



Climate risks and predictability of the conditional distributions of rare earth stock returns and volatility

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Abstract

Using a nonparametric causality-in-quantiles test, we examine the predictability of rare earth stock returns and volatility based on physical and transition climate risks over the period 2nd January 2008 to 31st January 2025. Our results indicate that, although the linear Granger causality test fails to show any evidence of predictability due to model misspecifications arising from nonlinearity and structural breaks, the nonparametric causality-in-quantiles test shows significant predictability over the entire conditional distribution of rare earth stock returns and volatility. The evidence of predictability is robust to alternative choices of rare earth stock indexes, measures of climate risk, conditional estimates of volatility, and multiple macroeconomic and financial control variables. Further analyses involving the signs of the causal impact and a rolling-window estimation reveal that returns are negatively impacted over the range of lower conditional quantiles till the median, corresponding to weak global conditions; volatility, however, is increased over its entire conditional distribution. The implications of our findings are discussed.

Keywords Rare earth stock returns and volatility · Climate risks · Higher-order nonparametric causality-in-quantiles test

JEL classification C22 · C32 · G10 · Q54

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1 Introduction

In the context of the 2015 Paris Agreement and the global shift toward cleaner energy sources, rare earth elements (REE) are critical to enabling a sustainable energy transition. Their unique magnetic or conductive properties contribute to the production of efficient wind turbines, electric vehicle batteries, solar panels, energy storage systems, hydrogen, and catalytic converters (Apergis and Apergis 2017; Depraeter and Goutte, 2023; Fan et al. 2023). They are also used in the electronics, aerospace, healthcare, and defence industries (Müller et al. 2016; Buchholz and Brandenburg 2018; Zuo et al. 2021; Fan et al. 2023), hence the required term “industrial vitamins” (Wang et al. 2015). Not surprisingly, with a strong global commitment to decarbonisation, rare earth (RE) production increased to around 390 thousand metric tons worldwide in 2024, up from less than 130 thousand metric tons in 2015¹ (see Fig. 1) to meet growing demand, which is set to reach 51.9 thousand metric tons by 2030 just from clean technologies (Zhou et al. 2017).

Understandably, the associated increase in REE prices, due to higher demand and limited supply, has attracted widespread attention of global investors in many countries for the development of new mining and recycling projects aimed at securing alternative supply chains to reduce dependence on the largest producer – China² (Barteková and Kemp 2016; Fernandez 2017; Schmid 2019; Reboredo and Ugolini 2020; Pawar and Ewing 2022). Given this, the REE market size, which was 3.74 billion US dollars in 2024, is expected to be 8.14 billion US dollars by 2032.³ The International Energy Agency (IEA 2021) predicts a sevenfold increase in REE production by 2040 to fuel the clean energy sector. However, maintaining and expanding these investment efforts in the REE sector requires a clear understanding of how the risk-return profile of the stocks of RE companies is driven by climate risks, originating from the over-reliance on fossil fuels, and the associated reason for the demand for clean renewable energy sources.

Against this backdrop, the objective of this paper is to analyse the predictability of global RE stock returns and volatility based on the textual metrics of physical and transition climate risks.

Higher physical climate risks (resulting from natural disasters and rising temperatures) and transition climate risks (stemming from government intervention through carbon taxation and incentives for green technology development) are expected to have a mixed impact on RE stock returns. Climate risks can lead to higher returns for RE stocks because more people invest in renewable energy and REE to help lower carbon emissions. Conversely, climate risks can negatively impact stock (asset) valuations due to reduced productivity and/or increased stochastic capital depreciation rates (Donadelli et al. 2017, 2021, 2022; Bonato et al. 2023; Cepni et

¹ For details, see: <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>.

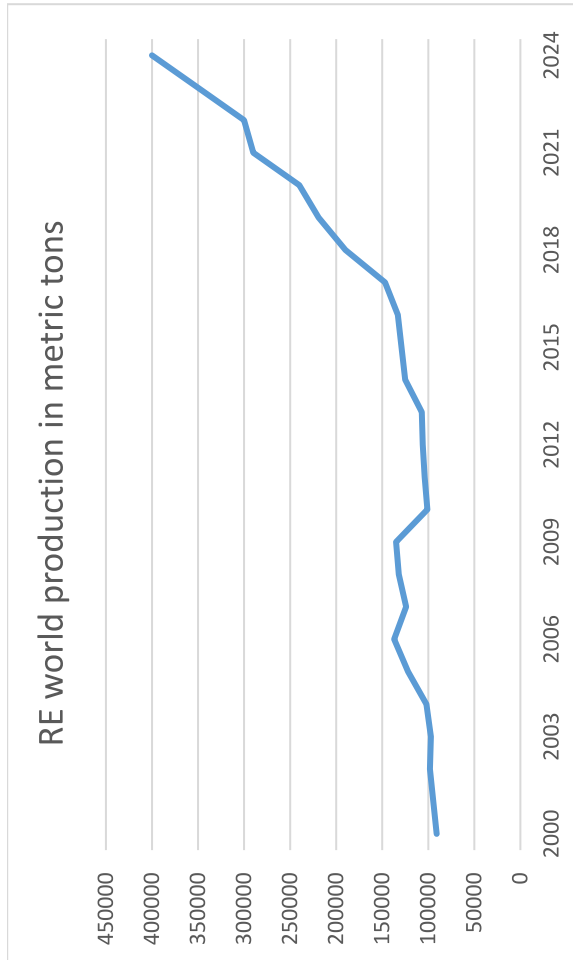


Fig. 1 Rare Earth (RE) world production in metric tons

al. 2023). Using time-varying parameter vector autoregression (TVP-VAR) models and impulse response functions, Ding et al. (2024) show that US physical climate risk shocks (temperature) lead to an increase in RE stock prices only at long-term forecast horizons, while being preceded by a decline in RE stock prices in the short term. In the quantile framework we use in our analysis, this could imply the hypothesis of a negative effect of climate risk at the lower conditional quantiles on RE stock returns. This would be explained by a slowdown in the economy then, as the demand for renewable energy and therefore investment in REE increases to mitigate higher physical climate and transition risk, RE stock returns should react positively at higher conditional quantiles. In other words, the sign of the predictive relationship between climate risk and RE stock returns is likely to be regime-dependent: negative in the bear regime and positive during the bull regime, related to the length of the investment horizon. Given the well-known “leverage effect” (Black 1976) associated with financial assets, one might expect that lower RE stock prices, induced by climate risks, would decrease the volatility of RE stocks at lower conditional quantiles (i.e. during the low volatility state of RE stocks). 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 assume that RE stock 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 rare earth markets and climate risk. Firstly, 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 examining the ability of climate risks to predict of the entire conditional distribution of the first and second moments of rare earth stock returns. It does so using a higher-order nonparametric causality-in-quantiles test, which controls for underlying nonlinearity and structural breaks in these relationships. Specifically, we use the nonparametric higher-order quantile causality test proposed by Balcilar et al. (2018) because it is ideally suited to handle 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 k -th order nonparametric quantile causality framework has the major advantage of allowing us to detect predictability across the entire set of conditional distributions, i.e., regimes, of returns and volatility due to climate risks. It simultaneously controls for model misspecification resulting from nonlinearity and structural breaks in these relationships, for which we provide statistical evidence. The nonparametric higher-order quantile causality test enables the distinction among various market conditions (normal, bullish, and bearish) in the rare earth stock index, as identified through the quantiles of the conditional distributions of returns and volatility. This provides a better insight into the high-frequency predictability of rare earth market fluctuations related to climate risks. Secondly, we select a study period (January 2, 2008 to January 31, 2025) including the signing of the 2015 Paris Agreement, the peak of the Sino-American embargo (2018–2019), the launch of the 2019 European Green Deal, 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 2022

Inflation Reduction. This turbulent period is marked by high uncertainty regarding the rare earth market but also by a sharp increase in prices, with global markets and supply chains being strongly affected. Thirdly, our research highlights an important distinction between physical and transition climate risks (Faccini et al. 2023) in their impacts on the returns and volatility of rare earth stocks. It also indicates the presence of a variable link between climate risk and the value of rare earths over time. This distinction allows us to assess the behaviour of investors faced with these variations, in terms of both physical risk and transition risk.

Owing to the presence of nonlinearity and structural breaks, the linear causality test fails to provide evidence for predicting rare earth stock returns. However, the nonparametric quantile causality test provides strong evidence that climate risks can predict returns and volatility across the entire conditional distribution of rare earth stocks.. Our findings are robust to choices of rare earth stock indexes, climate risk measures, conditional volatility estimates, and multiple macroeconomic and financial control variables. Considering the sign-of-causal impact analyses and moving window estimation, we also show that rare earth stock returns are negatively impacted at the lower conditional quantiles up to the median. This corresponds to weak global conditions. Conversely, the volatility of RE stocks increases across the entire conditional distribution, highlighting the leverage effect and the link between surging risks and climate catastrophes.

Our analysis of the rare earth stock market and climate risks provides insights into investment prospects. Rare earth stocks may serve as a hedge against climate risks during market rallies. Conversely, when the rare earth stock market is weak or moderate, investors should consider extreme climate risks when diversifying their rare earth stock portfolios. Political decision-makers should better anticipate the combined impacts of climate risks and the energy transition on rare-earth markets. Optimizing and stabilizing the supply of rare earths is essential to support 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 considers the impact of returns and volatility on renewable energy stock prices 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 transmitted rapidly from market to market, with rare earths market acting as the main transmission vector, notably between crude oil and renewable energy markets. They also find that correlations between rare earth and new energy market returns are positive and relatively stable over time. In contrast, correlations between crude oil and rare earth stocks are weaker and fluctuate substantially. 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. This is a sign of greater contagion. Even in this case, however, the impact remains relative. Kamal and Bouri (2023), who study this same type of connectedness, show variations in correlation depending on the short or medium 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, notably during the COVID-19 pandemic period. Combining an MS-VAR approach and quantile-based generalized variance decomposition (GFEVD), Bouri et al. (2021) analyse rare earths' connectedness to clean energy, consumer electronics, defence, healthcare, and telecommunications for the period 2010–2020, focusing on yield and volatility. They show that the rare earths market continues to act as a net receiver of shocks, especially in times of crisis. At the same time, clean technologies and electronics transform from receivers to transmitters of volatility. Combining the quantile time-frequency connectedness model and the inter-quantilogram interdependence method, Madaleno et al. (2023) analyse the relationships among rare earth minerals, clean energy, renewable technologies, and carbon emissions. They show that the impact of rare earths on renewable energies differs across market conditions and time horizons. In the short term, rare earth minerals behave as net receivers of shocks. Similarly, Hanif et al. (2023) use wavelet, spillover index, and squared wavelet coherence (WTC) techniques to study the connectedness of returns and volatility between the rare earth market and six major stock market indexes in the renewable energy sector. They attest to an amplification of connectedness between rare earths and renewable energy stocks during the COVID-19 pandemic, and find that rare earths are net receivers of risk, especially from clean energies. Gao and Liu (2024) reach comparable conclusions. Gao et al. (2024) underscore the importance of geopolitical tensions. They find evidence of segmentation in the markets of clean energies (wind, solar, electric vehicles, nuclear), highlighting an intensification of extreme risks in these markets during geopolitical crises.

A second strand of literature attempts to forecast returns and volatility using univariate and multivariate models. These studies rely on macroeconomic and financial variables, trade policy uncertainties and geopolitical risks as predictors. By analysing the volatility of rare earth minerals using autoregressive moving average (ARMA), autoregressive fractionally integrated moving average (ARFIMA) and GARCH models, Proelss et al. (2020) highlight 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 is 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) study its links with

rare earth prices and global economic activity. According to their results, prices are far more dependent 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) use 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 provide an understanding of the connectedness between renewable energies and other financial markets, they are not without limitations. Most are limited to the analysis of an average impact and postulate linear links between variables. They also ignore volatility as a transmission channel. Depending on whether markets are trending upwards or downwards, responses vary widely. Neither extreme effects nor nonlinear evolutions are sufficiently captured for periods of financial or climatic shock. To date, no attempt has been made to simultaneously predict the returns and volatility of renewable energy stocks as a function of climate risk, which is certainly an important factor in the context of renewable energy demand formation.

Our study therefore analyses the links between climate risks (physical and transitional) and rare earth stocks using the nonparametric causality test in quantiles proposed by Balcilar et al. (2018). This test facilitates the examination of variations in predictability across the quantiles of the conditional distributions of rare earth returns and volatility. Notably, applying this test with a rolling-window framework enables the detection of changes in predictability over time.

3 Data

To track 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, with the data being extracted from Refinitiv Datastream, includes 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. The MVREMX contains companies generating at least 50% of their revenues from REs and strategic metals, 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.⁵

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

⁵The fact that REEs are important for the development of renewable energy technologies is confirmed in a preliminary fashion by the positive correlation (covariance) between the log-returns of the MVREMX and the log-returns of Invesco Global Clean Energy ETF, Invesco Wilderhill Global Clean Energy ETF, Invesco Solar ETF, and First Trust Global Wind Energy ETF indexes, with the values being: 0.590 (2.077), 0.537 (2.357), 0.494 (2.585), and 0.516 (1.608), respectively. The data on these additional indexes are sourced from Refinitiv Datastream over the same sample period.

The measures of climate risk used to predict RE stock returns and volatility, are derived from 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. Faccini et al. (2023) 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, as the LDA technique identifies the topics, Faccini et al. (2023) give every topic an economic interpretation and compute time series for the topic shares (that is, the proportion of an article’s text associated with a given topic) that represent how news coverage evolves 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).⁶ We consider ND and GW to reflect physical risks of climate change, and USCP and IS to primarily capture transition risks.

Based on the availability of data at the time of writing, our daily sample covers the period 2nd January 2008 to 31st January 2025. Log-returns of the MVREMX index, along with levels of ND, GW, USCP and IS are plotted in Appendix Fig. 3. The summary statistics (see Appendix Table 6) show that RE stock returns and the four climate risks are not normally distributed, as evidenced by the Jarque-Bera statistics. This provides a preliminary motivation to use a quantiles-based approach to causality.

4 Econometric methodology

In this section, we briefly outline 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 returns and w_t a specific measure of climate risk. 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 $F_{v_t|\bullet}(v_t|\bullet)$ 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:

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

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

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

⁶The data is available for download from: <https://sites.google.com/site/econrenatofaccini/home/research?authuser=0>.

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

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

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

Balcilar et al. (2018) extend the framework of Jeong et al. (2012) 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 risk and REE stock returns volatility. In this case, the null and alternative hypotheses are:

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

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

The nonparametric causality-in-variance test can 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 $\hat{J}_T$ follows a standard normal distribution, with the 1%, 5%, and 10% critical values being 2.575, 1.96, and 1.645, respectively.

The empirical implementation of the testing framework presented above involves the specification of three key parameters, the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. Our lag order is selected 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

Although our focus is on the results of the k -th order nonparametric causality-in-quantiles framework, for the sake of completeness and comparability, we conduct the linear Granger causality test and report the results in Table 1. As can be seen, 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.

Table 1 Linear Granger Causality Test

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

Entries correspond to $\chi^2(p)$ test statistic of the null hypothesis of no Granger causality from climate risk to RE (MVREMX) stock returns, with 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) (Faccini et al. 2023)

Table 2 Brock et al. (1996) BDS Test of Nonlinearity

Climate Risk	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$
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***

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 the 1% level of significance

We further examine whether the findings of non-causality are due to model misspecification that assumes a linear predictability relationship. In order to explore whether the linear model is misspecified, we first test for the presence of nonlinearity in the relationship between RE stock returns and the four metrics of climate risk. 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) is rejected or not. The results reported in Table 2 show that 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 of significance across all four predictive cases considered. This result 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 captured by our nonparametric causality-in-quantiles approach.

On a related front, we address the issue of instability in the linear model and, hence, another layer of potential misspecification by examining the presence of possible structural breaks in the relationship between RE stock returns and indicators of climate risk. For this purpose, we use the powerful *UDmax* and *WDmax* tests for multiple structural breaks as proposed by 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 in each of the relationships between RE stock returns and the four climate risk variables. The dates of regime-change correspond primarily to REE production control in China during 2011,⁷ the US-China trade war, and the COVID-19 pandemic, with the latter two periods also associated with supply constraints in the RE market. Given that the parameter estimates are indeed unstable over the full sample period, we conclude that our linear Granger causality results are not reliable.

⁷ <https://www.mining.com/we-need-to-talk-about-how-rare-earth-prices-are-imploding/>.

Table 3 Bai and Perron (2003) Breakpoint Dates

Climate Risk	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

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

<i>(a). Dependent Variable: Returns</i>				
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***
<i>(b). Dependent Variable: Squared Returns (Volatility)</i>				
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***

See Notes to Table 1. *** indicates 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

To ensure robust inference of the causal analysis, we rely on an econometric model that is inherently time-varying, which we accomplish through our quantiles-based, i.e., regime-specific, nonlinear set-up.

In light of the presence of nonlinearity and regime changes in the relationships between RE stock returns and ND, GW, USCP, and IS considered separately, we use the k -th order nonparametric causality-in-quantiles testing framework, which can accommodate such misspecifications, while simultaneously providing results for the second-moment, i.e., RE stock returns volatility. We present the standard normal test statistics, derived from the quantiles-based results, over the range 0.10 (low quantiles) to 0.90 (high quantiles) in Table 4. As can be seen from sub-Table 2(a) and (b), all four metrics of climate risk strongly predict not only 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.

5.2 Robustness checks

Here, we conduct four robustness checks. Firstly, we use the VanEck Rare Earth/Strategic Metals ETF (REMX),⁸ also sourced from Refinitiv Datastream, to compute RE stock returns. The causality-in-quantiles test results, reported in Table 7 in the Appendix, show strong evidence of predictability for the entire conditional distributions of both RE returns and volatility from ND, GW, USCP, and IS over the period 29th October 2010 to 31st January 2025.

Secondly, using the physical and transition climate risks measures of Bua et al. (2022),⁹ derived from text-based approaches and authoritative and scientific texts, we show causality running to the entire conditional distributions of the MVREMX-based returns and volatility, over the period 2nd January 2008 to 28th June 2024, as evidenced in Appendix Table 8. In the same table, we report similar findings derived from the newspaper articles-reliant Global Climate Policy Uncertainty (GCPU) indexes of Ji et al. (2024),¹⁰ covering the sample period 2nd January 2008 to 31st December 2023. Given that the CPU indexes of Ji et al. (2024) are available for 12 countries of the G20, we select 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 9. Though there is generally evidence of causality for a minimum of 5 of 9 quantiles 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 quantiles of RE stock returns (at least at the 5% level of significance) and volatility (at the 1% level of significance). The country-specific indicators of climate risk given in Table 10 show the first- and second-moment causal impact on RE stock returns from the Twitter-based Climate Attention Indexes (CAIs) of Arteaga-Garavito et al. (2023) constructed for 25 economies.¹¹ Using data for the major REE producers: Australia, Canada, Chile, China, France, the UK, the US, and Switzerland, over the period 1st October 2014 to 31st December 2022, we find statistically significant causal influences for both RE stock returns and volatility across all the conditional quantiles emanating from these 8 countries. Notwithstanding the sample period and 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 reflect the latter (Ben Ameur et al. 2024).

Thirdly, 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, then apply the nonparametric quantile-causality under

⁸ See: <https://www.vaneck.com/de/en/investments/rare-earth-etf/>, for further details.

⁹ The data can be downloaded from: <https://sites.google.com/view/lavinia-rognone-library/research-impact-data?authuser=0>.

¹⁰ The data is downloadable from: <http://www.cnefn.com/data/download/climate-risk-database/>.

¹¹ The data is accessible at: <https://sites.google.com/view/internationalclimatenews/download?authuser=0>.

$k=1$. In general, as can be observed from Table 11 in the Appendix, 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, rather than squared returns, from ND, GW, USCP, and IS.

Fourthly, in line with the existing literature concerning spillovers of RE returns and volatility with other asset markets and predictability of returns and volatility due to a host of macroeconomic and financial variables,¹² we filter out the log-returns of MVREMX from these 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 Table 12 in the Appendix, except for IS over the quantile range 0.40–0.70 and the quantile 0.90 for filtered returns, ND, GW, USCP, and IS continue to predict in a statistically significant manner the conditional distributions of predictor-controlled RE stock returns and volatility.

Taken together, the above robustness analyses show that our results in Table 4 are robust to the use of an alternative index capturing the behaviour of the RE stock market, various metrics of climate risk, conditional, i.e. models-based, estimates of volatility, and the information of other control variables.

5.3 Additional analyses

Although robust predictive inference is derived based on the k -th order nonparametric causality-in-quantiles test, it is interesting to estimate the sign of the causal effect of the four climate risks on RE stock returns and volatility at various quantiles. It is especially important 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 we need to employ the first-order partial derivatives. Estimation of the partial derivatives for nonparametric models can give rise to complications, because of slow convergence rates, the 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

¹²The 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) SP500 Volatility Index (VIX); CBOE Crude Oil ETF VIX; CBOE Gold ETF VIX; Newspaper-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: <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>; <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>.

Table 5 Average Derivative Estimates

<i>(a). Dependent Variable: Returns</i>					
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	
<i>(b). Dependent Variable: Squared Returns (Volatility)</i>					
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	

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

negative effects of ND, GW, USCP, and IS on RE stock returns generally till near the median, i.e., the normal-state of the REE market, then a positive relationship beyond it. This finding, 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 in the short run, i.e., at lower conditional quantiles, and the renewable energy demand route in the medium to long run corresponding to the upper conditional quantiles. As far as the squared returns of RE, i.e., volatility, is concerned, we show in sub-Table 5(b) that the effects of ND, GW, USCP, and IS are always positive. This finding seems to align with our hypothesis, which suggests the role of the leverage effect¹³ due to the negative effect of climate risk on RE returns till around the conditional median, and, beyond it, higher trading volumes due to increased returns pushing up the level of volatility. In other words, if the initial state of the RE stock returns are weak, climate risks tend to make such investments risky, but are likely to be preferred if the initial returns perform strongly.

While the 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 analyse whether these causal relationships remain consistent over time. Given this, we plot the rolling

¹³ Using two asymmetric GARCH models, the exponential GARCH (EGARCH) (Nelson 1991) and the Glosten- Jagannathan-Runkle (GJR-GARCH) (Glosten et al. 1993), we confirm that negative shocks to MVREMX returns increase its volatility in a statistically significant manner at the 1% level. Complete details of these results are available upon request from the authors.

causality with a 500 days rolling-window in Fig. 2.¹⁴ As can be seen, 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 be 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 the two ends of the conditional distribution of returns, especially during weak economic conditions, possibly reflects herding behaviours across firms (Balcilar et al. 2013), causing information content of climate risk to become insignificant. Consistent strong effects over time are, however, witnessed for volatility, which is generally not surprising given that climate risks are expected to have stronger second-moment impacts through jumps risks (Del Fava et al. 2024).

6 Conclusions

This paper examines the predictability of rare earth stock returns and volatility based on the information contained in physical and transition climate risks over the period 2nd January 2008 to 31st January 2025. The results of the causality-in-quantiles test indicate strong evidence of significant predictability over the entire conditional distribution of not only returns but also volatility. Predictability is found to be robust to alternative choices of rare earth stock indexes, measures of climate risk, conditional estimates of volatility, and multiple macroeconomic and financial control variables. Further analysis of the sign of the causal impact and rolling-window estimation generally reveals that returns of rare earth stocks are negatively impacted for lower conditional quantiles till the median, corresponding to weak global conditions. In contrast, volatility 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 inferences about the high-frequency predictability of rare earth stock market movements based on climate risks. From an investor's perspective, our findings imply that rare earth stocks can serve as a hedge against climate risks, but only when the market is in a bullish-regime. Finally, policymakers must account for the simultaneous effect of climate risks and energy transition on the rare earth market to optimize and stabilize its supply.

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

¹⁴ Given that the causality-in-quantiles test statistic follows a standard normal distribution, the critical values are 1.645, 1.96, and 2.575 for the 10%, 5%, and 1% significance levels, respectively.

Fig. 2 Rolling Nonparametric Causality-in Quantiles Test Results.

(a). *Dependent Variable: Returns.*

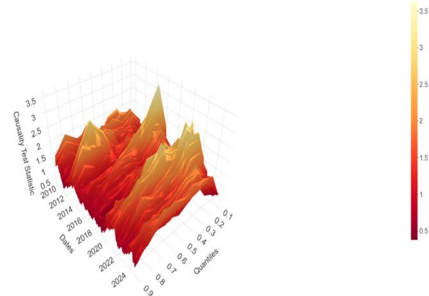
(i). *ND.* (ii). *GW.* (iii). *USCP.*

(iv). *IS.* (b). *Dependent Variable: Squared Returns (Volatility).*

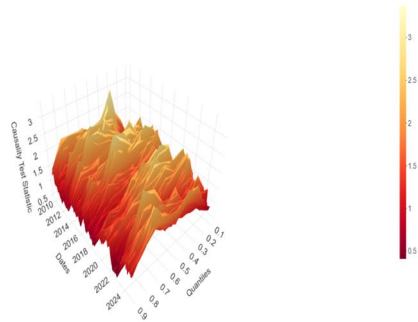
(i). *ND.* (ii). *GW.* (iii). *USCP.* (iv). *IS.* Note: See Notes to Table 1.

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

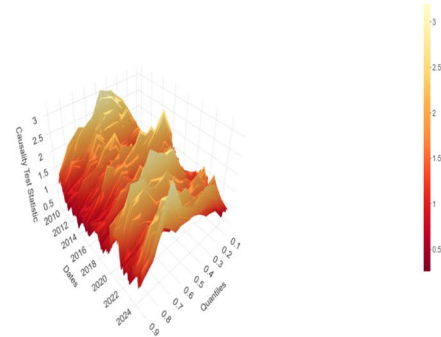
(i). *ND*



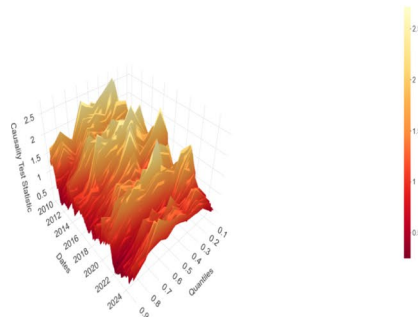
(ii). *GW*



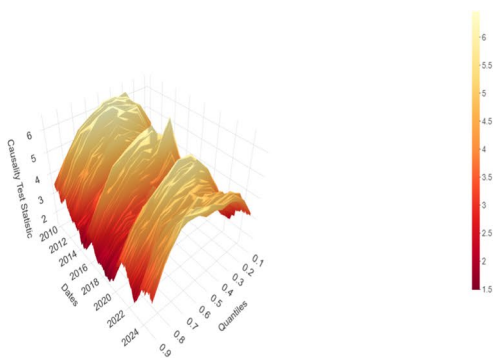
(iii). *USCP*



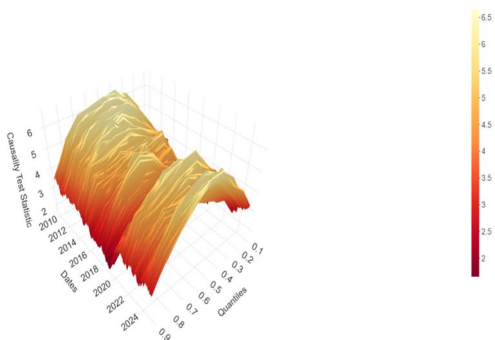
(iv). *IS*



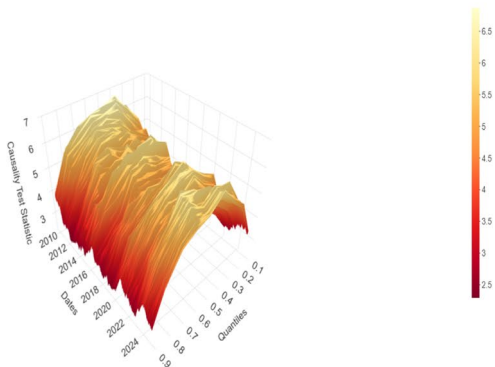
(i). *ND*



(ii). *GW*



(iii). *USCP*



(iv). *IS*

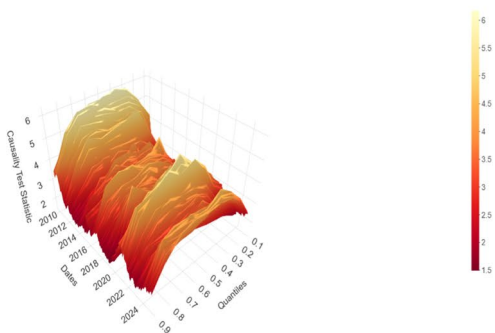


Fig. 2 (continued)

Appendix

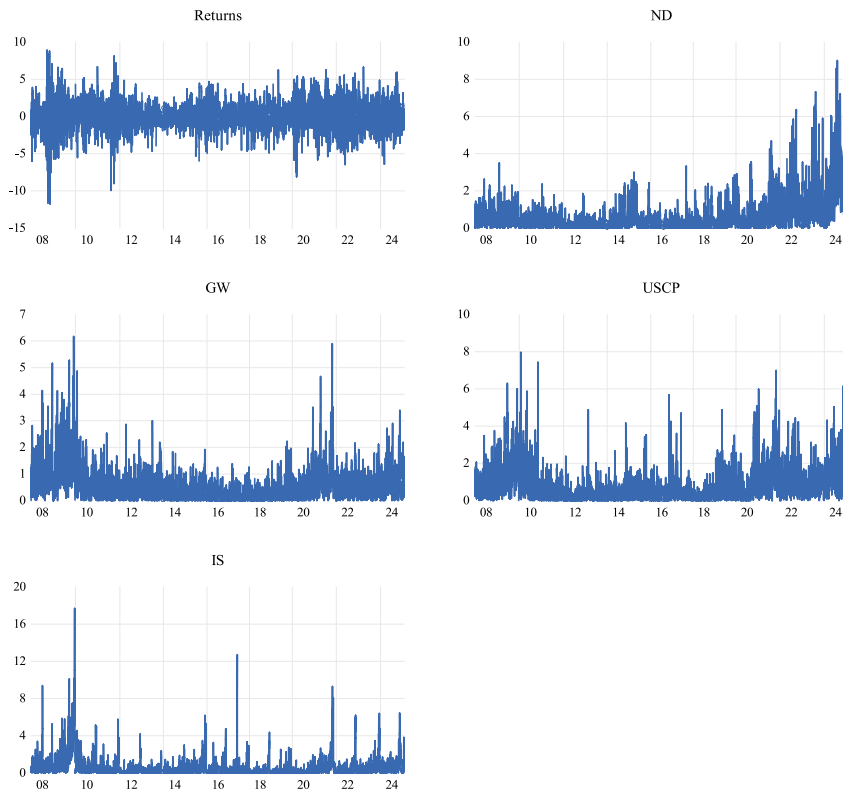


Fig. 3 Data Plot. Note: See Notes to Table 1

Table 6 Summary Statistics (2nd January 2008 to 31 st 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***	33,381.290***	26,984.530***	11,981.650***	349,059.700***
Observations	4329				

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

Table 7 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***

See Notes to Table 1. *** indicates 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 8 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***

***, **, 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 the Physical Risks Index (PRI) or Transition Risks Index (TRI) of Bua et al. (2022), as well as from the 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 as GCPU1; and GCPU3: equal-weighted for the same 12 countries as GCPU1

Table 9 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

***, **, 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 the Climate Policy Uncertainty (CPU) Index of Ji et al. (2024) to RE (MVREMX) stock returns or squared returns for a particular quantile

Table 10 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***

***, **, 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 the Climate Attention Index (CAI) of Arteaga-Garavito et al. (2023) to RE (MVREMX) stock returns or squared returns for a particular quantile

Table 11 Causality-in-Quantiles Test Results for Conditional Estimates of Volatility

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 ARFIMA model for a particular quantile

(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

Table 12 Causality-in-Quantiles Test Results with Controls

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 are filtered by a set of control variables

(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***

Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest There is no conflict of interest to disclose.

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

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