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Cyber, Geopolitical, and Financial Risks in Rare Earth Markets: Drivers of Market Volatility

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Abstract: This study examines the integrated impacts of cyberattacks, geopolitical, and financial market volatility on rare earth markets during the 2014–2024 period, using Time-Varying Parameter Vector Autoregression and wavelet analysis. By bridging critical gaps in the literature, this research provides a comprehensive framework for understanding the compounded effects of emerging risks on market dynamics. The analysis includes key market indices (SOLLIT, PICK, SPGSIN, GSPTXGM, MVREMXTR, and XME), alongside green energy prices, to capture cross-market dependencies. The findings reveal that financial volatility exerts the most persistent long-term influence, while geopolitical events, such as the US-China trade tensions and the Ukraine conflict, trigger significant market disruptions. Cyberattacks, although episodic, exacerbate short-term volatility, especially during global crises. Rising green energy prices further amplify vulnerabilities in supply chains, underscoring the interconnectedness of rare earth markets and the sustainable energy transition. This research provides actionable insights for integrated risk management strategies, emphasizing supply chain diversification, enhanced cybersecurity, and international cooperation to ensure market stability and resilience in the energy transition.

Keywords: rare elements; risk; cyberattack; GPR; VIX; TVP-VAR; wavelet; price; return

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1. Introduction

Rare earth materials (REM) are indispensable strategic resources for the global energy transition, essential for modern technologies such as electric vehicles, energy storage batteries, solar panels, and wind turbines. The demand for these resources is rising rapidly worldwide, driven by international decarbonization goals, making them highly significant to the global economy (Considine et al. 2023; D'orazio 2024). Forecasts indicate that the demand for rare elements may grow up to sevenfold by 2040, further reinforcing their role in green technology development (Henriques and Sadorsky 2023). However, access to these resources is constrained by significant challenges, such as vulnerabilities in global supply chains (International Energy Agency 2024).

Advanced technologies require REM such as lithium, cobalt, neodymium, and dysprosium. This dynamic is amplified by the geographical concentration of production in regions such as China, the Democratic Republic of Congo, and Australia, where economic, technical, and environmental challenges limit the capacity to meet growing demand (USGS 2022). Nearly half of the critical metals with high supply risks are tied to the manufacturing of electric vehicles, highlighting the urgent need for sustainable strategies to support clean energy (CE) initiatives (Yuan et al. 2024).

The extraction and processing of REM generate significant environmental risks, including soil degradation and human health hazards, which, combined with market volatility, emphasize the need for sustainable solutions to manage these resources (Diao et al. 2024; Gupta et al. 2024). Consequently, recycling existing resources and utilizing alternative materials have become strategic priorities. Although recycling involves high costs and technological challenges, policy support and technological innovations create significant opportunities for diversifying supply chains (Zhang et al. 2024).

The geographical concentration of over 90% of global REM production in China creates significant vulnerabilities in supply chains, exposing economies to systemic geopolitical and economic risks (Park et al. 2023). The vulnerability of global supply chains has been highlighted by recent events, such as the trade dispute between the United States and China and Russia's invasion of Ukraine, contributing to market volatility and increased global economic uncertainties (Nasir et al. 2024; Pham and Hsu 2024). Moreover, rising green energy prices and protectionist policies, such as restrictions on critical resource exports, have heightened the complexity of interactions between REM and energy markets (Shuai et al. 2023).

An emerging factor contributing to market instability is cyberattacks (CA), which frequently target critical infrastructures, disrupting global supply chains and amplifying volatility. While existing literature primarily concentrates on the impact of cyber risks on the conventional energy sector, their influence on REM markets remains underexplored (Aloui et al. 2023). Unlike traditional supply chain disruptions, cyberattacks can trigger cascading effects across industries by compromising digital logistics infrastructures and operational technologies, creating instability in the supply of essential raw materials (ENISA 2023). This highlights the need for an integrated assessment of cyber risks alongside geopolitical and financial uncertainties. Existing literature lacks a comprehensive framework to simultaneously analyse the interplay of geopolitical, financial, and cyber risks with green energy price dynamics, particularly in the context of rare earth markets critical to the global energy transition (Song et al. 2021).

Global financial volatility and green energy price dynamics also profoundly influence REM markets. Studies show that REM markets often assume the role of net recipients of spillovers from financial and energy markets during periods of high volatility, making them vulnerable to global uncertainties (Apergis and Apergis 2017; Reboredo and Ugolini 2020). Nonetheless, the integrated analysis of geopolitical, financial, and cyber risks and green energy prices on REM markets remains insufficiently explored, despite the relevance of these interactions in shaping market volatility and global instability (Mohammed et al. 2023). The price dynamics of critical minerals and oil significantly affect renewable energy production, emphasizing the interdependencies between resource markets and the global energy transition (Islam and Sohag 2024).

The motivation for this study arises from the need to address these gaps and develop an analytical framework capable of simultaneously capturing the episodic and structural influences of multiple risks on REM markets. This study bridges a critical gap by leveraging Time-Varying Parameter Vector Autoregression (TVP-VAR) and wavelet analysis to provide an integrated, frequency-dependent understanding of risk interactions, offering a robust approach for policy and investment decisions. The TVP-VAR method is recognized for its capacity to capture variations in the relationships between economic variables (Antonakakis and Gabauer 2017; Koop and Korobilis 2009), while wavelet analysis provides a two-dimensional perspective on structural and episodic relationships (Su et al. 2024).

The results highlight that geopolitical risks and global financial volatility are the primary destabilizing factors, while cyber risks and green energy prices have significant short-term impacts. The study further demonstrates that cyber risks, though often considered episodic, can amplify systemic uncertainties, particularly when combined with geopolitical instability. These insights are valuable for developing more resilient policies and integrated risk management strategies, offering crucial support for investors and decision-makers involved in the global energy transition.

This research not only addresses key theoretical gaps but also delivers actionable insights for stakeholders to develop integrated risk mitigation strategies in REM: Section 2 reviews the literature, identifying gaps and building the theoretical foundation of the research; Section 3 details the advanced methodology and data used, offering clarity on the analytical approach; Section 4 presents empirical results, including robustness tests to ensure the validity of the findings; Section 5 synthesizes the conclusions; Section 6 discusses the results, highlighting critical connections between the analysed variables; finally, Section 7 proposes innovative directions for future studies.

2. Literature Review

2.1. Importance of REM in the Energy Transition and Clean Energy

From the perspective of an industrial chain, the unbalanced structure of the global trade network for REM significantly contributes to price volatility and market instability, highlighting the complexity of associated risks (Salim et al. 2022). Yang et al. (2024) noted a significant association between REM prices and the CE market, which is especially noticeable during times of high volatility, such as the COVID-19 epidemic and the Russia–Ukraine war. Beyond geopolitical risks, recent studies suggest that cyberattacks on critical infrastructures can exacerbate supply chain disruptions, leading to amplified price volatility in rare earth markets (ENISA 2023). This underscores critical vulnerabilities in supply chains, necessitating more effective risk management measures. Additionally, REM recycling represents a strategic solution to reduce pressures on supply chains. According to Lai et al. (2024), integrating recycling processes into supply chains can enhance efficiency and economic sustainability without disrupting downstream markets. According to Lee et al. (2024), fully decarbonizing the US energy system by 2050 will require material flows up to 300 times greater for rare earths, underscoring the challenges associated with supply.

2.2. Cyberattacks on Supply Chains

CA on critical infrastructures represents an increasingly significant threat to global economic security, profoundly impacting supply chains and amplifying volatility in international markets. The European Union Agency for Cybersecurity (ENISA) report (ENISA 2023) provides a comprehensive assessment of emerging cyber threats and their impact on critical infrastructures. It highlights an exponential increase in the frequency and severity of cyberattacks over the past decade, affecting key sectors such as energy, telecommunications, and natural resources. For instance, the ransomware attack on Colonial Pipeline significantly influenced stock prices in the oil sector and the US fuel market. Corbet and Goodell (2022) demonstrated that these effects extended even to companies without direct ties to the industry, showing the far-reaching economic repercussions of cyber threats on commodity markets.

CAs take various forms, such as ransomware, distributed denial of service attacks, or the exploitation of software vulnerabilities, and are perpetrated by individuals, organized criminal groups, or state entities. These attacks can cause significant financial losses, operational disruptions, and compromise of sensitive data. Hiller et al. (2024) emphasize that cybersecurity challenges have become increasingly difficult to manage, directly affecting digital and automated supply chains. This vulnerability can significantly interrupt the REM supply, a critical factor in supporting CE technologies.

REM markets are particularly exposed to these risks due to their reliance on critical infrastructures and their strategic importance in the energy transition. Haq et al. (2022) showed that insufficient security in infrastructures increases the susceptibility of REM markets to volatility induced by CA. Additionally, Zheng et al. (2021) identified dynamic interdependencies between renewable energy and REM markets, yet they stress that the specific influence of CA on these interactions remains underexplored. This lack of research underscores the need for a framework that captures how cyber risks interact with other sources of market volatility. Fan et al. (2023) highlight the need for an integrated analysis of geopolitical and cyber risks, as separate approaches limit the understanding of the complex dynamics of global markets. The increasing digitalization of supply chains amplifies their vulnerabilities, justifying the need for robust and integrated strategies. These strategies should aim to protect critical infrastructures and manage emerging risks in an interconnected economic environment.

2.3. Geopolitical Risks and REM Markets

Geopolitical risks are a key driver of volatility in REM markets, influencing both prices and the stability of supply chains. Caldara and Iacoviello (2022) developed the Geopolitical Risk Index (GPR), a widely used tool to measure geopolitical uncertainties and their impact on international markets. Significant swings in REM pricing and other vital resources have been provoked by recent events, including the COVID-19 epidemic, Russia's invasion of Ukraine, and the US-China trade war. Li et al. (2023) highlighted the bidirectional connection between REM prices and geopolitical risks, emphasizing the strategic role of these resources in light of geopolitical tension and economic uncertainties.

Spillovers between regional and global markets destabilize other sectors, including renewable energy. Hu and Borjigin (2024) observed that these interactions become particularly pronounced during periods of geopolitical crisis. Spillovers affect not only REM markets but also investments in CE technologies. For instance, rising geopolitical tensions have led to restrictions on critical mineral exports, which directly impact the cost structures of clean energy projects. The volatility of rare resources poses a major barrier to expanding renewable energy projects, although markets demonstrated relative resilience during the Russia–Ukraine conflict. Geopolitical tensions significantly influence energy market dynamics, driving up oil prices during periods of extreme uncertainty and causing adverse reactions in CE markets. These effects underscore a decoupling between the two sectors during times of geopolitical stress (Ben Cheikh and Zaied 2023). However, most geopolitical risk indicators transmit positive shocks to green markets, except for direct geopolitical acts, which negatively impact green bonds and eco-friendly stocks at extreme quantiles (Sohag et al. 2022). Additionally, geopolitical instability has been linked to increased cyber threats against critical infrastructure, further amplifying market volatility. Major political and financial crises significantly increase the spillover index, highlighting the sensitivity of REM to such events (Zhou et al. 2021). A contrasting perspective is presented by Ojiambo and Adachi (2023), who argue that critical metal reserves do not represent a constraint, yet the geopolitical and environmental risks associated with their extraction remain a major obstacle. This suggests that while resource availability is not an immediate concern, regulatory barriers, trade conflicts, and supply chain disruptions continue to shape market instability.

2.4. Financial Market Volatility, Green Energy Prices, and the Role of VIX Indices

Financial market volatility, often measured by the VIX index, is a critical indicator of global uncertainty, significantly impacting REM markets. This index is used by investors to assess financial risks and adjust capital allocation decisions in critical markets (Whaley 2000; Baker et al. 2016). During periods of global crisis, sudden spikes in the VIX generate significant uncertainties that amplify the volatility of REM markets. The dynamics of green energy prices also shape the demand for these resources, with important implications for global markets. In low-volatility regimes, rare earth elements company stocks exhibit strong connections with base metal markets, whereas, in high-volatility regimes, their linkages with CE, general stock markets, and oil increase significantly (Reboredo and Ugolini 2020). This suggests that during financial turmoil, rare earth markets become more sensitive to macroeconomic shocks, reflecting broader trends in global risk sentiment.

The REM market is particularly vulnerable to volatility due to the geographical concentration of production and limited supply. Indirect volatility spillovers between oil and CE markets are facilitated by the rare element market, suggesting a high level of interdependence between these sectors (Chen et al. 2020). These financial risks are exacerbated during periods of extreme volatility when correlations between financial markets and rare earth commodity markets become more pronounced.

Green energy prices significantly influence the demand for REMs used in sustainable technologies. Research indicates that rising green energy costs increase demand for vital commodities such as cobalt and lithium, which are necessary for wind turbines and batteries (Shuai et al. 2023). During periods of green energy price volatility, REM markets face additional pressures, leading to substantial price fluctuations. However, these traditional models often assume constant relationships over time, which may not fully capture dynamic market fluctuations (Li et al. 2023).

To overcome these limitations, recent studies have incorporated time-varying parameter VAR (TVP-VAR) models. Unlike standard VAR, TVP-VAR allows for structural changes in relationships over time, making it suitable for analysing volatile markets. Specifically, TVP-VAR has been used in financial market research to assess evolving risk spillovers and nonlinear transmission effects. Similarly, wavelet coherence analysis has been employed to identify co-movements between commodity and financial markets at different time scales. Zhou et al. (2021) explored the time and frequency spillover relationship between political risk and the stock returns of China's rare earths, finding that short-term spillovers play a dominant role, especially during major financial and political events. This spillover perspective is particularly relevant for understanding market volatility in response to geopolitical uncertainty.

The literature reveals two main gaps in research related to financial market volatility and green energy prices in REM markets. First, financial, cyber, and geopolitical risks are often analysed in isolation, without considering their cumulative effects on REM markets. For example, cyberattacks on financial institutions or trading platforms could disrupt commodity price stability, introducing additional layers of volatility that traditional models fail to capture. Second, commonly used methods, such as VAR models or variance analyses, fail to capture the nonlinear, time-dependent, and multi-scale dynamics among these risks. These limitations reduce the ability to fully understand market behaviours during global crises when volatility becomes extreme and nonlinear.

An integrated approach that combines TVP-VAR with wavelet analysis provides a more robust framework for understanding these interactions. TVP-VAR allows for evolving risk relationships, while wavelet methods capture market synchronization at different time horizons. This combination enhances our ability to identify both short-term and long-term volatility spillovers, making it particularly suitable for studying the interplay between REM markets, financial uncertainty, and geopolitical instability. By addressing critical gaps in the literature, this study contributes to the development of risk mitigation strategies, ensuring market stability and supporting the sustainable energy transition.

3. Data and Methodology

3.1. Dataset

The dataset includes representative indices for REM markets and explanatory variables such as GPR, VIX, CA, and global green energy prices (Table 1). These variables were selected for their relevance in capturing geopolitical, financial, and cyber risks affecting critical markets. The performance of businesses in the rare and strategic materials sector is captured by the MVREMXTR index, which is also useful for evaluating how REMs contribute to vital green technologies such as electric cars (Ghorbani et al. 2024).

Table 1. Variables description.

Type	Variable	Symbol	Summary	Unit
Dependent	Solactive Global Lithium	SOLLIT	Representative of the lithium sector.	Closing Price (USD/unit)
Dependent	iShares MSCI Global Metals & Mining Producers ETF	PICK	Focused on industrial metals and essential minerals.	Closing Price (USD/unit)
Dependent	GSCI Industrial Metals	SPGSIN	A barometer of the global industrial metals market.	Closing Price (USD/unit)
Dependent	S&P/TSX Global Mining Index	GSPTXGM	Represents the global mining sector.	Closing Price (USD/unit)
Dependent	MVIS Global Rare Earth/Strategic Metals TR Net Index	MVREMXTR	Representative of the global rare and strategic metals market.	Closing Price (USD/unit)
Dependent	SPDR® S&P Metals and Mining ETF	XME	Focused on mining companies and metal producers.	Closing Price (USD/unit)
Independent	Number of Cyberattacks	CA	The total frequency of cyberattacks recorded on the days of their occurrence.	Number of Cyberattacks
Independent	Geopolitical Risk Index	GPR	A quantitative measure of risks associated with geopolitical events.	Indexed values, without a specific unit.
Independent	CBOE Volatility Index	VIX	Indicates the expected volatility in the financial market.	Expressed as percentages.
Independent	Green Energy Price	SPGTCLEN	S&P Global Clean Energy Index.	Closing Price (USD/unit)

Note: The table provides an overview of the variables used in the study, including their type, symbol, description, and unit of measurement.

Simultaneously, GSPTXGM provides a broader view of the global mining sector, facilitating the analysis of interactions between mineral markets and geopolitical or financial risks. To incorporate the perspective of the CE market, SPGTCLEN was used as an indicator reflecting the price dynamics and correlations between REM markets and sustainable energy (Lai et al. 2024).

The data for all indices were adjusted to a weekly frequency and transformed logarithmically to reduce the impact of outliers and ensure a more stable distribution (Nasir et al. 2024). The analysis period, 2014–2024, was selected to capture major global events that influenced REM markets (Figure 1). Additionally, this period encompasses the accelerated transition to CE technologies, driven by international commitments to reduce carbon emissions and the increasing demand for lithium and cobalt (International Energy Agency 2024).

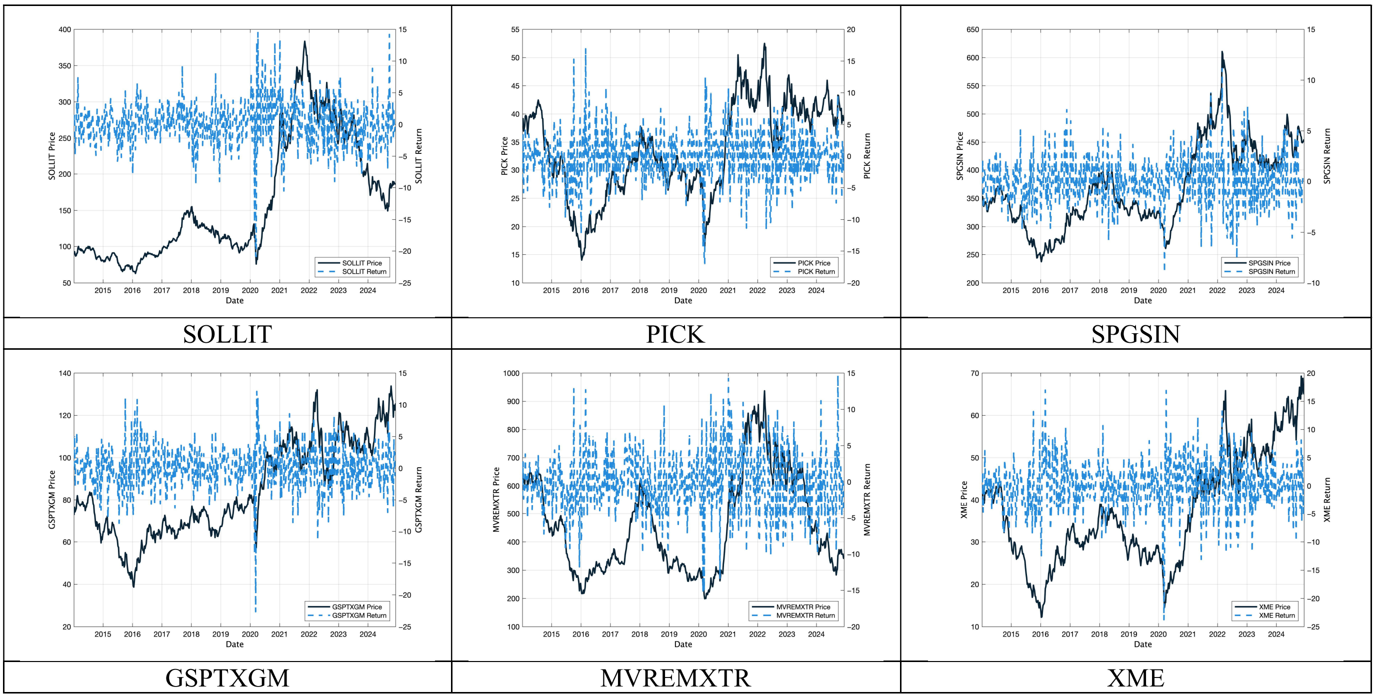

Figure 1. The evolution of prices and returns of representative indices for REM markets. Note: The charts depict the evolution of prices (solid line) and weekly returns (dotted line) for the selected indices.

The variable associated with cyber risks was constructed based on the number of days with reported attacks, reflecting the frequency of such incidents during the analysed period. The data were collected from public sources and specialized databases recognized for their accuracy and detail, such as Privacy Rights Clearinghouse (Privacy Rights Clearinghouse n.d.), Hackmageddon (Hackmageddon n.d.), Eurepoc (Eurepoc n.d.), and CSIS (CSIS n.d.). These sources provided detailed information on CA targeting critical infrastructure in the energy sector, including the date of the incident, the type of attack, and its impact on infrastructure. Geopolitical risk data were sourced from the GPR index developed by Matteo Iacoviello (Iacoviello n.d.), while all other financial and market-related data, including stock indices and commodity prices, were retrieved from Investing.com (Investing.com n.d.).

To ensure consistency and relevance, only confirmed incidents reported by at least two independent sources were included. However, it should be noted that data may suffer from underreporting due to the sensitive nature of CA and the lack of global reporting standards.

3.2. Statistical Characteristics of the Variables

Table 2 presents the descriptive statistics of the analysed indices, including mean, maximum, minimum, and standard deviations, as well as skewness and kurtosis coefficients. These statistics highlight the high volatility of REM markets. For instance, the MVREMXTR index fluctuates significantly, indicating the markets' high sensitivity to external factors such as geopolitical risks and CA.

Asymmetric distributions, reflected by high skewness and kurtosis coefficients, suggest the presence of rare or extreme events that disrupt market stability. The normality hypothesis is rejected by the Jarque-Bera test, underscoring that these markets do not follow a normal distribution and are influenced by irregular and unexpected factors. This finding justifies the use of advanced econometric methods, such as TVP-VAR modelling, which can capture the nonlinear and episodic dynamics of the markets.

Table 2. Descriptive statistics.

Index	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Prob.	IQR
SOLLIT	0.126	0.230	14.49	−20.85	3.760	−0.387	7.183	0.000	4.51
PICK	0.000	0.038	16.92	−16.96	4.144	−0.095	4.611	0.000	4.87
SPGSIN	0.048	−0.032	11.14	−8.986	2.441	0.242	4.195	0.000	2.91
GSPTXGM	0.097	0.035	12.11	−22.65	3.477	−0.449	6.616	0.000	4.13
MVREMXTR	−0.108	−0.130	14.71	−15.48	4.471	0.070	3.509	0.036	5.79
XME	0.075	0.257	16.97	−23.77	4.571	−0.188	4.849	0.000	5.43

Note: The table provides descriptive statistics for REMs, including measures of central tendency, dispersion, and distribution.

Additionally, the high standard deviations reflect the overall uncertainty in REM markets, while the maximum and minimum values illustrate significant fluctuations in prices and returns. These characteristics emphasize the vulnerability of REM markets to emerging risks.

3.3. Correlation and Stationarity Test Results

The stability of the time series was evaluated using the stationarity tests ADF (Augmented Dickey-Fuller) (Dickey and Fuller 1979), PP (Phillips-Perron) (Phillips and Perron 1988), and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) (Kwiatkowski et al. 1992). The results confirm that most variables used (GPR, VIX, CA, and SPGTCLEN indices) are non-stationary at level but become stationary after first-order differencing, as indicated by the critical statistics and p-values. This suggests the presence of integration of order I(1), which justifies the application of the chosen methodology. Detailed results of stationarity tests are provided in Table 3.

Table 3. Stationarity tests.

Index	ADF				PP				KPSS			
	Level		1st Diff		Level		1st Diff		Level		1st Diff	
SOLLIT	−23.30	0.000	−14.92	0.000	−23.30	0.000	−256.0	0.000	0.140	0.423	0.226	0.997
PICK	−23.98	0.000	−15.10	0.000	−23.98	0.000	−240.8	0.000	0.109	0.999	0.073	0.971
SPGSIN	−23.31	0.000	−13.21	0.000	−23.31	0.000	−301.3	0.000	0.091	0.640	0.105	0.992
GSPTXGM	−24.59	0.000	−13.60	0.000	−24.59	0.000	−282.4	0.000	0.079	0.507	0.104	0.985
MVREMXTR	−22.18	0.000	−14.95	0.000	−22.22	0.000	−268.7	0.000	0.148	0.566	0.144	0.990
XME	−23.18	0.000	−15.08	0.000	−23.20	0.000	−400.1	0.000	0.197	0.694	0.166	0.986

Note: The table shows the outcomes of the stationarity, using the ADF, PP, and KPSS tests.

The correlation analysis between REM market indices and emerging risk variables highlights relevant interdependencies. The relationships between REM indices and CA are weak, suggesting an indirect impact through disruptions in the supply chains or the amplification of other structural vulnerabilities. In contrast, geopolitical risks influence more consistently, with the MVREMXTR index significantly correlating with GPR, reflecting its sensitivity to events such as trade tensions or regional conflicts, as noted in the literature (Achzet and Helbig 2013).

The VIX index exhibits the strongest correlations with REM indices such as XME, indicating a significant influence of global uncertainties on these markets. Mohammed et al.

(2023) observed a similar effect, emphasizing that global financial volatility affects both the supply and the demand of critical resources, as well as investments in CE technologies.

The results of the stationarity tests and correlation analysis provide a detailed image of the interdependencies between REM markets and emerging risk factors. The close relationship between VIX and the XME and SPGSIN indices confirms the high sensitivity of these markets to global macroeconomic conditions. Figure A1 in Appendix A provides a clear visualization of the correlations, highlighting the most important interactions among the analysed variables.

3.4. Econometric Methodology

Wavelet analysis enables the simultaneous examination of signals in both time and frequency domains, providing a two-dimensional perspective on their dynamics. This approach has been shown to be effective in studies of critical metals markets (Su et al. 2024) and was adapted to analyse REM markets in this context.

The Continuous Wavelet Transform (CWT) was employed to decompose the time series into specific components, capturing the frequency-dependent relationships between variables (Torrence and Compo 1998). The Morlet wavelet function was chosen for its optimal balance between frequency and time resolution, mathematically defined as follows:

$$\Psi(t) = \pi^{-\frac{1}{4}} \cdot e^{i\omega_0 t} \cdot e^{-\frac{t^2}{2}}, \tag{1}$$

where $\Psi(t)$ is wavelet function, $\omega_0 = 6$ is the central frequency, and t is the time.

The CWT function of a signal x(t) is calculated as follows:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \Psi^* \left(\frac{t - \tau}{s} \right) dt, \tag{2}$$

where $W_x(\tau, s)$ represents the CWT of the signal x(t), s is the wavelet scale, inversely proportional to frequency (f = 1/s), τ represents the temporal translation, and ψ indicates the complex conjugate of the wavelet function ψ(t).

The power spectrum associated with the wavelet transform provides details about the signal's energy at different frequencies and moments in time and is defined as follows:

$$WPS_x = |W(\tau, s)|^2. \tag{3}$$

To investigate the relationships between two variables, wavelet coherence was used as a measure of correlation in the time-frequency domain. Wavelet coherence is expressed as follows:

$$R^2(s, t) = \frac{\left|W_{xy}(\tau, s)\right|^2}{|W_x(\tau, s)| \cdot \left|W_y(\tau, s)\right|}, \tag{4}$$

where $R^2(s, t)$ wavelet coherence spans between 0 and 1, where 0 indicates no relationship and 1 indicates a perfect connection, $W_{xy}(\tau, s)$ represents the cross-wavelet spectrum of the signals x(t) și y(t), $W_x(\tau, s)$ and $W_y(\tau, s)$ are the individual wavelet spectra.

The results were represented as scalograms, indicating areas of high coherence through colour coding, which highlights the frequencies and moments with significant relationships. Phase relationships were analysed using phase vectors, which indicate the direction and synchronization of the relationships between variables. Rightward-oriented vectors indicated synchronization, while leftward-oriented vectors signalled inverse relationships.

This approach ensures a detailed analysis of the complex interactions between variables, rigorously documenting the parameters and preprocessing methods to guarantee the reproducibility of the analysis by other researchers.

4. Robustness Test

The TVP-VAR method was selected for its ability to track dynamic relationships and temporal evolutions among the studied variables. Unlike traditional VAR models, which assume constant coefficients over time, the TVP-VAR model allows these coefficients to vary (Koop and Korobilis 2009), a critical feature for analysing REM markets, which are heavily influenced by external events and emerging risk factors. This method is well-suited for capturing dynamic relationships because financial and REM markets are characterized by complex interactions that evolve over time (Aloui et al. 2023). In contrast to traditional models, TVP-VAR can accommodate the frequent structural changes in critical resource markets driven by fluctuating trade policies and regulations.

The use of the Generalised Forecast Error Variance Decomposition (GFEVD) enables the assessment of reciprocal influences between variables, measuring both the relative contributions of each variable to overall volatility and net spillovers. This approach enhances the understanding of interdependencies between REM markets and emerging risks, highlighting how the volatility of one variable can influence the entire market dynamic (Diebold and Yilmaz 2008).

The TVP-VAR model is described by the following relationship:

$$y_t = A_t y_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N(0, \Sigma t), \quad (5)$$

where y_t is the vector of endogenous variables at time t, A_t is the time-varying coefficient matrix, and ε_t represents the vector of residuals, presumed to have a time-varying covariance matrix and a normal distribution Σ_t.

The time-varying coefficient matrix follows a stochastic dynamic process of the random walk type:

$$A_t = A_{t-1} + \eta_t,\ \eta_t \sim N(0, Q_t), \quad (6)$$

where A_t is the coefficient matrix from the previous period, η_t is the noise associated with coefficient variations, and Q_t is the covariance matrix of the noise.

For the covariance matrix of the errors Σ_t, the following relationship is assumed:

$$\log(\Sigma_t) = \log(\Sigma_{t-1}) + \zeta_t,\ \zeta_t \sim N(0, R_t), \quad (7)$$

where Σ_{t-1} is the covariance matrix from the previous period, ζ_t is the noise associated with stochastic volatility, and R_t is the covariance matrix of the noise.

GFEVD measures the contribution of variables to the variation in forecast errors:

$$\phi^g_{ij,t}(h) = \frac{\sum_{k=1}^{h} \psi^2_{ij,t,k}}{\sum_{j=1}^{G} \sum_{k=1}^{h} \psi^{2,g}_{ij,t,k}}, \quad (8)$$

where $\phi^g_{ij,t}(h)$ is the contribution of variable j to the prediction variance of variable i at h-step ahead, $\psi^2_{ij,t,k}$ are the coefficients for the generalised forecast errors.

Spillover that a variable exerts on another variable j is given by the relationship:

$$TO_{jt} = \frac{\sum_{j=1,\ j\neq i}^{G} \phi^g_{ij,t}(h)}{\sum_{j=1}^{G} \phi^g_{ji,t}(h)} \cdot 100. \quad (9)$$

The influence that variable i obtains from additional variables j is defined as follows:

$$FROM_{jt} = \frac{\sum_{j=1,\ j\neq i}^{G} \phi^g_{ij,t}(h)}{\sum_{j=1}^{G} \phi^g_{ji,t}(h)} \cdot 100. \quad (10)$$

The difference between the influence exerted ("TO") and that received ("FROM") defines the net spillover ("NET"):

$$NET_{jt} = TO_{jt} - FROM_{jt}. \quad (11)$$

A positive result indicates a variable that transmits influences, while a negative result indicates one that receives.

The global measure of connectedness (GC) is given by the following:

$$GC_t = \frac{\sum_{j=1}^{G} TO_{jt}}{G} = \frac{\sum_{j=1}^{G} FROM_{jt}}{G}. \quad (12)$$

5. Results

5.1. Wavelet Coherence Results

The analysis demonstrates a profound interconnectedness between REM markets and emerging global risks. By employing CWT and the TVP-VAR model, dynamic and differentiated influences of CA, GPR, VIX, and SPGTCLEN were highlighted. The results emphasize the distinct contributions of each factor to the studied markets.

5.1.1. Influence of CA on REM Market Indices

The scalogram analysis in Figure A2 highlights significant coherence between CA and REM market indices, manifested at different frequencies and distinct periods. At low frequencies, corresponding to long-term relationships, areas of maximum intensity marked in green suggest a structural impact of CA on the MVREMXTR index, associated with mining companies and global supply chains. This structural impact indicates that cyber risks not only introduce short-term shocks but also shape long-term market stability, potentially amplified by high financial volatility, as reflected by the VIX index. In contrast, at high frequencies, episodic influences predominate and are concentrated in the periods 2016–2017, 2019–2020, and 2022–2023 characterized by global instability. Such findings align with major cyber incidents affecting critical infrastructure during these periods, reinforcing the link between cyber risks and heightened market volatility. These episodic influences are more evident for the SOLLIT and PICK indices, highlighting the short-term reactions of markets to major cyber shocks.

The directions of the arrows in the scalograms mostly reveal a causal relationship from CA to market indices, suggesting that cyber risks act as a volatility trigger, rather than a passive risk factor. These observations are supported by the literature, such as Zheng et al. (2021), which emphasizes the decisive influence of cyber risks on global financial markets.

The influence of CA varies in intensity and period, with some timeframes exhibiting a stronger and more persistent effect. High coherence areas at low frequencies in 2015–2016, 2019–2020, and 2022–2023 suggest a persistent but delayed relationship between cyber events and the evolution of REM indices. These periods coincide with intensified attacks on critical infrastructure, as highlighted by the ENISA report (ENISA 2023), which identifies a significant increase in digital threats over the past decade.

The observed relationships are heterogeneous across different market indices, with some markets being more sensitive to fluctuations generated by cyber risks than others. Indices with higher structural volatility respond more strongly, suggesting a heightened interdependence between CA and the stability of supply chains for REM. The vulnerability of digital logistics and automated processes in the natural resources sector can explain this correlation.

Furthermore, the direction and orientation of the arrows in the scalograms indicate that the relationships between CA and REM indices are predominantly synchronous at low and medium frequencies, meaning that cyber shocks propagate almost immediately into market volatility. During periods of global economic instability, these relationships become more pronounced, suggesting an amplifying effect of cyber risks on REM markets. Thus, wavelet analysis confirms that the influence of CA is not only episodic but also dependent on the economic and geopolitical context, serving as an amplifying factor in market-wide risk contagion mechanisms.

5.1.2. Influence of GPR on REM Market Indices

The scalograms demonstrate the influence of GPR on the six indices related to REM, reflecting complex relationships across different frequencies and time intervals. Areas of high coherence are particularly visible during the periods 2016–2018 and 2020–2022, corresponding to episodes of global geopolitical instability. During these times, the indices exhibit heightened sensitivity to GPR variations, indicating a strong connection between geopolitical uncertainty and REM market volatility.

The relationships are more pronounced at low frequencies, suggesting a persistent and structural effect of geopolitical shocks on these markets. The influence of geopolitical risks manifests in a predominantly synchronous relationship, as indicated by the direction of the arrows, in which variations in GPR directly drive fluctuations in the indices, as highlighted by the study of Pata et al. (2023). Significant comovements between export and domestic prices of rare earth elements are observed at medium and low frequencies, emphasizing the dynamic nature of market relationships (Seiler 2024).

Simultaneously, the influences vary by index, reflecting differences in the degree of exposure to geopolitical risks. Indices that include resources essential for the energy transition are more sensitive to GPR variations, as geopolitical disruptions imbalanced supply and demand. This volatility is exacerbated during crises when markets become vulnerable to protectionist policies and trade restrictions.

5.1.3. Influence of VIX on REM Market Indices

The scalograms capture the influence of the VIX index, a proxy for global financial market volatility, on the six REM indices. The high coherence observed at low and medium frequencies highlights a persistent relationship between financial volatility and the evolution of REM prices, particularly during periods of global economic crises or systemic uncertainties, such as the COVID-19 pandemic or the economic shocks of 2016–2017. During these periods, REM indices tend to synchronize with VIX variations, suggesting that episodes of extreme financial market volatility are rapidly transmitted to rare resource markets, amplifying their instability.

This relationship is particularly pronounced for indices with higher structural volatility, in which global investor sentiment strongly influences prices. The downward and rightward-pointing arrows indicate that, in many cases, REM indices respond with a certain lag to financial shocks, confirming the findings of Kamal and Bouri (2023) regarding more intense correlations during periods of financial stress. Additionally, increased VIX volatility can spill over into REM markets due to declining investor confidence and capital repositioning toward safer assets.

According to the coherence analysis, which measures the co-movement and phase relationship between two-time series across different time horizons, VIX's influence on REM markets is greatest during times of crisis, when the long-term linkages become more stable and coordinated. All things considered, these findings demonstrate that global financial volatility plays a significant role in developing REM by impacting market dynamics via investment channels and global risk perception.

5.1.4. Influence of SPGTCLEN on REM Market Indices

The scalograms present the influence of SPGTCLEN on the six REM indices, providing a detailed perspective on the relationships over time and across different frequencies. The coherence is lower than that of other analysed variables, indicating a limited influence of green energy prices on REM markets. Coherence areas are primarily visible at medium frequencies and during specific periods, such as 2016–2017 and 2020–2022, suggesting that the influence of green energy prices on REM is episodic and depends on global economic and political contexts.

During these intervals, the predominant direction of the arrows indicates a synchronous or slightly lagged relationship, due to the increasing demand for critical resources driven by renewable energy project developments. However, the influence of SPGTCLEN on indices such as MVREMXTR and XME remains insignificant, suggesting that structural and geopolitical factors influence mineral markets more than fluctuations in green energy prices.

The lack of extended coherence indicates that the relationship between SPGTCLEN and REM is indirect, mediated by technological demand or energy policies, and does not manifest consistently over the long term. Overall, the results suggest that the impact of green energy prices on REM markets is not only limited in magnitude but also nonlinear, varying across different economic and geopolitical contexts. Specifically, our findings indicate that during periods of increased investment in sustainable technologies, the relationship strengthens, whereas in low-investment phases, the connection weakens. This suggests that the demand for REM, driven by clean energy expansion, does not translate into proportional price movements at all times, but rather depends on external factors such as supply chain constraints, geopolitical risks, and financial market conditions. Moreover, wavelet coherence analysis highlights that this relationship is more pronounced at medium- and long-term time horizons, indicating that short-term fluctuations in green energy prices may not immediately translate into REM price volatility.

5.2. TVP-VAR Results

Figure 2 presents the estimated time-varying parameter interactions obtained from the TVP-VAR model. Each subfigure corresponds to the dynamic evolution of a specific independent variable: (a) cyberattacks (CA), (b) geopolitical risk (GPR), (c) financial market volatility (VIX), and (d) clean energy prices (SPGTCLEN).

5.2.1. CA Influence

CA has a limited direct influence on REM indices, as shown by the low values in Table A1 in Appendix B. for "TO" (1.51%) and minimal contributions in each category. Despite its overall modest contribution, cyber risk effects are not entirely negligible, as they exhibit non-uniform behaviour across different time periods and indices. The GSPTXGM and MVREMXTR indices receive higher influences compared to other indices, but these remain insignificant relative to other determining factors. The corresponding figure for CA (Figure 2) confirms this result, highlighting generally low volatility and a marginal role for cyber risks in driving long-term price dynamics. This pattern suggests that CA does not act as a primary driver of volatility but rather as an episodic shock amplifier under specific economic and political conditions. The observed relationship between CA and REM indices may also be mediated by indirect channels, such as investor sentiment, supply chain disruptions, or correlations with VIX and GPR spikes.

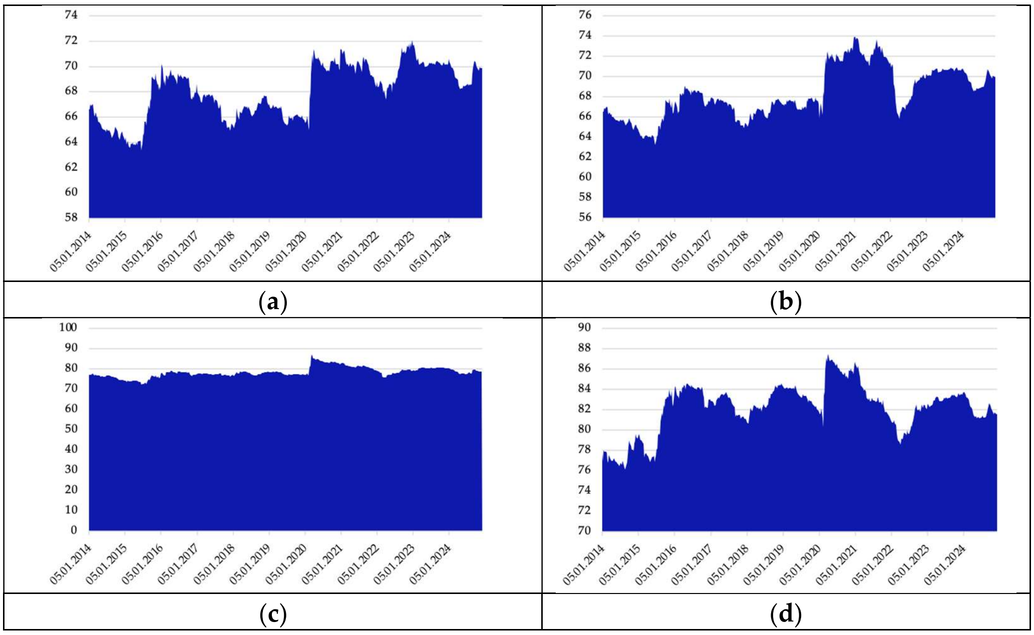

Figure 2. TVP-VAR estimates showing dynamic interactions between CA (**a**), GPR (**b**), VIX (**c**), and SPGTCLEN (**d**). The *y*-axis represents the estimated coefficients, while the *x*-axis denotes the time period from 2014 to 2024.

5.2.2. GPR Influence

GPR represents a key determinant for REM markets, majorly impacting the PICK and XME indices, in which total spillover "TO" values exceed 92% (Table A2). The corresponding figure for GPR (Figure 2) shows extensive areas of coherence at low frequencies, particularly during periods of global instability, such as 2016–2017 and 2020–2022. However, GPR contributions as individual percentages (1.15–1.74%) are modest, becoming significant through indirect transmissions to connected markets. The results confirm the structural nature of GPR, which, through cumulative effects, destabilizes REM markets.

5.2.3. VIX Influence

VIX significantly impacts REM, with high "TO" values for PICK (92.32%) and XME (70.39%, Table A3). The figure associated with VIX (Figure 2) shows pronounced areas of coherence during the periods 2016–2017 and 2020–2022, suggesting an amplified transmission of financial volatility during global crises. The 2016–2017 period aligns with the aftermath of the Brexit vote, U.S. presidential elections, and increased trade tensions between the U.S. and China. The 2020–2022 period reflects the COVID-19 pandemic, global supply chain disruptions, and geopolitical tensions, particularly the Russia-Ukraine conflict. The observed synchronous relationship confirms that financial shocks trigger immediate reactions from REM markets, further amplifying their instability. These findings validate the conclusions of Kamal and Bouri (2023), who emphasise the central role of financial volatility in propagating risks globally.

5.2.4. Influence of Green Energy Prices

SPGTCLEN moderately but variably influences REM indices, with "TO" values of 13.02% for SOLLIT and 7.55% for PICK (Table A4). The figure corresponding to SPGTCLEN (Figure 2) indicates limited and fragmented coherence over time, with visible influences at medium frequencies, particularly between 2018–2019 and 2021–2022, periods when investments in renewable energy grew significantly. The reduced contribution of SPGTCLEN to other indices, such as GSPTXGM and SPGSIN, suggests a more indirect relationship conditioned by technological demand for critical resources.

6. Discussion

6.1. Contributions to the Literature

The current study extends the existing literature by an integrated exploration of emerging risks in REM markets, contributing to a comprehensive understanding of global dynamics. Unlike Zheng et al. (2022), who highlighted the volatility of CE markets, this study incorporates cyber risks as a distinct but interconnected factor influencing rare earth markets. While the influence of CA on REM appears to be limited when viewed in isolation, the results indicate a significant impact during critical periods, such as 2016–2017, 2019–2020, and 2022–2023, confirming their episodic nature. This finding complements the literature, which has often underestimated the role of digital risks in market stability (Haq et al. 2022).

Regarding GPR, the results confirm their role as structural factors of market instability, in line with Bouri et al. (2021). For instance, the disruption of global supply chains by the US-China trade war (2018–2019) and the turmoil in Ukraine illustrate the long-term effect of GPR on volatility. While existing literature, such as Ha (2023), explores directional variations and the intensity of shock transmission between renewable energy and geopolitical risks, this study focuses on the role of GPR in amplifying systemic instability. By doing so, it contributes to understanding how geopolitical uncertainty interacts with other risk factors to influence REM price movements.

Financial volatility was identified as the strongest destabilizing factor during global crises, such as the COVID-19 pandemic. The outcomes complement the findings of Gao et al. (2024), which support the predominant VIX influence across all market conditions.

However, this study demonstrates that the impact of VIX volatility is context-dependent and becomes less relevant during periods of relative stability but highly disruptive in crisis periods. This insight provides a more nuanced interpretation of financial uncertainty, emphasizing the need for dynamic risk management strategies. Green energy prices exhibit a limited but consistent influence on indices such as SOLLIT and PICK. Additionally, CE markets appear to be transitioning from passive recipients of external risks to active contributors to market volatility. This observation aligns with broader trends in sustainable finance, where fluctuations in renewable energy investments increasingly shape commodity markets rather than merely responding to them (Du and Xu 2024).

6.2. Impact of Emerging Risks on the Global Energy Transition

The current study highlights that emerging risks play a central role in intensifying volatility in REM markets and amplifying global economic instability, directly affecting the energy transition. Financial volatility destabilizes REM markets during global crises, increasing uncertainty and limiting investments in sustainable technologies. Empirical evidence suggests that a 1% increase in CE production reduces global rare earth element reserves by 0.18%, highlighting the limitations of existing resources to support this transition (Golroudbary et al. 2022). Companies with less diversified production portfolios face higher risks, emphasizing the importance of diversification as a strategy to mitigate financial risks in the critical metals sector (Restrepo et al. 2023).

Geopolitical risks, including trade conflicts and international tensions, have introduced structural disruptions into global supply chains. For example, trade restrictions imposed by China and the conflict in Ukraine have sharply increased volatility, particularly for indices such as PICK and XME, confirming the conclusions of Buchholz and Brandenburg (2018). Furthermore, geopolitical risks do not act in isolation but have cumulative effects, amplifying volatility in conjunction with other risks. In this context, to ensure stable trade flows of critical mineral resources, institutional mechanisms must be implemented to mitigate the influence of geopolitical tensions and economic uncertainties. These measures would help maintain demand for mineral imports even during high volatility (Islam et al. 2022). Extreme market conditions intensify the spillover effects between energy markets and green assets, and the volatility of green assets is significantly influenced by uncertainties related to pandemics and geopolitical risks, such as those measured by Infectious Disease Equity Market Volatility and GPR (Liu et al. 2024). On a short-term time scale, REM markets reduce dependencies between CE markets, buffering during periods of increased volatility.

CA, despite its sporadic nature, act as a catalyst during crisis periods, intensifying the effects of other risks and exposing vulnerabilities. Unlike existing literature, such as Kamran et al. (2023), the current study positions cyber risks as a critical but underexplored determinant of REM volatility analysis, suggesting the need for adaptive strategies to protect critical infrastructures. While the results of this study indicate a limited impact of CA on REM markets compared to geopolitical and financial risks, this finding is valuable from several perspectives.

The limited impact of cyber risks does not imply irrelevance but rather reflects the indirect and context-dependent nature of their influence. Unlike geopolitical or financial shocks, which have immediate and quantifiable effects, CA primarily destabilizes critical infrastructure and disrupts logistics networks. These indirect effects are difficult to capture in traditional econometric models because they propagate through complex channels, such as logistical delays, data security breaches, or heightened risk perceptions. For example, a high coherence between CA and market volatility is observed only during certain global crisis periods. Outside these episodes, REM markets appear more resilient to cyber risks, suggesting that their impact depends on the broader economic and geopolitical context.

Differences in market sensitivity to CA suggest that certain sectors in the supply chain are more vulnerable than others. For instance, the results show that the MVREMXTR index, which includes strategic mining companies, is more sensitive to cyber risks than other markets. This observation suggests that while CA may not destabilize the entire REM market, their sectoral impact can be substantial, particularly for firms heavily reliant on automated supply chains. This finding adds an important nuance to the existing literature. While CA is often portrayed as an imminent threat, the results of this study suggest that REM markets have a certain resilience to these risks, particularly in the absence of major global or regional crises.

Finally, green energy prices indirectly influence REM markets, but the results are increasingly correlated during periods of technological and investment expansion, confirming the observations of Yang et al. (2024). This interdependence underscores the importance of sustainable energy policies for the stability of critical resource markets (Chen and Zheng 2019). Without integrated policy frameworks addressing both energy and resource security, the energy transition may face significant volatility-induced disruptions.

6.3. Directions for Risk Management

To effectively manage the emerging risks affecting REM markets, this study proposes a series of strategic measures adapted to the dynamics of these markets. By integrating these strategic measures, the study offers a comprehensive and adaptive approach to managing emerging risks, strengthening the stability of REM markets, and supporting the global energy transition. Geopolitical risks significantly influence rare earth metal markets, with variable effects over time and between markets, highlighting the importance of developing dynamic risk management strategies (Zhou et al. 2020).

1. Diversification of supply sources: Reducing dependency on dominant regions, such as China, by supporting exploration and local production in other regions is a priority.

This approach aligns with researches which emphasize the importance of accelerating investments in recycling and developing alternative supply chains (Gulley 2024). The current study complements this perspective by highlighting the importance of international partnerships in stabilizing global markets and minimizing risks of geographic concentration. Additionally, diversification should include proactive measures such as strategic storage of critical resources. To mitigate the impact of conflicts on critical metal markets, measures such as the development of strategic stockpiles, stimulating domestic production, and investing in alternative technologies are essential (Khurshid et al. 2023);

2. Promoting the circular economy: Efficient recycling of REM, used in batteries and other green technologies, is crucial for reducing dependence on primary resources vulnerable to external shocks (Torta et al. 2024). Innovative solutions by Rabbani et al. (2024) highlight the potential of the circular economy not only to support ecological development but also to mitigate the negative environmental impact and market instabilities from disruptions in supply chains. Implementing efficient recycling processes can reduce pressure on global demand and stabilize rare material prices. With electric motors, the depletion of resources such as copper and its accompanying metals significantly contributes to the effects of the life cycle on the environment, underscoring the importance of recycling strategies and material substitution (André and Ljunggren 2022). Policies promoting the sustainability of critical metal supply should include ethical governance and environmental sustainability to ensure a fair and just transition to a circular and green economy (Rachidi et al. 2021). Additionally, we emphasize the role of recycling programs in enhancing the resilience of rare earth markets by reducing dependency on primary extraction, stabilizing supply chains, and mitigating price volatility in response to geopolitical and economic disruptions;
3. Cybersecurity: Integrating advanced cybersecurity measures into operational strategies is crucial given the findings of this study regarding the amplification of the effects of financial and geopolitical risks by CA. Such a need is also observed by Martins and Moutinho (2024), who emphasized the need for robust policies to minimize firms' exposure to cyber risks. Creating early warning mechanisms and promoting international coordination can enhance supply chain resilience against cyber threats. This observation partially contradicts the conclusions of Gao et al. (2024), who minimize the influence of cyber risks compared to financial risks. The results of this study demonstrate that CA can act as an amplifier of volatility during critical periods, underscoring the need for proactive and immediate countermeasures;
4. Robust financial instruments: The development of futures contracts, options, and other financial instruments specific to REM markets can significantly help reduce uncertainty and stabilize markets, especially during particularly during periods of heightened geopolitical and financial volatility. These measures align with the conclusions of Lorente et al. (2022), who highlight the potential of green financial instruments and sustainable assets as stabilizing mechanisms in critical market volatility. Furthermore, empirical findings emphasize that financial risk indicators, such as VIX, exert significant pressure on REM price volatility, reinforcing the need for effective hedging strategies. By integrating structured financial instruments, market participants can enhance price predictability, reduce exposure to extreme fluctuations, and support long-term investment stability in the critical infrastructure necessary for the energy transition;
5. Managing the impact of CA: The damage caused by CA is often felt most acutely in the short term; however, their broader implications may be immediate or manifest in a delayed manner, contributing to the systemic instability of markets. A detailed analysis of the sequence and transmission mechanisms of cyber risk events is crucial

for identifying vulnerabilities and implementing preventive measures. The outcomes of this study suggest that a deeper understanding of how CA interacts with financial and geopolitical risks can facilitate the development of rapid remediation solutions and prevent amplified effects.

7. Conclusions

This study extensively analysed the interactions between REM markets and the emerging risks in these markets, using a dynamic econometric framework. The results provide clarity on the complexity and interdependencies between these risks and offer essential insights for understanding the dynamics of market volatility in the current context.

7.1. Main Contributions

The results of this research confirm that global financial market volatility is the main exogenous determinant of REM markets, especially during economic crises. The VIX amplifies short-term volatility and acts as a primary channel for transmitting financial risks between markets.

Concurrently, geopolitical risks function as major structural factors, destabilizing supply chains and generating persistent volatility, as observed during the Russia–Ukraine war and the U.S.-China trade tensions. These results demonstrate that GPR effects are not only long-term but can also manifest episodically during periods of intense tension.

While cyberattacks (CA) exert a comparatively weaker influence, they act as risk amplifiers in vulnerable contexts, intensifying the impact of financial and geopolitical shocks. This finding highlights the growing importance of digital risks, an aspect that has remained underexplored in existing literature. The results underscore the necessity of integrating advanced cybersecurity measures into supply chain management and risk mitigation strategies.

By employing a unified dynamic framework, this study bridges critical gaps in the literature, offering a comprehensive understanding of how financial, geopolitical, and cyber risks interact to influence REM market dynamics.

7.2. Practical and Policy Implications

The findings of this investigation demonstrate the need for coordinated and adaptive measures to manage the emerging risks affecting REM markets. Given the volatility induced by geopolitical tensions, international cooperation should focus on strengthening supply chain resilience through enhanced risk-sharing mechanisms and regulatory frameworks. Incentivizing research into alternative and sustainable materials remains crucial in reducing dependence on rare earth metals and mitigating supply risks. Additionally, global cybersecurity standards should be implemented to protect critical infrastructures and reduce technological risks.

Companies and investors must develop hedging mechanisms to mitigate the impact of market volatility and enhance financial stability during crises. A more structured integration of financial, cyber, and geopolitical risks into supply chain planning can improve firms' ability to anticipate disruptions and adjust investment strategies accordingly. Investments in technological innovations, including the recycling of critical materials, can significantly contribute to more efficient resource use and reduce dependence on vulnerable primary sources.

The academic community plays an important role in supporting these efforts by expanding interdisciplinary collaborations to advance risk modelling techniques and improve market forecasting accuracy. Integrating financial, geopolitical, and cyber risk assessments into dynamic econometric models can provide policymakers and industry leaders with valuable insights into emerging threats.

7.3. Limitations and Future Research Directions

The study has several shortcomings that open opportunities for future research. Although the analysis focuses on the interactions between REM markets and emerging risks, more detailed investigations are needed on the links with other economic and technological sectors, such as CE and transportation markets.

Another aspect worth exploring is the incorporation of environmental and social risks into the analysis models to better understand the systemic vulnerabilities of these markets. Moreover, while this study integrates key geopolitical, financial, and cyber risk indicators, it does not account for broader macroeconomic variables, such as global GDP growth and interest rates, which may also influence REM market trends. Future research could extend the analysis by incorporating these macroeconomic factors to provide a more comprehensive assessment of market volatility and interconnected risks. Additionally, the long-term effect of the energy transition on REM markets, including the implications of technological innovations and international regulations, represents a valuable direction for further research.

By highlighting the impact of emerging risks on the volatility of REM markets, this study significantly contributes to understanding the factors shaping these markets, which are essential for the global energy transition. The results support decision-makers and the academic community in formulating effective risk management policies and securing supply chains, thus contributing to global economic stability and the transition to a sustainable economy.

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Abbreviations

The following abbreviations are used in this manuscript:

REM	Rare earth materials
CA	Cyberattacks
TVP-VAR	Time-Varying Parameter Vector Autoregression
CE	Clean energy
GPR	Geopolitical Risk
VIX	Volatility Index
VAR	Vector Autoregression
SOLLIT	Solactive Global Lithium
PICK	iShares MSCI Global Metals & Mining Producers ETF
GSPTXGM	S&P/TSX Global Mining Index
MVREMXTR	MVIS Global Rare Earth/Strategic Metals TR Net Index
XME	SPDR® S&P Metals and Mining ETF

SPGTCLEN	Green Energy Price
CWT	Continuous Wavelet Transform
GFEVD	Generalised Forecast Error Variance Decomposition
IDEMV	Infectious Disease Equity Market Volatility

Appendix A

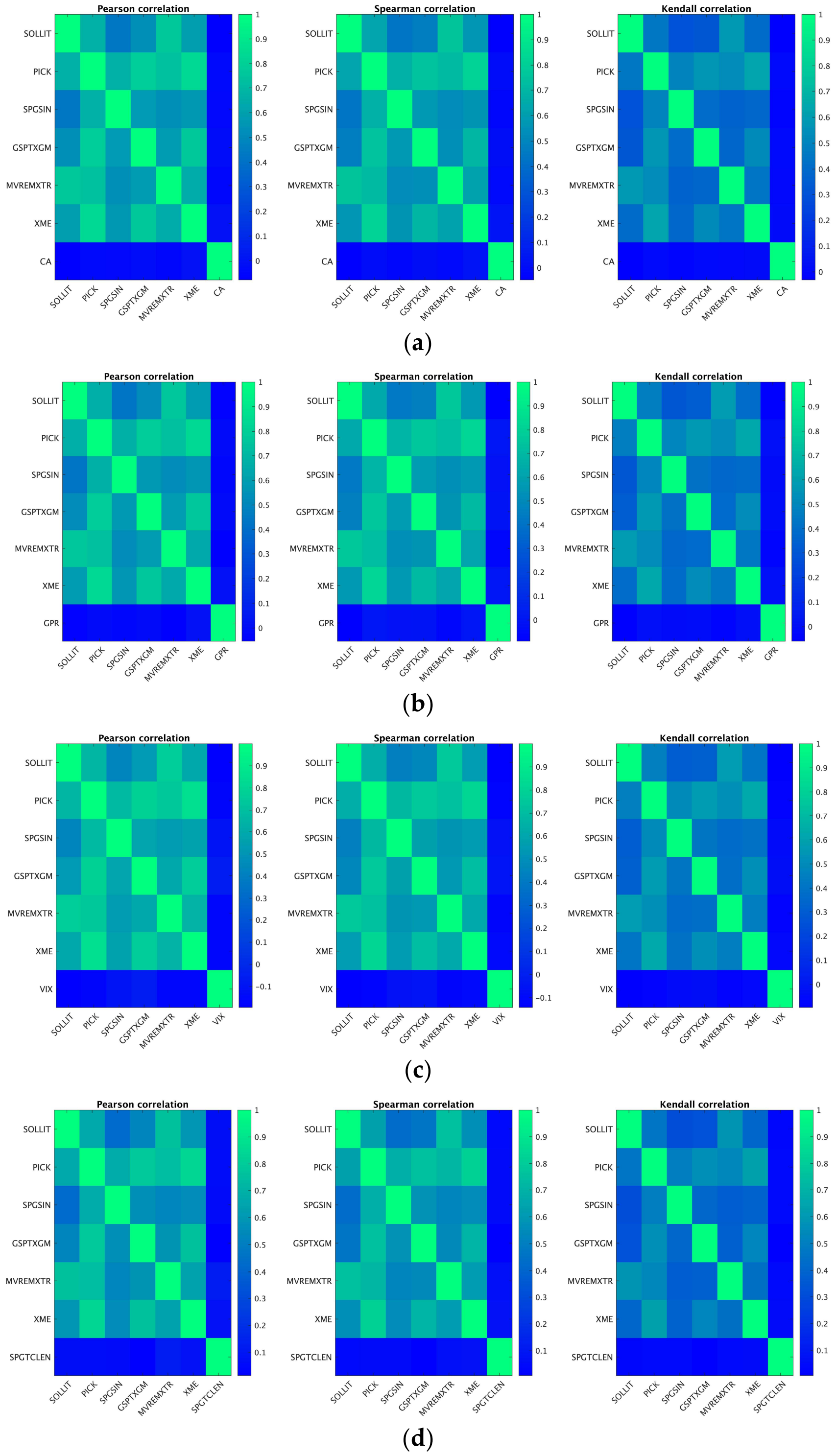


Figure A1. Correlation results. Note: (**a**) presents the correlation between indices and CA using Pearson, Spearman, and Kendall coefficients. (**b**) shows the correlation between indices and GPR using the same statistical coefficients. (**c**) highlights the correlation between indices and VIX index. (**d**) illustrates the correlation between indices and SPGTCL.

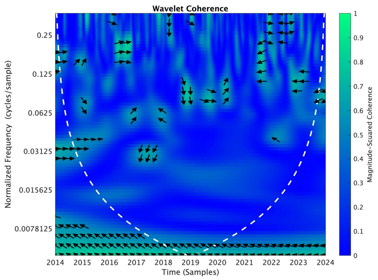
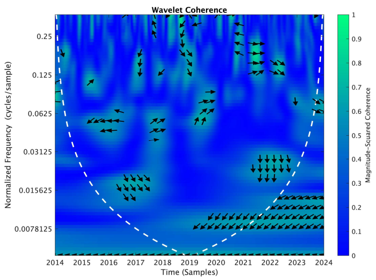
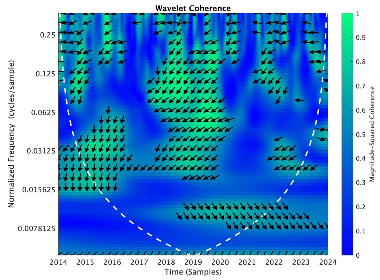
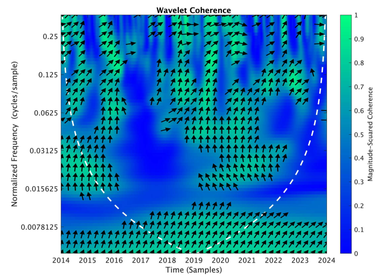
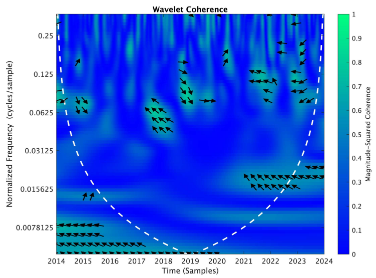
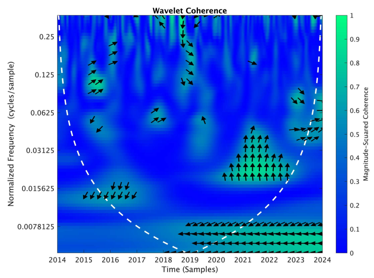
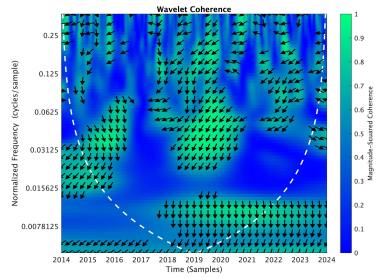
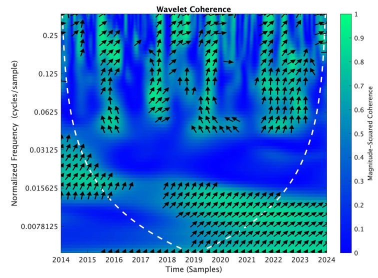
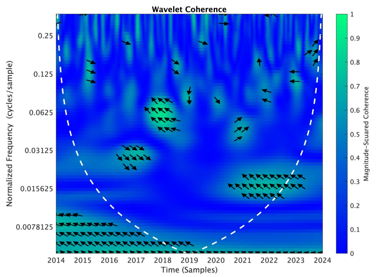
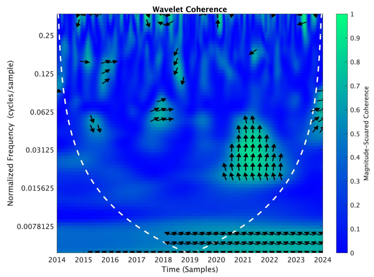
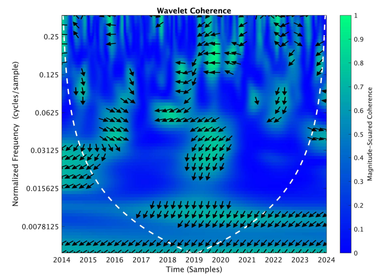
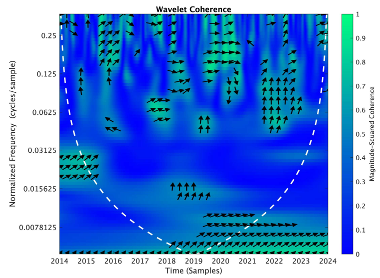
Index	**CA**	**GPR**	**VIX**	**SPGTCLEN**
SOLLIT				
PICK				
SPGSIN				

Figure A2. *Cont.*

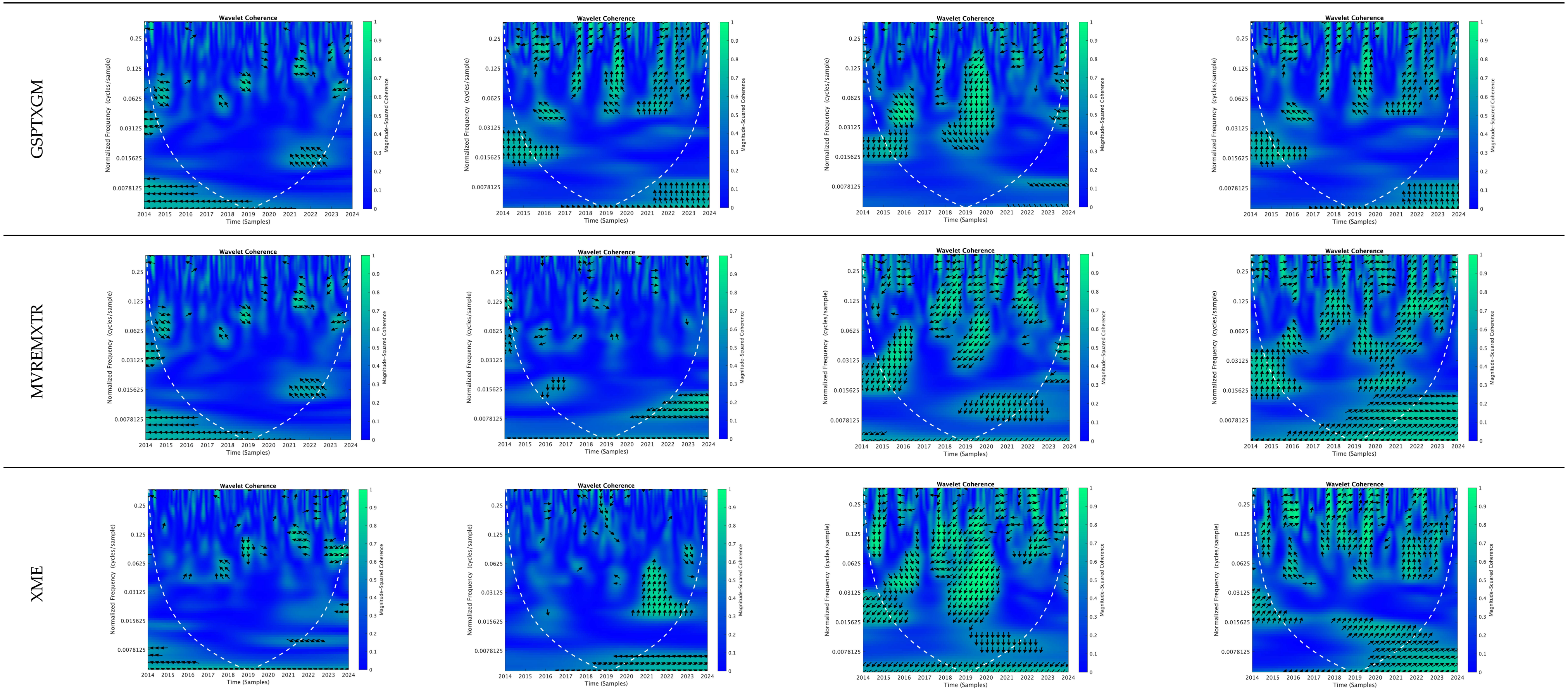


Figure A2. CWT results. The arrows indicate phase differences: → in-phase, ← anti-phase, ↑ first series leads, ↓ first series lags.

Appendix B. TVP-VAR Results

Table A1. TVP-VAR results for cyberattacks.

Index	SOLLIT	PICK	SPGSIN	GSPTXGM	MVREMXTR	XME	CA	FROM
SOLLIT	36.83	16.21	5.95	9.48	18.36	13.01	0.17	63.17
PICK	11.91	26.73	11.84	15.84	14.99	18.51	0.18	73.27
SPGSIN	7.04	17.69	39.62	11.89	10.26	13.05	0.44	60.38
GSPTXGM	8.59	19.07	9.56	32.44	10.95	19.11	0.28	67.56
MVREMXTR	16.68	18.24	8.42	11.02	31.58	13.86	0.20	68.42
XME	10.72	20.37	9.57	17.27	12.21	29.61	0.25	70.39
CA	0.42	0.73	0.56	0.97	1.00	1.29	95.03	4.97
TO	55.37	92.32	45.90	66.48	67.76	78.83	1.51	408.16
NET	−7.81	19.05	−14.48	−1.08	−0.66	8.44	−3.46	58.31

Table A2. TVP-VAR results for geopolitical risk.

Index	SOLLIT	PICK	SPGSIN	GSPTXGM	MVREMXTR	XME	GPR	FROM
SOLLIT	36.69	16.20	5.96	9.55	18.32	13.15	0.13	63.31
PICK	11.91	26.67	11.90	15.81	14.98	18.60	0.12	73.33
SPGSIN	7.03	17.70	39.32	12.06	10.22	13.31	0.36	60.68
GSPTXGM	8.66	19.06	9.74	32.39	11.02	18.96	0.17	67.61
MVREMXTR	16.61	18.20	8.43	11.07	31.48	14.03	0.17	68.52
XME	10.79	20.39	9.79	17.05	12.33	29.45	0.19	70.55
GPR	1.74	0.79	0.81	0.89	0.67	1.19	93.91	6.09
TO	56.75	92.35	46.64	66.43	67.55	79.23	1.15	410.10
NET	−6.56	19.02	−14.04	−1.17	−0.98	8.68	−4.94	58.59

Table A3. TVP-VAR Results for financial market volatility.

Index	SOLLIT	PICK	SPGSIN	GSPTXGM	MVREMXTR	XME	VIX	FROM
SOLLIT	32.80	14.39	5.41	8.37	16.36	11.55	11.11	67.20
PICK	10.97	24.63	11.03	14.36	13.76	17.03	8.23	75.37
SPGSIN	6.88	17.33	38.19	11.54	10.06	12.83	3.18	61.81
GSPTXGM	8.19	18.06	9.19	30.82	10.45	17.94	5.34	69.18
MVREMXTR	15.52	16.96	7.97	10.21	29.61	12.97	6.77	70.39
XME	9.97	18.90	9.03	15.67	11.44	27.28	7.71	72.72
VIX	14.15	13.72	2.27	5.18	8.08	10.50	46.10	53.90
TO	65.68	99.36	44.90	65.33	70.13	82.82	42.34	470.58
NET	−1.52	23.99	−16.91	−3.84	−0.26	10.10	−11.56	67.23

Table A4. TVP-VAR results for clean energy prices.

Index	SOLLIT	PICK	SPGSIN	GSPTXGM	MVREMXTR	XME	SPGTCLEN	FROM
SOLLIT	29.62	14.32	5.93	9.12	16.06	11.93	13.02	70.38
PICK	11.51	23.51	11.26	14.87	14.18	17.12	7.55	76.49
SPGSIN	7.47	16.95	34.96	12.00	10.50	12.95	5.18	65.04
GSPTXGM	8.89	17.85	9.55	28.32	11.17	17.71	6.51	71.68
MVREMXTR	15.27	16.65	8.28	10.88	26.99	13.17	8.76	73.01
XME	10.58	18.74	9.40	16.03	12.04	25.78	7.44	74.22
SPGTCLEN	17.45	11.71	4.85	7.61	11.29	9.54	37.55	62.45
TO	71.16	96.21	49.27	70.50	75.24	82.41	48.46	493.26
NET	0.79	19.72	−15.77	−1.18	2.23	8.19	−13.99	70.47

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