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The impact of geopolitical risk on sustainable markets: A quantile-time-frequency analysis

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Introduction

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A B S T R A C T

We examine the impact of Geopolitical Risk (GPR) on green, clean, and socially responsible markets by employing the newly proposed Wavelet Quantile Correlation, Cross-quantilogram and Causality-in-quantiles. Unlike earlier studies, we incorporate the GPR index to encompass the risk linked to conflict, acts of terrorism, and political tensions. In brief, our findings show that GPR emerges as a significant factor influencing market behavior, with distinct patterns observed across different time scales and trading horizons. Our results are beneficial for investors and portfolio managers to adopt more rational investment strategies and for policymakers to make appropriate policy arrangements.[1]

1. Introduction

Over the last decade, there has been a noticeable shift in the global economy towards sustainability and energy transition to tackle climate concerns and to limit global warming to a maximum of 2 °C through the development of green, clean, and socially responsible markets. This drew the attention of researchers, investors, and policymakers to the importance of green finance and clean energy markets in promoting socially and environmentally responsible investments (Broadstock and Cheng, 2019; Lee et al., 2021; Madaleno, et al., 2022; Ozili, 2022). In this regard, existing literature extensively explored the relationship between different climate financial assets under different market conditions such as green bonds, sustainable energy, and socially responsible markets (Chatziantoniou et al., 2022; Elsayed et al., 2022; Nguyen et al., 2021; Liu et al., 2021). Another stand of the literature stresses the major threats to the development of these markets caused by uncertainty and unfavorable market conditions such as oil shocks (see e.g., Billah et al., 2023; Ghorbal and Belaïd, 2022; Yousfi and Bouzgarrou, 2024; Wang et al., 2022).

Despite the importance of geopolitical instability as one of the significant challenges facing the development of sustainable markets, there is a dearth of research on the interdependence between geopolitical risks and clean, green, and socially responsible markets.

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Geopolitical events including political tensions, wars, and terrorist acts have harmed the economic outlook, stock markets, and environmental repercussions (Adams et al., 2020; Dogan et al., 2021; Fiorillo, et al., 2024; Riti et al., 2022). On the one hand, these events harm the environment and exacerbate the climate crisis by releasing significant amounts of greenhouse gases. On the other hand, geopolitical risks (GPR) play a crucial role in shaping investment decisions across different financial markets and assets. It increases uncertainty, which impedes sustainable financial market progress (Du and He, 2015; Elsayed and Helmi, 2021; Dutta and Dutta, 2022; Caldara and Iacoviello, 2022; Sohag et al., 2022). Furthermore, geopolitical instabilities induce investors' panic, resulting in abnormal market fluctuations and ultimately, impacting return and volatility within financial markets including green and clean energy markets (Hudson and Urquhart, 2015; Omar et al., 2017; Mei et al., 2020; Qin et al., 2020).

There have been few relevant studies on the relationship between geopolitical risk and the green finance markets. For example, Lee et al. (2021) using data for the us economy from December 2013 to January 2019, examined the relationship between geopolitical risks, oil, and green bonds. They confirmed the presence of causality running from geopolitical risks to the green bond, particularly in the lower quantiles of the distribution. Similarly, Li et al. (2023) found that GPR has a negative (positive) impact on green energy markets in the short term (long term) using a multi-quantile framework. In a recent study by Pata, et al. (2023), they examined the environmental impacts of geopolitical risk and uncertainty caused by the Russia-Ukraine conflict. Empirical results indicate that the GPR increases CO2 emissions from transportation during geopolitical conflict. Further, Sweidan (2023) found that GPR could exacerbate environmental degradation. In a similar vein, Su et al. (2021) studied the relationship between geopolitics instability and renewable energy. They argued that the evolution of clean energy is shaped by geopolitical factors, leading to opportunities, and necessitating adjustments, including institutional reforms. Finally, Sweidan (2021) confirmed that GPR stimulates countries to be more independent and rely on renewable energy sources to reduce risks from fossil fuel inflows. Hence, the impact of geopolitical risks on green, clean, and socially responsible markets remains uncertain, presenting both challenges and opportunities.

Against this backdrop, understanding the interaction between GPR and green finance is of supreme importance for investors, offering insights into the benefits of diversified portfolios and illustrating how political and extreme events can influence green bond returns and other environmentally friendly financial instruments (Liu et al., 2023; Lorente et al., 2023). Thus, this paper attempts to fill this gap by examining the effects of GPR on the green, clean, and socially responsible markets from a more elaborated and holistic approach. Specifically, we consider several green, clean, and ESG markets to gain a better insight. Unlike most studies, to generate more informative disclosures, our analysis employs a series of quantile-based methods including Wavelet Quantile Correlation (WQC) and the Cross-quantilogram (CQ) approaches. Further, we analyse the causal relation between GPR and our variables using a non-parametric causality-in-quantiles test. By doing so, we can investigate the asymmetric short and long-run connections as well as causality relationships among geopolitical risks and socially responsible markets under various market states and different risk exposures. These innovative approaches provide nuanced insights into complex relationships between markets under consideration. We utilized the cross-quantilogram framework introduced by Han et al. (2016) to explore the general dependence structures across different distribution segments and frequencies, offering a comprehensive analysis spanning daily, weekly, and monthly intervals. Additionally, we employed the wavelet quantile correlation method developed by Kumar and Padakandla (2022) to examine frequency-quantile dynamics and causal relationships between geopolitical risk and socially responsible market returns. This method enables measurement of causal impacts across various quantiles, encompassing normal and extreme market conditions.

Our findings show that GPR emerges as a significant factor influencing market behavior, with distinct patterns observed across different time scales and trading horizons. However, the GPR's role in predicting returns for green bond (GB) and S&P Global 1200 ESG (ESG) appears limited, as indicated by causality-in-quantiles tests. Overall, this study contributes valuable insights for investors and policymakers, emphasising the need for a nuanced understanding of GPR's impact on different financial instruments and markets.

The rest of the paper is organized as follows. Section 2 presents the dataset and the econometric methods while Section 3 discusses the empirical results. Finally, Section 4 concludes and provides some policy implications.

2. Dataset and methods

2.1. Dataset

We utilise the S&P Green Bond Index (GB), and the Global Clean Energy Index (GCE) as proxies for the global green bond and clean energy markets. Recently, the green bond has evolved into an international arena, leading to the development of diverse and substantial entities, including large corporations, public organisations, and investors from around the globe. To monitor the performance of the green bond market worldwide, various market indices have been developed that evaluate the performance of the market such as the S&P Green Bond Index, MSCI Green Bond Index, Solactive Green Bond Index, Dow Jones Green Bond Index, and Bank of America Merril Lynch Green Bond Index. Each of these market indices measures the performance of green bonds through unique estimation tools and criteria, selecting bonds from the constituents of the index. As all of these indices demonstrate comparable characteristics and behaviors, with a near-one correlation coefficient as shown in previous research (e.g., Roberedo 2018), our study regards the S&P Green Bond Index as a suitable proxy for the worldwide green bond market. We select the S&P Green Bond Index as our primary proxy for assessing green bond market performance due to its comprehensive coverage of the international green bond market. The Global Clean Energy Index is utilized to measure the dependent variable pertaining to clean energy markets, encompassing the top 30 stocks within the clean energy sector. Following the literature, socially responsible markets are presented by the S&P Global 1200 ESG Index (ESG), S&P Global 1200 Carbon Efficient Index (CE), and S&P Global 1200 Fossil Fuel Free Index (FFF). All data is retrieved from the S&P Global website. Furthermore, the Geopolitical Risk (GPR) data developed by Caldara and Iacoviello (2022) is retrieved from the Geopolitical Risk website. This index gauges adverse geopolitical occurrences (geopolitical conflicts, nuclear tensions, war threats, and terrorist attacks) and associated risks by analyzing the automatic text search findings from the electronic archives of 11 national and international newspapers focusing on geopolitical risks. For more details, we refer the reader to Caldara and Iacoviello (2022). The sample runs from the 28th of June 2013 to the 1st of June 2023 and is determined by the availability of the data. Since the considered markets are inactive during weekends, we haven't considered the returns on these days, i.e., we utilized data spanning a trading week, encompassing Monday through Friday, and excluded holidays to synchronize our dataset. For the sake of convenience of analysis, the sample periods for all variables are identical.

As can be seen from Fig. 1, a distinct upward trend is observed across all series, distinguished by significant surges after COVID-19, followed by a period of fluctuation. In addition, Table 1 represents descriptive statistics of all series under consideration. All variables have positive mean returns except for the green bond market. Moreover, GPR demonstrates the highest fluctuation among the variables with a standard deviation equal to 0.44. Finally, all series display stationarity at levels but are not normally distributed.

2.2. The wavelet quantile correlation (wqc)

This study adopts wavelet quantile correlation and cross-quantilogram approaches to examine the impact of geopolitical risks on green, clean, and socially responsible markets. In addition, the causality-in-quantile method is used to check the robustness of our empirical results. The wavelet quantile correlation (wqc) is introduced by Kumar & Padakandla (2022) to investigate the quantile-time-frequency dependence between two series A(t) and B(t). This technique is an extension of Li et al. (2015) method where $Q_{q,A}$ is the qth quantile of A and $Q_{q,B}$ is the qth quantile of B. Considering A as the independent variable, while B is the dependent variable, the quantile correlation (qc) proposed by Li et al. (2015) could be written as:

$$qcor_t(B,A) = \frac{qcov_t(B,A)}{\sqrt{var\left(\psi_q\left(B - Q_{q,B}\right)\right)var(A)}} \tag{1}$$

Where $qcov_t(B,A)$ is the quantile covariance, $0 < q < 1$, and $\psi_q(w) = q - I(w < 0)$. Later, Kumar & Padakandla (2022) extended the qc as follows:

$$wqc_q\left\{d_j(A), d_j(B)\right\} = \frac{qcov_t\left\{d_j(A), d_j(B)\right\}}{\sqrt{var\left(\theta_q\left(d_j(B) - Q_{q,d_j(B)}\right)\right)var\left(d_j(A)\right)}} \tag{2}$$

Where $d_j(A)$ and $d_j(B)$ are the wavelet details at the jth level extracted from A(t) and B(t) by using the maximal overlap discrete wavelet transform (MODWT). The wqc enables us to measure the asymmetric dependence between A and B while providing the outcome over several quantiles of the joint distribution.

2.3. The cross-quantilogram (cq)

The *cq* technique is propounded by Han et al. (2016). It enables us to measure the asymmetric transmission channel and directional predictability among pairs of series. The *cq* has two main interests: (i) by incorporating all components of the distribution (central and extreme events), it captures the symmetric and asymmetric time-varying nexus among quantile pairs of series. (ii) it offers a broader openness to assess the lead-lag relationship between two variables in the sense of Granger causality.

Considering two stationary variables $\{(B_t, A_t) : t \in \mathbb{Z}\}$ containing $B_t = (B_{1t}, B_{2t})^T \in \mathbb{R}^2$ and $A_t = (A_{1t}, A_{2t}) \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$, where $A_{it} = [A_{it}^1 \cdots A_{it}^{d_i}]^T \in \mathbb{R}^{d_i}$ with $d_i \in \mathbb{N}$. The conditional distribution among A and B follows the process $F_{B_i|A_i}(\cdot|A_{it})$, which indicates the directional predictability in the designed variables concurring to $q_{i,t}(\tau_i) = \inf\{v : F_{B_i|A_i}(v|A_{it}) \geq \tau_i\}$ for $\tau_i \in [0, 1]$, for i=1,2.

According to Han et al. (2016), the *cq* framework explores the serial dependence among the shocks $\{B_{1t} \leq q_{1,t}(\tau_1)\}$ and $\{B_{2,t} \leq q_{2,t-k}(\tau_2)\}$ for a special couple $(\tau_1, \tau_2)^T \in \mathscr{g}$ for lag k. where $\mathscr{g}$ is a Cartesian product of two closed intervals in [0, 1], in other words, $\mathscr{g} \equiv$ *AptCommandmathcalg*$_1 \times$ *AptCommandmathcalg*$_2$, at which *AptCommandmathcalg*$_1 = [\tau_i, \overline{\tau}_i]$ for certain $0 < \tau_i < \overline{\tau}_i < 1$. Consequently, the *cq* mathematical formula is given by[2]:

$$\rho_\tau(k) = \frac{E\left\{\varphi_{\tau_1}(B_{1t} \leq q_{1t}(\tau_1))\varphi_{\tau_2}\left(B_{2,t-k} \leq q_{2,t-k}(\tau_2)\right)\right\}}{\sqrt{E\left\{\varphi^2_{\tau_1}(B_{1t} \leq q_{1t}(\tau_1))\right\}E\left\{\varphi^2_{\tau_2}\left(B_{2,t-k} \leq q_{2,t-k}(\tau_2)\right)\right\}}} \tag{3}$$

2.4. The causality-in-quantile

The causality-in-quantile is a non-parametric Granger causality method (*npgc*) introduced by Balcilar et al. (2017). This approach is an extension of the methods developed by Nishiyama et al. (2011) and Jeong et al. (2012). Balcilar et al. (2017) used the kth order non-parametric causality to examine the non-linear causality among time series.

Let A_t be the independent variable and B_t the dependent variable. To test the causality for B_t, Balcilar et al. (2017) defined the

[2] For additional details about the method, we refer the reader to Han et al., (2016).

Fig. 1. Dynamics of the variable used in the study.

Table 1
Summary statistics.

	Mean	Std.Dev	Skew.	Kurt.	JB test	ADF test	PP test
GB	-2.90E-05	0.0036	-0.2219	7.657	2360.936***	-13.29***	-2479.76***
GCE	0.000292	0.0147	-0.4296	11.6	8057.464***	-12.01***	-2341.99***
ESG	0.000268	0.0092	-1.0764	20.846	34,856.85***	-13.69***	-2686.19***
FFF	0.00028	0.0092	-1.057	20.679	34,197.74***	-13.67***	-2672.79***
CE	0.000264	0.0093	-1.105	21.814	38,712.95***	-13.69***	-2705.17***
GPR	0.000618	0.4419	-0.0501	4.65	294.7445***	-20.18***	-2984.69***

Note: JB is the Jarque-Bera test for normality. ***, and ** indicate statistical significance at the 1 % and 5 % levels, respectively.

following mathematical equation to measure the causality in high-order moments:

$$B_t = f(B_{t-1}) + \sigma(A_{t-t})u_t \tag{4}$$

Where u_t is the white noise model, σ(·) and f(·) are unknown processes. Consequently, the hypotheses for causality in high order quantile θ would be:

$$\begin{aligned} H_0 &: P\left\{G_{B_t^k}|C_{t-1}[Q_\theta(B_{t-1})|C_{t-1}] = \theta\right\} = 1 \text{ for } k = 1, \cdots, K \\ H_a &: P\left\{G_{B_t^k}|C_{t-1}[Q_\theta(B_{t-1})|C_{t-1}] = \theta\right\} < 1 \text{ for } k = 1, \cdots, K \end{aligned} \tag{5}$$

The *npgc* technique may calculate the causality between A_t and B_t even if the variables are not under the normality assumption.[3]

[3] For further details about the method, we refer to Balcilar et al., (2017).

3. Results and discussion

3.1. Results from wavelet quantile correlation (WQC)

We analyse the WQC across various time scales, ranging from 2 to 4 days to 1024–2048 days, following the methodology outlined by Kumar and Padakandla (2022). To simplify the analysis process, our analysis concentrated on understanding the dynamics over short (2–4 days), medium (16–32 days), and long-term (128–256 days) investment horizons.

In the short-term (Fig. 2-Panel A), the correlation between GPR and GB is around zero across low quantiles and transitions to a negative correlation at medium quantiles. This neutrality may stem from short-term market fluctuations and investor sentiment, where the impact of geopolitical risks on green bond investments is not immediately evident. Contrarily, in the medium-term (16–32 days), it turns positive from the median to high quantiles (except at the uppermost quantile over 0.85). This change suggests that as the impact of geopolitical risks becomes more predictable, investors may regain confidence in green bonds, leading to a positive correlation.

The heatmap (Panel B), suggests a negative correlation between GPR and GCE across all investment horizons and becomes more negative as the quantiles increase. This negative correlation intensifies with higher quantiles, implying that as geopolitical risks escalate, investor interest in clean energy investments diminishes. This trend may reflect concerns about the stability of global energy markets and the susceptibility of clean energy projects to geopolitical tensions and regulatory uncertainties.

Panel C, ESG shows a negative (positive) correlation across the low (median and high) quantiles for one trading week. The correlation is consistently negative across all quantiles for the medium-term (16–32 days). It shows a positive (negative) correlation across the median (high) quantiles for one trading year, suggesting that over longer timeframes, investors prioritize sustainability and environmental considerations, leading to increased interest in ESG investments. This aligns with investors' tendency to seek refuge in high-quality assets during periods of economic decline, as observed in previous studies (Næs et al., 2011), a trend also applicable to GPR.

Fig. 2- Panel D regarding FFF shows a positive correlation with GPR across low quantiles for all trading days. It is a positive (negative) correlation across both low and median (high) quantiles for one trading year. The impact of GPR on FFF for one trading month is inconclusive overall quantiles as it switches between positive to negative and the other way around. Fig. 2- Panel E regarding CE shows a negative correlation with GPR across low quantiles for one trading week. It is a negative correlation across low quantiles for one trading month. It is positive (negative) across both low and median (high) quantities for one trading year.

Overall, the impact of GPR on green, clean, and socially responsible markets is mostly negative in the short term, while this impact is mostly positive over the long term. Our results are in line with those of Li et al. (2023) who concluded that the clean energy market is poised to experience a notable influence from external uncertainties. Further, Vakulchuk et al. (2020) and Flouros et al. (2022) confirm that GPR has a significant impact on clean energy stocks. Our findings could also be explained by the fact that geopolitical conflicts can result in high competition for controlling clean energy resources (Sivaram and Saha, 2018; Sweidan, 2021). The long-term positive impact could be attributed to the notation that GPR encourages the future development of green and clean energy technologies and promotes the usage of renewable energy sources (Dutta and Dutta, 2022). Su et al. (2021) contend that geopolitical factors play a pivotal role in shaping the trajectory of clean energy advancement, which consequently engenders prospects for institutional reforms and adaptations. Further, ESG assets benefit from enhanced credibility and more lenient financial restrictions, leading to greater resilience to external shocks such as GPR (Fiorillo et al., 2024).

3.2. Cross-quantilogram analysis

Findings from the Cross-quantilogram analysis are presented in Fig. 3 in the form of heatmaps for the lags of daily (1 day), weekly (5 days), and monthly (22 days) following Han et al. (2016). Several observations are noticed from the results. First, we can see that the increase in GPR is followed by a change in the return of all markets and the magnitude of this causal behavior is significant and negative (blue dominated) in both the short and long run (one trading day and one trading month). In contrast, He (2023) found that the response of investor sentiment in stock markets appears to be more pronounced in the short and medium term than in the long term. Second, GB has a mostly positive relationship (red dominated) with GPR for short and medium run across all quantiles, but it becomes negative during the long run (one trading month) across low and medium quantiles. Third, the heatmaps for the medium term (one trading week) show a mix of blue and red, indicating a negative (positive) relationship in the lower (median to higher except at 0.9) quantiles. Heightened geopolitical tensions or uncertainty may lead investors to adopt a more cautious stance, thereby exerting downward pressure on market returns. Conversely, periods of relative geopolitical stability or positive developments may bolster investor confidence, contributing to positive correlations between GPR and market returns (Li et al., 2023).

The varying relationships observed across different market indices, such as GCE, ESG, CE, and FFF, can be attributed to sector-specific dynamics and market characteristics. For instance, the positive association between GCE and GPR in the short and medium term may reflect the perception of clean energy investments as a safer haven during geopolitical turmoil. Conversely, the transition to negative correlations in the long term suggests a reassessment of risk factors or market conditions influencing the clean energy sector over extended timeframes.

3.3. Causality-in-quantiles test results

To test the robustness of our empirical results, we conducted the causality-in-quantiles tests running from GPR to GB, GCE, ESG, FFF, and CE over the quantile range of low, median, and high. In Fig. 4, our findings indicate that we fail to reject the null hypothesis

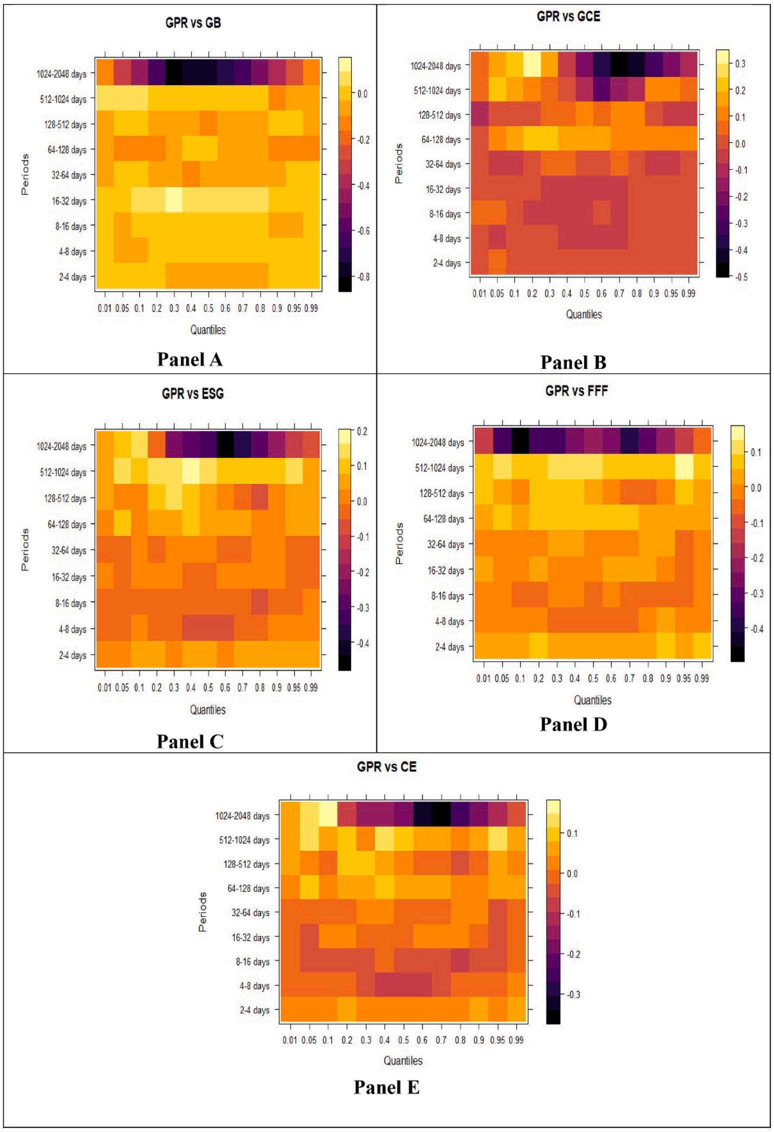

Fig. 2. Wavelet Quantile Correlation of GPR versus Clean, Green, and SRM markets.

that GPR does not Granger cause returns for both GB and ESG, with significant levels consistently below 5 % across all quantiles. However, the causality is confirmed at 5 % level in the case of GCF, FFF, and CE markets across all quantiles except for GCE at high quantile. In fact, our findings provide a broader picture of the dependence between GPR and returns in the three markets, namely GCF, FFF, and CE, and uncover the insignificant role of GPR in predicting both GB and ESG returns.

4. Conclusion

We tested the impact of geopolitical risks on green, clean, and socially responsible markets by employing the newly proposed Wavelet Quantile Correlation (WQC), the Cross-quantilogram (CQ) approaches, and Causality-in-quantiles. We found that GPR has a negative impact on all markets in one trading day and one trading month. Further, the causality is confirmed in the cause of GCF, FFF, and CE market across all quantiles except for GCE at a high quantile of 90 % using the causality-in-quantiles test. However, the diverse correlations identified among distinct market indices, including GCE, ESG, CE, and FFF, may stem from sector-specific dynamics and unique market attributes. The influence of political events on the green and clean energy market is notable and a factor that cannot be ignored. The utilization of clean energy resources has the potential to impact a nation's energy security and competitive positioning in the global energy landscape. Geopolitical disputes can consequently precipitate conflicts over the acquisition and control of clean energy reservoirs. Conversely, during periods of heightened geopolitical tensions, clean energy emerges as a viable alternative, particularly given the inherent constraints associated with conventional energy sources like crude oil. (Sivaram and Saha, 2018;

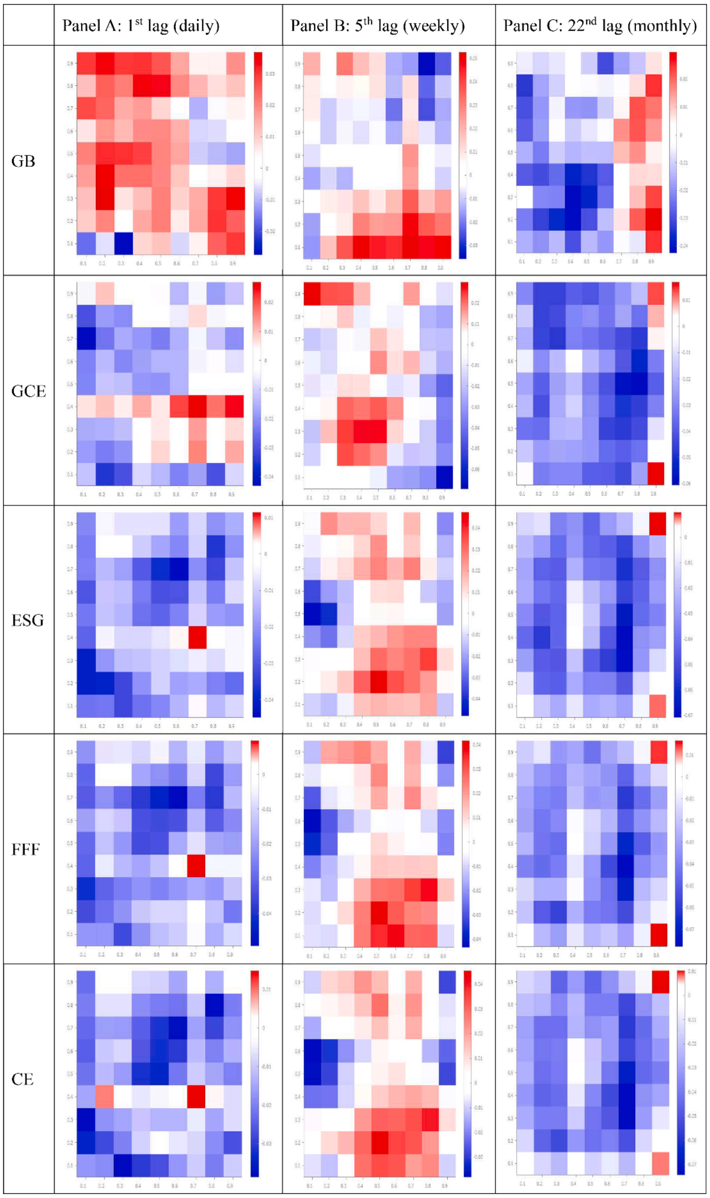

Fig. 3. Impacts of GPR on Green, Clean, and Socially Responsible Markets.
These heatmaps show the cross-quantile connectedness of geopolitical uncertainty on green, clean, and socially responsible markets. The quantile of GPR is depicted in the horizontal axis, while the quantile of the different markets is depicted in the vertical axis. Following Han et al. (2016), the lags of lengths 1, 5, and 22 correspond to the daily, weekly, and monthly time horizons, respectively. The intensity of the causal effect spans from deep blue (largely negative) to deep red (largely positive), which is shown by the multicolor bar displayed at the right-hand side of each heatmap.

Sweidan, 2021; Dutta and Dutta, 2022). GPR represents a dual-edged phenomenon, an opportunity and a challenge, rendering it complex to definitively determine its predominant function. However, it is important to acknowledge that our findings may be constrained by limitations regarding causality. Other confounding factors or the possibility of reverse causality could influence the observed relationships.

The insights presented in this article offer several important policy implications. First, understanding this relationship is helpful for investors to construct more rational investment strategies. Second, promoting transparency and information dissemination about GPR can empower investors and market participants to make more informed decisions. Third, policymakers should develop and implement robust risk management policies that consider the impact of geopolitical risk on green, clean, and socially responsible markets to maintain sound and stable financial markets. Finally, it can be anticipated that heightened geopolitical uncertainty will spur the advancement of new energy technologies, consequently diminishing reliance on conventional energy sources like fossil fuels. Future research attempts could explore the potential transition towards renewable and clean energy in response to heightened geopolitical

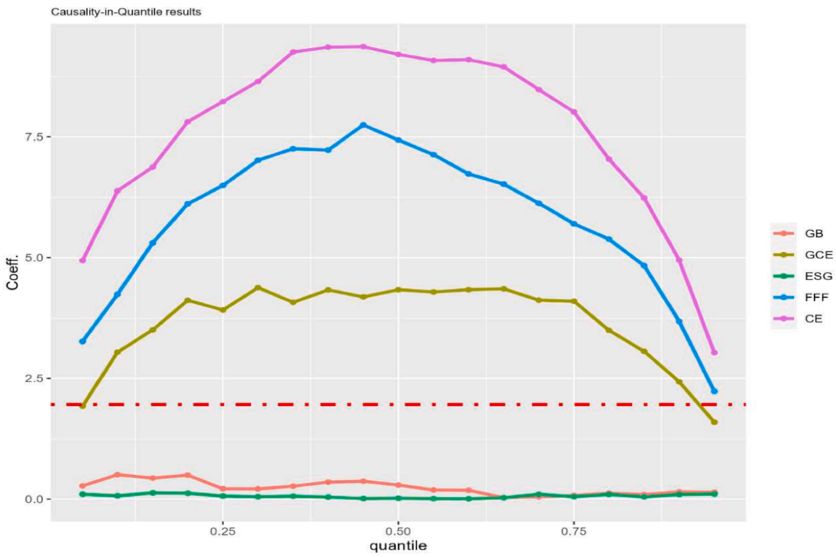

Fig. 4. Causality-in-quantiles test results.
The red dotdash line is the 5 % critical value of 1.96. The x-axis indicates the various quantiles while the y-axis defines the tests statistic value. The lines corresponding to GB, GCE, ESG, FFF, and CE demonstrates the rejection (non-rejection) of the null of no Granger causality from GPR to the returns of green, clean and socially responsible markets at the 5 % level, if the lines are above (below) 1.96 for a specific quantile.

risk.

CRediT authorship contribution statement

Mohamad Husam Helmi: Writing – original draft, Project administration, Formal analysis, Conceptualization. **Ahmed H. Elsayed:** Writing – original draft, Project administration, Conceptualization, Data curation. **Rabeh Khalfaoui:** Software, Formal analysis, Conceptualization, Writing – original draft.

Declaration of competing interest

All authors have contributed equally.

Data availability

Data will be made available on request.

References

Adams, S., Adedoyin, F., Olaniran, E., Bekun, F.V., 2020. Energy consumption, economic policy uncertainty and carbon emissions; causality evidence from resource rich economies. Econ. Anal. Policy. 68, 179–190.
Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? a quantiles-based approach. Econ. Model. 64, 74–81.
Billah, M., Elsayed, A.H., Hadhri, S., 2023. Asymmetric relationship between green bonds and Sukuk markets: the role of global risk factors. J. Int. Financ. Mark. Inst. Money. 83, 101728.
Broadstock, D.C., Cheng, L.T.W., 2019. Time-varying relation between black and green bond price benchmarks: macroeconomic determinants for the first decade. Financ. Res. Lett. 29, 17–22.
Caldara, Dario, Iacoviello, Matteo, 2022. Measuring Geopolitical Risk. American Economic Review 112 (4), 1194–1225.
Chatziantoniou, I., Abakah, E.J.A., Gabauer, D., Tiwari, A.K., 2022. Quantile time frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. J. Clean. Prod. 361, 132088.
Dogan, E., Majeed, M.T., Luni, T., 2021. Analyzing the impacts of geopolitical risk and economic uncertainty on natural resources rents. Resour. Policy. 72, 102056.
Du, L., He, Y., 2015. Extreme risk spillovers between crude oil and stock markets. Energy Econ. 51, 455–465.
Dutta, A., Dutta, P., 2022. Geopolitical risk and renewable energy asset prices: implications for sustainable development. Renew. Energy 196, 518–525.
Elsayed, A.H., Helmi, M.H., 2021. Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. Ann. Oper. Res. 305 (1–2), 1–22.
Elsayed, A.H., Naifar, N., Nasreen, S., Tiwari, A.K., 2022. Dependence structure and dynamic connectedness between green bonds and financial markets: fresh insights from time-frequency analysis before and during COVID-19 pandemic. Energy Econ. 107, 105842.
Fiorillo, P., Meles, A., Pellegrino, L.R., Verdoliva, V., 2024. Geopolitical risk and stock price crash risk: the mitigating role of ESG performance. Int. Rev. Financ. Anal. 91, 102958.
Flouros, F., Pistikou, V., Plakandaras, V., 2022. Geopolitical risk as a determinant of renewable energy investments. Energies. (Basel) 15 (4), 1498.
Ghorbal, S., Belaïd, F., 2022. Exploring the nexus between green finance, innovation, clean energy and oil. Question (s) de management (1), 59–70.

Han, H., Linton, O., Oka, T., Whang, Y.-J., 2016. The cross-quantilogram: measuring quantile dependence and testing directional predictability between time series. J. Econom. 193 (1), 251–270.
He, Z., 2023. Geopolitical risks and investor sentiment: causality and TVP-VAR analysis. The North American J. Econ. Finance 67, 101947.
Hudson, R., Urquhart, A., 2015. War and stock markets: the effect of World War Two on the British stock market. Int. Rev. Financ. Anal. 40, 166–177.
Jeong, K., Härdle, W.K., Song, S., 2012. A Consistent Nonparametric Test for Causality in Quantile. Econ. Theory. 28 (4), 861–887.
Kumar, A.S., Padakandla, S.R., 2022. Testing the safe-haven properties of gold and bitcoin in the backdrop of COVID-19: a wavelet quantile correlation approach. Financ. Res. Lett. 47, 102707.
Lee, C.C., Lee, C.C., Li, Y.Y., 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. The North American J. Econ. Finance 55, 101309.
Li, G., Li, Y., Tsai, C.-L., 2015. Quantile Correlations and Quantile Autoregressive Modeling. J. Am. Stat. Assoc. 110 (509), 246–261.
Li, Y., Yan, C., Ren, X., 2023. Do uncertainties affect clean energy markets? Comparisons from a multi-frequency and multi-quantile framework. Energy Econ. 121, 106679.
Liu, R., He, L., Xia, Y., Fu, Y., Chen, L., 2023. Research on the time-varying effects among green finance markets in China: a fresh evidence from multi-frequency scale perspective. The North American J. Econ. Finance 66, 101914.
Liu, N., Liu, C., Da, B., Zhang, T., Guan, F., 2021. Dependence and risk spillovers between green bonds and clean energy markets. J. Clean. Prod. 279, 123595.
Lorente, D.B., Mohammed, K.S., Cifuentes-Faura, J., Shahzad, U., 2023. Dynamic connectedness among climate change index, green financial assets and renewable energy markets: novel evidence from sustainable development perspective. Renew. Energy 204, 94–105.
Madaleno, M., Dogan, E., Taskin, D., 2022. A step forward on sustainability: the nexus of environmental responsibility, green technology, clean energy and green finance. Energy Econ. 109, 105945.
Mei, D., Ma, F., Liao, Y., Wang, L., 2020. Geopolitical risk uncertainty and oil future volatility: evidence from MIDAS models. Energy Econ. 86, 104624.
Næs, R., Skjeltorp, J.A., Ødegaard, B.A., 2011. Stock market liquidity and the business cycle. J. Finance 66 (1), 139–176.
Nguyen, T.T.H., Naeem, M.A., Balli, F., Balli, H.O., Vo, X.V., 2021. Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. Financ. Res. Lett. 40, 101739.
Nishiyama, Y., Hitomi, K., Kawasaki, Y., Jeong, K., 2011. A consistent nonparametric test for nonlinear causality—Specification in time series regression. J. Econom. 165 (1), 112–127.
Omar, A.M., Wisniewski, T.P., Nolte, S., 2017. Diversifying away the risk of war and cross-border political crisis. Energy Econ. 64, 494–510.
Ozili, P.K., 2022. Green finance research around the world: a review of literature. Int. J. Green Econ. 16 (1), 56–75.
Pata, U.K., Kartal, M.T., Zafar, M.W., 2023. Environmental reverberations of geopolitical risk and economic policy uncertainty resulting from the Russia-Ukraine conflict: a wavelet based approach for sectoral CO2 emissions. Environ. Res. 231, 116034.
Qin, Y., Hong, K., Chen, J., Zhang, Z., 2020. Asymmetric effects of geopolitical risks on energy returns and volatility under different market conditions. Energy Econ. 90, 104851.
Riti, J.S., Shu, Y., Riti, M.K.J., 2022. Geopolitical risk and environmental degradation in BRICS: aggregation bias and policy inference. Energy Policy 166, 113010.
Reboredo, J.C., 2018. Green bond and financial markets: co-movement, diversification and price spillover effects. Energy Econ. 74, 38–50.
Sivaram, V., Saha, S., 2018. The geopolitical implications of a clean energy future from the perspective of the United States. The Geopolitics Renew. 125–162.
Sohag, K., Hammoudeh, S., Elsayed, A.H., Mariev, O., Safonova, Y., 2022. Do geopolitical events transmit opportunity or threat to green markets? Decomposed measures of geopolitical risks. Energy Econ. 111, 106068.
Su, C.W., Khan, K., Umar, M., Zhang, W., 2021. Does renewable energy redefine geopolitical risks? Energy Policy 158, 112566.
Sweidan, O.D., 2021. The geopolitical risk effect on the US renewable energy deployment. J. Clean. Prod. 293, 126189.
Sweidan, O.D., 2023. The effect of geopolitical risk on environmental stress: evidence from a panel analysis. Environ. Sci. Pollut. Res. 30 (10), 25712–25727.
Vakulchuk, R., Overland, I., Scholten, D., 2020. Renewable energy and geopolitics: a review. Renew. Sustain. Energy Rev. 122, 109547.
Wang, X., Li, J., Ren, X., 2022. Asymmetric causality of economic policy uncertainty and oil volatility index on time-varying nexus of the clean energy, carbon and green bond. Int. Rev. Financ. Anal. 83, 102306.
Yousfi, M., Bouzgarrou, H., 2024. Quantile network connectedness between oil, clean energy markets, and green equity with portfolio implications. Environ. Econ. Policy Studies 1–32.