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The impact of economic outlook on green finance: insights from linkages between green and inflation-indexed bonds

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Abstract
While inflation-indexed bonds focus on mitigating the impact of inflation and preserving the purchasing power of investors, green bonds prioritize investments in environmentally responsible projects. These bond types offer distinct investment opportunities that cater to the diverse preferences and objectives of investors. With this in mind, this study aims to explore the dynamic relationship between inflation-indexed bonds and green bonds using wavelet analysis, quantile regression, and the Diebold-Yilmaz procedures for the period spanning October 2016 to January 2021. By considering green bonds as indicative of green energy outlooks and inflation-indexed bonds as reflective of overall economic conditions, we investigate the hypothesis that inflation-indexed bonds dominate green bonds within a sample of emerging markets. Our findings reveal significant interdependence between green bonds and inflation-indexed bonds across various wavelet time scales. Consistent with recent research, inflation-indexed bonds exhibit a dominant influence on the relationship, while the nature of this dependence alternates between positive and negative. Furthermore, quantile connectedness analysis demonstrates that spillover transmissions are more pronounced during extreme positive and negative market conditions. The outcomes of this study hold relevance for both investors and policymakers alike.

Keywords Green finance · Green bonds · Inflation-indexed bonds · Co-movement · Wavelet analysis · Connectedness analysis · Asset networks

JEL E20 · F21 · G11

1 Introduction

In the wake of the UN's proclamation of the 2030 Agenda, there has been an unprecedented surge in the proliferation of diverse categories of green climate bonds within the market. These encompass Social Bonds, Sustainability Bonds, Environmental, Social and Governance (ESG) Bonds, and Sustainable Development Goal (SDG) Bonds. Consequently, green bonds have emerged as a pivotal conduit for establishing a connection with the SDGs, as they assume a critical role in tackling climate change mitigation and adaptation, which are

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indisputably indispensable for the triumphant realization of the SDGs (https://doi.org/10.1002/ijfe.2787). However, the pursuit of sustainable development goals driven by green bonds encounters substantial obstacles primarily stemming from the suboptimal utilization of these bonds due to the inflationary pressures exerted on green commodities. Despite the introduction of the inflation-indexed bond paradigm by various developed nations, particularly emerging economies, to safeguard investments in environment-friendly projects, this commendable initiative is somewhat hindered by the absence of appropriate policy frameworks. Moreover, the enticement of investor sentiment toward green investments remains largely unobserved, owing to the scarcity of conducive investment climates precipitated by policy interventions. Given this problematic scenario, this research endeavors to formulate a compelling research question: How do inflation-indexed bonds and green bonds interact in serving the best interests of the global green revolution?

The study at hand is driven by a multitude of motivations. *First,* it recognizes the paramount importance and practicality of inflation-indexed bonds in shaping macroeconomic dynamics, particularly within the realm of green financial instruments employed by economies. While these bonds are widely acknowledged as one of the most secure investment vehicles, offering cash flows that align with actual consumption plans (Campbell & Viceira, 2001), they are intricately tied to the prices of consumption goods as measured by an inflation index, such as the consumer price index (CPI). In stark contrast to conventional nominal bonds, inflation-indexed bonds guarantee a real interest rate that remains unaffected by potential future inflationary pressures, safeguarding its value until maturity. Put simply, indexed bonds provide stable payments in real terms, shielding investors from the perils of inflationary risk (Eksi & Filipovic, 2014; Lucas & Stokey, 1983). In this regard, inflation-indexed bonds are inherently intertwined with both national and global macroeconomic conditions, particularly domestic demand. By delving into the co-movements of green financial products alongside inflation-indexed bonds, we can glean further insights into how these environmentally conscious products fluctuate in response to prevailing economic outlooks.

Second, the imperativeness of the green movement, propelled by the advent of green bonds, has assumed a pivotal role in supplanting fossil fuel-driven climatic occurrences, thereby propelling the trajectory toward sustainable development. Essentially, green bonds serve as financial instruments earmarked for the financing of environmentally friendly assets and projects (Weber & Saravade, 2019). These bonds provide the necessary funding for initiatives that champion the use of low-carbon energy sources, ultimately contributing to the mitigation of global climate crises (Gianfrate & Peri, 2019; Nguyen et al., 2020). In recent times, governments and investors in financial markets have widely embraced green bonds under the auspices of green finance (Reboredo et al., 2020). The green bond market has experienced substantial growth over the years, owing to its pivotal role in funding eco-conscious projects and mitigating the adverse impacts of climate change (Hammoudeh et al., 2020; Reboredo et al., 2020). While it is of paramount importance to assess the co-movements between green bonds and inflation-indexed bonds, enabling investors to discern their financial incentives or ascertain the efficacy of green bonds as a hedging tool, it is equally crucial to comprehend the interplay between green finance products and economic forecasts. We posit that the examination of the co-movement of green and inflation-indexed bonds represents a significant yet under-researched area of investigation. Notably, there are few scholarly papers that explore the relationship between green bonds and other asset classes, with exceptions including Pham (2016) and Nguyen et al. (2020), who provide evidence of the noteworthy heterogeneity in the utility of green bonds in relation to equity and commodities.

Third, amidst the scholarly fascination with investment safe havens, particularly during periods of heightened market volatility (Campbell et al., 2002), the co-movement of green and inflation-indexed bonds during the COVID-19 pandemic emerges as an intriguing subject of inquiry. Our motivation also stems from the recent interest surrounding the impact of COVID-19 on green energy and green energy finance (Ahonen et al., 2022; Ashok et al., 2022; Corbet et al., 2020). Corbet et al., 2020 present an intriguing observation: while the conventional expectation is for green energy firms and associated products to appreciate in value when fossil fuel prices decline, the unprecedented plunge in WTI oil prices, even reaching negative territory, in April 2020 paradoxically resulted in heightened valuations for green energy firms. Corbet et al., 2020 attribute this phenomenon to downward revisions in global energy demand estimates, which, in turn, influenced industry leaders and policymakers to contemplate the potential of green energy alternatives to meet future demand. Naturally, as the global economy rebounded subsequently, with the recent escalation of energy prices due to the Russian invasion of Ukraine and the accompanying sanctions, it becomes all the more intriguing to assess the impact of economic shocks on green finance products. In this study, we posit that the valuations of national inflation-indexed bonds will serve as a reflection of their respective national economic forecasts.

Based on the aforementioned motivations, our study seeks to investigate the correlation between green bonds and inflation-indexed bonds in Brazil, China, Mexico, and Turkey during the period from October 2016 to January 2021, which is further divided into pre- and post-pandemic phases. The selection of bonds from these countries aims to ensure representation of emerging markets that possess well-established markets for both green and inflation-indexed bonds, while also encompassing geographic diversity. Our findings reveal that the inflation-indexed bond market exhibits greater influence over the green bond market, as demonstrated by a significant interdependence between green bonds and inflation-indexed bonds across various wavelet time scales. As anticipated, inflated bonds dominate this relationship, with the correlation alternating between positive and negative values. We interpret these results as indicating that inflation-indexed bonds serve as reflections of economic outlooks, with the valuation of green finance products being contingent upon economic forecasts. The presence of mixed positive and negative co-movements suggests that green valuations often experience positive movements alongside projected increases in economic demand, as energy prices exert an impact on all substitute sources. Conversely, green products can exhibit negative co-movements with inflation-indexed bonds during periods of pessimistic economic forecasts, as planners reassess the adequacy of green energy sources in meeting future needs.

This study contributes to the understanding of the relationship between green bonds and inflation-indexed bonds in the emerging markets of Brazil, China, Mexico, and Turkey. (i) By examining the correlation between these two types of bonds during the period from October 2016 to January 2021, including pre- and post-pandemic phases, our research sheds light on the dynamics of these markets in relation to each other. (ii) The selection of bonds from these countries ensures a comprehensive representation of emerging markets that have well-established markets for both green and inflation-indexed bonds, while also considering geographic diversity. This allows for a broader perspective on the interplay between these bonds in different economic contexts. (iii) The findings of this study reveal that the inflation-indexed bond market holds a significant influence over the green bond market. This is evidenced by the existence of a strong interdependence between green bonds and inflation-indexed bonds across various wavelet time scales. (iv) Our analysis demonstrates that inflated bonds dominate this relationship, with the correlation between the two types of bonds alternating between positive and negative values. This suggests that the valuation of green finance products is closely tied to economic outlooks, with inflation-indexed bonds serving as reflections of these economic forecasts. (v) The presence of mixed positive and negative co-movements further highlights the dynamic nature of green valuations. Positive movements often coincide with projected increases in economic demand, as energy prices impact all substitute sources. Conversely, green products can exhibit negative co-movements with inflation-indexed bonds during periods of pessimistic economic forecasts, as planners reevaluate the adequacy of green energy sources in meeting future needs. (vi) This research contributes to the understanding of the relationship between green bonds and inflation-indexed bonds in emerging markets, providing insights into the factors influencing their valuations and highlighting the importance of economic forecasts in shaping these markets.

The remainder of this study is organized as follows. Section 2 presents a background on green bonds. In Sect. 3, we go through the details of data and the methods employed in the study. Section 4 provides results and discussions. Conclusion is presented in Sect. 5.

2 Review of literature

The review of this literature section encompasses the theoretical arguments and empirical investigations in the case of the relationship between green bonds and inflation-indexed bonds.

2.1 Theoretical perspectives: critical interplay between green bonds and inflation-indexed bonds

Green bonds and inflation-indexed bonds are two types of financial instruments that serve different purposes in an economy. However, there are some ways in which these bonds can be related to each other. First, environmental focus has become a core issue in explaining the nexus between these two macroeconomic determinants. In general, green bonds are specifically designed to finance projects with environmental benefits. These projects can include renewable energy infrastructure, energy efficiency improvements, sustainable agriculture, and other initiatives aimed at reducing carbon emissions and promoting environmental sustainability (Taghizadeh-Hesary et al., 2022). By investing in green bonds, investors can support these environmentally friendly projects and contribute to the transition to a greener economy. Inflation-indexed bonds, on the other hand, are fixed-income securities whose principal and interest payments are adjusted for inflation. While they are not directly related to environmental concerns, the impact of climate change and environmental factors can have indirect effects on inflation (Pflueger & Viceira, 2016). For instance, extreme weather events or shifts in agricultural production can impact food prices, which in turn can influence overall inflation levels. Therefore, the environmental factors that green bonds aim to address can potentially have implications for inflation, making these two types of bonds indirectly related (Dikau & Volz, 2018).

Beyond environmental concerns, the connection between green bonds and inflation-indexed bonds is contingent upon market demand and investor preferences. There is a growing demand for sustainable and socially responsible investment options. Investors are increasingly interested in aligning their investment portfolios with their environmental values. Green bonds provide an avenue for investors to support environmentally friendly projects and contribute to sustainable development. As the demand for green bonds increases, it can have an impact on the overall bond market and influence the pricing and availability of other types of bonds, including inflation-indexed bonds (Maltais & Nykvist, 2021; Ning et al., 2023). Inflation-indexed bonds are primarily influenced by changes in inflation expectations and the demand for inflation protection. However, the increased demand for green bonds can potentially affect the broader bond market dynamics, including investor preferences and risk appetite. This, in turn, can indirectly influence the demand for inflation-indexed bonds as investors allocate their portfolios based on their environmental priorities.

From an economic governance perspective, both green bonds and inflation-indexed bonds can be influenced by policy and regulatory frameworks. Governments and regulatory bodies can play a significant role in promoting the issuance of green bonds by providing incentives, establishing green bond standards, or incorporating environmental criteria into investment guidelines. These policies can encourage issuers to issue green bonds, expand the market for these bonds, and potentially impact the pricing and availability of other bond types, including inflation-indexed bonds (Liu et al., 2022). Similarly, government policies and central bank actions aimed at managing inflation can impact the demand and issuance of inflation-indexed bonds. Environmental policies, such as carbon pricing or regulations on carbon-intensive industries, can have indirect effects on inflation and, consequently, on the demand for inflation-indexed bonds.

Finally, while green bonds and inflation-indexed bonds serve different purposes in an economy, there are potential connections between them. The environmental focus of green bonds and the indirect effects of environmental factors on inflation can create links between these two types of bonds. Additionally, market demand, investor preferences, and policy/regulatory frameworks can influence the dynamics of both green bonds and inflation-indexed bonds. Understanding these relationships can provide insights into the broader impact of sustainable finance and environmental considerations on the bond market and the economy as a whole.

2.2 Empirical literature

The critical interplay between green bonds and inflation-indexed bonds holds significant importance, yet empirical research on this topic remains limited within the academic sphere. Nevertheless, a few quasi-relevant studies have emerged, primarily emphasizing the significance of these bonds and their role in various macroeconomic indicators. Notably, green bonds exhibit substantial differences from traditional bonds (Lautsi, 2019). For instance, Nanayakkara and Colombage (2019) provide evidence suggesting that green bonds are perceived as having lower risk. Furthermore, Kuchin et al. (2019) propose that the issuance of green bonds is associated with favorable market responses, leading to increased firm valuations (Flammer, 2020; Huynh et al., 2020; Tang & Zhang, 2020). Given the immense financial support and investment required for the transition to a low-carbon economy, green bonds play a socially significant role in funding eco-friendly, low-carbon, and energy-efficient projects (Huynh et al., 2020; Nguyen et al., 2020; Reboredo et al., 2020). Moreover, green financial products are favored by clientele who prioritize sustainability (Reboredo & Ugolini, 2020). However, contrary to these perspectives, Banga

(2019) suggests that green bonds may also offer financial benefits to investors when considering portfolio diversification.

The existing literature on green bonds is relatively scarce. Pham (2016) investigates the volatility dynamics across multiple bond markets, revealing the presence of volatility clustering within the green bond market and spillover effects from regular and inflation-indexed bonds. Reboredo (2018) suggests that green bonds provide diversification options for investors in the energy and stock markets, despite exhibiting relatively similar movements to treasury and corporate bonds. In their examination of the price relationship between the green bond market and other financial markets, Reboredo and Ugolini (2020) find that the green bond market experiences significant volatility shocks from both major financial markets, indicating close associations with currency and fixed income markets. Le et al. (2021) explore the interconnectivity and spillover effects among green bonds, fintech, and cryptocurrencies, suggesting that green bonds receive volatility shocks from Bitcoin, equities, and fintech stocks. Hammoudeh et al. (2020) provides causal evidence for green bonds based on the US 10-year note. Febi et al. (2018) demonstrate that liquidity exhibits a time-decreasing effect on the return margin of green bonds. Similarly, Broadstock and Cheng (2019) argue that green bonds are susceptible to financial turbulence, energy prices, and news-based sentiment regarding economic activity and economic policy uncertainty. Ehlers and Packer's (2017) research highlight significant financial risks associated with the environment in the context of green bonds.

Nguyen et al. (2020) conduct a comprehensive examination of the evolving relationship over time between green bonds and various financial markets. Their study reveals the wide-ranging diversification benefits of green bonds in the commodity and stock markets. Furthermore, the findings demonstrate a robust co-movement between green bonds, commodities, and clean energy stocks. However, there remains a scarcity of research exploring the potential of green bonds as diversifiers and hedges. In a similar vein, Larcker and Watts (2019) investigate the willingness of investors to exchange their wealth for societal benefits. Their findings indicate limited evidence of price differentials between green and non-green bonds, suggesting that investors may not significantly prioritize sustainability factors in their investment decisions. Saeed et al. (2020) delve into the ability of green stocks and bonds to act as protective assets for environmentally harmful investments. Their study explores the potential of green financial instruments to serve as hedges against the risks associated with traditional dirty assets. Additionally, Huynh et al. (2020) analyze the diversification potential of green bonds. They assess the extent to which green bonds can contribute to a diversified investment portfolio. Similarly, Reboredo et al. (2020) establishes a strong linkage between green bonds and treasury and corporate bonds in the USA and the European Union. Their findings provide evidence of the interdependence between green bonds and other segments of the bond market, suggesting that green bonds are influenced by the high volatility observed in these related markets.

Based on the literature review, the literature gap lies in the limited empirical research on the critical interplay between green bonds and inflation-indexed bonds, as well as the financial benefits of green bonds for investors in terms of portfolio diversification and their potential as diversifiers and hedges. Further research in these areas would contribute to a more comprehensive understanding of the role and impact of green bonds in the financial market.

3 Materials and methods

This section of the study outlines the data and their respective sources, as well as the economic methodologies employed, including the wavelet coherence analysis procedure and the quantile connectedness approach, which encompass quantile spillover investigation and no return spillover analysis. To enhance comprehension, a flowchart depicting the materials and methods utilized in this study has been developed (see Fig. 1).

3.1 Data

For the purpose of analysis, high-frequency data were collected from Bloomberg for the period of October 11, 2016 to January 15, 2021 in this study. The data include 10-year inflation-indexed government bonds for four E7 countries. The green bond indices include Green Bond MSCI and Green Bond China.

3.2 Wavelet coherence analysis

Using t time spacing, a Morlet wavelet function $\psi_0(\eta)$, which relies on the non-dimensional "time" parameter, and a time-series with $\{X_n\}$ where $n=0\cdots N-1$ are the assumptions made. The Morlet wavelet function is expressed in its simplest form as follows:

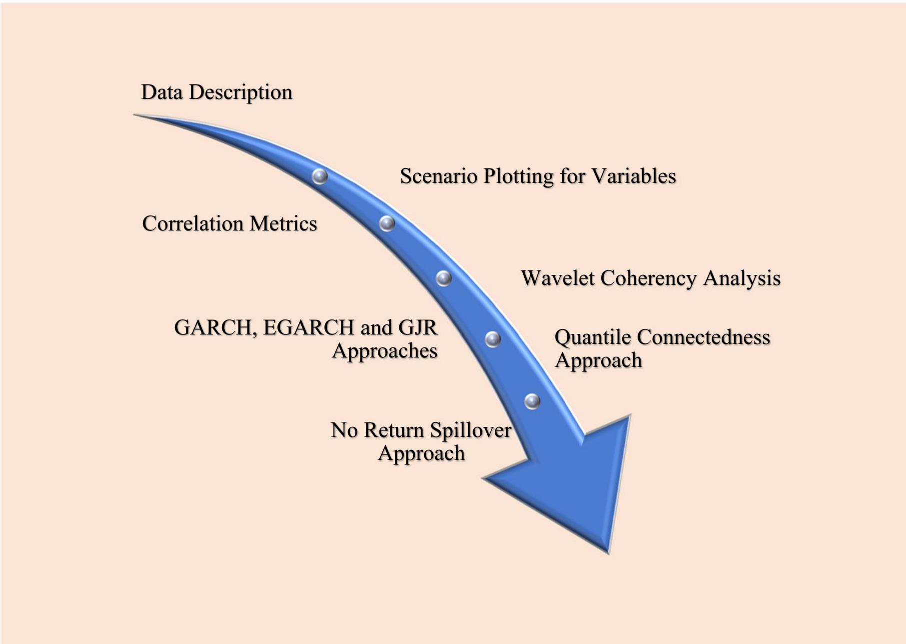

Fig. 1 Schematic diagram of the methodological flow

$$\psi_0(\psi_0) = \pi^{-\frac{1}{4}} e^{i\omega_0\eta_0 - \frac{1}{2}\eta^2}, \tag{1}$$

where ω_0 summarizes the non-dimensional amplitude, in this case 6 to satisfy Farge (1992)'s requirement for admissibility, and i is $\sqrt{-1}$.

The cross wavelet transform of a discrete time series process $\{X_n\}$ of N observations with $\{X_n,\ n = 0, \cdots, N-1\}$, scale s, and time step δ_t is denoted as displayed as follows:

$$w_n^x = \frac{\delta_t}{\sqrt{s}} \sum_{n=0}^{N-A} x_{n^1} \psi^* \left((n^{\cdot} - m) \frac{\delta_t}{s} \right) \tag{2}$$

with $m = 0, 1, \cdots, N-1$

With the use of the wavelet power spectrum, abbreviated as $\left|W_n^x\right|^2$, we can calculate the local variance. We use the null hypothesis, where the data generation mechanism is viewed as a stationary process with a distinct baseline power spectrum of P_f, to examine the relevance of the wavelet power. The dispersion of the local wavelet power spectrum is defined as follows from the null hypothesis.

$$D\left(\left(\frac{\left|W_n^x(s)\right|2}{\sigma_x^2} < p\right)\right) = \frac{1}{2} P_f x_v^2, \tag{3}$$

where P_f stands for the mean spectrum for the wavelet scale s at the Fourier frequency f ,that is, $s \approx {}^1\!/_f$. The variance is given by σ, while the combination of two stationary distributions is given by χ^2. Since v is equal to one for an actual wavelet and two for a complex one, the likelihood dedicated to a stationary series P_f is greater than p. In general, Monte-Carlo simulations are used in the procedures.

Basing on the seminal literature of Hudgins et al. (1993), the cross-wavelet power (XWT) which connects time series,$\mathcal{X}P_f = \{X_n\}$ and $y = \{y_n\}$ together as displayed as follows:

$$W_n^{xy} = W_n^x W_n^{y*}, \tag{4}$$

where W_n^x and W_n^{y*} represent wavelet transforms of time series $\mathcal{X}$ and y, respectively, whereas $\left|W_n^{xy}\right|$ denotes the cross-wavelet power. When depending on the Fourier power spectra P_f^x and P_f^y, the WXT displays the confined covariance between the two-time series, for both wavelet scale.

In line with Torrence and Compo (1998), the distribution theoretically is:

$$D\left(\left(\frac{\left|W_n^x W_n^y\right|}{\sigma_x \sigma_y} < p\right)\right) = \frac{Z_v(P)}{V} \sqrt{P_f^x P_f^y} \tag{5}$$

where $Z_v(p)$ denotes the confidence level of the likelihood p for a *pdf* indicating the square root of the product of the two series χ^2 distributions.

In line with the Aguiar-Conraria et al. (2008), the wavelet coherency (WTC) is denoted as:

$$R_n(S) = \frac{\left|S\left(s^{-1} W_n^{xy}(s)\right)\right|}{S\left(s^{-1}\left|W_n^x\right|\right)^{\frac{1}{2}} S\left(s^{-1}\left|W_n^y\right|\right)^{\frac{1}{2}}} \tag{6}$$

where the smoothing operator in both scale and time is reported by S.

The point in the time series' pseudo-cycle is shown by the phase ϕ_x time series $\chi = \{\chi_n\}$, according to Aguiar-Conraria et al. (2008). The expansion of status across $\chi = \{\chi_n\}$ and $y = \{y_n\}$ timer series, the phase shift $\phi_{x,y}$ expressed by the mean and confidence interval of the phase shift is of the form:

$$\phi_{x,\,y} = \tan^{-1}\left(\frac{\Im\{W_n^{xy}\}}{\Re\{W_n^{xy}\}}\right) \text{ and } \phi_{x,y} \in [-\pi,\ \pi], \tag{7}$$

where $\Re$ and $\Im$ signify the real and imaginary part of a complex number, respectively. The two-time series in situation where the phase discrepancy is 0 goes together at a particular frequency. Therefore, we conclude the two series are in phase and χ leads y when $\phi_{x,y} \in \left[0, \frac{\pi}{2}\right]$, and y leads χ for $\phi_{x,y} \in \left[-\frac{\pi}{2}, 0\right]$. In terms of discrepancy, when the phase dichotomy is $-\pi$ or π, we say that the two series are in anti-phase. Thus, χ lead y for $\phi_{x,y} \in \left[-\pi, -\frac{\pi}{2}\right]$, and y lead χ when $\phi_{x,y} \in \left[\frac{\pi}{2}, \pi\right]$.

3.3 Quantile connectedness procedure

We utilize the quantile regression approach to survey the reliance of a dependent variable u_t on v_t at every quantile τ for the joint distribution stationed to quantile τ,where $\tau \in (0,\ 1)$, moderated by Basset and Koenker (1978). The specification of the quantile vector auto-regression (VAR) with order m is denoted as.

$$u_t = c(\tau) + \sum_{j=1}^{m} A_j(\tau)u_{t-j} + \upsilon_t(\tau), \quad \tau \in (0,\ 1) \tag{8}$$

The internal variable u_t is $N \times 1$ vector, the lag length is m, $c(\tau)$ is the vector of means. The quantile VAR matrix of coefficients is $N \times N$ matrix expound with $A_j(\tau)$. The residual term is $\upsilon_t(\tau)$, and the variance–covariance matrix of $N \times N$ elements is $\sum(\tau)$.

To calculate $\hat{A}_j$ and $\hat{c}_j$ over quantiles, we presume that $Q_\tau\left(\upsilon_t(\tau)|u_{t-1}, \cdots, u_{t-m}\right) = 0$. The τ th conditional quantile of response u can be denoted as:

$$Q_\tau\left(u_t|u_{t-1}, \cdots, u_{t-m}\right) = \hat{c}(\tau) + \sum_{j=1}^{m} \hat{A}_j(\tau)u_{t-j} \tag{9}$$

In line with Ando et al. (2022), we build the τ th quantile connectedness matrices. So, the denotation of the vector moving average with infinite order of the quantile VAR process is denoted as:

$$u_t = \delta(\tau) + \sum_{i=1}^{\infty} \Theta_i(\tau)\upsilon_{t-i}(\tau),\ t = 1, \cdots, T,\ \tau \in (0, 1) \tag{10}$$

$$\xi_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} \left(e_i' h_k \sum e_j\right)^2}{\sum_{k=0}^{H-1} \left(e_i' h_k \sum e_j\right)} \tag{11}$$

where the parameter $\xi_{ij}^{g}(H)$ explains the contribution of the jth variable to the variance for prognosed error for the variable i at the horizon H_t. e_t represents unit vector on the ith position. Every vector of the matrix for variance decomposition is made regular as follows.

$$\hat{\xi}_{ij}^{g}(H) = \frac{\xi_{ij}^{g}(H)}{\sum_{j=1}^{N} \xi_{ij}^{g}(H)} \tag{12}$$

We define the following spillovers metrics based on GFEVD. Diebold and Yilmaz (2009, 2014) introduced the total connectedness index at the τ th quantile, TSI(τ) denoted by:

$$\mathrm{TSI}_t(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1,\, i\neq j}^{N} \varpi_{ij}^{h}(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \varpi_{ij}^{h}(\tau)} \times 100 \tag{13}$$

The second index goes in line with the directional spillover effects from all variables to variable i at the quantile τ.

$$\mathrm{FROM}_{j,\,t}(\tau) = \frac{\sum_{j=1,\, i\neq j}^{N} \varpi_{ij}^{h}(\tau)}{\sum_{j=1}^{N} \varpi_{ij}^{h}(\tau)} \times 100 \tag{14}$$

The third index explains the directional spillover implications from variable i spreading to all other variables at the quantile τ.

$$\mathrm{TO}_{j,\,t}(\tau) = \frac{\sum_{j=1,\, i\neq j}^{N} \varpi_{ji}^{h}(\tau)}{\sum_{j=1}^{N} \varpi_{ji}^{h}(\tau)} \times 100 \tag{15}$$

The fourth index is the net total directional spillover (NET) determined as.

$$\mathrm{NET}_{j,\,t}(\tau) = \mathrm{TO}_{j,\,t}(\tau) - \mathrm{FROM}_{j,\,t}(\tau) \tag{16}$$

This index identifies the positive value of $\mathrm{NET}_{j,\,t}(\tau)$ and negative value of $\mathrm{NET}_{j,\,t}(\tau)$ of spillovers from the other variables. In our literature, we have employed in the calculation 200-day rolling window, 10 days as prognosed horizon, and lag order of 2 (AIC).

4 Empirical results and discussion

This section of the analysis presents the empirical findings derived from various statistical and econometric methodologies, including descriptive analysis, scenario plotting technique, pairwise correlation test, wavelet coherency analysis, GARCH, EGARCH and GJR approaches, quantile connectedness procedure, and no return spillover analysis method. In addition, a comprehensive analysis and interpretation of the outcomes is provided in the dedicated subsection titled ‘Discussion.’

4.1 Descriptive statistics

To investigate the dynamic co-movement between inflation-indexed and green bonds, particularly in emerging markets, we obtained price series for MSCI Green Bonds and Green

Table 1 Descriptive statistics

	Mean	Min	Max	Skewness	Kurtosis	JB
Turkey	−0.01058	−13.99145	7.52240	−1.75391	26.98688	3437.603863***
Mexico	0.03792	−8.92712	7.04466	−0.94615	10.8456	5626.07373***
Brazil	0.01146	−11.62597	5.28444	−1.06641	10.45957	5289.2604***
China	−0.00296	−0.92843	10.8885	0.12406	4.98508	1156.3615***
Green Bond China	0.01254	−1.84343	0.77870	−3.31272	45.77658	99303.476***
MSCI Green Bond	0.01830	−2.98507	2.22186	0.01830	4.98508	4164.232***

JB denotes Jarque Bera normality test. * represents 1% significant level

Bonds China. Additionally, we acquired inflation-indexed bond indices for Mexico, Turkey, Brazil, and China. All the data were sourced from Bloomberg for the period of October 11, 2016 to January 15, 2021. The daily returns are presented in log form. Table 1 provides the summary statistics for all the series. As demonstrated, CPI Bonds-Brazil exhibits the largest magnitude with a mean of 0.0379, whereas CPI-Turkey records the lowest mean of −0.01058. The highest maximum value is observed for CPI Bonds-Turkey, while the lowest maximum value is for Green Bonds China. Skewness, kurtosis, and Jarque–Bera values indicate that all the variables significantly deviate from the normality assumption at a 1% significance level.

4.2 Scenario plotting for variables

Figure 2 illustrates time series plots of the level series, while Fig. 3 presents time series plots of the return series for each variable under investigation. As depicted in Fig. 3, a significant number of variables exhibit substantial fluctuations and volatility clustering during the COVID-19 outbreak. This heightened level of movements indicates the COVID-19

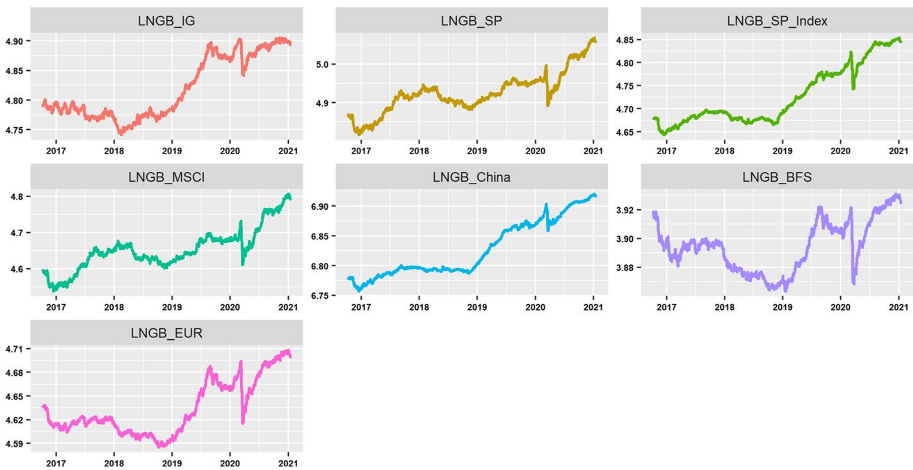

Fig. 2 Plots of the level series

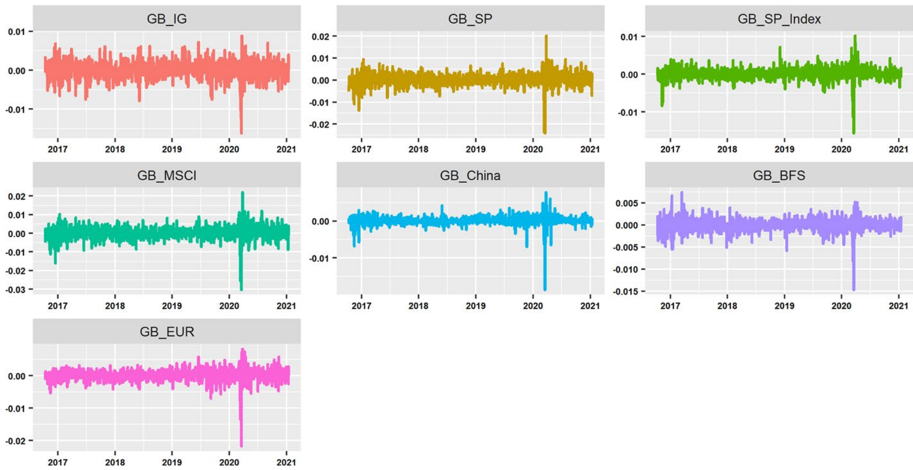

Fig. 3 Plots of the return series

period as an opportune context to analyze the co-movements between the green and inflation-indexed bond markets.

4.3 Pairwise correlation matrices

Figures 3, 4 present the pairwise correlation between the series under examination. We observe a very low pairwise correlation between green and traditional bonds. Turning to the correlation among the inflation-indexed bond markets, we find the highest correlation between Mexico and Brazil (0.50), followed by Turkey and Brazil (0.347). However, we note that the correlation between China and Mexico is negative, with a correlation coefficient value of − 0.001. Overall, we observe low correlations among the series under examination. Appendix Table 6 provides the detailed report of pairwise correlations.

4.4 Wavelet coherency analysis

To investigate the co-movement between green and inflation-indexed bonds, we analyze the wavelet power spectrum of each series, as illustrated in Fig. 5. The frequency bands are categorized into three groups: low frequency (greater than 256 days), high frequency (less than 64 days), and medium frequency (between 64 and 256 days). Figure 5 exhibits the high and significant power of Mexico's inflation-indexed bond between 2019 and 2020 at a scale of 1–128 days (ranging from high to medium frequency), coinciding with the COVID-19 pandemic era and its peak volatility. The results for Turkey's inflation-indexed bond reveal high and substantial power during the time periods of 2017–2019 at 64–256 days (low frequency), and in 2018 at 4–32 days (high frequency). Brazil's inflation-indexed bond demonstrates significant and considerable power throughout the years 2018–2019 at a scale of 64–128 days, and 2020–2021 at a scale of 16–256 days.

The wavelet power spectrum presented in Fig. 5 indicates a high and significant power spectrum for China's inflation-indexed bond from 2018 to 2020 at a scale of 128–256 days, and from 2016 to 2017 at a scale of 1–64 days. The considerable price volatility observed

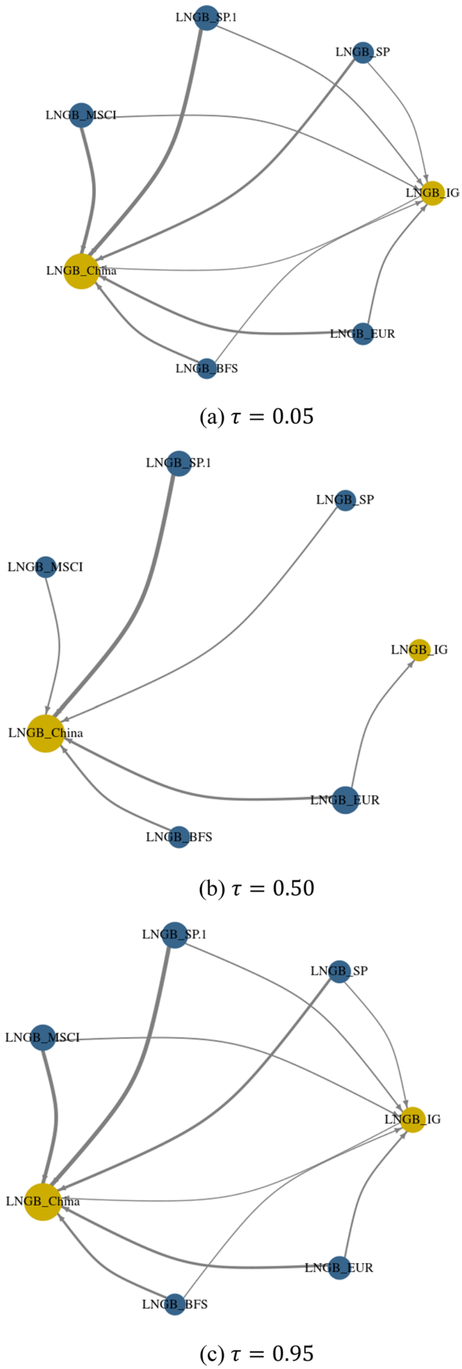

Fig. 4 Spillovers network among markets. The figure depicts the network diagrams of the net pairwise directional spillovers among green bonds and inflation-indexed markets. **a** the network at extreme lower quantile (bearish market). **b** The network at intermediate quantile (normal market). **c** The network at extreme upper quantile (bullish market). The direction of information spillovers between pairs is given by the arrows, while the magnitude of strengtheness for the net spillovers is shown by the thickness of arrows. The blue color in the nodes denotes that the market is net contributor of shocks, while the yellow color designates that the market is net receiver of shocks

in the inflation-indexed bond markets in 2016 is likely attributed to the 25-basis point interest rate hike by the Fed and the June 2016 Brexit. Moreover, the high volatility observed in China's inflation-indexed bond in 2020 is also associated with the recent COVID-19 pandemic.

Turning our attention to the power spectrum of the green bond markets, it is noteworthy that both MSCI Green Bonds and Green Bonds China exhibit common features with a high and significant power spectrum between 2019 and 2020 at a scale of 1–256 days (encompassing both high and low frequency). The increased variability seen in green bonds can be attributed to the outbreak of the COVID-19 pandemic. We use wavelet coherency analysis using Morlet wavelets to estimate local synchronization of traditional bonds and green bonds at various frequencies as an extra robustness check. Figure 6 displays the wavelets coherency plot between inflation-indexed and green bond index returns.

At a 5% level of significance, the black tick contour region obtained through Monte Carlo simulations is used to denote significance. The magnitude of the power spectrum is represented by a color code, with red indicating high power and blue indicating low power. The cone of influence (COI), represented by the illuminated shadow, is where edge effects can distort the image. The phase difference between the green bond market and the inflated bond is indicated by arrows. When the arrows point to the right, the two assets are positively connected. The conclusion drawn is that inflation-indexed (green) bonds are leading when the arrows point right and up (or down). When the arrows point to the left, the two assets are out of phase and negatively connected. In the situation where the arrows point up and to the left, green (inflation-indexed) bonds are leading (down). The interaction between the variables is cyclical when they are in phase, but anticyclical when they are out of phase.

Figure 6 presents the Wavelet coherency (WTC) plots, revealing interesting relationships. In Panel A, significant co-movements are found between the inflated bond Mexico and the Green Bond China index returns for the period of 2020–2021 at a scale of 1–128 days (both high and low frequency). Notably, the arrows point to the right, indicating a positive relationship where the inflated bond Mexico leads the relationship. Thus, a significant dependence is observed between the inflated bond Mexico and the Green Bond China index returns.

Similar findings are obtained for the dependence between the inflated bond Mexico and the MSCI Green Bond index returns. A notable positive comovement is found between the inflated bond Mexico and the MSCI Green Bond for the period of 2020–2021, with the inflated bond Mexico leading the MSCI Green Bond price returns in the short and medium time scales. Strong coherency and dependence between the inflated bond Mexico and the green bond markets are observed, with the inflated bond Mexico leading the green bond market.

Panel B of Fig. 6 illustrates the co-movement between the inflated bond Turkey and the green bond price series. In terms of the dependence between the inflated bond Turkey and the MSCI Green Bond price index returns, significant co-movements are observed for two periods: (1) 2018–2019, and (2) 2020–2021. Both periods are at high frequency. For the first period, the arrows point to the left and up, indicating a negative relationship where the MSCI Green Bond leads. For the second period, the arrows point to the right and up, suggesting that the variables are in phase. This result is interesting as it shows a negative dependence between the inflated bond Turkey and the MSCI Green Bond during normal market conditions, but a positive dependence during bearish market conditions marked by the outbreak of the coronavirus. Therefore, holding a portfolio with these two assets requires close monitoring, as the nature of the dependence is influenced by the state of the markets.

Next, the connection between the inflated bond Turkey and the Green Bond China is examined. Significant co-movements are observed for two periods: (1) 2018–2019 at a high-frequency scale, and (2) 2020–2021 at a scale of 16–128 days. Once again, the arrows point to the left and up for the first period, indicating a negative relationship. However, for the second period, at higher frequency bands, the arrows point to the right and down, suggesting that at higher frequency, Green Bond China leads the inflated bond Turkey. Additionally, for the second period, at lower frequency bands, the arrows point to the right and up, indicating a positive relationship where the inflated bond Turkey leads Green Bond China.

Panel C of Fig. 6 displays the dependence between inflated bond_Brazil and the green bond markets. We find a significant dependence between inflated bond_Brazil and MSCI Green Bonds for 2020–2021 at different frequency bands (both high and low frequency). We note that for all frequency bands, the arrows point to the right and up (positively related), with inflated bond_Brazil leading green bonds.

For the co-movement running from the inflated bond_Brazil to Green Bonds China, we observe significant linkages at two periods: (1) 2016–2017 at a 64–128 days scale and (2) 2020–2021 at both high and low frequency bands. For this period, we observe significant interdependence, with the arrows pointing to the right and up (positively correlated). Green bond China advances in tandem with Brazil's inflated bonds during extremely unfavorable market conditions because the first period corresponds with the 2016 European debt crisis and the second period with COVID-19.

Figure 6 Panel D documents the connection between the inflated bond_China and green bond markets. We observe significant co-movement between inflated bond_China and the MSCI Green Bond. At a higher frequency (4–64 days scale), the arrows point right and up (positively correlated), indicating that inflated bond_China is leading. However, at a lower frequency scale (128 and above), we observe the arrows point to the left and up (negatively correlated), which denotes green bond leading inflated bond_China at high-frequency scaling. For the dependence between inflated bond_China and Green Bond China, we find results similar to the findings between inflated bond_China and MSCI Green Bond. Overall, inflated bond_China can serve as a hedge against green assets. In all, the WTC plots show significant interdependence and co-movement among the green bond market and the inflation-index bond markets of Mexico, Turkey, Brazil, and China at varied frequency scales. However, the nature of dependence is event-dependent and varies with time.

For robustness, we examine the dependency among green bonds and inflated bonds in the COVID-19 time, from January 1, 2020 to December 1, 2020. This is illustrated in Fig. 7. We observe significant connections between the inflated bond_Mexico and Green Bond China during the early days of the COVID-19 outbreak. In the medium to long-term time scales, the arrows point to the right, suggesting a positive relationship between the two assets. On the other hand, the arrows pointing right and up imply inflation-index bonds led the interactions. In the short term, the arrows point left and down, indicating the dominance of inflation-indexed bonds. For inflated bond_China and MSCI Green Bonds, in the short to medium time scales, we obtain similar findings with inflated bond_China leading MSCI Green Bonds (positively related).

Panel B of Fig. 7 displays the co-movement between inflated bond_Turkey and Green Bonds during the COVID-19 period. Again, we find strong co-movement in the less to medium period scale. In the long run, we find no association between inflated bond_Turkey and Green Bonds. In the short term, the assets are in phase, while in the short term, the two assets are out of phase. Thus, during bearish market states, green bonds co-move with inflated bonds. Thus, green bonds are not a good hedge for inflated bonds during volatile market conditions.

Panel C of Fig. 7 shows the association between inflated bond_Brazil and Green Bonds. We note strong coherence between inflated bond_Brazil and green bond markets during the peak of the pandemic from January to May 2020 in the short to medium term. Panel D documents the connection between inflated bond_China and Green Bonds. We note inflated bond_China co-moves with green bond market indices during extreme market conditions, evidenced by the positive connectedness between the two assets. The COVID-19 period results reported in Fig. 7, we noticed that the dependency between the inflated bonds and the green bond market was stronger than what we observed during normal market conditions.

4.5 GARCH, EGARCH, and GJR estimation techniques.

The GARCH, EGARCH, and GJR parameter estimates of order (1, 1) are presented in Table 2. By using the Akaike Information Criterion (AIC), we determine the suitable model for each asset under examination to be as follows: Green Bond China (GARCH), MSCI Green Bonds (EGARCH), inflated bond_Turkey (GARCH), inflated bond_Brazil (GJR), inflated bond_Mexico (EGARCH), and inflated bond_China (EGARCH).

The best-fit models indicate the most appropriate model among the other GARCH models. The GARCH (1, 1) model shows evidence of volatility clustering in Green Bond China and inflated bond_Turkey. However, the summation of the ARCH term and GARCH term is less than unity (1), confirming the stability, predictability, and stationarity of the conditional variance. This suggests a lack of persistence of shocks in inflated bond_Turkey and Green Bond China.

On the other hand, the asymmetric GJR-GARCH (1,1) modeling for inflated bond_Brazil and the EGARCH (1,1) modeling for MSCI Green Bond, inflated bond_Mexico, and inflated bond_China result in statistically significant parameters exhibiting marginal persistence of shocks. The mean reverting estimates appear to be less than one for both models.

The leverage effect and zero asymmetric parameter in both models confirm the prevalence of asymmetric response across the daily returns of inflated bonds of Brazil, Mexico, China, and the MSCI Green Bond market. The significant positive leverage effect parameter observed in EGARCH (1, 1) connotes that positive shocks increase volatility more than negative shocks of the same sign. In the case of the GJR-GARCH (1, 1), the observed significant positive leverage effect estimate suggests that market retreats (positive shocks) lead to a decline in volatility compared to market advances (negative shocks) of the same magnitude.

4.6 Quantile spillover analysis

In this subsection, we delve into spillovers and connectedness among green bonds and inflation-indexed bonds of the selected countries, using the quantile VAR framework of Ando et al. (2022). We analyze the connectedness and spillover transmission among the green bond market at the lower ($\tau = 0.05$) and upper ($\tau = 0.95$) quantiles, as well as at the intermediate ($\tau = 0.50$) quantile of the joint distribution. The Diebold and Yilmaz (2009,

2014) technique is used to measure the connectedness among markets. The results of applying the DY method are presented in Tables 3, 4 and 5, respectively, for the extreme lower (negative shocks), intermediate, and extreme upper (positive shocks) quantiles of the joint distribution.

This table presents the quantile VAR(2) estimate results at the extreme lower quantile ($\tau = 0.05$). We used a 10-day-ahead forecast horizons for the quantile VAR process. 200-day rolling window is used for the total connectedness spillover index. The term 'FROM' measures the directional connectedness and spillovers that a green market i takes the shocks from all other green bonds and inflation-indexed bond markets, while the term 'TO' is a measure of the directional connectedness and spillovers that a green market i contributes its shocks to all other green markets used in the study. The term 'NET' measures the difference between the TO and FROM metrics.

Based on the results displayed in Table 3, it appears that LNGB_IG is the market least affected by the other green bond markets and further contributes the second most to all other markets. On the other hand, LNGB_EUR contributes the most to spillovers from all other green bond markets, while LNGB_SP.1 and LNGB_MSCI contribute the most spillovers to other green bond markets. Furthermore, it is interesting to note that the green markets under consideration demonstrate quite similar receiver patterns, as well as similar contribution behavior compared to all other markets. The exceptions to this are LNGB_IG and LNGB_China, both of which show a weak contributing spillover effect compared to LNGB_SP, LNGB_SP.1, LNGB_MSCI, and LNGB_EUR. The TCI spillover index in the VAR system is 81.34%, suggesting strong spillover power among green bonds and inflation-indexed markets under negative information spillovers.

Table 4 displays the connectedness and spillovers for normal market circumstances. It is clear that LNGB_China is the least contributor of shock spillovers (15.74), while LNGB_EUR appears as the highest contributor of spillovers (87.51), followed by LNGB_SP.1 (77.01). Furthermore, LNGB_EUR remains the highest receiver of spillovers from others in the VAR system (67.96). Additionally, it is noteworthy that LNGB_SP, LNGB_SP.1, and LNGB_MSCI green bond markets continue to contribute high spillovers under normal market forces, indicating their dominance in the system of green bonds and inflation-indexed bonds. Based on Table 4, we can also highlight that the TCI in the system under normal scenarios reaches 62.44%, implying a high intensity of connectedness among the markets under consideration.

The connectedness between markets under extreme upper tail ($\tau = 0.95$) is presented in Table 5 to demonstrate the spillover transfer behavior among green and inflation-indexed markets during positive shocks. We observe excess spillovers among markets relative to the shock spillovers during normal market conditions. This finding is consistent with previous studies by Su (2020), Saeed et al. (2021), Khalfaoui et al., (2022a, 2022b), Chen et al. (2022), among others.

As shown in Table 5, the TCI value indicates strong connectedness between markets, as the spillovers account for 82.17% of the total forecast error variance of the VAR system. In other words, 82.17% of the predicted error variance in one green bond market may be connected to the innovations in all others. In terms of contribution from others, the highest spillovers come from LNGB_China (83.77), followed by LNGB_EUR (83.00). These results suggest that green and inflation-indexed markets react primarily to LNGB_China and LNGB_EUR. Overall, we observe a similar connectedness and spillover structure from others for each market examined in the study. Regarding contribution to others, the most impactful are LNGB_SP.1 (89.26) and LNGB_EUR (87.54), while LNGB_China contributes the least to others (67.57). This indicates that LNGB_China has the least spillover effect on other green bonds and inflation-indexed markets during bearish and bullish market conditions.

In summary, our quantile spillover results suggest that the connectedness and spillovers between green bonds and inflation-indexed markets exhibit relatively similar patterns under extreme lower and extreme upper market conditions. We also find that the spillover effects from/to others during bearish and bullish markets show excess spillovers compared to normal market conditions, indicating that connectedness and spillovers are more pronounced during extreme market circumstances. The TCI values of market systems are approximately 81.34 and 82.17% for far lower and far upper quantiles, respectively, compared to the intermediate quantile of 62.44%. These results demonstrate that connectedness and spillovers among markets are heightened during extreme negative and positive shocks. Furthermore, the strength of connectivity between green bonds and inflation-indexed markets increases in proportion to the extreme negative and positive information spillovers. These results highlight that significant effects influencing market development prompt market operators and investors to reassess the risk levels of their investment portfolios (Chen et al., 2022).

4.7 Net return spillovers analysis

To thoroughly understand the interconnectedness and spillovers between green bonds and inflation-indexed markets, we conducted a weighted degree network analysis of the pairwise directional spillovers using the VAR method. The results of this analysis are presented in Fig. 4a, b and c. Upon examining the network diagrams in (a) and (c), it becomes evident that the pairwise directional spillovers exhibit similarities, particularly in terms of the direction and magnitude of the spillover impacts on the system. There is evidence of greater information spillovers between markets during both bearish and bullish periods, indicating a high level of co-movement among markets during times of financial uncertainty as compared to more tranquil periods.

These results are consistent with those discussed in previous studies by Shahzad et al. (2021), Mensi et al. (2021), Kamal and Hassan (2022), Chen et al. (2022), Pham and Cepni (2022), and Khalfaoui et al., (2022a, 2022b), among others. Furthermore, we find that under both bearish and bullish market scenarios, LNGB_China and LNGB_IG serve as net receivers of shock spillovers in the system, with LNGB_China being the largest net receiver. On the other hand, the markets of LNGB_SP.1, LNGB_MSCI, LNGB_SP, LNGB_BFS, and LNGB_EUR act as net contributors of spillovers in all market circumstances, with LNGB_SP.1 being the highest net contributor. Upon examining Fig. 4, we observe that the network spillovers between markets are less complex in (b) than those presented in (a) and (c). This observation is consistent with a greater interdependence between green bonds and inflation-indexed bonds during extreme positive and negative events. Nevertheless, our network results align with previous studies that demonstrate the spread of extreme occurrences to the upper and lower quantiles of the joint distribution (Londono 2019; Naeem et al., 2021; Bouri et al., 2020; Khalfaoui et al., 2022a, 2022b; Pham & Cepni, 2022).

4.8 Discussion

This study examines the co-movement between green bonds and inflation-indexed bonds in the contexts of emerging countries, specifically Turkey, China, Brazil, and Mexico, both

Table 2 Comparison of parameter estimates for GARCH, EGARCH and GJR modeling

	GREEN BOND_CHINA			GREEN BOND_MSCI			CPI BOND TURKEY			CPI BOND BRAZIL		
Order (1, 1)	GARCH	EGARCH	GJR	GARCH	EGARCH	GJR	GARCH	EGARCH	GJR	GARCH	EGARCH	GJR
Constant	**0.0002 [5.286] (0.000)**	−0.054 [−4.262] (0.000)	0.000 [5.323] (0.000)	0.0042 [3.489] (0.000)	**−0.0609 [-2.774] (0.000)**	0.0041 [3.284] (0.000)	**0.0876 [8.3402] (0.000)**	0.9545 [1.363] (0.173)	0.0320 [6.2308] (0.000)	0.1421 [6.2386] (0.000)	0.0386 [7.6686] (0.000)	**0.1485 [5.6325] (0.000)**
GARCH{1}	**0.8747 [91.567] (0.000)**	0.9831 [332.59] (0.000)	0.8729 [89.467] (0.000)	0.8744 [47.801] (0.000)	**0.9715 [8.991] (0.000)**	0.8731 [44.634] (0.000)	**0.7262 [30.17] (0.000)**	0.9545 [202.82] (0.000)	0.8589 [66.112] (0.000)	0.7799 [25.007] (0.000)	0.9367 [66.206] (0.000)	**0.7777 [24.158] (0.000)**
ARCH{1}	**0.1136 [13.22] (0.000)**	0.2171 [18.362] (0.000)	0.1077 [7.5611] (0.000)	0.0885 [4.446] (0.000)	**0.1947 [8.990] (0.000)**	0.1023 [6.0634] (0.000)	**0.2068 [4.446] (0.000)**	0.1799 [14.259] (0.000)	0.0277 [3.459] (0.000)	0.1372 [6.2866] (0.000)	0.2295 [8.6329] (0.000)	**0.1174 [4.163] (0.000)**
Leverage{1}		−0.029 [−2.854] (0.000)	0.0162 [0.9214] (0.000)		**0.0221 [1.662] (0.000)**	−0.0260 [−1.348] (0.000)		−0.1377 [−17.16] (0.000)	0.1796 [12.509] (0.000)		−0.0134 [−1.058] (0.289)	**0.0336 [1.1737] (0.000)**
AIC	**−1.913**	−1.919	−1.929	612.950	**619.031**	613.733	**2.9856**	2.9364	2.9378	3.5051	3.4944	**3.5064**
BIC	**−1.916**	−1.899	−1.909	627.997	**639.094**	633.795	**1.12e+03**	1.23e+03	1.54e+03	3.5202	3.5144	**3.5266**

	CPI BOND MEXICO			CPI BOND CHINA		
Order (1, 1)	GARCH	EGARCH	GJR	GARCH	EGARCH	GJR
Constant	0.0625 [4.555] (0.000)	**−0.0029 [−0.408] (0.000)**	0.0583 [4.7752] (0.000)	0.0014 [6.8935] (0.000)	**−0.199 [5.287] (0.000)**	0.0015 [5.8695] (0.000)
GARCH{1}	0.7412 [23.344] (0.000)	**0.9405 [71.214] (0.000)**	0.7581 [24.302] (0.000)	0.8823 [68.873] (0.000)	**0.9425 [92.171] (0.000)**	0.8811 [61.954] (0.000)
ARCH{1}	0.1985 [9.7122] (0.000)	**0.3086 [10.075] (0.000)**	0.1436 [6.848] (0.000)	0.0673 [8.318] (0.000)	**0.1158 [10.38] (0.000)**	0.0608 [6.543] (0.000)
Leverage{1}		**−0.0709 [−3.807] (0.000)**	0.0873 [2.371] (0.000)		**0.0005 [0.0752] (0.000)**	0.0105 [0.9106] (0.000)
AIC	2.8277	**2.8368**	2.8265	−940.38	**−920.51**	−939.03
BIC	2.8427	**2.8568**	2.8465	−925.63	**−900.45**	−918.96

NB: We report the coefficient, t-statistics in [] and p-value in (). The best model fit based on the AIC is in BOLD before and after the COVID-19 pandemic. The findings reveal significant relationships between these bonds, shedding light on the volatility and dynamics of the bond markets. Understanding this volatility is crucial for investors, policymakers, and market participants to assess risks and make informed decisions.

In the case of Turkey, the study identifies both positive and negative co-movements between green bonds and inflation-indexed bonds, indicating volatility in the market. This volatility can be attributed to various factors, such as market sentiment, investor behavior, macroeconomic conditions, and regulatory changes. By comprehending the volatility in the relationship between these bonds, stakeholders can gain insights into market trends and potential areas of concern within the Turkish context. These findings align with prior research by Pham (2016), which also observed volatility spillovers between inflated bonds and green bonds.

Similarly, the study reveals a positive co-movement between green bonds in China and Brazil's inflated bonds during periods of extremely unfavorable market conditions, such as the European debt crisis and the COVID-19 pandemic. Despite the challenging market conditions, the findings suggest that the green bond market offers opportunities for portfolio diversification. This aligns with the research of Reboredo (2018), indicating that green bonds provide diversification benefits even during normal market conditions. The co-movement observed during these periods of market uncertainty highlights the potential role of green bonds as resilient and sustainable investment options.

Additionally, the study investigates the relationship between inflated bonds in China and green assets, finding significant negative connections during volatile periods in the long term. This finding is consistent with similar research conducted by Hammoudeh et al. (2020) on the relationship between green bonds and the US Treasury bond index. The study employs wavelet coherence plots to analyze the interdependence and co-movement between the green bond market and inflation-index bond markets across Mexico, Turkey, Brazil, and China at different frequency scales. These plots reveal significant dependence and co-movement, with the nature of dependence varying with time and being event dependent. These findings emphasize the importance of considering the dynamics between different types of bonds when constructing investment portfolios.

Moreover, the study explores the connections between the inflated bond in Mexico and the green bond in China during the early days of the COVID-19 outbreak. However, these correlations weakened with the implementation of anti-COVID-19 restrictions by governments. This pattern aligns with the impact of COVID-19 policy responses on financial markets, as noted by Le et al. (2021).

Furthermore, the study addresses the case of Turkey specifically during the COVID-19 pandemic, revealing that green bonds are not an effective hedge for inflated bonds in volatile market conditions. This finding highlights the need for careful consideration of the dynamics between different types of bonds and their performance during periods of market volatility. It is important to note that this finding is specific to the Turkish market during the COVID-19 pandemic and may not be generalizable to other regions or time periods.

On the other hand, the study uncovers a significant connection between the inflated bond market in China and green bond market indices during extreme market conditions. This positive relationship suggests that these assets tend to move together during periods of market stress or volatility, with a stronger dependency observed during the COVID-19 period. This finding underscores the potential role of green bonds as a source of stability or a hedge during extreme market conditions. The positive connectedness between inflated bonds and green bond market indices indicates that investors may consider green bonds as a safe haven or a diversification option during times of market uncertainty.

Table 3 Spillover connectedness under bearish market ($\tau = 0.05$)

	LNGB_IG	LNGB_SP	LNGB_SP.1	LNGB_MSCI	LNGB_China	LNGB_BFS	LNGB_EUR	FROM
LNGB_IG	19.47	11.06	14.41	11.49	11.62	15.49	16.45	80.53
LNGB_SP	10.08	19.17	14.23	19.11	11.71	12.74	12.94	80.83
LNGB_SP.1	13.23	14	18.26	14.25	11.49	14.37	14.39	81.74
LNGB_MSCI	10.37	18.66	14.12	19.44	11.56	12.63	13.22	80.56
LNGB_China	12.49	13.84	14.76	14.43	17.99	12.98	13.5	82.01
LNGB_BFS	14.56	12.76	14.79	12.97	11.12	18.76	15.05	81.24
LNGB_EUR	15.07	13.11	14.63	13.33	11.45	14.89	17.53	82.47
TO	75.81	83.43	86.95	85.59	68.94	83.11	85.55	569.37
NET	−4.72	2.6	5.21	5.03	−13.06	1.86	3.08	TCI = 81.34%
NPT	1	4	5	6	0	2	3	

Table 4 Spillover connectedness under normal market ($\tau = 0.50$)

	LNGB_IG	LNGB_SP	LNGB_SP.1	LNGB_MSCI	LNGB_China	LNGB_BFS	LNGB_EUR	FROM
LNGB_IG	40.95	4.42	9.61	4.18	2.27	15.16	23.4	59.05
LNGB_SP	3.8	35.6	10.1	34.03	2.41	6.22	7.84	64.4
LNGB_SP.1	8.07	10.17	37.61	10.06	3.75	13.51	16.83	62.39
LNGB_MSCI	3.55	33.62	9.77	35.21	2.4	6.25	9.2	64.79
LNGB_China	4.96	7.93	17.84	7.92	40.62	8.56	12.16	59.38
LNGB_BFS	13.86	5.57	14.35	5.82	1.43	40.88	18.09	59.12
LNGB_EUR	18.14	7.05	15.34	8.23	3.49	15.72	32.04	67.96
TO	52.39	68.76	77.01	70.25	15.74	65.43	87.51	437.09
NET	−6.66	4.36	14.62	5.45	−43.64	6.31	19.55	TCI = 62.44%
NPT	1	3	3	4	0	4	6	

This table presents the quantile VAR(2) estimate results at the extreme lower quantile ($\tau = 0.50$). We refer the reader to note in Table 3

Table 5 Spillover connectedness under bullish market ($\tau = 0.95$)

	LNGB_IG	LNGB_SP	LNGB_SP.1	LNGB_MSCI	LNGB_China	LNGB_BFS	LNGB_EUR	FROM
LNGB_IG	18.93	11.11	14.98	11.37	11.62	15.78	16.21	81.07
LNGB_SP	11.12	18.35	14.41	18.02	11.15	13.4	13.56	81.65
LNGB_SP.1	14.22	13.43	17.87	13.45	11.35	14.95	14.72	82.13
LNGB_MSCI	11.4	17.86	14.39	18.03	11.21	13.41	13.7	81.97
LNGB_China	13.8	13.21	15.24	13.16	16.23	14.15	14.22	83.77
LNGB_BFS	15.07	12.72	15.12	12.7	10.86	18.41	15.13	81.59
LNGB_EUR	15.64	12.74	15.12	12.95	11.39	15.16	17	83
TO	81.26	81.06	89.26	81.64	67.57	86.84	87.54	575.17
NET	0.19	−0.59	7.14	−0.34	−16.2	5.25	4.54	TCI = 82.17%
NPT	3	1	6	2	0	5	4	

This table presents the quantile VAR(2) estimate results at the extreme lower quantile ($\tau = 0.95$). we refer the reader to note in Table 3

5 Conclusions

In response to recent studies examining the interplay between macroeconomic conditions and the green finance and industry sectors, our research focuses on investigating the dynamic co-movement between inflation-indexed bonds and green bonds. To achieve this, we analyze the price series of MSCI Green Bonds and Green Bonds China as representative of the global green bonds market and the green bond market in an emerging country (China), respectively. Additionally, we obtain price data for inflated bond indices in Mexico, Turkey, Brazil, and China for the period of October 11, 2016 to January 15, 2021. Across various wavelet time scales, our analysis reveals significant connections between green bonds and inflation-indexed bonds throughout the entire sample period, with inflation-indexed bonds leading the relationship. This aligns with our expectations that green financial products are responsive to macroeconomic conditions.

Furthermore, we observe periods where the relationship between green bonds and inflation-indexed bonds is positive, as well as periods where it is negative. This ambiguity mirrors what has been observed in the co-movement of green energy with fossil fuel commodities. For instance, previous research has found that green energy firms and associated products tend to positively co-move with fossil fuels, increasing in value as fossil fuel prices rise. This relationship is intuitive, as green energy becomes more valuable as a substitute when fossil fuels become less affordable. However, as highlighted by Corbet et al. (2020), when oil prices experienced an unprecedented decline in April 2020, green energy firms responded with higher valuations. This phenomenon can be explained by downward estimations of global energy demand, which influenced industry and policymakers to consider green energy alternatives as capable of meeting future demand.

During the COVID-19 period, we identify pronounced co-movement between green bond markets and inflated bonds in the short to medium terms, particularly during periods of high market volatility. These findings have important implications, especially for policymakers. Our results suggest that during extreme market conditions, inflated bonds co-move with green bond markets to a greater extent compared to normal market states. Hence, policymakers involved in developing strategies aimed at improving environmental securities should consider the effect of inflated bonds and carbon emissions in their policy formulation for green bond markets. Additionally, it is crucial to consider the interconnectedness under different market conditions, as we found that the extent of shock transmission and causality differs across market states.

In summary, our study highlights the differences in connectedness and information shock transfer mechanisms across market states, as demonstrated by the quantile vector autoregression and dynamic conditional correlation techniques employed. Moreover, our results reveal significant spillovers between green bonds and inflation-indexed bonds markets during extreme positive and negative events, indicating the stronger impact of larger shocks on a given market relative to smaller shocks. Furthermore, our analysis demonstrates that these spillovers between markets persist over time and frequency.

Based on our network connectedness analysis, LNGB_China emerges as the largest net recipient of spillovers within the system under all trade scenarios, while LNGB_SP.1 market stands out as the largest net contributor of shocks. In comparison to the connectedness observed during stable market conditions, the connectedness and spillovers among markets during bearish and bullish markets exhibit greater intensity and higher levels of information transfer.

The results of this study have significant implications for both investors and policymakers. For investors, the findings underscore the importance of monitoring the effects of extreme positive and negative shocks in the green bonds and inflation-indexed bonds markets. This awareness can aid in making informed trading decisions and improving risk management when constructing portfolios that include green bond and inflation-indexed bond assets. Additionally, policymakers can benefit from the quantile connectedness and spillover analysis conducted in this study, as it provides valuable insights into the transmission pathways among the markets under consideration. Specifically, the study highlights the lower co-movement of the green bond market during extreme market states. This understanding can inform regulatory efforts aimed at managing risk spreads within the green bonds and inflation-indexed bonds system.

In conclusion, our study contributes to the broader understanding of the co-movement between green bonds and inflation-indexed bonds in emerging countries, shedding light on the inherent volatility and dynamics of these markets. The findings emphasize the importance of considering the relationships between different types of bonds when making investment decisions. Moreover, the study highlights the potential role of green bonds as resilient and sustainable investment options, offering opportunities for portfolio diversification and stability, particularly during periods of extreme market conditions.

While the present study focuses on the connectedness and time–frequency dynamics between inflation-indexed bonds and green bonds from 2016 to 2021, it is essential to acknowledge the limitation of the chosen time period. Future avenues for research could include extending the sample period to cover events such as the Russia-Ukraine conflict. Additionally, researchers can explore the connectedness between the markets under consideration using the wavelet quantile correlation (WQC) method proposed by Kumar and Padakandla (2022), which expands on the quantile coherency approach. The WQC method allows for the detection of asymmetric linkages among model parameters, providing a comprehensive understanding of the relationships across multiple quantiles.

Appendix

See Table 6 and Figs. 5, 6 and 7.

Table 6 Pairwise correlation matrix

	DLNGB_IG	DLNGB_SP	DLNGB_MSCI	DLNGB_China	DLNGB_BFS	DLNGB_EUR
DLNGB_IG	1					
DLNGB_SP	0.0157	1				
DLNGB_MSCI	0.0725	0.9856	1			
DLNGB_China	0.2329	0.3801	0.3796	1		
DLNGB_BFS	0.6444	0.3761	0.3952	0.2275	1	
DLNGB_EUR	0.7171	0.6046	0.6452	0.4064	0.713	1

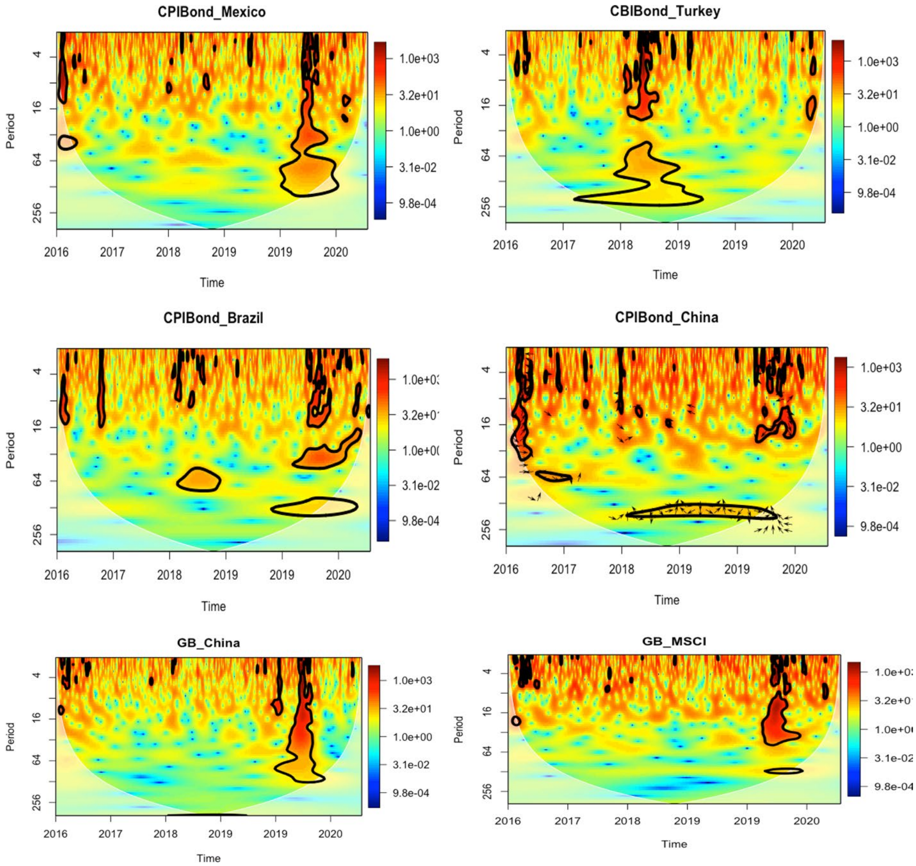

Fig. 5 Wavelet power spectrum. NB: (1) The thick black contour designates the 5% significance level against red noise and the cone of influence (COI) where edge effects might distort the picture is shown as a lighter shade. The color code for power ranges from blue (low power) to red. (2) The color code for power ranges goes from blue (low power) to yellow (high power); (3) The *X*-axis denotes the studied time period, whereas the *Y*-axis illustrates the frequency

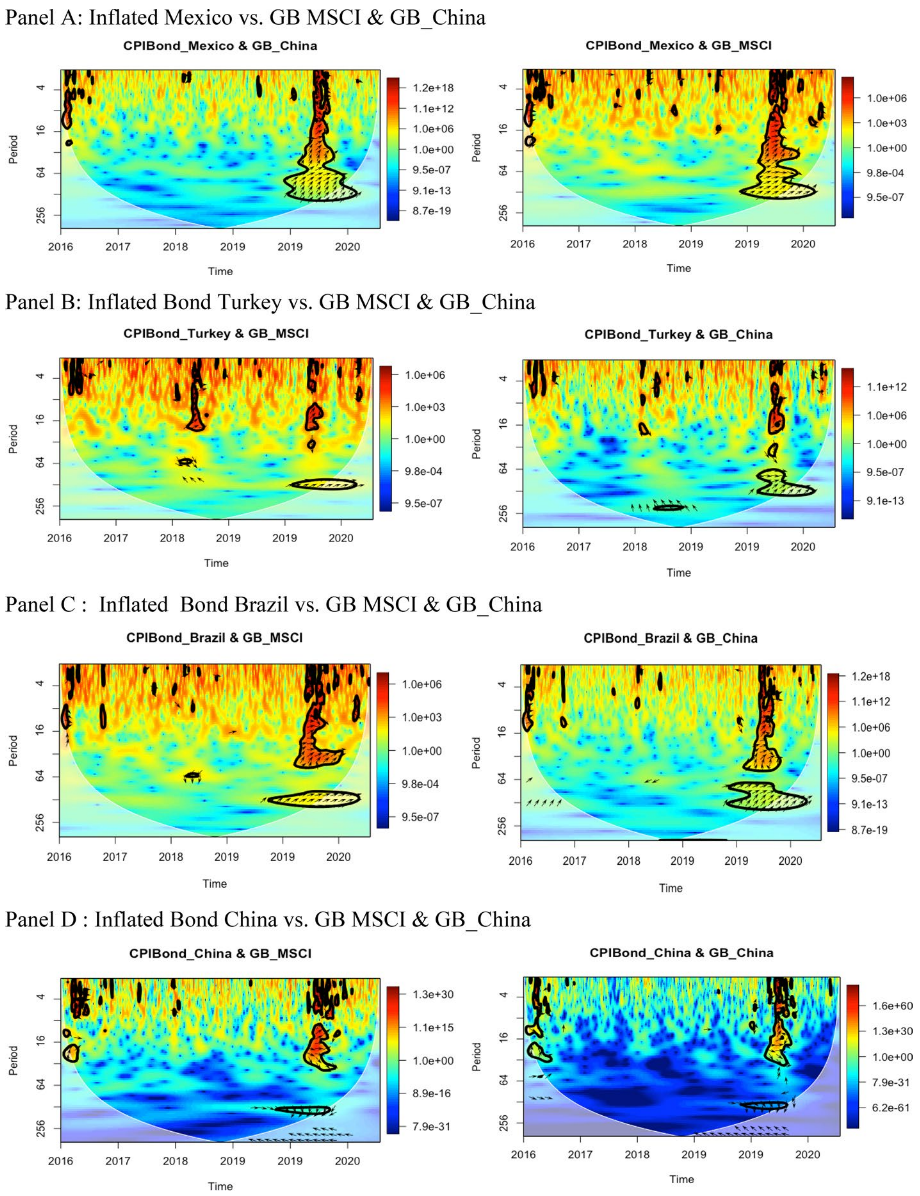

Fig. 6 Pairwise wavelet coherency. NB: (1) The thick black contour designates the 5% significance level against red noise and the cone of influence (COI) where edge effects might distort the picture is shown as a lighter shade. The color code for power ranges from blue (low power) to red. (2) The color code for power ranges goes from blue (low power) to yellow (high power); (3) The *X*-axis denotes the studied time period, whereas the *Y*-axis illustrates the frequency

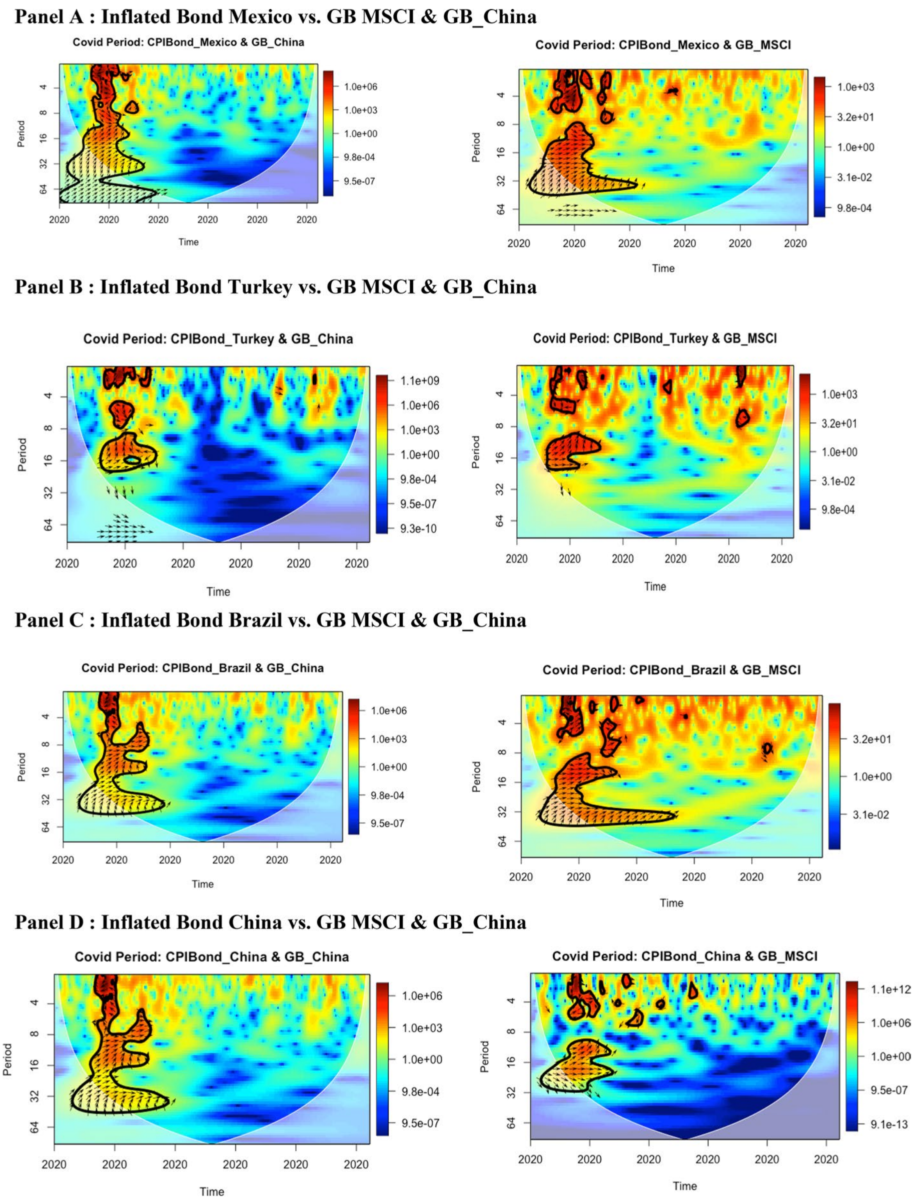

Fig. 7 COVID-19 period pairwise wavelet coherency between green bonds and inflated bond. NB: (1) The thick black contour designates the 5% significance level against red noise and the cone of influence (COI) where edge effects might distort the picture is shown as a lighter shade. The color code for power ranges from blue (low power) to red. (2) The color code for power ranges goes from blue (low power) to yellow (high power); (3) The *X*-axis denotes the studied time period, whereas the *Y*-axis illustrates the frequency

Data availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

Conflict of interest The author declares no conflict of interest.

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