International Journal of Global Economics and Management
ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 6, Number 2, Year 2025
DOI: https://doi.org/10.62051/ijgem.v6n2.14
Journal homepage: https://ijgem.org

Dynamic Connectedness of Green Bond Markets in China and America: A R^2 Decomposed Connectedness Approach

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ABSTRACT

This study investigates the connectedness of two key green bond markets: the Shanghai Stock Exchange Green Bond Index (SSEGB) in China and the S&P U.S. Municipal Green Bond Index (SPMGB) in the United States. Using an R2 decomposed connectedness approach, we analyze the distinct dynamics between these indices. SSEGB demonstrates relative independence, driven by China's policy-oriented stability, making it attractive for long-term sustainable investments. In contrast, SPMGB exhibits heightened sensitivity to global shocks, offering short-term portfolio adjustment opportunities. These complementary roles underscore the critical importance of green bonds in promoting financial resilience and sustainability. The findings provide actionable insights for policymakers and investors, enhancing understanding of global green bond markets.

KEYWORDS

Green bond; Risk spillovers; Contemporaneous connectedness; Lagged connectedness

1. INTRODUCTION

Climate change poses an urgent and potentially irreversible threat to human society and the planet. In recognition of this, the vast majority of the world's countries adopted the Paris Agreement in December 2015, whose primary goal is to control the increase in global average temperature below 2◦C. Scaling up the transition to a climate-resilient economy requires the mobilisation of financial resources for green projects and fossil energy divestment (OECD, 2016). Against this back ground, and green bonds (GB) are becoming increasingly popular and established financial instruments in the sustainability-oriented financial community, as they channel financial resources to environmentally friendly projects (Flaherty et al., 2017; Fatica et al., 2021; Lian et al., 2022). As shown in Figure 1, the market for green bonds has been growing steadily since their first issuance. In relative terms, the green bond market is still quite small compared to the conventional bond market (around 3% in 2022). Green bonds differ from conventional bonds only in the way the proceeds are used (Reboredo and Ugolini, 2020; Lau et al., 2022).

The continual deepening of integration within global financial markets has augmented the interdependence of information across diverse markets and regions within the financial system. The heightened correlation observed in financial markets has not only facilitated the ongoing development and maturation of financial markets in various countries and regions but has also concurrently intensified the contagion effects associated with financial risks. Consequently, the effective measurement of interconnectivity between financial markets in different countries and regions establishes a robust foundation for advancing the development of financial markets and mitigating financial risks (Lin and Chen, 2021).

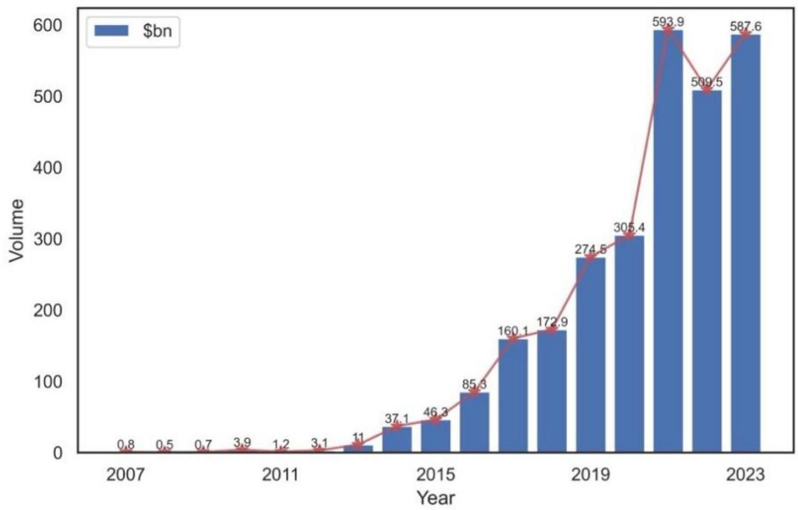

Figure 1. Total amount of Green Bonds issued yearly (billions of US dollars, Source: Climate Bonds Initiative (2022))

Literature has studied the impacts of climate risks on firm performance (Ozkan et al., 2023; Pankratz et al., 2023), cost of bank loans (Ho and Wong, 2023), corporate cash holdings (Lee et al., 2023), energy markets (Jin et al., 2023), stock markets (Zhu et al., 2023; Wu and Wan, 2023) and bond markets (Cevik and Jalles, 2022; Huynh and Xia, 2023). Given the impacts of climate risks on firm performance, cost of debt, stock markets and bond markets, firms have motivation for the implementation of environmental strategy to mitigate the negative impacts of climate risks (Kaesehage et al., 2019). Green bonds can be used to support the financial need of pro-environmental activities to reduce the negative impacts of climate risks (Flaherty et al., 2017; Lian et al., 2022) and to support transition to a low carbon economy for the future generations.

The benefits of pro-environmental activities and the connectedness of green bonds and the other assets can affect investment behaviors. Therefore, literature has studied the connectedness of green bonds and the other assets, such as conventional bond (Arif et al., 2021; Karim et al., 2022), stock (Elsayed et al., 2022; Mensi et al., 2022), and commodities (Mensi et al., 2022; Yousaf et al., 2024). The above studies examine the connectedness between green bonds and the other assets. The information related to the connectedness of green bond and the other assets (both contemporaneous spillover and lagged spillover effects) can be used to evaluate the green bond performance, green bond investment, portfolio investment, and hedge (Reboredo, 2018). However, both contemporaneous spillover and lagged spillover effects of green bonds and the other assets have not been addressed in the literature.

Considering China and the United States as the two largest economies globally, the bilateral relationship between these two nations assumes paramount significance. Since 2018, the interplay of frequent trade tensions between China and the United States, coupled with the unforeseen emergence of COVID19, has resulted in the extension of trade and investment contradictions between these two nations into the realm of finance. Within this context, the alterations in correlation within the green bond markets of China and the United States have attracted substantial attention. The U.S. and China play pivotal roles in the global green bond market, contributing significantly to its expansion and evolution. In 2023, China remained the largest source of aligned green bond volumes globally, accounting for 14% of the total market. Despite a slight decline, with issuance dropping to USD 83.5 billion from USD 86.5 billion in 2022, the country reinforced its leadership in green finance through 288 deals, representing 10% of all transactions and ranking second by deal count. Meanwhile, the U.S. green bond market exhibited a distinct pattern, characterized by a high number of smaller transactions. Over the same period, 1,231 deals were priced in the U.S. market, averaging USD 48.6 million per transaction, reflecting its decentralized and diverse issuer base [49]. This dynamic interplay between the U.S. and Chinese green bond markets underscores their complementary roles in shaping the future of sustainable finance. Their combined efforts not only catalyze innovation in green technologies but also set benchmarks for other nations. As the green bond market continues to grow, the collaboration and competition between these two economic giants will likely influence the global transition to a sustainable economy.

Previous empirical research on green bond markets has examined the spillover effects between green bonds and other financial assets such as traditional bonds, stocks, and commodities. By using a multivariate GARCH model, Pham (2016) argues that shocks across the conventional bond market tend to spill over into the green bond market, and that this spillover effect is time-varying. Reboredo (2018) find that corporate and treasury fixed-income markets create significant spillovers for green bond prices. Leitao et al. (2021) analyses the non-linear relationship that exists between carbon prices and the green and conventional bond markets, as well as with energy commodity prices. They highlight that there is greater investor demand for green assets because these assets show greater transparency and less volatility. Ferrer et al. (2021) show that the correlation between the global green bond market and traditional financial and energy markets occurs mainly on a short time scale, with shock transmission often lasting less than a week. By using the wavelet correlation approach, Nguyen et al. (2021) show that green bonds have a weak and negative correlation with stock and commodity markets, meaning they can be used as a diversified investment asset. This conclusion is supported by Arif et al. (2021), but they only consider normal market conditions; in fact, different time frequency conditions, the relationship between green bonds and other assets may be different. Furthermore, the existing literature provides evidence for the small size of the green bond market, and this market is always subject to spillovers from others. Gao et al. (2021) conclude that the green bond market is affected by the unidirectional risk spillovers from the stock market and commodity market. Similarly, Elsayed et al. (2022) examine the interdependence between green bonds and financial markets in the time-frequency domain and find that the green bond market receives more but transmits less volatility. Moreover, Chatziantoniou et al. (2022) propose that green bonds appear to be a net receiver of shocks of other green indices in both the short and long run. This view is further confirmed by (Tiwari et al., 2022), who employ a TVP-VAR approach to show that green bonds are emerging as a major receiver of shocks. This study aims to study the spillover effects between the green bond markets in China and the U.S. by using a R^2 decomposed Connectedness Approach.

The contributions of this study are threefold. First, it introduces a novel application of the R^2 decomposed connectedness approach to analyze the dynamic interconnectedness of green bond markets, offering a clear distinction between contemporaneous and lagged spillovers. This methodology provides a deeper understanding of the transmission mechanisms within the green finance ecosystem. Second, the study focuses on the Chinese and U.S. green bond markets, respectively, and offers a comparative analysis of their roles in the global financial network. Finally, the findings provide actionable insights for policymakers and investors, highlighting strategies to enhance market resilience and manage systemic risks, thus contributing to the broader literature on sustainable finance and investment.

The remainder of the paper is laid out as follows. Section 2 contains the background of green bonds in China and United States. Section 3 provides the data sources and methodology. Section 4 analyzes the empirical results. And Section 5 outlines the conclusions and implications of our study.

2. BACKGROUND

2.1. Green bond in China

Since 2014, the scale of China's green bond issuance has continued to grow, driven by policy measures and active guidance from regulators. The Chinese government strongly advocates sustainable economic development and emphasises green financial innovation in its policies, which has triggered the launch of the green bond market in China. In China, green bonds issued in the interbank bond market should follow the guidelines set by the People's Bank of China (PBOC, 2015) regarding issuer qualifications, relevant materials and certification bodies. According to the guidelines, issuers are required to disclose a special audit report in addition to an annual report on the use of funds raised in the previous fiscal year. The People's Bank of China (PBOC) monitors the use of funds raised by green financial bonds and regularly publishes the statistical results. The issuance of the Guiding Opinions on Building a Green Financial System in 2016 signalled that a high degree of consensus has been formed in China, from the highest strategic level to the level of the relevant ministries and commissions, with a determination to fully support and promote green investment and financing in China and to accelerate the transformation of the economy into a greener one (Wang et al., 2020). In addition, the People's Bank of China (PBOC) and the China Securities Regulatory Commission (CSRC) (2017) provide the official standards for green bond certification in China and encourage issuers to obtain third-party certification approved by professional associations (Li et al., 2020). The China Green Bond Principles, the first unified standard for China's green bond market, were officially released in July 2022, setting a unified standard for China's green bond market, which is over one trillion dollars in size. The Principles make full reference to international green finance standards and take into account the actual situation in China, further clarifying the core elements of green bonds and setting out the basic requirements for green bond issuers and related institutions.

In 2022, China stock market issued over 85.4 billion worth of green bonds, making it the largest issuer worldwide, according to a report by the Climate Bond Initiative (CBI). As green bonds do not yet have a unified identification standard, there are differences in the standard setting of green bonds with those in the international arena, the relevant institutional system is not yet perfect, and the information disclosure mechanism is not sound, etc., which, to a certain extent, affects investors' choices and decision-making, and the current information disclosure mechanism focuses on the financial aspect, and there is a lack of disclosure and attention related to the fulfilment of social responsibility.

2.2. Green bond in United States

Prior to 2013, financial instruments targeting specific sustainability outcomes were virtually non-existent (Baker et al., 2022). Governments represent but one facet of engagement within the green bonds market. This burgeoning arena has witnessed active participation from a diverse array of stakeholders, including banks, investment funds, public and private institutions, and corporate entities, all of whom have contributed to the proliferation of this innovative financial instrument. Notably, in the United States, Fannie Mae, a government-sponsored enterprise, emerged as the foremost green bond issuer, unveiling its inaugural issuance in 2012. Concurrently, U.S. banks have embraced this paradigm shift, channeling billions of dollars into green bond issuances, thereby bolstering endeavors aimed at fostering a more sustainable and resilient financial ecosystem [50].

Emerging as a focal point within the green bond landscape are municipal green bonds, which are issued by local and state governments to support green projects. This prominence is attributed to the tax-exempt nature of the interest accrued from such securities (Fidelity, 2021). Against this backdrop, the global issuance of green bonds surged to nearly 500 billion U.S. dollars in 2022, underscoring the increasing prominence of sustainable finance initiatives worldwide. Within this landscape, the U.S. market accounted for approximately 13 percent of the total issuance volume, signifying its growing significance as a hub for green bond activity. Noteworthy is the robust growth trajectory observed in green bond issuance within the United States, particularly evident in recent years, culminating in a pinnacle of over 90 billion U.S. dollars' worth of issuances in 2021. According to the Climate Bonds Initiative, the U.S. issued more than $10 billion in green bonds in each quarter of 2023, totalling $58.30 billion for the year. Such trends highlight the escalating momentum behind sustainable finance endeavors within the U.S. context, underscoring the pivotal role of green bonds in facilitating the transition towards a more environmentally conscious and resilient financial system.

Green bonds exhibit risk-return profiles akin to municipal bonds, albeit with a distinct emphasis on environmental, social, and governance (ESG) considerations outlined within their green framework. This framework mandates a heightened level of transparency regarding the alignment of proceeds with sustainable objectives, thereby necessitating greater disclosure of ESG risks relative to conventional municipal bonds issued by the same municipal entity. The appeal of a bond to investors is contingent, in part, upon the credit rating assigned to the issuing entity. Notably, green bonds serve as a strategic instrument for policymakers to convey their commitment to advancing energy efficiency and renewable energy initiatives, thereby signaling their policy priorities in the sustainable finance domain.

3. DATA AND METHODOLOGY

3.1. Data

Table 1. Summary Statistics

	SSEGB	SPMGB	STOXX	LC100	LOVOL	MIWOIPUS	SP500LV	BCOM	BCOMCL
Mean	0.0002	0.0001	0.0005	0.0005	0.0002	0.0003	0.0004	0.0001	0.0000
Std.Dev	0.0006	0.0029	0.0099	0.0080	0.0097	0.0096	0.0105	0.0092	0.0281
Skewness	0.7074***	-0.8209***	-1.1651***	0.3169***	-1.2345***	-1.0891***	-1.4291***	-0.5536***	-1.7668***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ex.Kurtosis	20.0373***	60.3470***	19.1397***	10.4798***	16.6985***	16.3240***	37.0863***	4.1166***	28.4345***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
JB	31220.4407***	281990.1415***	28764.7468***	8528.8771***	22046.9063***	20985.3929***	107053.3824***	1406.0554***	63525.3203***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ERS	-8.8083***	-15.1279***	-7.9683***	-12.1114***	-16.4730***	-9.2672***	-15.3112***	-5.8346***	-10.3978***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q (20)	661.9671***	607.6255***	78.7947***	24.2726***	44.7313***	61.0796***	184.6787***	38.7162***	31.4387***
	(0.0000)	(0.0000)	(0.0000)	(0.0025)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Q^2 (20)	22.2272***	1435.2658***	1455.4728***	968.7041***	627.6159***	1199.9395***	2744.6343***	392.5383***	579.6674***
	(0.0064)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: (1) ***, **, * denote significance at 1%, 5% and 10% significance level. (2) the D'Agostino (1970) and Anscombe and Glynn (1983) statistics are used for skewness and kurtosis. (3) The Jarque-Bera statistic is the normal distribution test with the null hypothesis that the series is normally distributed. (4) ERS unit-root test (Elliott et al., 1996) tests for stationarity. (5) Q(20) and Q^2 (20) denote the Fisher and Gallagher (2012) weighted portmanteau test.

Most of the predictors in this study come from the financial markets and are inspired by previous studies. To this end, we select the following indexes, namely the Chinese Green Bond Index at the Shanghai Stock Exchange (SSEGB), the S&P U.S. Municipal Green Bond Index (SPMGB). STOXX Low Carbon indices, which calculates a comprehensive family of Low Carbon Indices and Low Carbon 100 Europe (LC100) (Leitao et al., 2021). CBOE Low Volatility (LOVOL), MSCI World Low Volatility Factor Price USD (MIWOIPUS), S&P 500 Low Volatility (SP500LV) (Blitz, 2016; Blitz and Vidojevic, 2017; Chow et al., 2014). Bloomberg Commodity (BCOM) (Naeem et al., 2021;

Nguyen et al., 2021), Bloomberg WTI Crude Oil (BCOMCL) (Lee et al., 2021; Pham and Nguyen, 2022). Our data spans over the period from January 3, 2017 to November 15, 2024 (In the year 2017, People's Bank of China and the China Securities Regulatory Commission established official standards for green bond certification. In the year 2017, Shanghai Stock Exchange and the Luxembourg Stock Exchange jointly launched the Green Bond Index).

For the data that were not stationary, we conducted a logarithmic differencing process. Table 1 presents the summary statistics. It appears that the means of all variables are positive, the China's green bond return volatility is the lowest. Furthermore, we find that SSEGB and LC100 are significantly positively skewed, whereas the rest of the variables are significantly negatively skewed. In addition, all series are significantly leptokurtically distributed. The results of the Jarque-Bera test indicate that none of the variables is normally distributed. According to the ERS unit-root test, all variables are stationary. Furthermore, the weighted Ljung-Box statistics show that all series are significantly autocorrelated and exhibit ARCH/GARCH errors (Fisher and Gallagher, 2012).

3.2. Methodology

To accurately estimate the transmission mechanism of green bond returns in China and the US, we employ a novel R^2 decomposed connectedness approach following (Balli et al., 2023), which can distinguish between contemporaneous spillovers and lagged spillovers. This method is an extension of the previous connectedness method (Zhang et al., 2023; Naeem et al., 2024; Gabauer et al., 2023). Start with a VAR(p) with contemporaneous effects which can be formulated as follows,

$$y_t = \sum_{i=0}^{p} B_i y_{t-i} + \epsilon_t \epsilon_t \sim N(0, \Sigma) \tag{1}$$

Where y_t and y_{t-1} are $K \times 1$ dimensional vectors of endogenous variables, ϵ_t is an $K \times 1$ dimensional vector of independent and identically distributed disturbances, B_t is $K \times K$ dimensional vectors of time-varying model coefficients. By using principal component analysis (PCA) where the number of latent factors is equal to the number of right-hand side (RHS) variables. The R^2 decomposition for a multivariate linear regression (MLR) can be computed by:

$$R_{xx} = V\Lambda V' = CC' \tag{2}$$

$$C = V\Lambda^{1/2}V' \tag{3}$$

$$R^{2,d} = C^2 (C^{-1} R_{yx})^2 \tag{4}$$

Where V , $\Lambda = diag(\lambda_1, \dots, \lambda_{K(p+1)-1})$, and R_{xx} represent $[K(p+1)-1] \times [K(p+1)-1]$ eigenvector, eigenvalue, and Pearson correlation matrices, respectively, while R_{yx} and $R^{2,d}$ illustrate $[K(p+1)]$ Pearson correlation and R^2 contribution vectors, respectively. The first $K-1$ values of $R^{2,d}$ represent the contemporaneous R^2 contributions while the remaining highlight the lagged R^2 contributions. In this way, various connectedness measures can be calculated. The total connectedness index (TCI) is equal to the average R^2 of the k MLRs, which measures the degree of network interconnectedness of the system, can be calculated as,

$$TCI = \frac{1}{K} \sum_{k=1}^{K} R_k^2 \tag{5}$$

The contemporaneous and lagged TCI,

$$TCI = \frac{1}{K}\sum_{k=1}^{K} R_k^2$$
$$= \left(\frac{1}{K}\sum_{k=1}^{K} \sum_{j=1}^{K} R_{C,k,j}^{2,d}\right) + \left(\frac{1}{K}\sum_{k=1}^{K} \sum_{j=1}^{K} R_{L,k,j}^{2,d}\right) \quad (6)$$
$$= TCI^C + TCI^L$$

Where TCI^C and TCI^L represent the contemporaneous and lagged TCI, respectively.

The total directional connectedness illustrates how much of the overall (contemporaneous/lagged) variance in all left-hand side (LHS) variables is explained by series j (TO effect),

$$TO_j = \sum_{k=1}^{K} R_{C,k,j}^{2,d} + \sum_{k=1}^{K} R_{L,k,j}^{2,d}$$
$$= TO_j^C + TO_j^L \quad (7)$$

The total directional connectedness demonstrates how much all RHS variables explain of the overall (contemporaneous/lagged) variance in series j (FROM effect) is:

$$FROM_j = \sum_{k=1}^{K} R_{C,j,k}^{2,d} + \sum_{k=1}^{K} R_{L,j,k}^{2,d}$$
$$= FROM_j^C + FROM_j^L \quad (8)$$

The net directional connectedness of series j is the the difference between the total directional connectedness TO others and the total directional connectedness FROM others:

$$NET_j^C = TO_j^C - FROM_j^C \quad (9)$$

$$NET_j^L = TO_j^L - FROM_j^L \quad (10)$$

$$NET_j = NET_j^C + NET_j^L \quad (11)$$

If $NET_j > 0$ ($NET_j < 0$), series j is a net transmitter (net receiver) of spillover effects in the network system indicating that it can explain more (less) of the variation in others than vice versa. Same way of interpreting contemporaneous and lagged connectedness.

4. EMPIRICAL RESULTS

First, we present the results of the connectedness measure at the overall level. It considers the overall R^2 decomposed measures, rather than contemporaneous and lagged R^2 decomposed measures. As can be seen in Table 2, elements on the main diagonal correspond to idiosyncratic shocks, whereas elements on the off-diagonal correlate with interactions between specific network variables. For the SSEGB, the self-explained share of forecast error variance accounts for 17.66%, while the remaining 10.32% (FROM effects) receive the largest spillover from BCOM (1.67%), followed by SPMGB (1.62%), BCOMCL (1.56%), SP500LV (1.14%), MIWOIPUS (1.13%), STOXX (1.09%), LC100 (1.08%) and LOVOL (1.03%). SSEGB contributes most the spillover share to SPMGB (1.52%), followed by BCOM (0.92%), BCOMCL (0.89%), LOVOL (0.60%), SP500LV (0.53%), MIWOIPUS (0.48%), LC100 (0.47%) and STOXX (0.44%), the summation of them constitutes the TO effects (5.86%).

Table 2. The overall R^2 decomposed measures table

	SSEGB	SPMGB	STOXX	LC100	LOVOL	MIWOIPUS	SP500LV	BCOM	BCOMCL	FROM
SSEGB	17.66	1.62	1.09	1.08	1.03	1.13	1.14	1.67	1.56	10.32
SPMGB	1.52	16.50	3.24	2.20	2.50	3.11	3.02	1.69	2.25	19.53
STOXX	0.44	2.06	0.46	27.39	16.51	28.70	15.25	3.34	1.91	95.60
LC100	0.47	1.74	29.44	0.52	7.74	21.85	19.56	1.76	1.37	83.93
LOVOL	0.60	2.14	21.23	10.29	0.62	21.01	7.16	2.75	1.87	67.05
MIWOIPUS	0.48	1.99	29.39	20.86	17.41	0.40	13.47	5.78	3.61	92.99
SP500LV	0.53	2.44	16.36	21.94	5.65	14.33	0.61	2.12	1.36	64.73
BCOM	0.92	1.20	4.36	2.43	2.90	7.18	2.26	0.53	41.82	63.07
BCOMCL	0.89	1.92	2.80	2.02	2.06	4.83	1.49	43.07	0.48	59.07
TO	5.86	15.11	107.90	88.22	55.80	102.12	63.36	62.18	55.75	cTCI/TCI
NET	-4.46	-4.42	12.29	4.29	-11.25	9.13	-1.37	-0.89	-3.32	69.54/61.81

Notes: (1) "cTCI" represents corrected TCI value. (2) R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (SBIC).

Table 3. Contemporaneous R^2 decomposed measures table

	SSEGB	SPMGB	STOXX	LC100	LOVOL	MIWOIPUS	SP500LV	BCOM	BCOMCL	FROM
SSEGB	0.00	1.12	0.61	0.43	0.55	0.69	0.56	1.01	0.72	5.69
SPMGB	1.03	0.00	2.18	1.52	1.83	2.12	1.71	1.01	1.69	13.09
STOXX	0.23	1.66	0.00	26.80	16.20	28.30	14.76	3.15	1.78	92.88
LC100	0.24	1.21	28.98	0.00	7.07	21.42	19.20	1.49	1.23	80.85
LOVOL	0.34	1.59	20.18	8.80	0.00	20.31	6.07	2.44	1.54	61.27
MIWOIPUS	0.28	1.62	28.86	20.08	17.14	0.00	12.87	5.49	3.41	89.75
SP500LV	0.28	1.43	15.77	21.29	5.23	13.81	0.00	1.70	1.00	60.52
BCOM	0.74	0.86	3.88	1.90	2.46	6.79	1.83	0.00	41.29	59.75
BCOMCL	0.55	1.43	2.32	1.50	1.58	4.37	1.11	42.73	0.00	55.58
TO	3.69	10.94	102.78	82.31	52.06	97.81	58.10	59.02	52.65	cTCI/TCI
NET	-2.01	-2.15	9.90	1.46	-9.20	8.06	-2.42	-0.72	-2.93	64.92/57.71

Notes: (1) "cTCI" represents corrected TCI value. (2) R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (SBIC).

Next, turning to the net spillovers for each series. The spillover from other series received by SSEGB is 10.32%, while the spillover sent to others is 5.86%, suggesting that SSEGB is a net receiver (-4.46%) of spillovers. It is also evident that the main net receiver of this network is (overall) the LOVOL (-11.25%), followed by the SSEGB (4.46%), SPMGB (-4.42%), BCOMCL(-3.32%), SP500LV (-1.37%) and BCOM(-0.89%). However, we note that in this variables network, STOXX Low Carbon is (overall) the main net transmitter of spillovers within this network of variables

(12.29%), followed by MIWOIPUS (9.13%) and LC100 (4.29%). Moreover, the spillovers of each variable indicating that they are net pairwise transmitter for others.

According to the total connectedness index (TCI), the average spillover of all series is 69.54% (the corrected TCI (cTCI) value is 61.81%), indicating that there is a non-negligible link between the network. Interestingly, for SSEGB, the share of R^2 decomposed measures from itself is 14.22%, which is larger than 16.50% of SPMGB.

The above results are based on an estimation of the average condition, but this estimate does not capture the contemporaneous and lagged R^2 decomposed measures. For this reason, We present the results for spillovers under contemporaneous and lagged connectedness values in Table 3 and Table 4.

Table 4. Lagged R^2 decomposed measures table

	SSEGB	SPMGB	STOXX	LC100	LOVOL	MIWOIPUS	SP500LV	BCOM	BCOMCL	FROM
SSEGB	17.66	0.50	0.48	0.66	0.48	0.44	0.58	0.66	0.84	4.63
SPMGB	0.49	16.50	1.05	0.69	0.67	0.99	1.31	0.68	0.56	6.44
STOXX	0.21	0.40	0.46	0.59	0.31	0.39	0.49	0.19	0.13	2.72
LC100	0.23	0.53	0.46	0.52	0.67	0.43	0.36	0.26	0.14	3.08
LOVOL	0.26	0.55	1.05	1.49	0.62	0.70	1.09	0.31	0.33	5.78
MIWOIPUS	0.20	0.37	0.53	0.78	0.27	0.40	0.60	0.29	0.20	3.24
SP500LV	0.25	1.00	0.59	0.65	0.43	0.51	0.61	0.42	0.36	4.21
BCOM	0.18	0.33	0.48	0.53	0.44	0.39	0.43	0.53	0.53	3.32
BCOMCL	0.34	0.49	0.48	0.52	0.48	0.46	0.38	0.34	0.48	3.49
TO	2.17	4.18	5.11	5.90	3.74	4.31	5.26	3.15	3.09	cTCI/TCI
NET	-2.46	-2.27	2.39	2.82	-2.05	1.07	1.04	-0.17	-0.39	4.61/4.10

Notes: (1) "cTCI" represents corrected TCI value. (2) R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (SBIC).

By decomposing this indicator into contemporaneous and lagged components, we find that 64.92% of the effects is due to contemporaneous dynamics, while only 4.61% is related to lagged interdependencies. Notably, all contemporaneous FROM and TO connectedness measures are significantly higher than the lagged ones.

In addition, we illustrate the overall, contemporaneous and lagged network connectedness measures in Figure 2. The nodes in blue (yellow) illustrate the net transmitter (receivers) of shocks. The size of the nodes represents the average net total directional connectedness. For the value of dynamic net pairwise connectedness, a min-max normalization is used, after normalization all values (the thickness of the lines) are within zero and unity. The direction of the arrow of the line indicates the direction of net pairwise spillover between the two variables.

For the net transmitter it is evident that the main net transmitter of this network is (overall) the STOXX (12.29%), whereas in the contemporaneous-term the main net transmitter is still the STOXX (9.90%), in the lagged-term the main net transmitter is LOVOL (2.82%). Turning to net receiver, it is also evident that the main net receiver of this network is (overall) the LOVOL (-11.25%), whereas in the lagged-term the main net receiver is the SSEGB (-2.46%), in the contemporaneous-term the main net receiver is still the LOVOL. With regard to time-varying behavior, the SP500LV transformed into a net transmitter in the lagged-term. SSEGB and SPMGB are net receiver in both cases.

The SSEGB exhibits a substantial level of self-explained variance, accounting for 17.66% of its forecast error variance. This finding underscores the relative independence of China's green bond market within the studied network. The lagged connectedness measures reveal that historical spillovers significantly influence SSEGB, especially during periods of macroeconomic instability. For instance, the COVID-19 pandemic and the Russia-Ukraine conflict amplified spillover effects, with SSEGB becoming more reactive to external shocks. The relatively high degree of independence exhibited by SSEGB indicates its potential as a diversification tool for global portfolios. From the lagged perspective, SPMGB is influenced significantly by the STOXX Low Carbon Index and other global indicators like SP500LV. These influences suggest that while the SPMGB is primarily local, it remains sensitive to global risk dynamics, particularly during crisis events. Contemporaneous connectedness measures show that SPMGB is more reactive to immediate shocks than SSEGB. This reactivity underscores the importance of real-time risk assessment in managing U.S. municipal green bonds. Additionally, the role of tax exemptions and ESG transparency in attracting investors may explain SPMGB's increased integration within the network. The dynamic nature of SPMGB's connectedness highlights its dual role as both a stabilizing element in sustainable finance and a conduit for systemic risks.

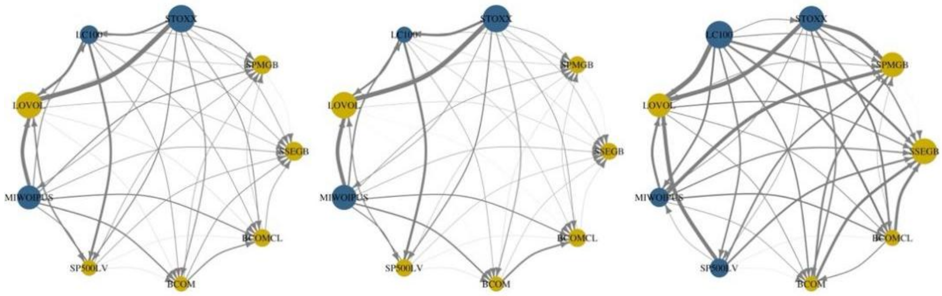

Figure 2. Network plot of specific network

Next, We present the dynamic total dynamic directional connectedness plot results for all series in Figure 3. It represents the dynamic evolution of the TCI over the time interval of the study sample. For the purpose of completeness, Figure 3 not only considers the overall evolution of the TCI (i.e., the black shaded area), but also decomposes it into the contemporaneous-term (i.e., the red line) and the lagged-term (i.e., the green shaded area).

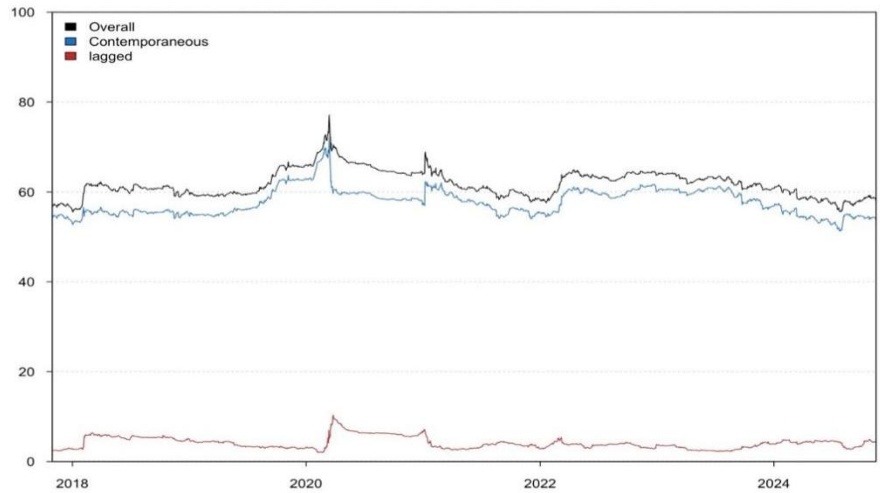

Figure 3. The dynamic total connectedness

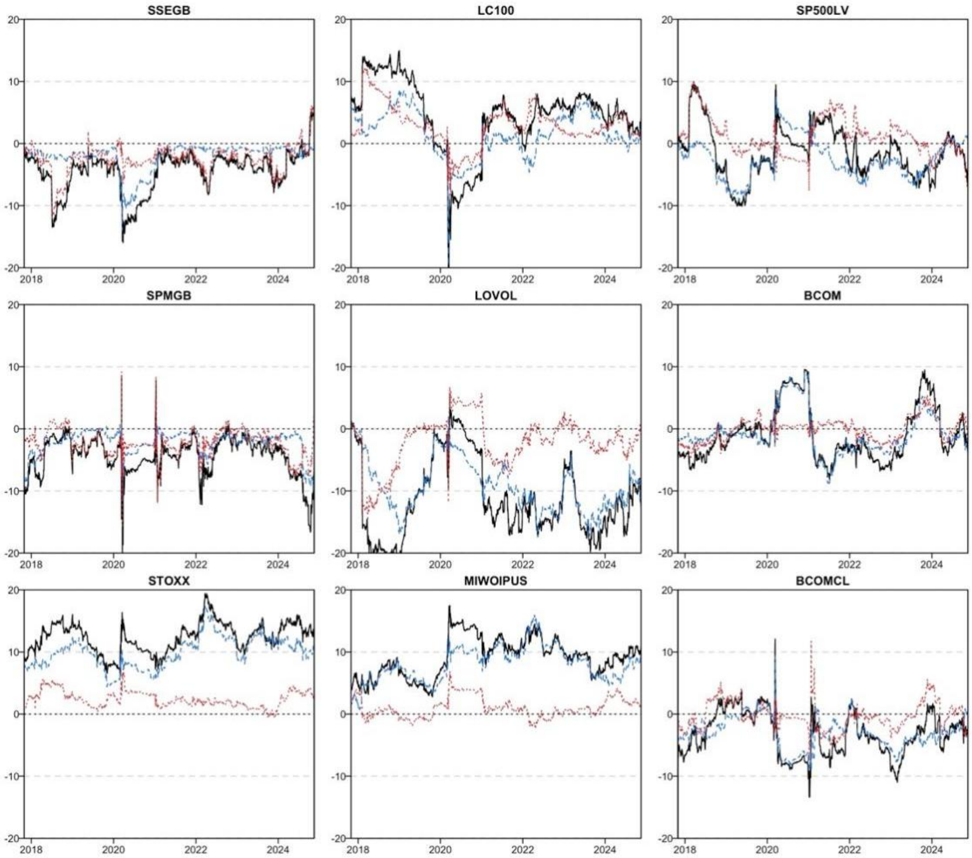

Figure 4. The dynamic net total directional connectedness

The results of the overall TCI (i.e. the black shaded area) in Figure 3 show that the index exhibits a time-varying magnitude that fluctuates between about 50 and 80 percent. We can see one peak in the plot. It occurs in the early 2020s and is caused by the COVID-19 pandemic. In addition, it should be noted that contemporaneous interdependencies are more pronounced than lagged interdependencies, as they account for the majority of market risk dynamics. There is evidence of a relatively high level of system-wide integration of all the variables that make up the entire sample period, while the level of integration reaches fairly high stage levels from time to time.

Next, we aim to identify the net transmitter and net receivers in the network. These findings are illustrated in Figure 4. It is worth noting that when the shaded area in the figure is within the positive range, the corresponding series of returns is the net transmitter of the system shocks. Conversely, when the plotted area falls within the range of negative values, the series of returns is classified as the net receiver of shocks. The difference between the total directional connectedness TO and FROM results in the net total directional connectedness (NET), which illustrates the net influence on the network system. If NET > 0 (NET < 0), which implies that the impact series j has on all others is larger (smaller) than the impact all others have on series j. Thus, series j is considered as a net transmitter (receiver) of shocks and hence driving (driven by) the network. The net spillovers vary noticeably over time. Figure 4 provides results not only for average total directional connectedness (i.e., black shading), but also for contemporaneousterm (i.e., red shading) and lagged-term (i.e., green shading) directional connectedness. Figure 4 confirms that SSEGB and SPMGB are net receiver for most of the sample period.

Finally, Figure 5 provides robustness checks based on the dynamic total connectedness. The black line visualizes the Pearson correlation method while the Spearman correlation and Kendall correlation are illustrated in red and green, respectively. Solid lines represent average connectedness, dotted lines represent contemporaneous connectedness, and dashed lines represent lagged connectedness. The results indicate that the contemporaneous, lagged and overall correlation dynamics under different correlation coefficients appear to be quantitatively similar.

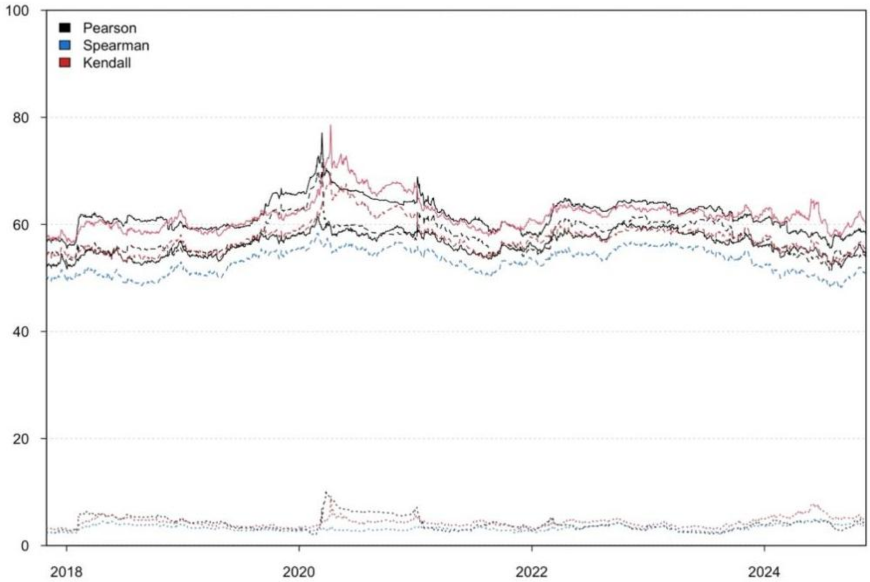

Figure 5. Robustness check

The findings emphasize the critical need for tailored strategies to enhance the stability and resilience of green bond markets amidst systemic risks. In the case of China, policymakers should prioritize reducing SSEGB's dependency on external influences, such as global commodity indices, by promoting diversification within the domestic green bond market. Such measures would enhance its ability to withstand international volatility. Additionally, strengthening regulatory frameworks and aligning with global best practices could foster SSEGB's evolution into a more robust and independent entity within the global green finance landscape. For the United States, addressing SPMGB's pronounced sensitivity to contemporaneous global shocks necessitates a multifaceted strategy. Policymakers should focus on advanced risk management practices, including the adoption of sophisticated hedging mechanisms and regulatory safeguards to mitigate abrupt external disruptions. Moreover, greater coordination between municipal and federal regulatory bodies could reduce market fragmentation, align ESG standards, and stabilize the U.S. green bond market. These interventions are crucial for ensuring that the SPMGB remains a resilient component of the global green finance ecosystem while minimizing exposure to systemic vulnerabilities.

From an investment perspective, the SSEGB and SPMGB provide distinct complementary diversification opportunities within the green bond market. The SSEGB's relative independence and policy-driven framework position it as a stable option for long-term sustainable investments, particularly for investors seeking exposure to China's expanding green finance sector. In contrast, the SPMGB's heightened sensitivity to immediate global shocks offers investors flexibility for dynamic portfolio adjustments and the potential to capitalize on short-term market fluctuations. Together, these attributes underscore the critical role of green bonds in achieving sustainable investment goals while effectively managing systemic financial risks.

5. CONCLUSIONS AND IMPLICATIONS

From an investment perspective, the SSEGB and SPMGB provide distinct complementary diversification opportunities within the green bond market. The SSEGB's relative independence and policy-driven framework position it as a stable option for long-term sustainable investments, particularly for investors seeking exposure to China's expanding green finance sector. In contrast, the SPMGB's heightened sensitivity to immediate global shocks offers investors flexibility for dynamic portfolio adjustments and the potential to capitalize on short-term market fluctuations. Together, these attributes underscore the critical role of green bonds in achieving sustainable investment goals while effectively managing systemic financial risks.

As a green financial instrument with both economic and environmental benefits, green bonds have received widespread attention from academia and industry. It is an effective way to finance the transition to a low-carbon economy and is becoming a hot topic of interest for investors around the world. In view of this, this paper adopts a R2 decomposed connectedness approach based on a VAR model to investigate the spillover effects between the green bond markets of the United States and China. At the same time, we also considered separately the connectedness occurring in the contemporaneous- and lagged-term.

Within the framework of our study, the main findings suggest a high degree of market integration. Relatively high levels of connectedness suggest a high likelihood of risk contagion within a given network of variables. Regarding the dynamics of connectedness in the contemporaneous- and lagged-term, we find that contemporaneous interdependencies are more pronounced than lagged interdependencies, as they account for the majority of market risk dynamics. This result suggests that the network process relevant information contemporaneously. Since the peak occurred during the outbreak of the new COVID-19 epidemic in the early 2020s, the results suggest that the event could have a significant impact on the existing correlations and dynamics between the network variables. More specifically, in either case, the Chinese Green Bond return and U.S. Green Bond return have been net receivers during the sample period, the Chinese Green Bond market is relatively independent compared to the U.S Green Bond market, a fact that may hint at the potential for portfolio diversification. The rest of the endogenous variables within the system have different dynamic connectedness throughout the system over time. This study is therefore relevant to both policy makers who wish to better understand developments in the international green bond market and investors who wish to better understand and manage risk. This study provides fertile ground for continued research on the development of green bonds. Future research could be extended to include studies related to green bond markets in other countries.

REFERENCES

[1] Anscombe, F.J., Glynn, W.J., 1983. Distribution of the kurtosis statistic b2 for normal samples. Biometrika 70, 227–234. https://doi.org/10.1093/biomet/70.1.227

[2] Arif, M., Hasan, M., Alawi, S.M., Naeem, M.A., 2021. Covid-19 and time-frequency connectedness between green and conventional financial markets. Global Finance Journal 49, 100650. https://doi.org/10.1016/j.gfj.2021.100650

[3] Baker, M., Bergstresser, D., Serafeim, G., Wurgler, J., 2022. The Pricing and Ownership of US Green Bonds. Annual Review of Financial Economics 14, 415–437. https://doi.org/10.1146/annurev-financial-111620-014802

[4] Balli, F., Balli, H.O., Dang, T.H.N., Gabauer, D., 2023. Contemporaneous and lagged R 2 decomposed connectedness approach: New evidence from the energy futures market. Finance Research Letters 57, 104168. https://doi.org/10.1016/j.frl.2023.104168

[5] Blitz, D., 2016. The Value of Low Volatility. The Journal of Portfolio Management 42, 94–100. https://doi.org/10.3905/jpm.2016.42.3.094

[6] Blitz, D., Vidojevic, M., 2017. The profitability of low-volatility. Journal of Empirical Finance 43, 33–42. https://doi.org/10.1016/j.jempfin.2017.05. 001

[7] Cevik, S., Jalles, J.T., 2022. This changes everything: Climate shocks and sovereign bonds∗. Energy Economics 107, 105856.

[8] Chatziantoniou, I., Abakah, E.J.A., Gabauer, D., Tiwari, A.K., 2022. Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. Journal of Cleaner Production 361, 132088. https://doi.org/10.1016/j. jclepro.2022.132088

[9] Chow, T.m., Hsu, J.C., Kuo, L.l., Li, F., 2014. A Study of Low-Volatility PortfolioConstruction Methods. The Journal of Portfolio Management 40, 89–105. https://doi.org/10.3905/jpm.2014.40.4.089

[10] D'Agostino, R.B., 1970. Transformation to normality of the null distribution of g1. Biometrika 57, 679–681. https://doi.org/10.2307/2334794

[11] Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64, 813–836.

[12] Elsayed, A.H., Naifar, N., Nasreen, S., Tiwari, A.K., 2022. Dependence structure and dynamic connectedness between green bonds and financial markets: Fresh insights from time-frequency analysis before and during covid-19 pandemic. Energy Economics 107, 105842. https://doi.org/10.1016/j.eneco.2022.105842

[13] Fatica, S., Panzica, R., Rancan, M., 2021. The pricing of green bonds: Are financial institutions special? Journal of Financial Stability 54, 100873. https://doi.org/10.1016/j.jfs.2021.100873

[14] Ferrer, R., Shahzad, S.J.H., Soriano, P., 2021. Are green bonds a different asset class? Evidence from time-frequency connectedness analysis. Journal of Cleaner Production 292, 125988. https://doi.org/10.1016/j.jclepro.2021.125988

[15] Fidelity, 2021. In the municipal market, green is the new black. URL: https://www.fidelity.com/bin-public/060_www_fidelity_com/ documents/fixed-income/Green-Bond-White-Paper.pdf

[16] Fisher, T.J., Gallagher, C.M., 2012. New weighted portmanteau statistics for time series goodness of fit testing. Journal of the American Statistical Association 107, 777–787. https://doi.org/10.1080/01621459.2012.688465

[17] Flaherty, M., Gevorkyan, A., Radpour, S., Semmler, W., 2017. Financing climate policies through climate bonds – A three stage model and empirics. Research in International Business and Finance 42, 468–479. https://doi.org/10.1016/j.ribaf.2016.06.001

[18] Gabauer, D., Chatziantoniou, I., Stenfors, A., 2023. Model-free connectedness measures. Finance Research Letters 54, 103804. https://doi.org/10.1016/j.frl.2023.103804

[19] Gao, Y., Li, Y., Wang, Y., 2021. Risk spillover and network connectedness analysis of china's green bond and financial markets: Evidence from financial events of 2015–2020. The North American Journal of Economics and Finance 57, 101386. https://doi.org/10.1016/j. najef.2021.101386

[20] Ho, K., Wong, A., 2023. Effect of climate-related risk on the costs of bank loans: Evidence from syndicated loan markets in emerging economies. Emerging Markets Review 55, 100977.

[21] Huynh, T.D., Xia, Y., 2023. Panic selling when disaster strikes: Evidence in the bond and stock markets. Management Science 69, 7448–7467.

[22] Jin, Y., Zhao, H., Bu, L., Zhang, D., 2023. Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. International Review of Financial Analysis 87, 102597.

[23] Kaesehage, K., Leyshon, M., Ferns, G., Leyshon, C., 2019. Seriously personal: The reasons that motivate entrepreneurs to address climate change. Journal of Business Ethics 157, 1091–1109.

[24] Karim, S., Naeem, M.A., Hu, M., Zhang, D., Taghizadeh-Hesary, F., 2022. Determining dependence, centrality, and dynamic networks between green bonds and financial markets. Journal of Environmental Management 318, 115618.

[25] Lau, P., Sze, A., Wan, W., Wong, A., 2022. The Economics of the Greenium: How Much is the World Willing to Pay to Save the Earth? Environmental and Resource Economics 81, 379–408. https://doi.org/10.1007/s10640-021-00630-5

[26] Lee, C.C., Lee, C.C., Li, Y.Y., 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. The North American Journal of Economics and Finance 55, 101309. https://doi.org/10.1016/j.najef.2020.101309

[27] Lee, C.C., Wang, C.W., Thinh, B.T., 2023. Green development, climate risks, and cash flow: International evidence. Pacific-Basin Finance Journal 79, 102021.

[28] Leitao, J., Ferreira, J., Santibanez-Gonzalez, E., 2021. Green bonds, sustainable development and environmental policy in the European Union carbon market. Business Strategy and the Environment 30, 2077–2090. https://doi.org/10.1002/bse.2733

[29] Li, Z., Tang, Y., Wu, J., Zhang, J., Lv, Q., 2020. The Interest Costs of Green Bonds: Credit Ratings, Corporate Social Responsibility, and Certification. Emerging Markets Finance and Trade 56, 2679–2692. https://doi.org/10.1080/1540496X.2018.1548350

[30] Lian, Y., Gao, J., Ye, T., 2022. How does green credit affect the financial performance of commercial banks? —— Evidence from China. Journal of Cleaner Production 344, 131069. https://doi.org/10.1016/j.jclepro.2022.131069

[31] Lin, S., Chen, S., 2021. Dynamic connectedness of major financial markets in China and America. International Review of Economics and Finance 75, 646–656. https://doi.org/10.1016/j.iref.2021.04.033

[32] Mensi, W., Naeem, M.A., Vo, X.V., Kang, S.H., 2022. Dynamic and frequency spillovers between green bonds, oil and g7 stock markets: Implications for risk management. Economic Analysis and Policy 73, 331–344.

[33] Naeem, M.A., Adekoya, O.B., Oliyide, J.A., 2021. Asymmetric spillovers between green bonds and commodities. Journal of Cleaner Production 314, 128100. https://doi.org/10.1016/j.jclepro.2021.128100

[34] Naeem, M.A., Chatziantoniou, I., Gabauer, D., Karim, S., 2024. Measuring the g20 stock market return transmission mechanism: Evidence from the R2 connectedness approach. International Review of Financial Analysis 91, 102986. https://doi.org/10.1016/j.irfa.2023.102986

[35] Nguyen, T.T.H., Naeem, M.A., Balli, F., Balli, H.O., Vo, X.V., 2021. Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. Finance Research Letters 40, 101739. https://doi.org/10.1016/j.frl.2020.101739

[36] OECD, 2016. Green bonds. mobilising the debt capital markets for a low-carbon transition. OECD Policy Perspectives.

[37] Ozkan, A., Temiz, H., Yildiz, Y., 2023. Climate risk, corporate social responsibility, and firm performance. British Journal of Management 34, 1791–1810.

[38] Pankratz, N., Bauer, R., Derwall, J., 2023. Climate change, firm performance, and investor surprises. Management Science 69, 7352–7398.

[39] Pham, L., 2016. Is it risky to go green? A volatility analysis of the green bond market. Journal of Sustainable Finance & Investment 6, 263–291.

[40] Pham, L., Nguyen, C.P., 2022. How do stock, oil, and economic policy uncertainty influence the green bond market? Finance Research Letters 45, 102128. https://doi.org/10.1016/j.frl.2021.102128

[41] Reboredo, J.C., 2018. Green bond and financial markets: Co-movement, diversification and price spillover effects. Energy Economics 74, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

[42] Reboredo, J.C., Ugolini, A., 2020. Price connectedness between green bond and financial markets. Economic Modelling 88, 25–38. https://doi.org/10.1016/ j.econmod.2019.09.004

[43] Tiwari, A.K., Aikins Abakah, E.J., Gabauer, D., Dwumfour, R.A., 2022. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during covid-19 pandemic: Implications for hedging and investments strategies. Global Finance Journal 51, 100692. https://doi.org/10.1016/j.gfj.2021.100692

[44] Wang, J., Chen, X., Li, X., Yu, J., Zhong, R., 2020. The market reaction to green bond issuance: Evidence from China. Pacific-Basin Finance Journal 60, 101294. https://doi.org/10.1016/j.pacfin.2020.101294

[45] Wu, G.S.T., Wan, W.T.S., 2023. What drives the cross-border spillover of climate transition risks? evidence from global stock markets. International Review of Economics & Finance 85, 432–447.

[46] Yousaf, I., Mensi, W., Vo, X.V., Kang, S.H., 2024. Dynamic spillovers and connectedness between crude oil and green bond markets. Resources Policy 89, 104594.

[47] Zhang, X., Yang, X., Li, J., Hao, J., 2023. Contemporaneous and noncontemporaneous idiosyncratic risk spillovers in commodity futures markets: A novel network topology approach. Journal of Futures Markets 43, 705–733. https://doi.org/10.1002/fut.22407

[48] Zhu, B., Hu, X., Deng, Y., Zhang, B., Li, X., 2023. The differential effects of climate risks on non-fossil and fossil fuel stock markets: Evidence from China. Finance Research Letters 55, 103962.

[49] https://www.climatebonds.net/resources/reports/global-state-market-report-2023

[50] https://www.fanniemae.com/media/48156/display