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Contagion between investor sentiment and green bonds in China during the global uncertainties

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A B S T R A C T

This study explores the connectedness between investor sentiment (IS) and Chinese green bonds using a QVAR from 30th June 2017 to 29th June 2022. Dynamic connectedness is more apparent in the short term (23%) compared to the long term (4%). Net total directional connectedness over quantiles suggests that IS is a main net receiver of shocks during our sample period under 20% and over 80% quantile. However, IS is also a net transmitter of shocks between 20% and 80% quantile. Green bond is a net receiver of shocks over quantiles. Uncertainties such as the recent COVID-19 pandemic are attributed to changes in investor sentiment and Chinese green bonds. The findings of this article have profound implications for investors, policymakers, and the broader financial community, in terms of gaining insights into and warnings about how uncertainty occurrences can spread, and accordingly designing appropriate investment policies for stabilizing the stock market in China, and the emerging economies at large.

1. Introduction

Once a notion of curiosity as a niche market in the 1970s, "socially responsible investing" (SRI) has evolved as a global movement, leading to an upsurge in research on SRI over the last two decades (Otek Ntsama et al., 2021; Widyawati, 2019). As a hybrid investment approach, SRI aims to achieve "sustainable development goals" (SDG) (PRI, 2017) by addressing the "Environmental, Social or Governance" (ESG) framework (Avetisyan & Hockerts, 2017; Friede, 2019). Literature however has revealed various shortcomings of the ESG, and issues related to climate change management. Against this backdrop, a "climate-aligned" instrument (Piñeiro-Chousa et al., 2021), namely "green bond" (GB, hereafter), has evolved as a sensible method of supporting sustainable development through green investments (Elsayed et al., 2022; Otek Ntsama et al., 2021). The European Investment Bank (EIB) first issued the GB in June 2007 (Piñeiro-Chousa et al., 2021), and the World Bank followed suit in 2008 (Anh Tu & Rasoulinezhad, 2021). In 2009, the

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Copenhagen Accord provided a substantial boost to the green stock market by mandating the financial markets play a central role in mobilising private investments to fight against the climate change (Piñeiro-Chousa et al., 2021). In 2014, the acceptability of GB enhanced following the release of the Green Bond Principles (GBP) by the International Capital Markets Association (ICPA) (Roboredo, 2018). As an outcome of these positive developments, the GB market continued to expand remarkably at an astonishing annual average growth rate of 95%, irrespective of the financial adversities caused by the COVID-19 pandemic (Bouteska et al., 2023), from $1.5 billion in 2007 to $1501 billion in 2021 (Hyun et al., 2022). In view of the ongoing market entries of large corporate issuers (e.g., Toyota, followed by Apple, Starbucks, SNCF, Berlin Hyp, ENGIE, ICBC, Crédit Agricole), about 150 during 2016–21 (Hyun et al., 2022), the GB market has been projected to reach a value of $5 trillion by 2025 (Bouteska et al., 2023a). However, given that the global ESG assets market is forecasted to surpass $53 trillion by 2025, it anticipated that attempts to raise investor conscience and awareness may secure a higher stake for the GB market (Hacıömeroğlu et al., 2022).

In the post-Millennium decades, investors have displayed strong consciousness of the subjectivity of the investment-related decisions to the trade-off between potential risks and profits in the increasingly uncertain financial markets (Bouteska et al., 2023a; Yadav et al., 2023). As a diversifier, an effective hedger and a safe-haven asset, majority of the investors display enthusiasm about including green energy stocks in their asset portfolios in order to achieve both investment returns and manageable risks (Arif et al., 2022; Naeem & Karim, 2021; Nguyen et al., 2020). Consequently, the growing interactions of green energy stocks with other financial assets in the portfolios necessitate investors' understanding of the terms of their co-existence (Uddin et al., 2019, 2021). Pham (2016) pioneered researching on the interfaces between green energy stocks and additional resources, and a flurry of studies then ensued (e.g., Roboredo, 2018; Baulkaran, 2019; Broadstock & Cheng, 2019; Arif et al., 2022; Elsayed et al., 2022; Bouteska et al., 2023a; Wang et al., 2024). All these studies investigated the connectedness of GB with other markets, e.g., currency, stock, corporate and treasury bond, energy, green equity, etc., and observed considerable transmissions of volatility spillovers from the latter to the former market. In consideration of the fact that noise traders make trades driven by sentiment, a number of researchers, e.g., Nayak (2010), Fang et al. (2018), Broadstock and Cheng (2019), Piñeiro-Chousa et al. (2021), Min Liu (2022), among others, pinpointed the significant influence the investor sentiments (IS, henceforth) have on the linkages of GB market with other markets, suggesting IS as a measure for capturing and forecasting asset returns and volatility. Due to the contribution of noise traders to volatility in asset pricing, IS has been used as a measure for capturing and forecasting asset returns and volatility (Chen et al., 2021; Gong & Lin, 2018). In recent analyses, the use of IS has been considerably increased in relation to return, volatility, IPO pricing, and bank financial products (Chen et al., 2021). Nevertheless, there is scope in literature to examine whether dynamic connectedness between IS and energy market dynamics exists or not. Given that the attention of the investors on GB as a reasonably easier and safer asset to incorporate in their portfolios has grown in the recent years (Korkmaz & Nur, 2022) and, on the contrary, the extant literature has negligible amount of insights to offer with regard to the nexus between the IS and GB market volatility (Piñeiro-Chousa et al., 2021), this study considers it vital to cover current gaps in the literature by investigating possible dynamic connectedness between IS and GB market.

In recent times, the financial markets have become increasingly volatile following the emergence of two major Black Swan events, i.e., the COVID-19 and the Russia-Ukraine war (Bouteska et al., 2023; 2023a). The dramatic increase in the number of deaths and the restrictive measures such as lockdowns as a consequence of the COVID-19 led to instability of financial and energy markets worldwide. In addition to this, the ongoing Russia–Ukraine war has been inevitably affecting the financial and energy markets. Both of these events resulted in significant shrinkage in the world stock markets, while commodities and energy prices swelled abruptly (Bouteska et al., 2023; Chen et al., 2023). There has been a rapid rise in news and reports related to these events on many platforms of the internet, including Toutiao, WeChat, and Weibo, influencing investors' outlook and sentiment regarding the stock market to some extent (Sun et al., 2020). In China, the largest developing economy in the world, anxiety and panic among investors badly affected the stock market (Gao et al., 2022). For example, the A-share market fell suddenly on trading day 1 following the Lunar New Year in 2020. In addition to this, following Russian invasion of Ukraine, the blue-chip CSI300 index closed 2% lower at 4529.32, while the Shanghai Composite Index lost 1.7% to 3429.96 after 24 February 2022 (Yadav et al., 2023). The conditions of these events thus set a right background for exploring IS and stock returns in extreme conditions, and make a novel contribution to the literature related to stock markets, green stocks in particular. The context of China is important since the existing studies (e.g., Cevik et al., 2022; Gao et al., 2022; Hu & Liu, 2010) indicating the critical impacts of IS on stock market returns and volatility may offer bias findings and conclusions due to some inherent limitations. First, the measures used to capture the IS in these papers are not purpose-built, hence not fully and timely reflecting fluctuations in the behavior of investors in the markets. Second, IS affects stock market volatility, while a rise in stock market volatility also leads to fluctuations in IS (Bouri et al., 2022). The existence of their interlinkages may result in more severe consequences. On the contrary, the extant articles focus on the unidirectional effects of IS on the stock market volatility, while extracting some insightful lessons from their bidirectional relationship is critical (Bissoondoyal-Bheenick et al., 2021; Bouri et al., 2022). More importantly, in terms of the volume of GB issuance during 2016–22, China outperformed the world's largest issuer (the US), rising from about $4 billion in 2016 to $85.3 billion in 2022 (Zenno & Aruga, 2024). Since the inception of GB in 2016 (Liu et al., 2022), green finance has become an indispensable part of Chinese national strategy (Wang & Zhang, 2017) due to its growing significance in economic activities that support the Chinese government's targets of reaching peak carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060 (Liu et al., 2022; Su et al., 2023). Given the aforementioned gaps in literature and the increasing emphasis on green investments and the unpredictable nature of global events, we consider it vital to answer some important questions, i.e., What is the relationship between IS and green stocks in China during global uncertainties? Why is this relationship significant both theoretically and practically? Accordingly, we aim to assess the dynamic connectedness between IS and the green stock market's volatility, especially during the aforementioned periods of global uncertainties.

The findings of this study provide insights of how climate changes, ecological and environmental effects can influence the sentiment of one of the vital economic agents, investors in this study, to consider inclusion of GB in their investment portfolios. This study suggests that dynamic connectedness is more apparent in the short term compared to the long term. IS was the main net receiver of shocks during our sample period under 20% and over 80% quantile, and also a net transmitter of shocks between 20% and 80% quantile. Green stock is a net receiver of shocks over quantiles. Uncertainties like the COVID-19 pandemic and the Russia-Ukraine war are attributed to changes in IS and Chinese green stocks. Based on the findings, we emphasise considering sentiment indexes as essential in incorporating market insights into volatility forecasts. Altogether, this paper makes at least four contributions to the literature. Firstly, we pioneer an attempt to account for the impacts of uncertainties on the aforementioned interconnectedness in the wake of the recent Black Swan events, i.e., the COVID-19 pandemic and the Ukraine-Russia conflict. As Gao et al. (2022) emphasised, we consider it vital to explore the connectedness during various global uncertainties to observe changes in their behavior in the difficult times. Secondly, we demonstrate how conditional volatility relates to IS, and use quantile vector autoregressive (QVAR) methodologies for analysing interlinkages among volatility of IS and GB. This approach aligns well with previous studies, e.g., Abakah, Ullah, et al. (2023), Abakah, Tiwari, et al. (2023), that employed QVAR methodology to analyze volatility interlinkages across various types of markets that did not extend itss coverage to GB yet. Thirdly, unlike the conventional studies that mostly used monthly data, we employ a daily data of social media investor sentiment (*SI*), a version decentralized from GB tweets that lets users protect themselves of turbulences and temporal losses in market, from 30 June 2017 to 29 June 2022. Given that sentiment changes over time, the financial derivatives market is immature, and IS affects short-term volatility (Chiu, Chung et al., 2018; Chiu, Harris et al., 2018), we prefer using daily data in our study. We consider this methodological approach an effective way to examine dynamic connectedness in various markets (Abakah, Ullah, et al. (2023), Abakah, Tiwari, et al. (2023); Chatziantoniou et al., 2022; Gong et al., 2023). Compared to other methods like VAR, BEKK, time-varying copulas, or DCC, this method allows us to tackle the problem of data shortage. Fourthly, we compare Baruník and Křehlík (2018) frequency-domain measurements and the Diebold and Yılmaz (2012, 2014) time-domain estimates to enjoy higher flexibility in reaching the measures of net pairwise connection. Fifthly, given the increasing emphasis on green investments and the unpredictable nature of global events, the insights of this relationship can have profound implications for economists and policymakers to develop and implement economic and financial policies that can stabilize financial markets more effectively.

2. Literature review

Through the lens of Psychological Finance, researchers have long studied the impact of sentiment among investors on equity markets. They have studied how it influences market prices. They use internet platforms and apps to extract keywords from news reports and media reports to create variables that measure the sentiment of investors. Some examples include Facebook, Google Trends, Baidu index data, and so on (Bouteska et al., 2023a). Investing decisions and the behavior of traders in the financial market are affected by second-order effects on IS. The extant literature highlights that a sentiment index can be constructed based on the impact of major events in order to describe how IS changes when such events occur. For example, after the outbreak of COVID-19 began, Wuhan became the center of the public's attention, and the lockdown of Wuhan heightened public panic and anxiety at the beginning of the outbreak which subsequently affected investors' sentiment. Given these backdrops, the extant literature is reviewed below in three major sections, covering the nexus of investor sentiment with social and green bonds (GB) in Sections 2.1 and 2.2, and with stock markets including GB during the COVID-19 period in Section 2.3.

2.1. Social media and investor sensitivity nexus

Contemporary literature in behavioral finance have investigated the influence of daily news and social media on investors' sensitivity and decision-making, and their consequence on firm values and stock prices. For instance, Karabulut (2013) emphasised that searches on the Internet can effectively estimate and affect asset prices, and that the Gross National Happiness index of Facebook is effective in estimating US daily returns due to its effect on IS. Using data from Nasdaq and Dow Jones, S&P 500, Vozlyublennaia (2014) investigated the correlation between small- and midsize enterprise stock values and Google searches, and concluded that Google searches temporarily affected investors' stock values. Afkhami et al. (2017) indicated that the use of Google search activities is an important forecaster of energy commodity price volatilities which heavily influences investors' attention and associated behavior. Wang and Kim (2017) investigated 232 companies and found that social media enhanced their performance through improved customer relationship management (CRM). Jung et al. (2017) examined S&P 1500 firms' use of Twitter for making strategic announcements of quarterly earnings when the news is good in nature. The study suggested that motivations for such strategic are more when the firms has a larger social media audience or the level of investor sophistication is low. Majumdar and Bose (2019) investigated manufacturing companies and observed evidence of higher value additions through social media activities. Zu et al. (2019) examined the intensity of social media activity and the firm performance on the Chinese stock market during the 2010–2014 period, and revealed an inverted U-shaped relationship of stock prices and company news on virtual platforms with investors' attention. Giannini et al. (2019) observed a strong correlation between social media and stock markets, implying that the activities of social media will have a direct impact on stock price fluctuations. Zhang et al. (2020) has researched the correlation between fluctuations in the CSI 300 index and social media, and found that these variables are highly correlated. On the contrary, earlier studies suggested no or poor linkage between social media data and firm performance. For instance, Nofer and Hinz (2015) examined how 100 million tweets affected German investors between 2011 and 2013 with an outcome of finding no association of Twitter mood status with stock market performance. Furthermore, media studies evaluated the impact of stock price jumps and crashes. For example, Fang and Peress (2009), Bushee et al. (2010), and Aman (2013) noted that media can cause stock crashes whereas it cannot influence stock gains. Altogether, our review above shows an interesting transition in the social media impact, from no or poor to strong connectedness between social media data and firm performance over the years.

Investing decisions and attitudes toward financial assets are analyzed using investor sentiment as a behavior factor (Aloui et al., 2016; Bahloul & Bouri, 2016). For instance, Diebold and Yılmaz (2014) observed sharing of a bidirectional distribution effect between renewable energy stocks and social media. Earlier, Guo and Ji (2013) studied how Google volume searches on oil prices influence the anticipations of market traders, and found an enduring link between the oil price changes and external events. Han et al. (2017) used the Google search volume index (SVI) to construct investor attention index and observed an association between Google searches and oil prices. Moreover, the authors provided evidence that investor attention can directly forecast oil prices for both daily and weekly data. Ji et al. (2019) analyzed the application of the connectedness approach to assessing the correlation among investor sentiment indexes and WTI (West Texas Intermediate) returns and revealed that the impacts of investor sentiments increase dramatically while oil prices are falling.

2.2. Investor sensitivity and green bond nexus

Literature documents a number of recent studies (e.g., Agyekum et al., 2021; Anh Tu & Rasoulinezhad, 2021; Hyun et al., 2022; Mohsin et al., 2021; Piñeiro-Chousa et al., 2021) that investigated the significance of green bonds (GB) in the fight against climate and environmental issues. For example, Piñeiro-Chousa et al. (2021) looked into the portfolios of green-labelled financial assets, and highlighted GB as a more efficient, candid and novel option for diversifying capital to financing projects associated with climate change. The authors also suggested the implications of social media-based information in investor sentiment in both equity and bond markets, the GB in particular. Anh Tu and Rasoulinezhad (2021) found evidence of a positive nexus between GB financing and energy efficiency in 37 OECD member countries, following the issuance of GB by the World Bank in 2008. Likewise, Mohsin et al. (2021) recognised the role of GB in promoting climate-friendly economic growth through green investments in renewable energy infrastructure while reducing greenhouse gas (GHG) emissions at the same time. While holding PESTLE analysis of the renewable energy sector environment in Ghana, Agyekum et al. (2021) pinpointed the need for promoting a well-organised GB market to facilitate a green growth trajectory in 25 developing economies in Asia. Some of the recent studies provide evidence in favour of GB market in China. For instance, based on a unique dataset of 77 green investment stocks from China, Su (2021) and Fang et al. (2021) revealed that green investment stocks outperform conventional stocks and generate higher average returns. Su et al. (2023) studied GB and green stock markets in China and found both diversification and hedging benefits of GB, especially during extreme depression periods. Other researchers (e.g., Karpf & Mandel, 2018; Liu et al., 2022; Zerbib, 2019) suggested that GB has relatively lower environmental risks and good effectiveness, and also that the risk premium of GB becomes lower than matching conventional bonds.

Despite the importance of GB in fighting against climate changes, only a few publications can be traced that discuss the connection between renewable energy stock and investor sentiment. In the first occasion, Reboredo and Ugolini (2018) used investor sentiment indexes that are generated from Twitter data from businesses, and examined the links among sentiment of investor and the returns, volatility, and amount of trade for 17 renewable energy using companies. Their findings highlighted that emotion on Twitter had little bearing on trade volumes, volatility, or returns from renewable energy sources. In the second occasion, Song et al. (2019) used the index of Google search volume (GSVI) as an indicator of sentiment of investor, and calculated the spread of information among sentiment of investor indicators, fossil fuels, and some sustainable energy sources enterprises. The authors observed that markets for renewable energy (clean energy) were not affected by investor sentiment indices. Flammer (2020) highlighted the ways GB exerts positive effects on the ESG (particularly environment) performance of the issuer companies, eventually causing sentiments to make green investments and innovations. More recently, Liu and Hamori (2021) studied the interlinkages between investor sentiment and natural gas, but they also found a weak association between these variables. Chen et al. (2021) however provided evidence that sentiment of investor has been playing a vital role in improving the forecasting power of the energy futures markets' volatility in China. By using Twitter sentiment, Yilmaz et al. (2022) explored the influence of social media activities on green energy stock in the US. Although Tweets appeared to have a positive influence on the values of the company trading volume, the authors observed no significant effect of the Twitter sentiment on the returns and volatility of the companies. Given that there is not enough material on our topic of research, we are convinced that more research into the link between investor sentiment and green bond stocks is required to determine if the attitude of investors affects the price of GB equities and whether the extent of the impact is crucial.

2.3. Nexus of investor sensitivity with stock and green bond markets during the COVID-19

Both the COVID-19 and stock markets are gaining a lot of attention in recent literature. Using textual analysis of news mentions, Baker et al. (2020) explore that COVID-19 begot the greatest volatility in the stock market among all current infections, comprising the pandemic of flu in Spain in 1918, among the recent outbreaks of infectious disease. Erdem (2020) recognizes that the pandemic contributes to a decrease in stock returns and an increase in stock volatility. Zhang et al. (2020) found that the COVID-19 contributed to the growth in market finance all over the world risk. However, there are few studies that analyze sentiment among investors and the effects of the COVID-19 from the viewpoint of local bias, an anomaly in finance that can be affected by the asymmetry of information, or behavioral factors, such as relative optimism or familiarity (Bouteska et al., 2023a, 2024; Ha et al., 2024; Uddin et al., 2024). By using the Diebold and Yilmaz (2012) approach, Samitas, Papathanasiou, et al. (2022) examined the dynamic interconnection between fine wine, stocks, bonds, crude oil, commodities, gold, copper, shipping and real estate. They find that market volatility spillovers are moderate over time, whereas total connectedness is vulnerable to exogenous shocks, peaking during stressful periods. The markets for equities, crude oil, gold, and fine wine are the net contributors of spillovers, while the markets for commodities, copper, bonds, and shipping are the net receivers of diffused shocks. Furthermore, they estimated and compared fine wine's hedging ability before and after the emergence of the pandemic in order to provide investors with guidance on how to rebalance their portfolio strategies during uncertainties. Samitas, Kampouris, and Polyzos (2022) identified volatility and contagion risk among stock markets during the COVID-19 using dependence dynamics and network analysis on a bivariate basis. The findings of this study contributed to the existing body of literature since previous studies have not placed an emphasis on topological metrics when it comes to financial networks, particularly during the COVID-19 period. In light of the lockdown and the spread of the novel Coronavirus, there is evidence of immediate financial contagion.

Global uncertainties play a significant role on green stock market and IS across countries including China (Ma & Cheok, 2023). Hau et al. (2023) found that the number of GBs issued in China alone increased by 17 in 2020 compared with the pre-pandemic year (2019). During the pandemic, GB in particular appeared as a viable risk mitigation instrument, witnessed by an increasing trend in different types of green activities such as bond credit rating, green certifications, and CSR score which reduce the cost of funding for a GB issuer (Akhtaruzzaman et al., 2022). Akhtaruzzaman et al. (2022) examined the role of GB in hedging the risks associated with industry portfolios and other major asset classes. The study addressed how the greenness of the portfolio reduces the risk of green portfolios that contain GBs as well as 11 industrial sectors and major financial assets during October 2014–November 2021. According to the results, green portfolios are associated with a lower risk than unhedged (non-green) portfolios and also more effective at hedging during the COVID-19. Li et al. (2023) also showed that the COVID-19 pandemic strengthened the dominant role of the Chinese green energy stock market on crude oil futures market price changes. Likewise, Wei et al. (2023, p. 1) argue that "the economic and social impacts of the COVID-19 pandemic have left investors focusing on the short-term substitution between oil and green bond markets". Akhtaruzzaman et al. (2024) has investigated impact investing as a tool to manage risk for precious metals (i.e., palladium, platinum, gold, and silver) during calm and turbulent periods. The results of the study demonstrated that precious metals portfolios and impact investing portfolios have higher hedging effectiveness. In addition, the results of the study indicate that hedging effectiveness increased during the COVID-19 crisis for the portfolio of gold and impact investments.

2.4. Summary

The above review of literature is indicative of possible limitations of the findings and conclusions in providing an unbiased and purpose-built measure of IS, and portraying a clear nexus between IS and green markets. Firstly, the measures used to quantify IS in extant literature are very simple and do not adequately and timely reflect fluctuations in the behavior of investors in the markets. Secondly, these articles only focus on the one-sided effects of IS on stock market volatility, whereas their inter-relationship is important and provides a wealth of illuminating lessons, as emphasised by Bissoondoyal-Bheenick et al. (2021) and Bouri et al. (2022). This implies that the volatility of the stock market affects IS, and volatility of the stock market also influences investor behavior (Bouri et al., 2022). Their interconnection may therefore have more severe consequences due to their interdependence. Thirdly, it is essential that their connectedness be explored during different types of global uncertainty, such as pandemic crises or global political conflicts, so as to observe how their behavior changes in more challenging circumstances, as stressed by Gao et al. (2022). Our study will fill these gaps by employing the QVAR model to explore dynamic interlinkages between IS and stock market volatility in China.

Table 1
Descriptive statistics.

	SENCN	CSIGR300	EUGB	USCOGB	BLMSCIGB
Mean	−0.302	−0.003	0.016**	0.024***	0.015
	(0.924)	(0.960)	(0.047)	(0.009)	(0.277)
Variance	1.022***	2.563***	0.066***	0.086***	0.180***
Skewness	−1.254***	−3.384***	−1.363***	−3.289***	−1.142***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	4.304***	39.718***	12.090***	44.514***	12.330***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB (Jarque–Bera)	793.638***	68586.392***	6489.497***	85546.771***	6643.204***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−17.485***	−0.626	−4.114***	−3.026***	−9.799***
	(0.000)	(0.531)	(0.000)	(0.003)	(0.000)
Q (20)	155.159***	13.748	26.142***	109.219***	29.066***
	(0.000)	(0.184)	(0.001)	(0.000)	(0.000)
Q2 (20)	159.268***	57.273***	550.426***	176.452***	232.987***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: SENCN stands for IS Index in China, USCOGB for Bloomberg US Green Bond Index: Corporate, CSIGR300 for CSI 300 Green Leading Stock Index, BLMSCIGB for Bloomberg MSCI Global Green Bond Index, and EUGB for Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged EUR for the period 2019 to 2022.
Jarque–Bera testing is utilized to determine whether the distribution of returns is normal.
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

3. Methodology

3.1. Statistical analysis

Our research provides a daily dataset from GubaSenti (SENCN) (Sun et al., 2021), which used text-based analysis of millions of postings retrieved from Chinese financial online forums to determine the emotions of individual investors. IS Index in China (SENCN), Bloomberg MSCI Global Green Bond Index (BLMSCIGB), Bloomberg US Green Bond Index: Corporate (USCOGB), Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged EUR (EUGB), CSI 300 Green Leading Stock Index (CSIGR300) are used to examine the linkage between IS and green stock volatility in China. The time range of this study is from 30th June 2017 to 29th June 2022. We derive the first log-differenced series. In Table 1, Chinese green stocks are shown to be the riskiest indicator due to their high variability of IS in China. This finding is consistent with Deng et al. (2022), Hong et al. (2022) and Shen et al. (2023). We found that our indicators are leptokurtic. The results presented in Fig. 1 mean that their distributions have a bigger tail than the normal distributions.

3.2. Empirical methodology

All connectivity measures are then calculated using this model once we have estimated a quantile vector autoregression, or QVAR (p).

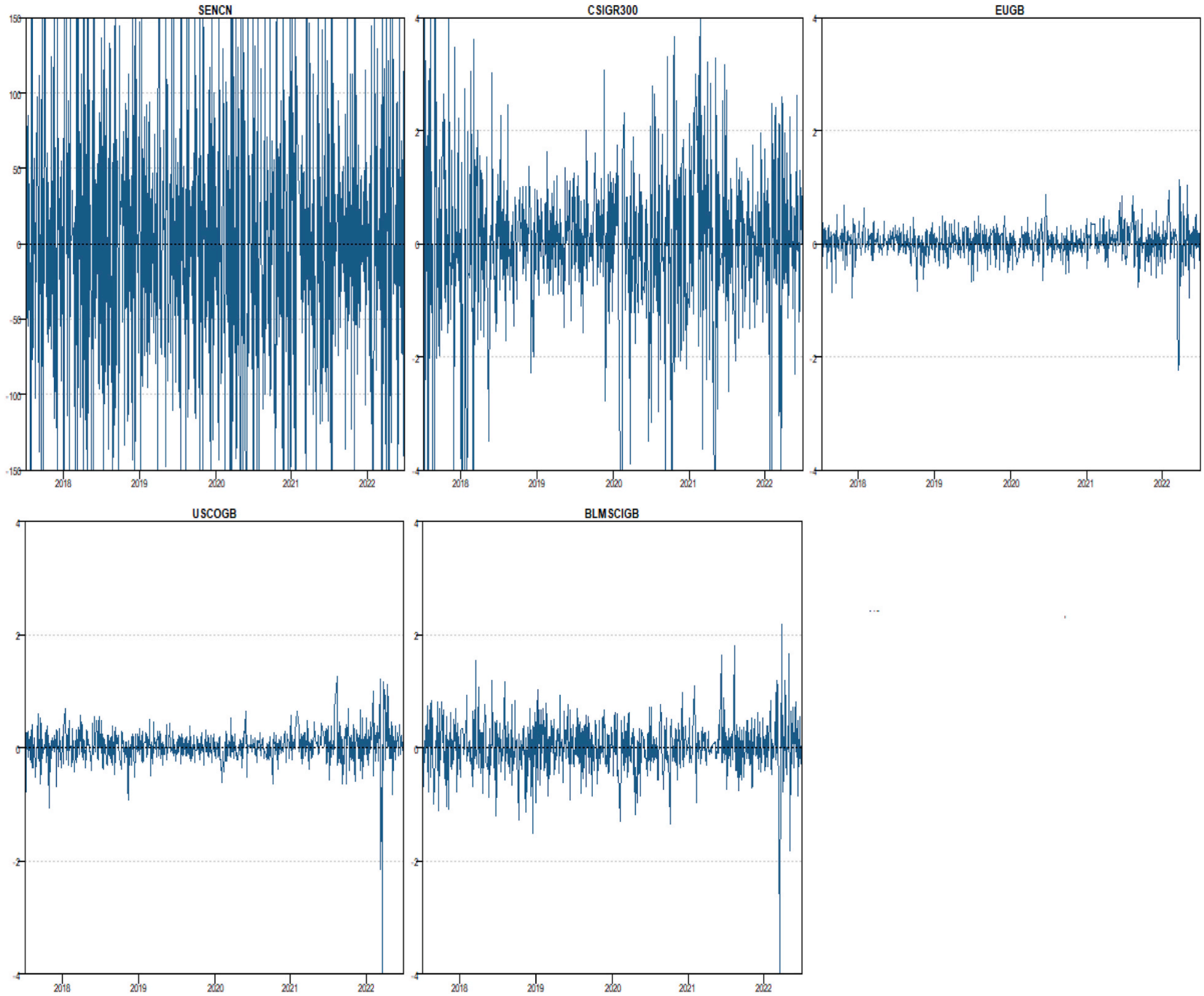

Fig. 1. Retruns of green bond and other indices. *Note*: SENCN stands for returns of IS Index in China, USCOGB for returns of Bloomberg US Green Bond Index: Corporate, CSIGR300 for returns of CSI 300 Green Leading Stock Index, BLMSCIGB for returns of Bloomberg MSCI Global Green Bond Index, and EUGB for returns of Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged EUR for the period 2019 to 2022. Horizontal axis (X-axis) indicates Time while vertical axis (Y-axis) denotes quantiles. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

$$\mathbb{z}_t = \boldsymbol{\mu}_t(\tau) + \mathbf{d}_1(\tau)\mathbb{z}_{t-1} + \mathbf{d}_2(\tau)\mathbb{z}_{t-2} + \ldots + \mathbf{d}_p(\tau)\mathbb{z}_{t-p} + \boldsymbol{u}_t(\tau). \tag{1}$$

where $\mathbb{z}_t$ and $\mathbb{z}_{t-i}$, $i = 1, \ldots, p$ are endogenous variable vectors with $N \times 1$ dimension, τ describes the quantile of indicators, belonging to the interval [0, 1, p is the lag length of the QVAR model, $\boldsymbol{\mu}(\tau)$ is a conditional mean vector with the dimension $N \times 1$, $\mathbf{d}_j(\tau)$ is an $N \times N$ dimensional QVAR coefficient matrix, and $\boldsymbol{u}_t(\tau)$ is a $N \times 1$ dimensional error vector with an $N \times N$ dimensional variance-covariance matrix, $\sum(\tau)$. We employ Wold's approach to convert the QVAR(p) to its QVMA (∞) description: $\mathbb{z}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p}\mathbf{d}_j(\tau)\mathbb{z}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty}\mathbf{Z}_i(\tau)\boldsymbol{u}_{t-i}$.

We continue with the connectedness evaluation in the frequency area. Stiassny's (1996) spectral decomposition technique can be used to investigate connectivity in the frequency domain. The starting point is the equation: $\mathbf{Z}(\boldsymbol{e}^{-i\boldsymbol{\omega}}) = \sum_{\text{ŭ}=0}^{\infty}e^{-iwh}\mathbf{Z}_{\text{ŭ}}$, in which $i = \sqrt{-1}$ and ω denotes the frequency to keep up with the spectral density of x_t at frequency ω illustrated as in a Fourier transformation of the QVMA (∞):

$$\boldsymbol{S}_{\mathbb{z}}(\omega) = \sum_{\text{ŭ}=-\infty}^{\infty} E\left(\mathbb{z}_t\mathbb{z}_{t-h}^{'}\right)e^{-iwh} = \mathbf{Z}\left(e^{-i\omega h}\right)\sum\nolimits_t \mathbf{Z}\left(e^{+i\omega h}\right) \tag{3}$$

The frequency GFEVD is obtained by combining the spectral density and the *GFEVD*. Applying a similar logic to the time domain situation, we normalize the frequency *GFEVD* as follows:

$$\Upsilon_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{\text{ŭ}=0}^{\infty}(\mathbf{Z}(\tau)(e^{-iwh})\Sigma(\tau))_{ij}\right|^2}{\sum_{\text{ŭ}=0}^{\infty}(\mathbf{Z}(e^{-iwh})\Sigma(\tau)\mathbf{Z}(\tau)(e^{iwh}))_{ii}} \tag{4}$$

$$\widetilde{\Upsilon}_{ij}(\omega) = \frac{\Upsilon_{ij}(\omega)}{\sum_{k=1}^{N}\Upsilon_{ij}(\omega)} \tag{5}$$

where $\widetilde{\Upsilon}_{ij}(\omega)$ is the portion of the ith variable's spectrum at a certain frequency ω that may be associated with a shock in the jth series. It may be understood as a within-frequency indication.

To assess the connectedness in both short-term and long-terms, all frequencies are combined within a certain range instead of measuring them separately as a single frequency, $d = (a, b) : a, b \,\epsilon\, (-\pi, \pi), a < b$:

$$\widetilde{\Upsilon}_{ij}(d) = \int_a^b \widetilde{\Upsilon}_{ij}(\omega)d\omega \tag{6}$$

Frequency interconnectedness estimates show details on spread within a specific frequency range d:

$$NPDC_{ij}(d) = \widetilde{\Upsilon}_{ij}(d) - \widetilde{\Upsilon}_{ji}(d) \tag{7}$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \widetilde{\Upsilon}_{ji}(d) \tag{8}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \widetilde{\Upsilon}_{ij}(d) \tag{9}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{10}$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \tag{11}$$

According to Baruník and Křehlík (2018), all contribution metrics of each frequency band should be weighed by $\Gamma(\text{d}) = \sum_{i,j=1}^{N}\widetilde{\Upsilon}_{ij}(\boldsymbol{d})/\boldsymbol{N}$.

$$\widetilde{NPDC}_{ij}(d) = \Gamma(\text{d}) \bullet NPDC_{ij}(d) \tag{12}$$

$$\widetilde{TO}_i(d) = \Gamma(\text{d}) \bullet TO_i(d) \tag{13}$$

$$\widetilde{FROM}_i(d) = \Gamma(\text{d}) \bullet FROM_i(d) \tag{14}$$

$$\widetilde{NET}_i(d) = \Gamma(\text{d}) \bullet NET_i(d) \tag{15}$$

$$\widetilde{TCI}(d) = \Gamma(\text{d}) \bullet TCI(d) \tag{16}$$

Lastly, we compare Baruník and Křehlík (2018) frequency-domain measurements and the Diebold and Yılmaz (2012, 2014) time-domain estimates:

$$NPDC_{ij}(\check{U}) = \sum_{d} NPDC_{ij}(d) \tag{17}$$

$$TO_{i}(\check{U}) = \sum_{d} TO_{i}(d) \tag{18}$$

$$FROM_{i}(\check{U}) = \sum_{d} FROM_{i}(d) \tag{19}$$

$$NET_{i}(\check{U}) = \sum_{d} NET_{i}(d) \tag{20}$$

$$TCI(\check{U}) = \sum_{d} TCI(d) \tag{21}$$

4. Results

4.1. Time -variation in average dynamic connectivity over time

In Table 2, various indicator interlinkages within the network are illustrated with average results. In Panel A, the mean TCI is 26.61%, implying that this network might cause 26.61% of the variability in the network of investigated indicators. These results show that idiosyncratic effects are responsible for 74% of the system error variance. Table 2 also displays the contribution of each indicator. IS is a net shock receiver. Moreover, IS transmits the most shocks to Chinese green stocks, equaling 9.24%, respectively. USCOGB significantly influences the transmission of shocks and volatility to all indicators. It is worth noting that CSIGR300 and BLMSCIGB are the most susceptible to shocks. Chinese green stocks are also a net receiver of shocks.

This analysis explores the time-variant role of each indicator by dividing the observational portions into short duration and long duration. The short-duration history of the system can be partially explained by the system of all indicators (TCI is 23.01%). Similarly,

Table 2
Averaged joint connectedness.

Panel A: Total						
	Total					
	SENCN	CSIGR300	EUGB	USCOGB	BLMSCIGB	FROM
SENCN	88.43	8.73	0.52	1.56	0.76	11.57
CSIGR300	9.24	87.30	0.90	1.02	1.54	12.70
EUGB	0.40	0.41	64.11	23.41	11.68	35.89
USCOGB	0.98	0.79	21.62	59.69	16.92	40.31
BLMSCIGB	0.81	1.25	12.06	18.48	67.39	32.61
TO	11.43	11.18	35.10	44.47	30.89	TCI
NET	−0.15	−1.51	−0.79	4.16	−1.71	26.61
Panel B: 1–5						
	1–5					
	SENCN	**CSIGR300**	**EUGB**	**USCOGB**	**BLMSCIGB**	**FROM**
SENCN	81.10	8.08	0.49	1.48	0.70	10.75
CSIGR300	8.29	73.14	0.74	0.92	1.24	11.19
EUGB	0.34	0.34	54.21	19.79	9.90	30.37
USCOGB	0.82	0.65	18.50	51.87	14.58	34.55
BLMSCIGB	0.73	1.04	10.74	15.70	57.91	28.21
TO	10.17	10.12	30.48	37.89	26.42	TCI
NET	−0.58	−1.07	0.11	3.33	−1.79	23.01
Panel C: 5-inf						
	5-inf					
	SENCN	**CSIGR300**	**EUGB**	**USCOGB**	**BLMSCIGB**	**FROM**
SENCN	7.32	0.64	0.04	0.08	0.06	0.82
CSIGR300	0.95	14.17	0.16	0.10	0.29	1.50
EUGB	0.06	0.07	9.89	3.62	1.78	5.53
USCOGB	0.16	0.14	3.11	7.82	2.34	5.76
BLMSCIGB	0.08	0.21	1.32	2.78	9.48	4.40
TO	1.26	1.07	4.62	6.58	4.48	TCI
NET	0.43	−0.44	−0.90	0.83	0.08	3.60

Note: The above table highlights various indicator interlinkages within the network which have been illustrated with average results.

idiosyncratic effects are attributable to around 77% of the system forecast uncertainty fluctuation in the short duration. However, this number plummeted considerably to 3.60% over the long term. These findings confirm the perception that the significance of shock transmission of indicators commonly in the short term is higher than that in the long term. Chinese green stocks have been found to be net receivers of network shocks in both short duration and long duration. Our empirical evidence shows that IS can be attributed to explaining the green stock volatility in China. These findings are critical for policymakers in designing policies to mitigate the volatility of green stocks in China in both the short-term and long-term. Our findings suggest that stabilizing investor psychology in the market is extremely important to limit the diffusion of negative information, system risks, and shocks in the financial market. In the case of China, green stocks, which play the role of a net receiver of shocks, are more likely to become more volatile under the impacts of diverse types of uncertainties if confusion and fear spread widely among investors. Hence, governments and financial policies should pay more attention to the mood of investors during uncertain times and propose a long-term plan to deal with negative information and uncertainties that raise their confusion and fear.

Fig. 2 illustrates total dynamic connectedness over a quantile. Warmer colors on the graph are associated with larger levels of interconnectedness. Changing IS and the volatility of green stocks in China exhibit a strong negative and positive correlation (below the 20% quantile and above the 80% quantile), indicating the symmetry of impact. In addition, the median quantile of connectedness throughout the whole time is 50%. Colors along the vertical axis represent times when there is greater uncertainty across quantiles, which could indicate a generalized financial and economic crisis. There was stricter lending regulation in 2019, the COVID-19 pandemic that began in 2020, and the Russia-Ukraine war in 2022. Additionally, we find that market risk was higher in 2019 when market interconnection dramatically increased between the 20% quantile and the 80% quantile. In 2019, investors have been warned about this danger because credit expansion has consistently outpaced nominal GDP growth for years. Bond yields have moved more significantly in response to changes in policy rates, which is partially attributable to stricter lending regulations. The interconnectedness around the middle of the y-axis is quite symmetric, suggesting that spillovers between very positive returns and negative returns follow similar behavior. In accordance with these results, Ren and Lucey (2022) found that clean energy stocks had a tenuous correlation with cryptocurrencies, indicating that clean energy may one day serve as a method of hedging and diversification for cryptocurrencies. According to Zhang and Broadstock (2020), some commodity markets have grown in conjunction with financial crises (2007–2009). A decline in the TCI followed between the middle of 2020 and 2022, when it suddenly rose following the outbreak of the Russian-Ukrainian conflict. As a result of the Russian-Ukraine invasion, energy firms performed better than Russian suppliers of renewable energy, fossil fuels, and uranium on the export market. The Ukrainian-Russian war could also have a significant impact on the EU energy market and businesses. In this article, the risks associated with disruptions in the Russian energy supply, the rise in energy prices, and the prospects for the European Union, which remains heavily dependent on Russian energy, are examined.

Then, we focus on net total directional connectedness over quantiles. These results are illustrated in Fig. 3. On these graphs, warmer colors indicate indicators of the net transmitter. Among all the indicators, IS's reaction shows the highest level of consistency. The incident in 2020 (the COVID–19 duration) and the Russia-Ukraine war in 2022 are significant. When IS is present, property prices are pushed away from the equilibrium rate justified by underlying fundamentals (Smales, 2017). Generally, IS is the main net receiver of shocks during our sample under the 20% quantile and over 80% quantile, as in Fig. 4. However, IS is also a net transmitter of shocks during 2020–2021 between the 20% quantile and 80% quantile. CSIGR300 is a net receiver of shocks over quantiles.

Finally, IS is dominated by other indicators during the COVID-19 duration and the Russia-Ukraine war. According to Fig. 5, short-term net pairwise connectedness stresses on the dominance of IS almost constantly all the time. The trend of IS in the short term is similar to that in the long term, except in 2019 and 2021. That means the short-term volatility of the indicators is the basis for considering their long-term roles. IS dominates Chinese green stocks most of the time except in 2018, in 2020 during the COVID-19 duration in both durations, and during the Russia-Ukraine war.

SENCN stands for IS Index in China, USCOGB for Bloomberg US Green Bond Index: Corporate, CSIGR300 for CSI 300 Green Leading

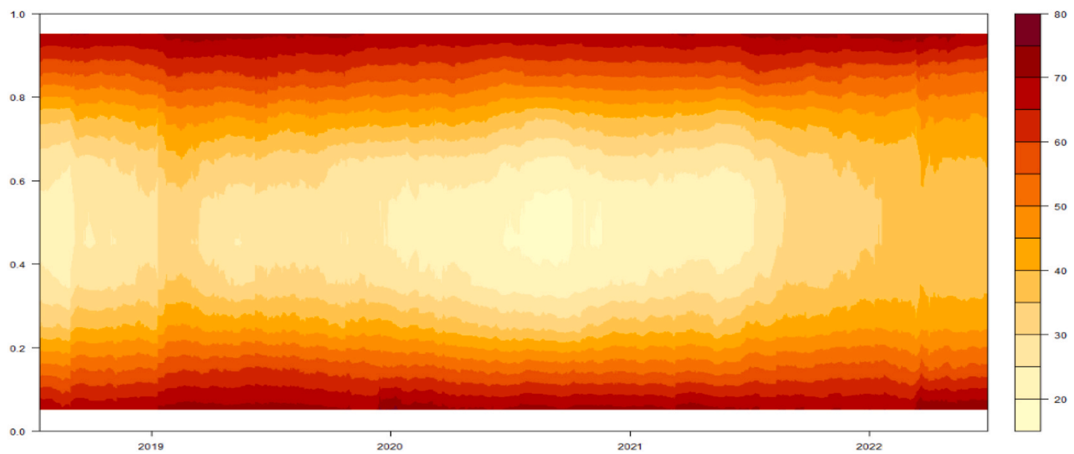

Fig. 2. Dynamic total directional connectedness over quantiles. *Note*: Horizontal axis (*X*-axis) indicates Time, while vertical axis (*Y*-axis) denotes quantiles.

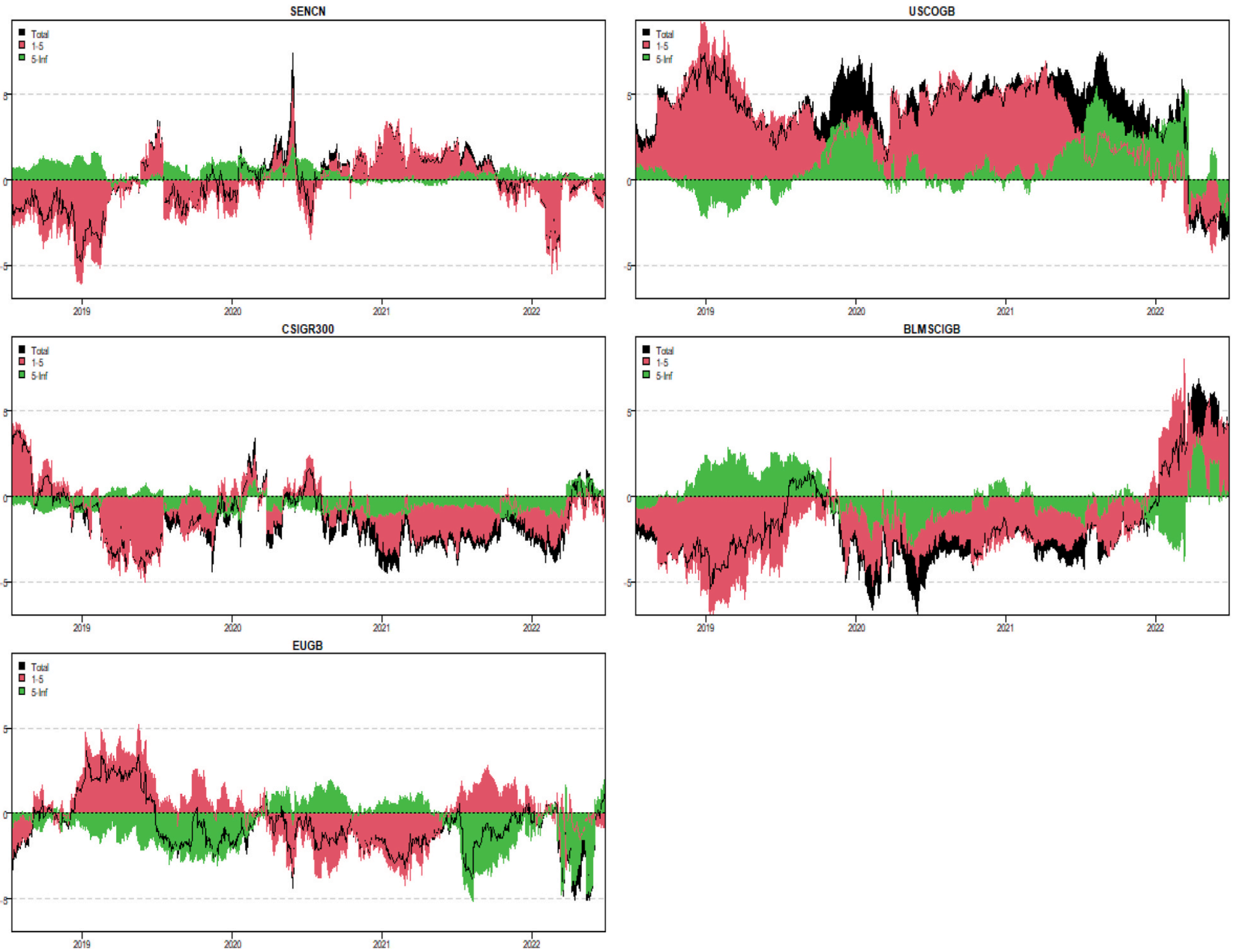

Fig. 3. Net directional connectedness over quantile: QVAR. *Note*: In the figure above, the net total directional connectedness is illustrated for SENCN, USCOGB, CSIGR300, BLMSCIGB, and EUGB for the period 2019 to 2022. Horizontal axis (*X*-axis) indicates time while vertical axis (*Y*-axis) denotes quantiles.

Stock Index, BLMSCIGB for Bloomberg MSCI Global Green Bond Index, and EUGB for Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged EUR for the period 2019 to 2022. Horizontal axis (*X*-axis) indicates time.

5. Conclusions

Climate change has potential to do substantial economic damage in many countries, particularly posing worrying tail risks for a large number of lower income economies (Sharif et al., 2022). Given the crucial role of economic agents in the fight against the climate challenges (Uddin et al., 2021), this paper recognizes the role of investors as one of the key economic agents and makes the first empirical attempt to comprehend how volatility in renewable energy market may influence their sentiment, exploring in particular the nexus between the Investor Sentiment Index (ISI) and Green Bond (GB) Volatility. Moreover, since climate changes, the COVID-19, and the Russia-Ukraine conflict has emerged to be a unique set of global stressors in the recent times (Bouteska et al., 2023, 2023a), we study the GB dynamics and check whether twitter sentiment investor plays the role of a net receiver or transmitter of shocks during these periods of time. We have applied a framework QVAR for examining the linkage between IS and GB volatility in China, based on measuring the connectedness network of five different financial indexes, i.e., IS Index in China (SENCN), and Bloomberg MSCI Global Green Bond Index (BLMSCIGB), Bloomberg US Green Bond Index: Corporate (USCOGB), Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged EUR (EUGB), CSI 300 Green Leading Stock Index (CSIGR300). Our time series daily data for these indexes are collected data for a period of five years, from 30th June 2017 to 29th June 2022. Furthermore, we have employed the strategy suggested by Baruník and Křehlík (2018) to enjoy higher flexibility while reaching the measures of net pairwise connection.

The findings of this study highlight that dynamic connectedness is more apparent in the short term compared to the long term. More specifically, net total directional connectedness over quantiles suggests that IS is a main net receiver of shocks during the sample period under the 20% quantile and over 80% quantile. However, IS is also a net transmitter of shocks between the 20% and 80% quantiles. GB

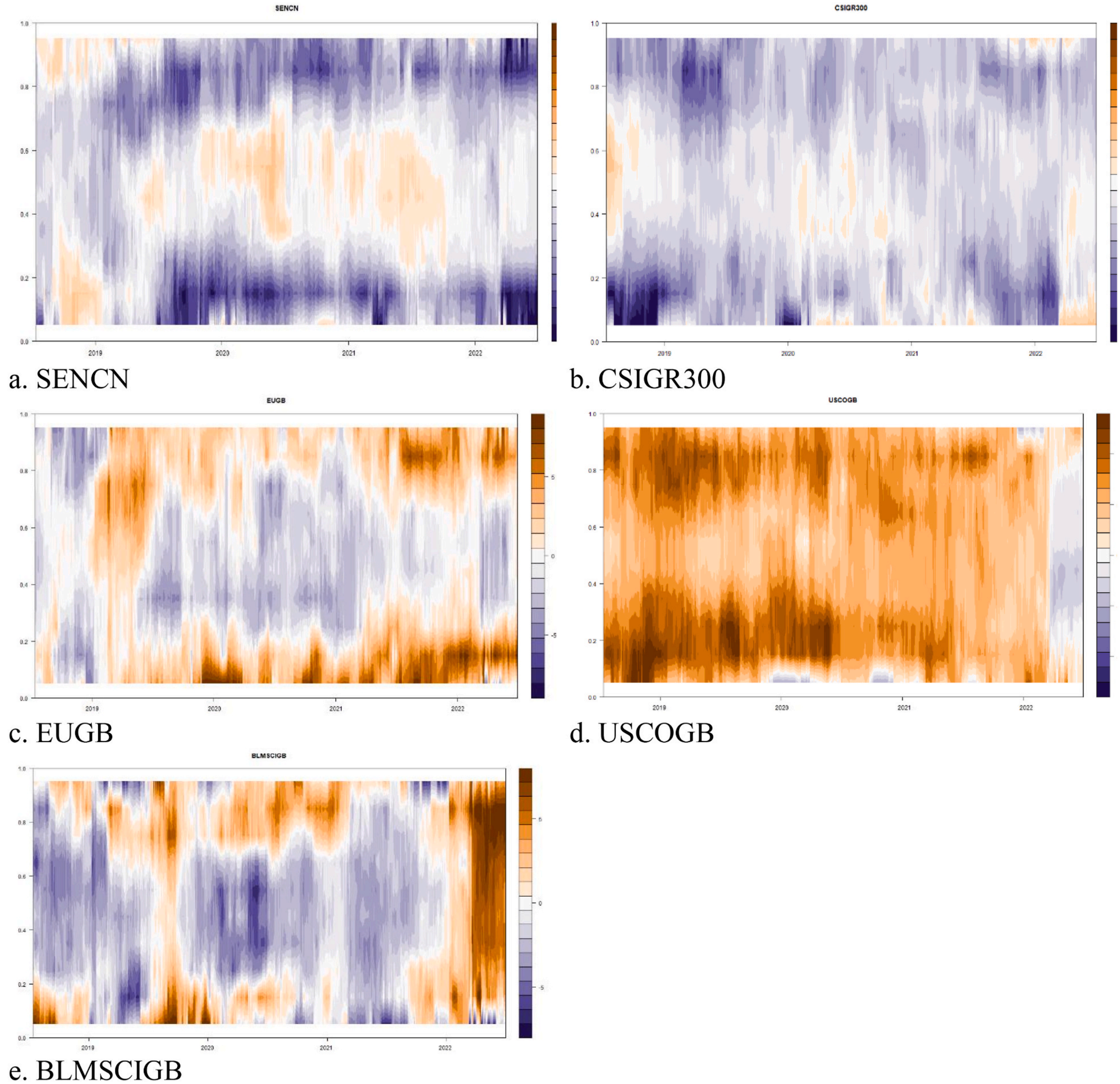

Fig. 4. Net directional link over quantile: QVAR. *Note*: In the figure above, the net directional link over quantile is illustrated for SENCN, CSIGR300, EUGB, USCOGB, and BLMSCIGB for the period 2019 to 2022. Horizontal axis (*X*-axis) indicates time while vertical axis (*Y*-axis) denotes quantiles.

is a net receiver of shocks over quantiles. Furthermore, IS and Chinese GBs are affected by uncertain events such as the COVID-19 pandemic.

Our study contributes to the literature in various ways. First, this article provides a thorough explanation of the dynamic connectedness between IS and green GB in the context of China, specifically in chaotic events like the COVID-19 pandemic, and the dynamic connectedness over quantile between these indicators. Second, we suggest that the net pairwise connectedness between IS and GBs in China can be determined using quantile estimates. Specifically, this study contributes to other studies that were based on the QVAR technique to analyze volatility interlinkages across different types of variables (Abakah, Ullah, et al., 2023, Abakah, Tiwari, et al., 2023), providing the suitability of using QVAR technique in interconnected analysis. Third, the findings of our study advance the relevant literature that studied IS, volatility in pricing, bank financial products, GB markets, and similar other variables (Chen et al., 2021; Campbell et al., 1993; Chen & Xu, 2019) with the findings on the association between IS, chaotic events like the COVID-19 pandemic and the Russia-Ukraine war, and GBs. Finally, this study extends the findings that the extant literature, though very limited, found on the association between IS, the effects of COVID-19 from the viewpoint of local bias or behavioral factors, such as relative optimism or familiarity.

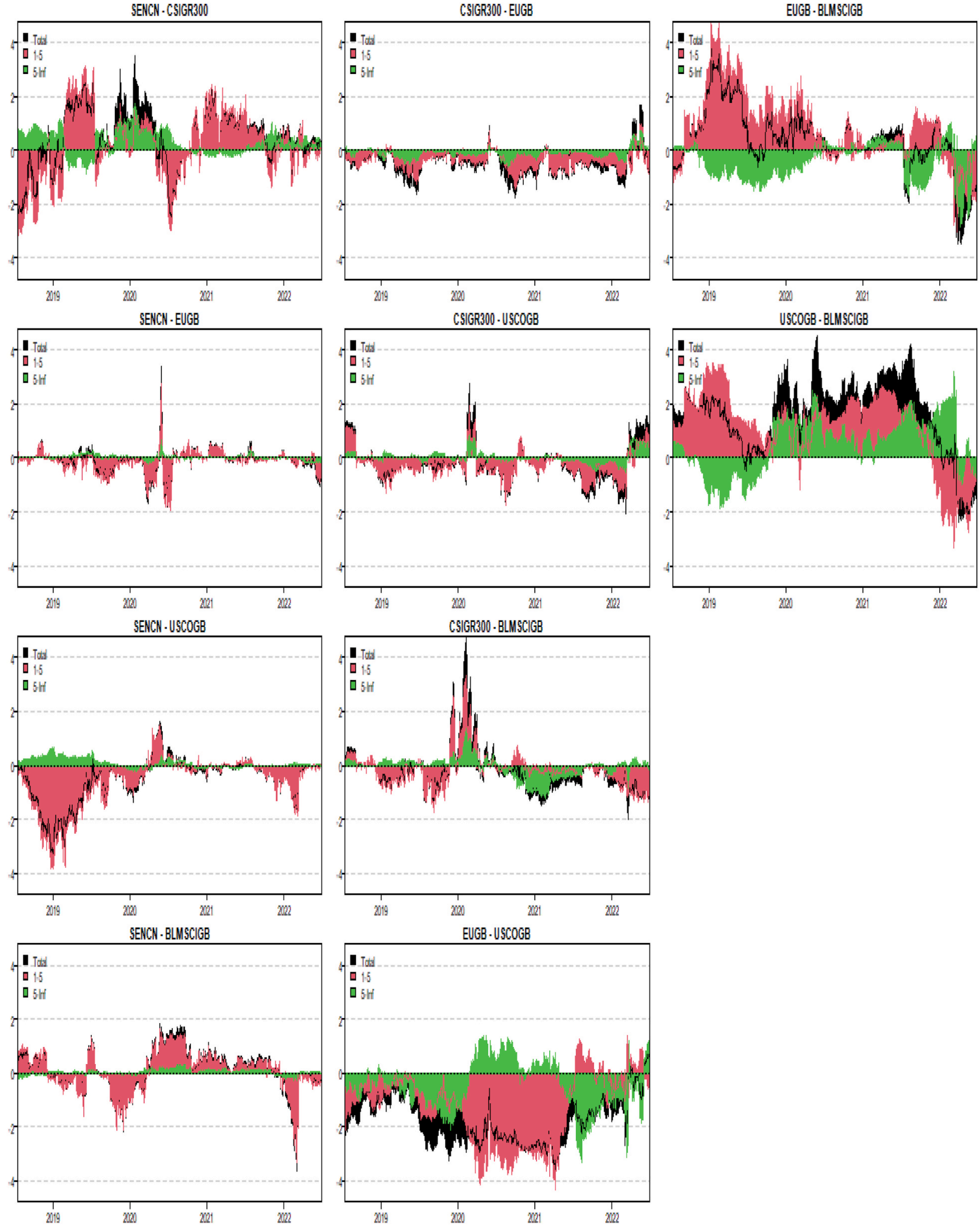

Fig. 5. Dynamic net pairwise directional connectedness: Compare Investor Sentiment Index to other indicator. *Note*: In the figure above, the dynamic net pairwise directional connectedness is illustrated for SENCN, CSIGR300, EUGB, USCOGB, and BLMSCIGB for the period 2019 to 2022.

The findings of our study have several implications for various stakeholders, including investors and policymakers, and these might be useful for gaining vital insights into and warnings about how uncertainty occurrences can spread in order to design appropriate investment policies for stabilizing the stock market across countries including China. Specifically, the findings could be useful for investors to understand the impact of changing IS on stock market in general, China's GBin particular, especially during chaotic periods like the COVID-19. Furthermore, they can be aware of the impact of the occurrences of uncertainties on the changes in IS and the subsequent impact on GBs in the context of developing countries including China. Findings also highlight the importance of managing global uncertainties towards minimizing the risk of the negative impact of the uncertainties in financial assets and markets. Based on the findings, we suggest that sentiment indexes are essential in incorporating market insights into volatility forecasts. Moreover, policymakers and practitioners may wish to choose a measure of volatility most suitable for their needs. Further, the volatility of the stock market hastens the transition from one stock to another when investors are skeptical about the future development of the market due to the COVID-19 health crisis or international political turmoil. Politicians may also be able to benefit from the findings of this study in order to improve the social welfare system, which is directly affected by the volatility of the stock market. Among the useful critical observations is that stock market risk and volatility affect investors' moods and vice versa. Developing policies for disadvantaged groups must incorporate them in order to promote the welfare of society.

Like other studies, there are some ways to improve this current work in further study. First, owing to the limitations of the approach used in our study, we only consider the Chinese financial market. Different scenarios may be revealed if we could consider the study in the context of other underdeveloped, developing, and developed countries. Second, the analysis of this study is limited to the stock market only, and thus, they may not be generalizable to other asset classes such as green equities, green mutual funds, green ETFs, etc. Finally, this study considers five years of data to analyze the relationship between the study variables. A further study considering a longer data period might provide more insights into the field of this study.

In conclusion, this study has been a pioneering attempt to provide insights of the way: (i) investors' social media activities may enrich their understanding of the energy market volatility, (ii) climate changes, ecological and environmental awareness of investors can influence their sentiment to make conscious decision making on the inclusion of GB in the investment portfolios.

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Declaration of competing interest

We (the authors) declare that we do not have any conflict (financial or non-financial) of interest.

Data availability

Data will be made available on request.

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