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Climate Risks and Predictability of the Conditional Distributions of Rare Earth Stock Returns and Volatility

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Abstract

We use a *k*-th order nonparametric causality-in-quantiles test to predict rare earth stock returns and volatility based on physical and transition climate risks over the period of 2nd January 2008 to 31st January 2025. The results indicate that, even though linear Granger causality fail to show any evidence of prediction of rare earth stock returns, due to model misspecifications from nonlinearity and structural breaks, the nonparametric framework depicts statistically show significant evidence of predictability over the entire conditional distribution of returns and volatility. They are robust to alternative choices of rare earth stock indexes, measures of climate risks, conditional estimates of volatility, and various macroeconomic and financial control variables. Further analyses involving the signs of the causality and rolling-window estimation reveal that rare earth stock index returns are negatively impacted at lower conditional quantiles till the median, corresponding to bearish market conditions; volatility, however, is positively impacted (i.e., it increases) over its entire conditional distribution.

Keywords: Rare earth stock returns and volatility; Physical and transition climate risks; Higher-order nonparametric causality-in-quantiles test; Condition distribution

JEL Codes: C22, C32, G10, Q54

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1. Introduction

As pointed out by Li et al. (2020), the global temperature is expected to be 4 °C to 6 °C higher during the 21st century than in pre-industrial era, which is expected to have posing serious consequences for human lives and biodiversity. This is why the goal of the 2015 Paris Climate Agreement is to keep the temperature increase below 2°C. In this regard, the transition from fossil fuels to renewable energy sources is of paramount importance to reduce greenhouse gas emissions.

Rare earth elements (REE) are therefore essential for the development and deployment of renewable energy technologies. Their magnetic or conductive properties enable the production of efficient wind turbines, electric vehicle batteries, solar panels, energy storage systems, hydrogen, and catalytic converters (Apergis and Apergis, 2017; Depraiter and Goutte, 2023; Fan et al., 2023). These metals are also used in the electronics, aerospace, healthcare, and defense industries (Müller et al., 2016; Buchholz and Brandenburg, 2018; Zuo et al., 2021; Fan et al., 2023). Hence, REE are called "industrial vitamins" (Wang et al., 2015). Not surprisingly, with global emphasis on decarbonisation, rare earth (RE) production reached 390 thousand metric tons worldwide in 2024, up threefold from 132 thousand metric tons in 2017[1], and is expected to reach 51.9 thousand metric tons by 2030 to meet growing demand (Zhou et al., 2017). REE prices has naturally attracted the attention of global investors. In many countries, new extraction and recycling projects have been developed, aiming to secure alternative supply chains to reduce dependence on China[2], the world's largest producer (Bartekova and Kemp, 2016; Fernandez, 2017; Schmid, 2019; Pawar and Ewing, 2022). Given this, the REE market size, which reached 3.39 billion US dollars in 2023, is expected to be 8.14 billion US dollars by 2032.[3] The International Energy Agency (IEA, 2021) predicts a sevenfold increase in their production by 2040 to fuel the clean energy sector. This is why maintaining and expanding these investment efforts in REE sector requires a clear understanding of how the risks-returns profile of the stocks of the RE companies are driven by climate risks.

In this context, our study seeks to analyze the predictability of global rare earth stock returns and their volatility based on the information contents of textual measures of physical and transition climate risks. Our predictability analysis involves a nonparametric causality-in-quantiles test, covering the conditional distributions of rare earth stock index returns and volatility.

On one hand, higher physical climate risks (resulting from natural disasters and rising temperatures) and transition climate risks (due to government intervention through carbon

[1] See for details at: https://investingnews.com/daily/resource-investing/critical-metals-investing/rare-earth-investing/rare-earth-metal-production/.
[2] As per the United States (US) Geological Survey, in 2024, China produced 270 thousand metric tons (out of the 390 thousand metric tons) followed by the US as a distant second with 45 thousand metric tons (see: https://pubs.usgs.gov/periodicals/mcs2025/mcs2025-rare-earths.pdf).
[3] https://www.fortunebusinessinsights.com/rare-earth-elements-market-102943.

taxation and incentives for green technology development) are expected to contribute to higher RE stock returns due to increased demand for renewable energy and REE investments to reduce carbon emissions. On the other hand, these climate risks are also expected to negatively impact stock valuations due to reduced productivity and/or increased stochastic capital depreciation rate (Donadelli et al., 2017, 2021, 2022). It should also be noted that while this decline in returns is associated with the short term, the increase can only occur in the medium to long term. This is the reasoning of Ding et al. (2024) whose article is the only one to show that US physical climate risk shocks (e.g. extreme temperature) lead to an increase in RE stock returns only at longer forecast horizons, while being preceded by a decline in the short term. To reach this conclusion, these authors used time-varying impulse response functions from a time-varying parameter vector autoregression (TVP-VAR). In our quantile-based framework of causality, this could imply the hypothesis of a negative effect of climate risks at the lower conditional quantiles on RE stock index returns. It would be explained by a slowdown in the economy but then, as the demand for renewable energy, and therefore investment in REE, increases to mitigate higher physical climate and transition risks, RE stock returns should react positively at the higher conditional quantiles. In other words, the sign of the predictive relationship between climate risks and RE stock index returns is likely to be regime-dependent: negative in the bear regime and positive during the bull state, related to the length of the investment horizon. Given the well-known "leverage effect" (Black, 1976) associated with financial asset prices, one might expect that lower REE returns, induced by climate risks, would reduce the volatility associated with the REE sector at lower conditional quantiles. However, higher trading volumes associated with higher returns at higher conditional quantiles are concurrently likely to increase volatility, consistent with mixed distribution (Clark, 1973) and/or sequential information arrival (Copeland, 1976) theories. We can therefore conjecture that REE stock index volatility increases across its entire conditional distribution as a result of the increase in physical and climatic transition risks.

Our paper makes novel contributions to a limited literature on the returns and volatility of rare earth market and climate risk. First, it enriches the recent literature on renewable energy stock market movements from a climate finance perspective (for an in-depth review, see Giglio et al. (2021), and Zhai et al. (2024)) by analyzing for the first time the predictability of the entire conditional distribution of the first and second moments of rare earth stock index due to climate risks. It does so using a higher-order nonparametric causality-in-quantiles test, which controls for underlying nonlinearity and structural breaks in these relationships. Specifically, the nonparametric higher-order quantile causality test of Balcilar et al. (2018) is ideally suited to handling fat tails in the distribution of the dependent variable, which, unsurprisingly, turns out to be the case. Compared to static methods employed in previous literature, the nonparametric higher-order quantile causality framework has the major advantage of allowing us to detect predictability across the entire set of conditional distributions, i.e., regimes, returns, and volatility due to climate risks. It also simultaneously controls for model misspecification resulting from nonlinearity and structural breaks in these relationships, for which we provide statistical evidence. With this approach, we can distinguish between different market conditions (normal, bullish, and bearish). These are perceived through the quantiles of the conditional distribution of returns and volatility. This provides a better insight into the high-frequency predictability of rare earth market fluctuations related to climate risks.

Second, we select a rich study period (from January 2, 2008 to January 31, 2025) including the signing of the Paris Agreement (2015), the peak of the Sino-American embargo (2018–2019), the launch of the European Green Deal (2019), the outbreak of the COVID-19 pandemic (2020), the crisis specific to the rare earth market (2020), the Russo-Ukrainian conflict (2022) and the adoption of the US Inflation Reduction Act (2022). This relatively long period is marked by high uncertainty regarding the rare earth market and a sharp increase in the prices of rare earth stocks. Global markets and supply chains have been strongly affected.

Third, our research strengthens our understanding of textual uncertainty indices, such as climate risk indicators from the recent work of Faccini et al. (2023). We also highlight the important distinction between physical and transition climate risks, as there is a variable link between climate risk and the value of rare earths over time. This distinction allows us to assess the behavior of investors faced with these variations, both in terms of physical risk and transition risk.

Although due to specification errors resulting from nonlinearity and structural breaks, linear Granger causality does not provide any evidence for predicting rare earth stock returns, but our results show that our nonparametric framework exhibits strong, statistically significant evidence of predictability across the entire conditional distribution, not only of returns but also of squared returns, i.e., volatility. They also prove robust to alternative choices of rare earth stock indices, climate risk measures, conditional volatility estimates, and multiple macroeconomic and financial control variables. Further analysis involving sign-of-causal impact analyses and moving window estimation tends to reveal that rare earth stock returns are negatively impacted for the lower conditional quantiles up to the median. This corresponds to weak global conditions. Conversely, volatility increases across the entire conditional distribution, highlighting the leverage effect and the link between surge risks and climate catastrophes.

Our findings shed light on rare earth stock investments under various climate risks, raising serval implications. Investors can thus realize that rare earth stocks are subject to both physical and transition risk and, in the event of a market rally, they can act as a hedge against these climate risks. In contrast, if the market is in bearish or normal states (corresponding to low and mid-quantiles, respectively), the returns of these stocks decline despite an amplification of volatility across the entire conditional distribution. In other words, the more uncertainty grips the markets, the more investors must take extreme climate risks into account to diversify their portfolios and hedge their rare earth stock investments. As for policy-makers, they should better anticipate the joint repercussions of climate risks and the energy transition on this type of market, which is important for optimizing and stabilizing the supply of rare earths to facilitate their energy transition policies.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents the data. Section 4 outlines the basics of our econometric framework, with Section 5 presenting the empirical findings, and Section 6 concluding the paper.

2. Literature review

A first strand of literature analyzes the impact of returns and volatility on renewable energy stock prices and on other financial assets and commodities (energy and non-energy). For example, Chen et al. (2020) use asymmetric multivariate generalized autoregressive conditional heteroscedasticity (GARCH) models to examine the links between crude oil, new energy and rare earth markets in China for the period 2012-2018. Their results show that volatility is rapidly transmitted from market to market, with the rare earths market acting as the main transmission vector, notably between crude oil and renewable energy markets. The correlations between rare earth and new energy market returns are positive and hardly change over time. In contrast, correlations between crude oil and rare earths appear weak, fluctuate and can be reversed. Using a Markov switching vector autoregressive (MS-VAR) model, Reboredo and Ugolini (2020) examine the price transmission mechanisms between rare earth stocks, gold, oil, clean energy, base metals, and MSCI world stock markets. They find that, where connectedness is weak, it is mainly rare earth equities that are connected to base metals. There are few links between the other markets, hence the potential for diversification. Conversely, when volatility is high, covariation increases between rare earths and the other assets included in the study, which is a sign of greater contagion. But even in this case, the impact remains relative. Kamal and Bouri (2023) study the tail dependence among rare earth metals, clean energy, gold, world equities, base metals, and crude oil, while considering various timescales. They show that the dynamic dependencies of most indices ease after accounting for the impact of rare earth metals. In this regard, a heterogeneity is noticed between the medium and long term. Song et al. (2021) use the TVP-VAR method to study the dynamic connectedness between rare earths and energy markets. Their results show that rare earths are indeed at the heart of connectedness chains. This was particularly the case during the COVID-19 pandemic, as stocks are the first to receive shocks in the event of a crisis. Combining an MS-VAR approach and quantile-based generalized variance decomposition (GFEVD), Bouri et al. (2021) analyze rare earths' connectedness to clean energy, consumer electronics, defense, healthcare, aerospace and defence, and telecommunications for the period 2010-2020, focusing on both return and volatility. They show that the rare earths market act as a net receiver of shocks, especially in times of crisis. Clean technologies and electronics are switched from receivers to transmitters of volatility. Bouri et al. (2021) underline the impact of the U.S.–China trade war on the return and volatility sectoral indices superseding the demand-driven dynamics for rare earth materials. Combining the quantile time-frequency connectedness model and the inter-quantilogram interdependence method, Madaleno et al. (2023) analyze the relationship between rare earth minerals, clean energy, renewable technologies and carbon emissions. They show that the impact of rare earths on renewable energies evolves according to market conditions and time horizons. In the short-term, rare earth minerals behave as net receivers of shocks. Hanif et al. (2023) study the connectedness in terms of returns and volatility between the rare earth market and six major stock market indices in the renewable energy sector. Using wavelet, spillover index, and squared wavelet coherence (WTC) approach, they attest to an amplification of connectedness between rare earths and renewable energy stocks during the COVID-19 pandemic. In this context, rare earths are net receivers of risk, especially from clean energies. Gao and Liu (2024) reach the same conclusions, by adding base metals and environmental, social and governance (ESG) factors in the model for spillover analysis. Gao et al. (2024) underscore the importance of geopolitical tensions. The segmentation of clean energies (wind, solar, electric vehicles, nuclear) and the use of VAR and GARCH models with variable parameters enabled them to highlight an intensification of extreme risks on all markets during geopolitical crises.

A second strand of research attempts to forecast returns and volatility of rare earth stocks using univariate and multivariate models. Existing studies rely on macroeconomic and financial variables, trade policy uncertainties and geopolitical risks as predictors. By analyzing the volatility of rare earth minerals using autoregressive moving average (ARMA), autoregressive fractionally integrated moving average (ARFIMA) and GARCH models, Proelss et al. (2020) also show the influence of memories of past crises and the importance of forecasts for supply management. Henriques and Sadorsky (2023) point out that with machine learning methods (support vector machines, random forests, highly randomized trees), it was possible to forecast the evolution of rare earth stocks for almost three weeks with over 85% accuracy. These models are clearly superior to lasso and naive Bayes, as are other technical indicators. Using Caldara and Iacoviello's (2022) geopolitical risk index, Li et al. (2023) studied its links with rare earth prices and global economic activity. According to their results, prices are far more predominant on the geopolitical risk index during supply shocks, which reverses after the COVID-19 pandemic. But geopolitical risks still drive-up rare earth prices. Giol et al. (2025) have recently used a TVP-VAR model to examine the impact of cyber-attacks and geopolitical and financial volatility on rare earth markets over the last ten years. Their results show that, in the long term, financial volatility has the greatest impact, while in the short term, cyber-attacks have the greatest impact, particularly in times of crisis.

While the above-mentioned studies extend our understanding of the linkages between renewable energies and other financial markets, they are not without limitations. Most of these studies postulate linearity in the linkages and often ignore volatility as a transmission channel. Furthermore, they do not account into the upwards or downwards trending of the rare earth stock and their low and high volatility states. Specifically, neither extreme effects nor non-linear evolutions were sufficiently captured for periods of financial or climatic shock, which is certainly an important factor in the context of renewable energy demand formation. Our study extends the above strands of research by analyzing the Granger causal links between two types of climate risks (physical and transitional) and the reruns and volatility of rare earth stock indices. To this end, it uses the non-parametric causality test in quantiles proposed by Balcilar et al. (2018), which allows us to check its variations as a function of the quantiles of the conditional distribution. While classical parametric approaches tend towards a certain rigidity, this test adds flexibility to the apprehension of non-linear dynamics.

3. Data

To track changes in the performance of RE companies globally, MVIS computes a Global Rare Earth/Strategic Metals (Total Return) Index (MVREMX) in US dollars, which we use as representative of the stock market value of RE companies. The MVREMX, which we source from Refinitiv Datastream, covers the largest and most liquid companies involved in RE activities, and is, a capitalization-weighted index that covers at least 90% of the investable universe. It includes companies generating at least 50% of their revenues from REs and strategic metals, with them being based in China (32.46%), Australia (23.90%), the US (13.31%), Canada (9.63%), Chile (7.42%), the Netherlands (4.13%), France (4.08%), the United Kingdom (UK; 2.72%), and Switzerland (2.36%).[4] We compute the log-returns of the MVREMX.

To predict the RE stock index returns and volatility, we use the climate risk measures constructed by Faccini et al. (2023). These authors employ the latent Dirichlet allocation (LDA) technique, an unsupervised textual analysis method, to dissect climate-change risks and construct climate-risk factors. They apply LDA to articles that contain the words "climate change" and "global warming", published daily in the Thomson Reuters News Archive. LDA deconstructs the news corpus into so-called "topics" that can be characterized in terms of the frequency distribution of words. Hence, once the LDA technique identifies the topics, Faccini et al. (2023) give every topic an economic interpretation and, in addition, are able to compute time series of the topic shares (that is, the proportion of an article's text associated with a given topic) that represent how news coverage has evolved over time for any given topic. Finally, Faccini et al. (2023) identify four major climate-related topics of interest: the occurrence of natural disasters (ND), the role of emissions in relation to global warming (GW), US climate policy (USCP), and climate change-related international summits (IS).[5] We consider ND and GW to reflect physical risks of climate change, and USCP and IS to be capture transition risks.

Based on availability of data at the time of writing this paper, our daily sample period covers 2nd January 2008 to 31st January 2025, yielding 4329 daily observations per series.

[4] The reader can refer to: https://www.marketvector.com/indexes/hard-asset/mvis-global-rare-earth-strategic-metals, for further details on this index.

[5] The data is available for download from: https://sites.google.com/site/econrenatofaccini/home/research?authuser=0.

Log-returns of the MVREMX, along with levels of ND, GW, USCP and IS are plotted in Appendix Figure A1, with summary statistics provided in Appendix Table A1. As can be seen from Table A1, RE stock index returns are not normally distributed (as are the four climate risks), as depicted by the overwhelming rejection of the null of normality under the Jarque-Bera test, and hence provides us with a preliminary motivation to utilize a quantiles-based approach of causality.

4. Econometric Methodology

In this section, we employ the k-th order nonparametric causality-in-quantiles test methodology of Balcilar et al. (2018), which combines the higher order nonparametric approach of Nishiyama et al. (2011) with the quantiles-based framework of Jeong et al. (2012).

Let v_t denote RE stock index returns and w_t a specific measure of climate risks. Also, let $V_{t-1} \equiv (v_{t-1}, \dots, v_{t-p})$, $W_{t-1} \equiv (w_{t-1}, \dots, w_{t-p})$, $U_t = (W_t, V_t)$, and $F_{v_t|\cdot}(v_t| \bullet)$ denote the conditional distribution of v_t given $\bullet$. We define $Q_\theta(U_{t-1}) \equiv Q_\theta(v_t|U_{t-1})$ and $Q_\theta(V_{t-1}) \equiv Q_\theta(v_t|V_{t-1})$ to have $F_{v_t|U_{t-1}}\{Q_\theta(U_{t-1})|U_{t-1}\} = \theta$ with probability one. The θ-th quantile (non)causality hypotheses to be tested are as follows:

$$H_0\text{:}\ \ P\{F_{v_t|U_{t-1}}\{Q_\theta(V_{t-1})|U_{t-1}\} = \theta\} = 1 \tag{1}$$

$$H_1\text{:}\ \ P\{F_{v_t|U_{t-1}}\{Q_\theta(V_{t-1})|U_{t-1}\} = \theta\} < 1 \tag{2}$$

Jeong et al. (2012) show that the feasible kernel-based test statistics is given by:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{U_{t-1} - U_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{3}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(V_{t-1})\} - \theta$ is the regression error, with $\hat{Q}_\theta(V_{t-1})$ being an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. Note that, with $L(\bullet)$ denoting the kernel function, we use the *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(V_{t-1})$, which is given by:

$$\hat{Q}_\theta(V_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{V_{t-1} - V_{s-1}}{h}\right) \mathbf{1}\{v_s \leq v_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{V_{t-1} - V_{s-1}}{h}\right)} \tag{4}$$

Balcilar et al. (2018) extend the framework of Jeong et al. (2012) framework to the second (or higher) moment, following Nishiyama et al. (2011), which, in turn, allows us to test the causality between a metric of climate risks and REE stock returns volatility. In this case, the null and alternative hypotheses are as follows:

$$H_0\text{:}\ \ P\left\{F_{v_t^k|U_{t-1}}\{Q_\theta(V_{t-1})|U_{t-1}\} = \theta\right\} = 1, \quad k = 1,2, \dots, K \tag{5}$$

$$H_1\text{:}\ \ P\left\{F_{v_t^k|U_{t-1}}\{Q_\theta(V_{t-1})|U_{t-1}\} = \theta\right\} < 1, \quad k = 1,2, \dots, K \tag{6}$$

The nonparametric causality-in-variance test can then be conducted by replacing v_t in (3) and (4) with v_t^2. The testing approach is sequential, therefore, failing to reject the null hypothesis for $k = 1$ does not automatically imply non-causality for $k = 2$. As pointed out by Balcilar et al. (2018), a rescaled version of the $\hat{J}_T$ follows standard normal distribution, with 1%, 5%, and 10% critical values being 2.575, 1.96, and 1.645, respectively.

The empirical implementation of the above-mentioned test involves the specification of three key parameters namely, the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. In this regard, the selection of the lag order is based on the Bayesian Information Criterion (BIC), with h being determined by the leave-one-out least-squares cross validation, and Gaussian kernels used for $K(\cdot)$ and $L(\cdot)$.

5. Empirical Findings

5.1. Main Results

Before presenting the results from the nonparametric causality-in-quantiles test, we conduct the linear Granger causality test for the sake of completeness and comparability. Table 1 show that the null of no-Granger causality from ND, GW, USCP and IS for RE stock returns cannot be rejected even at the 10% level of significance.

[INSERT TABLE 1]

Having observed a lack of causality from climate risks to RE stock index returns based on a linear specification, we next examine whether the finding of non-causality is due to model misspecification that assumes a linear predictability relationship. Therefore, we first test for the presence of nonlinearity in the relationship between RE stock returns and the four metrics of climate risks, and then consider the potential presence of structural breaks in the relationship. Regarding the nonlinearity, we use the Brock et al. (1996, BDS) test on the residuals from the linear model used in the linear Granger causality test, and check whether the null hypothesis of *i.i.d.* residuals at various dimensions (m) can be rejected or not. As seen from Table 2, the BDS test yields overwhelming evidence of nonlinearity, i.e., we reject the null hypothesis of linearity (*i.i.d.* residuals) at the 1% level level of significance, consistently across all the 4 predictive cases considered. In sum, the BDS test confirms that the linear model is indeed misspecified due to the existence of uncaptured nonlinearity, and hence, further causal inference must rely on a nonlinear model, which is given by our nonparametric causality-in-quantiles approach.

[INSERT TABLE 2]

Regarding the issue of instability in the linear model and, hence, we address another layer of potential misspecification by examining the presence of possible structural breaks in the relationship between RE stock returns and indicators of climate risks. For this purpose, we utilize the powerful *UDmax* and *WDmax* tests for multiple structural breaks as proposed by of Bai and Perron (2003) on the equations of the linear Granger causality test. Based on the results reported in Table 3, we find that there are three breaks each in the relationships between RE stock returns and the four climate risks variables. The dates of regime-change correspond primarily to REE production control in China during 2011,[6] the US-China trade war, and the COVID-19 pandemic, with the last two dates being associated with supply constraints in the RE market. Given that the parameter estimates are unstable over the full sample period, the linear Granger causality results seem unreliable. To ensure robust inference of the causal analysis in our context, we therefore must rely on an econometric model that is inherently non-linear, which is accomplished through our quantiles-based, i.e., regime-specific, nonlinear set-up.

[INSERT TABLE 3]

In light of the presence of nonlinearity and regime changes in the relationship between RE stock returns and ND, GW, USCP and IS considered separately, our linear Granger causality results are clearly unreliable. This provides us with a strong statistical motivation to utilize the *k*-th order nonparametric causality-in-quantiles testing method, which can accommodate such misspecifications, while simultaneously providing results for the second-moment, i.e., RE stock returns volatility. Table 4 presents the standard normal test statistics, derived from the quantiles-based results, over the range of 0.10 to 0.90. As can be seen from sub-tables 2(a) and 2(b), all the four metrics of climate risks, not only strongly predicts the entire conditional distribution of RE stock returns, but also its volatility, given that the null of non-causality is rejected at the 1% level of significance.

[INSERT TABLE 4]

5.2. Robustness Checks

In this sub-section, we provide five robustness checks to our findings on causality.

First, instead of MVREMX, we use the VanEck Rare Earth/Strategic Metals ETF (REMX),[7] also sourced from Refinitiv DataStream, to compute the RE stock index returns, the nonparametric causality-in-quantiles test results, reported in Appendix Table A2, depict strong evidence of predictability for the entire conditional distributions of both RE returns and its volatility from ND, GW, USCP and IS, over the period of 29th October 2010 to 31st January 2025.

Second, we replace the climate measures of Faccini et al. (2023) with the physical and transition climate risks measures of Bua et al. (2024),[8] derived from text-based approaches and

[6] https://www.mining.com/we-need-to-talk-about-how-rare-earth-prices-are-imploding/.
[7] See: https://www.vaneck.com/de/en/investments/rare-earth-etf/,for further details.
[8] The data can be downloaded from: https://sites.google.com/view/lavinia-rognone-library/research-impact-data?authuser=0.

authoritative and scientific texts. The results are reported in Appendix Table 4, depicting a significant causality running to the entire conditional distributions of the MVREMX-based returns and volatility, over the period of 2nd January 2008 to 28th June 2024. In the same table, we also report similar findings derived from the newspaper articles-reliant Global Climate Policy Uncertainty (GCPU) indexes of Ji et al. (2024),[9] covering the sample period of 2nd January 2008 to 31st December 2023, suggesting the robustness of our findings to the choice of the climate risk proxies.

Third, given that the CPU indexes of Ji et al. (2024) are also available for 12 countries of the G20, we chose Australia, Canada, China, France, the UK, and the US from that list to correspond to the major producers of REE and their associated importance in the MVREMX index, and analyse their individual predictive impact on RE stock returns and volatility in Table A4. Though there is generally evidence of causality for a minimum of 5 quantiles out of 9 across the countries for returns, the effect on volatility is relatively stronger, with a minimum of 7 quantiles depicting causality. Not surprisingly, given its dominance as the main producer of REE, China stands out showing strong predictability for all the quantiles of RE stock returns (at least at the 5% level of significance) and volatility (at the 1% level of significance). In this regard of country-specific indicators of climate risks, we report in Table A5 the first- and second-moment causal impact on RE stock returns from Twitter-based Climate Attention Indexes (CAIs) of Arteaga-Garavito et al. (2023) constructed for 25 economies.[10] Utilizing the data for the major REE producers: Australia, Canada, Chile, China, France, the UK, the US, and Switzerland, over the period of 1st October 2014 to 31st December 2022, we find statistically significant causal influence for both RE stock returns and volatility across all the conditional quantiles emanating from these 8 countries. Notwithstanding the sample period and the underlying method of constructing the indexes, the relatively stronger effect from the country-specific CAIs relative to those from the GCPU indexes, is possibly a reflection of the fact that the attention indicators capture both physical and transition climate risks, but the climate policy uncertainties only reflects the latter (Ben Ameur., 2024).

Fourth, following Proelss et al. (2020), we obtain conditional measures of volatility using the GARCH and ARFIMA models fitted to MVREMX log-returns and absolute returns, respectively, and then apply the nonparametric quantile-causality under $k = 1$. As can be observed from Appendix Table A6, barring the case of IS for the extreme quantiles of the volatility derived from the ARFIMA model, there is again evidence of predictability of the entire conditional distributions of these alternative measures of volatility from ND, GW, USCP and IS.

Fifth, in line with the existing literature involving spillovers of RE returns and volatility with other asset markets, and predictability of returns and volatility due to a host of macroeconomic

[9] The data is downloadable from: http://www.cnefn.com/data/download/climate-risk-database/.
[10] The data is accessible at: https://sites.google.com/view/internationalclimatenews/download?authuser=0.

and financial variables,[11] we filter out the log-returns of MVREMX from these macroeconomic and financial predictors by estimating a linear regression. Then, we conduct the bivariate k-th order nonparametric quantile causality on the residual and its squared values recovered from the above regression. As reported in Appendix Table A7, except for IS over the quantile range of 0.40-0.70 and the quantile of 0.90 for filtered returns, ND, GW, USCP and IS continue to predict in a statistically significant manner the conditional distributions of predictors-controlled RE stock returns and volatility.

Taken together, our results reported earlier in Table 4 are robust to an alternative index capturing the behaviour of the RE stock market, to different metrics of climate risks, to conditional, i.e., models-based, estimates of volatility, and to the information of other control variables.

5.3. Additional Analyses

Besides the robust predictive inference derived from the nonparametric causality-in-quantiles test, it is interesting to estimate the sign of the effect of the four climate risks on RE stock returns and its volatility at various quantiles, especially to check whether the theoretical channels outlined in the introduction are regime-specific. However, in a nonparametric framework, a sign-analysis is not straightforward, as it requires the employment of the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can give rise to complications, because of slow convergence rates, dimensionality, and smoothness of the underlying conditional expectation function. Alternatively, one can look at a statistic that summarizes the overall effect or global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. A natural measure of global curvature is the average derivative (AD) using the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al. (2019), which allows us to estimate the partial ADs.

Based on the ADs reported in sub-table 5(a), we find evidence of negative effect of ND, GW, USCP and IS on RE stock returns generally till near the median, i.e., the normal-state of the REE market, and then a positive relationship beyond it. This observation, in turn, confirms our hypothesis regarding the behaviour of the sign of the predictive relationship between RE stock returns and climate risks outlined in the introduction via the productivity channel at the short-

[11] The control variables used are: the Aruoba-Diebold-Scotti (ADS, Aruoba et al., 2009) Business Conditions Index; the Office of Financial Research (OFR) Financial Stress Index (FSI); the Chicago Board of Options Exchange (CBOE)'s SP500 Volatility Index (VIX); CBOE's Crude Oil ETF VIX; CBOE's Gold ETF VIX; Newspapers-based indexes of: Geopolitical Risks due to Acts and Threats (Caldara and Iacoviello, 2022); Trade Policy Uncertainty (Caldara et al., 2020), and; Supply Bottlenecks associated with China, the European Monetary Union (EMU), the UK, and the US (Burriel et al., 2024). The respective web-links are as follows: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads; https://www.financialresearch.gov/financial-stress-index/; https://fred.stlouisfed.org/series/OVXCLS; https://fred.stlouisfed.org/series/VIXCLS; https://fred.stlouisfed.org/series/GVZCLS; https://www.matteoiacoviello.com/gpr.htm; https://www.matteoiacoviello.com/tpu.htm, and; https://www.bde.es/wbe/en/areas-actuacion/analisis-e-investigacion/recursos/indices-de-cuellos-de-botella-en-la-oferta-basados-en-articulos-de-prensa.html.

run, i.e., at the lower conditional quantiles, and the renewable energy demand route in the medium- to long-run corresponding to the upper conditional quantiles. Regarding the impact on squared RE returns, i.e., volatility, sub-table 5(b) shows that the effects of ND, GW, USCP and IS on RE stock index volatility are always positive. This finding seems to align with our hypothesis, which suggests the role of the leverage effect in increasing volatility[12] due to the negative impact of climate risks on RE returns till around the conditional median, and beyond it, higher trading volumes resulting from increased returns pushes up the volatility. In other words, if the initial state of the RE stock returns is weak, climate risks would tend to make such investments risky, but are likely to drive investors into the RE market if the current returns are depicting strong performance.

[INSERT TABLE 5]

While the *k*-th order nonparametric causality-in-quantiles test reveals statistically significant evidence of predictability for RE stock returns and its volatility due to ND, GW, USCP and IS when the entire sample period is used, it would be interesting to analyze if these causal relationships are consistent over time. Given this, in Figure 1, we plot the rolling causality with a 500 days rolling-window, showing that the predictability of returns at the extreme quantiles is generally sporadic, especially at the upper quantiles. However, the corresponding full-sample results of causal evidence, though weaker than at the conditional median, are likely to have been driven by the large significant values of the standard normal test statistic during periods aligning with the 2015 Paris Climate Agreement, and a strong global economy. The lack of predictability at two ends of the conditional distribution of returns, especially during weak economic conditions, is possibly reflective of herding across firms (Balcilar et al., 2013), instigating information content of climate risks to become insignificant. Consistent strong effects over time are, however, witnessed for volatility. Thisis perhaps not surprising given that climate risks are expected to have stronger second-moment impacts through jumps risks (Del Fava et al., 2024).

[INSERT FIGURE 1]

6. Conclusion

We use a higher-order nonparametric causality-in-quantiles test to analyse the predictability of rare earth stock returns and volatility based on the information contained in physical and transition climate risks over the period from of 2nd January 2008 to 31st January 2025. Our results indicate that, while linear Granger causality fail to show any evidence of prediction of rare earth stock returns, due to misspecifications arising out of nonlinearity and structural breaks, our nonparametric quantile-based framework depicts strong statistically significant

[12] Using two asymmetric GARCH models, namely the Exponential GARCH (EGARCH; Nelson, 1991) and the Glosten- Jagannathan-Runkle (GJR-GARCH; Glosten et al., 1993), we are able to confirm that negative shocks to MVREMX returns increases its volatility in a statistically significant manner at the 1% level. Complete details of these results are available upon request from the authors.

evidence of predictability over the entire conditional distribution of not only returns, but also volatility of rare earth stock index. Our results are robust to alternative choices of rare earth stock indexes, measures of climate risks, conditional estimates of volatility, and multiple macroeconomic and financial control variables.

Analyses of the sign of the causal impact and rolling-window estimation, however, tend to reveal that returns of rare earth stock index are negatively impacted for lower conditional quantiles till the median, corresponding to weak global conditions. In contrast, the volatility of rare earth stock index increases over the entire conditional distribution, highlighting the leverage effect as well as the link between jump risks and rare disaster events, as proxied by climate risks.

From an academic standpoint, our analysis highlights the importance of accounting for nonlinearity and regime shifts through a nonparametric framework, when drawing robust statistical inference about predictability of rare earth stock market movements due to climate risks. From investors' perspective, our findings imply that rare earth stocks can serve as a hedge against climate risks when the rare earth market is in a bullish state.

For future analysis, it would be interesting to extend our paper into a forecasting exercise, along the lines of Bonaccolto et al. (2018), given that in-sample predictability does not guarantee out-of-sample forecasting gains.

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TABLES and FIGURE:

Table 1: Linear Granger Causality Test

	Predictor			
Dependent Variable	ND	GW	USCP	IS
Returns	3.678	3.570	5.757	1.327

Note: See Note to Table 1. Entries correspond to $\chi^2(p)$ test statistic of the null hypothesis of no Granger causality from climate risks to RE (MVREMX) stock returns, with the lag-length p = 6, 5, 5, 4, respectively, determined by SIC for Natural Disasters (ND), Global Warming (GW), US Climate Policy (USCP), and International Summits (IS) of Faccini et al., 2023.

Table 2: Brock et al. (1996) BDS Test of Non-Linearity

Climate Risks	m=2	m=3	m=4	m=5	m=6
ND	11.120^{***}	14.785^{***}	17.297^{***}	19.050^{***}	21.214^{***}
GW	10.973^{***}	14.778^{***}	17.328^{***}	19.118^{***}	21.278^{***}
USCP	11.081^{***}	14.847^{***}	17.384^{***}	19.147^{***}	21.319^{***}
IS	11.016^{***}	14.786^{***}	17.371^{***}	19.156^{***}	21.302^{***}

Note: See Notes to Table 1. Entries correspond to the z-statistic of the BDS test with the null of *i.i.d.* residuals across various dimensions (m), with the test applied to the residuals recovered from the equation of RE (MVREMX) stock returns with p lags each of RE stock returns and ND, GW, USCP or IS; *** indicates rejection of the null hypothesis at 1% level of significance.

Table 3: Bai and Perron (2003) Breakpoint Dates

Climate Risks	Break Dates
ND	09/08/2011, 12/05/2016, 25/09/2020
GW	09/02/2011, 24/10/2016, 25/03/2020
USCP	11/01/2011, 08/01/2016, 28/01/2021
IS	09/02/2011, 08/01/2016, 15/07/2020

Note: See Notes to Table 1. Entries correspond to the dates (in day/month/year format) of structural breaks, with the test applied to the equation of RE (MVREMX) stock returns with p lags each of RE stock returns and ND, GW, USCP or IS.

Table 4: Causality-in-Quantiles Test Results

(a). Dependent Variable: Returns

Quantile	ND	GW	USCP	IS
0.10	15.031^{***}	12.792^{***}	8.702^{***}	16.645^{***}
0.20	9.661^{***}	16.387^{***}	11.728^{***}	11.527^{***}
0.30	14.570^{***}	12.809^{***}	8.951^{***}	15.604^{***}
0.40	10.444^{***}	17.894^{***}	11.180^{***}	13.133^{***}
0.50	12.892^{***}	12.842^{***}	10.184^{***}	18.009^{***}
0.60	7.102^{***}	16.068^{***}	17.131^{***}	12.977^{***}
0.70	10.714^{***}	11.399^{***}	10.040^{***}	16.257^{***}
0.80	7.374^{***}	16.484^{***}	15.427^{***}	13.383^{***}
0.90	9.022^{***}	12.058^{***}	12.015^{***}	18.202^{***}

(b). Dependent Variable: Squared Returns (Volatility)

Quantile	ND	GW	USCP	IS
0.10	7.246^{***}	6.661^{***}	7.259^{***}	9.381^{***}
0.20	4.650^{***}	7.879^{***}	10.318^{***}	5.384^{***}
0.30	6.817^{***}	5.745^{***}	7.977^{***}	8.947^{***}
0.40	5.346^{***}	8.546^{***}	10.824^{***}	5.950^{***}
0.50	6.283^{***}	6.929^{***}	4.425^{***}	8.451^{***}
0.60	3.875^{***}	7.198^{***}	19.390^{***}	6.260^{***}
0.70	5.392^{***}	5.460^{***}	5.395^{***}	8.228^{***}
0.80	3.093^{***}	7.523^{***}	14.586^{***}	6.044^{***}
0.90	4.438^{***}	6.483^{***}	5.252^{***}	8.394^{***}

Note: See Notes to Table 1. *** indicate rejection of the null hypothesis of no Granger causality at the 1% level of significance (given the critical value of 2.575 for the standard normal test statistic) from ND, GW, USCP or IS to RE (MVREMX) stock returns or squared returns for a particular quantile.

Table 5: Average Derivative Estimates

(a). Dependent Variable: Returns

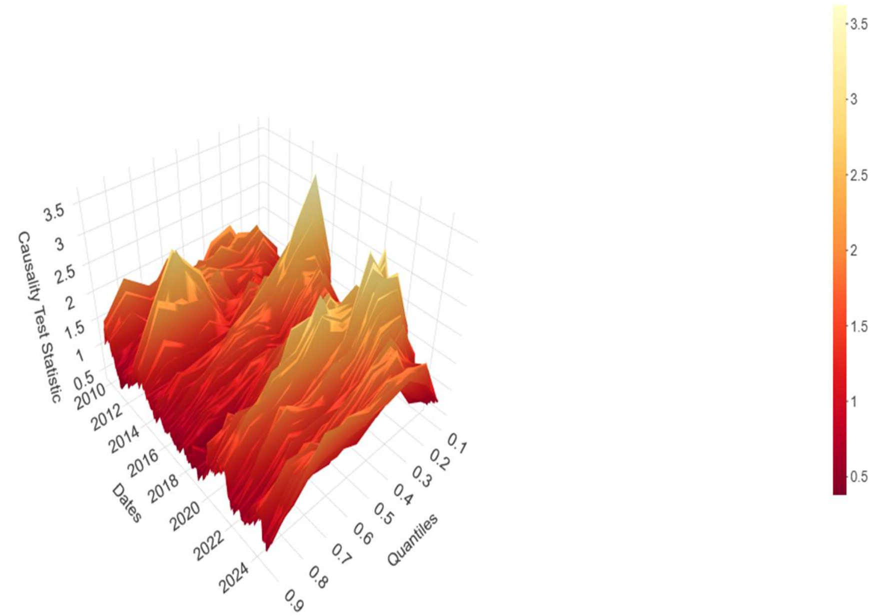
Quantile	ND	GW	USCP	IS
0.10	-0.140	-0.236	-0.095	-0.059
0.20	-0.167	-0.218	-0.141	-0.080
0.30	-0.087	-0.115	-0.122	-0.048
0.40	-0.084	-0.097	-0.042	0.003
0.50	-0.047	0.008	-0.004	0.005
0.60	-0.009	0.091	0.042	0.026
0.70	0.038	0.108	0.099	0.052
0.80	0.080	0.150	0.116	0.106
0.90	0.121	0.191	0.154	0.065

(b). Dependent Variable: Squared Returns (Volatility)

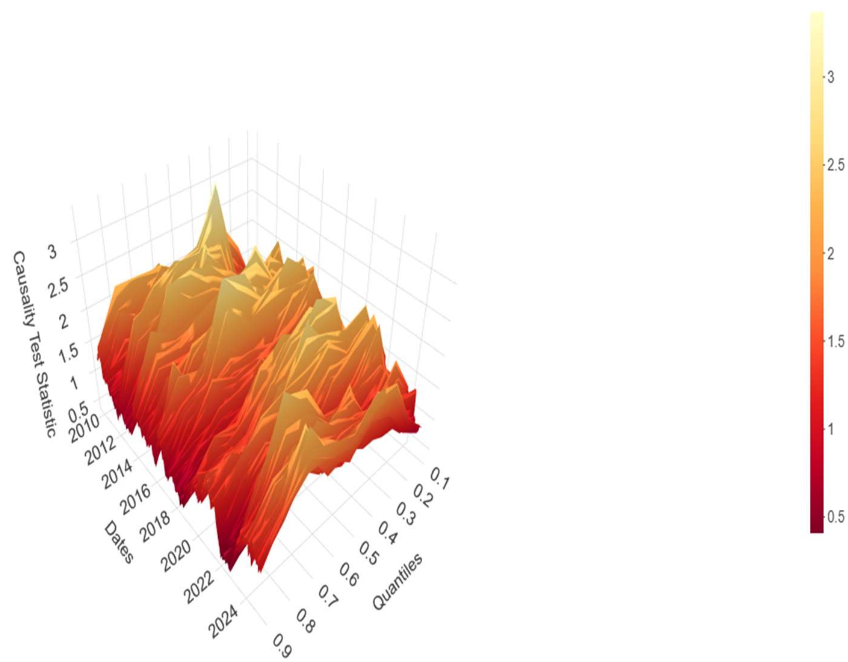
Quantile	ND	GW	USCP	IS
0.10	0.010	0.018	0.011	0.000
0.20	0.042	0.059	0.023	0.014
0.30	0.075	0.114	0.061	0.034
0.40	0.126	0.196	0.148	0.053
0.50	0.164	0.282	0.199	0.118
0.60	0.208	0.399	0.298	0.166
0.70	0.403	0.538	0.439	0.243
0.80	0.594	0.660	0.562	0.147
0.90	1.000	1.366	0.724	0.259

Note: Entries correspond to average derivative (AD) estimates of the sign of the effect of ND, GW, USCP or IS on RE (MVREMX) stock returns or squared returns for a particular quantile.

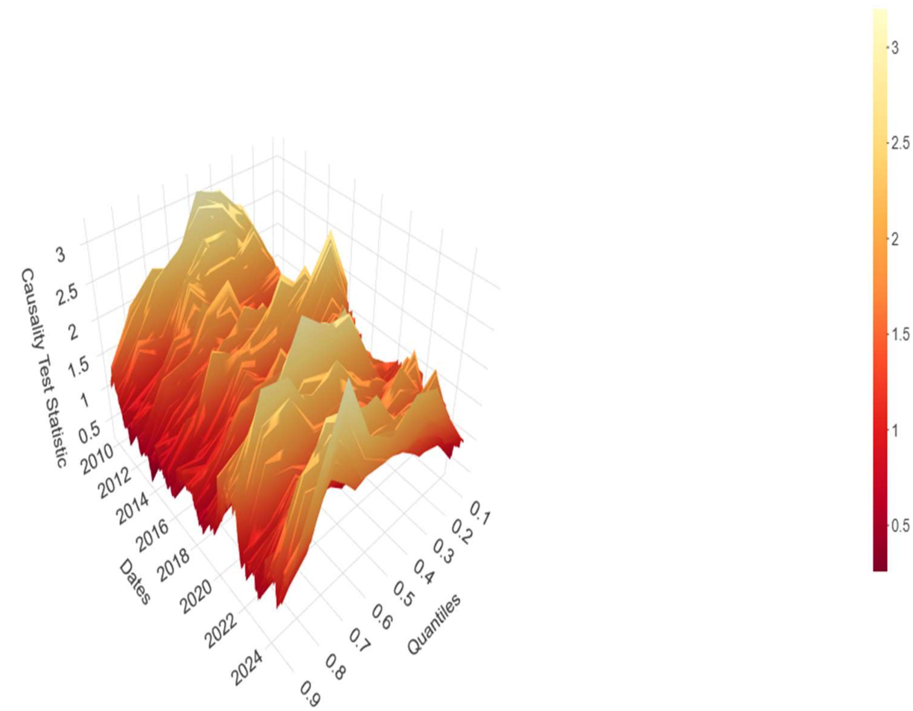
Figure 1. Rolling Nonparametric Causality-in Quantiles Test Results
(a). Dependent Variable: Returns
(i). *ND*



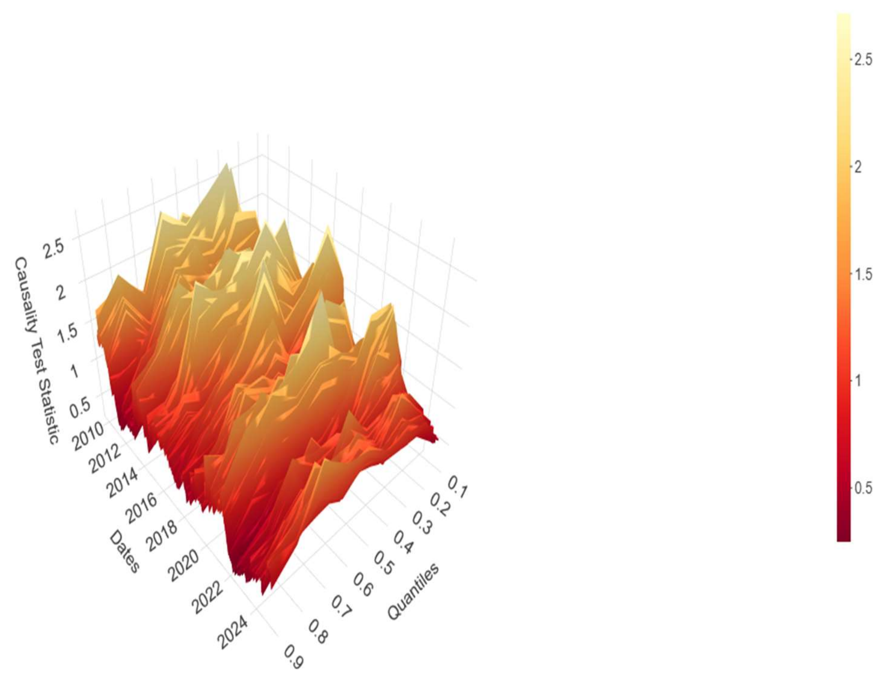
(ii). *GW*



(iii). *USCP*

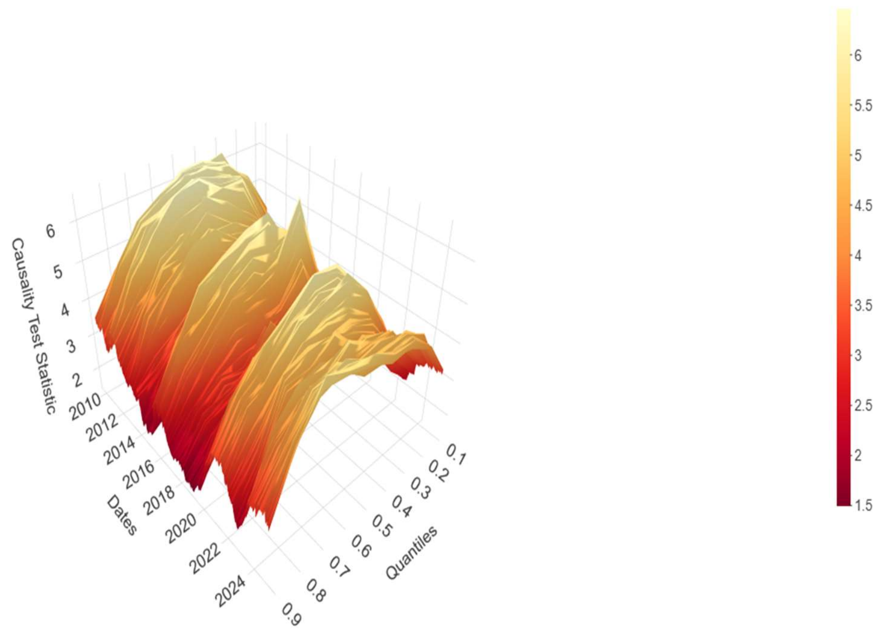


(iv). *IS*

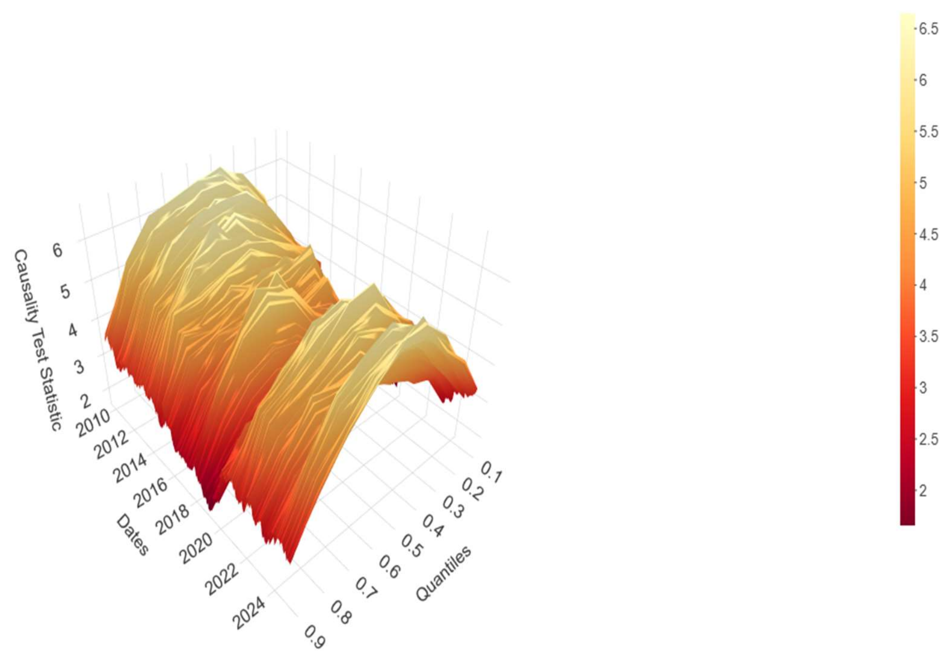


(b). Dependent Variable: Squared Returns (Volatility)

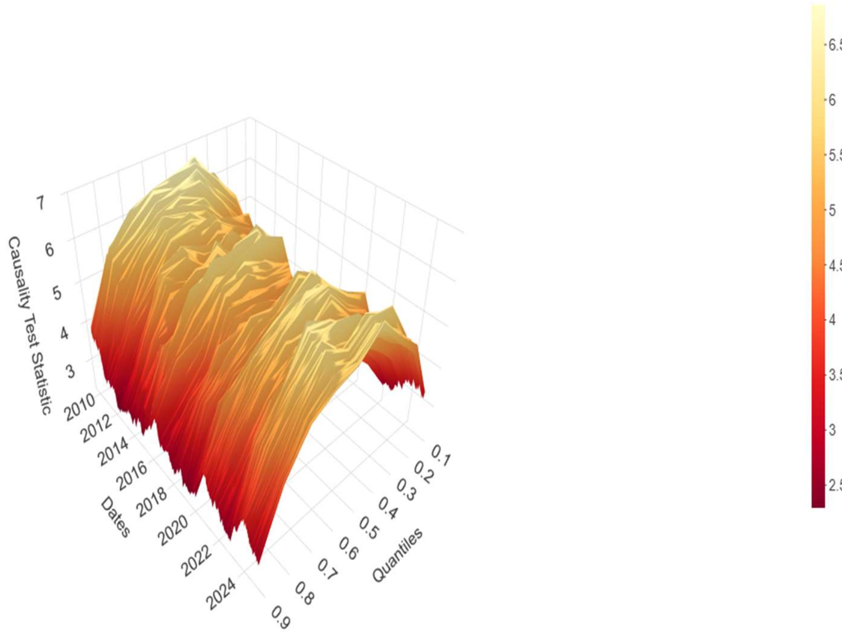
(i). ND



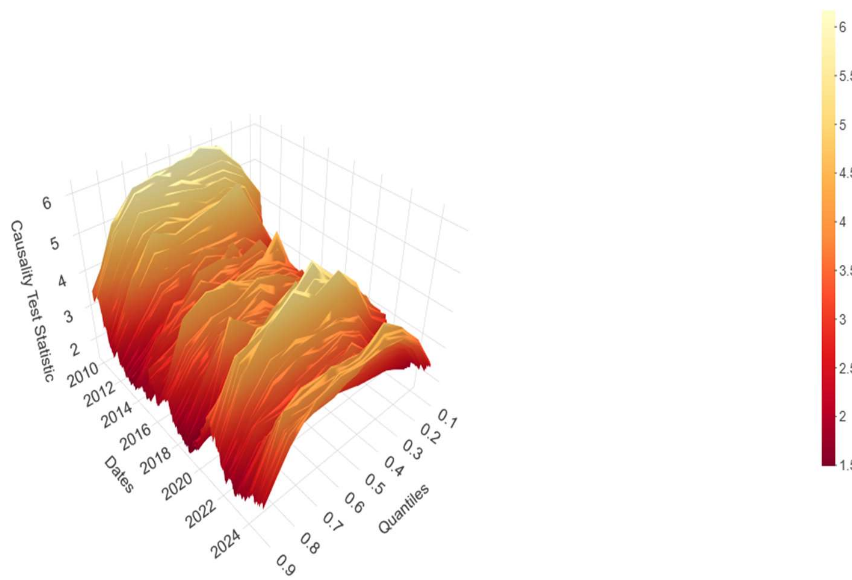
(ii). GW



(iii). USCP



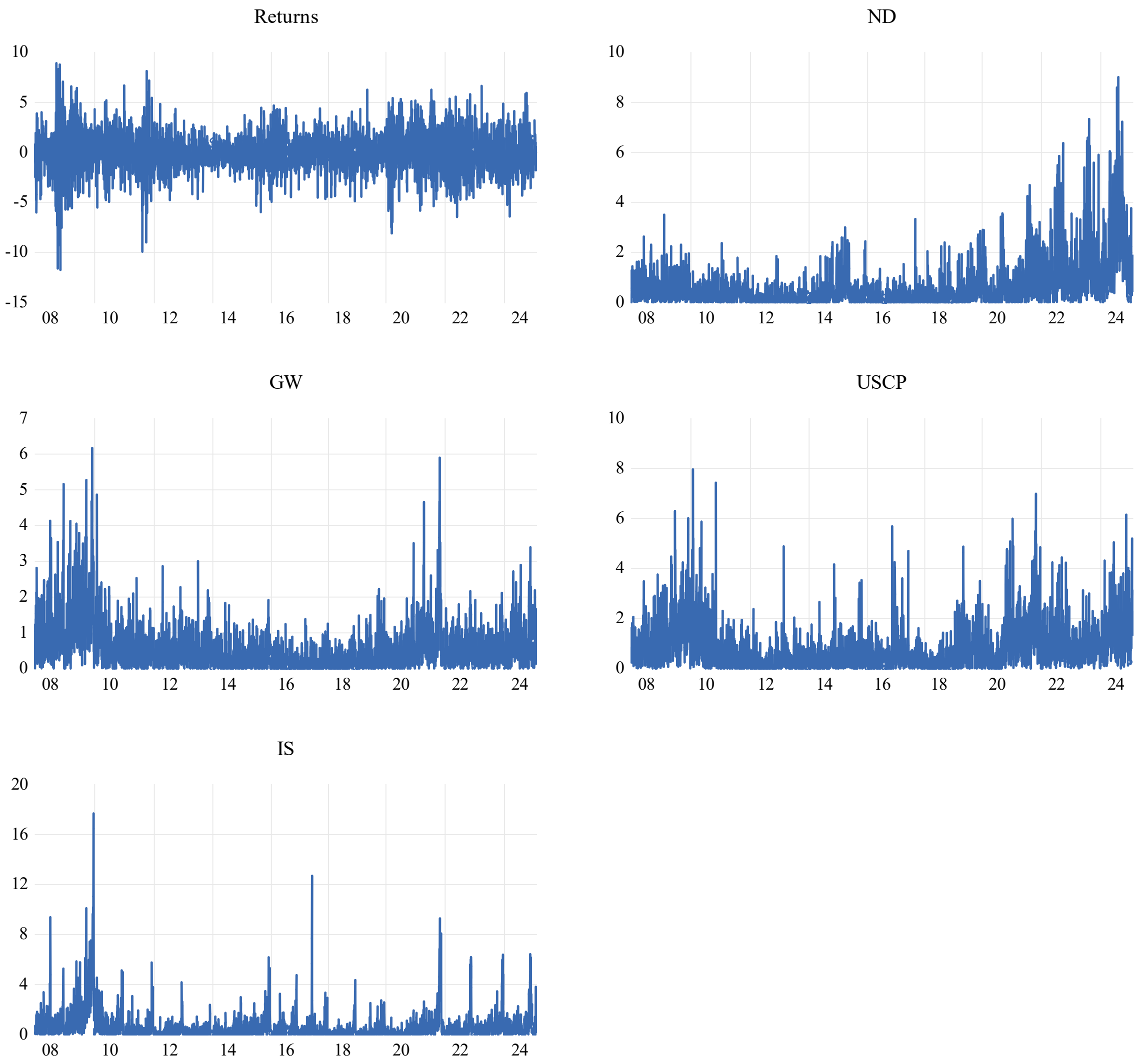
(iv). IS



Note: See Notes to Table 1. Results based on a rolling-window of 500 observations, with dark to light color being the strength of causality from weak to strong; 1%, 5%, 10% critical values of 2.575, 1.96, and 2.575, respectively.

APPENDIX:

Figure A1: Data Plot



Note: See Notes to Table 1.

Table A1: Summary Statistics (2nd January 2008 to 31st January 2025)

Statistic	MVREMX Returns	ND	GW	USCP	IS
Mean	-0.028	0.631	0.541	0.788	0.605
Median	-0.024	0.299	0.367	0.509	0.239
Maximum	8.911	9.003	6.170	7.962	17.690
Minimum	-11.750	0.000	0.000	0.000	0.000
Std. Dev.	1.874	0.935	0.617	0.892	1.093
Skewness	-0.187	3.023	2.628	2.184	5.043
Kurtosis	5.488	15.186	14.044	9.880	45.819
Jarque-Bera	1141.843***	33381.290***	26984.530***	11981.650***	349059.700***
Observations	4329				

Note: See Notes to Table 1. Std. Dev. stands for standard deviation; the null hypothesis of the Jarque-Bera test correspond to normality; *** indicates rejection of the null hypothesis at the 1% level of significance.

Table A2: Causality-in-Quantiles Test Results for Rare Earth ETF Returns

(a). Dependent Variable: Returns

Quantile	ND	GW	USCP	IS
0.10	13.031***	12.229***	8.051***	13.408***
0.20	9.429***	14.509***	10.087***	10.553***
0.30	11.590***	11.682***	8.421***	15.191***
0.40	9.106***	14.675***	10.006***	11.201***
0.50	10.924***	11.501***	8.872***	14.565***
0.60	6.305***	14.343***	14.261***	12.184***
0.70	8.565***	10.935***	9.636***	14.348***
0.80	6.518***	14.032***	14.944***	11.747***
0.90	8.077***	10.436***	10.536***	14.432***

(b). Dependent Variable: Squared Returns (Volatility)

Quantile	ND	GW	USCP	IS
0.10	7.035***	6.000***	7.197***	7.587***
0.20	4.391***	6.527***	9.565***	5.392***
0.30	5.916***	5.322***	8.162***	13.025***
0.40	5.008***	8.264***	10.514***	4.863***
0.50	5.472***	6.260***	4.072***	7.462***
0.60	2.868***	6.543***	15.289***	6.359***
0.70	4.174***	4.972***	5.114***	7.145***
0.80	3.140***	8.801***	19.236***	5.632***
0.90	3.653***	5.907***	4.384***	7.687***

Note: See Notes to Table 1. *** indicate rejection of the null hypothesis of no Granger causality at the 1% level of significance (given the critical value of 2.575 for the standard normal test statistic) from ND, GW, USCP or IS to RE (REMX) stock returns or squared returns for a particular quantile.

Table A3: Causality-in-Quantiles Test Results for Alternative Metrics of Climate Risks

(a). Dependent Variable: Returns

Quantile	PRI	TRI	GCPU1	GCPU2	GCPU3
0.10	6.114***	3.788***	2.579***	2.629***	3.390***
0.20	5.407***	6.629***	3.545***	3.815***	4.227***
0.30	4.388***	5.427***	2.885***	3.052***	3.451***
0.40	4.255***	4.526***	2.507**	2.371***	3.211***
0.50	6.051***	3.668***	2.685***	2.540**	3.371***
0.60	5.229***	5.588***	3.014***	2.761***	3.640***
0.70	3.865***	5.813***	3.190***	2.984***	4.551***
0.80	3.911***	4.586***	3.411***	3.356***	4.438***
0.90	4.544***	3.880***	2.960***	3.178***	3.474***

(b). Dependent Variable: Squared Returns (Volatility)

Quantile	PRI	TRI	GCPU1	GCPU2	GCPU3
0.10	6.257***	2.007**	9.666***	9.661***	10.977***
0.20	4.504***	7.164***	13.755***	13.570***	14.630***
0.30	2.501**	4.640***	16.072***	15.935***	16.279***
0.40	2.742***	2.430**	16.885***	17.566***	17.902***
0.50	6.771***	1.807*	17.442***	17.618***	18.126***
0.60	4.895***	5.718***	16.839***	16.987***	17.919***
0.70	2.584***	5.037***	15.741***	15.950***	16.721***
0.80	2.446**	2.584***	13.428***	13.918***	14.115***
0.90	4.352***	1.816*	9.653***	10.020***	10.185***

Note: ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%, 5% and 10% levels of significance (given the critical values of 2.575, 1.96 and 1.645 respectively, for the standard normal test statistic) from Physical Risks Index (PRI) or Transition Risks Index (TRI) of Bua et al. (2024), as well as from Global Climate Policy Uncertainty (GCPU) Indexes of Ji et al. (2024) to RE (MVREMX) stock returns or squared returns for a particular quantile. GCPU1: weighted by current prices Gross Domestic Product (GDP) for Australia, Brazil, Canada, China, France, Germany India, Japan, South Africa, South Korea, the UK and the US; GCPU2: weighted by Purchasing Power Parity (PPP) GDP for the same 12 countries in GCPU1, and; GCPU3: Equal-weighted for the same 12 countries in GCPU1.

Table A4: Causality-in-Quantiles Test Results for Country-Specific Climate Policy Uncertainty Index

(a). Dependent Variable: Returns

Quantile	Australia	Canada	China	France	UK	US
0.10	2.254**	2.019**	2.309**	1.588	2.685***	1.776*
0.20	1.800*	2.137**	3.004***	2.505**	2.947***	1.868*
0.30	1.028	1.374	2.313**	1.672*	1.213	1.216
0.40	0.687	1.532	2.109**	1.353	1.222	0.715
0.50	0.914	2.017**	2.280**	1.903*	1.895*	0.944
0.60	1.578	2.232**	2.204**	2.607***	2.088**	1.268
0.70	2.380**	2.398**	2.438**	2.581***	2.331**	1.759*
0.80	2.629***	2.329**	2.787***	2.621***	2.938***	2.378**
0.90	2.442**	2.183**	2.636***	2.449**	3.023***	2.064**

(b). Dependent Variable: Squared Returns (Volatility)

Quantile	Australia	Canada	China	France	UK	US
0.10	1.761*	1.664*	3.427***	2.059**	1.727*	1.133
0.20	2.432**	2.316**	4.332***	3.097***	2.718***	1.927*
0.30	2.216**	2.888***	4.739***	2.924***	2.821***	2.455**
0.40	3.112***	3.427***	5.253***	3.584***	3.236**	2.915***
0.50	2.568**	3.148***	5.857***	3.263***	2.900***	2.955***
0.60	2.147**	2.873***	4.919***	3.569***	3.068***	2.982***
0.70	1.848*	2.249**	4.485***	3.958***	3.089***	2.140**
0.80	1.603	1.868*	4.146***	3.008***	2.837***	1.802*
0.90	1.189	1.277	2.576***	1.890*	1.869*	1.328

Note: ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%. 5% and 10% levels of significance (given the critical values of 2.575, 1.96 and 1.645 respectively, for the standard normal test statistic) from Climate Policy Uncertainty (CPU) Index of Ji et al. (2024) to RE (MVREMX) stock returns or squared returns for a particular quantile.

Table A5: Causality-in-Quantiles Test Results for Country-Specific Climate Attention Index

(a). Dependent Variable: Returns

Quantile	Australia	Canada	Chile	China	France	UK	US	Switzerland
0.10	4.019***	2.262***	2.571**	2.697***	2.872***	2.699***	3.158***	3.201***
0.20	4.773***	2.651***	3.236***	3.185***	3.264***	2.933***	3.190***	3.525***
0.30	3.731***	2.687***	2.944***	3.059***	2.962***	2.527**	2.777***	2.650***
0.40	3.375***	2.358***	3.436***	3.097***	2.930***	3.152***	3.252***	2.691***
0.50	3.078***	2.970***	2.969***	3.645***	3.426***	3.377***	3.370***	3.222***
0.60	3.259***	3.066***	3.071***	3.173***	3.765***	3.582***	2.850***	3.667***
0.70	3.562***	2.854***	3.467***	2.995***	3.779***	3.008***	3.349***	4.570***
0.80	4.137***	2.612***	3.442***	2.945***	3.776***	3.087***	3.636***	4.210***
0.90	2.908***	1.940*	2.767***	2.551**	2.947***	2.565**	2.916***	2.987***

(b). Dependent Variable: Squared Returns (Volatility)

Quantile	Australia	Canada	Chile	China	France	UK	US	Switzerland
0.10	7.586***	7.340***	7.413***	7.335***	7.190***	7.325***	6.891***	7.383***
0.20	10.236***	9.819***	10.356***	10.596***	10.177***	9.969***	9.673***	10.101***
0.30	12.066***	11.579***	11.839***	12.276***	11.847***	11.305***	11.697***	12.436***
0.40	12.454***	12.545***	12.829***	13.072***	12.922***	12.412***	12.419***	13.207***
0.50	12.962***	12.714***	13.252***	13.114***	13.344***	12.572***	13.040***	13.224***
0.60	12.889***	12.797***	13.002***	13.034***	12.503***	12.231***	12.999***	12.896***
0.70	11.937***	11.810***	11.771***	12.058***	11.662***	11.410***	11.579***	12.323***
0.80	10.179***	10.194***	10.109***	10.515***	10.141***	10.018***	9.899***	10.718***
0.90	7.336***	7.241***	7.418***	7.729***	7.460***	7.433***	7.228***	7.712***

Note: ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%. 5% and 10% levels of significance (given the critical values of 2.575, 1.96 and 1.645 respectively, for the standard normal test statistic) from Climate Attention Index (CAI) of Arteaga-Garavito et al. (2024) to RE (MVREMX) stock returns or squared returns for a particular quantile.

Table A6: Causality-in-Quantiles Test Results for Conditional Estimates of Volatility

(a). Dependent Variable: GARCH-Based Volatility

Quantile	ND	GW	USCP	IS
0.10	2.597***	3.512***	3.053***	3.076***
0.20	2.646***	3.495***	4.004***	3.063***
0.30	3.951***	4.514***	5.046***	4.069***
0.40	3.853***	4.300***	5.725***	3.920***
0.50	4.084***	4.471***	5.544***	3.618***
0.60	4.792***	4.886***	5.575***	3.485***
0.70	4.168***	4.511***	4.586***	3.466***
0.80	3.272***	3.624***	3.826***	3.046***
0.90	2.252**	2.650***	2.510**	1.782*

(b). Dependent Variable: ARFIMA-Based Volatility

Quantile	ND	GW	USCP	IS
0.10	2.092**	3.068***	1.778*	1.502
0.20	2.919***	3.841***	2.908***	2.226**
0.30	3.329***	4.558***	3.576***	2.638***
0.40	3.882***	4.647***	3.633***	3.109***
0.50	3.834***	3.970***	3.678***	2.634***
0.60	4.187***	3.732***	3.400***	2.452**
0.70	3.769***	2.874***	3.693***	2.231**
0.80	2.640***	2.857***	2.679***	2.086**
0.90	1.764*	1.816**	1.919*	1.494

Note: See Notes to Table 1. ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%, 5% and 10% levels of significance (given the critical values of 2.575, 1.96 and 1.645 respectively, for the standard normal test statistic) from ND, GW, USCP or IS to conditional volatility of RE (MVREMX) stock returns based on a GARCH or a ARFIMA model for a particular quantile.

Table A7: Causality-in-Quantiles Test Results with Controls

(a). Dependent Variable: Filtered-Returns

Quantile	ND	GW	USCP	IS
0.10	2.488**	2.161**	2.437**	2.065**
0.20	2.562**	2.761***	2.937***	2.542**
0.30	1.888*	3.001***	2.069**	1.744**
0.40	1.834*	1.955*	2.027**	1.530
0.50	1.694*	1.977**	2.229**	1.504
0.60	1.781*	2.386**	2.248**	1.400
0.70	1.894*	2.251**	2.921***	1.593
0.80	2.217**	2.299**	2.626***	1.848*
0.90	1.957*	1.664*	1.922**	1.213

(b). Dependent Variable:Filtered-Squared Returns (Filtered Volatility)

Quantile	ND	GW	USCP	IS
0.10	4.171***	4.787***	6.237***	3.796***
0.20	6.112***	6.732***	8.721***	5.445***
0.30	7.280***	7.812***	10.293***	6.356***
0.40	7.649***	8.478***	11.002***	6.786***
0.50	7.809***	9.161***	11.382***	7.692***
0.60	7.740***	9.119***	10.960***	7.682***
0.70	7.257***	8.111***	10.275***	6.988***
0.80	6.222***	7.123***	8.315***	5.634***
0.90	4.612***	5.210***	6.055***	3.821***

Note: See Notes to Table 1. ***, ** and * indicate rejection of the null hypothesis of no Granger causality at the 1%, 5% and 10% levels of significance (given the critical values of 2.575, 1.96 and 1.645 respectively, for the standard normal test statistic) from ND, GW, USCP or IS to RE (MVREMX) stock returns or squared returns for a particular quantile, where the returns have been filtered with a set of control variables.