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CAN GREEN BONDS HEDGE AGAINST GEOPOLITICAL RISK? A CROSS-MARKET CONNECTEDNESS ANALYSIS WITH PORTFOLIO IMPLICATIONS

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Abstract. This study investigates whether green bonds (GBs) can hedge against geopolitical risk (GPR). This study extends the booming literature on GPR and GBs, develops a modified connectedness network model to measure the connectedness between GPR and GBs, confirms the hedging property of GBs against GPR, and becomes the first to discuss alternative hedging properties of GBs against GPR. We find evidence of market-, time-, and quantile-varying linkage between GPR and GB markets based on the time-varying Granger causality test and quantile extended joint spillover index model. We confirm via a regression model that only the GB markets in China and Japan can hedge against GPR. At the same time, GB in China remains a weak hedging and safety-haven asset simultaneously. The results remain robust for alternative proxy variables, data frequency, and model specification. Finally, the MVP approach provides superior performance while maintaining weak hedging and safety-haven properties against GPR. This study has considerable portfolio-related implications: (1) it offers an efficient hedge (i.e., GB) against GPR, (2) the heterogeneous performance of regional GB markets reminds investors to be cautious when selecting GBs assets, and (3) it encourages reasonable investment allocations on GBs to achieve a balance between profit and risk.

Keywords: green bonds, geopolitical risk, hedge asset, connectedness analysis, portfolio construction method.

JEL Classification: G15, G11, G32.

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1. Introduction

With the overwhelming evidence of climate change over the past decades, Druckman and McGrath (2019) have raised concerns about reducing carbon emissions and promoting sustainable development. Although considerable progress has been achieved, a lack of financing remains a significant barrier, especially for underdeveloped regions. The Organization for Economic Cooperation and Development [OECD] estimated that a US$3.7 trillion funding gap exists to meet sustainable development goals by 2030 (OECD, 2020). Green bond (GB), which shares similar features with conventional fixed-income bonds, has been extensively issued since they enable capital-raising for projects with environmental benefits (Banga, 2019). By the end of 2022, US$2.185 trillion GBs have been issued, financing various sectors, including energy, transportation, sewage treatment, eco-friendly building, land management and marine resources, industry, waste reduction, and pollution mitigation (Climate Bonds Initiative, 2023). As an emerging type of asset, the GB has been able to attract the attention of investors (Flammer, 2021; McInerney & Bunn, 2019) and is regarded as a good hedging asset for farsighted investors (Arif et al., 2022). There has been abundant evidence that emerging assets can hedge against the stock market (Naeem et al., 2023), carbon market (Jin et al., 2020), cryptocurrency indices (Karim et al., 2022), and economic policy uncertainty (EPU) (Wei et al., 2022).

Uncertainty shocks, such as EPU, climate policy uncertainty (CPU), or geopolitical risk (GPR), are potent drivers of market fluctuation and turbulence, and the equity and bond markets are typically exposed to uncertainty shocks (Alexopoulos & Cohen, 2015). Among these uncertainty shocks, GPR has recently attracted much attention (Caldara & Iacoviello, 2022). Recent geopolitical events, for example, the China-United States trade conflict, the COVID-19 pandemic, and the Russia-Ukraine conflict, continue to increase geopolitical uncertainty, thereby posing pressure on economic activities and (green) market fluctuation. According to a Wells Fargo/Gallup Survey conducted in 2017, GPR became the top investment climate threat.

Theoretically, GPR can influence the GB market through two potential channels: direct and indirect. Regarding the direct channel, severe GPR can lead to lower asset prices and returns, which is supported by Hoque et al. (2019), Smales (2021), and Zhang et al. (2022). Based on the real options theory, GPR can be strongly associated with economic recession and turbulence since it may delay consumption and investments (Bloom, 2009). Recent studies even revealed that GRP could harm sustainable development (Ahmad et al., 2024) and renewable energy development in relatively weak economic and social areas (Lee & Lee, 2024). Moreover, a positive shock in GPR can lead to negative renewable energy production when energy security is the primary concern (Husain et al., 2024). Thus, adverse geopolitical shocks and slow economic growth may influence the price and return of GBs via the shrinking demand. Concerning the indirect channel, GPR can also affect the GB market by the substitution effect or, more specifically, oil shock (Wang et al., 2023). Due to the dramatic exposure of crude oil to GPR (Bouoiyour et al., 2019; Ivanovski & Hailemariam, 2022), oil prices tend to surge with geopolitical tension. Consequently, as a substitute for fossil energy, renewable energy will receive increasing investment through GBs (Azhgaliyeva et al., 2022; Lee et al., 2021). Some recent studies have empirically confirmed the GPR-GB nexus (Lee et al., 2021; Qin et al., 2020; Sohag et al., 2022). Moreover, it is noteworthy that some complex patterns regarding the connectedness between GPR and the financial market, such as time-varying impact (Ivanovski & Hailemariam, 2022), heterogeneity across economies (Lee & Chen, 2020), long- and short-run asymmetries (Tang et al., 2023), and asymmetric effects under different market conditions (Qin et al., 2020; Xia et al., 2023), have been traced in prior studies.

Given the two potential channels, we are therefore motivated to investigate the connectedness between GPR and GBs thoroughly. Moreover, GPR is typically associated with terrorist attacks and conflict between states, which may be hard to diversify since it is potentially global and systematic. Market participators must search for an effective hedge against GPR, given the high GPR in recent years. Prior studies have confirmed that precious metals (Baur & Smales, 2020), commodities (Hasan et al., 2022), and crypto assets (Colon et al., 2021) have some ability to hedge against GPR. These assets share one common characteristic: they exhibit a negative correlation or an absence of correlation to GPR, according to the definition of Baur and Smales (2020). Relative to these assets, GBs are expected to exhibit lower risk (Sartzetakis, 2021) since GBs are similar to conventional bonds in that the holders receive fixed coupon payments until maturity. Furthermore, GBs may also be promising hedging assets against GPR for the following reasons:

- The resiliency hypothesis (Albuquerque et al., 2020). To understand the resiliency hypothesis, we can consider sustainable and responsible investments and investor's ESG preferences. GBs are typically raised to finance ESG projects and can be considered a different financial product from traditional bonds. The advantage of the differentiation strategy may attract loyal investors who process a lower price elasticity of demand for the GBs and may not make shortsighted investment decisions during market fluctuations. As a result, GBs can be resilient from exogenous shocks compared to conventional bonds (Contractor et al., 2023).
- The GB premium. It describes the yield difference between a GB and a conventional bond with similar characteristics (Bhutta et al., 2022). Traditional bond pricing theory determines the fair price of a bond and fails to explain the GB premium. Social, economic, and environmental factors, such as investors' preferences and exposure to the salient environment, are potential explanations for the GB premium (Bhutta et al., 2022; Hu et al., 2022). Due to the investors' long-lasting ESG preference (Cornell, 2021) and irreversible climate change (Solomon et al., 2009), the GB premium will likely exist in the long term. Given a fixed price, the demand for GBs tends to increase, which may provide a cushion against the GPR.

This paper, therefore, expects to find solutions to these questions: how is GPR connected with the GB markets? Is the connectedness time-varying, different across economies, or different across bullish and bearish markets? Can GB hedge against GPR? Furthermore, the famous modern portfolio theory shows us the superiority of portfolios; how can we allocate among GBs to achieve the dual goals of making profits and hedging against GPR? The answer to these questions will inevitably extend the literature on the GPR-GB nexus and benefit global investors. Recently, Caldara and Iacoviello (2022) developed a dictionary-based GPR index by reckoning the share of articles covering GPR-related keywords that appeared in leading newspapers to measure the degree of GPR and released it at a daily frequency on the official website. The GPR index can be further decomposed into geopolitical threats and geopolitical acts. The former indicates the threats and military buildups, and the latter implies the realization of geopolitical events. The availability of these indices affords a chance to perform a heterogeneous analysis of the asymmetric effect of GPR indices on GB markets. Furthermore, besides several global GB indices released by S&P and Bloomberg that track the performance of the global GB market, some national GB indices have been released for a few years. Concretely, the EU, the US, China, and Japan, the leading economies regarding the value of GBs issued in 2021, have all developed local GB indices that capture the local market's performance within the economies. Since Chiesa and Barua (2019) revealed a dramatic difference between GB markets in non- and emerging economies, we presume that the connectedness between GPR and local GB markets and the hedging property may also exhibit an asymmetric pattern.

We believe this paper contributes to the existing studies on GBs from four perspectives, including both theoretical and empirical ones. First, we extend the booming literature on GPR and the GB market. Considering the escalating geopolitical tension and the meaty role of GBs in promoting sustainable development, this paper builds a profound nexus between GPR and the GB market, which is very different from previous literature that performs a connectedness analysis between GPR and a broader market, i.e., green assets market (Dutta & Dutta, 2022; Sohag et al., 2022). Consequently, we believe this paper enriches the theory of GB-GPR nexus. Second, a modified connectedness network model (i.e., quantile extended joint spillover model, QEJ), which integrates quantile vector autoregression (QVAR) and extended joint spillover model (Balcilar et al., 2021) is developed in this study. The proposed model can address the network connectedness between GPR and GBs under different quantiles (interpreted as various market conditions, such as upward or downward ones) and describe the connectedness more accurately than the conventional model developed by Diebold and Yilmaz (2012). We will elaborate on this empirical contribution in the methodology section. Third, this paper checks the hedging and safety-haven properties of various GB markets against GPR and highlights that the GB market in China can act as a hedge and safety-haven asset empirically. Although the hedging capability of other assets, such as precious metals, has been confirmed by Baur and Smales (2020), as far as we know, no prior studies have considered GBs a potential hedging asset against GPR. Finally, due to the limited research on portfolio construction based on green assets (Xia et al., 2023), this paper is the first to discuss alternative hedging strategies of GBs against GPR, which may contribute to the decision-making of market participators and offer portfolio implications.

To this end, a modified Granger causality test is initially adopted to analyze the time-varying causal relationships between GBs and the GPR index over time. Subsequently, a novel quantile connectedness approach is established to perform a connectedness analysis between GPR and GB markets. We then employ several econometric models and robustness checks to confirm the hedging and safety-haven properties of GBs against GPR. Notably, the Granger causality test, connectedness model, and regression model have been commonly used in identifying hedging properties of asset classes (Baur & Smales, 2020; Lee et al., 2023; Wu et al., 2023). We use all three types of methods to provide a comprehensive analysis of the hedging and safety-haven properties of GBs against GPR. Finally, we discuss several hedging strategies for alleviating the adverse effect of GPR on bond returns and boosting investment profits.

The main results are concluded as follows. First, market- and time-varying linkage pattern is observed for Granger causality between GPR and GB markets. GB in China is a hedging and safety-haven asset against GPR since the GPR is a significant Granger causality to returns of the GB in other markets, but not to the Chinese market, especially since the year 2022. Second, connectedness analysis suggests that connectedness between GB markets and GPR behave differently across quantiles and are prone to exogenous shocks such as pandemics and geopolitical conflict. The pairwise connectedness between GPR and GBs demonstrates limited spillover reception and transmission, which supports the findings of the time-varying Granger causality test and indicates that the GB market in China can act as a candidate hedging and safety-haven asset against GPR. Third, GB in Japan is empirically confirmed as a weak safety-haven asset against GPR, while GB in China has properties of hedging and safety-haven simultaneously. The results remain robust for alternative proxy variables, data frequency, and model specification. Fourth, the diversified performance of GB markets facilitates an investment allocation across markets. The comparison shows that a simple portfolio construction method MVP can provide superior performance relative to other popular portfolio methods and individual GB assets, meanwhile maintaining weak hedging and safety-haven properties against GPR. Finally, this paper also provides several considerable portfolio-related implications.

The remainder of this paper is organized as follows. Section 1 summarizes the literature review on the relationship between GPR and financial market performance, the connectedness measurement approach, and the hedging assets of GPR. Subsequently, Section 2 introduces the methodologies used in this paper, including the time-varying Granger causality test, quantile extended joint spillover index model, and several portfolio construction methods. Section 3 introduces the data, and the results are reported in the next section. The robustness check is performed in Section 5. Subsequently, in Section 6, we discuss the hedging strategies and portfolio implications. Finally, in the last section, the conclusions and directions of future research are summarized.

2. Literature review

2.1. Geopolitical risk and market performance

The first strand of research mainly centers on the effect of GPR on financial market performance. Abundant empirical studies have confirmed the considerable impact of GPR on financial market performance (Hoque et al., 2019; Smales, 2021; Zhang et al., 2022). GPR can significantly affect the underlying asset's performance (Bouri et al., 2019) and the financial market (Elsayed & Helmi, 2021) via the channel of investment decision-making.

In contrast to the vast body of literature on the GPR-financial market nexus, minimal attention was devoted to the GPR-green market association, perhaps due to their low market share relative to the whole financial market: although the green markets have grown explosively during the last decade, they still only account for 2% of total financing activities over 2012–2021, as revealed in a recent report released by TheCityUK (2022). Among the green finance tools, GBs have been rising in popularity globally as an option to promote sustainable development and fight against climate change (Ning et al., 2023). Moreover, emerging GBs have also launched bi-directional transmission channels within the GPR-GB nexus. For one thing, the energy market can be easily affected by GPR (Bouoiyour et al., 2019; Ivanovski & Hailemariam, 2022). The shocks in energy prices are eventually transmitted to its substitution, namely renewable energy, which is the primary funding project of GBs. For another thing, a mature GB market will also promote renewable energy development, which ensures higher energy self-sufficiency and alleviates GPR (Dutta & Dutta, 2022).

A vast body of literature has confirmed the nexus between GPR and the GB market. In Lee et al. (2021), the causal relationship between crude oil, GPR, and GB was investigated, and the causality from GPR to GB was confirmed in low quantiles. Sohag et al. (2022) employed the cross-quantilogram approach to investigate the volatility spillovers between GPR and green investment, which revealed that GPR exhibits positive shocks to the GB market from bearish to bullish market states. Similarly, Lee et al. (2022) found that positive changes in GPR can lead to an increase in China's GB returns. In contrast, a heterogeneous pattern can be found for different categories of GPR. Based on the results of wavelet coherence analysis, Będowska-Sójka et al. (2022) argued that GBs were resistant to GPR fluctuations, indicating the great potential of GBs as a hedge against GPR. Tian et al. (2022) employed a nonlinear autoregressive distribution lag approach to demonstrate the asymmetric impacts of GPR on different GB markets. GB is also found to possess some hedging capability against EPU, as claimed by Xia et al. (2023). However, no prior studies have confirmed the hedging property of GB against GPR across quantiles via a comprehensive analysis.

2.2. Connectedness measurement approach of green bonds

Various techniques, including wavelet coherence analysis (WCA), multivariate Generalized AutoRegressive Conditional Heteroskedasticity (MGARCH), cross-quantilogram, copula model, generalized forecast error variance decompositions (GFEVD)-based method, have been applied to measure the inter-market connectedness. Table 1 summarizes the features and recent studies employing the specific technique.

WCA can be employed to analyze the coherence relationship between two time series regardless of stationarity (Ahmed, 2022). The main advantages of WCA lay in its capability of handling non-stationary data and simultaneously performing time- and frequency-domain analysis. WCA has been regularly employed in measuring the connectedness between GBs and financial markets (Nguyen et al., 2021; Ul Haq et al., 2023; Wei et al., 2022), whereas it can hardly provide evidence on the pairwise spillovers or tail-dependence.

MGARCH models include a few variants, such as BEKK-GARCH, CCC-GARCH, and DCC-GARCH, depending on how the variance matrix is specified (Bauwens et al., 2006). As a type

Table 1. Features and recent studies of connectedness measurement approach of GBs

Methodology	Features	References
WCA	▪ Perform time- and frequency-domain time series analysis simultaneously ▪ Process non-stationary data	Nguyen et al. (2021), Ul Haq et al. (2022), Wei et al. (2022)
MGARCH	▪ Easy to interpret ▪ Capture dynamic correlations	Broadstock and Cheng (2019), Huang et al. (2022)
Cross-quantilogram	▪ Measure connectedness under extreme market condition ▪ Works well for heavy-tailed financial time series	Pham (2021), Arif et al. (2022)
Copula	▪ Allow modeling dependency between variables that do not follow the same distributions ▪ Flexible copula functions	Liu et al. (2021), Naeem et al. (2021), Mensi et al. (2022)
GFEVD-based	▪ Output high-frequent and pair-wise connectedness ▪ Many variants enable the inspection of quantile and time-varying connectedness	Le et al. (2021), Naeem et al. (2022)

of parameterized model, MGARCH offers a straightforward interpretation of the dynamic structure of the conditional covariance, which explains its wide utilization in measuring the correlations between GBs and other assets (Broadstock & Cheng, 2019; Huang et al., 2022), but it cannot output the degree of spillover a certain asset transmit to or receiver from other assets, just like WCA.

The cross-quantilogram is a measure of nonlinear connectedness between two time series via either (un)conditional quantile function, which naturally enables connectedness measure under extreme market conditions and provides sound performance for heavy-tailed financial time series (Han et al., 2016). Pham (2021) and Arif et al. (2022) have used a cross-quantilogram approach to measure the connectedness between GBs and other assets. Although cross-quantilogram can offer directional spillover of a specific asset, it only measures connectedness over a period and can hardly demonstrate the time-varying pattern.

The copula model is another popular technique to measure the dependence between GBs and the market and the financial market (Liu et al., 2021; Mensi et al., 2022; Naeem et al., 2023). The dependence structure across markets is fully characterized by a joint distribution that a copula function can represent. Relative to MGARCH model, the copula function provides more modeling adaptability by allowing separate modeling of marginals and dependence structures. However, the directional spillover across markets can hardly be derived by copula models.

The GFEVD-based method consists of two representative ones, namely Diebold and Yilmaz (2012) (DY approach) and Baruník and Křehlík (2018) (BK approach). This type of method can capture the time- and frequency- dynamics of connectedness. Despite its popularity in examining the connectedness between GBs and other asset classes (Le et al., 2021; Naeem et al., 2022), some recent extensions of GFEVD-based methods are typically organized from two aspects, on the one hand, joint connectedness (Lastrapes & Wiesen, 2021) and extended joint connectedness (Balcilar et al., 2021) were proposed to pursuit more accurate estimates on the connectedness. On the other hand, time-varying vector autoregression (TVP-VAR) and quantile vector autoregression (QVAR) have been incorporated with the GFEVD-based method to measure the time-varying and quantile connectedness, respectively. Despite that, limited studies have combined extended joint connectedness and QVAR in measuring the dependence between GB and other assets. We aim to fill the research gap in this paper by employing a novel quantile extended joint spillover index.

2.3. Hedging asset of geopolitical risk

Frequent geopolitical events have motivated researchers to explore potential hedging assets of GPR, including precious metals, commodities, and cryptocurrencies. Due to its reputation as a hedge or safety-haven asset, precious metal has received net capital inflow under extreme stress conditions. In previous literature, gold has been deemed as a promising hedge in the face of GPR by most scholars and market participators (Cheng et al., 2022). Several prior studies have checked the hedging property of precious metals to GPR and reached an agreement that parts of precious metals, such as gold and silver, can hedge against GPR (Baur & Smales, 2020; Będowska-Sójka et al., 2022; Cheng et al., 2022), whereas some heterogeneities were observed. Concretely, Cheng et al. (2022) and Kamal et al. (2022) revealed a time-varying hedge effectiveness of precious metals against GPR.

Commodities, essential inputs for various productions, play a critical role in the global economy. Consequently, many market participators invest in commodities to hedge their portfolios. Hasan et al. (2022) found that soybeans and GSCI commodities offer safe-haven property against GPR. Umar et al. (2022) deemed commodities critical for diversification and hedging against GPR.

The booming cryptocurrency market has recently offered investors a promising hedge to GPR. Based on a Bayesian Graphical Structural Vector Autoregressive technique, Aysan et al. (2019) claimed that Bitcoin can be used as a hedge against GPR. Similarly, Colon et al. (2021) and Patel and Pereira (2021) provided supplementary evidence on the hedging role of the cryptocurrency market against GPR. However, the hedge effectiveness was inconsistent without considering the adverse effects of the arrangement (Su et al., 2020).

GBs attract various long-term investors who strongly prefer supporting a sustainable economy, which means they would probably not liquidate their GB investments (Dutta et al., 2021). Consequently, GB plays the potential role of an effective portfolio diversifier and hedge against uncertainty. Based on the WCA technique, Będowska-Sójka et al. (2022) found that GBs are the most resistant to GPR fluctuations and may serve as the optimal hedge against GPR. Dong et al. (2023) compared the safe-haven function of traditional bonds and GBs and found they both processed safe-haven functions when the GPR index was high, while GBs had a prominent safe-haven role. However, little evidence has been uncovered concerning the hedging property of GB against GPR via a comprehensive analysis.

3. Methodology

3.1. Time-varying Granger causality test

To investigate the causal relationship between variables, we employ a time-varying Granger causality (TVGC) test (Rossi & Wang, 2019) built on a VAR-based approach, which is more robust to the presence of instabilities than the conventional Granger causality test with constant parameters and capable of the structural breakpoint in terms of the Granger causality. Suppose that a time-varying parameter VAR (TVP-VAR) specification is initially considered, namely

$$y_{t+h} = \boldsymbol{\Phi}_{\boldsymbol{1},\boldsymbol{t}} y_{t-1} + \boldsymbol{\Phi}_{\boldsymbol{2},\boldsymbol{t}} y_{t-2} + \ldots + \boldsymbol{\Phi}_{\boldsymbol{p},\boldsymbol{t}} y_{t-p} + \epsilon_{t+h}, \tag{1}$$

where $\boldsymbol{\Phi}_{\boldsymbol{j},\boldsymbol{t}}$, t = 1, 2, ..., T are the functions of time-varying coefficient matrices. ϵ_{t+h} denotes the moving average (MA) of the errors from time t to $t + h$, which is assumed to be uncorrelated with the regressors but serially correlated. Let θ_t denote a subset of $vec\left(\boldsymbol{\Phi}_{\boldsymbol{1},\boldsymbol{t}}, \boldsymbol{\Phi}_{\boldsymbol{2},\boldsymbol{t}}, \ldots, \boldsymbol{\Phi}_{\boldsymbol{p},\boldsymbol{t}}\right)$. The null hypothesis of the TVGC test is described as follows:

$$H_0 : \theta_t = 0, \forall t = 1, 2, \ldots, T. \tag{2}$$

Four statistics to test H_0 in Eq. (2) are proposed in Rossi (2005), namely the exponential Wald (*ExpW*) test, the mean Wald (*MeanW*) test, the Nyblom test, and the Quandt likelihood ratio (*SupLR*) test. A brief explanation of these statistics can be found in Rossi and Wang (2019). We will report the four statistics to examine the causality relationship between GPR and the GB market.

3.2. Quantile extended joint spillover index (QEJ) model

The QEJ model is inherently an integration of QVAR and the extended joint connectedness approach. We initially introduce an n-variable QVAR model with p lag:

$$y_t = c(\tau) + \sum_{s=1}^{p} \Theta_s(\tau) y_{t-s} + \varepsilon_t(\tau), \tag{3}$$

where quantile $\tau \in (0, 1)$. y_t is the return series with n observations and p implies the lag. $c(\tau)$, $\Theta_s(\tau)$, and $\varepsilon_t(\tau)$ are intercept term, parameter matrix, and error term vector at quantile τ, respectively. To derive $c(\tau)$ and $\Theta_s(\tau)$, $\varepsilon_t(\tau)$ is presumed to satisfy the population quantile restrictions, which means Eq. (3) can be converted into an MA process:

$$y_t = \mu(\tau) + \sum_{s=0}^{p} A_s(\tau) \varepsilon_{t-s}(\tau), \tag{4}$$

where $\mu(\tau) = \left(\boldsymbol{I}_n - \Theta_1(\tau) - \cdots - \Theta_p(\tau)\right)^{-1} c(\tau)$, and

$$A_s(\tau) = \begin{cases} 0, s < 0 \\ \boldsymbol{I}_n, s = 0 \\ \Theta_1(\tau) A_{s-1}(\tau) + \cdots + \Theta_p(\tau) A_{s-p}(\tau), s > 0 \end{cases}. \tag{5}$$

Compared with the DY and BK approaches, QEJ mainly makes two modifications. QEJ allows us to inspect the connectedness pattern under the extremely upward or downward market situation, being different from traditional approaches that can only provide information on the normal market situation. Moreover, using an extended joint spillover index remedies the inherent shortcomings of the DY or BK approach in terms of biased spillover index calculation. Concretely, the joint spillover of market i received from all other markets at quantile τ is represented as:

$$J_{\cdot i}^{H}(\tau) = \frac{\sum_{h=0}^{H-1} e_i^T A_h(\tau) \Sigma M_i \left(M_i^T \Sigma M_i\right)^{-1} M_i^T \Sigma A_h(\tau)^T e_i}{\sum_{h=0}^{H-1} \left(e_i^T A_h(\tau) \Sigma A_h(\tau)^T e_i\right)}, \tag{6}$$

where $J_{\cdot i}^{H}(\tau)$ is inherently the proportional reduction of the H-step GFEV of market i jointly conditioning on the future shocks of all other markets at quantile τ. Σ is the variance matrix of the error term vector. e_i is a vector with a 1 in the i-th element and all other elements assigned with 0. M_i is a $K \times K$ identity matrix with the i-th column removed. The quantile extended joint spillover index at quantile τ is computed as

$$JSI(\tau) = \frac{1}{K} \sum_{i=1}^{K} J_{\cdot i}^{H}(\tau). \tag{7}$$

Besides the overall connectedness within the system, one may be curious about the pairwise connectedness. However, the pairwise JSI can not be computed directly. To avoid the pitfall, Balcilar et al. (2021) proposed a row-varying scaling factor λ_i:

$$\lambda_i = \frac{J_{\cdot i}^{H}(\tau)}{S_{\cdot i}^{H}(\tau)}, \tag{8}$$

where $S_{\cdot i}^{H}(\tau)$ denotes the directional spillover from other markets to market *i* given by the DY approach. The directional JSI from market *i* to *j* at quantile τ is subsequently calculated as:

$$J_{ij}(\tau) = \lambda_i DSI_{ij}(\tau), \tag{9}$$

where $DSI_{ij}(\tau)$ implies the directional spillover from market *i* to *j* provided by the DY approach at quantile τ. Specifically, the net directional pairwise spillover index (NDSI) between market *i* and *j* at quantile τ can be computed as $J_{ij}(\tau) - J_{ji}(\tau)$.

3.3. Portfolio construction methods

After analyzing the connectedness between GBs and GPR and their potential hedging or safety-haven property against GPR, an additional insight of this paper is to construct a portfolio to hedge against the fluctuation of GPR or make profits from the investment. The core of portfolio construction lies in determining the weight allocated to each asset. Besides some simple portfolio methods (e.g., equal-weight portfolio), we aim to introduce some dynamic portfolio construction methods that can adaptively adjust the weight of each asset.

3.3.1. Minimum variance portfolio

The minimum variance portfolio (MVP) method is proposed by Markowitz (1959), which aims to establish a portfolio with the lowest return variance and thus can be easily transformed into the following optimization problem:

$$\begin{gathered}\min_{\boldsymbol{\omega}} \boldsymbol{\omega}'\Sigma\boldsymbol{\omega} \\ \text{s.t. } \boldsymbol{\omega}'\boldsymbol{I} = 1,\end{gathered} \tag{10}$$

where $\boldsymbol{\omega} = (\omega_1, \omega_2, \ldots, \omega_N)$ denotes the weight vector of a number of *N* assets and $\boldsymbol{I}$ is an *N*-dimensional identity vector. The portfolio weights of MVP can be computed as follows:

$$\boldsymbol{\omega}_{MVP,t} = \frac{\Sigma_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\Sigma_t^{-1}\boldsymbol{I}}, \tag{11}$$

where $\boldsymbol{\omega}_{MVP,t}$ denotes the $N \times 1$ dimensional weight vector at period *t* and Σ_t is an $N \times N$ dimensional conditional variance-covariance matrix.

3.3.2. Minimum correlation portfolio

The minimum correlation portfolio (MCP) is developed by Christoffersen et al. (2014) and derives portfolio weights via the conditional correlation matrix. MCP is inherently a portfolio weighting scheme. Specifically, the conditional correlation matrix is computed as follows:

$$C_t = diag(\Sigma_t)^{-0.5} \Sigma_t diag(\Sigma_t)^{-0.5}, \tag{12}$$

where C_t is the $N \times N$ dimensional conditional correlation matrix, and $diag(\cdot)$ is a function that creates a diagonal matrix. The dynamic weights of MCP are provided by:

$$\boldsymbol{\omega}_{MCP,t} = \frac{C_t^{-1}\boldsymbol{I}}{\boldsymbol{I}C_t^{-1}\boldsymbol{I}}. \tag{13}$$

3.3.3. Minimum connectedness portfolio

The minimum connectedness portfolio (MCoP) is inspired by MVP and MCP but differs in that it replaces the conditional variance-covariance matrix or conditional correlation matrix with pairwise connectedness indices. The rationale behind MCoP is to construct a portfolio that is resilient to network shock by minimizing the connectedness across assets. To do so, MCoP assigns a higher weight to the asset that transmits (receives) limited spillovers to (by) other assets. The dynamic weights of MCoP are given by:

$$\boldsymbol{\omega}_{MCoP,t} = \frac{PC_t^{-1}\boldsymbol{I}}{\boldsymbol{I}PC_t^{-1}\boldsymbol{I}}, \tag{14}$$

where PC_t is the pairwise connectedness index matrix at period t.

4. Data

4.1. Geopolitical risk index

The sample period starts from September 1, 2018, to August 31, 2022. It covers several major geopolitical events, such as the China-United States trade conflict, the COVID-19 pandemic, and the Russia-Ukraine conflict. We follow the common practice of Kamal et al. (2022) and Umar et al. (2022) to use the GPR index designed by Caldara and Iacoviello (2022). The daily series is obtained from its official website https://www.matteoiacoviello.com/gpr.htm on September 15, 2022. and transformed into the first differences and the first differences of the natural log, which provides two core variables, namely ΔGPR and $\Delta\log(GPR)$ that reflects the changes of GPR. Caldara and Iacoviello (2022) further decomposed the GPR index into two components, namely Geopolitical Threats (GPT) and Geopolitical Acts (GPA). The former indicates the threats and military buildups, and the latter implies the realization of geopolitical events (e.g., the outbreak of a conflict or a global pandemic). Figure 1 displays the GPR index over the sample period. Two peaks can be observed in the figure. The first notable spike

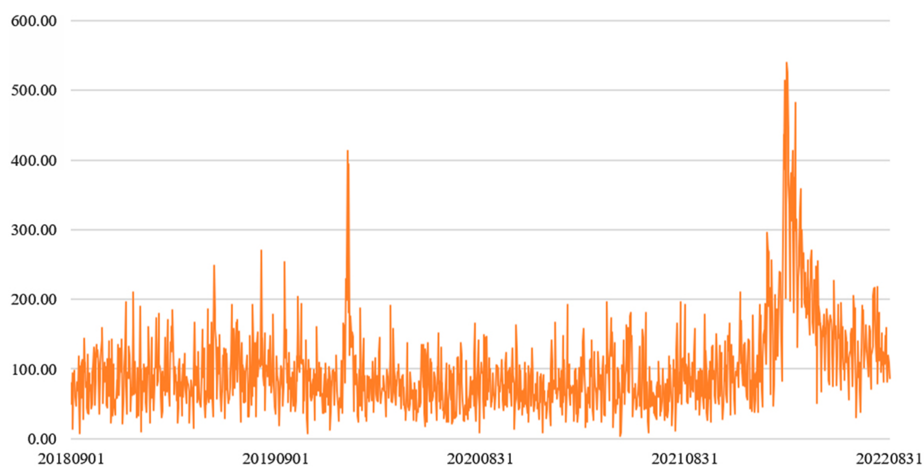


Figure 1. GPR index over the sample period

occurred in January 2020, reaching a high point of over 400, and overlapped with the beginning of the COVID-19 pandemic. The second peak starts in February 2022, with its highest point exceeding 500, which corresponds to the outbreak of the Russia-Ukraine conflict and remains high for a few months.

4.2. Green bond data

Regarding the GB market, we utilize the price data from Bloomberg MSCI European Green Bond Issuer Capped EUR Index, US Green Bond Index: Corporate, S&P Green Bond Select Index JPY, and FTSE Chinese (Onshore CNY) Green Bond Index to track the top four representative GB markets in European Union, United States, Japan, and China, respectively. Figure 2 illustrates the price dynamics of the four GB markets. This figure demonstrates the shock of the global pandemic on GB prices, whereas some different patterns are observed across markets. The prices of GBs in the EU, the US, and Japan experienced dramatic downturns when the COVID-19 pandemic burst. Although the price recovered to a higher level than that in the pre-pandemic period, the prices of these markets quickly went down as the Russia-Ukraine conflict started. The GBs in the EU and the US even reached their lowest price over the sample period. However, the price of the Chinese GB market exhibited an increasing trend, despite a short downturn in early 2020. The shock of the Russia-Ukraine conflict seemed to pose little pressure on it. The asset price data is then transformed into log-return series r_t as follows:

$$r_t = \ln\left(P_t / P_{t-1}\right) \times 100, \tag{15}$$

where P_t represents the closing price on trading day t. Due to data unavailability, we can hardly calculate the intraday volatility for each GB market. We, therefore, estimate the conditional volatility via the GARCH (1,1) model[1]. Panel A of Table 2 shows the descriptive statistics of the GPR index and GB data. The table suggests that the Chinese GB market leads to the

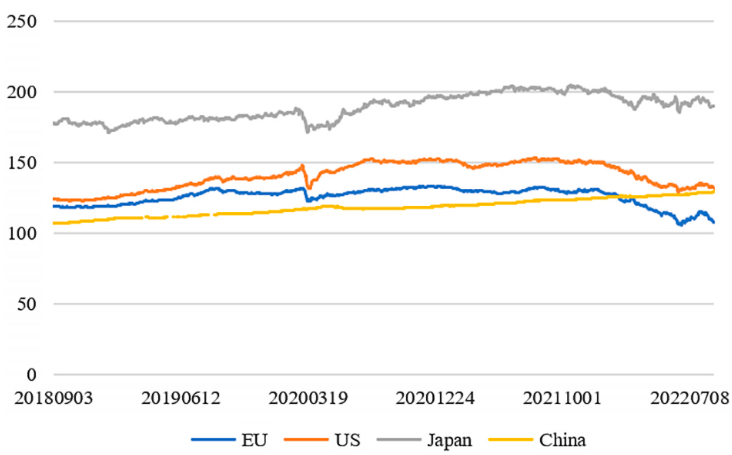


Figure 2. Price indexes of green bond marekts in EU, US, Japan, and China

[1] A GJR-GARCH (1,1) model is also considered, whereas this specification led to no qualitative effect on our main results in the empirical analysis.

Table 2. Summary statistics and correlation matrix

	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	ADF	PP
Panel A. Summary statistics								
GPR index								
Δ*GPR*	0.02856	49.49399	–232.85	213.85	–0.08841	4.64033	–52.263***	–1265.985***
Δlog(*GPR*)	0.00038	0.50500	–2.99605	2.34508	–0.16431	4.79133	–54.249***	–1264.415***
GB market return								
EU	–0.00978	0.32261	–2.07136	1.75866	–0.34107	8.43892	–29.586***	–1042.094***
US	0.00547	0.33426	–3.32552	1.21255	–1.76159	17.02624	–28.210***	–981.604***
Japan	0.006357	0.41498	–2.53351	1.99350	–0.63633	8.64269	–32.683***	–1040.993***
China	0.02114	.052350	–0.34765	0.56275	1.11724	22.11728	–23.432***	–897.720 ***
GB market volatility								
EU	0.28506	0.15096	0.13826	0.95002	1.97263	6.49037	–3.222*	–28.167**
US	0.29738	0.15944	0.14149	1.77835	3.89025	25.57768	–4.745**	–50.941***
Japan	0.39040	0.13863	0.24414	1.14438	2.34271	9.71823	–3.808**	–34.085***
China	0.05271	0.02971	0.02923	0.33732	3.47144	21.35835	–10.423***	–201.229***

Panel B. Correlation matrix between GPR indexes and GB returns

	EU	US	Japan	China
Δ*GPR*	–0.0578*	–0.0607*	0.0156	0.0234
Δlog(*GPR*)	–0.0452	–0.0533*	0.0249	0.0305

Panel C. Correlation matrix between GPR indexes and control variables

	Δ*GPR*	Δlog(*GPR*)
EU		
Δ*Credit spread*	0.0278	0.0170
Δ*Term premium*	0.0224	0.0338
log(*Volume*)	–0.0020	–0.0017
US		
Δ*Credit spread*	0.0160	0.0109
Δ*Term premium*	0.0211	0.0218
log(*Volume*)	–0.0031	–0.0024
Japan		
Δ*Credit spread*	0.0796**	0.0773**
Δ*Term premium*	0.0119	0.0331
log(*Volume*)	0.0009	–0.0003
China		
Δ*Credit spread*	–0.0212	–0.0190
Δ*Term premium*	–0.0842***	–0.0575*
log(*Volume*)	–0.0030	–0.0027

Note: This table presents the summary statistics and correlation matrix for the variables of interest in this study. ADF means Augmented Dickey-Fuller unit root test statistic with trend and intercept. PP means Phillips–Perron unit root test statistic including a trend in the specification. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

highest log daily return (0.021%) and the lowest volatility among the four GB markets. The EU GB market even provides a negative mean return (–0.009%). All the return series exhibit a heavy-tailed pattern due to the very high kurtosis. All the markets except China have negative skewness, implying that the return series of these three markets are skewed left.

Panel B of Table 2 demonstrates the correlation coefficient across GPR indexes and GB returns. Return for GBs in the EU or US market exhibits a significant negative correlation with ΔGPR. The correlation matrix also shows that GB returns of China and Japan exhibit an insignificant positive correlation with ΔGPR, indicating the potential hedging properties for the two types of assets.

4.3. Control variables

To further examine the hedging and safety-haven properties of GBs against GPR, we employ a regression model that includes several control variables that reflect the situations of the macroeconomy and market. These control variables are consistent with those considered in Baur and Smales (2020). Concretely, we utilize the following control variables:

- *Credit spread* is calculated as the spread between yields on bonds rated Aaa and Baa.
- *Term premium* is defined as the difference between yields on 2-year and 10-year Treasury bonds.
- *Volume* is defined as the amounts outstanding in the bond market on a given day.

We employ the difference of the former two control variables and perform a log transformation to the third variable, namely Δ*Credit spread*, Δ*Term premium*, and log(*Volume*). It is noteworthy that the three control variables are region-dependent. Panel C of Table 2 describes the correlation coefficients between changes in GPR indexes and control variables across different markets. The control variables in EU, US, and Japan exhibit similar patterns: Δ*Credit spread* and Δ*Term premium* are positively correlated with changes of GPR indexes, whereas log(*Volume*) is negatively related with Δlog(*GPR*). Interestingly, all the correlation coefficients between control variables and changes in GPR indexes in GB market of China are below zero.

5. Empirical results

5.1. Results of time-varying Granger causality test

The results of TVGC are shown in Table 3, and the two panels indicate the results for the return and volatility series, respectively. The first column describes the direction of Granger causality. The remaining four columns report the four types of test statistics.

Table 3 provides preliminary evidence of the impact of GPR on the returns of GB markets. Specifically, the ExpW, MeanW, and SupLR test statistics indicate that the null hypothesis that GPR is not the Granger causality of the return of GB markets in the EU, US, and China is rejected at a significance level of 5%. Nevertheless, no similar phenomenon is found in the Japanese GB market. This result suggests the heterogeneous causal effects of GPR on different GB markets. Notably, the four test statistics do not reach a consensus, and a possible explanation for this is that the power of these tests is prone to the data characteristic and may be flat around the size of the tests (Rossi, 2005). The effect of the GB market on the changes in the GPR index is negligible, partly due to the low market capitalization of the GB market relative to the whole energy market. Furthermore, the Granger causality between GB volatility and the GPR index is insignificant, as displayed in Panel B of Table 3.

Table 3. Time-varying Granger causality test

	ExpW	*MeanW*	*Nyblom*	*SupLR*
Panel A. Return series				
GPR → EURO	15.646***	17.851**	1.416	43.918***
GPR → US	10.067**	17.553**	2.856	26.839**
GPR → Japan	8.183	9.594	1.662	24.065*
GPR → China	9.831**	11.080	2.974	27.154**
EURO → GPR	6.395	11.460	2.278	16.276
US → GPR	6.791	13.126	3.167	19.118
Japan → GPR	3.845	7.325	1.319	11.458
China → GPR	2.881	4.856	1.451	11.262
Panel B. Volatility series				
GPR → EURO	4.878	4.959	1.096	18.797
GPR → US	3.374	5.539	1.582	12.889
GPR → Japan	6.844	10.631	3.894	19.468
GPR → China	4.665	5.799	1.746	15.900
EURO → GPR	3.235	3.766	0.609	13.552
US → GPR	2.040	3.848	1.359	6.255
Japan → GPR	1.239	2.105	0.462	5.876
China → GPR	4.892	8.840	4.131	14.338

Note: This table reports the results of the TVGC test for return and volatility series in Panels A and B, respectively. GPR indicates Δ*GPR*. The first column describes the null hypothesis that the left side of the arrow symbol does not the Granger cause the right side. For example, GPR → EURO implies that changes in the GPR index are not the Granger cause of the return of the GB market in the EU. The columns *ExpW*, *MeanW*, *Nyblom*, and *SupLR* correspond to test statistics of the exponential Wald, the mean Wald, the Nyblom, and the Quandt likelihood ratio. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In addition to Table 3, we present the *MeanW* statistics between the GB markets and GPR across time in Figures 3 to 6. Figures 3 and 4 imply the results of the return series, and Figures 5 and 6 indicate the results of the volatility series. Relative to Table 3, these figures can provide more information on the time-varying Granger causality. Concretely, Figure 3a, 3b, and 3c illustrates that the mean Wald statistics for a Granger causal effect of GPR on returns of GB markets in the EU, US, and Japan exhibit an increasing trend and exceed the threshold after early 2022. A potential explanation for this is that the long-lasting pandemic and regional conflict rocket the uncertainty to a historically high level, which causes a downturn risk to asset prices (Będowska-Sójka et al., 2022). As shown in Figure 3d, the Granger causality between GPR and the return of the Chinese GB market exhibits a very different pattern:

the *MeanW* statistic only exceeds the threshold in the middle of 2019. It stays below the threshold in the remaining period. This phenomenon may be attributed to the fact that the globalization of the Chinese GB market enhances its connection with the global market and bridges the spillover between GPR and asset return in the short term[2]. Another explanation is that the Sino-U.S. trade conflict temporarily increases the connectedness between GPR and asset return (Wu et al., 2023). Notably, the heterogeneous dependence is also observed in Lee et al. (2023).

Interestingly, even in the period of high GPR (e.g., early 2022), no significant Granger causality is observed between GPR and asset return of China's GB market, suggesting the potential safety-haven property of the Chinese GB market against GPR. Furthermore, we observe no significant Granger causality of return of GB markets on GPR across time, as displayed in all the subplots in Figure 4, for the pair of GB volatility and GPR in all subplots of Figures 5 and 6. This result is consistent with those in Table 3.

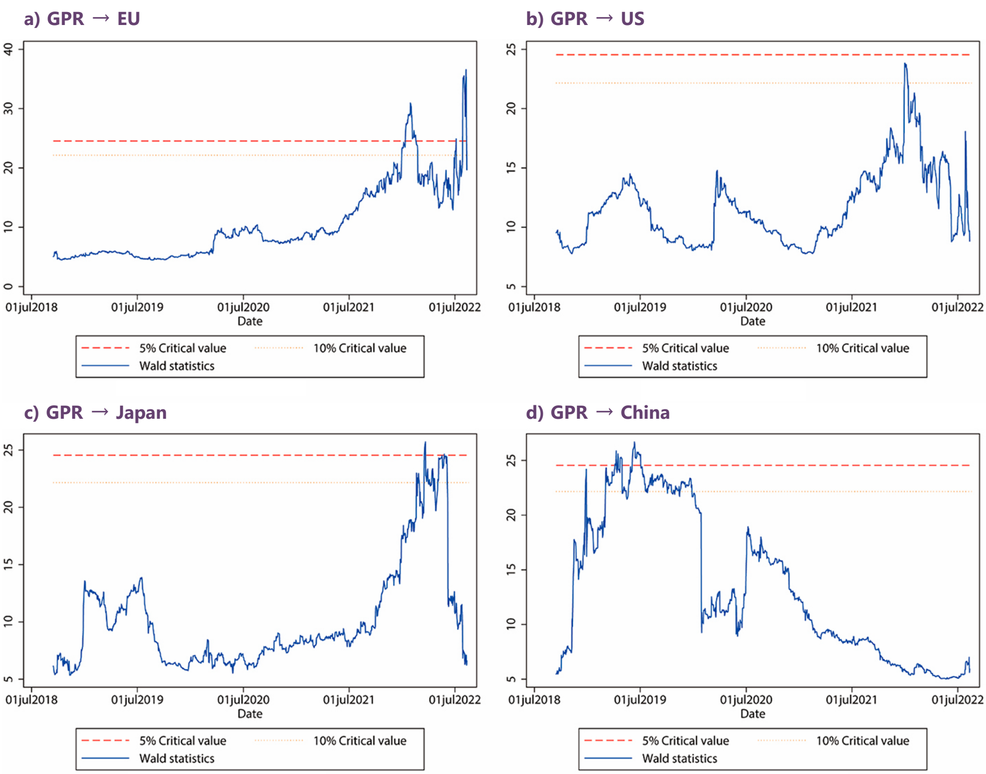


Figure 3. Results of time-varying Granger causality test of GPR on green bond market for return seires

[2] As part of a cross-border cooperation, on June 8, 2018, the Shanghai Stock Exchange (SSE) and the Luxembourg Stock Exchange signed an Index Agreement, the SSE domestic green bond index were displayed on both exchanges' websites synchronously, which provided an efficient channel for international investors to obtain relevant information on China's green bonds.

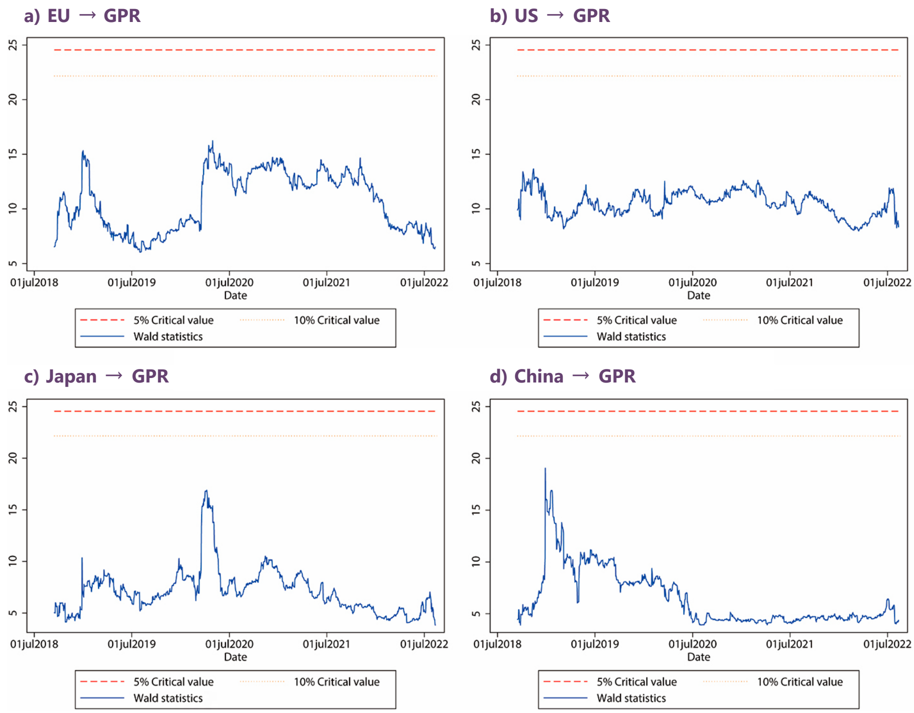


Figure 4. Results of time-varying Granger causality test of green bond market on GPR for return seires

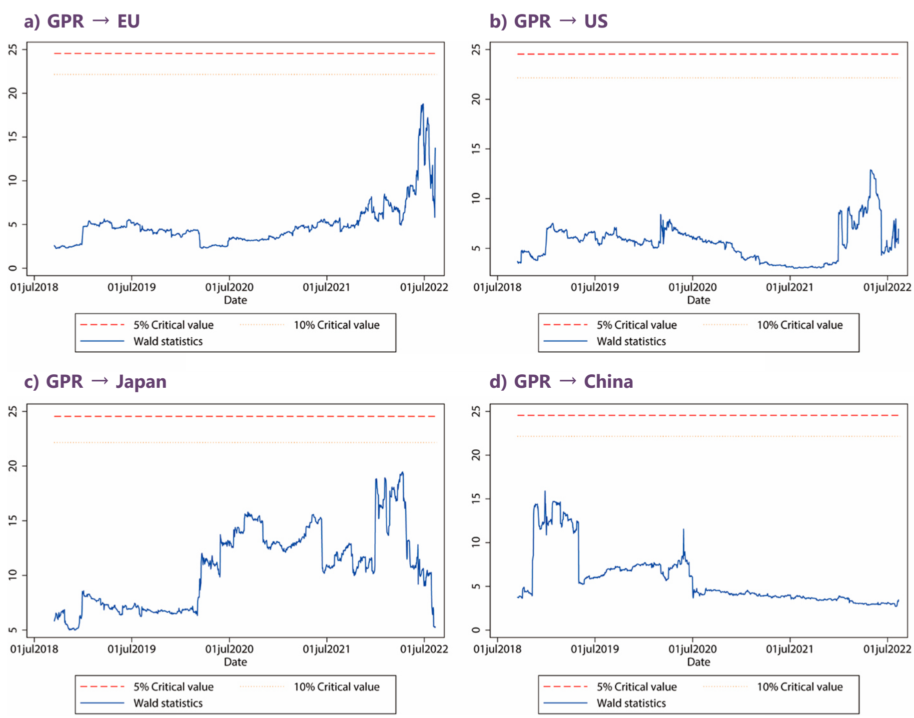


Figure 5. Results of time-varying Granger causality test of GPR on green bond market for volatility seires

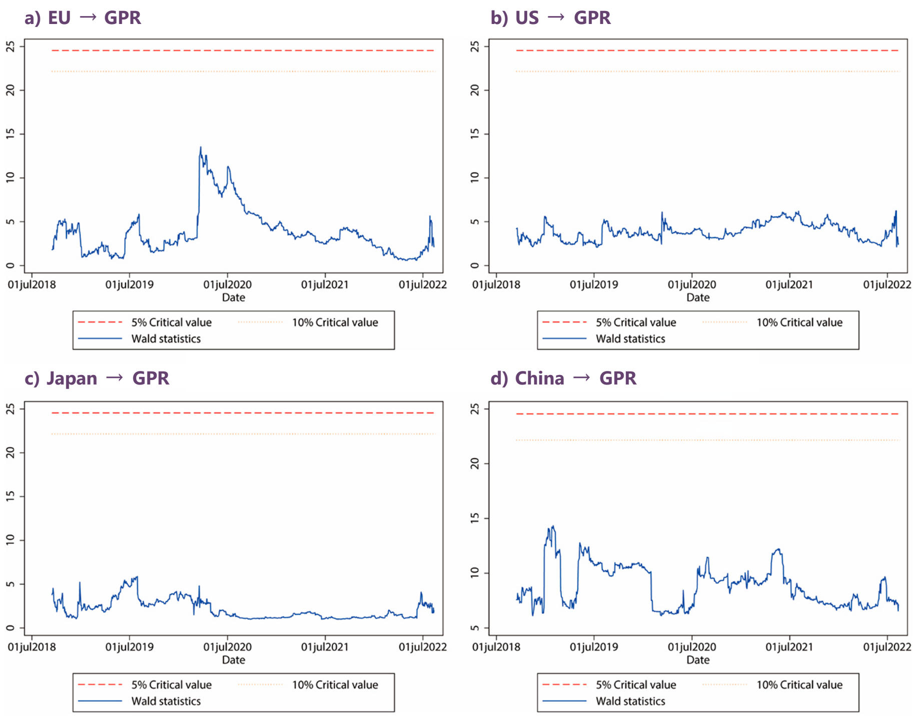


Figure 6. Results of time-varying Granger causality test of green bond market on GPR for volatility seires

5.2. Connectedness analysis between green bond markets and GPR based on the QEJ model

After performing the TVGC test between GB markets and GPR, we subsequently turn to connectedness analysis to investigate the relationship between GB markets and GPR. Tables 4 and 5 illustrate the joint spillover index matrix at different quantiles. Figure 7a and 7b illustrate the JSI of return and volatility series over the sample period respectively, which clearly shows the time-varying dynamics of JSI. The JSI is estimated by the QEJ model described in Subsection 3.2, the Schwarz information criterion determines the optimal lag length, and a 50-day-ahead forecasting is employed.

Table 4. Quantile extended joint spillover index for return series

Panel A. JSI at 0.05 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	23.26	17.87	19.30	21.61	17.97	76.74
Euro	19.05	14.66	24.30	21.88	20.11	85.34
US	19.67	23.01	14.95	22.35	20.01	85.05
Japan	19.70	18.68	20.29	22.57	18.77	77.43
China	17.98	17.89	19.15	19.87	25.11	74.89
To others	76.40	77.45	83.03	85.71	76.87	399.46
All	99.66	92.10	97.98	108.28	101.98	JSI
						79.89%

End of Table 4

Panel B. JSI at 0.5 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	85.39	3.91	4.25	3.58	2.86	14.61
Euro	3.48	56.30	30.68	6.78	2.76	43.70
US	4.36	29.02	57.71	5.80	3.11	42.29
Japan	3.00	6.66	4.89	81.99	3.47	18.01
China	2.52	4.39	3.97	3.91	85.21	14.79
To others	13.36	43.98	43.80	20.07	12.19	133.4
All	98.75	100.28	101.51	102.06	97.40	JSI
						26.68%
Panel C. JSI at 0.95 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	25.08	17.86	17.86	18.98	20.22	74.92
Euro	17.68	20.41	24.16	19.52	18.22	79.59
US	18.59	23.41	20.19	18.83	18.98	79.81
Japan	17.81	19.23	18.48	26.00	18.49	74.00
China	18.85	18.75	18.63	17.38	26.39	73.61
To others	72.93	79.24	79.12	74.72	75.91	381.92
All	98.01	99.66	99.32	100.72	102.3	JSI
						76.38%

Note: This table reports the quantile extended joint spillover index of return series at different quantiles based on a lag order of 2 (as determined by the Schwarz information criterion) and 50-day-ahead forecast error. The (i, j)-th element of the table shows the directional spillover index from market j to market i. The diagonal elements (i = j) are the own variance shares estimates, which show spillover to market i due to its own shocks. The last column "From others" shows the total spillovers received by a particular market from all other markets, while the row "To others" shows the total spillovers transmitted by a particular market to all other markets. The lower left corner "All" indicates the level of total spillovers of the specific market in the column. "JSI" shows the overall spillover index of the panel.

Table 5. Quantile extended joint spillover index for volatility series

Panel A. JSI at 0.05 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	52.91	14.37	10.00	10.90	11.82	47.09
Euro	15.81	65.98	4.94	5.73	7.54	34.02
US	10.27	5.31	56.51	17.85	10.07	43.49
Japan	11.14	5.62	17.60	56.14	9.49	43.86
China	9.29	6.09	9.05	8.70	66.86	33.14
To others	46.52	31.39	41.59	43.18	38.92	201.60
All	99.42	97.37	98.10	99.33	105.78	JSI
						40.32%

End of Table 5

Panel B. JSI at 0.5 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	89.8	2.83	3.40	2.03	1.94	10.20
Euro	1.00	73.31	9.02	5.73	10.94	26.69
US	1.40	6.81	55.15	21.36	15.28	44.85
Japan	1.09	5.72	25.58	54.42	13.20	45.58
China	1.00	10.26	13.04	8.95	66.74	33.26
To others	4.49	25.62	51.04	38.06	41.35	160.57
All	94.3	98.94	106.19	92.48	108.1	JSI
						32.11%
Panel C. JSI at 0.95 quantile						
	GPR	Euro	US	Japan	China	From others
GPR	10.55	21.30	22.93	22.82	22.40	89.45
Euro	15.31	16.11	22.08	22.70	23.79	83.89
US	15.89	21.75	13.67	24.46	24.23	86.33
Japan	16.40	22.45	24.30	12.51	24.34	87.49
China	16.14	22.79	23.16	23.79	14.12	85.88
To others	63.74	88.29	92.47	93.77	94.77	433.04
All	74.29	104.4	106.14	106.28	108.88	JSI
						86.61%

Note: This table reports the quantile extended joint spillover index of volatility series at different quantiles based on a lag order of 2 (as determined by the Schwarz information criterion) and 50-day-ahead forecast error. The (i, j)-th element of the table shows the directional spillover index from market j to market i. The diagonal elements $(i = j)$ are the own variance shares estimates, which show spillover to market i due to its own shocks. The last column "From others" shows the total spillovers received by a particular market from all other markets, while the row "To others" shows the total spillovers transmitted by a particular market to all other markets. The lower left corner "All" indicates the level of total spillovers of the specific market in the column. "JSI" shows the overall spillover index of the panel.

Several findings are demonstrated in the Tables 4 and 5. First, the connectedness between GB markets and GPR behaves differently in quantiles. Specifically, the spillovers in the extremely downward and upward quantiles are much higher than in the normal time, consistent with prior studies on quantile connectedness, such as Bouri et al. (2021) and Xia et al. (2022). The results indicate the greater effect of extremely negative and positive shocks on the whole system's connectedness. This phenomenon can be explained by the fact that the connectedness between financial markets is stronger in chaotic times than in regular periods (Ang & Bekaert, 2002) and highlights the necessity of heterogeneous analysis across quantiles. Second, asymmetric volatility connectedness is revealed in Table 5, which aligns with those of Park et al. (2020) and suggests that investors employ different strategies during normal and extreme global conditions. Third, the connectedness at lower and upper quantiles is higher than the median, while the connectedness at the median can exceed that in the tail when encountering exogenous shocks. We find a sudden rise of JSI in early 2020 and 2022, which overlaps with the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict, during which the JSI of volatility series exceeds 70% at the median quantile. Connectedness dynamics are driven by crisis events, consistent with findings in Liu et al. (2021). Fourth, regarding the pairwise connectedness between GPR and GBs, we clearly observe that the Chinese GB market receives the lowest return and volatility spillovers from GPR in most cases (except for volatility spillover at 0.95 quantile).

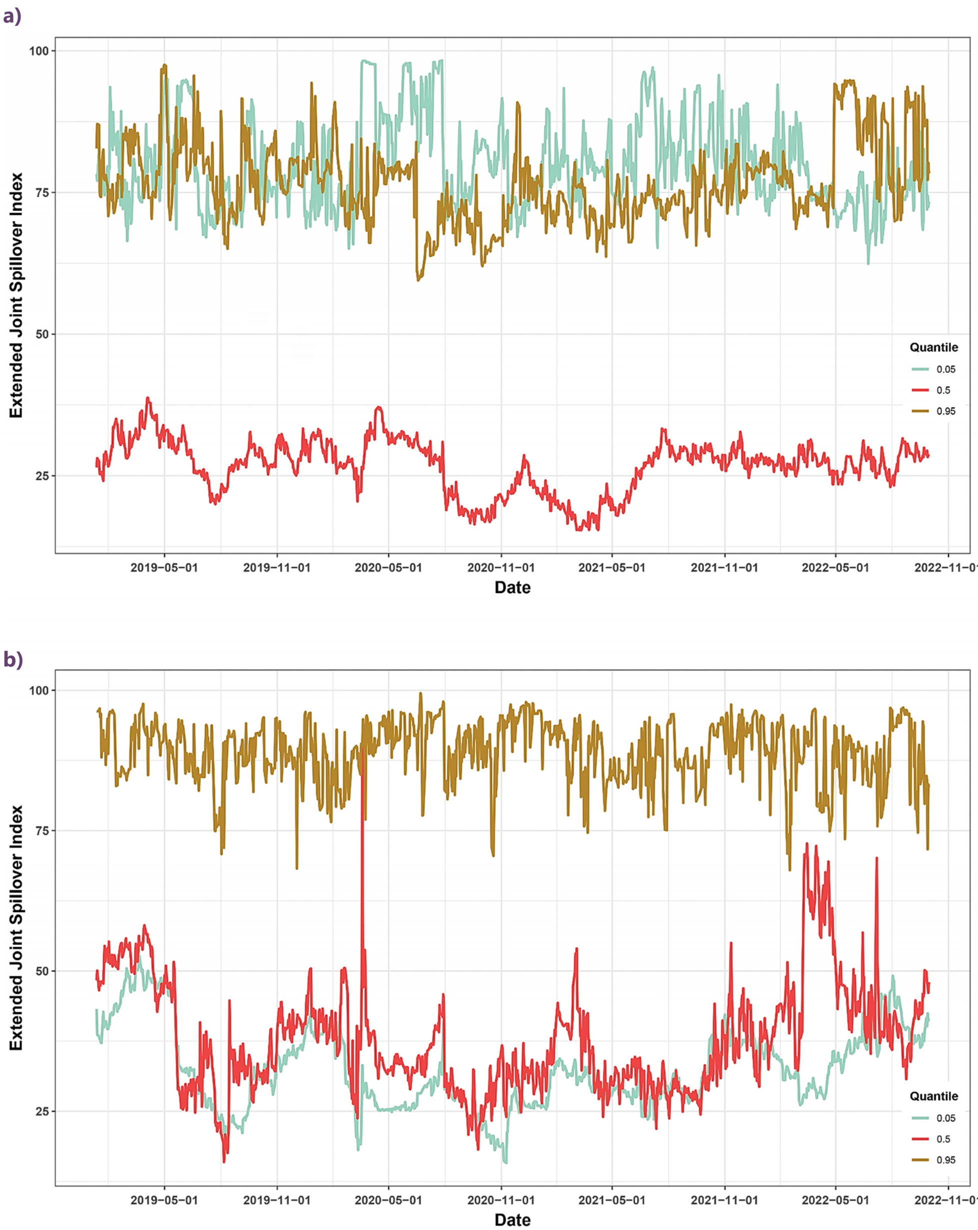


Figure 7. JSI on return and volatility series between GPR and the green bond markets

On the contrary, the two tables show that the GB market in China only transmits limited spillovers to GPR. This conclusion again supports the results of the TVGC test and indicates that the Chinese GB market is a candidate hedging and safety-haven asset against GPR. Finally, when we focus on the NDSI between GPR and GBs illustrated in Figures 8 and 9, an obvious market-, time, and quantile-varying pattern can be observed. The subplots a, b, and c in Figures 8 and 9 correspond to the case of 0.05, 0.5, and 0.95 quantiles, respectively.

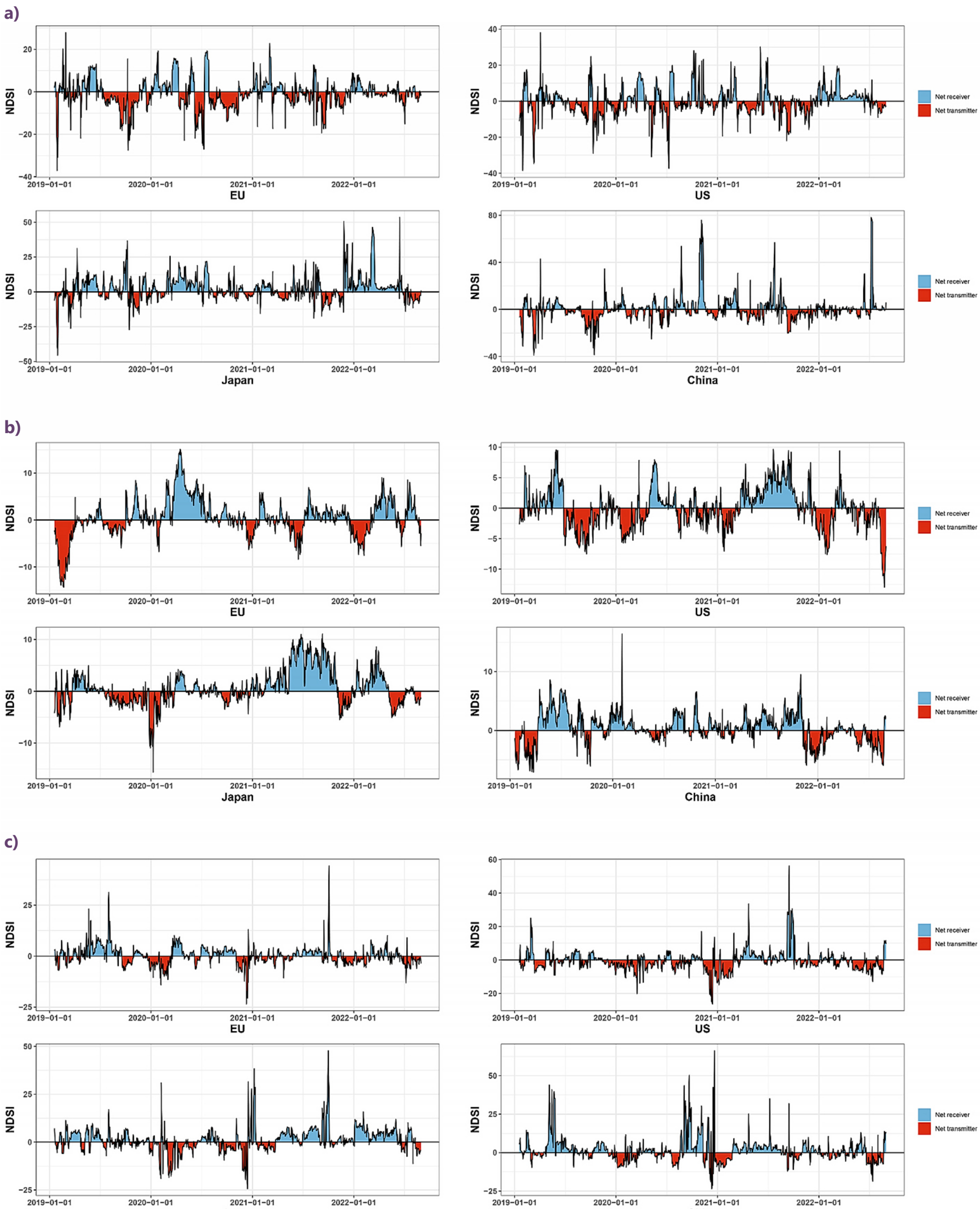
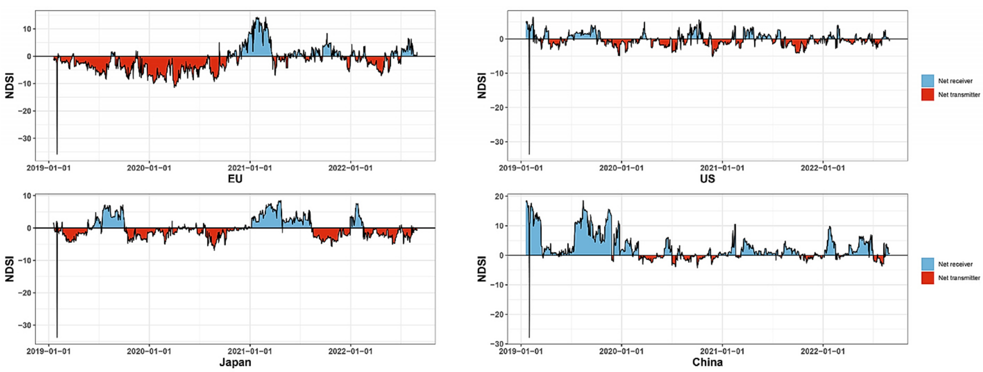


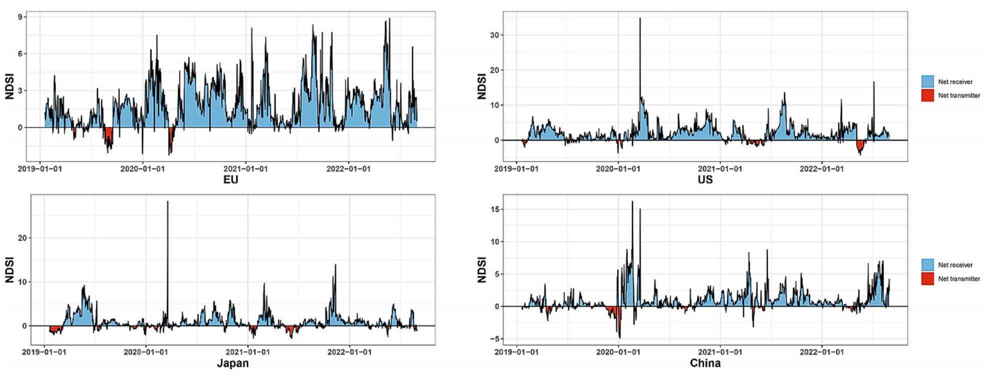
Figure 8. NDSI between GPR and green bond returns at different quantiles

Although NDSI differs across markets, it is sensitive to exogenous shocks, leading to an impulsive increase or decline when major events happen. Furthermore, the returns and volatility of green bonds are typically net spillover receivers in most cases, which is consistent with the findings in Section 5.1.

a)



b)



c)

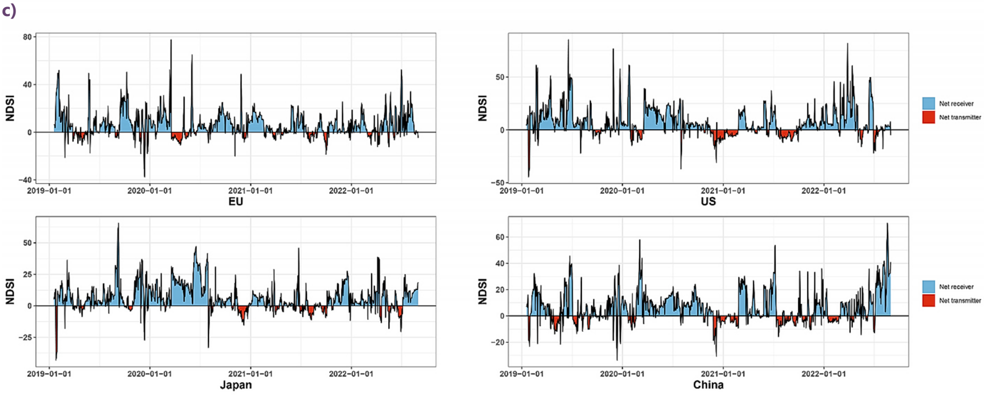


Figure 9. NDSI between GPR and green bond volatility at different quantiles

5.3. Hedging and safety-haven properties of green bonds against GPR

We need to define the two terms to empirically examine whether the GB is a hedge or safety-haven asset against GPR. We follow the definitions of Baur and Smales (2020) as follows:

A strong (*weak*) *hedge against GPR is an asset whose returns are positively correlated* (*uncorrelated*) *with changes in GPR*.

A safety-haven asset against GPR is an asset whose returns are positively correlated (*uncorrelated*) *with changes in GPR during turbulent periods*.

After a clear definition of hedge and safety-haven, we employ the following regression specifications to examine the potential hedging and safety-haven properties of GBs against GPR, following Baur and Smales (2020):

$$y_t = \beta_0 + \beta_1 \Delta \log\left(GPR_t\right) + \varepsilon_t, \tag{16}$$

$$y_t = \beta_0 + \beta_1 \Delta \log\left(GPR_t\right) + \beta_2 M_t + \varepsilon_t, \tag{17}$$

where y_t is the daily log return of the particular GB market (EU, US, Japan, and China). The key explanatory variable Δlog(*GPR*) denotes the first differences of natural-log GPR. M_t indicates a set of control variables described in Subsection 5.3 (Δ*Credit spread*, Δ*Term premium*, and log(*Volume*)). ε_t is the error term. The standard errors reported in parentheses are calculated following the approach of Newey and West (1987), which is presumed to be heteroskedastic and possibly autocorrelated up to some lags. We employ a rule-of-thumb to determine the maximum lag order of autocorrelation for Newey-West standard errors as 5[3].

The results estimated coefficients for baseline regression models are reported in Table 6. For each market, the left column shows the results of the univariate regression that includes only Δlog(*GPR*) as the explanatory variable and the right column considers extra control variables. The results demonstrate that the hedging property of GBs varies across markets, which complements the conclusions of Arif et al. (2022), who solely used global GB indexes. Specifically, the EU and US GB markets can hardly hedge GPR since the coefficients for Δlog(*GPR*) are negative and significant for columns (1), (3), and (4). On the contrary, the GB markets in Japan and China are the weak hedge assets against GPR due to the positive and insignificant coefficients of Δlog(*GPR*) as revealed in the remaining columns. This finding supports the analyses in Będowska-Sójka et al. (2022) and Dong et al. (2023). A possible explanation for this phenomenon is that the returns of the two GB markets are relatively stable during the fluctuation of GPR.

[3] Newey and West (1987) showed the lag grows with the sample size and maintains at a slower rate than $T^{1/4}$, where T is the number of observations. In the light of this, many practitioners simply employ determine the maximum lag order of autocorrelation for Newey-West standard errors as the integer part of $T^{1/4}$. We therefore set the lag as $\text{int}(1039^{1/4}) = 5$.

Table 6. Regression results for testing hedging property

	EU		US		Japan		China	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	–0.0098	1.3493**	0.0055	2.7223***	0.0063	0.3393	0.0211***	0.2021**
	(0.0117)	(0.6638)	(0.0124)	(0.6516)	(0.0127)	(0.7426)	(0.0024)	(0.0955)
Δlog(*GPR*)	–0.0288***	–0.0176	–0.0353**	–0.0274*	0.0205	0.0314	0.0032	0.0038
	(0.0141)	(0.0125)	(0.0173)	(0.0157)	(0.0265)	(0.0280)	(0.0031)	(0.0030)
Δ*Credit spread*		–1.4342***		–1.8803***		–1.9318***		–0.0008
		(0.5224)		(0.5293)		(0.5494)		(0.0011)
Δ*Term premium*		–5.7045***		–4.1614***		2.6540		0.1604
		(0.7241)		(0.5520)		(1.7659)		(0.1094)
log(*Volume*)		–0.2891**		–0.5008***		–0.1520		–0.0300**
		(0.1422)		(0.1205)		(0.3405)		(0.0157)
Adj. R^2	0.0011	0.2239	0.0019	0.2474	–0.0005	0.0386	0.0000	0.0122
F-Statistic	4.18	20.53	4.14	28.81	0.6	3.3	1.05	2.07
Number of obs	1039	1039	1039	1039	1039	1039	1039	1039

Note: This table presents the regression results for baseline regression models described in Eqs. (16) and (17). Concretely, columns (1), (3), (5), and (7) correspond to model specifications in Eq. (16) and the remaining ones indicate the specifications in Eq. (17). Newey-West standard errors are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Having identified the hedging property of GBs against GPR, we, therefore, turn to examine whether GBs are safety-haven against GPR, namely, the returns of GBs are positively correlated (uncorrelated) with changes in GPR during the intense periods (i.e., extreme levels of GPR and extreme changes of GPR). Two approaches are employed to identify the safety-haven property. The first one is a modified Eq. (17) specification that includes a dummy variable and interaction term. The second one separates the sample into subsamples containing only the periods of extreme GPR levels or changes. Further, the modified specification of Eq. (17) is as follows:

$$y_t = \beta_0 + \beta_1 \Delta \log\left(GPR_t\right) + \beta_2 HGPR_t + \beta_3 \left[\Delta \log\left(GPR_t\right) \times HGPR_t\right] + \beta_4 M_t + \varepsilon_t, \tag{18}$$

where *HGPR* is a dummy variable assigned as 1 if it lies in the top decile of GPR or Δlog(*GPR*), and 0 otherwise. The estimated results for Eq. (18) are displayed in Panels A and B of Table 7 for different settings of *HGPR*. Regarding each GB market, we carry out a univariate regression that contains only the interaction term Δlog(*GPR*)×*HGPR* and a full specification described in Eq. (18). The results shown in the two panels are relatively similar: in both specifications, GB markets in EU and Japan are not safety-haven assets against GPR since the negative coefficients of their returns and the interaction term. This finding indicates that GBs in the EU and Japan are risky assets and are sensitive to extreme GPR changes. Concerning GB markets of the US, the results in columns (3) and (4) provide different signs for the interaction term; we prefer to consider that GB in the US is not a candidate safety-haven asset since the positive coefficients of the interaction term in column (4) may be caused by its multicollinearity with the control variables. GB in China is a weak safety-haven asset due to its positive coefficients of interaction terms shown in columns (7) and (8).

Table 7. Regression results for testing safety-haven property with dummy variable and subsample

	EU		US		Japan		China	
Panel A. HPGR: top 10% Δlog(*GPR*)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	–0.0078	1.0706	0.0063***	2.2969	0.0069	0.8134	0.0210***	0.1815*
	(0.0119)	(0.6558)	(0.0128)	(0.6824)	(0.0129)	(0.7919)	(0.0025)	(0.0999)
Δlog(*GPR*)		–0.0088		–0.0259		0.0335		0.0034
		(0.0130)		(0.0166)		(0.0305)		(0.0033)
HGPR		–0.0654		–0.0707*		0.1012*		–0.0052
		(0.0585)		(0.0422)		(0.0594(		(0.0054)
Δlog(*GPR*)×*HGPR*	–0.0830	–0.0314	–0.0359	0.0603	–0.0246	–0.1343	0.0055	0.0095
	(0.0576)	(0.0891)	(0.0539)	(0.0652)	(0.0873)	(0.1190)	(0.0091)	(0.0108)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.0004	0.2267	–0.0007	0.0842	–0.0009	0.0405	–0.0007	0.0110
F-Statistic	2.08	15.11	0.44	19.69	0.08	2.55	0.36	1.64
Number of obs	1039	1039	1039	1039	1039	1039	1039	1039
Panel B. HPGR: top 10% *GPR*								
Constant	–0.0077	1.0699	0.0064	2.2928***	0.0070	0.8182	0.0210***	0.1806
	(0.0118)	(0.6557)	(0.0128)	(0.6828)	(0.0129)	(0.7921)	(0.0025)	(0.0999)
Δlog(*GPR*)		–0.0089		–0.0261		0.0339		0.0034
		(0.0130)		(0.0165)		(0.0305)		(0.0033)
HGPR		–0.0655		–0.0718*		0.1028*		–0.0054
		(0.0589)		(0.0425)		(0.0596)		(0.0053)
Δlog(*GPR*)×*HGPR*	–0.0863	–0.0309	–0.0387	0.0642	–0.0261	–0.1401	0.0061	0.0106
	(0.0580)	(0.0902)	(0.0542)	(0.0661)	(0.0878)	(0.1203)	(0.0090)	(0.0108)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.0005	0.2267	–0.0007	0.2487	–0.0009	0.0406	–0.0007	0.0112
F-Statistic	2.21	15.19	0.51	19.71	0.09	2.56	0.45	1.69
Number of obs	1039	1039	1039	1039	1039	1039	1039	1039
Panel C. subsample: top 10% Δlog(*GPR*)								
Constant	0.0905	–0.2682	0.2377**	1.2293	–0.0651	0.0904	0.0001***	0.5407**
	(0.0865)	(0.9964)	(0.1106)	(1.2939)	(0.1428)	(2.5241)	(0.0227)	(0.2643)
Δlog(*GPR*)	–0.1048	–0.0781	–0.2420*	–0.1576	0.1272	0.0875	0.0302	0.0377*
	(0.0847)	(0.0545)	(0.1240)	(0.0972)	(0.1339)	(0.1345)	(0.0251)	(0.0223)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.005	0.483	0.0262	0.5432	–0.0013	0.0706	0.0089	0.1584
F-Statistic	1.53	29.86	3.81	15.74	0.90	2.60	1.44	3.24
Number of obs	104	104	104	104	104	104	104	104

End of Table 7

	EU		US		Japan		China	
Panel D. subsample: top 10% *GPR*								
Constant	–0.1144	2.8940**	–0.0745	1.0242	0.0634	2.0600	0.0137**	0.4116
	(0.0330)	(1.4382)	(0.0473)	(1.4764)	(0.0551)	(2.1322)	(0.0063)	(0.4102)
Δlog(*GPR*)	0.0340**	–0.0515	0.0529	0.0581	–0.0867	–0.1232	0.0135	0.0079
	(0.0875)	(0.0870)	(0.0745)	(0.0771)	(0.1103)	(0.1267)	(0.0096)	(0.0105)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	–0.0088	0.0175	–0.0072	0.0762	–0.0046	0.0355	0.0067	0.0211
F-Statistic	0.15	2.64	0.50	11.8	0.62	3.34	1.98	1.88
Number of obs	104	104	104	104	104	104	104	104

Note: This table presents the regression results for testing the safety-haven property with a dummy variable described in Eq. (18) and subsample where the dependent variable is the daily log-returns of GB markets in the EU, US, Japan, and China, respectively. For simplicity, the estimated coefficients for control variables are not reported. Newey-West standard errors are reported in parentheses. Panel A reports the estimated coefficients when the dummy variable *HGPR* is determined depending on the highest decile of Δlog(*GPR*). Panel B reports the estimated coefficients when the dummy variable *HGPR* is determined depending on the highest decile of GPR. Panel C reports the estimated coefficients when the sample is restricted to observations with the highest decile of Δlog(*GPR*). Panel D reports the estimated coefficients when the sample is restricted to observations with the highest decile of GPR. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The estimated results for subsample regression are reported in Panels C and D of Table 7 for different definitions of extreme times. In the analogy to Panels A and B, both univariate regression and full specification including control variables are established. Although the results differ in the remaining three markets, the key explanatory variable for the GB market of China remains positive. These results again indicate that GBs in China can act as a safety-haven asset when the GPR rises sharply.

To summarize, we present evidence that GBs in China can act as weak hedging and safety-haven assets against GPR. The evidence for the GB markets is inconsistent in general.

5.4. Further analysis of the sub-index of GPR

Caldara and Iacoviello (2022) decomposed the GPR index into two components, GPT and GPA, reflecting the geopolitical threats and acts that have occurred. We aim to examine the potential hedging property of GBs against GPT and GPA, respectively. To do so, we modify Eq. (17) slightly as follows:

$$y_t = \beta_0 + \beta_1 \Delta \log\left(GPT_t\right) + \beta_2 \Delta \log\left(GPA_t\right) + \beta_3 M_t + \varepsilon_t, \tag{19}$$

where Δlog(*GPT*) and Δlog(*GPA*) denote the difference between the logarithmic transformation of GPT and GPA indexes, respectively. The estimation results of parameters are displayed in Table 8.

The estimated results of the decomposed GPR index demonstrate that the returns of GB markets in Japan and China are insignificant but positively correlated with Δlog(*GPT*) and Δlog(*GPA*), but not for the US market. The disaggregation of GPR confirms the hedging property of GBs in Japan and China, which is consistent with those revealed in Subsection 5.3.

Table 8. Regression results for testing hedging property against Geopolitical Threats and Geopolitical act

	EU	US	Japan	China
	(1)	(2)	(3)	(4)
Constant	1.3502**	2.7204***	0.2022	0.3385
	(0.6642)	(0.6516)	(0.1268)	(0.7429)
Δlog(*GPT*)	–0.0193*	–0.0143	0.0019	0.0131
	(0.0105)	(0.0137)	(0.0026)	(0.0242)
Δlog(*GPA*)	0.0039	–0.0101*	0.0009	0.0160
	(0.0053)	(0.0061)	(0.0012)	(0.0113)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.2236	0.2469	0.0384	0.0108
F-Statistic	17.49	23.99	2.66	1.49
Number of obs	1039	1039	1039	1039

Note: This table presents the regression results for testing hedging property against Geopolitical Threats and Geopolitical act described in Eq. (19). Δlog(*GPT*) and Δlog(*GPA*) denote the difference between the logarithmic transformation of Geopolitical Threats and Geopolitical act indexes, respectively. Newey-West standard errors are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6. Robustness check

6.1. Regression with monthly data

One may doubt the hedging and safety-haven capabilities of GBs in Japan and China are caused by the biased explanatory variable. Specifically, the GPR index is derived by automated text-mining of 10 mainstream Western newspapers. It is intuitive that these newspapers emphasize events in the Western world and pay limited attention to the current events and developments occurring in the Eastern part of the world (e.g., Japan and China). Thus, the prototype of the GPR index may be biased. To alleviate this concern, we employ the monthly GPR index of Japan and China as the proxies of geopolitical risk, respectively in Eqs (16) and (17). The monthly country-specific GPR index is calculated by reckoning the share of three newspapers that satisfy the standard of the GPR index and mentioning the nation or its major metropolises within the month. The restriction of the country-specific GPR index lies in that it is solely released in monthly series. We, therefore, perform a univariate analysis of Eq. (16) and the full specification described in Eq. (17) that use the country-specific GPR index of Japan and China as the key explanatory variable. The results with monthly country-specific GPR index are displayed in Table 9. Following the rule-of-thumb, the maximum lag order of autocorrelation for Newey-West standard errors is determined as 1.

The results reveal that Δlog(*GPR* – *Japan*) and Δlog(*GPR* – *China*), indicating the first difference between Japan and China's log country-specific GPR index, respectively, are positively but insignificantly related to the returns. This finding is consistent with those revealed in Table 6 and suggests that the weak hedging property of GBs in Japan and China remains robust for monthly data.

Table 9. Regression results for monthly data on country-specific GPR index

	Japan		China	
	(1)	(2)	(3)	(4)
Constant	0.1374	1.4039	0.3949***	0.0729
	(0.2333)	(20.0109)	(0.0594)	(0.9232)
Δlog(*GPR – Japan*)	0.0100	0.1291		
	(0.3644)	(0.3674)		
Δlog(*GPR – China*)			0.0585	0.0637
			(0.1445)	(0.1451)
Control	No	Yes	No	Yes
Adj. R^2	–0.0217	0.0469	–0.0186	0.0345
F-Statistic	0.00	2.64	0.16	1.01
Number of obs	48	48	48	48

Note: This table presents the regression results for monthly data on the country-specific GPR index. Δlog(*GPR – Japan*) and Δlog(*GPR – China*) denote the first difference of the log country-specific GPR index of Japan and China, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6.2. Alternative model specification

To further confirm the hedging and safety-haven capabilities of specific GB markets, we follow Baur and Lucey (2010) and Wu et al. (2019) to employ a GARCH model with dummy variables as follows:

$$y_t = a + by_{t-1} + c\Delta\log\left(GPR_t\right) + d\left[\Delta\log\left(GPR_t\right) \times HGPR_t\right] + \varepsilon_t, \tag{20}$$

$$\text{with } \sigma_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2, \tag{21}$$

where a Gaussian innovation is employed. In the above model specifications, the coefficients *c* and *d* indicate the hedging and safety-haven properties of specific GB markets (Wu et al., 2019). The regression results for the four GB markets are reported in Table 10. The signs of coefficients *c* and *d* are positive for markets in Japan and China, whereas no hedging property is revealed for the EU and US due to the negative relationship between Δlog(GPR_t) and daily returns. The empirical results again support the statement that GBs in Japan and China are weak hedging assets and GBs in China process certain safety-haven properties.

Table 10. Robustness check with alternative model specification

	Euro	US	Japan	China
	(1)	(2)	(3)	(4)
Constant	0.0079	0.0234***	0.0122	0.0194***
	(0.0075)	(0.0073)	(0.0107)	(0.0013)
y_{t-1}	0.0288	0.0054	–0.0314	0.2938***
	(0.0340)	(0.0330)	(0.0311)	(0.0391)
Δlog(*GPR*)	–0.0161	–0.0272**	0.0214	0.0011
	(0.0129)	(0.0139)	(0.0204)	(0.0029)
Δlog(*GPR*)×*HGPR*	0.0111	–0.0428	0.0091	0.0505***
	(0.0461)	(0.0642)	(0.0761)	(0.0044)
Variance Equation				
Constant	0.0012***	0.0029***	0.0044***	0.0002***
	(0.0003)	(0.0008)	(0.0009)	(0.0000)
ε^2_{t-1}	0.0932***	0.1622***	0.0852***	0.3027***
	(0.0127)	(0.0191)	(0.0093)	(0.0342)
σ^2_{t-1}	0.8969***	0.8155***	0.8891***	0.7168***
	(0.0134)	(0.0230)	(0.0106)	(0.0172)
Adj. R^2	0.0000	–0.0015	–0.0026	0.0615
Number of obs	1038	1038	1038	1038

Note: This table presents the regression results for alternative model specification. Δlog(*GPR*) denotes the first difference of the log GPR index and *HGPR* is determined depending on the highest decile of GPR. Standard errors are reported in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

7. Hedging strategies and portfolio implications

Having confirmed the hedging and safety-haven properties of certain GB markets, we subsequently formulate hedging strategies to alleviate the adverse effect of GPR on bond returns. Besides individual GB assets, we consider a few portfolio construction methods, such as a simple equal-weighted portfolio (each GB asset accounts for a quarter of the whole investment), MVP, MCP, and MCoP. Figure 10 illustrates the cumulative returns of individual GB assets and four types of portfolio construction methods. The figure demonstrates several vital conclusions. First, an obvious heterogeneity is observed among the performance of single assets and portfolios. The US GB market provides the highest cumulative returns during most of the time frame. MVP and the GB market in China are powerful challengers in the remaining period. The Japanese market performs poorly; the EU market even achieves a negative cumulative return in 2022.

Regarding portfolio construction methods, the performance gaps between equal-weighted, MCP, and MCoP are relatively minor. Second, it clearly shows the dynamics of cumulative returns of GB markets and portfolios. The cumulative returns generally exhibit an increasing trend during the sample period, whereas two major market fluctuations are found, corresponding to the spreading of COVID-19 and the geopolitical tension from the beginning of

2022. Finally, MVP is the best-performing one among the portfolio construction methods, but it still underperforms the GB market in China at the end of the sample period.

To further explain why MVP behaves so differently, we plot the dynamic portfolio weights in Figure 11. The figure demonstrates that the weight composition of MVP differs dramatically from those in MCP and MCoP, whereas the weights compositions of MCP and MCoP are relatively similar. This partially explains the indistinguishable portfolio performances of MCP and MCoP. When further inspecting the determinants of the performance gap between

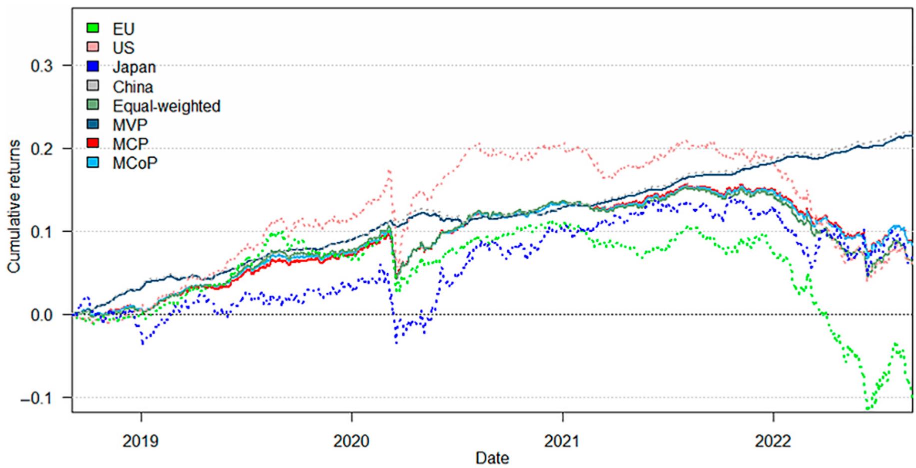


Figure 10. Cumulative returns of individual green bond assets and portfolio construction methods

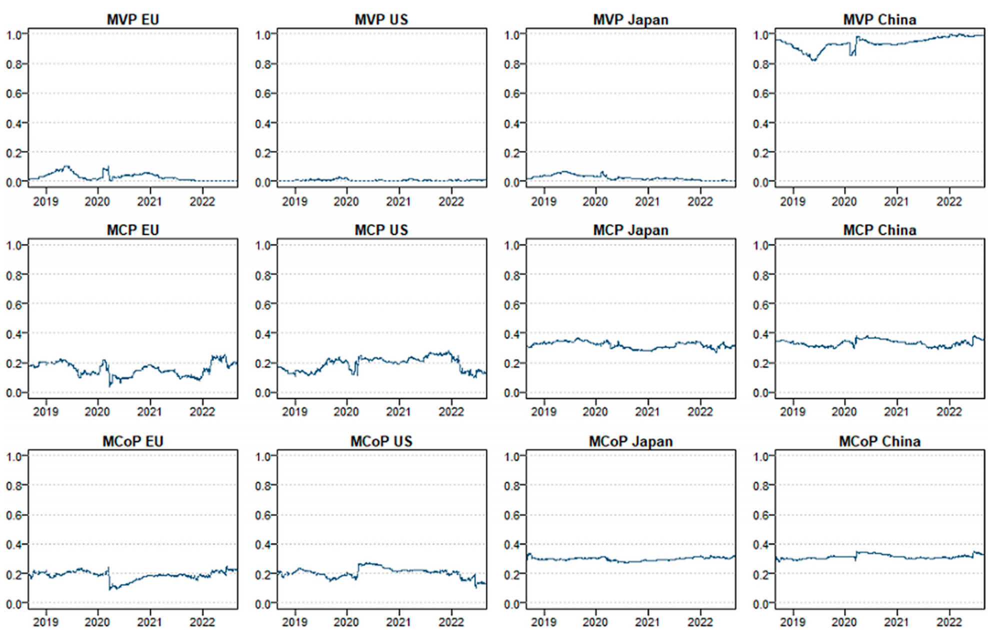


Figure 11. Dynamic portfolio weights of portfolio construction methods

portfolio construction methods, we found that MVP assigns a large portion of the investment to the Chinese market (at least higher than 80%) and a minor portion to the remaining three markets. Due to this, MVP achieves sound portfolio performance since early 2022. The weights of each asset are comparatively balanced for MCP and MCoP. Moreover, sharp weight adjustments are revealed when encountering exogenous shocks such as the COVID-19 pandemic and the Russia-Ukraine conflict.

The sequential task lies in examining portfolio construction methods' hedging or safety-haven properties. Since the control variables are region-specific, we conduct a univariate analysis described in Eqs (17) and (18) to inspect portfolios' potential hedging and safety-haven properties, respectively. The regression results are reported in Table 9 and reveal that MVP remains a weak hedging and safety-haven asset, similar to the GB market in China. The other three portfolios process limited hedging or safety-haven property. The Sharpe ratio shown in the last row of Table 11 also indicates that MVP is superior to other portfolio construction methods and any other individual GB assets.

Table 11. Regression results for testing the hedging and safety-haven properties of portfolio construction methods

	Equal-weighted	MVP	MCP	MPoC
	(1)	(2)	(3)	(4)
Panel A. Results for testing hedging property				
Constant	0.00580	0.00021	0.00008	0.00008
	(0.00743)	(0.00002)	(0.00006)	(0.00007)
$\Delta\log(GPR)$	–0.01013	0.00002	–0.00002	–0.00005
	(0.00852)	(0.00003)	(0.00009)	(0.00008)
Adj. R^2	–0.0003	–0.0004	–0.0009	–0.0007
F-Statistic	1.41	0.65	0.07	0.39
Number of obs	1039	1039	1039	1039
Panel B. Results for testing safety-haven property				
Constant	0.00662	0.00020	0.00009	0.00009
	(0.00755)	(0.00002)	(0.00007)	(0.00007)
$\Delta\log(GPR)\times HGPR$	–0.03452	0.00007	–0.00020	–0.00028
	(0.03555)	(0.00009)	(0.00034)	(0.00035)
Adj. R^2	–0.0003	–0.0005	–0.0007	–0.0004
F-Statistic	0.94	0.62	0.36	0.66
Number of obs	1039	1039	1039	1039
Sharpe ratio	0.0299	0.4206	0.0455	0.0439

Note: This table presents the regression results for testing the hedging and safety-haven properties of portfolio construction methods that include GB markets in the EU, the US, Japan, and China. $\Delta\log(GPR)$ denotes the first difference of the log GPR index and *HGPR* is determined depending on the highest decile of GPR. Newey-West standard errors are reported in parentheses. Since we are unavailable for the control variables for the global portfolios, we exclude control variables in this table. The Sharpe ratio is computed as $SR = \frac{\overline{r_p}}{\sqrt{Var(r_p)}}$, where r_p denotes the return of the portfolio. As a comparison, the Sharpe ratios of GB markets in the EU, the US, Japan, and China are –0.0303, 0.0164, 0.0153, and 0.4039.

In summary, the diversified performance of GB markets facilitates an investment allocation across markets. The comparison shows that a simple portfolio construction method MVP can provide superior performance relative to other popular portfolio methods and individual GB assets, meanwhile maintaining weak and safety-haven properties against GPR.

The above results have several considerable portfolio implications. First, our finding offers a new asset class, namely GBs, as an efficient hedge against GPR, apart from conventional hedging assets such as gold and silver (Baur & Smales, 2020). Despite being typically ignored, the GB asset is expected to enrich the asset pool hedging against GPR, which is important at this stage. Second, the heterogeneous performance of regional GB markets reminds investors to be cautious when selecting GB assets. The performance of GB markets in Eastern countries (e.g., China and Japan) provides better returns and maintains hedging properties against GPR during the sample period, while the returns of GB markets in the EU and US are disappointing and can hardly hedge against GPR. The portfolio performance reveals that GBs in China contribute a meaningful role to dynamic portfolio construction methods, with weights ranging from approximately 80% to over 90% in MVP. The performance gap may be due to the firm determination of sustainable development in China and Japan and comparatively strict epidemic prevention and control. Finally, the empirical findings encourage us to make reasonable regional investment allocations on GBs to achieve dual goals: making profits and hedging against GPR. Concretely, MVP is an alternative portfolio construction method that provides a superior Sharpe ratio and maintains weak hedging and safety-haven properties against GPR. The finding again supports the modern portfolio theory and highlights the usefulness of the classical MVP approach developed in the 1950s.

8. Conclusions and directions of future research

GPR is typically associated with terrorist attacks and conflict between states, which may be hard to diversify since it is potentially global and systematic. This paper analyzes the role of GBs in different markets regarding hedging against GPR or functioning as safety-haven assets. The study is expected to extend knowledge of the nexus between GPR and GBs. The novel quantile extended joint spillover model used in this paper can also address the network connectedness between GPR and GBs under different quantiles and measure the connectedness more accurately than conventional models. Moreover, it broadens the view on hedging and safety-haven assets more than precious metals such as gold and silver.

The empirical analysis demonstrates a heterogeneous and time-varying linkage between GPR and GB markets. The TVGC test shows that GPR is a significant Granger causality to returns of the GB market in the EU, US, and Japan, but not to the Chinese market, especially since 2022. The results of the connectedness analysis imply that connectedness between GB markets and GPR behave differently across quantiles and are prone to exogenous shocks such as pandemics and geopolitical conflict. The pairwise connectedness between GPR and GBs in China demonstrates limited spillover reception and transmission. Moreover, the regression results indicate that only the GB market in China and Japan has some ability to hedge against GPR. In contrast, GB in China has properties of hedging and safety-haven simultaneously. The results remain robust for alternative proxy variables, data frequency, and model specification.

Finally, the diversified performance of GB markets facilitates an investment allocation across markets. A simple portfolio construction method MVP can provide superior performance relative to other popular portfolio methods and individual GB assets while maintaining weak hedging and safety-haven properties against GPR.

This paper also has several considerable portfolio-related implications. First, our finding offers a new asset class, namely GBs, as an efficient hedge against GPR, apart from conventional hedging assets such as gold and silver. Second, the heterogeneous performance of regional GB markets reminds investors to be cautious when selecting GB assets. Finally, the empirical findings encourage us to make reasonable regional investment allocations on GBs to achieve profits and hedge against GPR.

Although rigorous and comprehensive research is our pursuit, some limitations do exist in this study. First, limited GB markets are considered in this paper, which ignores the booming GB markets in other emerging economies or other potential hedging assets. Second, the newspaper-based GPR index used in this paper may be a biased reflection of the geopolitical risk since it can hardly capture private information in social media. Furthermore, only three classical portfolio models are employed in this paper. Regarding future research directions, one can investigate the connectedness between GBs and other emerging asset classes (e.g., cryptoassets) and include them as an alternative hedge against GPR and enrich the portfolio. Moreover, it is interesting to check the potential hedging and safety-haven properties of GBs against other uncertainties, such as EPU and CPU. Finally, advanced portfolio construction methods can be applied to better allocate funds for hedging.

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