Dynamic Connectedness Between Climate Risk, Geopolitical Shocks and Sustainable Investment in Global Equity Market

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Abstract

While the influence of climate risk and geopolitical risk on the sustainable investment markets is increasingly acknowledged, the exact direction and nature of the dynamic connectedness between climate and geopolitical risk and the sub-sectors of clean energy markets remain unclear. This research fills that void by using a dynamic connectedness approach to explore the relationship between the Physical Risk Index, the Transition Risk Index and the Global Geopolitical Risk Index and five global sustainable investment indices (GRNBIO, GRNFUEL, GRNGEO, GRNAM and GRNDO) over the monthly sample period from December 2010 to December 2024. Using the Dynamic Conditional Correlation GARCH, GJR-GARCH and the external connectedness framework, the study shows that the total connectedness index is at 62.8 percent across the sample, suggesting a high degree of systemic interdependency among all variables. The Geopolitical Risk Index is found to be the leading short run shock transmitter, particularly between 2012 and 2014, while the Physical Risk Index has a long run two-way effect on solar and wind related sub-indices across the sample period. GRNFUEL presents the highest external connectedness among the five clean energy categories, and is most exposed to simultaneous climate and geopolitical shocks, while GRNBIO is the least connected, and may offer diversification benefits to a green energy portfolio. The Transition Risk Index is an endogenous variable that is driven by market and geopolitical shocks. The paper suggests institutional investors to adopt sub-sector specific dynamic risk models, regulators to expand climate stress testing to green investment products, and policymakers to craft stable and consistent clean energy support policies to minimise policy uncertainty in the transition finance system.

Keywords: Climate Risk, Geopolitical Shock, Sustainable Investment, DCC-GARCH, Dynamic Connectedness.

JEL Classification: G10, G11, E44, Q42

1. Introduction

The last decade and half of global financial market developments has been a tale of multiple shocks of unprecedented magnitude and breadth (Yao et al., 2025). Even before the world had recovered from the Global Financial Crisis (GFC) of 2008-2009, a new series of shocks began to be encountered in global equity markets. The Eurozone debt crisis of 2010 and 2012 highlighted the key deficiencies in the design of cross-border financial markets and simultaneously brought into question the fiscal sustainability of several major industrialised economies. The Chinese stock market crash of 2015/2016 wiped out some five trillion United States dollars (US$) in market capitalisation within a period of weeks, highlighting the extent to which volatility in emerging markets had come to pose a systemic risk for international investors. The June 2016 UK vote to exit the European Union (Brexit) delivered a prolonged policy uncertainty shock that had a significant impact on European and global equity markets, and also cast new doubt over the sustainability of multilateral economic agreements. The escalation of the US-China trade relationship between 2018 and 2019 created an environment of uncertainty regarding corporate investment and put pressure on stock prices across a range of sectors, and introduced an element of geopolitical risk into the valuation of globally interconnected supply chains (Sha et al., 2025: Gräf & Schmalz, 2026).

In the midst of this backdrop of episodic financial and political volatility, the physical impacts of climate change emerged as a new and tangible source of financial risk. The lessons from the US experiences in the Atlantic hurricane season of 2017 that resulted in a loss of $200 billion US dollars indicate extreme weather can affect economy and cause loss. The fires that ravaged large parts of Australia in 2019/2020 burnt through 18.6 million hectares of land, caused estimated damages in excess of one hundred billion Australian dollars, raised risk premiums on Australia's sovereign debt, and increased volatility in the stock prices of resource companies. California wildfires between 2017 and 2021 caused insured losses in excess of fifty billion United States dollars, and played a central role in the bankruptcy of Pacific Gas and Electric - the second largest corporate bankruptcy in US history, and one that was brought on by climate change litigation (Marcoux & Wagner, 2024; Singh et al., 2025).

The COVID-19 pandemic that swept across the world from early 2020 onwards delivered the most severe single shock to global equity markets recorded since the era of the Great Depression (Chowdhury et al., 2022: Goldberg & Reed, 2023). In the five weeks spanning late February to late March of 2020, global equity markets shed approximately twenty-six trillion United States dollars in market capitalisation, registering the fastest transition into bear market territory in financial history. Yet the same period catalysed an unprecedented reorientation of public and private capital toward the clean energy transition. The European Union unveiled the NextGenerationEU recovery framework valued at approximately 1.8 trillion euros, with more than thirty percent of that total directed toward climate and green transition objectives. In the United States, Congress enacted the American Rescue Plan of 2021 before following it with the Inflation Reduction Act of 2022, a piece of legislation committing approximately 369 billion United States dollars to clean energy and climate programmes and representing the largest public climate investment in the history of that country. The announcement of China's commitment to ensure they attain by 2060 carbon neutrality led to a substantial reallocation of domestic investment capital channeled toward a lower carbon technology (Zhao et al., 2022; Wang et al., 2025).

Russia's invasion of Ukraine in February 2022 marked the inclusion of a short-term geopolitical shock into an economic environment vastly different from that of pre-covid times, due to the recovery from the pandemic and the rapid intensification of policy responses to climate change. International stock markets shrank by around eight to 12 percent in the month following the onset of the war, while global energy commodity prices spiked to 20-year highs, with Brent crude oil hitting 139 United States dollars (US$) per barrel and European natural gas prices increasing by over 400 percent from pre-conflict levels. The conflict produced contradictory effects on the clean energy transition: on one side, it accelerated the pace of renewable energy investment in Europe as governments responded to energy supply vulnerabilities by expanding domestic clean energy capacity; on the other, it severely disrupted the supply chains on which clean energy hardware depends, affecting the availability of neon, titanium, nickel, and other materials in which Russia and Ukraine are major global producers. The geopolitical risk environment reached its highest recorded level since the Gulf War of 1991 as a result of this (Tampubolon, 2022; Hu et al., 2025; Tyushka, 2026).

It is within this complex and consequential context that the present study situates its empirical investigation. This study is justified on three grounds. First, no existing work has jointly examined

all five major clean energy sub-sectors alongside both physical and transition climate risk dimensions and a geopolitical risk measure within a single connectedness framework, leaving sub-sector level risk heterogeneity largely undocumented in the literature. Second, the fourteen year sample from December 2010 to December 2024 captures the most consequential external shocks to sustainable investment markets in the modern era, including the Paris Agreement of 2015, the COVID-19 green recovery stimulus of 2020 and 2021, and the Russia-Ukraine energy security disruption of 2022, a combination of episodes that has not been examined jointly for its implications on clean energy market connectedness. Third, at a time when financial regulators are actively designing climate stress testing frameworks and governments are directing unprecedented fiscal resources toward the low carbon transition, empirical evidence on how physical climate risk, transition policy uncertainty, and geopolitical instability transmit shocks across different segments of the sustainable investment market constitutes a necessary foundation for sound portfolio management, regulatory design, and climate policy calibration.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 details the data and variables. Section 4 discusses the full model specifications. Section 5 discusses the results. Section 6 offers conclusion.

2.0 Literature Review

2.1 Sustainable Investment

The concept of sustainable investment has received a number of definitions in the literature that reflect the different authors' emphasis on the financial, ethical or governance aspects of the concept. Gillan et al (2021) define it as long term investment strategy in which environmental, social and governance factors are integrated into asset valuation and selection, with the objective of creating long term financial value in a manner that is also beneficial to a wider range of stakeholders than just the investor. By way of contrast, Friede et al (2015) describe sustainable investment as a portfolio investment strategy that explicitly considers the non-financial performance of the investee companies based on the premise that companies with better environmental, social and governance performance are less risky in the long term and have more stable earnings over time. Both definitions coalesce around the perspective that sustainable investment is not merely a value oriented activity but a financially driven investment strategy based on the understanding that environmental, social, and governance factors have material

implications for the prices that assets attract, the risks that they face, and the risk adjusted returns and portfolio diversification that they deliver across various market states.

2.2 Climate Risk

Climate risk in financial markets refers to the economic and investment risks that flow from both the physical changes in the global climate and from the societal and policy measures in response to these changes. Giglio, et al (2021) characterise climate risk as having two conceptually distinct but empirically related components: physical risk, which accounts for the financial effects of the direct impacts of climatic change such as extreme weather, increasing temperatures, and changing precipitation patterns; and transition risk, which accounts for the financial impacts of the policy, technological, legal, and market adjustments associated with the transition to a low-carbon world. The distinction was previously institutionalised by Carney (2015) in his landmark speech to the insurance industry, arguing that the financial system is ill-equipped to price risks that are associated with time horizons that are much longer than those that govern investment and lending decisions (a situation that has come to be referred to as the tragedy of the horizon and which has since become a foundational reference in the finance and climate literature). Between them, these two sources map out climate risk as a multidimensional financial variable whose components need to be measured separately and whose pathways to the asset markets vary in terms of speed, direction and intensity.

2.3 Geopolitical risk

Geopolitical risk is the financial uncertainty arising from geopolitical events such as political disputes, military conflicts, terrorist attacks and general geopolitical tensions in so far as these events and expectations of them lead to financial disruptions in trade, investment and financial markets. Caldara and Iacoviello (2022) capture geopolitical risk via a text based index based on systematic searches of a broad set of international newspaper articles to generate a continuous monthly measure of geopolitical risk, which captures both the threat and the occurrence of adverse geopolitical events and has become the benchmark measure in the empirical finance literature on this topic. From a portfolio allocation standpoint, Smales (2021) shows that the increased geopolitical risk is associated with increased volatility and decreased returns in the equity markets across a broad cross section of markets around the world, and concludes that the impact of

geopolitical uncertainty on investors' risk appetite is different from the impact of macroeconomic uncertainty, and should be treated as a separate factor in asset pricing and risk management models.

2.4 Empirical Review

There is a growing body of empirical work on connectedness between climate risk, geopolitical shocks and sustainable investment markets, with a number of studies providing evidence of time varying and asymmetric connectedness across a range of markets and investment classes. Li and Zhong (2025) studied the asymmetric spillover connectedness between clean energy markets and industrial stock markets in a time varying parameter framework and concluded that clean energy sub-markets are always net receivers in the system of equity markets. Similarly, Aliu et al., (2024) employed variance decomposition techniques to a system of energy market variables including clean energy equity indices and found that the total mean connectedness index is around 60 percent.

On the geopolitical front, Cunado, et al., (2024) used a time varying connectedness method to study spillovers in realized volatility between energy and metal markets and report that geopolitical events induce significant spikes in short run spillover and dissipation into longer time intervals. Similarly, Antonakakis, et al., (2023) studied dynamic connectedness among implied volatilities of oil prices and financial assets during the COVID-19 period and found that crisis episodes dramatically amplify total connectedness across the system.

On the climate risk and sustainable finance side, Caporaleet al (2023) examined connectedness between fossil and renewable energy stock indices and documented significant structural breaks around major climate policy events including the Conference of the Parties agreements, finding that transition policy developments alter the directional connectedness architecture of clean energy equity markets. Pham (2021) studied frequency domain connectedness between green bond and green equity markets and concluded that short run connectedness dominates the medium to long run.

3.0 Methodology

3.1 Data and Variables

To empirically assess the dynamic connectedness between climate risk, geopolitical shocks and sustainable investment in the global equity market, the study uses monthly data covering the period

from December 2010 to December 2024. Sustainable investment is captured using sector specific green investment indices, including Advanced Materials (GRNAM), Bio Clean Fuels (GRNBIO), and Renewable Energy indices namely Green Oil (GRNDO), Green Fuel (GRNFUEL), and Green Geothermal (GRNGEO). These sectors Climate risk is captured using two key dimensions which are the Transition Risk Index (TRI) and the Physical Risk Index (PRI), consistent with the approach of Bua et al (2024). Geopolitical risk is measured using the Geopolitical Risk Index developed by Caldara and Iacoviello (2022).

Data on climate risk for both Physical Risk Index and Transitional Risk Index was sourced from https://www.policyuncertainty.com/climate_risk_indexes.html . The Geopolitical Risk Index was sourced from https://www.matteoiacoviello.com/gpr.html while the data on sustainable investment was sourced https://www.investing.com.

In other to deal with the problem of non-stationarity problem, all stock prices are converted to their return's series using the following formula:

$$\mathcal{R}_{\varsigma,\mho} = ln\left({}^{\nu_{\varsigma,\mho}}/_{\nu_{\varsigma,\mho-1}}\right) \quad (1)$$

Where $\mathcal{R}_{\varsigma,\mho}$ represents the returns of the ςth variable at time $\mho$, ln stands for natural logarithm, $\nu_{\varsigma,\mho}$ and $\nu_{\varsigma,\mho-1}$ are the values of the ςth variables are periods $\mho$ and $\mho - 1$, respectively. Also, the Transition Risk Index (TRI) and the Physical Risk Index (PRI) as well as the Geopolitical risk, were converted to their growth rate using the following formula:

$$\Re = \left(\frac{h_t - h_{t-1}}{h_{t-1}}\right) \times 100 \quad (2)$$

Here, h_t is the current value of the index and h_{t-1} is its value in the previous period. The result $\Re$ measures the percentage increase or decrease in the index from one period to the next. A positive value indicates rising risk, while a negative value indicates declining risk. This transformation accounts for the changing risk and is ideal for subsequent econometric analysis.

Figure 1 and 2 below illustrates the return and growth series of the variables over the sample period.

As can be seen from the graphs, the returns of all five indices show mean reverting patterns around zero throughout the sample period, with the returns fluctuating between positive and negative

values, but no long trend upwards or downwards, which is in line with the stationarity of return series that is observed in many financial markets. GRNFM and GRNBO show comparatively moderate volatility over the sample period, and the volatility of the return series appears to be fairly stable. By contrast, GRNDO shows relatively larger and more frequent fluctuations, especially in the second half of the sample period (after around 2020), which appears to reflect the impact of the COVID-19 pandemic and other global events on its returns. GRNFUEL also exhibits significant volatility clustering with extreme return observations observed in several sub-periods, mainly due to the policy-driven and highly speculative nature of the fuel cell and hydrogen energy sector. GRNECO shows relatively stable return variations. All five indices display some degree of volatility clustering (high returns are followed by high returns and vice versa and low returns by low returns), which justifies the use of the GARCH-family modelling approach used in this study and suggests that risk in sustainable investment markets is time-varying over the period of analysis.

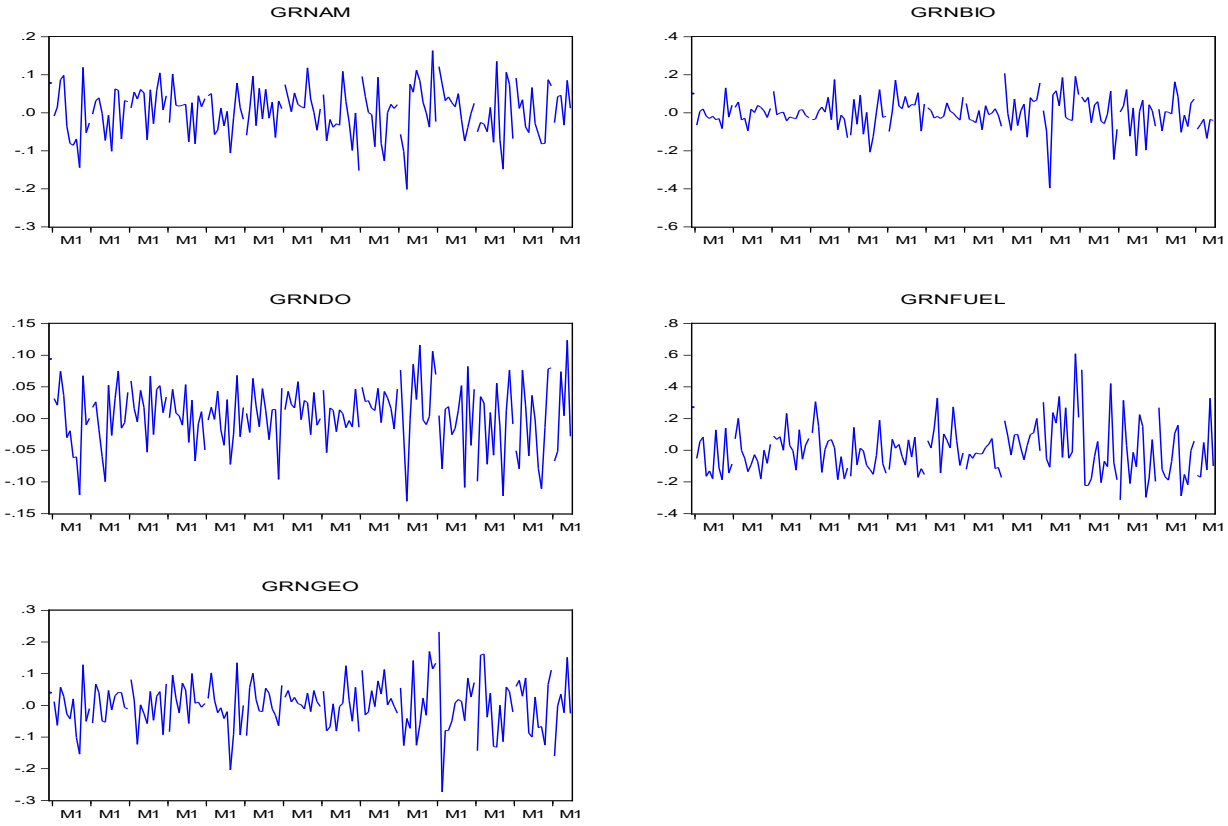


Figure 1: Time series plot of return series

Figure 2 shows the growth rate of the three explanatory variables GPR (Geopolitical Risk Index), PRI (Physical Risk Index) and TRI (Transition Risk Index. The GPR series shows a pattern of

relatively low growth rates in the early sample period with oscillations around zero from 2010 to around 2019, followed by a dramatic and unprecedented surge to around 250 in the later part of the sample period, coinciding with the onset of major geopolitical events such as the war in Ukraine in 2022 and subsequent global geopolitical tensions this spike confirms that geopolitical risk increased dramatically in the latter sample period and has not returned to pre-crisis levels, suggesting a structural increase in global geopolitical uncertainty. The PRI series oscillates within a narrow band around -99.975 to -100.025 through the sample period, with relatively stable fluctuations, with a large spike around the middle of the sample period that likely reflects a major physical climate risk event such as an extreme weather event or natural disaster, before reverting to the original band this lack of variability suggests that physical climate risk, while persistent, evolves steadily without significant structural shifts during the sample period. The TRI series also fluctuates around -100.00 in a narrow band throughout the entire sample period, from 2010 to 2024, exhibiting mean-reverting dynamics with relatively small fluctuations that are consistent with the policy-driven nature of climate transition risk in contrast to the GPR which exhibits a major structural break, the TRI evolves smoothly, consistent with the gradual pace of global policy change over the sample period.

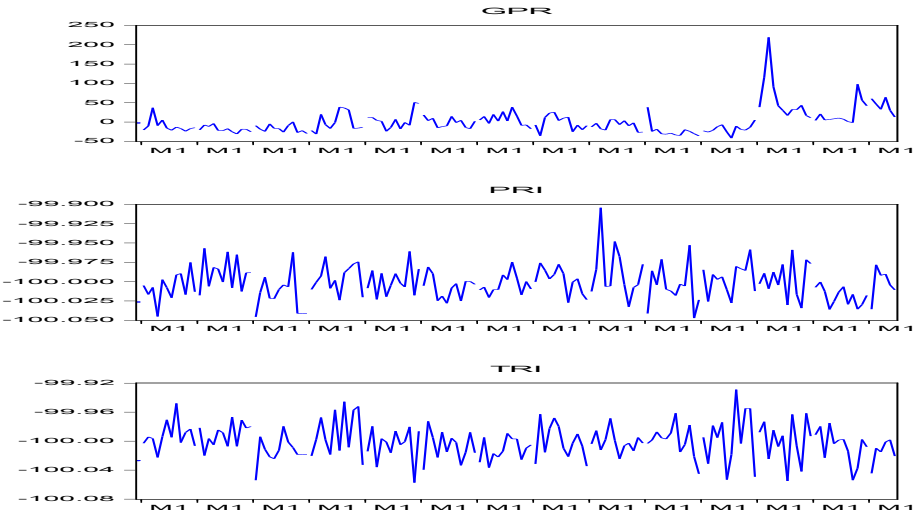


Figure 2: Time series plot of growth rate of geopolitical risk, physical risk index and transitional risk index

3.2 Model Specification

Prior to estimating the GARCH models, the stationarity properties of all variables are examined using the unit root test developed by Stock et al (1996). The unit root test refers to the DF-GLS

(Dickey–Fuller GLS) test which is more efficient than the standard ADF unit root test because it improves power by removing deterministic components before estimation. The series is first detrended using Generalized Least Squares (GLS), then the ADF regression is applied:

$$\Delta y_t^* = \rho y_{t-1}^* + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j}^* + \varepsilon_t \quad (1)$$

Here, y_t^* represents the GLS-detrend series, Δ is the first difference operator, ρ stands for coefficient for unit root testing; γ_j represents the coefficient of lagged differences, p is the lag length and ε_t is the error term.

ARCH-LM Test

Before estimating GARCH models, it is necessary to confirm the presence of autoregressive conditional heteroskedasticity (ARCH effects), which indicate time-varying volatility clustering. This is tested using the ARCH Lagrange Multiplier (LM) test proposed by Engle (1982). First, a mean equation is estimated using ordinary least squares and residuals $\in_t$ are obtained. The squared residuals are then regressed on their lagged values:

$$\in_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \in_{t-j}^2 + \nu_t \quad (2)$$

The test statistic is given by TR^2 where T is the sample size and R^2 is the coefficient of determination. Under the null hypothesis of no ARCH effects, the statistic follows a chi-square distribution with q degrees of freedom.

3.3 Model Specification

In this paper we adopt the dynamic DCC-GARCH connectedness framework proposed by Gabauer (2020) to implement our empirical analysis, an approach that has attracted much attention in the recent literature on financial econometrics for its ability to model the dynamics of return series co-movements in a dynamic, parsimonious and statistically efficient way. Liu and Lee (2021) observe that the framework is highly appropriate for situations in which the analyst needs a flexible representation of time varying interdependence while Liu (2022) further observes that the approach is highly efficient in estimating multiple pairwise dynamic conditional correlation coefficients while allowing for the presence of conditional heteroscedasticity across equations, and parsimony in the number of parameters. Another distinctive feature of this approach relative to other methods is its agnosticism to an arbitrarily selected window size: in contrast to the approach

of rolling window estimation to generate time varying measures of connectedness, the dynamic estimates are generated by the DCC-GARCH model itself, and are therefore free from window size problems that cause noise and inconsistency in rolling window inference. Gabauer et al (2021) additionally observe that a single model specification is sufficient to identify and quantify the entire conditional volatility transmission mechanism across all variables in the system, a parsimony advantage that becomes increasingly valuable as the dimensionality of the variable set grows.

The DCC-GARCH framework stands in contrast to the connectedness approach of Diebold and Yilmaz (2014), which constructs measures of volatility transmission by applying the generalised impulse response functions of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) to evaluate the J-step-ahead propagation of a shock originating in one variable to all other variables in the system. While the Diebold and Yilmaz (2014) approach has proved influential and is widely used, its reliance on rolling window estimation to generate time varying connectedness measures introduces two well documented limitations: the first concerns the subjective nature of window length selection, which can materially alter the qualitative conclusions drawn from the connectedness estimates; and the second concerns the loss of observations at the beginning of the sample that is an unavoidable consequence of the rolling window construction. The DCC-GARCH approach circumvents both of these shortcomings by employing the DCC test of Engle and Sheppard (2001) in place of the rolling window mechanism, so that the dynamic character of the connectedness estimates is embedded within the estimation procedure itself rather than imposed through an external windowing choice. It is on these methodological grounds that the DCC-GARCH framework is selected as the primary analytical tool in the present study, and following the specification of Gabauer (2020), the total connectedness index for the system is constructed from the estimated conditional volatilities and their pairwise dynamic correlations as set out in the equations that follow.

$$c_{\cup}^{\cup L}(\mathbb{Z}) = \frac{\sum_{\zeta,\mathrm{T}=1,\zeta\neq\mathrm{T}}^{N} \theta_{\zeta\mathrm{T},\cup}^{\cup}(\mathbb{Z})}{N} \tag{3}$$

Where $\theta_{\zeta\mathrm{T},\cup}^{\cup}$ stands for the generalized forecast error variance decomposition.

The net total connectedness is computed as follows:

$$\mathrm{C}_{\varsigma,\cup}^{\cup} = \mathrm{C}_{\varsigma\to\mathrm{T},\cup}^{\cup}(\mathbb{Z}) - \mathrm{C}_{\varsigma\leftarrow\mathrm{T},\cup}^{\cup}(\mathbb{Z}) \tag{4}$$

In Equation (4), $C^{\cup}_{\varsigma\rightarrow\intercal,\cup}(\mathbb{Z})$ and $C^{\cup}_{\varsigma\leftarrow\intercal,\cup}(\mathbb{Z})$ represent the total directional connectedness transmitted to others and received from others, respectfully and are computed as follows:

$$C^{\cup}_{\varsigma\rightarrow\intercal,\cup}(\mathbb{Z}) = \frac{\sum_{\zeta,\intercal=1,\zeta\neq\intercal}^{N}\theta^{\cup}_{\zeta\intercal,\cup}(\mathbb{Z})}{\sum_{\intercal=1}^{N}\theta^{\cup}_{\zeta\intercal,\cup}(\mathbb{Z})} \quad (5)$$

$$C^{\cup}_{\varsigma\leftarrow\intercal,\cup}(\mathbb{Z}) = \frac{\sum_{\zeta,\intercal=1,\zeta\neq\intercal}^{N}\theta^{\cup}_{\zeta\intercal,\cup}(\mathbb{Z})}{\sum_{\zeta=1}^{N}\theta^{\cup}_{\zeta\intercal,\cup}(\mathbb{Z})} \quad (6)$$

As a final step, the net pairwise directional connectedness between ς and $\intercal$ is computed as:

$$NPDC_{\varsigma\intercal}(\mathbb{Z}) = \theta^{\cup}_{\intercal\zeta,\cup}(\mathbb{Z}) - \theta^{\cup}_{\zeta\intercal,\cup}(\mathbb{Z}) \quad (7)$$

Where a positive (negative) value of $NPDC_{\intercal\rightarrow}\varsigma(\mathbb{Z})$ indicates that variable $\intercal$ transmit more (less) shocks to variable ς than it receives, implying that $\intercal$ dominates (is dominated by) ς in the bilateral relationship.

4.0 Empirical Results and Discussion

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the variables, revealing important features of their distributional properties. The mean values of the green asset indices (GRNAM, GRNDO, GRNFUEL, GRNGEO, and GRNBIO) are relatively close to zero, indicating modest average returns over the sample period, with GRNBIO showing a slightly negative mean. In contrast, the climate risk indices (TRI and PRI) exhibit large negative mean values due to their transformation into growth rates, while the Geopolitical Risk index (GPR) has a positive average but extremely high variance, reflecting significant fluctuations over time. The variance statistics also indicate that the series GRNFUEL and GPR are the most volatile, implying greater uncertainty in these variables compared to other variables.

The skewness and kurtosis tests show most variables do not follow a normal distribution. The variables GPR and GRNFUEL are positively skewed, while others like GRNGEO and GRNBIO are negatively skewed, suggesting skewness in the returns. The kurtosis statistics, especially for GRNBIO and GPR, suggest the presence of thick tails, and this is also supported by the highly significant Jarque-Bera statistics for most of the variables. The results of the ERS unit root test indicate that all variables are stationary at standard levels. Moreover, the Q(10) and $Q^2(10)$ statistics show the presence of autocorrelation and ARCH effects in some series, such as

GRNFUEL, GRNGEO and GPR, suggesting the presence of volatility clustering and the use of GARCH models for further investigation.

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Table 1:Descriptive statistics

	GRNAM	GRNDO	GRNFUEL	GRNGEO	GRNBIO	TRI	PRI	GPR
Mean	0.005	0.006	0.001	0.002	-0.002	-100.001	-100.002	1.14
Variance	0.004	0.002	0.025	0.006	0.007	0.001	0.000	988.377
Skewness	-0.495**	-0.427**	0.845***	-0.889***	-0.663***	0.114**	0.661***	2.824***
	(0.022)	(0.026)	(0.000)	(0.00)	(0.001)	(0.036)	(0.001)	(0.000)
Kurtosis	0.024	0.205	1.093**	0.818*	3.037***	0.19	1.574***	14.094***
	(0.742)	(0.436)	(0.020)	(0.053)	(0.000)	(0.457)	(0.004)	(0.000)
JB	4.286**	9.234**	27.516***	5.522*	74.563***	13.599***	28.686***	1565.760***
	(0.019)	(0.033)	(0.000)	(0.063)	(0.000)	(0.001)	(0.000)	(0.000)
ERS	-2.347**	-3.319***	-6.416***	-4.282***	-2.132**	-2.225**	-2.165**	-3.549***
	(0.020)	(0.009)	(0.000)	(0.000)	(0.035)	(0.028)	(0.032)	(0.001)
Q(10)	1.944	4.525	8.984	10.684*	6.738	10.412*	2.356	143.811***
	-0.943	-0.58	-0.111	-0.051	-0.28	-0.058	-0.902	0
Q2(10)	7.238	9.094	21.571***	30.510***	5.112	10.409*	2.356	26.541***
	-0.231	-0.106	0	0	-0.489	-0.058	-0.902	0

Note: ***,**, and * denotes significance at 1%, 5% and 10% respectively.

4.3 Empirical Results

All the figures showing the pattern of connectedness are shown in the appendix in Figure 3 to 8.

4.3.1 Dynamic Connectedness between Climate Risk Geopolitical Shock and GRNAM

As for the dynamic connectedness between climate risk, geopolitical risk and GRNAM as displayed in Figure 3 in the appendix, the results confirm that the global natural resource and materials-linked sustainable investment index (GRNAM) shows a total connectedness index that starts high (at a level of approximately 53 to 54 percent) in the early sample in 2012 to 2013 and quickly declines subsequently to a steady state of approximately 33 to 35 percent from 2015, i.e. the high total connectedness between GRNAM and the other variables in the system was confined to the early sample period (post-GFC period), with a steady state level of total connectedness from 2015 onwards. The TO others panel confirms that GRNAM sends only limited shocks to the remainder of the system - with a distinct spike to around 40 percent in the early sample period of 2012 to 2013 and rapidly decays toward zero for the rest of the sample - while the FROM others panel confirms that PRI is a persistent absorber of shocks (with values consistently in the range of 40 to 50 percent on average), TRI has relatively large FROM values (in the range of 45 to 50 percent) and GPR has a very significant spike (above 80 percent) in the early sample before rapidly decaying, confirming that geopolitical risk was a dominant source of shocks to the entire system in the early sample period. The net total directional connectedness shows that GRNAM fluctuates slightly around zero and is a modest net receiver in 2013 to 2015, that PRI is a persistent net receiver with large negative values in 2013 to 2014, that TRI is a modest net receiver in the early sample and that GPR is a dominant net transmitter in 2012 to 2014 (the largest net transmitter among all variables) before decaying to close to zero in the later sample.

Turning to the pairwise connectedness findings, GRNAM is a net transmitter with small positive values against both TRI and PRI in the earliest sample years of 2012 to 2013, meaning that there was a brief period of bilateral dominance of both climate risk dimensions by GRNAM, before these values decay to near zero and remain there through 2024. The GRNAM-GPR pair is most instructive - it shows clearly negative net pairwise values in the 2012 to 2015 period, implying that GPR clearly dominated GRNAM in bilateral connectedness during that time period, sending more tail shocks to the natural resource and materials index than it received in return, which is

economically sensible given that geopolitical risks in energy and resource regions impact the investment environment for natural resource-based sustainable assets. The dynamic pairwise connectedness plots reflect this: both the GRNAM-TRI and GRNAM-PRI pairs exhibit early-sample dynamic pairwise values of about 10 to 35 percent that decay to zero by 2015 and remain there, and GRNAM-GPR exhibits early-sample dynamic pairwise values of about 20 to 30 percent in 2012 to 2014 that also decay. The TRI-PRI pair continues to show its characteristic near-perfect bilateral connectedness of approximately 80 to 100 percent throughout the sample period - further confirming the result across all the sub-indices that physical and transition climate risks are interconnected at all times - while TRI-GPR and PRI-GPR both show initially strong dynamic pairwise values of around 20 to 30 percent that decay to near zero after 2015, reflecting the general pattern of early-sample geopolitical risk shock dominance that dissipates into a more stable and segmented risk structure after 2015.

4.3.2 Dynamic Connectedness between Climate Risk Geopolitical Shock and GRNBIO

The findings in Figure 4 in the appendix show that the total directional connectedness of the global bioenergy investment index (GRNBIO) to the Physical Risk Index (PRI), Transition Risk Index (TRI) and Geopolitical Risk Index (GPR) is comparatively weak and mostly unidirectional throughout the sample. The TO others panel reveals that GRNBIO only transmits very little shock to the other three variables, with a time-varying value around zero for most of the sample, while the FROM others panel reveals that PRI and TRI are the main absorbers of shocks from others, with PRI receiving nearly 40 to 50 percent of the forecast error variance from others and TRI maintaining similarly high values around 45-50 percent across the entire sample. GPR, on the other hand, is a strong transmitter in the early part of the sample period, reaching more than 100 in 2013, but declining thereafter, implying that geopolitical risk was a crisis driver of connectedness in the early post-GFC period but became more idiosyncratic since then. The net total directional connectedness confirms that PRI is a net receiver (large negative values in 2013 and 2014), TRI is a net transmitter and receiver across the sample and GPR was a net transmitter in the 2012 to 2014 period and reverts to near-zero net values thereafter, while GRNBIO is net-positive and therefore a net transmitter for most of the sample. This overall suggests that the bioenergy equity market does not have a significant systemic influence on climate and geopolitical risk variables, while it itself is only modestly influenced by the latter, implying a certain degree of market segmentation between bioenergy investment and the climate-geopolitical risk complex.

The pairwise connectedness results and dynamic pairwise connectedness plots show that the pairwise connections between the four variables are highly dynamic and mostly present in the early sample period. The TRI-PRI pair is the most significant and persistent dynamic pairwise connectedness (staying at around 80-100 percent throughout the entire sample period), suggesting that physical and transition climate risks remain strongly and permanently coupled, with physical climate change events continually feeding into perceptions of transition risk and vice versa over the entire sample period. The TRI-GPR and PRI-GPR pairs show strong and dramatic spikes in the 2012 to 2015 period, but then fall quickly to zero, suggesting geopolitical shocks produced short-lived acute co-movements with both climate risk measures in the early sample period rather than structural connections - a result consistent with the acute geopolitical events of the early 2010s, such as the Ukrainian-Russian Crimea crisis and Middle Eastern unrest, driving temporary but not permanent links between geopolitical and climate risk transmission channels. Interestingly, GRNBIO exhibits very low pairwise connectedness with all three external variables (TRI, PRI and GPR) in the net pairwise and dynamic pairwise plots, with values close to zero for the entire sample period from 2013 to 2024. This intriguing result implies that the bioenergy equity market is largely decoupled from climate and geopolitical risk, and suggests that GRNBIO may actually provide diversification benefits within a sustainable investment portfolio precisely because it is insulated from the major climate-geopolitical risk channels that are evident in other clean energy sub-sectors such as GRNSOLAR and GRNWIND, and this decoupling occurs even during major global shocks such as the COVID-19 pandemic and Russia-Ukraine conflict of 2022 to 2023.

4.3.3 Climate Risk Geopolitical Shock and GRNDO dynamic connectedness

As for GRNDO (see Figure 5 in the appendix), the results show that the global diversified clean energy and hydroelectric investment index presents a total connectedness index that peaks at around 48 to 55 percent in the early sample period from 2012 to 2013, then rapidly falls and settles down to a lower and more stable level of around 32 to 35 percent from 2015 onwards to the end of the sample in 2024, with minor spikes around 2015, 2020 and 2023, but still well below the early sample peak. The TO others panel shows that GRNDO is a relatively low and decreasing transmitter of shocks to the system (peaking at around 30% in the early sample, then rapidly declining towards zero, with a minor spike in 2020 to 2022 likely representing the "COVID-19 green recovery" when diversified clean energy was attracting particular attention from policymakers and investors), albeit that the largest spillovers are consistently received by PRI

(approximately 40 to 55% in the early sample and TRI exhibits large FROM values of approximately 45 to 50% throughout the sample. GPR is a noticeably strong transmitter in the TO others panel, recording the highest values in the early sample, and then falling rapidly after 2014 before stabilising at values close to zero, thus confirming that the geopolitical environment of the early 2010s was the main source of system-wide contagion. The net total directional connectedness confirms that GRNDO fluctuates around zero, with a short-lived net transmission phase in the early sample and a net reception phase with negative values of approximately minus 10 to minus 20 in 2013 to 2015, while the PRI is a consistent net receiver with large negative values of approximately minus 40 to minus 55 between 2013 and 2014, and GPR is clearly the dominant net transmitter with high positive values of positive 60 to positive 65 in 2012 to 2013 before rapidly decaying to zero.

As far as the pair-wise connectedness results for GRNDO, the GRNDO-TRI pair shows modest positive net pairwise values in the early sample period, confirming that GRNDO led TRI only marginally in 2012 to 2013, before rapidly reverting to zero and remaining flat until 2024 - so the diversified clean energy index does not exert a persistent bilateral leadership over transition risk. The GRNDO-PRI pair shows a similar pattern, with small positive values early in the sample, rapidly converging to near zero by 2015 and remaining stable thereafter, thus confirming that physical climate risk does not exert a permanent and structurally important influence on GRNDO returns beyond the initial sample period. The most notable feature of the GRNDO pairwise results is the GRNDO-GPR pair, which shows clearly negative net pairwise values of approximately minus 15 to minus 35 in the 2013 to 2015 window - confirming that GPR bilaterally dominated GRNDO in those years, as geopolitical shocks to energy markets and resource sectors directly affected diversified clean energy investment sentiment - before this connection decays toward zero and has remained stable ever since, aside from a brief negative blip around 2020 to 2021. The dynamic pairwise connectedness plots support these results: GRNDO-TRI and GRNDO-PRI display dynamic pairwise values of about 10 to 20 percent in the early sample that revert around 2015 and remain flat at zero, while GRNDO-GPR shows dynamic pairwise values of about 20 to 35 percent in 2012 to 2014 that decay thereafter. The TRI-PRI pair still reads its signature almost-perfect dynamic pairwise connectedness of 80 to 100 percent across the whole sample - as do the findings for all sub-indices in this study - while TRI-GPR and PRI-GPR both feature large early-sample dynamic pairwise values that decay rapidly after 2015, reconfirming that the geopolitical

shocks of the early 2010s contributed to the connectedness of the GRNDO system in a way that did not endure in later sample years.

4.3.4 Dynamic connectedness between Climate Risk Geopolitical Shock and GRNFUEL

The appendix figure 6 presents the dynamic connectedness between Climate Risk, Geopolitical Shock and GRNFUEL. As shown, In the case of GRNFUEL, the results demonstrate that the fuel cell and hydrogen energy index is a relatively inactive player in the connectedness system, but the directional patterns of the connectedness reveal some key differences with the other clean energy sub-indices. The total connectedness index ranges between 33 and 55 percent with the highest level in the early sample period around 2012 to 2013 and then gradually settling around a lower level of 33 to 37 percent from 2015 onwards. The TO others panel confirms that GRNFUEL is a relatively low transmitter of shocks to the overall system - with the TO index below 20 percent for most of the sample period and only occasional mild spikes around 2014 and around 2019 to 2021, presumably driven by the renewed investor interest in hydrogen as part of the COVID-19 green recovery packages. By contrast, the FROM others panel confirms that PRI and TRI are the main recipients of shocks throughout the sample - with PRI receiving consistently between 40 and 55 percent and TRI receiving persistently high FROM shocks around 45 to 50 percent - while GPR registers a very strong value in the FROM others panel in the early part of the sample around 2012 to 2014 before dropping to near zero, in line with the escalation of geopolitical tensions during that period. The net total directional connectedness panel indicates that GRNFUEL oscillates around zero with periods of mild net transmission in the early sample and episodes of mild net reception in 2019 to 2022, while PRI is a consistent net receiver with strong negative values in 2013 to 2014, TRI is a mixed net transmitter and net receiver, and GPR is a strong net transmitter in 2012 to 2014 but then reverts to near zero.

The pairwise and dynamic pairwise connectedness results offer further insights into the role of GRNFUEL. The GRNFUEL-TRI pairwise pair registers modest positive net pairwise connectedness in the initial portion of the sample - suggesting a marginal dominance of GRNFUEL in the bilateral relationship around 2013 - before collapsing to near zero in the latter sample, consistent with the policy-hydrogen nexus where transition policy uncertainty started to inform hydrogen market valuations rather than the other way around as the sector evolved. The GRNFUEL-PRI pair shows a similar pattern, with small positive values in 2013-2014 before reverting to near zero for the rest of the sample - implying that physical climate shocks had little

sustained bilateral influence on the fuel cell and hydrogen markets after the initial period of the sample. Most significantly, the GRNFUEL-GPR pair stands out from GRNBIO in that it shows negative net pairwise connectedness in 2014 to 2015 and around 2019 to 2021, suggesting that GPR dominated GRNFUEL in the bilateral relationship during these periods - consistent with geopolitical tensions giving rise to energy security concerns that directly impacted hydrogen investment sentiment during Russia-Ukraine's annexation of Crimea and the onset of the full-scale invasion respectively. The TRI-PRI pair shows 80 to 100 percent dynamic pairwise connectedness across the entire sample - confirming the persistent dominant bilateral integration of physical and transition climate risk - and TRI-GPR and PRI-GPR show strong peak spikes in 2012 to 2015 before converging to near zero, consistent with GRNBIO. The level of dynamic pairwise connectedness of GRNFUEL with TRI, PRI and GPR, while generally low, is clearly much more time-varying and episodic than that of GRNBIO, indicating that the fuel cell and hydrogen sector is more responsive to geopolitical and policy shocks than GRNBIO over the sample period.

4.3.5 GRNGEO dynamic connectedness in Climate Risk Geopolitical Shock

As for GRNGEO in Figure 7, we can see that the global geothermal energy investment index presents a total connectedness index that abruptly spikes from a baseline of about 35 percent to a peak of about 47 to 58 percent in the early sample period of 2012 to 2013 (reflecting the elevated geopolitical and climate risks of the early post-GFC period) before crashing and settling at a relatively low and flat baseline of approximately 33 to 35 percent from 2015 with only a minor episode at about 2021 to 2022 likely due to the Russia-U The TO others panel shows that GRNGEO is a relatively low transmitter of shocks to the rest of the system (with a spike to about 55 percent in the early sample windows 2012-2013 and declining to near zero, and minor spikes around 2015 and 2020-2022), while PRI is consistently the largest receiver of shocks with the highest FROM values of about 40 to 65 percent across the entire sample, and TRI continues to record persistently high FROM values of about 45 to 55 percent, confirming that both climate risk dimensions are the net receivers of shocks in the entire system regardless of the particular sub-index for clean energy examined. GPR shows a huge peak TO value (above 60) in the early sample and reverts to near-zero after 2014, while the FROM panel for GPR remains at near-zero throughout, suggesting that GPR acted as a pure transmitter of shocks in this system. The net total directional panel confirms that GRNGEO is a mild positive net transmitter in the early-sample period, and a mild negative net receiver from 2013 to 2015 before returning to near-zero, while

TRI records deep persistent negative net connectedness values of approximately minus 40 to minus 55 in the 2013 to 2014 periods, and GPR records the highest positive net values of positive 50 to 60 in the same early window, before returning to near-zero in the remaining sample.

Turning to the results for the pairwise connectedness of GRNGEO, the GRNGEO-TRI bilateral pair registers positive net pairwise values of about 15 to 25 percent in the early sample of 2012-2013, indicating that GRNGEO briefly dominated TRI bilaterally during the period of peak geothermal investment interest, before reverting to near-zero by 2015 and staying flat with only minor fluctuations until 2024, suggesting that the geothermal energy index does not have a persistent or substantial bilateral influence on transition risk perceptions once the early geopolitical risk subsides. Similarly, the GRNGEO-PRI pair shows positive net pairwise values in the early sample of approximately 15 to 40 percent (clearly larger and more sustained than for other sub-indices, suggesting that GRNGEO remained a bilateral net transmitter to physical climate risk in 2013 to 2014) before dropping to near-zero values thereafter, suggesting that physical climate risks do not consistently affect geothermal equity market conditions once the early-sample peak in global risk abates. The GRNGEO-GPR bilateral pair is characterised by unambiguously negative net pairwise values of approximately minus 15 to minus 35 in 2013 to 2015, confirming that GPR dominated GRNGEO bilaterally in the early sample of heightened geopolitical risk, which is consistent with the resource-limited and highly concentrated nature of geothermal power generation, primarily concentrated in geopolitically sensitive regions such as the East African Rift Valley, Iceland, Indonesia and the Philippines; this means that geothermal investment sentiment is highly sensitive to geopolitical risks in these regions. The dynamic pairwise connectedness graphs confirm these results: GRNGEO-TRI and GRNGEO-PRI show dynamic values 15 to 40 percent in 2012 to 2014 and decaying to zero in 2015, while GRNGEO-GPR shows dynamic pairwise values of approximately 20 to 35 percent in the same early window with a minor peak in 2022 to 2023 that is likely attributable to renewed geopolitical focus on energy security and the role of domestic geothermal resources. The TRI-PRI pair records its usual near-perfect dynamic pairwise connectedness of approximately 80 to 100 percent across the entire sample, as do all the other sub-indices considered in this paper, confirming that the permanent and deep integration of physical and transition climate risks at the global level applies to all sub-indices.

4.4 Comparative Analysis and Policy Implication for Asset Market Participant.

Looking across all the connectedness results obtained for GRNBIO, GRNFUEL, GRNGEO, GRNAM, and GRNDO, the evidence consistently points to a well-defined ordering in terms of vulnerability to climate risk and geopolitical disruptions. Among the five sustainable investment sub-sectors examined, GRNFUEL records the highest degree of external exposure across virtually every connectedness dimension considered in this study. Its total connectedness index reaches the widest range over the sample horizon, its FROM measure persistently exceeds those of the remaining sub-indices, and the bilateral relationship between GRNFUEL and the Geopolitical Risk Index turns negative at multiple points, most notably during 2014 to 2015 and again between 2019 and 2021, a pattern that reflects the acute sensitivity of hydrogen and fuel cell valuations to geopolitical developments involving energy supply security. GRNAM and GRNDO occupy the middle tier of this hierarchy, each recording substantial early period connectedness and meaningful GPR driven bilateral transmission before settling at lower but non-trivial baseline levels in the latter years of the sample. GRNGEO occupies a somewhat different position in the ranking: while its aggregate connectedness is not the highest, the bilateral channel between geothermal equity returns and the Physical Risk Index is comparatively stronger and more sustained than what is observed for the other sub-indices, a finding that can be traced to the geographic reality that commercially viable geothermal resources are disproportionately located in regions that are simultaneously exposed to climatic and political instability. GRNBIO stands apart from the others entirely, exhibiting negligible pairwise connectedness with the Physical Risk Index, Transition Risk Index, and Geopolitical Risk Index across the full sample and the lowest external shock absorption of all five indices, a result that confirms the bioenergy sub-sector evolves largely outside the risk transmission channels that shape the remainder of the clean energy investment universe.

The implications of these comparative findings for asset market participants are substantive and carry direct relevance for portfolio strategy. The high and recurrent external exposure of GRNFUEL to both physical climate shocks and geopolitical disruptions means that investors with concentrated positions in hydrogen and fuel cell equities face a compounding risk profile in which adverse outcomes along one dimension, such as a major climate event or an escalation of energy related geopolitical conflict, tend to coincide with simultaneous deterioration along the other, amplifying drawdown severity precisely when portfolio resilience is most needed. For holders of

GRNAM and GRNDO, the primary concern is the demonstrated capacity of geopolitical shocks to re-enter these markets with considerable force during periods of resource sector tension, even after a prolonged period of relative calm, as illustrated by the modest but observable GRNDO and GPR resurgence around 2020 to 2022. GRNGEO investors, meanwhile, face a climate risk profile that is structurally tied to the physical geography of their underlying assets rather than to broader market sentiment, a distinction that conventional portfolio risk frameworks typically fail to capture. The low and stable connectedness of GRNBIO across all risk dimensions, by contrast, positions bioenergy equities as a potential stabiliser within a diversified sustainable investment portfolio, one that retains its return characteristics during climate and geopolitical stress episodes that adversely affect the other sub-sectors. Collectively, these results caution against treating the clean energy investment space as a uniform risk category and instead support a sub-sector differentiated approach to green portfolio construction, dynamic correlation modelling, and climate adjusted risk measurement.

5.0 Conclusion

This study examines the dynamic connectedness between climate risk, geopolitical risk and sustainable investment in global equity market for the period covering December, 2020 and December 2024. Across the sub-indices, the total connectedness index values confirm a significant degree of connectedness among the variables, with higher values concentrated in the early part of the sample that reflect the heightened geopolitical and climate risk backdrop of the 2012-14 period before a partial normalisation at lower but still elevated levels in later years. The Geopolitical Risk Index stands out as the most prominent short run transmitter of shocks throughout the system, producing its most intense spillovers during the early sample period of elevated political risk before falling back to a more subdued role in subsequent years, while the Physical Risk Index is a consistent net receiver of shocks to the system but one whose bilateral relationships with solar, wind and geothermal resource sub-indices remain economically significant throughout the sample period. Of the five sustainable investment categories, GRNFUEL emerges as the most widely connected to geopolitical and climate risk transmission, having the broadest range of connectedness values and the most consistent net receiver status, while GRNBIO displays the lowest connectedness in all dimensions from a baseline that is less sensitive to the dominant risk transmission channels than any of the other sub-indices. GRNGEO stands out in the system, with

its bilateral connections with physical risk indices reflecting the localised nature of geothermal resource endowments and both GRNAM and GRNDO display early sample vulnerability to geopolitical shocks that fades in subsequent years. The Transition Risk Index does not function as an independent source of systemic risk, which suggests that perception of climate policy risk adjusts to the clean energy market and geopolitical environments rather than unidirectionally impacting them, at the monthly level of analysis. Viewed collectively, the above results confirm that the clean energy investment universe, while not internally uniform in its risk characteristics, nor externally uniform in its sensitivity to the two main categories of global risk considered here, and that the network of bilateral connectedness between sub-sectors displays a dynamic that responds to changes in the economic and geopolitical settings.

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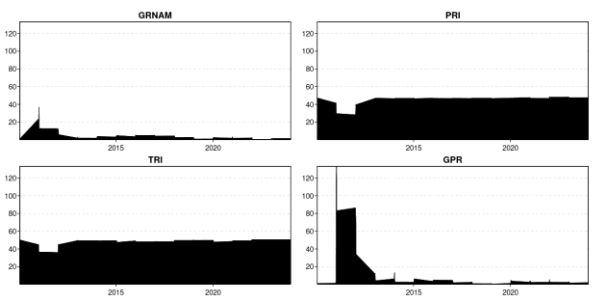
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APPENDIX

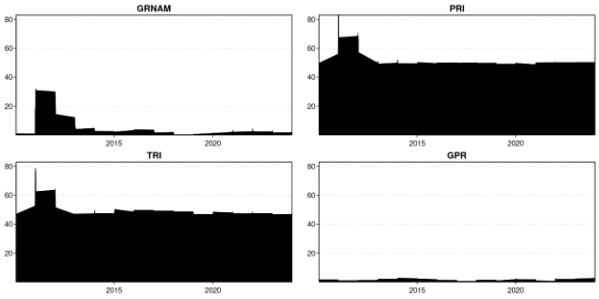
Dynamic Total Connectedness



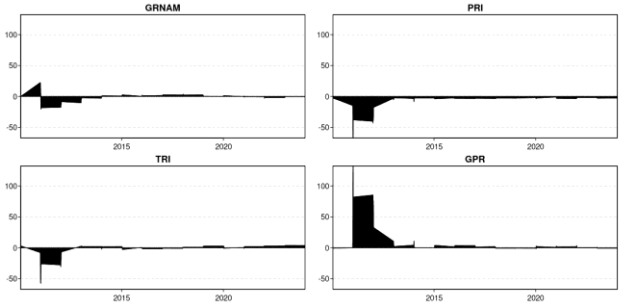
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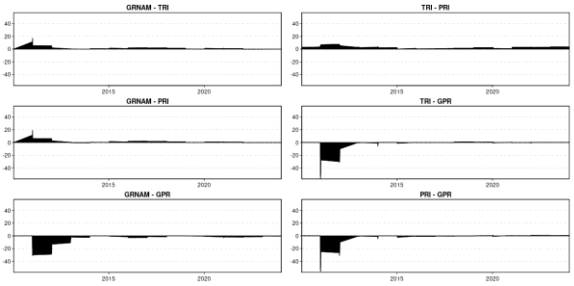
From Others



Net Total Directional Connectedness



Pairwise Directional Connectedness



Dynamic Pairwise Directional Connectedness

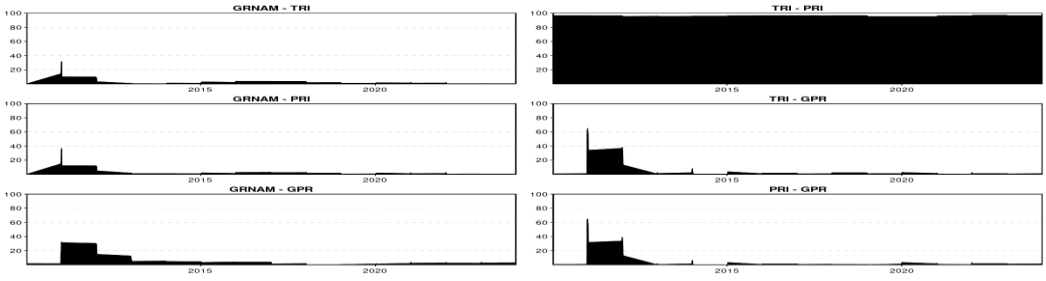
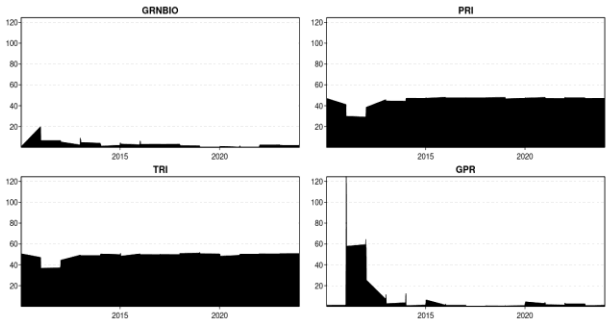


Figure 3 Dynamic Connectedness between Climate Risk, Geopolitical Shock and GRNAM

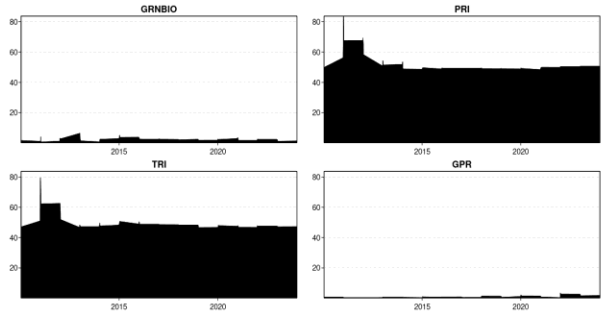
Dynamic Total connectedness



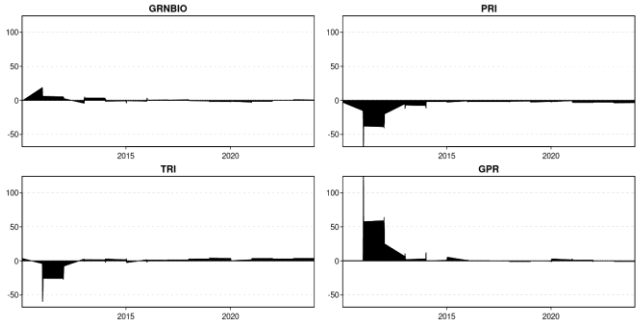
TO Others



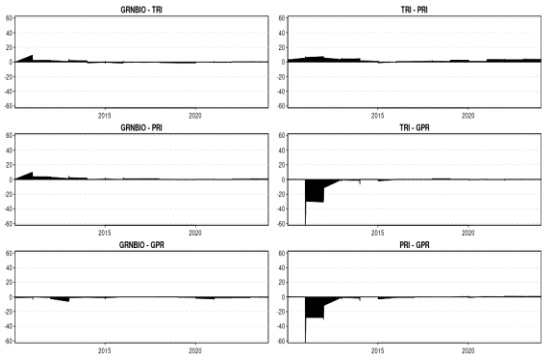
From Others



Net Total Directional Connection



Net Pairwise Total Directional Connection



Dynamic Pairwise Connectedness

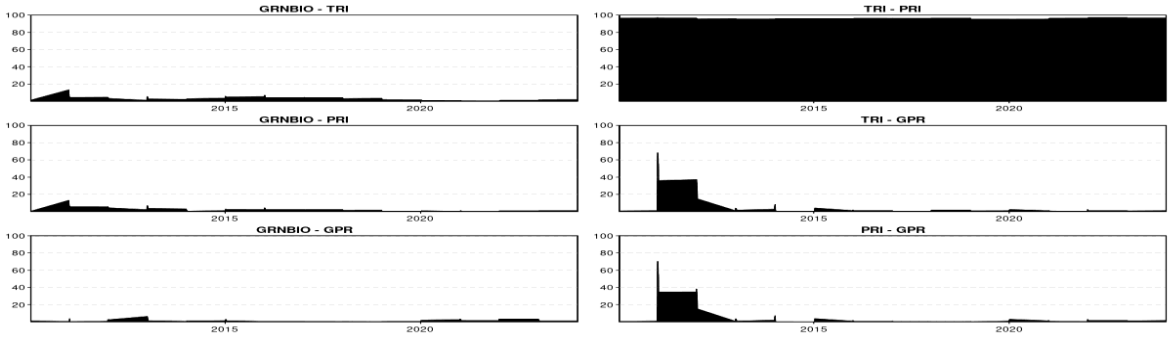
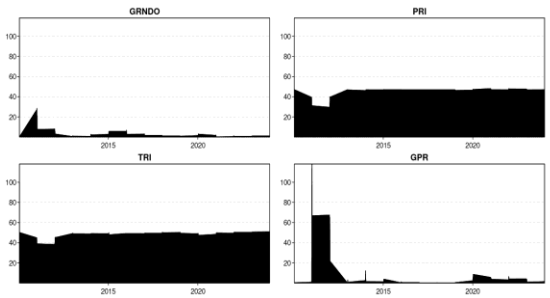


Figure 4 Dynamic Connectedness between Climate Risk, Geopolitical Shock and GRNBIO

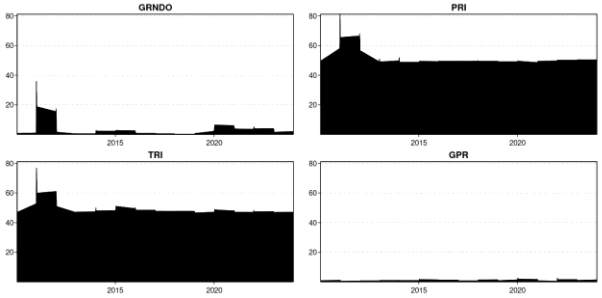
Dynamic Total Connectedness



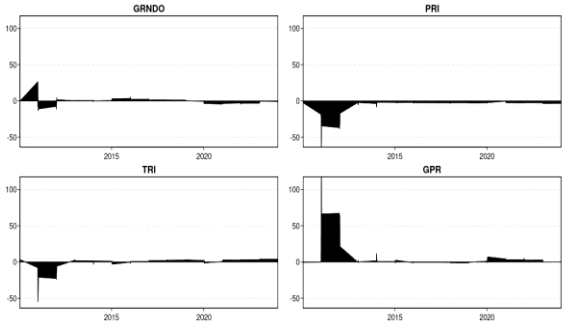
To Others



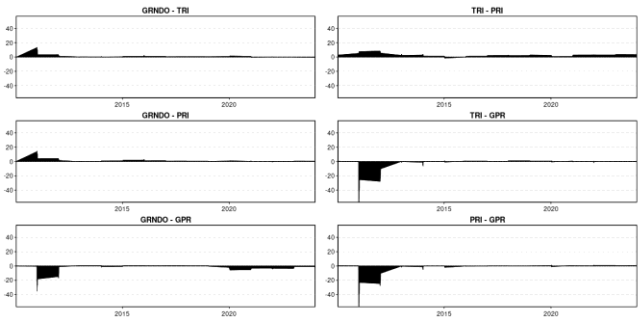
From Others



NET Total directional Connectedness



Pairwise Directional Connectedness



Dynamic Pairwise Connectedness

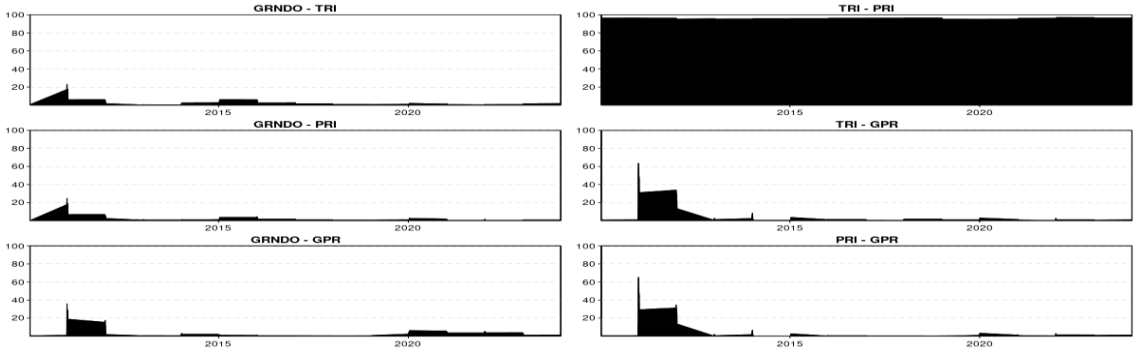
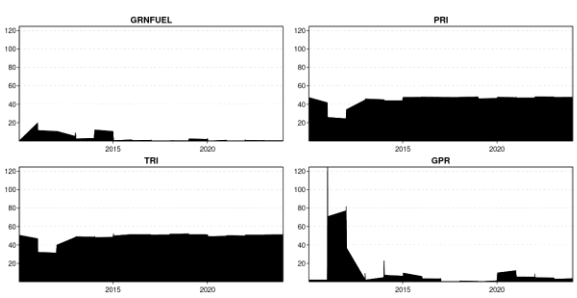


Figure 5 Dynamic Connectedness between Climate Risk, Geopolitical Shock and GRNDO

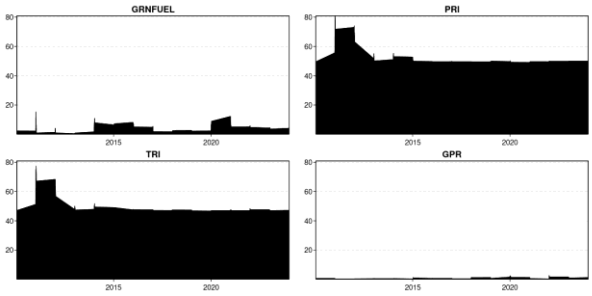
Dynamic Total Connectedness



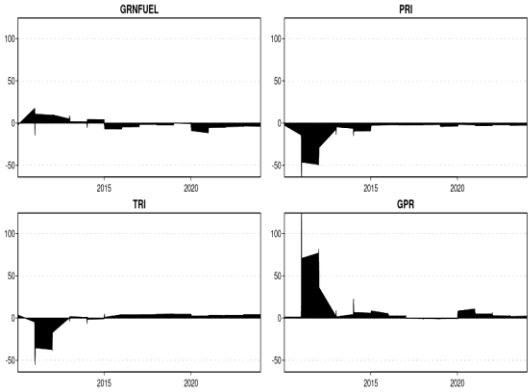
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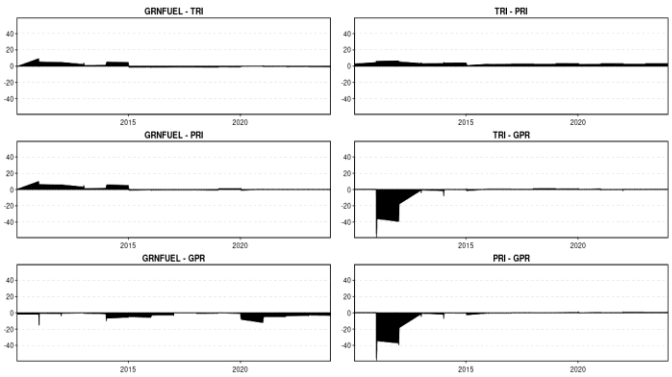
From Others



NET Total directional Connectedness



Pairwise Directional Connectedness



Dynamic Pairwise Connectedness

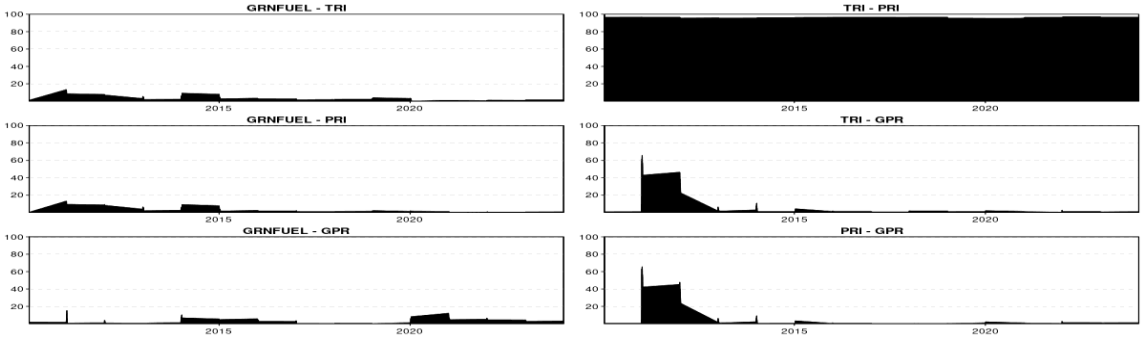
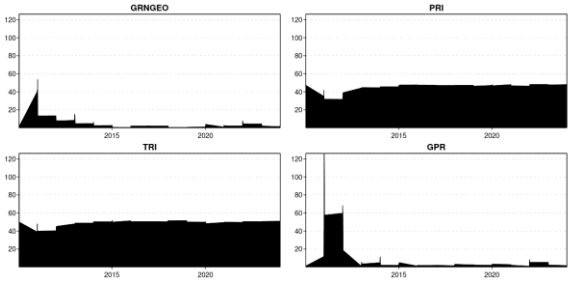


Figure 6 Dynamic Connectedness between Climate Risk, Geopolitical Shock and GRNFUEL

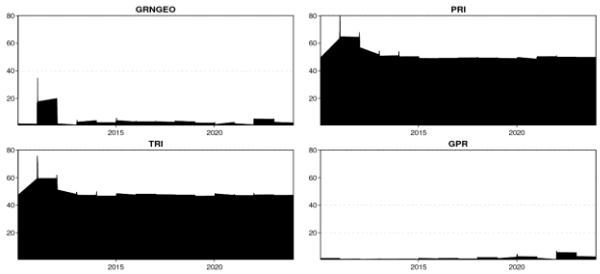
Dynamic Total Connectedness



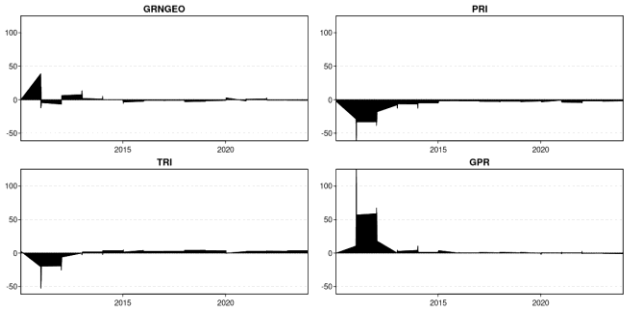
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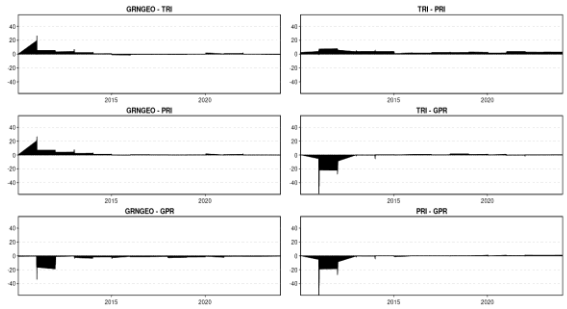
From Others



Net Total Directional Connectedness



Net Pairwise Directional Connectedness



Dynamic Pairwise Connectedness

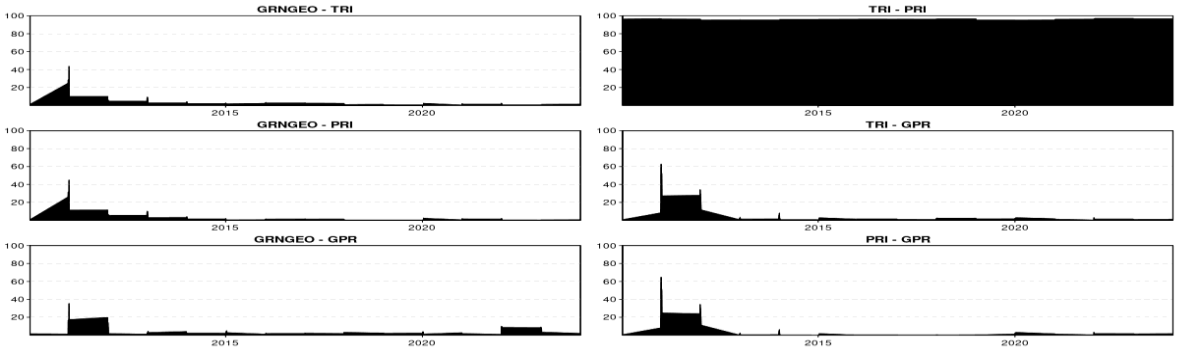


Figure 7 Dynamic Connectedness between Climate Risk, Geopolitical Shock and GRNGEO