



ELSEVIER

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Global Finance Journal

journal homepage: [www.elsevier.com/locate/gfj](http://www.elsevier.com/locate/gfj)

# An examination of green bonds as a hedge and safe haven for international equity markets

Boru Ren<sup>a</sup>, Brian Lucey<sup>b,c,d,e,\*</sup>, Qirui Luo<sup>b</sup>

<sup>a</sup> School of Management, Swansea University, Swansea, Wales, United Kingdom

<sup>b</sup> Trinity Business School, Trinity College Dublin, Dublin 2, Co., Dublin, Ireland

<sup>c</sup> Institute of Business Research, University of Economics Ho Chi Minh City, Ho Chi Minh City, Viet Nam

<sup>d</sup> Institute for Industrial Economics, Jiangxi University of Economics and Finance, Nanchang, Jiangxi, China

<sup>e</sup> Abu Dhabi University, Zayed City, United Arab Emirates

## ARTICLE INFO

### JEL code:

C5  
C32  
F3  
G11  
G15

### Keywords:

Green bond  
Hedge  
Safe haven  
Spillovers  
Connectedness  
Stock markets  
Uncertainty

## ABSTRACT

Green bonds are a type of fixed-income instrument that specifically designed to fund environmentally friendly projects. Investigating the performance of green bonds is essential to gain insights into the risk-return characteristics and dynamics within sustainable finance and their potential role in portfolio diversification. In this paper, we comprehensively examine the ability of green bonds to act as a hedge or a safe haven against nineteen international equity market movements (most of the G20 and Switzerland) over the 2014–2022 period. Using regression analysis, we find that green bonds had acted as a strong hedge for many countries but have lost such property for utmost after the COVID-19 outbreak, while they still provide safe haven benefit for many countries' equity indexes. By the use of a novel CAViAR-based TVP-VAR connectedness approach, we further examine the tail risk spillovers among green bond and international equities which extends the consideration in extreme loss (VaR) perspective. We show that the spillovers rapidly increased during the first wave of COVID-19 and has remained at relatively high level until recent days. In combination of all metrics, we argue that Saudi Arabia might be the only country that has received as good (or even better) protection from green bond in the post-pandemic era as (than) before. Overall, these should increase the attractiveness of green bonds as elements of a portfolio, enhancing the green transition.

## 1. Introduction

The COVID-19 pandemic caused significantly negative impact on global economies. Stock markets worldwide lost 30% of their market value in early stages. These have driven investors towards relatively stable and risk-averse options, such as the bond markets. Investors also shifted their preferences to safe haven featured assets and hedging tools to reduce the sharply increased risks in turbulent markets.

In 2015, the United Nations adopted the 2030 Agenda for Sustainable Development. Across the 17 SDGs, climate actions are urgently indicated. Green bonds, used as a vehicle to help finance green projects, are useful for answering the call of climate change (Piñeiro-Chousa, Ángeles López-Cabarcos, and Šević (2022)). Although both are fixed income securities, green bonds differentiate

\* Corresponding author at: Trinity Business School, Trinity College Dublin, Dublin 2, Co., Dublin, Ireland.

E-mail address: [blucey@tcd.ie](mailto:blucey@tcd.ie) (B. Lucey).

<https://doi.org/10.1016/j.gfj.2023.100894>

Received 28 January 2023; Received in revised form 20 September 2023; Accepted 20 September 2023

Available online 4 October 2023

1044-0283/© 2023 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

from the conventional bonds by their strict “use of proceeds” criteria. Specifically, the funds raised using green bonds must be used on environmentally friendly projects. Recently, green bonds have been recognized as a promising option for diversifying investment portfolios (e.g., Yi, Bai, Lyu, and Dai (2021), Cicchiello, Cotugno, Monferrà, and Perdichizzi (2022), Arif, Naeem, Farid, Nepal, and Jamasb (2022), Guo and Zhou (2021), etc). Under the umbrella of green finance, these environmentally-focused instruments have gained substantial popularity among both issuers and investors in the financial markets. For example, the property of its lower overall environmental risk ideally suits the attention of both individual and institutional investors with green preferences.

One strand of Current research about green bonds focuses on comparing the differences between green bonds and conventional bonds, especially the pricing difference, which is known as the green bond premium (e.g., MacAskill, Roca, Liu, Stewart, and Sahin (2021), Zerbib (2019), Nanayakkara and Colombage (2019), MacAskill et al. (2021), etc). Recent studies such as Flammer (2021) and Larcker and Watts (2020), contradict to previous studies, suggest there is no “greenium”.

Our study here is related to another strand that is interested in the financial relations between green bond and other non-bond financial assets (e.g., Lin & Su, 2022; Reboredo & Ugolini, 2020), Le, Abakah, and Tiwari (2021), Elsayed, Naifar, Nasreen, and Tiwari (2022), etc). How green bonds connect or co-move with other financial markets and what role green bonds could play in the financial system or portfolios are worth investigating. Green bonds are typically issued by entities committed to sustainable projects such as renewable energy, clean transportation, or energy-efficient infrastructure. These projects often have long-term revenue streams and should provide stable cash flows especially as there is a growing emphasis on environmental sustainability which reduces the default risk. As more investors seek socially responsible investments, the demand for green bonds has risen. This increased demand, coupled with the expanding market and support for green bonds, further reduce the liquidity and credit risks. Hence, theoretically, like other bond or fixed income products, green bonds can provide a level of stability and predictability compared to equities that are subject to more volatile market conditions. By investing in green bonds, investors can reduce their exposure to traditional equity markets and climate risks, and potentially benefit from lower correlation with equity movements.

The literature offers a fruitful list on green bonds’ interconnectedness. Using the copula method, Reboredo (2018) found that the green bond market strongly links to corporate and treasure markets but weakly links to the energy commodity and stock market. Reboredo and Ugolini (2020) later claimed that the green bond market is closely connected with the fixed-income and currency market by using a structural VAR model. Similar to what they have done, Yadav, Mishra, and Ashok (2023) examined the dynamic connectedness between green bonds and OECD financial markets by focusing on the top ten European countries. They followed two studies by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), adopting a dynamic connectedness approach using the VAR model and rolling-window VAR in the analysis. They found that volatility was connected across all frequency cycles and illustrate that the connectedness levels violate according to the term length. Furthermore, they concluded that green bonds can potentially reduce investment risk in the short term. Pham (2021) followed the same connectedness approach and suggests that the spillovers between green bonds and green equity dissipate in the medium and long term with the limitation that the spillovers are only sizeable under extreme market conditions. Besides the VAR-type connectedness modelling, another common method to test the dynamic interconnectedness of green bonds with financial markets are multivariate GARCH models. Since GARCH-typed models are ideally suitable for capturing independence and volatility clustering simultaneously, they are complementary to other approaches.

There are also many researchers have investigated the hedge and safe haven benefits of green bonds. We start from illustrating what hedge and safe haven assets are. Hedge and safe haven are fundamentally different. A strong (weak) safe haven asset refers to an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, that is, during extreme negative movements or extremely heightened market volatility (Baur and McDermott (2010) and Baur and Lucey (2010)). By comparison, a strong or weak hedge refers to an asset that is negatively correlated or uncorrelated with another normally, that is, on average (Baur and McDermott (2010) and Baur and Lucey (2010)). One potential scenario is the existence of assets that exhibit negative correlation specifically during crisis periods while generally co-moving with other assets in same direction. These assets are not hedge tools on average. In such cases, investors may only choose to acquire these assets during crisis periods as they maintain their value during those times, functioning as a safe haven. By distinguishing the difference, Baur and Lucey (2010) found that gold could be a short-lived hedge and safe haven for the stock markets, but not for the bond markets. Baur and McDermott (2010) further showed that gold could be both a hedge and a safe haven for major European and US stock markets but not for Australia, Canada, Japan and large emerging markets. Gold then is traditionally viewed as one representative safe haven asset. However, given that the health crisis resulted by COVID-19 has quickly transformed into a global economic crisis and global financial markets experienced their worst turmoil since the 1930s, safe haven assets may have lost their benefits. Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2021) re-examined the safe haven property of gold. They revealed that gold lost the safe haven benefit for equity market investors during the Phase II.

As we explained earlier, green bonds have the potential to serve as a hedge or a safe haven asset due to the special risk-return characteristics. The literature has provided some evidence. Pham and Do (2022) showed that green bonds are weakly connected to implied volatilities. They suggested that green bonds would be useful in financial risk management and hedging. Jiang, Wang, Ao, and Wang (2022) analysed the dependence of green bonds on various markets. They found that green bonds is generally insignificantly related to global stock market. Further analysis on hedge effectiveness suggested that green bonds could be used to mitigate portfolio risks especially for investors who are concerned about the exposure to environmental and regulatory risks. They also proposed that green bonds could potentially be a hedge or safe haven for US currency market. Arif et al. (2022) suggested that green bonds could be a hedge or safe haven instrument for currency and commodity investments. Naeem, Rabbani, Karim, and Billah (2023) focused on green bonds benefits for equity market investors. They attempted to investigate sukuk and green bond’s safe haven property with the estimation frameworks introduced by Baur and McDermott (2010) and Baur and Lucey (2010). The estimation process of Naeem et al. (2023) differs to the original return approach by the use of the Dynamic Conditional Correlations (DCC-) GARCH(1,1)-type (specifically the ADCC-GJR-GARCH) model which enables them to examine the time-varying correlations between green bond and equity

markets. They further used a less statistical/more arbitrary approach to examine protection power during the COVID-19 period and confirmed the usefulness of green bonds as a safe haven. Similarly, [Yousaf, Suleman, and Demirel \(2022\)](#) used the DCC-GARCH model to capture how green bonds behave during the COVID-19 pandemic. Compared with other alternatives and sustainable investments in their sample, green bonds are the only asset that displays a safe haven feature. [Dong, Xiong, Nie, and Yoon \(2023\)](#) compared the performance of conventional and green bonds with respect to S&P 500 and energy commodity prices. They found that both have safe haven feature when geopolitical risk levels are high, but green bonds are better than conventional bonds when economic and climate policy uncertainty levels are high. [Imran and Ahad \(2023\)](#) and [Chopra and Mehta \(2023\)](#) studied the safe haven property of green bonds for US sectoral stocks. More recently, [Lin and Su \(2022\)](#) studied the impact of various uncertainties on US and Chinese green bond markets. Results implied that green bonds may not function their safe haven role well during high national financial and oil uncertainties and the situations in the two countries vary. This casts doubt on whether green bonds could be a safe haven for international equity markets when the global uncertainty is heightened, especially when the financial contagion increased during first waves of COVID-19 outbreak ([Akhtaruzzaman, Boubaker, & Sensoy, 2021](#)).

Our study therefore contributes to the literature in four ways. First, most of previous studies that studied the safe haven property of green bonds or government bonds only considered the extreme movements in returns but not the volatilities. We employed the frameworks of both the volatility and return approaches introduced in the [Baur and McDermott \(2010\)](#) and applied in best-fitted (A) DCC-GARCH-type models to examine the hedge and safe haven property of green bonds against turbulence in global equity markets. The volatility approach which uses the conditional volatility of a world stock market index as a measure of global uncertainty. We show that green bonds are a safe haven for most selected countries (except the UK) during increased or extreme levels of global uncertainty. Green bonds could be a strong hedge for large Eurozone and North American countries, Switzerland, and Japan, and Saudi Arabia.

Second, We split our dataset into two to further explicitly gauge the difference in magnitudes between the pre- and post-COVID-19 outbreak periods. By analysing the correlation between green bond returns and extreme negative equity returns, we find that the hedge benefits of green bonds have lost for all country except for Saudi Arabia. Moreover, the scope for using green bonds as a safe haven for many countries becomes narrower after the COVID-19 outbreak in January 2020.

Third, we employed a novel CAViaR-based TVP-VAR connectedness model by [Chatziantoniou, Gabauer, and Perez de Gracia \(2022\)](#) to investigate the tail risk spillovers which extends our understanding of whether and how the green bonds are affected or exposed during extreme loss events. Results of VaR transmission show that at early stage of COVID-19 outbreak, the co-occurrence of extreme loss events became more often, which imply that safe haven benefit of green bonds has decreased at early stage of COVID-19 outbreaks from VaR perspective.

Fourth, previous study such as [Naeem et al. \(2023\)](#) only used limited number of equity markets that are not totally representative. We use 19 international equity markets, which covers major developed and developing countries across various continents. We provide new and exciting results. In particular, although results are mixed, we found that Saudi Arabia is the only country that can be both hedged and protected from extreme and tail risks using green bond and the protection is even better after the COVID-19 has spread all over the globe.

The remainder of this paper is organised as follows. We describe the data in [Section 2](#), followed by [Section 3](#) where we detail the methodology used in the analysis. We then present the empirical findings in [Section 4](#) and lastly, we conclude and address the implications of our study in [Section 5](#).

## 2. Data

We investigate the hedge and safe haven properties of green bonds in the global financial system. To accomplish this, we considered a sub-set of the World Index provided by Datastream, following and extending the selection of [Baur and McDermott \(2010\)](#). Our dataset includes 18 countries from the Group of Twenty (G20)<sup>1</sup> plus Switzerland. The G20 countries comprise the majority of the largest and most important economies in the world, including both developed and developing nations, while Switzerland is a Non-Eurozone European country with a strong/stable and important currency and a well-developed financial systems.

A number of ratings agencies and financial institutions have created indices to exclusively cover green bonds since the beginning of 2014. There are currently four green bond indices that could be considered as global representative benchmarks; the Bloomberg Barclays MSCI Global Green Bond Index (MSCIGB), the S&P Green Bond Index (SPGB), the Solactive Green Bond (SOLGB) Index, and the ICE Bank of America Merrill Lynch Green Bond (BAMLGB) Index. All of them were launched in 2014 with Solactive being the first in March, followed by S&P in July, Merrill Lynch in October, and MSCI being the last in November. However, to save space, we only present the main results of using MSCIGB. Results of using the other indices are qualitatively similar and are available upon request. We followed [Reboredo \(2018\)](#) to consider green bond data from October 14, 2014 to ensure homogeneous time periods across indices as this is the date when the MSCIGB started to be daily computed in the year when the Green Bond Principles which established the classification rules was released. The data spans to July 31, 2022 which covers several important events such as the Paris Agreement, Brexit, US-China Trade War, Oil price crash, COVID-19 outbreaks and the Russian aggression in Ukraine, in a 8-year period. We defined the date 24 January 2020, when a *Lancet* article by [Huang et al. \(2020\)](#) first indicated human transmission, as the outbreak separating the pre-COVID-19 and post-COVID-19 periods.

[Table 1](#) gives the descriptive statistics of the market returns. Unless otherwise specified, all price returns are denominated in the

<sup>1</sup> We excluded Russia due to the unavailability after March 2022 to ensure homogeneous time span across dataset.

local currency. From the table, we see that the green bond market and the Chinese stock market tend to be the only two that show negative average returns. Argentina is the most volatile market which has both the highest average return and the most extreme negative return. The stability of the green bond prices exhibits the potential of being a hedge or safe haven asset.

### 3. Methodology

#### 3.1. Safe haven analysis

##### 3.1.1. Dynamic conditional correlations

We adopt the estimation framework introduced by Baur and Lucey (2010) and Baur and McDermott (2010) to examine the hedge and safe haven property of green bond indices during financial turbulence. Similar to Akhtaruzzaman, Boubaker, Lucey, and Sensory (2021), Peng (2020), Ratner and Chiu (2013), and some others mentioned earlier, we start by using a DCC–GARCH model proposed by Engle (2002) to estimate the correlation of underlying asset pairs.

The estimation comprises two steps. The first is to estimate a GARCH(1,1) model. Let  $r_t$  be the  $N \times 1$  vector of pairs of return series  $r_{1t}$  and  $r_{2t}$ , given the information set  $I_{t-1}$ :

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t, \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{1}$$

where  $\varepsilon$  is the vector of residuals.

Secondly, we estimate the DCC parameter. Let  $H_t$  be the conditional covariance matrix of  $r_t$ . We have assumed  $r_t$  to be normally distributed with a zero mean and we write  $H_t$  as the following:

$$\begin{aligned} H_t &= D_t R_t D_t, \\ D_t &= \text{diag} \left[ h_{1t}^{1/2}, h_{2t}^{1/2} \right], \\ R_t &= \text{diag}[Q_t]^{-1/2} Q_t \text{diag}[Q_t]^{-1/2}, \end{aligned} \tag{2}$$

where  $R_t$  denotes the matrix of time-varying conditional correlations,  $Q_t$  is the positive definite matrix of  $q_{12,t}$ , and  $h_t$  is the conditional standard deviations (SDs). Then we can get the estimated DCC model as:

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}^T + b Q_{t-1}, \tag{3}$$

where  $a$  and  $b$  are non-negative scalars satisfying  $a + b < 1$ , and  $\bar{Q}$  is the unconditional variance matrix of standardised residuals  $u_t$ . We can thereby obtain the dynamic conditional correlations series  $\rho_{12,t}$  as:

$$\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t} q_{22,t}}. \tag{4}$$

**Table 1**  
Descriptive statistics of market returns (%).

Indices	Observations	Mean	Min	Max	Std. Dev
World (in USD)	2026	-0.0044	-3.0305	2.1975	0.3815
MSCIGB (in USD)	2026	0.0200	-9.7607	7.3811	0.8744
Argentina	2026	0.1095	-39.6351	8.9624	2.2120
Australia	2026	0.0144	-10.0961	6.6376	1.0046
Brazil	2026	0.0161	-14.8259	11.5250	1.4544
Canada	2026	0.0169	-13.0859	11.0707	0.9780
China	2026	-0.0081	-6.5972	15.5631	1.5383
France	2026	0.0292	-12.2850	7.9578	1.1714
Germany	2026	0.0128	-9.8302	7.0242	1.1143
India	2026	0.0392	-13.0347	7.3722	1.0328
Indonesia	2026	0.0097	-7.6021	12.1459	1.1166
Italy	2026	0.0090	-17.4311	7.4081	1.3539
Japan	2026	0.0219	-7.3811	7.5915	1.1209
Korea	2026	0.0135	-7.8946	8.6511	1.0316
Mexico	2026	0.0096	-5.0025	3.5796	0.7755
Saudi Arabia	2026	0.0053	-8.4119	8.5535	1.1544
South Africa	2026	0.0115	-9.9071	6.5390	1.2579
Switzerland	2026	0.0170	-9.3906	6.0520	0.9469
Turkey	2026	0.0656	-9.4910	6.4525	1.4369
United Kingdom	2026	0.0080	-11.0705	8.4390	1.0154
United States	2026	0.0360	-12.9235	8.9437	1.1475

### 3.1.2. Global uncertainty and markets' extreme movements

We examine the safe haven property of green bonds against the global uncertainty with the dynamic conditional correlation coefficients obtained in the last section. Following the work of [Ratner and Chiu \(2013\)](#), [Peng \(2020\)](#) and [Baur and McDermott \(2010\)](#), the dynamic conditional correlation  $DCC_t$  are regressed on dummy variables representing the increased and extreme global uncertainty. We followed [Baur and McDermott \(2010\)](#) to use the conditional volatility of the world index estimated with a GARCH(1,1) model as a proxy of global uncertainty:

$$DCC_{ij,t} = c_0 + c_1 D(v_{stock_i, q_{90,t-1}}) + c_2 D(v_{stock_i, q_{95,t-1}}) + c_3 D(v_{stock_i, q_{99,t-1}}), \tag{5}$$

where the dummy variables  $c_1$ ,  $c_2$  and  $c_3$  here are equal to one if the conditional volatility at  $t - 1$  exceeds the 90%, 95% and 99% quantiles, respectively. This allows us to examine the safe haven property of green bond against stock market during increased ( $c_1$  and  $c_2$ ) and extreme ( $c_3$ ) global uncertainty. According to the definition of safe haven in [Baur and Lucey \(2010\)](#), an asset is a weak hedge for an individual stock market during heightened global uncertainty if  $c_0$  is insignificantly different from zero, or a strong hedge if  $c_0$  is negative. Green bonds serve as a weak (strong) safe haven for an individual stock market under certain market condition if any of  $c_1$ ,  $c_2$  or  $c_3$  are non-positive (significantly negative).

Additionally, we examine the safe haven property of green bond against particular stock market turbulence given that stock markets have their own characteristics. Similarly, the  $DCC_t$  are regressed on dummy variables representing the extreme movements of a stock market as follows:

$$DCC_{ij,t} = c_0 + c_1 D(r_{stock_i, q_{10}}) + c_2 D(r_{stock_i, q_5}) + c_3 D(r_{stock_i, q_1}), \tag{6}$$

where  $D(\dots)$  are dummy variables that capture extreme negative returns of a stock market at the 10%, 5%, and 1% quantiles of the distribution.

## 3.2. Tail risk spillovers

### 3.2.1. Conditional autoregressive value-at-risk (CAViaR)

We follow [Chatziantoniou et al. \(2022\)](#) to measure the tail risk of variables by the asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) approach which was originally introduced by [Engle and Manganelli \(2004\)](#). [Chatziantoniou et al. \(2022\)](#) suggested that the asymmetric slope CAViaR is more flexible than the other existing techniques as it estimates the Value-at-Risk (VaR) in a direct way and allows for asymmetry.

The asymmetric slope CAViaR model assumes that the VaR of a certain quantile follows an Autoregressive (AR) process which can be written as:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x_{t-1}^+ + \beta_3 x_{t-1}^- \tag{7}$$

where  $f_{\alpha,t}$  is the VaR at the  $\alpha$  level in period  $t$ ,  $\beta_0$  is the constant,  $\beta_1$  and  $f_{\alpha,t-1}(\beta)$  are the weights of the lagged VaRs and the lagged VaRs, respectively.  $\beta_2$  and  $\beta_3$  are the effects of positive and negative returns on the VaR, respectively.

### 3.2.2. Time-varying parameter vector autoregressive (TVP-VAR) connectedness

We further apply a time-varying parameter VAR model (TVP-VAR) proposed by [Antonakakis, Chatziantoniou, & Gabauer, 2020](#) on changes in CAViaR to examine the tail risk spillovers across green bond and international stock markets. The TVP-VAR approach should have advantages over the DY connectedness framework ([Diebold and Yilmaz \(2012\)](#), [Diebold and Yilmaz \(2014\)](#)) which is based on a rolling window VAR approach as this does not require a window size to be biasedly assigned. It also avoids losing observations as it introduces a time-varying variance-covariance matrix by adopting the Kalman filter in estimation with forgetting factors assigned ([Antonakakis et al. \(2020\)](#)).

The TVP-VAR model with  $p$  lags is defined as the following:

$$\begin{aligned} y_t &= \Phi_t z_{t-1} + \varepsilon_t & \varepsilon_t | I_{t-1} &\sim N(0, \Sigma_t), \\ \text{vec}(\Phi_t) &= \text{vec}(\Phi_{t-1}) + e_t & e_t | I_{t-1} &\sim N(0, E_t), \end{aligned} \tag{8}$$

where  $y_t$  represents  $m \times 1$  vector of endogenous variables, while  $z_{t-1}$  represents  $pm \times 1$  vector of lagged  $y_t$  from  $t - p$  to  $t - 1$ .  $\varepsilon_t$  and  $e_t$  are vectors of error terms.  $I_{t-1}$  denotes all known information until  $t - 1$ .  $\Sigma_t$  and  $E_t$  are time-varying variance-covariance matrices.

We introduced the time-varying coefficients and the time-varying variance-covariance matrices in the generalized forecast error variance decomposition. For generalized VAR model,  $\phi_{ij}(H)$ , the  $H$ -step ahead generalized forecast error variance will be first decomposed and then normalised by its row sum. Before doing that, based on the Wold representation theorem, we transform the estimated TVP-VAR model into TVP- vector moving average (VMA) as:  $y_t = \sum_{i=1}^p \Phi_{it} y_{t-i} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j}$

$$\phi_{ij}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{9}$$

$$\tilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^N \phi_{ij}(H)}$$

where the  $\sigma_{ij}$  denotes the estimated SD of the error term for variable  $j$ ,  $\Sigma$  is the variance matrix for the error-term vector  $\epsilon$ , and  $e_i$  is the selection vector with one as the  $i^{th}$  element and zero otherwise.

Following Antonakakis et al. (2020), we initiate the Kalman filter using the Minnesota prior, followed by using the benchmark decay factors of (0.99, 0.99) in the estimation step.

The total connectedness/spillovers (TC), directional connectedness received by asset  $i$  from  $j$  ( $DS_{i \leftarrow j}$ ), directional connectedness transmitted to  $j$  by  $i$  ( $DS_{i \rightarrow j}$ ), and net connectedness (NC) indices are calculated as the following:

$$TC(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, j \neq i}^N \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{10}$$

$$DC_{i \leftarrow j}(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^N \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{11}$$

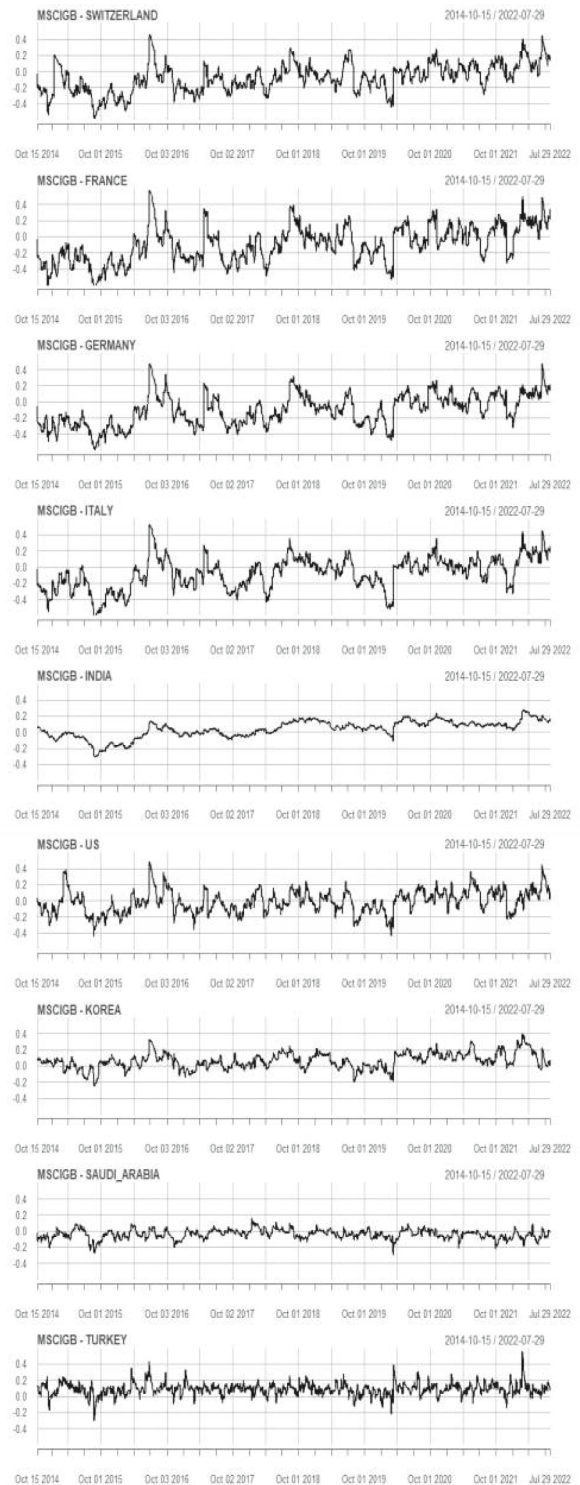
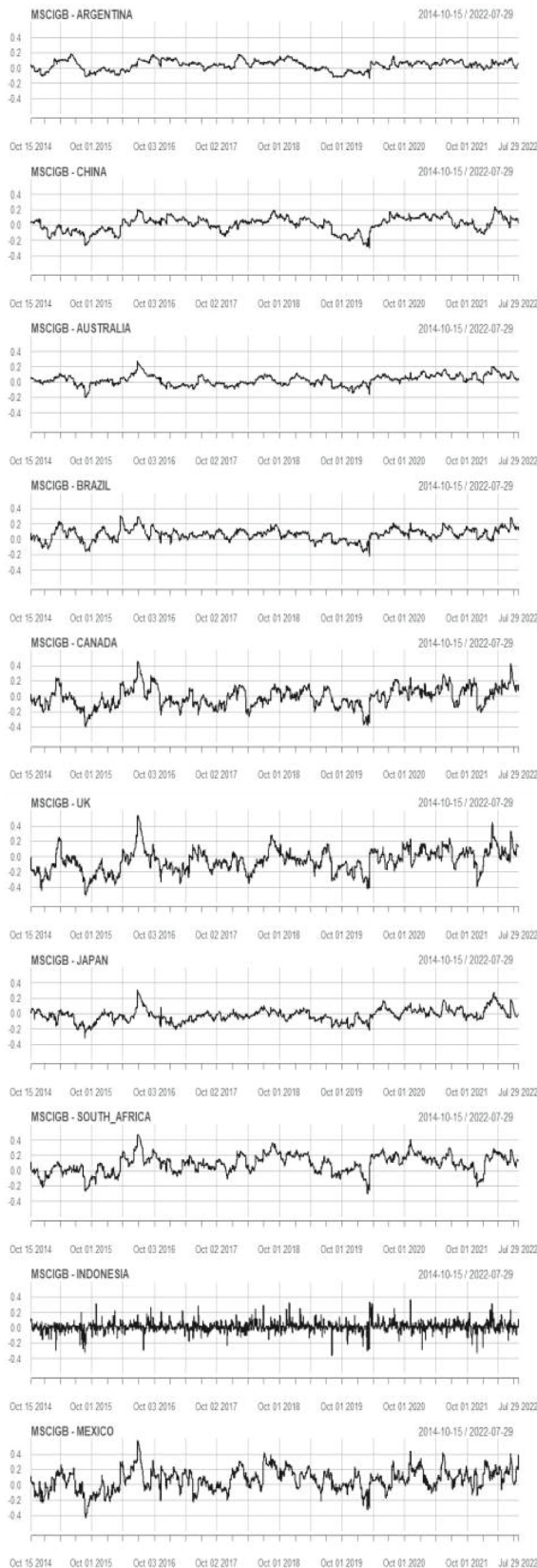
$$DC_{i \rightarrow j}(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ji}(H)}{\sum_{i,j=1}^N \tilde{\phi}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\phi}_{ji}(H)}{N} \times 100 \tag{12}$$

$$NC_i(H) = DC_{i \rightarrow j}(H) - DC_{i \leftarrow j}(H) \tag{13}$$

As the total connectedness by this measure is not in the range of (0,1), adjusted total connectedness computed by  $\frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij}(H)}{N-1} \times 100$  was used.

**Table 2**  
Selected bi-variate (A)DCC- GARCH type models.

Market	Model
Argentina	DCC-AR(1)-EGARCH(1,1)
Australia	DCC-EGARCH(1,1)
Brazil	DCC-EGARCH(1,1)
Canada	DCC-EGARCH(1,1)
China	DCC-GJR-GARCH(1,1)
France	DCC-EGARCH(1,1)
Germany	DCC-EGARCH(1,1)
India	DCC-AR(1)-EGARCH(1,1)
Indonesia	DCC-GJR-GARCH(1,1)
Italy	DCC-EGARCH(1,1)
Japan	DCC-EGARCH(1,1)
Korea	DCC-GJR-GARCH(1,1)
Mexico	DCC-GARCH(1,1)
Saudi Arabia	DCC-AR(1)-EGARCH(1,1)
South Africa	DCC-EGARCH(1,1)
Switzerland	DCC-EGARCH(1,1)
Turkey	DCC-GARCH(1,1)
United Kingdom	DCC-EGARCH(1,1)
United States	DCC-EGARCH(1,1)



(caption on next page)

**Fig. 1.** The optimal DCCs between green bond and international stock markets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## 4. Results

### 4.1. Safe haven analysis

#### 4.1.1. DCC estimates

Similar to [Urquhart and Zhang \(2019\)](#), we compare the performance of several dynamic conditional correlation (DCC) and Asymmetric DCC (ADCC) GARCH type models. Specifically, we used standard GARCH(1,1), and EGARCH(1,1) introduced by [Nelson \(1991\)](#) and GJR-GARCH(1,1) models by [Glosten, Jagannathan, and Runkle \(1993\)](#) which account for the asymmetry with leverage terms in the estimation process, where we first only included a constant in the mean equation, and then we further added an AR(1) term to capture the potential autoregressive behaviour in the error variance. [Table 2](#) reports the model selected based on the Akaike Information Criteria (AIC), the Bayesian Information Criterion (BIC) and the Hannan-Quinn Information Criterion (HQIC). We selected the model selected by most of the measures at the same time. If the selection by the criteria is unclear, we use the one preferred by BIC than AIC as BIC achieves better forecasts in some previous studies [see [Lütkepohl, 1985](#) & [Granger & Jeon, 2004](#) among others]. We note that all DCC models universally outperform the ADCC models in our study.

The time-varying correlations between green bond and stock market indices are plotted in the [Fig. 1](#). While the pairwise correlations have their own evolution, some common traits can be observed. We first notice that the trends of the correlations between green bond and European countries are quite similar, being different in terms of the magnitude. Moreover, the pattern of the correlations between green bonds and the Australian market is different from those between green bonds and developed European or North American countries, and is closer to those between Asian countries. These implies significant return or risk spillovers within vs across regions (e. g., Europe) ([Baele \(2005\)](#), [Li \(2020\)](#)). Therefore, when green bonds serve as a hedge or safe haven for a country, it is very likely that it also works for countries in the same region that share similar characteristics and not for others. Furthermore, the correlations seem to be sensitive to events related to climate policy. We find that the correlations rose significantly during and after the Paris Agreement in December 2015 and remained high in 2016. Similar to [Demiralay, Gencer, and Bayraci \(2022\)](#), we link this to the rising interest and awareness among investors in greener investments after the Paris Agreement, which significantly accelerated the green bond market growth ([Tolliver, Keeley, and Managi \(2020\)](#)). We can also easily see that the COVID-19's global outbreak may have changed the dependence structure as the correlations significantly increased and most have switched their signs in early 2020, which supports the systemic co-movement and spillovers between financial markets during periods of heightened uncertainty ([Abuzayed, Bouri, Al-Fayoumi, and Jalkh \(2021\)](#), [Demiralay et al. \(2022\)](#)).

Looking closer at each pair, we document that the range of the correlations between green bond and European countries are the

**Table 3**

Results of hedge and safe haven analysis of green bond for extreme global uncertainty.

Market	Hedge ( $\theta_0$ )	90% threshold ( $\theta_1$ )	95% threshold ( $\theta_2$ )	99% threshold ( $\theta_3$ )
Argentina	0.0348***	0.0050	-0.0042	-0.0087
Australia	0.0226***	0.0282***	0.0057	-0.0514***
Brazil	0.0605***	0.0222***	0.0026	-0.0478**
Canada	-0.0099***	0.0342**	-0.0019	-0.0573*
China	0.0099***	0.0208**	-0.0261*	-0.0682***
France	-0.1112***	0.1211***	0.0323	-0.0059
Germany	-0.1172***	0.1074***	0.0310	-0.0560
India	0.0301***	0.0676***	-0.0139	-0.0013
Indonesia	0.0110***	-0.0051	-0.0007	0.0803***
Italy	-0.0873***	0.1139***	-0.0053	-0.0586
Japan	-0.0269***	0.0540***	0.0118	-0.0839***
Korea	0.0567***	0.0442***	0.0026	-0.0069
Mexico	0.0637***	0.0126	-0.0105	-0.0295
Saudi Arabia	-0.0381***	-0.0109*	-0.0120	-0.0801***
South Africa	0.0839***	0.0579***	-0.0128	-0.0079
Switzerland	-0.0879***	0.0773***	0.0176	-0.0337
Turkey	0.0872***	-0.0019	-0.0086	0.0867***
United Kingdom	-0.0611***	0.0343**	0.0389*	0.0081
United States	-0.0166***	0.0379***	0.0282	-0.0588*

#### Notes

- Eq. 5 was used.
- Green bond is a weak hedge for stock market during extreme global uncertainty if  $\theta_0$  is insignificantly different from zero, or a strong hedge if  $\theta_0$  is negative. Green bond serves as a weak (strong) safe haven for a stock market under certain market condition if parameters  $\theta_1$ ,  $\theta_2$  and  $\theta_3$  are non-positive (significantly negative);
- We rule out the safe haven property if strong arbitrary estimates (e.g., significant and opposite signs in more extreme cases) are presented.
- \*\*\*, \*\* and \* denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.



widest. They had the lowest negative value in 2015 and have persisted at relatively high levels in the post-COVID-19 period, which implies that green bonds may have lost hedge benefits in more recent time. The correlation between green bonds and Indonesia and Turkey tend to be extremely volatile in the short term and mostly positive, which lowers the potential to serve as a hedge or safe haven asset. The correlation with Japan has been relatively less volatile and had had relatively high proportion of negative values. However, the correlation has become more positive in recent times, which may have resulted in similar situation as in the European markets. Lastly, we pay particular attention to the Saudi Arabian stock market. It stands out as it has been mostly negatively correlated with green bonds and less volatile in the long term especially after the pandemic of the COVID-19, so green bond should be able to provide hedge benefits to Saudi Arabian stock market given their negative linkage. Given the dominance of KSA in global oil markets this is not surprising but it is heartening to see this evidence.

#### 4.1.2. Regression estimates

DCC plots have provided a rough inference about the functionality of green bonds in the global stock markets. In this section, we present analysis of hedge and safe haven ability of green bonds for global turbulence and stock markets' extreme downturns.

We first compute the estimates for cases during increased or extreme global uncertainty (Table 3). We reiterate that estimates of  $\theta_1$  and  $\theta_2$  refer to cases during increased uncertainty, while  $\theta_3$  is for extreme uncertainty by the definition provided in Baur and McDermott (2010).  $\theta_0$  is the hedge coefficient. The results show that green bonds are a hedge for European countries, North American countries, Japan and Saudi Arabia, but not for the rest in times of increased or extreme global uncertainty. We proceed with looking at the estimates for safe haven property in columns 2–4. Here we need to be careful with inconsistent signs. Therefore, we rule out the capability of green bonds to be a safe haven if the estimate in 95% case is significant and inconsistent with 10% and 1% cases at the same time. Besides, we also depend on the total effect by summing the estimates to define whether its property is general or condition-specific. We first notice that while stock markets in most countries can only benefit from the use of green bonds as a safe haven under certain level(s) of uncertainty, two countries stand out being quite special. The first is the UK that although its  $\theta_0$  is significantly negative, none of the  $\theta_1$  to  $\theta_3$  is non-positive or significantly negative, and the sum of  $\theta_1$  to  $\theta_3$  are jointly positive exceeding the value of  $\theta_0$ . In this case, the green bond can not be a strong hedge or a safe haven for the UK. On the contrary, we see that all (most) estimates of  $\theta_0$  to  $\theta_3$  are (significantly) negative in the case of Saudi Arabia, which indicates that green bond is both a strong hedge and a strong safe haven for Saudi Arabian stock market. We also find relatively consistent results across Eurozone countries and Switzerland that green bonds are a weak safe haven only for very extreme (1%) case.

Having identified that green bonds can be treated as a hedge or safe haven for most equity markets when facing global uncertainty, we then take into account the different individual market dynamics, and we further consider the involvement of the COVID-19, where results are presented in Table Appendix A and 4, respectively.

**Table 4**

Results of hedge and safe haven analysis of green bond for extreme stock movements before and after the outbreaks of COVID-19.

Market	Hedge ( $\theta_0$ )	10% quantile ( $\theta_1$ )	5% quantile ( $\theta_2$ )	1% quantile ( $\theta_3$ )
Argentina	0.0311*** (0.0488***)	-0.0173* (-0.0124)	0.0093 (-0.0022)	-0.0468** (-0.0659***)
Australia	0.0055*** (0.0699***)	0.0150* (-0.0192**)	-0.0295** (-0.0142)	-0.0034 (-0.0552***)
Brazil	0.0528*** (0.0853***)	-0.0107 (0.0070)	0.0148 (-0.0214)	-0.0161 (-0.1542***)
Canada	-0.0294*** (0.0461***)	-0.0074 (-0.0011)	0.0120 (-0.0392)	-0.1185*** (-0.1543***)
China	-0.0062** (0.0452***)	0.0004 (0.0015)	-0.0113 (-0.0122)	-0.0311 (0.0467)
France	-0.1586*** (0.0365***)	0.0057 (0.0013)	-0.0625 (-0.0099)	-0.0397 (-0.0935)
Germany	-0.1626*** (0.0168**)	0.0252 (0.0265)	-0.0631* (-0.0403)	-0.0396 (-0.0926)
India	-0.0023 (0.1181***)	0.0115 (0.0088)	-0.0387** (-0.0118)	0.0228 (-0.0595**)
Indonesia	0.0089*** (0.0158***)	0.0001 (-0.0166)	0.0103 (0.0218)	-0.0209 (0.0260)
Italy	-0.1234*** (0.0262***)	0.0670*** (-0.0203)	-0.1751*** (0.0108)	0.0740 (-0.1462*)
Japan	-0.0440*** (0.0265***)	0.0077 (0.0041)	-0.0208 (0.0083)	-0.0217 (-0.1365***)
Korea	0.0336*** (0.1223***)	-0.0051 (-0.0225)	0.0131 (-0.0172)	-0.0221 (-0.0139)
Mexico	0.0507*** (0.0906***)	0.0345* (0.0100)	-0.0338 (-0.0417)	0.0057 (-0.0741)
Saudi Arabia	-0.0336*** (-0.0484***)	-0.0067 (-0.0073)	-0.0192* (-0.0433***)	-0.0213 (-0.0024)
South Africa	0.0722*** (0.1261***)	-0.0034 (0.0084)	0.0033 (-0.0153)	-0.0108 (-0.1454***)
Switzerland	-0.1274*** (0.0241***)	0.0202 (0.0459*)	-0.0698** (-0.0303)	-0.2170 (-0.3013***)
Turkey	0.0836*** (0.0967***)	-0.0069 (-0.0135)	0.0107 (-0.0131)	0.0359 (0.0519)
United Kingdom	-0.0862*** (0.0131***)	0.0138 (-0.0044)	-0.0475* (-0.0431)	-0.0110 (-0.0520)
United States	-0.0378*** (0.0505***)	-0.0274 (-0.0252)	0.0274 (-0.0117)	-0.0389 (-0.1474**)

#### Notes

- Eq. 6 was used.
- As mentioned in the Data section, we divided our dataset into two periods based on the date of 24 January 2020. Coefficient estimates outside and in parentheses are results before and after the COVID-19 outbreak, respectively.
- Green bond is a weak hedge for stock market during extreme movements if  $\theta_0$  is insignificantly different from zero, or a strong hedge if  $\theta_0$  is negative. Green bond serves as a weak (strong) safe haven for a stock market under certain market condition if parameters  $\theta_1$ ,  $\theta_2$  and  $\theta_3$  are non-positive (significantly negative);
- We rule out the safe haven property if strong arbitrary estimates (e.g., significant and opposite signs in more extreme cases) are presented.
- \*\*\*, \*\* and \* denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

**Table 5**  
Statistics of tail risk.

Statistics	MSCIGB	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia
Mean	0.007	-0.008	-0.023	-0.017	-0.004	-0.010	-0.029	-0.015	-0.012	-0.019
Variance	150.175***	206.701***	189.809***	118.083***	410.410***	105.995***	246.732***	222.658***	68.210***	76.000***
Skewness	1.233***	2.802***	1.789***	2.088***	1.538***	1.838***	1.745***	1.689***	2.082***	2.431***
Ex.Kurtosis	1.910***	18.968***	3.534***	6.409***	2.719***	4.422***	3.921***	3.317***	6.119***	8.796***
JB	820.989***	32,991.448***	2133.115***	4934.519***	1421.024***	2787.938***	2323.564***	1889.843***	4619.965***	8518.637***
ERS	-4.990***	-9.177***	-10.534***	-2.705***	-5.527***	-9.338***	-3.108***	-3.010***	-13.087***	-10.567***

#### Notes

1. The null hypothesis of Jarque–Bera (JB) test: the series is normally distributed.
2. The null hypothesis of Elliott-Rothenberg-Stock (ERS) test: the series is non-stationary.
3. \*\*\*, \*\* and \* denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

we put an emphasis on Table 4. As we have considered that the COVID-19 may have changed the connectedness or dependency between green bond and markets previously through the DCC plots, we split our dataset into pre-COVID-19 and during COVID-19 periods starting in January 2020.

We find that although previously green bonds could be used as a long-term hedge for some countries such as the European and North American countries, China, Japan, and Saudi Arabia, it has lost this property for almost all of them after the COVID-19 outbreak. The only exception is for the Saudi Arabia where green bonds still provides hedge benefit and the coefficient estimate is even more negative, which indicates that the hedge benefit of green bond for Saudi Arabia has increased even after COVID-19. Generally, emerging markets exhibit higher growth rates, less efficient and more volatile financial systems and may be more exposed to sectors with environmental impact, such as energy or natural resources. Positive correlations between green bonds and equity indexes in emerging markets could be attributed to the growth potential of both asset classes. As emerging markets undergo rapid development, green investments and sustainable practices may be seen as avenues for future growth and development. Investors seeking exposure to the growth prospects of emerging markets may invest in both green bonds and equities, resulting in positive correlations between the two. This positive outlook can lead to a positive coefficient between green bonds and equity markets in these economies. Conversely, advanced markets may have more mature economies and a greater emphasis on sustainable practices. In these markets, investors may already have incorporated sustainability factors into their investment decisions. Green bonds may be perceived as lower-risk investments compared to equities. During periods of market uncertainty or equity market downturns, advanced markets' investors may reallocate their investments from equities to green bonds, resulting in a negative correlation between the two. However, this correlation is time-changing and is differ country by country. Specific factors such as government policies, investor sentiment, or market regulations can create exceptions, as observed in Australia, South Korea, China. The COVID-19 pandemic and its associated economic uncertainties might have caused investors to seek safer investment options, such as green bonds. It can be observed through the DCC plots (Fig. 1) that during the first wave of COVID-19, green bonds exhibited negative relations with equity market when equity markets suffered huge loss. This might have been attracting more investor interest during this period and later led to a positive correlation with equity markets in more countries when the economics are recovering. Factors specific to Saudi Arabia could have influenced a different market sentiment and policy environment, resulting in a continued negative correlation. These factors might include a heavy reliance on the oil sector, differences in policy responses, or investor sentiment specific to the country. Future research conducting detailed analysis and considering country-specific factors would provide more accurate insights into the correlation patterns observed in each market. Regarding safe haven property of green bonds, we observe that for most developed countries especially the Europeans, we see that the estimates generally become more or nearly equal (less) negative or significantly negative in 1% (5%) cases, which indicates that the benefits of green bond have increased for more extreme cases but decreased for less extreme cases. This can be also found in some other emerging markets such as India, Mexico, South Africa, etc. Overall, green bonds could still be a strong or weak safe haven for international equity markets.

## 4.2. Tail risk spillovers

### 4.2.1. CAViaR estimates

Table 5 summarises the statistics of log changes of the tail risks measured as 5% VaR using the asymmetric slope CAViaR model. Results reveal that most of the mean tail risk changes are negative except for MSCIGB, South Africa, and United States. All series are stationary according to the ERS unit root test (Elliott, Rothenberg, and Stock (1996)) results. We visualise the tail risk series to show the co-movements across series in Fig. 2. Except for Argentina which depicts an exceptionally high risk in the third and fourth quarter of 2019, other series reached their peaks during the first wave of COVID-19. MSCIGB exhibits the lowest risk as expected. Using other levels such as 1% and 10% provides robust results with qualitatively similar pattern and slightly different magnitude (see Fig. Appendix C.1 and Appendix B.1).

### 4.2.2. TVP-VAR connectedness estimates

Since the previous safe haven approach is more of a static approach, the dynamic connectedness measures allow us to further investigate the tail risk transmission channel, which extends our understanding of the usefulness of using green bonds as risk reduction

Italy	Japan	Korea	Mexico	Saudi Arabia	South Africa	Switzerland	Turkey	United Kingdom	United States
-0.010	-0.023	-0.001	-0.002	-0.044	0.011	-0.014	-0.007	-0.016	0.013
290.980***	155.124***	145.533***	50.464***	475.751***	79.157***	290.286***	132.155***	165.579***	367.505***
1.445***	1.410***	1.838***	1.871***	1.836***	1.872***	1.378***	2.300***	1.749***	2.022***
3.673***	2.515***	3.550***	4.343***	4.580***	3.587***	3.600***	8.871***	3.634***	5.624***
1841.823***	1204.291***	2202.880***	2771.262***	2906.402***	2267.955***	1733.529***	8421.245***	2145.702***	4046.393***
-2.957***	-10.180***	-23.108***	-14.541***	-4.650***	-2.867***	-3.303***	-10.737***	-2.884***	-10.554***

tools during stock markets' extreme circumstances over time. We first examine Figs. 3 and 4 which visualise the time-varying total and net 5% tail risk connectedness. We note from Fig. 3 that when COVID-19 started to spread globally, the extreme risk connectedness/spillovers among global equities jumped significantly and reached all-time highs approaching approximately mid-2020 in our chosen window. Additionally, we see that before the COVID-19 outbreak, their tail risk connectedness had remained stable at 50% to 60% levels in 2018–2019 after a gradual decline since peaking in late 2016. The average connectedness from 2017 till 2020 (before COVID-19) was lower than that in the post-COVID-19 period, which shows that COVID-19 raised uncertainty in international financial markets. These results are similar to many studies analysing the dynamic connectedness among different financial products before and during the COVID-19 pandemic.

The net connectedness plots in Fig. 4 can be used to identify the general role each asset plays in the financial network. For example, variables with positive values will be considered tail risk transmitters, while with negative values, risk receivers. MSCIIB constantly serves as a risk taker in the system, while western developed countries are risk transmitter except for Australia which plays similar role as Asian countries. Of particular notice, Saudi Arabia as a major oil exporting country takes risk at most times. These interesting results encourage us to further look into the situations of pairs.

Fig. Appendix C present the net connectedness between all pairs. We see that developed European countries are major risk transmitter to the rest of the world, while the US transmits even higher risks to developed Asia-Pacific countries such as Japan and Australia. We zoom in to look at the dynamics between MSCIIB and international stock markets in Fig. 5. Notably, MSCIIB is a constant net risk receivers for all the European countries and the US. Except for Saudi Arabia, Korea and Australia, MSCIIB served as a risk receiver during the first waves of the COVID-19 in early 2022. We also note that during recent period when Russia has been invading Ukraine which causes anticipated energy crisis especially for European countries, we see that the risk spillovers between MSCIIB and most European countries have significantly increased, but not for the Asian and Middle East countries.

In the interests of consistency, we conclude the exposition of the last findings by looking at the evolution of pairwise co-movement magnitude over time as plotted in Fig. Appendix E.1. The spillovers between developed countries, especially westerns, are significantly higher than the others. This could be seen consistent with our DCC findings that the dynamics among European countries are similar especially those sharing the same currency. Focusing on the case of MSCIIB (Fig. 6), it is quite obvious that the spillovers become

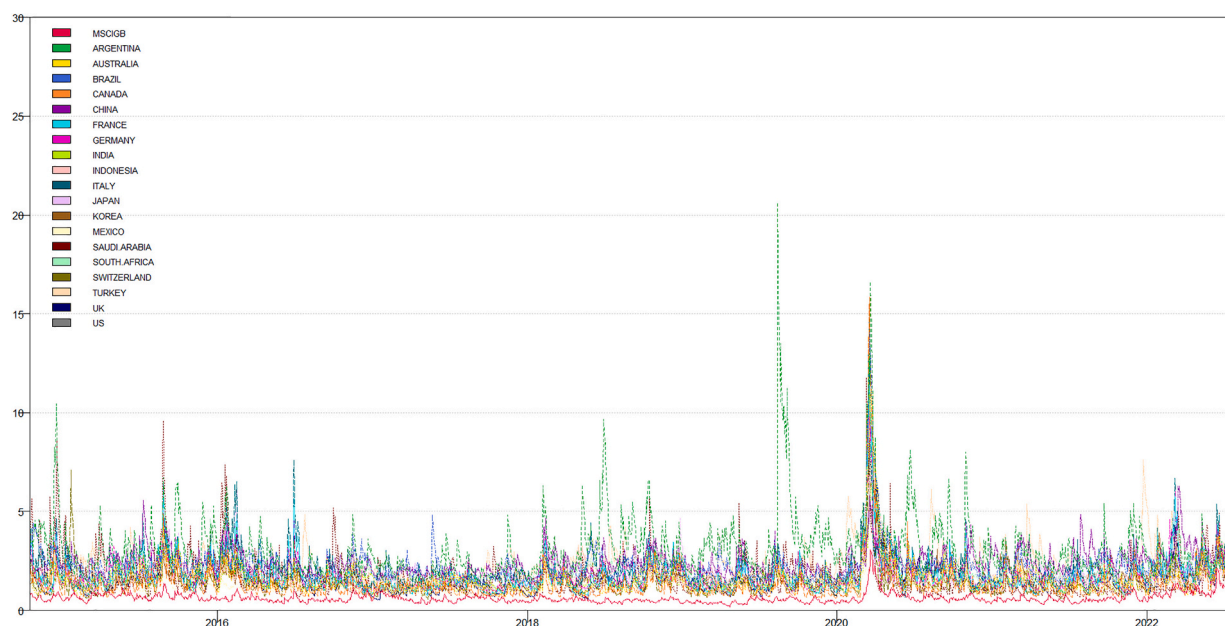


Fig. 2. Tail risk measured as 5% VaR using the asymmetric slope CAViaR model.

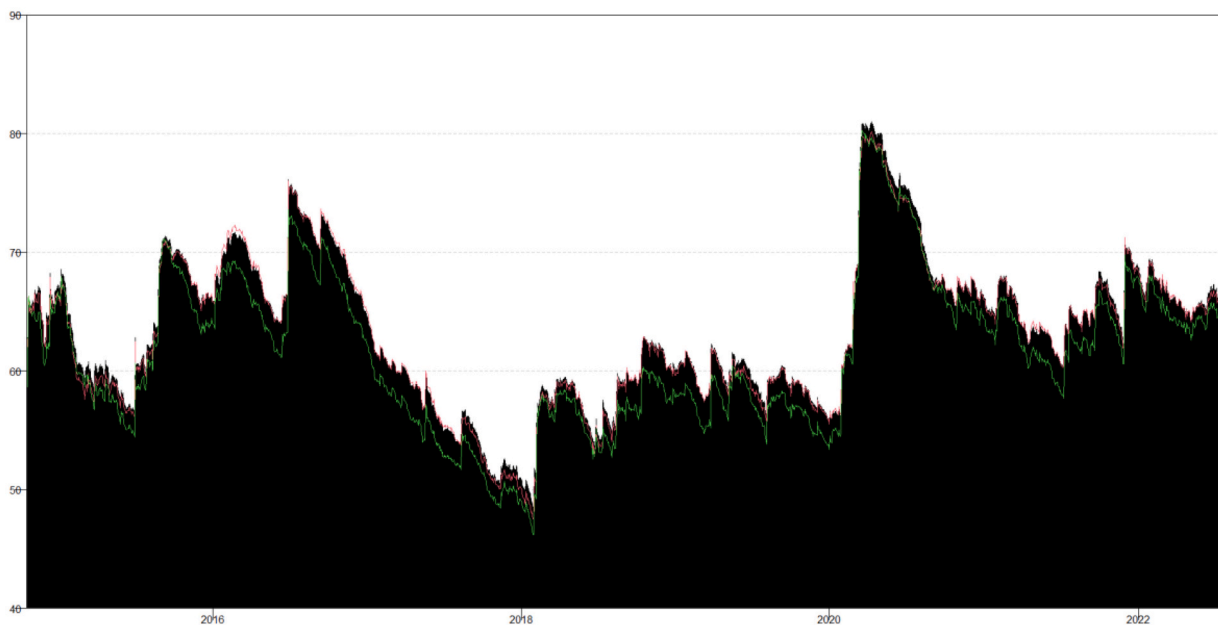


Fig. 3. Dynamic total tail risk connectedness (in %).

Note: Black area represents the findings based on the 5% VaR while the red and the green lines indicate the results of the 10% and 1% VaR, respectively.

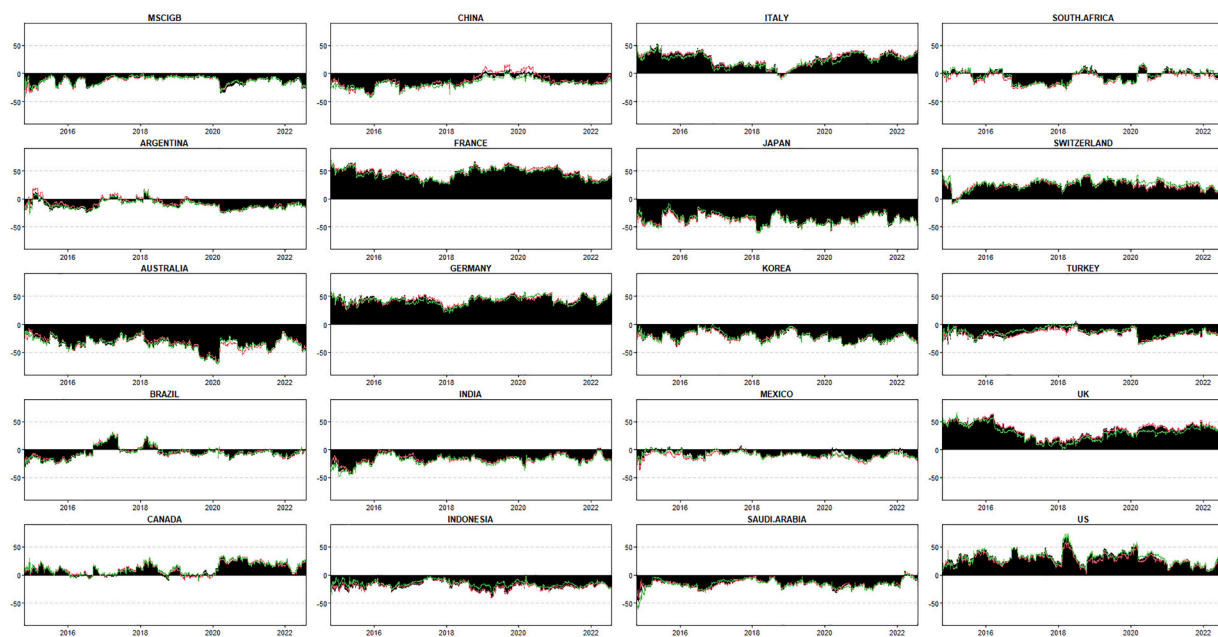


Fig. 4. Dynamic net tail risk connectedness (in %).

strong when the outbreaks started for most countries, which would suggest the safe haven benefit of the green bond has decreased, at least, at early stage. We notice that the risk transmission has become relatively low or has been declining in early 2021, except for Japan showing exactly the opposite. Towards the end of our sample period which coincides with the Russia-Ukraine War, we notice that the spillovers between green bond and most stock markets have increased significantly or have the tendency to increase. There are few countries were affected, or less affected such as South Africa. For example, the connectedness between MSCIGB and South Africa has significantly dropped in early 2022 and remained low. We will not list Australia as less affected as its level has been exceptionally high since late 2021. On average, we find that Saudi Arabia and Japan are the only countries that have significantly lower spillovers with MSCIGB in the post-COVID-19, which is also evidence in the Table Appendix F.1 and Table 6 which calculates the average

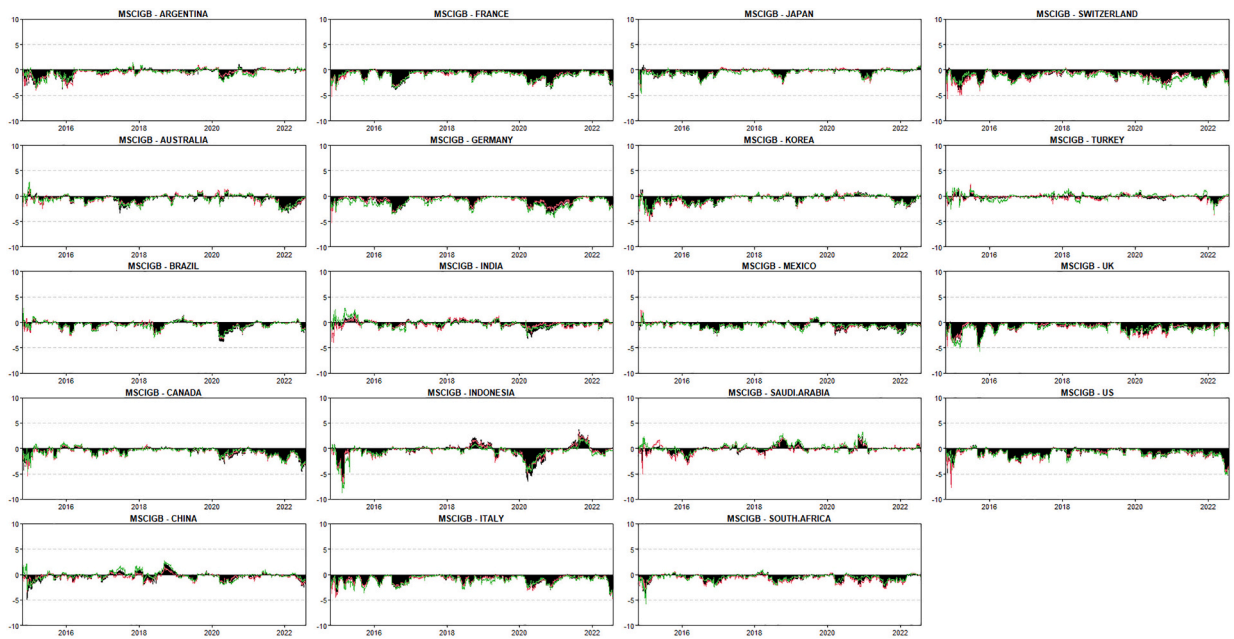


Fig. 5. Pairwise net connectedness (in %).

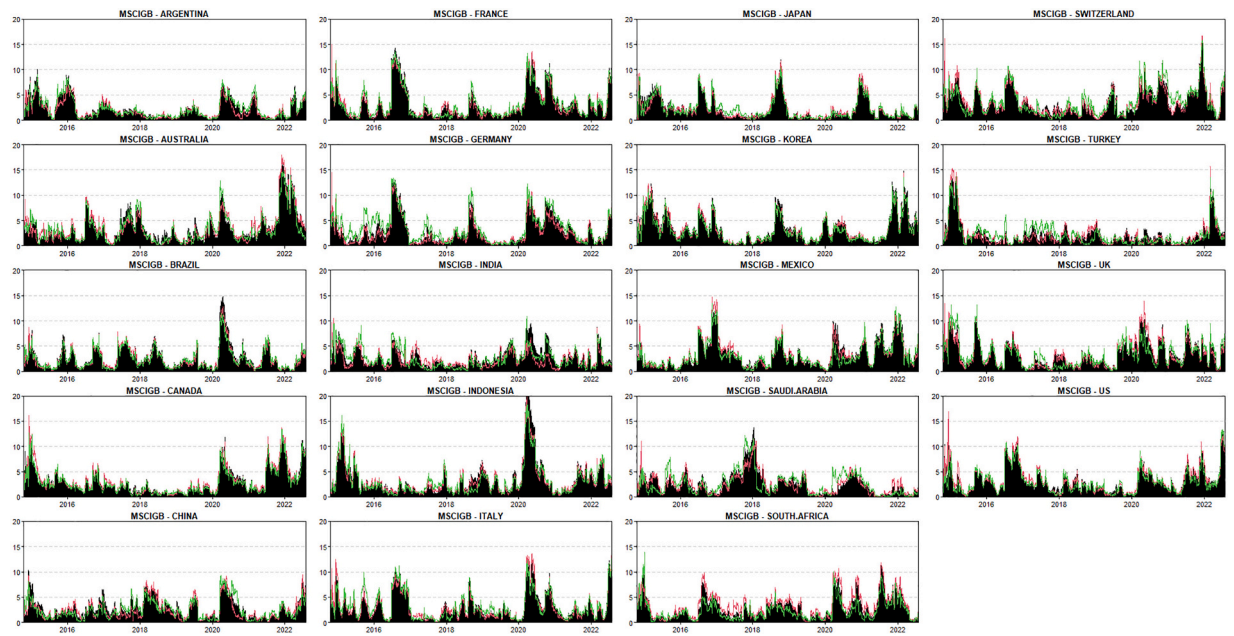


Fig. 6. Pairwise total connectedness (in %).

pairwise risk connectedness (with MSCIGB). Turkey has slightly lower average spillovers with MSCIGB in the post-COVID-19 era, but the relation was quite high in early 2022.

### 5. Conclusions

This paper provides a comprehensive insight of green bonds being a risk mitigation tool in the global financial system. We first study the role of green bonds as hedge or safe haven for 18 largest or most important economies' equities following various static frameworks of [Baur and Lucey \(2010\)](#). The results show that green bonds are a safe haven for most selected countries (except the UK) during increased or extreme levels of global uncertainty proxied by the conditional volatility of a world stock market index. Additionally, green bonds provide hedge benefits to large Eurozone and North American countries, Switzerland, and Japan, and Saudi

**Table 6**  
Pairwise tail risk connectedness between MSCIIGB and stock markets before and after the COVID-19 outbreak (in %).

Market	Pairwise tail risk connectedness (in %)	Change
Argentina	2.11 (2.42)	14.69%
Australia	2.56 (5.08)	98.44%
Brazil	2.26 (3.05)	34.96%
Canada	2.12 (4.70)	121.70%
China	2.61 (2.51)	-3.83%
France	2.49 (4.33)	73.90%
Germany	2.36 (3.68)	55.93%
India	2.34 (3.22)	37.61%
Indonesia	2.53 (4.87)	91.30%
Italy	2.58 (3.73)	44.57%
Japan	2.36 (1.80)	-23.73%
Korea	3.23 (3.63)	12.38%
Mexico	2.53 (4.58)	81.03%
Saudi Arabia	2.89 (1.48)	-48.79%
South Africa	2.21 (3.77)	70.59%
Switzerland	2.85 (4.94)	73.33%
Turkey	2.10 (1.98)	-5.71%
United Kingdom	2.75 (4.29)	56.00%
United States	2.72 (3.98)	46.32%

#### Notes

- As mentioned in the Data section, we divided our dataset into two periods based on the date of 24 January 2020. Values outside and in parentheses correspond to results before and after the COVID-19 outbreak, respectively.

Arabia. In particular, Saudi Arabia's stock market tends to be the strongest beneficiary as green bonds are both a strong hedge and safe haven tool for it. We also confirm that green bond serves well as a safe haven during extreme downturns for most countries but levels vary. Taking COVID-19 into consideration we show that the hedge benefits of green bond for utmost all countries may have lost, consistent with our findings of dynamic conditional correlations which have become mostly positive. However, the scope for using green bonds as a safe haven, especially for developed and some developing countries, becomes narrower after the outbreaks. For example, it may no longer work for less extreme cases (10% or 5%), but the protection from green bonds for more extreme movements such as 1% quantile's has strengthened for most countries. Since green bonds have been providing safe haven benefit to equity market investors, investor could use green bonds to reduce loss or mitigate risk during other markets' crisis periods and only need to hold for a short period of time if green bonds are not a hedge for that market on average. Although situations vary from country to country, we highlight that green bonds still provide significant hedge and safe haven benefits for Saudi Arabia market even in the post-COVID-19 period. Saudi Arabia market as a major oil exporting country whose economy significantly relies on the fossil fuel industry, investors seeking to use more sustainable products to mitigate risk would find green bond products beneficial for their portfolio constructions.

We further investigate the dynamic tail risk transmission channel using a novel CAViaR-based TVP-VAR models by Antonakakis et al. (2020). The finding of the dynamic total tail risk connectedness confirms that the green bond market tends to be the recipient of shocks rather than the initiator and that this interconnectedness has, with few exceptions, increased in recent months. On the pairwise spillovers, Japan and Saudi Arabia are the only two countries that have lower average risk spillovers with green bond. However, as green bonds mostly bears the risk from Japan, this weakens the safe haven property of green bond as it suggests that the exposure to extreme loss in Japanese equity market affects the exposure in the green bond market. Saudi Arabia might be the only country that shares benefits of using green bond to hedge or diversify based on all metrics we used.

Overall we can conclude the portfolio usefulness of green bonds remains, but the relationship with equity markets is very time dynamic and event driven. In attempting to deepen the green bond market as a fulcrum of green transition market participants and policy makers need to be cognizant of this. To gain a more comprehensive understanding, further analysis and research are necessary. This could involve examining country-specific factors, policy frameworks, sector-level data, and conducting in-depth econometric modelling to capture the unique dynamics of each country's market. Future research might be also interested in examining the performance by constructing different sets of dynamic VaR-optimised portfolios with green bonds and international equity markets.

#### Declaration of Competing Interest

Authors are not aware of any conflicts of interest for this paper.

#### Data availability

Data will be made available on request.

#### Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**Appendix A. Results of hedge and safe haven analysis of green bond for extreme stock movements**

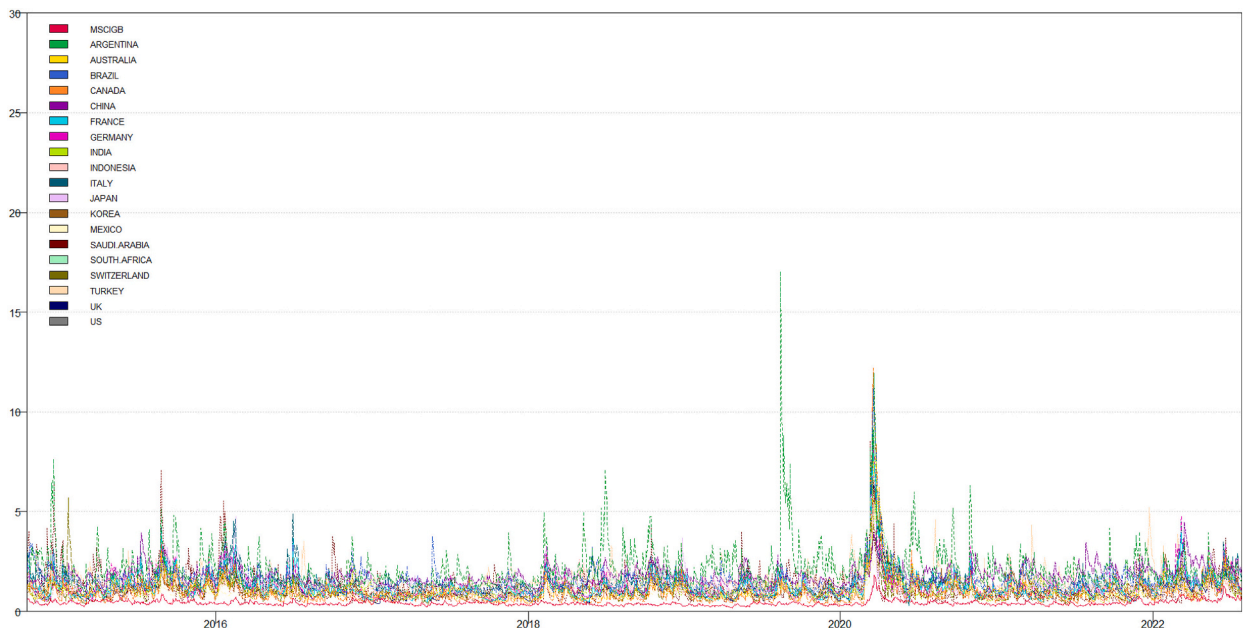
**Table A.1**  
Results of hedge and safe haven analysis of green bond for extreme stock movements.

Market	Hedge ( $\theta_0$ )	10% quantile ( $\theta_1$ )	5% quantile ( $\theta_2$ )	1% quantile ( $\theta_3$ )
Argentina	0.0369***	-0.0149**	0.0014	-0.0440***
Australia	0.0256***	0.0007	-0.0029	-0.0310*
Brazil	0.0631***	-0.0014	0.0035	-0.0316***
Canada	-0.0056*	-0.0104	0.0012	-0.0549*
China	0.0096***	0.0113	-0.0154	0.0032
France	-0.0986***	0.0392*	-0.0672**	0.0561
Germany	-0.1072***	0.0578**	-0.0853***	0.0259
India	0.0357***	0.0071	-0.0103	0.0220
Indonesia	0.0113***	-0.0049	0.0093	0.0068
Italy	-0.0757***	0.0340*	-0.0987***	0.0553
Japan	-0.0220***	0.0220***	-0.0221*	-0.0837***
Korea	0.0609***	-0.0019	0.0154	-0.0284
Mexico	0.0629***	0.0352**	-0.0441**	-0.0073
Saudi Arabia	-0.0386***	-0.0025	-0.0320***	-0.0145
South Africa	0.0892***	0.0021	-0.0021	-0.0316
Switzerland	-0.0795***	0.0143	-0.0138	-0.0830*
Turkey	0.0877***	-0.0091	0.0109	0.0133
United Kingdom	-0.0551***	0.0002	-0.0167	0.0327
United States	-0.0110***	-0.0116	0.0005	0.0160

Notes

- Eq. 6 was used.
- Green bond is a weak hedge for stock market during extreme movements if  $\theta_0$  is insignificantly different from zero, or a strong hedge if  $\theta_0$  is negative. Green bond serves as a weak (strong) safe haven for a stock market under certain market condition if parameters  $\theta_1$ ,  $\theta_2$  and  $\theta_3$  are non-positive (significantly negative);
- We rule out the safe haven property if strong arbitrary estimates (e.g., significant and opposite signs in more extreme cases) are presented.
- \*\*\*, \*\* and \* denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

**Appendix B. Tail risk measured at 10%**



**Fig. B.1.** Tail risk measured as 10% VaR using the asymmetric slope CAViaR model

Appendix C. Tail risk measured AT 1%

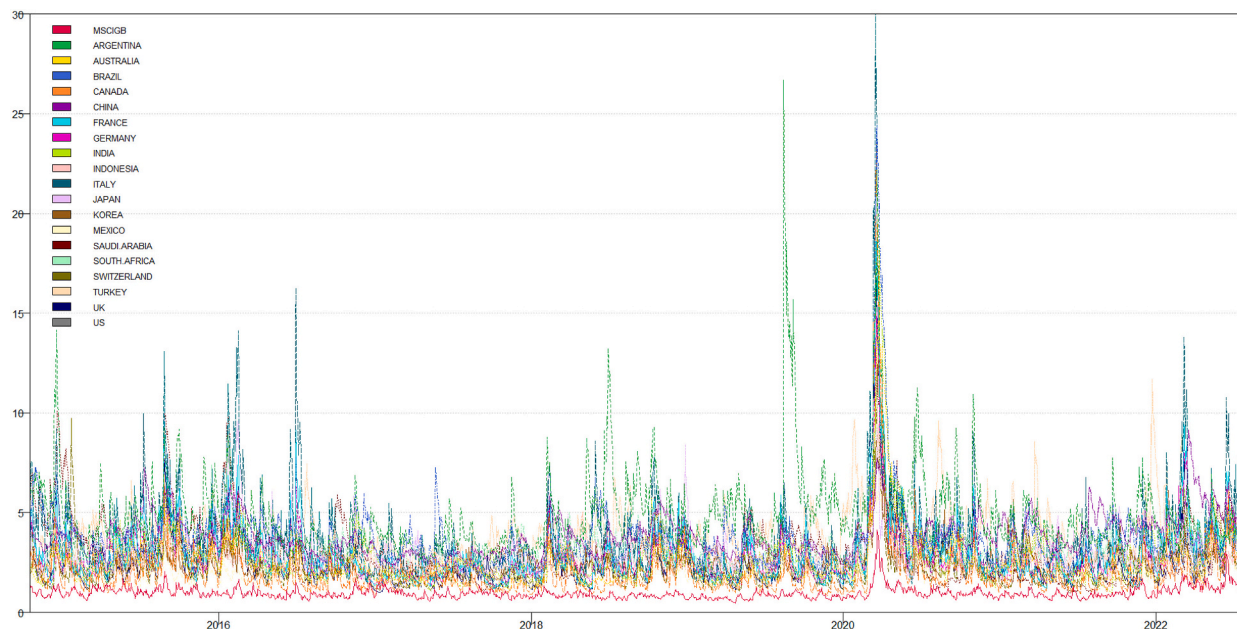


Fig. C.1. Tail risk measured as 1% VaR using the asymmetric slope CAViAR model

Appendix D. Net pairwise dynamic connectedness



Fig. D.1. Net pairwise dynamic connectedness (in %)



Appendix E. Pairwise total connectedness



Fig. E.1. Pairwise total connectedness (in %)

## Appendix F. Pairwise total connectedness table

**Table F.1**  
Pairwise connectedness table (in %).

	Pre-COVID-19 (COVID-19)	MSCIGB	Argentina	Australia	Brazil	Canada	China	France	Germany	India	Indonesia	Italy	Japan	Korea	Mexico	Saudi Arabia	South Africa	Switzerland	Turkey	United Kingdom	United States
MSCIGB	100.00 (100.00)	2.11 (2.42)	2.56 (5.08)	2.26 (3.05)	2.12 (4.70)	2.61 (2.51)	2.49 (4.33)	2.36 (3.68)	2.34 (3.22)	2.53 (4.87)	2.58 (3.73)	2.36 (1.80)	3.23 (3.63)	2.53 (4.58)	2.89 (1.48)	2.21 (3.77)	2.85 (4.94)	2.10 (1.98)	2.75 (4.29)	2.72 (3.98)	
Argentina	2.11 (2.42)	100.00 (100.00)	6.28 (6.75)	16.88 (26.00)	12.18 (18.43)	8.29 (8.67)	13.63 (14.84)	14.47 (17.44)	9.49 (10.94)	3.66 (8.86)	11.93 (14.53)	7.32 (3.84)	8.03 (3.72)	14.86 (12.34)	4.09 (2.46)	7.59 (11.35)	9.94 (7.14)	5.05 (7.59)	13.20 (16.49)	16.20 (14.70)	
Australia	2.56 (5.08)	6.28 (6.75)	100.00 (100.00)	8.45 (11.24)	13.55 (27.72)	11.76 (15.89)	22.59 (29.31)	21.64 (29.72)	10.28 (12.48)	4.80 (9.54)	18.12 (24.14)	21.56 (23.26)	16.42 (14.98)	8.53 (7.18)	4.48 (7.18)	14.58 (16.86)	19.93 (23.58)	2.68 (4.81)	24.43 (35.81)	22.00 (33.04)	
Brazil	2.26 (3.05)	16.88 (26.00)	8.45 (11.24)	100.00 (100.00)	15.14 (25.42)	8.14 (16.32)	15.71 (16.08)	17.43 (20.50)	11.59 (12.94)	8.13 (14.26)	13.82 (13.69)	7.16 (8.23)	8.11 (10.69)	20.95 (17.48)	2.56 (3.91)	11.39 (16.30)	12.48 (10.91)	4.63 (5.02)	17.21 (15.31)	24.57 (28.20)	
Canada	2.12 (4.70)	12.18 (18.43)	13.55 (27.72)	15.14 (25.42)	100.00 (100.00)	11.24 (22.05)	29.78 (41.07)	30.51 (47.28)	10.63 (14.47)	5.83 (16.20)	27.73 (40.06)	14.11 (19.24)	9.30 (11.04)	14.42 (32.86)	4.86 (5.75)	14.73 (25.01)	23.18 (36.09)	7.68 (9.56)	28.12 (40.47)	54.14 (67.49)	
China	2.61 (2.51)	8.29 (8.67)	11.76 (15.89)	8.14 (16.32)	11.24 (22.05)	100.00 (100.00)	19.35 (16.84)	19.06 (18.50)	14.88 (12.04)	9.08 (8.63)	13.97 (14.24)	13.87 (11.60)	25.92 (16.76)	8.03 (9.37)	4.47 (5.60)	18.29 (21.23)	16.70 (17.80)	5.41 (4.11)	21.33 (16.78)	20.30 (26.19)	
France	2.49 (4.33)	13.63 (14.84)	22.59 (29.31)	15.71 (16.08)	29.78 (41.07)	19.35 (16.84)	100.00 (100.00)	83.89 (80.64)	21.14 (33.22)	8.36 (18.22)	75.72 (85.68)	28.94 (31.44)	18.44 (21.60)	18.75 (26.95)	10.53 (9.41)	31.01 (43.69)	71.36 (72.74)	9.52 (18.20)	71.72 (81.21)	42.89 (38.97)	
Germany	2.36 (3.68)	14.47 (17.44)	21.64 (29.72)	17.43 (20.50)	30.51 (47.28)	19.06 (18.50)	83.89 (80.64)	100.00 (100.00)	21.24 (30.67)	7.09 (15.84)	69.39 (78.01)	26.95 (30.55)	16.60 (19.81)	20.17 (30.35)	8.04 (9.86)	26.98 (43.20)	68.17 (70.77)	8.58 (15.41)	63.43 (71.25)	49.12 (49.17)	
India	2.34 (3.22)	9.49 (10.94)	10.28 (12.48)	10.63 (12.94)	14.88 (14.47)	21.14 (12.04)	100.00 (33.22)	100.00 (30.67)	12.17 (100.00)	12.17 (19.80)	100.00 (28.25)	100.00 (11.07)	100.00 (20.04)	100.00 (17.24)	100.00 (6.44)	100.00 (28.78)	100.00 (27.89)	100.00 (14.71)	100.00 (32.34)	100.00 (15.60)	
Indonesia	2.53 (4.87)	3.66 (8.86)	4.80 (9.54)	8.13 (14.26)	5.83 (16.20)	9.08 (8.63)	8.36 (15.84)	7.09 (19.80)	12.17 (100.00)	100.00 (15.13)	5.56 (14.20)	5.61 (15.69)	11.97 (13.70)	7.50 (13.70)	3.65 (3.73)	12.79 (17.79)	7.83 (13.48)	3.31 (6.82)	9.38 (18.41)	8.74 (10.99)	
Italy	2.58 (3.73)	11.93 (14.53)	18.12 (24.14)	13.82 (13.69)	27.73 (40.06)	13.97 (14.24)	75.72 (85.68)	69.39 (78.01)	16.67 (28.25)	5.56 (15.13)	100.00 (100.00)	21.52 (27.00)	12.35 (17.15)	15.06 (25.45)	8.41 (9.27)	24.04 (40.67)	56.85 (67.91)	6.28 (16.22)	57.44 (74.95)	36.97 (36.54)	
Japan	2.36 (1.80)	7.32 (3.84)	21.56 (26.30)	7.16 (8.23)	14.11 (19.24)	13.87 (11.60)	28.94 (31.44)	26.95 (30.55)	11.79 (11.07)	5.61 (14.20)	21.52 (27.00)	100.00 (100.00)	23.33 (28.16)	10.20 (11.97)	4.77 (4.27)	9.86 (14.55)	23.20 (22.72)	5.24 (7.03)	23.50 (34.00)	24.68 (25.37)	
Korea	3.23 (3.63)	8.03 (3.72)	16.42 (23.26)	8.11 (10.69)	9.30 (11.04)	25.92 (16.76)	18.44 (19.81)	16.60 (20.04)	15.78 (15.69)	11.97 (17.15)	12.35 (28.16)	23.33 (100.00)	100.00 (6.92)	8.87 (3.46)	4.37 (22.11)	15.59 (16.47)	15.45 (16.47)	2.76 (6.49)	16.94 (23.11)	16.28 (14.90)	
Mexico	2.53 (4.58)	14.86 (12.34)	8.53 (14.98)	20.95 (17.48)	14.42 (32.86)	8.03 (9.37)	18.75 (26.95)	20.17 (30.35)	7.86 (17.24)	7.50 (13.70)	15.06 (25.45)	10.20 (11.97)	8.87 (6.92)	100.00 (100.00)	3.22 (4.71)	15.88 (21.61)	13.13 (25.93)	4.88 (4.84)	20.18 (28.70)	24.60 (29.57)	
Saudi Arabia	2.89 (1.48)	4.09 (2.46)	4.48 (7.18)	2.56 (3.91)	4.86 (5.75)	4.47 (5.60)	10.53 (9.41)	8.04 (9.86)	3.89 (6.44)	3.65 (3.73)	8.41 (9.27)	4.77 (4.27)	4.37 (3.46)	3.22 (4.71)	100.00 (100.00)	5.13 (5.09)	9.20 (9.43)	3.93 (2.28)	8.16 (8.55)	6.43 (7.50)	
South Africa	2.21 (3.77)	7.59 (11.35)	14.58 (16.86)	11.39 (16.30)	14.73 (25.01)	18.29 (21.23)	31.01 (43.69)	26.98 (43.20)	13.37 (28.78)	12.79 (17.79)	24.04 (40.67)	9.86 (14.55)	15.59 (22.11)	5.13 (21.61)	100.00 (5.09)	100.00 (100.00)	26.80 (41.84)	8.19 (13.83)	36.18 (45.55)	19.62 (19.32)	
Switzerland	2.85 (4.94)	9.94 (7.14)	19.93 (23.58)	12.48 (10.91)	23.18 (36.09)	16.70 (17.80)	71.36 (72.74)	68.17 (70.77)	18.01 (27.89)	7.83 (13.48)	56.85 (67.91)	23.20 (22.72)	15.45 (16.47)	13.13 (25.93)	9.20 (9.43)	26.80 (41.84)	100.00 (100.00)	6.80 (11.90)	63.62 (66.19)	36.78 (34.40)	
Turkey	2.10 (1.98)	5.05 (7.59)	2.68 (4.81)	4.63 (5.02)	7.68 (9.56)	5.41 (4.11)	9.52 (18.20)	8.58 (15.41)	6.13 (14.71)	3.31 (6.82)	6.28 (16.22)	5.24 (7.03)	2.76 (6.49)	4.88 (4.84)	3.93 (2.28)	8.19 (13.83)	6.80 (11.90)	100.00 (100.00)	8.76 (17.45)	7.88 (7.36)	
United Kingdom	2.75 (4.29)	13.20 (16.49)	24.43 (35.81)	17.21 (15.31)	28.12 (40.47)	21.33 (16.78)	71.72 (81.21)	63.43 (71.25)	22.36 (32.34)	9.38 (18.41)	57.44 (74.95)	23.50 (34.00)	16.94 (23.11)	20.18 (28.70)	8.16 (8.55)	36.18 (45.55)	63.62 (66.19)	8.76 (17.45)	100.00 (100.00)	40.94 (36.30)	
United States	2.72 (3.98)	16.20 (14.70)	22.00 (33.04)	24.57 (28.20)	54.14 (67.49)	20.30 (26.19)	42.89 (38.97)	49.12 (49.17)	16.20 (15.60)	18.74 (10.99)	36.97 (36.54)	24.68 (25.37)	16.28 (14.90)	24.60 (29.57)	6.43 (7.50)	19.62 (19.32)	36.78 (34.40)	7.88 (7.36)	100.00 (36.30)	100.00 (100.00)	

## References

- Abuzayed, B., Bouri, E., Al-Fayoumi, N., & Jalkh, N. (2021). Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. *Economic Analysis and Policy*, 71, 180–197.
- Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., & Sensoy, A. (2021). Is gold a hedge or a safe-haven asset in the COVID-19 crisis? *Economic Modelling*, 102, 105588.
- Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during covid-19 crisis. *Finance Research Letters*, 38, 101604.
- Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84.
- Arif, M., Naeem, M. A., Farid, S., Nepal, R., & Jamasb, T. (2022). Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19. *Energy Policy*, 168, 113102.
- Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, 40(2), 373–401.
- Barunfk, J., & Krehlik, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271–296.
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217–229.
- Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, 34(8), 1886–1898.
- Chatziantoniou, I., Gabauer, D., & Perez de Gracia, F. (2022). Tail risk connectedness in the refined petroleum market: A first look at the impact of the COVID-19 pandemic. *Energy Economics*, 111, 106051.
- Chopra, M., & Mehta, C. (2023). Going green: Do green bonds act as a hedge and safe haven for stock sector risk? *Finance Research Letters*, 51, 103357.
- Cicchiello, A. F., Cotugno, M., Monferrà, S., & Perdichizzi, S. (2022). Credit spreads in the European green bond market: A daily analysis of the COVID-19 pandemic impact. *Journal of International Financial Management & Accounting*, 33(3), 383–411.
- Demiralay, S., Gencer, H. G., & Bayraci, S. (2022). Carbon credit futures as an emerging asset: Hedging, diversification and downside risks. *Energy Economics*, 113, 106196.
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.
- Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.
- Dong, X., Xiong, Y., Nie, S., & Yoon, S.-M. (2023). Can bonds hedge stock market risks? Green bonds vs conventional bonds. *Finance Research Letters*, 52, 103367.
- Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64(4), 813–836.
- 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 Economics*, 107, 105842.
- Engle, R. (2002). Dynamic conditional correlation. *Journal of Business & Economic Statistics*, 20(3), 339–350.
- Engle, R. F., & Manganelli, S. (2004). CAViaR. *Journal of Business & Economic Statistics*, 22(4), 367–381.
- Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516.
- Glosten, L. R., Jagannathan, R., & Runcle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48(5), 1779–1801.
- Granger, C., & Jeon, Y. (2004). Forecasting performance of information criteria with many macro series. *Journal of Applied Statistics*, 31(10), 1227–1240.
- Guo, D., & Zhou, P. (2021). Green bonds as hedging assets before and after COVID: A comparative study between the us and China. *Energy Economics*, 104, 105696.
- Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Zhang, L., Fan, G., Xu, J., Gu, X., et al. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet*, 395(10223), 497–506.
- Imran, Z. A., & Ahad, M. (2023). Safe-haven properties of green bonds for industrial sectors (GICS) in the United States: Evidence from Covid-19 pandemic and global financial crisis. *Renewable Energy*, 210, 408–423.
- Jiang, Y., Wang, J., Ao, Z., & Wang, Y. (2022). The relationship between green bonds and conventional financial markets: Evidence from quantile-on-quantile and quantile coherence approaches. *Economic Modelling*, 116, 106038.
- Larcker, D. F., & Watts, E. M. (2020). Where's the greenium? *Journal of Accounting and Economics*, 69(2), 101312.
- Le, T.-L., Abakah, E. J. A., & Tiwari, A. K. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change*, 162, 120382.
- Li, H. (2020). Volatility spillovers across European stock markets under the uncertainty of Brexit. *Economic Modelling*, 84, 1–12.
- Lin, B., & Su, T. (2022). Uncertainties and green bond markets: Evidence from tail dependence. *International Journal of Finance and Economics*, 1–18.
- Lütkepohl, H. (1985). Comparison of criteria for estimating the order of a vector autoregressive process. *Journal of Time Series Analysis*, 6(1), 35–52.
- MacAskill, S., Roca, E., Liu, B., Stewart, R., & Sahin, O. (2021). Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. *Journal of Cleaner Production*, 280, 124491.
- Naeem, M. A., Rabbani, M. R., Karim, S., & Billah, S. M. (2023). Religion vs ethics: Hedge and safe haven properties of sukuk and green bonds for stock markets pre- and during COVID-19. *International Journal of Islamic and Middle Eastern Finance and Management*, 16(2), 234–252.
- Nanayakkara, M., & Colombage, S. (2019). Do investors in green bond market pay a premium? Global evidence. *Applied Economics*, 51(40), 4425–4437.
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2), 347–370.
- Peng, X. (2020). Do precious metals act as hedges or safe havens for China's financial markets? *Finance Research Letters*, 37, 101353.
- Pham, L. (2021). Frequency connectedness and cross-quantile dependence between green bond and green equity markets. *Energy Economics*, 98, 105257.
- Pham, L., & Do, H. X. (2022). Green bonds and implied volatilities: Dynamic causality, spillovers, and implications for portfolio management. *Energy Economics*, 112, 106106.
- Piñero-Chousa, J., Ángeles López-Cabarcos, M., & Šević, A. (2022). Green bond market and sentiment: Is there a switching behaviour? *Journal of Business Research*, 141, 520–527.
- Ratner, M., & Chiu, C.-C. J. (2013). Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis*, 30, 18–25.
- Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74, 38–50.
- Reboredo, J. C., & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, 88, 25–38.
- Tolliver, C., Keeley, A. R., & Managi, S. (2020). Drivers of green bond market growth: The importance of nationally determined contributions to the Paris agreement and implications for sustainability. *Journal of Cleaner Production*, 244, 118643.
- Urquhart, A., & Zhang, H. (2019). Is bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, 63, 49–57.
- Yadav, M., Mishra, N., & Ashok, S. (2023). Dynamic connectedness of green bond with financial markets of European countries under OECD economies. *Economic Change and Restructuring*, 56(1), 609–631.
- Yi, X., Bai, C., Lyu, S., & Dai, L. (2021). The impacts of the COVID-19 pandemic on China's green bond market. *Finance Research Letters*, 42, 101948.
- Yousaf, I., Suleman, M. T., & Demirer, R. (2022). Green investments: A luxury good or a financial necessity? *Energy Economics*, 105, 105745.
- Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98, 39–60.