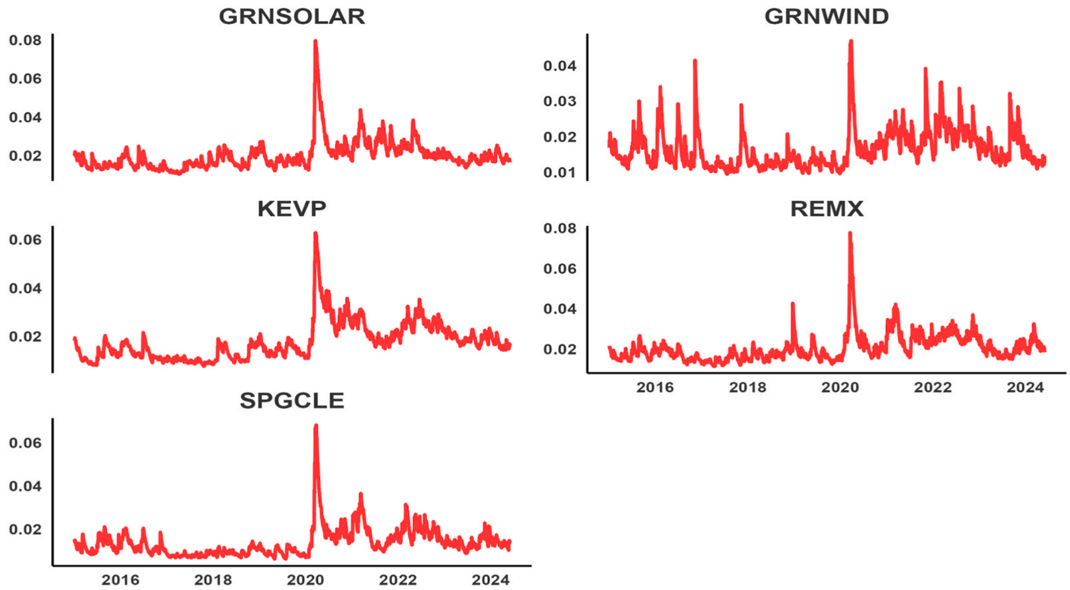

Fig. A5. Volatility of clean energy indices and rare earth elements

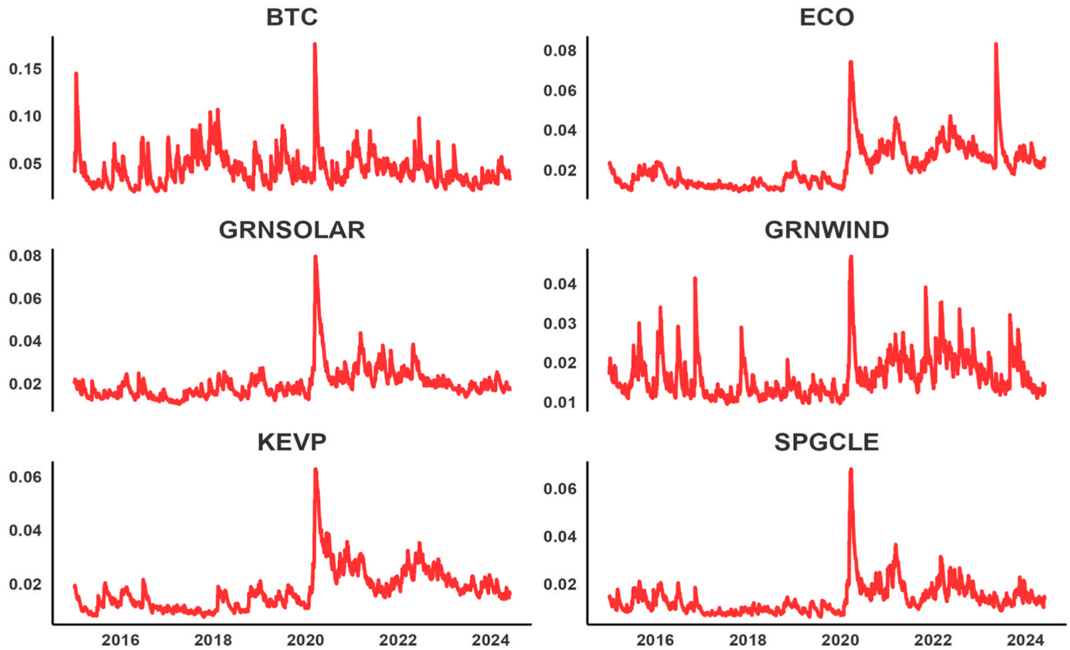

Fig. A6. Volatility of clean energy indices and Bitcoin

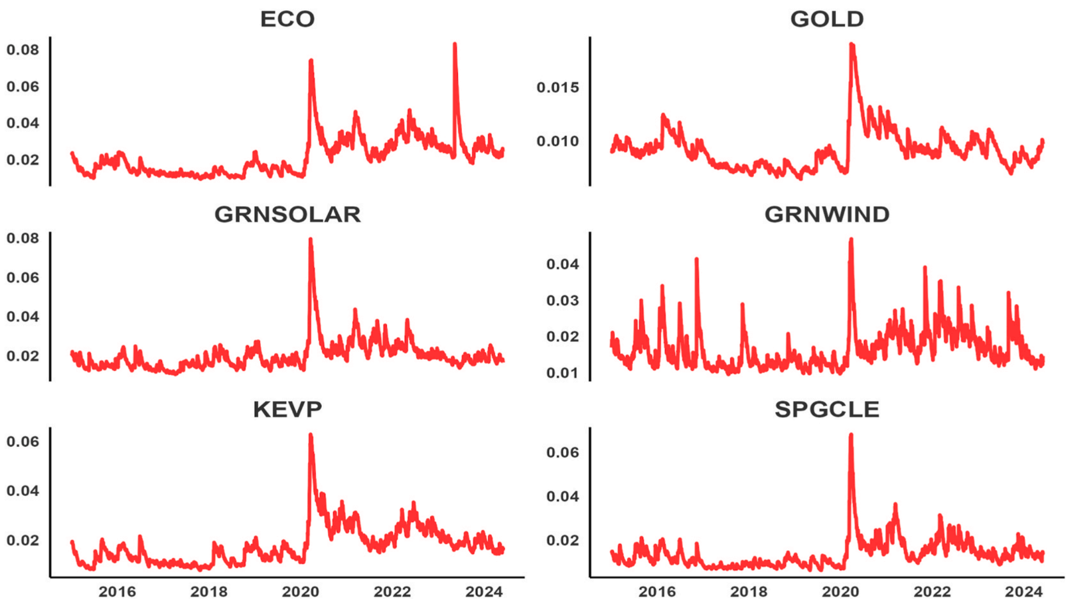

Fig. A7. Volatility of clean energy indices and gold

Data availability

Data will be made available on request.

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