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When markets panic: How green finance fails (or thrives) in times of geopolitical crisis

Azhar Mohamad

Department of Finance, Kulliyyah of Economics and Management Sciences, International Islamic University Malaysia, 53100 Kuala Lumpur, Malaysia

ABSTRACT

This study investigates how green finance responds to extreme geopolitical turbulence, revealing when sustainable investments collapse or unexpectedly flourish amid global instability. Specifically, we examine the time-varying causal relationship between green finance and geopolitical risk, together with eight other financial market indices: carbon allowances, bitcoin electricity consumption, clean energy, renewable energy, world equity, climate change, volatility, and oil price. Our dataset spans 12 years of weekly data from January 2012 to December 2024. Using a recursive evolving time-varying Granger causality estimation, we find that green finance and geopolitical risk strongly influenced the world equity market index in 2015 and 2024, respectively. Geopolitical risk exerted a strong causal influence on the volatility index in 2024. We document moderate bidirectional causality between green finance and clean energy, between green finance and renewable energy, and between geopolitical risk and clean energy. Interestingly, the Bitcoin Electricity Consumption index strongly influenced both green finance and geopolitical risk from 2020 to 2022. This finding reveals that the energy consumption of bitcoin mining carries significant environmental and geopolitical consequences, with direct effects on green finance and geopolitical risk.

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green finance; geopolitical risk; time-varying causality; green bond; Bitcoin electricity consumption

1. Introduction

The global financial system confronts two defining challenges of the twenty-first century: financing an urgent, sustainable transition and navigating escalating geopolitical instability. Christine Lagarde, President of the European Central Bank, crystallised this nexus in November 2022, warning that neglecting climate change risks a flawed economic outlook (Boungou & Urom, 2023). Climate risks, categorised as either transitional or physical by the Network for Greening the Financial System (NGFS, 2020), interact with shifting consumer preferences and carbon pricing to reshape financial landscapes (Faccini et al., 2023). Green bonds have emerged as a pivotal instrument to fund this transition, evolving into a liquid asset class since their inception and the establishment of the Green Bond Principles (Hammoudeh et al., 2020; Reboredo, 2018).

CONTACT Azhar Mohamad m.azhar@iium.edu.my; dr@azharmohamad.asia

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Concurrently, geopolitical risk (GPR), defined as threats from state tensions, terrorism, and war (Caldara & Iacoviello, 2022), is a critical determinant of financial market stability. Evidence shows geopolitical tensions disrupt trade, increase exchange rate volatility, and trigger capital outflows, thereby elevating systemic risk (Gupta et al., 2019; Soybilgen et al., 2019). These shocks negatively impact investment, employment, and equity prices (Balcilar et al., 2018; Demir & Danisman, 2021). The Russia-Ukraine war, in particular, has been shown to disrupt price discovery processes across global financial markets (Mohamad, 2024b). Within green finance, GPR's role is increasingly salient, with studies indicating its substantial impact on renewable energy investments and green bond volatility (C. Li et al., 2022; Sheenan, 2023; Zhang et al., 2023). During major crises such as the Russia-Ukraine war and the COVID-19 pandemic, herding behaviour has been observed across energy, metal, and grain commodities, suggesting similar dynamics may affect green asset markets (Mohamad, 2024a). GPR can induce volatility in green bonds (Lee et al., 2021), while geopolitical uncertainty may simultaneously deter and drive demand for green assets as a volatility hedge (Ma & Najam, 2024).

Despite these advances, the literature remains fragmented. While time-varying causality (TVGC) models are crucial for capturing evolving relationships in non-stationary systems (Baum et al., 2025; Shi et al., 2018, 2020), existing applications are limited in scope. Prior research examines causality within green asset categories (Madaleno et al., 2022), from traditional bonds and carbon markets to green bonds (Hammoudeh et al., 2020), or the impact of GPR on green asset returns and volatility (Qin et al., 2020; Zhang et al., 2023). A significant gap exists: no holistic, time-varying investigation maps the causal interplay between green finance, GPR, a comprehensive set of transmission channels, and broad market indices, including the energy footprint of digital assets. This omission is critical for the turbulent 2020s, a period where a pandemic, major conflicts, and technological disruptions have likely reshaped these relationships in ways static models cannot capture.

For practitioners, this gap presents a material problem. Asset allocators require evidence on whether sustainable investments offer reliable diversification during geopolitical shocks or introduce new correlated risks. Risk managers need to understand the dynamic channels through which political instability transmits to clean energy equities and green bond volatility. Furthermore, the escalating environmental externalities of cryptocurrency mining pose a novel ESG and geopolitical dilemma that may redirect capital flows, a linkage underexamined in financial research. Recent evidence on the fractal nature of investor demand for cryptocurrencies (Hairudin & Mohamad, 2026), and the isotropy of cryptocurrency volatility (Hairudin & Mohamad, 2024) suggests that digital asset markets exhibit complex behaviours that may amplify their environmental and financial spillovers.

This study directly addresses these gaps by investigating the time-varying directional causality between green finance (proxied by the Solactive Green Bond Index, SOLG), geopolitical risk (GPR), and eight critical market indices from January 2012 to December 2024. We pose four research questions to map this terrain: (1) Does green finance Granger-cause GPR and the other eight indices? (2) Do these nine indices Granger-cause green finance? (3) Does GPR Granger cause each of the nine indices? (4) Do the nine indices Granger-cause GPR?

We employ a recursive evolving TVGC framework. This approach is preferred over static Granger causality or correlation-based methods because it does not assume stable relationships across our 12-year sample, which is marked by structural breaks. While multivariate network analyses are valuable for measuring connectedness intensity, the TVGC framework is uniquely suited to identifying the precise timing and direction of causal relationships as they change, offering crucial insights for dynamic risk management.

Building on this methodological approach, this paper makes three distinct contributions to the literature. First, it identifies a novel, actionable signal from digital asset markets. Prior TVGC studies have focused on links between green assets, traditional bonds, and carbon markets (Hammoudeh et al., 2020) or within green asset categories (Madaleno et al., 2022). We provide the first evidence that Bitcoin Electricity Consumption (BEC) exerts a significant, time-varying causal influence on both green finance and geopolitical risk (2020 2022). This finding extends the growing literature on cryptocurrency market dynamics, including studies on price discovery in bitcoin markets (Mohamad, 2025a; Mohamad & Inani, 2023) and the impact of cybercrimes on digital assets (Mohamad & Dimitriou, 2026). For investment analysts, this study establishes BEC as a new leading indicator to monitor. Rising energy consumption from cryptocurrency mining can signal impending capital rotations into green assets and escalating geopolitical tensions over energy resources, directly informing hedging strategies and thematic asset allocation.

Second, it maps when geopolitical risk and green finance drive systemic market stress. While Zhang et al. (2023) established that GPR affects green asset volatility, we pinpoint when this risk transmits to broader markets. We document that GPR strongly Granger-caused the global volatility index (VIX) in 2024, and that green finance influenced world equity markets (MSCI) in 2015. This finding is vital for portfolio managers. It provides clear evidence that GPR is a primary driver of general market volatility during crises, necessitating its inclusion in dynamic risk models. It also shows that large-scale green bond issuance can have bullish, systemic effects on equities, offering a macro signal for tactical allocation.

Finally, it provides a framework for integrated sustainability and geopolitical risk assessment. The study reveals moderate bidirectional causality between green finance, clean energy equities, and GPR. This result demonstrates that these domains are dynamically linked rather than isolated. For practitioners, this finding underscores the need to move beyond siloed analysis. Effective portfolio resilience and security selection now require models that jointly account for ESG fundamentals and geopolitical risk exposures, as shocks in one domain spill over into the other.

The remainder of this paper is structured as follows. Section 2 provides a critical literature review. Sections 3 and 4 describe the data and methodology. Section 5 presents and discusses the empirical results. Section 6 concludes with implications and suggestions for future research.

2. Literature review

The evolving literature on green finance and geopolitical risk (GPR) can be conceptually mapped into three interconnected streams. Recent bibliometric work has documented significant shifts in this research domain following the COVID-19 pandemic, revealing changes in publication patterns, research themes, and collaborative networks within green and climate finance (Mohamad, 2025a, 2025b). Building on this foundation, a critical synthesis of recent empirical studies reveals a complex landscape of conditional effects, transmission channels, and a pressing need for dynamic, time-sensitive analysis.

The first stream establishes green finance, particularly green bonds, as a critical instrument for funding the low-carbon transition. Research demonstrates its role in reducing carbon emissions (Saeed Meo & Karim, 2022; Zhang & Umair, 2023) and financing renewable energy infrastructure, with multinational banks being key facilitators (Li et al., 2022; Tolliver et al., 2019). The integration of green finance with financial technology and inclusion is also highlighted as vital for enhancing energy efficiency in developing economies (Liu et al., 2022; Rasoulinezhad & Taghizadeh-Hesary, 2022). However, the market dynamics of green bonds show that they co-move more closely with traditional fixed-income assets than with equities or energy commodities, indicating both their integration into core portfolios and their potential vulnerability to conventional financial shocks (Reboredo, 2018; Reboredo & Ugolini, 2020). Recent work further refines this, showing green bonds offer diversification benefits with certain assets but exhibit higher risk spillovers during periods of market stress, such as the COVID-19 pandemic (Naeem et al., 2022).

Concurrently, a robust second stream of literature, catalysed by the text-based GPR index of Caldara and Iacoviello (2022), meticulously documents the deleterious effects of geopolitical risk on financial stability. Empirical studies confirm that heightened GPR suppresses investment and employment, increases economic disaster risk, and triggers financial contagion (Caldara & Iacoviello, 2022; Neto, 2025). The search for safe havens during geopolitical crises intensifies, as evidenced by the 48-hour period following Russia's invasion of Ukraine, which revealed rapid shifts in investor preferences across asset classes (Mohamad, 2022). Its impact is particularly acute in energy and commodity markets, where it drives price volatility and supply chain disruptions (Apergis & Fahmy, 2024; Khan et al., 2024; Yilmazkuday, 2024). During the Russia-Ukraine war and COVID-19 pandemic, significant herding behaviour emerged across energy, metal, livestock, and grain commodities, indicating that geopolitical shocks can trigger systematic behavioural responses in these markets (Mohamad, 2024a). Furthermore, GPR negatively affects equity returns, especially in internationally sensitive sectors (Zhang et al., 2024), and can deter cross-border investment flows (Choi & Havel, 2025). This body of work confirms that GPR is a significant exogenous market risk factor.

The third and most pertinent stream critically examines the direct interaction between geopolitical risk and sustainable finance, a domain that is rapidly expanding, as evidenced by high-quality studies from 2024 and 2025. Consensus indicates that GPR generally has an adverse impact on green finance flows, hindering green bond development and investment (Azam et al., 2025), while increasing carbon emissions (Hunjra et al., 2024; Ma & Najam, 2024). Crucially, this recent literature identifies pivotal moderating variables. Strong institutional governance is shown not only to buffer green finance from geopolitical shocks but potentially to reverse the negative relationship by fostering resilient policy frameworks (Azam et al., 2025; Hunjra et al., 2024). Simultaneously, green finance itself can act as a mitigator, enhancing national energy security and shielding against GPR's destabilising effects (Vo et al., 2025), while explicit environmental regulations have been proven catalysts for scaling green instruments (Al Mamun et al., 2025). The challenges are particularly pronounced in emerging markets, where adaptive governance and technological innovation are essential to direct sustainable capital flows (Narayan et al., 2025).

Methodologically, studies in this domain have employed advanced techniques to unpack these dynamics, as synthesised in Table 1. Research reveals that geopolitical tensions amplify volatility spillovers and dynamic connectedness between clean energy, conventional energy, and food markets, with effects intensifying during acute crises (Yousfi & Bouzgarrou, 2024). Geopolitical risks, especially threats, have been found to increase volatility and compromise the predictability of green investments (Adekoya et al., 2025) and to induce periods of market inefficiency in green energy indices (Bozkurt et al., 2025). Other studies employ time-varying Granger causality to show evolving linkages between green assets and GPR (Zhang et al., 2023), quantile-based approaches to reveal asymmetric dependencies during market extremes (Ahmed et al., 2025), and connectedness frameworks to identify GPR as a net transmitter of shocks to climate indices during stress periods (Lorente et al., 2023). Table 1 summarises the methodological plurality and key findings of these and other seminal studies, illustrating the field's progression from static correlations to dynamic, often nonlinear modelling.

Despite these significant advances, a conspicuous gap remains. The existing literature, while increasingly sophisticated, has not concurrently modelled the time-varying causal interactions among green finance, geopolitical risk, a comprehensive set of transmission channels, and broad market indices within a unified framework. Specifically, the role of emerging digital asset externalities, exemplified by Bitcoin's energy consumption (BEC), as a potential driver of both sustainable finance reallocation and geopolitical sentiment is underexplored. This gap is notable given the growing body of research on cryptocurrency acceptance, governance, and market dynamics (Hairudin et al., 2022), as well as evidence of time-varying herding behaviour in cryptocurrency markets during crises (Mohamad & Stavroyiannis, 2022). Furthermore, many studies rely on static models or analyse pre-2022 samples, thus failing to capture potential structural breaks caused by the Russia-Ukraine war, Middle East tensions, and subsequent global realignments. This study directly addresses this gap by employing a recursive evolving time varying Granger causality (TVGC) approach to investigate the dynamic causal relationships between green finance (proxied by SOLG), GPR, and eight other critical financial and environmental indices from 2012 to 2024, thereby providing a holistic, event-sensitive analysis of this critical nexus.

3. Data

This study employs weekly data from 6 January 2012 to 20 December 2024 to examine time-varying causality within a network of ten strategically selected financial and environmental indices. The core objective is to map the dynamic relationships between two pivotal forces: green finance and geopolitical risk (GPR). The remaining eight indices serve as critical transmission channels and broad market benchmarks, chosen to capture the primary avenues through which these core forces interact with the global economy. A weekly frequency balances the informational content relevant for investment decision-making with statistical robustness, mitigating the noise of

Table 1. Summary of key papers in green finance and geopolitical risk.

No	Author (year), journal	Sample period & Data	Methods	Findings
1	Madaleno et al. (2022); Energy Economics	Daily data Jul 2014 – Oct 2021. Clean energy, green bond, ESG and renewable energy indices.	Time-varying Granger Causality	Significant bidirectional and unidirectional causalities among the variables, with variations in strength during COVID-19.
2	Hammoudeh et al. (2020); Energy Economics	Daily data Jul 2014 – Feb 2020. Green bonds, treasury bonds, clean energy indices, and CO2 emission allowances prices.	Time-varying Granger Causality	Significant causality from US Treasury bonds to green bonds post-2016, CO2 allowances to green bonds until 2015, and clean energy indices to green bonds briefly in 2019.
3	Lee et al. (2021); North American Journal of Econ and Finance	Monthly data Dec 2013 – Jan 2019. Crude oil prices, green bond and Caldara-Iacoviello (2022) geopolitical risk (GPR) indices.	Granger-causality in quantiles	Geopolitical risk significantly influences oil prices at extreme quantiles. In bearish market conditions (lower quantiles), there is a bidirectional causality between oil prices and green bond dynamics.
4	Lorente et al. (2023); Renewable Energy	Daily data Jun 2012 – Jun 2022. Clean ocean, green bond, clean energy, GPR and Cambridge bitcoin consumption indices.	QVAR and wavelet coherence	Geopolitical risk (GPR) is a net transmitter of shocks to climate change indices and renewable energy markets during high-stress periods.
5	Zhang et al. (2023); Journal of Env Mgt	Daily data Mar 2012 – Feb 2022. Green bond, clean, renewable energy and GPR indices.	Time-varying Granger Causality	Geopolitical risk has a more prolonged impact on the volatility of green bonds and renewable energy than their returns.
6	Li et al. (2023), International Review of Financial Analysis	Monthly data Apr 2014 – Mar 2022. Carbon prices in Hubei and Guangdong, China green bond and China Economic Policy Uncertainty indices.	Time-varying parameter Vector Autoregressive model	EPU positively influences carbon prices in the short term, while green bonds negatively impact carbon prices in the short term. Hubei carbon prices are more sensitive to green bond impacts than Guangdong.
7	Naeem et al. (2022); Journal of Env Management	Daily data Dec 2008 – Dec 2020. Green bond, world stocks, energy, precious metals and agriculture indices.	Quantile-connectedness approach and GARCH	Green bonds show higher risk spillovers with bonds during high volatility, offering diversification with energy and agriculture. COVID-19 heightened the connectedness.
8	Reboredo (2018); Energy Economics	Daily data Oct 2014 – Aug 2017. Green, corporate, treasury bonds, world stocks and energy commodities indices.	Static and dynamic copula	Green bonds co-move strongly with corporate and treasury bonds but weakly with stocks and energy commodities.
9	Reboredo and Ugolini (2020); Econ Modelling	Daily data (2014–2019). Green bonds, treasury, corporate bonds, world stocks and energy indices.	SVAR heteroskedasticity identification	Green bonds show strong price connectedness with treasury bonds and currencies but have limited integration with stocks, high-yield bonds, and energy commodities.

(*Continued*)

Table 1. Continued.

No	Author (year), journal	Sample period & Data	Methods	Findings
10	Caldara and Iacoviello (2022); American Economic Review	25 million news articles (1900–2020) from US, UK, and Canadian newspapers; firm-level data from earnings calls; historical GDP and macroeconomic indicators.	Text-based algorithm using specific keywords to construct GPR indices; VAR models	The GPR index spikes during historical events (e.g. WWI, WWII, 9/11). Higher GPR correlates with reduced investment, employment, GDP growth and increased economic disaster risks. Firm-level exposure to geopolitical risks shows adverse investment patterns.

Note: This table summarises the key papers in green finance and geopolitical risks.

higher frequencies while remaining responsive to market shocks that unfold over weeks rather than months.

3.1. Rationale for index selection and economic linkages

The index selection enables a comprehensive examination of the theoretical links among sustainable finance, risk perceptions, and market outcomes. For investment professionals, these indices are essential components of modern portfolios and risk models. Understanding their causal relations is crucial for hedging strategies, dynamic asset allocation, and assessing the diversification benefits or compounded risks of sustainable assets during periods of geopolitical stress.

The indices fall into three conceptual groups. The first group contains the two core variables of interest. Green finance is represented by the Solactive Green Bond Index (SOLG). It is the primary measure for sustainable debt markets, reflecting capital flows dedicated to environmental projects. We analyse its sensitivity to risk factors and its influence on other asset classes. Geopolitical risk is measured by the Caldara and Iacoviello (2022) index (GPR). It quantifies market perceptions of political tensions and conflicts, serving as the key measure of an external shock that could disrupt all other financial variables under study.

The second group comprises key transmission channels and linked markets. These indices are direct targets of green finance or are theorised to be acutely sensitive to geopolitical and environmental shifts. The S&P Global Clean Energy Index (SPCE) and the S&P/TSX Renewable Energy and Clean Technology Index (SPRE) represent the primary destination for much green bond proceeds. Their performance is directly linked to climate policy and energy security concerns, making them potential carriers of both green financial momentum and geopolitical shocks. The price of EU carbon permits (CO_2) reflects climate policy stringency and industrial activity. It is a fundamental variable in environmental economics, connecting to energy costs, corporate profitability, and the valuation of green investments. BEC is a novel proxy that captures the environmental effects of a major digital asset. It is included to test a growing proposition: that the ESG footprint of cryptocurrencies influences investor allocations towards green assets and may itself become a source of geopolitical tension over energy resources.

The third group consists of broad market benchmarks and sentiment indicators. These indices provide context for overall market conditions, allowing us to determine whether the core relationships are specific to green themes or affect the broader financial system. The MSCI World Index (MSCI) represents the global equity market. Examining causality between this benchmark and green finance and GPR reveals whether these factors have systemic effects on mainstream investment portfolios. The CBOE Volatility Index (VIX), often called the 'fear gauge,' measures overall market risk sentiment. Establishing a link between GPR and green finance is critical for risk management, as it indicates whether these factors drive overall market uncertainty. West Texas Intermediate crude oil (WTI) is a traditional benchmark for energy costs, inflation, and geopolitical strife in commodity markets. It serves as a control and a point of comparison to assess if green financial indices behave differently from conventional energy assets. Finally, the Euronext Core Euro & Global Climate Change Equal Weight Index (EUCC) tracks firms providing climate solutions. It complements the clean energy indices by broadening the scope of 'green' performance and testing the consistency of results across related but distinct thematic investment categories.

3.2. Data sources and variable definitions

To examine the time-varying causality relations between green finance and geopolitical risk, we considered two green bond indices as proxies for green finance: the Solactive Green Bond Index (SOLG) and the S&P Green Bond Index (SPGB). We selected the SOLG because it covers a longer period from January 2012, whereas the SPGB is available only from December 2014. SOLG is a rules-based, market value-weighted index that systematically captures the global green bond market. The index includes bonds considered 'green' by the Climate Bonds Initiative, meaning proceeds from the portfolio are invested in projects with a positive environmental impact. Accordingly, SOLG is an effective benchmark for investors seeking systematic exposure to the green bond market, and structured products such as exchange-traded funds regularly use it to help investors direct capital towards green projects.

The GPR index is constructed using an automated text-search algorithm on digitised archives of ten mainstream newspapers. The algorithm counts the number of articles that include words associated with geopolitical risk, such as 'war,' 'terrorism,' and 'military tensions.' It then normalises this count against the total number of articles to produce an index score that measures the relative proportion of geopolitical risk-related news. For BEC, we use the Digiconomist's Bitcoin Energy Consumption Index, which employs an economic model to calculate the weekly energy consumption related to the proof-of-work consensus mechanism of bitcoin. This estimate is based on mining revenue data, with a proportion of this assumed to be spent on electricity costs according to average mining profit margins. As a proxy for the European Union Allowance contracts under the EU Emission Trading Scheme, the Solactive Carbon Emission Allowances Rolling Futures Index is used to represent carbon emission allowances. The effect of rollover is reduced by systematic rolling of the futures contracts, which also limits the potential for market disturbance.

The SPCE follows the performance of global companies that produce clean energy and develop clean energy technologies and equipment. SPRE tracks companies concurrently

Table 2. Description of variables and proxies.

No	Variable	Description of Proxy	Source (Ticker)
1	Green bond index	Solactive green bond index as a proxy for green finance; SOLG	Refinitiv (SOLGREEN)
2	Geopolitical risk index	GPR index by Caldara and Iacoviello (2022); GPR	https://www.matteoiacoviello.com/gpr.htm
3	Bitcoin's annual electricity consumption	Digiconomist's bitcoin energy consumption index; BEC	https://digiconomist.net/bitcoin-energy-consumption
4	Carbon emission allowances	Solactive carbon emission allowances rolling futures index; CO2	Refinitiv (SOLCARBF)
5	Clean energy index	S&P Global clean energy index; SPCE	Refinitiv (SPGTCL)
6	Renewable energy index	S&P/TSX renewable energy and clean technology index; SPRE	Refinitiv (GSPTXCT)
7	World equity markets	MSCI international world price index; MSCI	Refinitiv (MIWO00000PUS)
8	Climate change index	Euronext core euro & global climate change EW index; EUCC	Refinitiv (ECC5P)
9	Volatility or fear index	The CBOE volatility index; VIX	Refinitiv (VIX)
10	Oil price	NYMEX light sweet crude oil (WTI) front-month futures; WTI	Refinitiv (CLc1)

Note: This table describes the variables, sources and tickers of proxies used in the study.

listed in Canada and the United States that are active in the renewable energy and clean technology sectors. The MSCI World Price Index measures the performance of major and mid-cap corporates in 23 developed regions across the world. The EUCC index tracks the performance of companies actively tackling challenges related to climate. The VIX estimates the implied volatility of the S&P 500 Index and is commonly used as an indicator of investor sentiment, with high values indicating increased investor anxiety or uncertainty and low values indicating increased confidence. Finally, WTI front-month futures serve as a proxy for the oil price, as WTI is considered the benchmark for oil prices in the US market.

Table 2 lists the sources and tickers of all indices used in the study. Most data come from Refinitiv, while the GPR and BEC indices data come from Matteo Iacoviello's website and the Digiconomist website, respectively.

3.3. Data collection and preprocessing

Our dataset includes 12 years of weekly closing prices for the ten indices, covering the period from 6 January 2012 to 20 December 2024, except for BEC, which begins later on 10 February 2017. Weekly closing prices (Friday closes) were collected for all series. If Friday data were missing, the last available weekly closing price was used.

The following preprocessing steps were applied to ensure consistency and stationarity. First, logarithmic returns were computed as $R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t is the weekly closing price. Second, no winsorisation or truncation was applied, as extreme values reflect genuine market events such as the COVID-19 pandemic and major geopolitical shocks. Third, unit root tests (Augmented Dickey-Fuller and Elliott-Rothenberg-Stock DF-GLS) were conducted on both levels and first differences. The results, presented in Table 4, guided the use of first-differenced series where necessary, ensuring compatibility within the lag-augmented VAR framework. Finally, all series were aligned to a common weekly timeline, with BEC introduced in February 2017, resulting in an unbalanced panel for certain pairwise tests.

3.4. Descriptive statistics

Table 3 shows the descriptive statistics of the weekly logarithmic returns and the correlation matrix. Of the 10 indices/assets, the GPR appears to be the most volatile, with a standard deviation of 45.29, followed by the VIX, which has a standard deviation of 15.29. The GPR also recorded the highest weekly gain of 132.31% and the most significant weekly loss of −139.40. The high volatility and extreme returns observed for the GPR index reflect its construction from news-flow data, where discrete geopolitical events can lead to very large week-on-week percentage changes in the index value. These observations represent genuine shocks to the perceived risk environment and are included in the analysis. The Jarque-Bera test indicates that none of the index series are normally distributed, except for the GPR. In contrast, the green financial index SOLG is the most stable index with the lowest standard deviation of 1.02 and shows a weekly gain of 4.10% and a loss of −5.56%. In terms of correlations, the MSCI has the highest correlation of 0.839 with the EUCC and the lowest correlation of −0.709 with the VIX.

Figure 1 shows that almost all indices exhibited a sharp V pattern at the outbreak of the COVID-19 pandemic in early 2020, except for GPR and VIX. As a fear index, the VIX rose sharply during the pandemic. Three indices, namely MSCI, EUCC and BEC, show an upward trend, while SPCE, SPRE and CO2 show a downward trend from December 2024. Figure 2 illustrates the behaviour of the weekly returns of all indices studied. In line with the standard deviation in Table 1, the GPR is the index with the highest dispersion, followed by the VIX. In contrast, the green financial index SOLG is the most stable, as evidenced by the lowest dispersion.

4. Methods

The recursive evolving TVGC approach (Shi et al., 2020) is chosen for its specific advantages in our research context. Static Granger causality tests would obscure the dynamic nature of the relationships we hypothesise, particularly around crises. Correlation-based measures indicate association but cannot inform on direction or causality. Although multivariate network analyses (e.g. dynamic connectedness) are valuable for a system-wide perspective, our primary research question focuses on establishing time-sensitive, directional causality between specific variable pairs, such as from bitcoin energy use to green finance, which is the strength of the TVGC framework. It directly tests for periods in which one variable contains unique predictive information about another, allowing us to map the evolution of lead-lag relationships during turbulent market periods (Mohamad, 2025c; Mohamad & Fromentin, 2023).[1]

4.1. Time-varying Granger causality (TVGC): rationale and technique

The temporal stability associated with Granger causality can be evaluated using a stationary vector autoregressive (VAR) model or a lag-augmented VAR (LA-VAR) model. Generally, three time-varying methods are used to identify instability in causal relationships: recursive evolving, rolling, and forward expanding. Standard Granger causality assumes parameter constancy over the full sample, an assumption often violated during periods of

Table 3. Descriptive statistics.

	SOLG	GPR	CO2	BEC	SPCE	SPRE	MSCI	EUCC	VIX	WTI
Mean	0.001	−0.163	0.593	0.710	0.115	−0.064	0.175	0.111	0.128	0.062
Median	0.011	1.006	0.562	0.961	0.249	−0.025	0.350	0.220	−1.014	0.526
Max	4.10	132.31	19.28	12.48	16.61	11.30	10.42	10.93	85.37	27.58
Min	−5.56	−139.40	−30.89	−45.71	−24.65	−17.17	−13.30	−20.79	−49.53	−34.69
Stdev	1.02	45.29	6.22	4.46	3.98	3.01	2.36	2.52	15.29	5.86
Skewness	−0.34	0.09	−0.40	−5.20	−0.34	−0.50	−0.86	−1.54	0.71	−0.52
Kurtosis	7.27	2.83	5.63	47.56	7.69	7.44	10.11	17.09	6.21	9.07
Jarque – Bera	319***	1.05	129***	35.6k***	384***	354***	913***	3550***	210***	647***
# Obs	676	676	676	410	676	676	676	676	676	676
Correlation matrix										
SOLG	1									
GPR	−0.019	1								
CO2	0.140	0.032	1							
BEC	0.131	−0.032	0.119	1						
SPCE	0.467	0.005	0.225	0.103	1					
SPRE	0.396	0.019	0.195	0.138	0.777	1				
MSCI	0.533	−0.005	0.272	0.145	0.680	0.665	1			
EUCC	0.375	0.002	0.248	0.164	0.666	0.623	0.839	1		
VIX	−0.160	−0.016	−0.172	−0.039	−0.448	−0.471	−0.709	−0.621	1	
WTI	0.069	0.047	0.147	0.038	0.254	0.215	0.314	0.206	−0.273	1

Note: This table shows the descriptive statistics for weekly returns for all assets studied from January 2012 to December 2024, except for BEC, which started in February 2017. Mean, median, max and min are quoted in percentage returns. Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

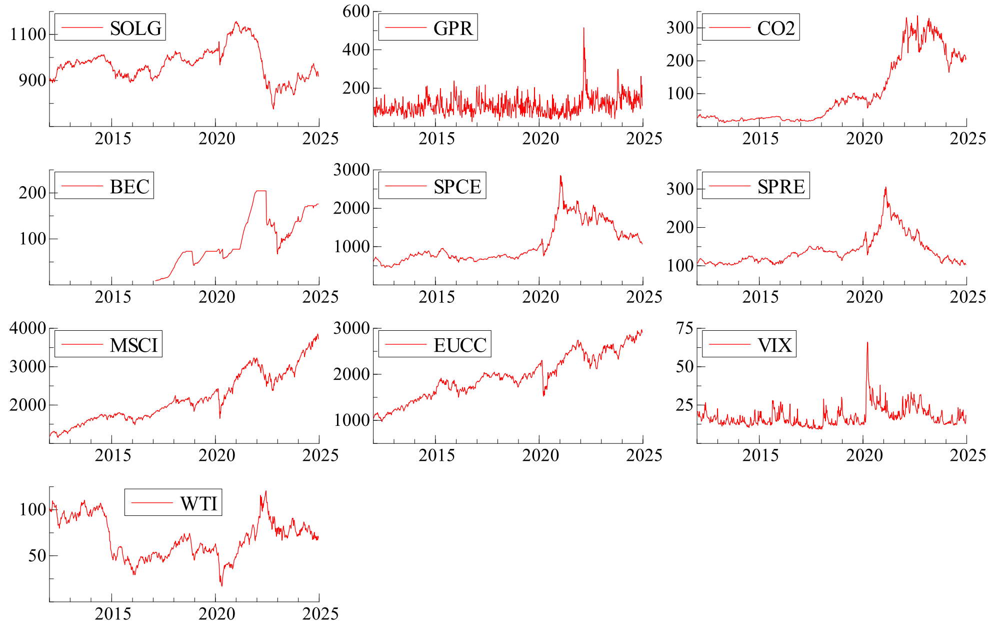

Figure 1. Time evolution of weekly closing prices.

Note: This figure shows the time evolution of the weekly closing prices of all assets/indices studied from January 2012 through December 2024. Only BEC starts in February 2017.

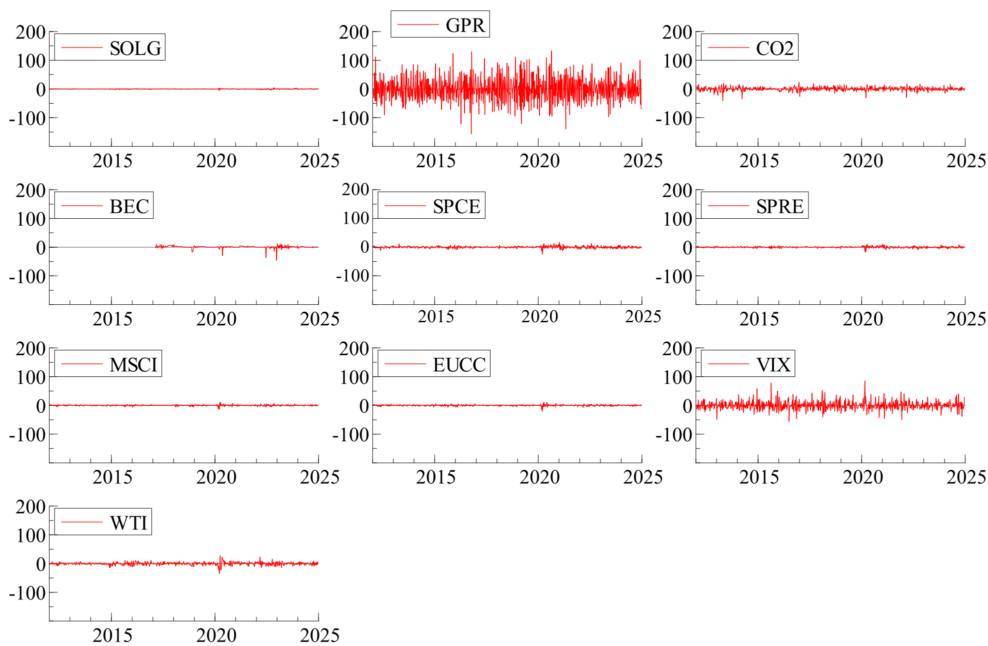

Figure 2. Behaviour of weekly returns.

Note: This figure shows the behaviour of the weekly percentage returns (*Y*-axis) of all assets/indices studied from January 2012 through December 2024. Only BEC starts in February 2017.

financial stress or structural change. To capture evolving relationships, such as how geopolitical risk's influence on green finance might intensify during a war, we employ the recursive evolving approach to TVGC (Shi et al., 2020). This method is preferred over rolling or expanding windows because it is particularly effective at detecting the onset and collapse of causal relationships.

Intuitive economic interpretation of recursive evolving approach; imagine an analyst testing each week whether a new causal link has emerged. The RE method does this by continuously re-estimating the causality test statistic, starting from all possible start points within the sample and ending at the current period. It then identifies the specific point in time where evidence for a causal relationship first becomes statistically significant (the origination date) and, if applicable, when it later ceases to be significant (the termination date). This method allows us to pinpoint when, within our 12-year sample, one variable began to predict the other.

4.2. Model specification and foundation

The investigation of dynamic causal relationships is grounded in a bivariate Vector Autoregressive (VAR) framework. For two stationary time series,y_{1t} and y_{2t} the model is specified as:

$$y_{1t} = \phi_{10} + \sum_{k=1}^{m} \phi_{11}^{(k)} y_{1,t-k} + \sum_{k=1}^{m} \phi_{12}^{(k)} y_{2,t-k} + \epsilon_{1t} \tag{1}$$

$$y_{2t} = \phi_{20} + \sum_{k=1}^{m} \phi_{21}^{(k)} y_{1,t-k} + \sum_{k=1}^{m} \phi_{22}^{(k)} y_{2,t-k} + \epsilon_{2t} \tag{2}$$

where m is the lag order, ϕ are parameters to be estimated, and εt are error terms. Within this system, y_{1t} is said to Granger-cause y_{2t} if the past values of y_{1t} (coefficients $\phi_{21}^{(k)}$) provide statistically significant information for forecasting y_{2t}, over and above the information contained in the past values of y_{2t} itself. This translates to testing the joint null hypothesis $H_0{:}\phi_{21}^{(1)} = \phi_{21}^{(2)} = \ldots = \phi_{21}^{(m)} = 0$.

4.3. Estimation details and key assumptions

The implementation follows these steps:

(1) Following Toda and Yamamoto (1995), we estimate a VAR in levels with $p = m + d_{\max}$ lags, where m is the optimal lag length for the VAR (selected by AIC) and $d_{\max} = 1$ is the maximum order of integration identified in Table 4. This procedure safeguards against spurious inference from potential cointegration.
(2) For each possible sub-sample defined by a start fraction f_1 and end fraction f_2 of the total sample, a Wald statistic is computed to test the Granger non-causality null hypothesis.
(3) The test statistic for a given end-point f is the supremum (maximum) value of the Wald statistic over all permissible start points f_1.

(4) The sequence of supremum statistics is compared to bootstrapped critical values (499 replications). A causal episode is identified when the supremum statistic exceeds the 95% critical value. Its start $(\widehat{f}_e)$ is the first time the statistic crosses this threshold, and its end $(\hat{f}_f)$. is when it falls back below.
(5) For the recursive evolving TVGC tests, we follow the standard implementation from Shi et al. (2020). The minimum window size fraction f_0 is set to 0.20 (i.e. 20% of the sample). This choice of f_0 determines the smallest subsample used for the initial VAR estimation. For our weekly dataset of approximately 676 observations, this corresponds to an initial window of about 135 weeks (2.6 years). This is a conservative, common choice in the TVGC literature (Baum et al., 2025; Shi et al., 2020) that ensures sufficient degrees of freedom for reliable initial estimation while allowing the recursive algorithm ample scope to detect causal changes in the remaining 80% of the timeline. The supremum Wald statistic $SWf\ (f_0)$ is computed by varying the start fraction f_1 from 0 to $\mathrm{f} - f_0$ and the end fraction $f_2\ = f$ across the interval $[f_0{,}1]$. This procedure creates a dense grid over which the potential causality is evaluated at each point in time.
(6) All estimations were performed using the TVGC Stata module (Otero et al., 2022), publicly available from the Statistical Software Components (SSC) archive via the IDEAS/RePEc repository: https://ideas.repec.org/c/boc/bocode/s458916.html.

The primary assumption is that the parameters of the underlying data-generating process are locally constant within the flexible windows used for estimation, but are allowed to change over time. The method is non-parametric with respect to the nature of the parameter change.

4.4. Robustness check: Rolling window TVGC estimation

To ensure the robustness of our primary findings based on the recursive evolving window approach (Baum et al., 2025; Otero et al., 2022), we supplement our analysis with a rolling window estimate. While Shi et al. (2020) focus on the recursive evolving algorithm, they note that rolling windows remain a standard method for detecting time-varying causality, particularly useful for identifying localised, transient relationships.

We implement the rolling window approach as follows:

(1) A fixed window length is chosen. To balance sufficient observations for reliable estimation with sensitivity to parameter changes in our weekly data, we use a 104-week (2-year) window. This length ensures robustness against short-term noise while capturing medium-term dynamics.
(2) For each time point t, the Granger causality Wald statistic is calculated using data from $t{-}L + 1$ to t, where $L = 104$.
(3) The window rolls forward one period at a time, generating a time series of test statistics.
(4) Significance is assessed against bootstrapped critical values specific to the rolling window design.

5. Empirical results and discussion

5.1. Empirical results

Before estimating an appropriate VAR model within the LA-VAR framework, we need to establish the order of integration of each asset series. This approach is essential to recognise the presence of TVGC. The following analyses, which include the entire sample and the tests for time-varying causality, are carefully performed following the procedures (Otero et al., 2022). Table 4 shows the results of the unit root tests based on weekly returns. ADF and ERS-DF-GLS indicate that GPR, VIX and EUCC are stationary at the levels, but the other eight variables are stationary in the first difference. As Shi et al. (2020) note, the LA-VAR framework does not require pre-filtering (such as detrending or differencing) but requires information on *d*max. By taking the first difference, both ADF and ERS-DF-GLS show that all series are stationary. By identifying *d*max = 1, we conclude that the maximum integration order of the variables is I(1), ensuring that the model accounts for non-stationarity and avoids spurious results.

All estimations are performed on stationary series. Following the results of the unit root tests (Table 4), the VAR models are specified using the weekly logarithmic return series for all variables. For the series identified as I(1), this is equivalent to using their first differences; for the I(0) series, the return series is used directly.

5.2. Does green finance Granger-cause other indices (recursive evolving estimation)?

The TVGC results are presented in Figure 3, and a table of *t*-statistics and critical values of the Wald test using recursive evolving estimation is shown in Table 5 (left panel). A

Table 4. Unit root test.

	Levels		First-difference		
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	Conclusion
ADF test					
SOLG	−1.62	−1.64	−24.98***	−24.99***	I(1)
GPR	−9.82***	−10.41***	−16.88***	−16.87***	I(0)
CO2	−0.79	−2.4	−25.77***	−25.76***	I(1)
BEC	−1.21	−1.78	−15.92***	−16.13***	I(1)
SPCE	−1.66	−1.99	−16.06***	−16.06***	I(1)
SPRE	−1.7	−1.47	−16.55***	−16.59***	I(1)
MSCI	−0.09	−2.44	−26.85***	−26.83***	I(1)
EUCC	−1.19	−4.05***	−26.57***	−26.55***	I(0)
VIX	−6.59***	−6.87***	−21.88***	−21.87***	I(0)
WTI	−2.2	−2.12	−22.93***	−22.92***	I(1)
ERS-DF-GLS test					
SOLG	−1.17	−1.29	−5.02***	−11.66***	I(1)
GPR	−9.61***	−10.25***	−17.08***	−3.15**	I(0)
CO2	−0.1	−1.89	−2.43**	−6.96***	I(1)
BEC	0.53	−1.72	−3.75***	−13.95***	I(1)
SPCE	−1.12	−2.03	−1.77*	−4.1***	I(1)
SPRE	−1.37	−1.61	−16.37***	−16.58***	I(1)
MSCI	1.6	−2.45	−25.19***	−25.93***	I(1)
EUCC	0.72	−3.83***	−4.15***	−24.47***	I(0)
VIX	−5.94***	−6.17***	−30.17***	−29.04***	I(0)
WTI	−0.99	−1.62	−6.1***	−21.84***	I(1)

Note: These unit root test results are based on the Augmented Dickey-Fuller (ADF) and Elliott-Rothenberg-Stock, Dickey-Fuller generalised least squares (ERS-DF-GLS) tests. Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively. *d*max = 1 means the maximum integration order of all variables is 1.

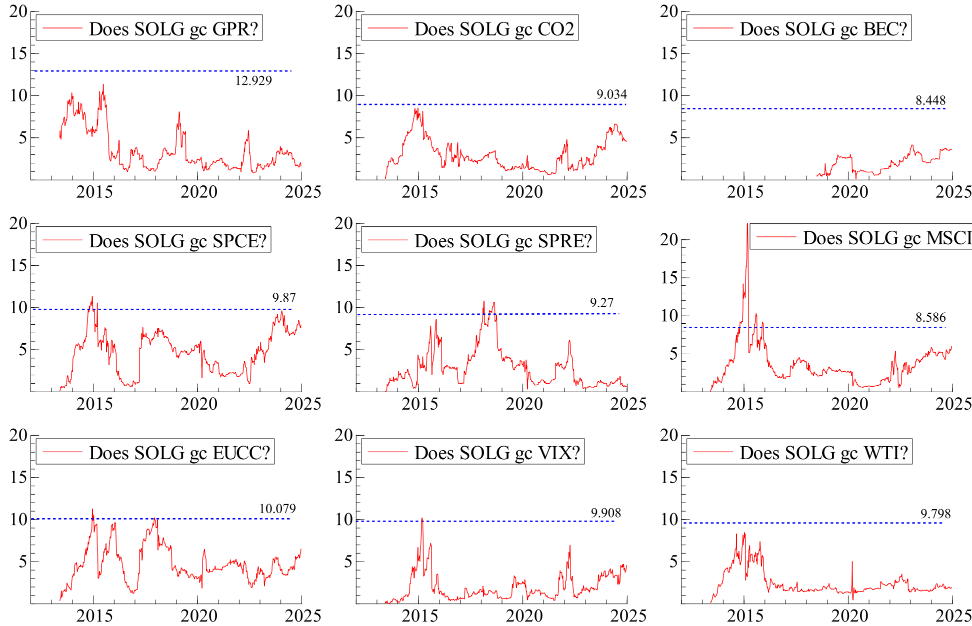

Figure 3. TVGC results – Does green finance (SOLG) Granger-cause (gc) other assets?

Note: This figure shows the Wald test *t*-statistics (*Y*-axis) and critical values of the time-varying Granger causality (TVGC) tests from green finance (SOLG) to other assets based on recursive evolving estimation. The horizontal blue dotted lines and the figure above the dotted lines mark the 95th percentile bootstrapped critical values (5% significance) based on 499 replications.

significant finding is related to whether green finance has a Granger effect on all nine indices/assets that have been analysed. Green finance appears to exhibit Granger causality with the MSCI between 2015 and 2016, as indicated by SOLG. Table 5 (6a) reveals that the critical value of the 95th percentile was 8.586, compared to the *t*-statistic of 22.146, which was much higher than the critical value of the 99th percentile. One can have several interpretations of this outcome. The green bond market in 2015 recorded significant growth, and that year turned out to be the most favourable for green bonds, with issuance totalling a record $ 41.8 billion.[2] The growth was marked by a large variety of issuers, including the emerging markets like India and China, thus leading to global proliferation of the green bonds. At the same time, the MSCI World Index (a benchmark for large and mid-cap equities across 23 industrialised countries) did well in 2015, delivering a return of 19.55%.[3] The empirical relationship found between TVGC, defined as the correlation between green financing (measured as green-bond issuance) and the MSCI World Index volatility, implies that the growth of the green-bond market could have had an impact on global equity markets.

This correlation can be explained in several ways. Firstly, an increase in green-bond issuance can be seen as a sign of a renewed commitment to sustainable initiatives, which will increase investor confidence and have a positive impact on equity markets. Secondly, the proceeds from green bonds are often allocated towards environmentally friendly projects, which can bolster sustainability-focused sectors within the equity market and thus improve index performance. Thirdly, mainstreaming of environmental,

Table 5. TVGC recursive evolving estimation result between SOLG and other assets.

1a) Does SOLG Granger-cause GPR?			1b) Does GPR Granger-cause SOLG?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
11.385			8.725		
	90th	10.592		90th	7.019
	95th	12.929		95th	8.724
	99th	19.595		99th	12.882
2a) Does SOLG Granger-cause CO2?			**2b) Does CO2 Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.542			10.397		
	90th	7.031		90th	6.911
	95th	9.034		95th	8.741
	99th	14.351		99th	12.644
3a) Does SOLG Granger-cause BEC?			**3b) Does BEC Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
4.155			50.857		
	90th	6.838		90th	7.319
	95th	8.448		95th	9.805
	99th	14.468		99th	15.003
4a) Does SOLG Granger-cause SPCE?			**4b) Does SPCE Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
11.362			11.329		
	90th	7.54		90th	7.472
	95th	9.87		95th	8.425
	99th	14.16		99th	13.36
5a) Does SOLG Granger-cause SPRE?			**5b) Does SPRE Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.802			15.609		
	90th	7.201		90th	6.536
	95th	9.27		95th	8.169
	99th	12.689		99th	13.143
6a) Does SOLG Granger-cause MSCI?			**6b) Does MSCI Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
22.146			8.023		
	90th	7.082		90th	7.494
	95th	8.586		95th	9.082
	99th	15.464		99th	13.749
7a) Does SOLG Granger-cause EUCC?			**7b) Does EUCC Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
11.290			5.949		
	90th	8.024		90th	8.519
	95th	10.079		95th	11.025
	99th	16.574		99th	16.344
8a) Does SOLG Granger-cause VIX?			**8b) Does VIX Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.211			9.797		
	90th	7.618		90th	7.491
	95th	9.908		95th	9.601
	99th	16.839		99th	13.744
9a) Does SOLG Granger-cause WTI?			**9b) Does WTI Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.479			7.700		
	90th	7.775		90th	8.166
	95th	9.798		95th	10.641
	99th	15.297		99th	15.621

Note: This table shows the Wald test *t*-statistics and critical values from time-varying Granger causality (TVGC) recursive evolving estimation tests between the Solactive green bond index (SOLG) and other assets. The critical values for the 90th, 95th, and 99th percentiles are derived from 499 replications.

social and governance (ESG) criteria into investment strategies may result in a capital reallocation towards firms with better ESG profiles, which in turn are likely to affect the performance of individual stocks and the indexes that include them. In summary, the strong increase in green-bond issuance in 2015 seems to be positively correlated with MSCI World Index performance. It hence highlights the increasing importance of sustainable finance in global capital markets. This finding is generally consistent with Tang and Zhang (2020), who documented that stock prices respond positively to green bond issuance.

Table 5 (4a, 5a, 7a, 8a) and Figure 3 all indicate that the SPCE, SPRE, EUCC, and VIX are also Granger-caused by the green finance at the 95th percentile critical value, which is equivalent to the 5 per cent level of significance. We believe SOLG Granger predominantly influenced SPRE in 2017 because the green bond market expanded significantly, with total issuance reaching a record USD 155.5 billion in 2017, a 78% increase over the previous year. The proceeds from green bonds (SOLG) are primarily used to fund renewable energy (SPRE), energy efficiency, and other environmentally friendly activities. The year 2017 saw significant policy support for green finance and renewable energy. Initiatives like China's expedited green bond issuance clearance and public sector issuers setting a positive example for the private sector were key to this growth.[4] Such policies will likely increase the issuance of green bonds and investment in renewable energy, increasing the Granger causation.

Figure 3 illustrates how SOLG Granger caused SPCE, EUCC, and VIX in 2015. We explain this by pointing out that the green bond market expanded significantly in 2015, with total issuance reaching $41.8 billion, indicating a more substantial global commitment to financing environmentally sustainable projects, particularly in the renewable energy sector, energy efficiency (SPCE), and other environmentally friendly initiatives (EUCC). The inflow of funds into clean and renewable energy projects can boost profitability and expansion for companies in the industry, positively influencing their stock performance and, as a result, the indices that track them. Furthermore, the expansion of the green bond market may have injected new dynamics into the financial system, influencing overall market volatility. The VIX, commonly referred to as the 'fear index,' forecasts future market volatility. Significant developments in the green bond market may have influenced market sentiment and the VIX. The TVGC discovered the relationship between green finance and key financial indices in 2015 and 2017, revealing the connection between sustainable finance instruments and overall market performance and volatility.

5.3. Do other indices Granger-cause green finance (recursive evolving estimation)?

Figure 4 and the right-hand side of Table 5 investigate the possibility of each of the analysed indexes or assets Granger-cause green finance (SOLG). The most glaring finding is that BEC is a significant Granger-cause of SOLG at the 1% significance level. The following reason can be used to explain this outcome. Bitcoin mining is also defined by extremely high energy demands, with estimates showing that miners use about 15.4 gigawatts of power per year (approximately 120 terawatt-hours).[5] The significant amount of carbon footprint of bitcoin mining has caused serious environmental issues, thus spurring more

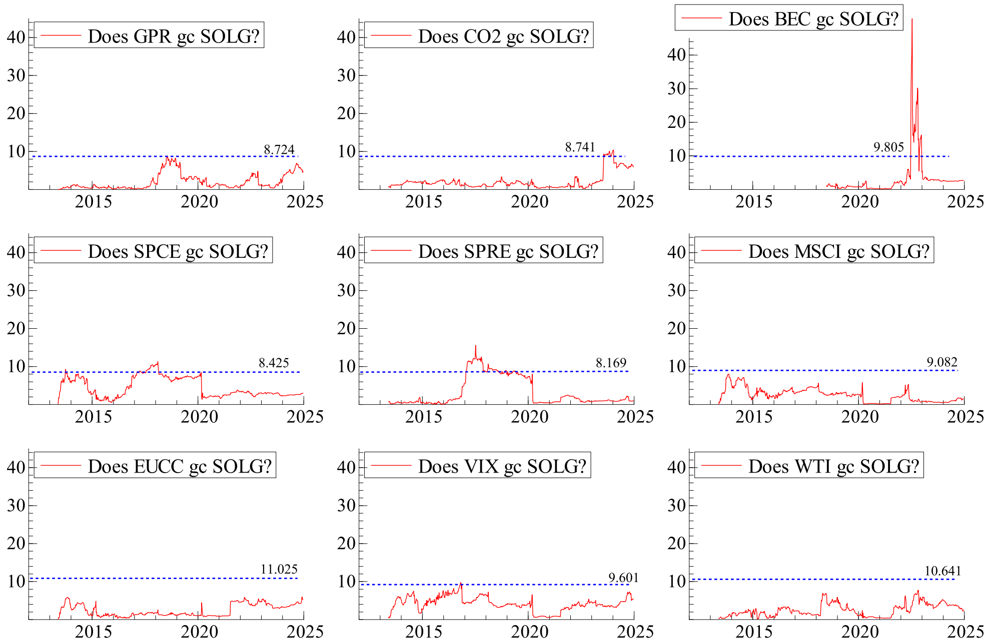

Figure 4. TVGC results – Do other assets Granger-cause (gc) green finance (SOLG)?

Note: This figure shows the Wald test *t*-statistics (*Y*-axis) and critical values of the time-varying Granger causality (TVGC) tests from other assets to green finance (SOLG) based on recursive evolving estimation. The horizontal blue dotted lines and the figure above the dotted lines mark the 95th percentile bootstrapped critical values (5% significance) based on 499 replications.

attention and questioning its sustainability in the eyes of the public. It is reasonable to assume that investors would tend to decrease the risk associated with bitcoin by shifting more capital to less risky assets (e.g. green bonds) as the environmental effects of this cryptocurrency become more apparent. This change in investor attitude could, in turn, raise the demand for and issuance of green bonds. The environmental performance of bitcoin mining has also sparked controversy regarding the regulation of energy consumption levels. Investing in green bonds for environmentally friendly projects can enjoy favourable policies, thereby encouraging more investment. The Granger relationship found between bitcoin's electricity consumption and green finance in 2022 and 2023 suggests that environmental concerns are becoming increasingly significant among investors and governments.

It is also represented in Figure 4 that SPRE and SPCE Granger-cause SOLG at 1-per cent and 5-per cent levels, respectively. There is bi-directional causality between SOLG, SPRE and SPCE. The next part describes the mutual relationship between green finance, renewable energy, and clean energy. Green bonds provide renewable and clean energy projects with specialised finance, totalling $41.8 billion in 2015. The capital inflow enables firms in such industries to expand their operations, invest in new technologies, and enhance their financial performance, which can impact the valuation of their stock and, in turn, the indices that track them. With the growth and profitability of renewable and clean energy companies, investor confidence in these sectors increases. This trust can drive demand for green bonds higher, leading to further growth in the industry, which will form a vicious circle between green bond issuance and energy indices. Indicatively, results have been found that examine the causation between green markets and economic policy uncertainty, revealing time-varying bidirectional causality between the two variables, which highlights the dynamic interaction between them (Wang et al., 2022).

5.4. Does geopolitical risk Granger-cause other indices (recursive evolving estimation)?

Moving on, Figure 5 depicts the TVGC results, while Table 6 (left panel) displays the corresponding Wald test *t*-statistics and critical values based on recursive evolving estimation – does geopolitical risk (GPR) Granger-cause each of the nine indices/assets examined? Two results stand out. GPR Granger caused both VIX and MSCI starting in mid-2023, with *t*-statistics of 19.852 and 17.322, respectively, at a 1% significance level. Furthermore, GPR appears to Granger-cause SPCE, SPRE, and EUCC at a 5% significance level. The geopolitical developments have been specific since the middle of 2023. For example, the Russia-Ukraine conflict, which started in February 2022 and carried on into 2023, has caused significant regional instability and global economic ripple effects. The conflict has been marked by widespread human distress and geopolitical conflict. Second, China heightened its military presence and activities in Taiwan, including massive exercises to intimidate Taipei and show off its capabilities in April 2023. In response, the Presidential Office of the Republic of Taiwan conducted the

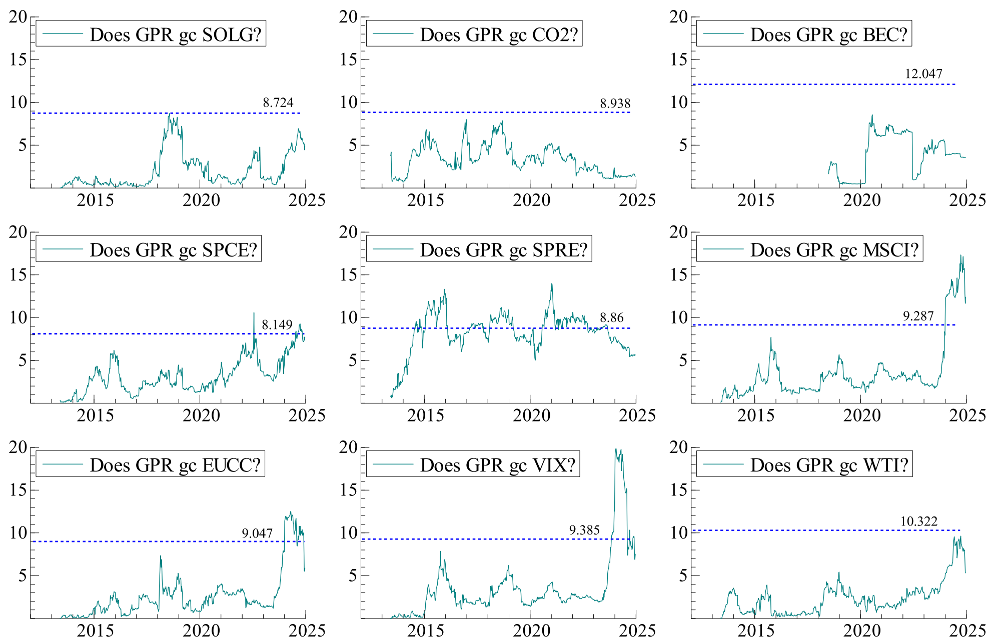

Figure 5. TVGC results – Does geopolitical risk (GPR) Granger-cause (gc) other assets?

Note: This figure shows the Wald test *t*-statistics (*Y*-axis) and critical values of the time-varying Granger causality (TVGC) tests from geopolitical risk (GPR) to other assets based on recursive evolving estimation. The horizontal blue dotted lines and the figure above the dotted lines mark the 95th percentile bootstrapped critical values (5% significance) based on 499 replications.

Table 6. TVGC recursive evolving estimation result between GPR and other assets.

1a) Does GPR Granger-cause SOLG?			1b) Does SOLG Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.725			11.385		
	90th	7.019		90th	10.592
	95th	8.724		95th	12.929
	99th	12.882		99th	19.595
2a) Does GPR Granger-cause CO2?			2b) Does CO2 Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.025			7.493		
	90th	7.357		90th	6.512
	95th	8.938		95th	8.332
	99th	13.574		99th	12.069
3a) Does GPR Granger-cause BEC?			3b) Does BEC Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.568			24.076		
	90th	8.81		90th	7.493
	95th	12.047		95th	10.063
	99th	17.497		99th	14.63
4a) Does GPR Granger-cause SPCE?			4b) Does SPCE Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.608			12.383		
	90th	6.577		90th	8.428
	95th	8.149		95th	10.572
	99th	13.32		99th	17.673
5a) Does GPR Granger-cause SPRE?			5b) Does SPRE Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
13.994			11.385		
	90th	7.215		90th	10.379
	95th	8.86		95th	12.688
	99th	14.452		99th	20.059
6a) Does GPR Granger-cause MSCI?			6b) Does MSCI Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
17.332			7.198		
	90th	7.499		90th	8.844
	95th	9.287		95th	11.318
	99th	15.295		99th	15.658
7a) Does GPR Granger-cause EUCC?			7b) Does EUCC Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
12.548			9.299		
	90th	7.366		90th	7.644
	95th	9.047		95th	9.826
	99th	13.257		99th	16.023
8a) Does GPR Granger-cause VIX?			8b) Does VIX Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
19.852			12.882		
	90th	7.193		90th	7.694
	95th	9.385		95th	9.145
	99th	13.989		99th	13.489
9a) Does GPR Granger-cause WTI?			9b) Does WTI Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
9.639			5.519		
	90th	8.035		90th	9.096
	95th	10.322		95th	11.041
	99th	14.48		99th	14.544

Note: This table shows the Wald test *t*-statistics and critical values from time-varying Granger causality (TVGC) recursive evolving estimation tests between the geopolitical risk index (GPR) and other assets. The critical values for the 90th, 95th, and 99th percentiles are derived from 499 replications.

first war games involving an emergency for China, illustrating the island's worries of possible confrontation with China. Third, in October 2023, Hamas attacked Israel, leading to a military response and extensive destruction in Gaza, including over 44,000 casualties. However, there were geopolitical developments that led to volatility and panic, and the GPR probably played a role in the VIX. In addition to Granger causality, the GPR may have caused the MSCI world equities market to suffer short-term volatility, but in the long term, it may continue to move higher as long as economic fundamentals remain strong. The influence of the TVGC from GPR to SPCE, SPRE and EUCC illustrates the interdependence of global politics with the renewable energy sector. Geopolitical tensions can directly influence the operations of renewable energy markets. Nations can invest more in renewable energy to make their energy security more secure due to geopolitical threats. For instance, the crisis in Ukraine has led Europe to reduce its dependence on fossil resources from Russia and invest in renewable energy.

5.5. Do other indices Granger-cause geopolitical risk (recursive evolving estimation)?

Next, Figure 6 and the right-hand panel of Table 6 answer the question, 'Do other indices/assets Granger-cause GPR? The findings indicate that BEC Granger causes GPR with a 1% level of significance (*t*-statistic = 24.076). Also, SPCE Granger-caused GPR with 5% confidence, which means that there is a cause-and-effect relationship between the variables GPR and SPCE. This realisation implies that geopolitical risks have a bearing on the clean-energy business, and that successful clean-energy business in turn influences geopolitics. Indeed, the high growth rate of renewable-energy technology, particularly in China, has changed the energy landscape of the world. The geopolitical relations and trade policy are influenced mainly by the fact that China has invested heavily in clean and renewable energy infrastructure, making it a leader in green technology. In addition, the US, Europe and China have intensified their overseas efforts to garner green-energy subsidies, and they are each vying for supremacy in the clean-energy industry. The outcome of this competition was competition and protection in the form of the Net-Zero Industry Act of the European Union and the Inflation Reduction Act of the United States; both acts have some implications for international trade relations and geopolitical strategies. Geopolitical risk typically affects clean-energy policies and investments, but new technologies and decisions in the clean-energy sector will change the world.

Correspondingly, the strong correlation between GPR and BEC indicates that geopolitical tensions can be forecasted through bitcoin energy consumption. Mining bitcoins is extremely electricity-intensive, and in many cases, more so than in some countries. This enormous demand can not only test the local and national electricity grid to its capacity, particularly in regions with poor energy infrastructure, but also lead to shortages and blackouts. These upheavals may fuel geopolitical tensions or serve as catalysts for new conflicts, particularly in energy-sensitive regions. Additionally, the carbon footprint of bitcoin mining, particularly when fuels derived from fossil sources are used, significantly contributes to global environmental challenges. This environmental influence may have an impact on international relations because governments argue about responsibilities

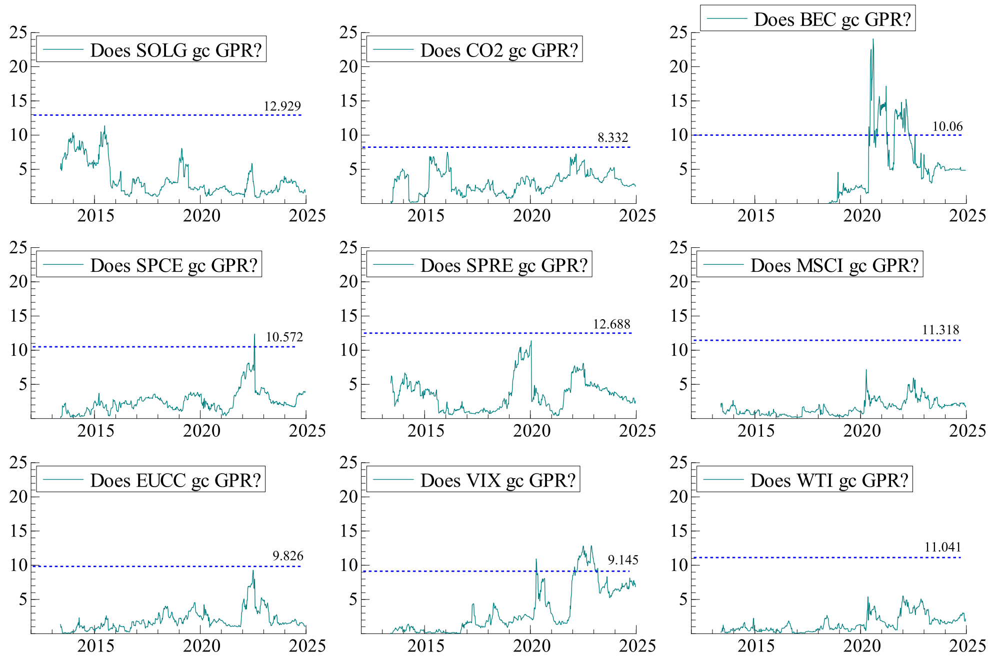

Figure 6. TVGC results – Do other assets Granger-cause (gc) geopolitical risk (GPR)?

Note: This figure shows the Wald test *t*-statistics (*Y*-axis) and critical values of the time-varying Granger causality (TVGC) tests from other assets to geopolitical risk (GPR) based on recursive evolving estimation. The horizontal blue dotted lines and the figure above the dotted lines mark the 95th percentile bootstrapped critical values (5% significance) based on 499 replications.

and policies to counter climate change, which can lead to geopolitical tension. Altogether, the more intensive the process of bitcoin mining becomes, the stronger its influence on global conflicts becomes.

These results shed light on the connection between green finance and geopolitical risks, as well as renewable energy markets. It is essential to recognise that sustainable financing dynamics extend beyond environmental considerations to encompass broader economic and geopolitical implications that are far-reaching in scope. The specified two-way relationships imply that the development of the green finance or renewable energy field may hurt the overall market levels and stability.

5.6. Robustness check (rolling window estimation): Does green finance Granger-cause other indices and vice-versa?

The rolling window time-varying Granger causality (TVGC) estimation, presented in Table 7, provides robust confirmation for the primary relationships involving green finance, proxied by SOLG. The core high-magnitude causal episodes identified in the recursive evolving analysis are strongly upheld. Most notably, the powerful influence of green finance on global equity markets (SOLG → MSCI) during the 2015–2016 period remains unequivocal. The test statistic of 22.105 clearly exceeds the 99th-percentile bootstrapped critical value of 15.464. Similarly, the significant causal flow from BEC to green finance (BEC → SOLG) is strikingly robust, with its exceptional *t*-statistic of

Table 7. Robustness check: TVGC rolling window estimation result between SOLG and other assets.

1a) Does SOLG Granger-cause GPR?			1b) Does GPR Granger-cause SOLG?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.679			8.057		
	90th	9.557		90th	6.712
	95th	12.506		95th	8.586
	99th	19.276		99th	12.698
2a) Does SOLG Granger-cause CO2?			**2b) Does CO2 Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
7.900			9.335		
	90th	6.329		90th	6.674
	95th	8.464		95th	8.084
	99th	14.243		99th	12.537
3a) Does SOLG Granger-cause BEC?			**3b) Does BEC Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
3.633			50.857		
	90th	6.459		90th	6.866
	95th	8.179		95th	9.726
	99th	14.061		99th	13.605
4a) Does SOLG Granger-cause SPCE?			**4b) Does SPCE Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.326			9.896		
	90th	7.241		90th	7.105
	95th	9.29		95th	8.198
	99th	13.509		99th	13.334
5a) Does SOLG Granger-cause SPRE?			**5b) Does SPRE Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
9.156			15.609		
	90th	6.855		90th	6.282
	95th	8.805		95th	7.768
	99th	12.509		99th	13.143
6a) Does SOLG Granger-cause MSCI?			**6b) Does MSCI Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
22.105			7.918		
	90th	6.856		90th	7.159
	95th	8.368		95th	8.515
	99th	15.464		99th	13.71
7a) Does SOLG Granger-cause EUCC?			**7b) Does EUCC Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
9.376			5.949		
	90th	7.872		90th	8.258
	95th	9.865		95th	10.228
	99th	16.275		99th	15.876
8a) Does SOLG Granger-cause VIX?			**8b) Does VIX Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.211			6.888		
	90th	7.406		90th	7.291
	95th	9.848		95th	9.448
	99th	16.765		99th	13.01
9a) Does SOLG Granger-cause WTI?			**9b) Does WTI Granger-cause SOLG?**		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.297			5.088		
	90th	7.49		90th	7.933
	95th	9.507		95th	10.438
	99th	15.137		99th	15.621

Note: This table presents the robustness check: Wald test *t*-statistics and critical values from time-varying Granger causality (TVGC) rolling window estimation tests between the Solactive green bond index (SOLG) and other assets. The critical values for the 90th, 95th, and 99th percentiles are derived from 499 replications.

50.857 replicated exactly in the rolling framework. This suggests these are strong, event-driven dynamics that are consistently detectable even within a shorter, fixed estimation window.

Beyond these strongest signals, Table 7 clarifies the nature of several moderate relationships. The bidirectional causality from the renewable energy index to SOLG (SPRE → SOLG) is strongly reaffirmed with a *t*-statistic of 15.609. However, other directional causalities originating from SOLG, such as those towards clean energy (SPCE), the climate change index (EUCC), and market volatility (VIX), show attenuated but persistent significance in the rolling window. Their test statistics hover around the 90th to 95th percentiles of the critical values. This pattern indicates that, while these influences are genuine, they may be more gradual or more sensitive to the chosen sample period than the flagship SOLG-to-MSCI relationship. Conversely, several hypothesised connections, such as from SOLG to geopolitical risk (GPR), carbon allowances (CO_2), or oil prices (WTI), remain statistically insignificant in the rolling-window check. This reinforces the specificity of the identified green finance transmission channels.

5.7. Robustness check (rolling window estimation): Does geopolitical risk Granger-cause other indices and vice versa?

The robustness of geopolitical risk (GPR) dynamics, as shown in Table 8, is equally well supported by the rolling window estimation. This confirms its role as a significant driver of financial market stress and a receptor of influence from the digital economy. The analysis robustly validates the two most critical findings from the primary model: GPR's strong causal impact on both the equity fear gauge (GPR → VIX) and the global stock market (GPR → MSCI) in the 2023–2024 period. The test statistics of 19.578 and 17.332, respectively, both exceed the 99th percentile critical values. This provides compelling, methodologically consistent evidence that escalating geopolitical tensions directly translate into heightened market volatility and equity market adjustments. Furthermore, the notable finding that bitcoin's energy consumption exerts a causal influence on geopolitical risk perceptions (BEC → GPR) is powerfully confirmed, with a *t*-statistic of 21.276. This reinforces the novel intersection of digital asset environmental externalities and global risk assessments.

Table 8 also solidifies the more moderate interactions involving GPR. Its bidirectional relationship with the clean energy sector (GPR ↔ SPCE) is maintained, with significant *t*-statistics in both directions, 10.608 and 11.180. This result affirms a tangible feedback loop between geopolitical instability and the clean energy transition. The causal effects from GPR to the renewable energy (SPRE) and climate change (EUCC) indices also persist at significant levels. As with the SOLG results, relationships that were weak in the primary model, such as those between GPR and carbon allowances (CO_2) or oil (WTI), remain correctly insignificant in the rolling window framework. Overall, the convergence of evidence across both estimation techniques solidifies the conclusion that GPR is a potent, time-varying force within the network of financial and sustainable investment indicators, with its most pronounced effects manifesting in volatility and global equity indices during periods of acute geopolitical strain.

Table 8. Robustness check: TVGC rolling window estimation result between GPR and other assets.

1a) Does GPR Granger-cause SOLG?			1b) Does SOLG Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
8.057			8.679		
	90th	6.712		90th	9.557
	95th	8.586		95th	12.506
	99th	12.698		99th	19.276
2a) Does GPR Granger-cause CO2?			2b) Does CO2 Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
7.071			6.791		
	90th	7.216		90th	6.028
	95th	8.907		95th	7.748
	99th	13.574		99th	12.069
3a) Does GPR Granger-cause BEC?			3b) Does BEC Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
5.685			21.276		
	90th	8.677		90th	7.064
	95th	11.38		95th	9.76
	99th	16.295		99th	14.071
4a) Does GPR Granger-cause SPCE?			4b) Does SPCE Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.608			11.180		
	90th	6.334		90th	7.602
	95th	7.7		95th	10.275
	99th	12.347		99th	17.279
5a) Does GPR Granger-cause SPRE?			5b) Does SPRE Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
10.723			10.115		
	90th	6.95		90th	9.481
	95th	8.469		95th	12.244
	99th	13.952		99th	18.796
6a) Does GPR Granger-cause MSCI?			6b) Does MSCI Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
17.332			7.198		
	90th	6.804		90th	8.495
	95th	8.1		95th	10.927
	99th	14.427		99th	14.76
7a) Does GPR Granger-cause EUCC?			7b) Does EUCC Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
11.657			6.917		
	90th	6.656		90th	7.314
	95th	8.667		95th	9.67
	99th	12.813		99th	15.008
8a) Does GPR Granger-cause VIX?			8b) Does VIX Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
19.578			12.386		
	90th	6.872		90th	7.369
	95th	9.207		95th	9.136
	99th	13.528		99th	13.059
9a) Does GPR Granger-cause WTI?			9b) Does WTI Granger-cause GPR?		
t-stat	Percentile	Max Wald	*t*-stat	Percentile	Max Wald
9.551			5.519		
	90th	7.694		90th	9.096
	95th	10.322		95th	10.934
	99th	13.886		99th	13.908

Note: This table presents the robustness check: Wald test *t*-statistics and critical values from time-varying Granger causality (TVGC) rolling window estimation tests between the geopolitical risk index (GPR) and other assets. The critical values for the 90th, 95th, and 99th percentiles are derived from 499 replications.

6. Conclusion

This study examines the time-varying causal relationships between green finance, proxied by the Solactive Green Bond Index (SOLG), geopolitical risk (GPR), and a network of eight critical financial and environmental market indices over a 12-year period from January 2012 to December 2024. By employing a time-varying Granger causality (TVGC) framework, we provide robust evidence that the interactions between sustainability-focused investments and geopolitical shocks are dynamic, episodic, and economically significant.

Our core findings reveal a complex web of directional influences. Most notably, we identify a novel crypto-environmental geopolitical nexus, demonstrating that BEC exerted significant causal influence on both green finance and geopolitical risk from 2020 to 2022. Furthermore, the analysis maps the temporal specificity of market impacts: green finance Granger caused global equity markets (MSCI World) during the 2015 green bond surge, while GPR strongly drove market volatility (VIX) in 2024. We also document moderate bidirectional causality between green finance and clean or renewable energy indices, and between GPR and the clean energy sector, confirming their linked nature. These results validate the theoretical premise that environmental and geopolitical factors act as dynamic, systematic forces within modern financial markets.

These findings carry important implications for academic researchers, investment professionals, and policymakers. For academic researchers, our results strongly advocate for adopting time-varying methodologies in financial research, as the causal relationships between sustainability indicators and market variables are not constant but evolve with market regimes and external shocks. The analysis also bridges the distinct literatures of green finance, geopolitical risk, and digital asset economics, providing an empirical foundation for more integrated theoretical models. The significant role of bitcoin's energy footprint calls for new research that incorporates the environmental effects of digital assets into traditional asset pricing and risk models. Finally, the findings highlight the need for approaches that combine insights from finance, political science, and environmental studies to fully understand the drivers of sustainable investment flows.

For investors and portfolio managers, the results offer concrete insights for investment practice. First, investors should monitor bitcoin's electricity consumption as a leading indicator of potential rotations in capital allocation, as it has been shown to influence both green asset demand and broader geopolitical risk sentiment. Second, risk management frameworks must be adapted to account for the time-varying link between geopolitical risk and clean energy equities. Our findings suggest that during periods of heightened GPR, the clean energy sector may not provide a reliable hedge and could itself become a channel for volatility transmission. Consequently, portfolio construction and dynamic hedging strategies should jointly consider ESG metrics and geopolitical risk exposures, moving beyond their current siloed analysis. The documented causality from green finance to global equities also suggests that large-scale sustainable debt issuance can have systemic market implications, information that is valuable for tactical asset allocation.

For policymakers and regulators, the findings highlight several actionable areas. The causal link between cryptocurrency energy consumption and green finance signals an urgent need for regulatory frameworks to mitigate the environmental impact of digital asset mining. Policymakers could consider measures such as standards for sustainable mining practices, carbon taxation for energy-intensive mining operations, or transparency mandates for crypto-related energy use. Furthermore, the bidirectional relationship between geopolitical risk and renewable energy indices reinforces the strategic importance of energy security policies. Accelerating investments in domestic renewable energy infrastructure is not only an environmental imperative but also a tool to enhance economic resilience and reduce vulnerability to geopolitical shocks in fossil fuel markets. Finally, financial stability authorities should consider the dynamics revealed here, particularly the capacity of GPR to drive broad market volatility, when designing macroprudential policies and stress testing scenarios.

This study has certain limitations that also define productive paths for future inquiry. First, using weekly data, while reducing noise, may not capture intra-week causal dynamics. Using higher-frequency data could reveal more granular interactions. Second, our reliance on broad, aggregate indices, though representative, may mask important regional or sector-specific variations. Future research could employ disaggregated data to explore these differences. Third, the pairwise TVGC framework, while ideal for establishing directed causality between two variables, does not capture the full system-wide network of dependencies simultaneously. A valuable extension of this work would be to employ a multivariate network analysis, such as a connectedness framework or a TVP VAR-based spillover approach. This future study would quantify the overall interconnectedness and identify net transmitters and receivers of shocks within the entire system of green finance, GPR, and financial markets, providing a complementary perspective on system stability and contagion channels. Lastly, the role of green finance in emerging markets and its interaction with local geopolitical processes remain important and underexplored areas for future study.

Notes

1. For each bivariate TVGC test, the recursive evolving estimation uses the longest available common sample for the two variables in question. Consequently, tests involving the Bitcoin Electricity Consumption (BEC) index utilise the sample from February 2017 onward, while all other pairwise tests utilise the full sample from January 2012.
2. See https://www.climatebonds.net/2016/01/2015-year-end-review-tall-trees-many-green-shoots-evolution-green-bond-market-continues-2015.
3. See https://www.msci.com/documents/10199/196ba60a-2528-4a94-9b54-502ec8a0a020.
4. See https://www.climatebonds.net/files/reports/cbi-policyroundup_2017_final_3.pdf.
5. See https://www.openmarketcap.com/bitcoin-environmental-impact/.

Ethical approval

This study did not involve human participants, animal subjects, or any primary data collection requiring ethical approval.

Disclosure statement

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Data availability

The data supporting this study's findings are available from me upon reasonable request. The geopolitical risk (GPR) index is publicly available from Matteo Iacoviello's website, and the BEC data is publicly available from Digiconomist. The remaining financial indices are available via subscription from Refinitiv.

ORCID iD

Azhar Mohamad http://orcid.org/0000-0002-1075-598X

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