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Research article

Measurement of spillover effect between green bond market and traditional bond market in China

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Abstract: With the aim of effectively preventing and controlling systemic risk, by stimulating the advancement of the green bond market, it is significant and imperative to help investors and policymakers adopt more effective measures, which will ensure them to maximize profit. We construct VAR, DCC-GARCH and Copula-CoVaR models, and study the spillover effect between the green bond market and traditional bond market from the three perspectives of mean spillover, volatility spillover and extreme risk spillover using the data on daily closing prices of green bond market and traditional bond market indices. The research findings of this paper are as follows: (1) There are three spillover effects of mean value, volatility and extreme risk among the green bond market, corporate bond market, enterprise bond market and conventional bond market. (2) From the perspective of mean spillover between markets, only the mean spillover between the conventional bond market and the green bond market is bidirectional, and there is the profoundest impact of spillover from the green bond market to the conventional bond market. (3) As far as the volatility spillover between markets is concerned, the volatility spillover between the three traditional bond market and the green bond markets are all positive. The volatility spillover between the conventional bond market and the green bond market is the largest, which is particularly obvious in the first half of 2018 and the first half of 2020. (4) In terms of inter-market extreme risk spillover, the risk spillover between the green bond market and the traditional bond market is positive. The green bond market contributes more to the risk spillover of the enterprise bond market, and it has a time-varying risk spillover effect on the traditional bond market.

Keywords: green bonds; traditional bonds; overflow effect

JEL Codes: C58, G12

1. Introduction

Environmental governance is challenged by the growing problem of global pollution. Policymakers and researchers have proposed various solutions in response. Among them, the concept of green finance is innovative and focuses on environmental interests to achieve sustainable development, and evaluates its activities' effectiveness through environmental benefits and resource utilization. Green bond is a financing tool that was vigorously developed and agrees with the concept of "carbon peak" advocated by the contemporary international community. Thus, they have received extensive attention from investors and institutions.

In 2007, the European Investment Bank (EIB) issued climate-conscious bonds, which is the world's first green bond. The United Nations Framework Convention on Climate Change established the concept of climate financing. The G20 and the International Monetary Fund officially confirmed that it is significant to progress the green bond market. The International Energy Agency also recommended the green bonds as one of the solutions to the problem of climate change financing (Chen & Zhang, 2022). Since 2013, investors have been increasingly concerned with environmental and climate issues, and green bonds have begun to develop leaps and bounds. There are more and more types of bonds, and the issuers are gradually diversified and the scope is gradually expanding.

Injurious for us is that human beings pollute the environment to evolve economy. It is green finance that is the most significant approach to facilitate the harmonious progression of economy and ecology (Bhatnagar et al., 2022). High-quality development is the prominent assignment to construct a comprehensive modern socialist country. As a part of high-quality development, the degree of green economic advancement has become an important indicator. The evolution of green finance can promote green development and is a key measure to realize the common prosperity. The first time a green bond was issued was in July 2015 in China. Since then, the market scale has gradually expanded. By the end of 2022, the stock of green bonds in China was about 3 trillion yuan, which has become the world's second largest green bond market. The green bonds have grown into a major factor in helping China's stable economic development and promoting environmental protection (Chen & Zhang, 2023; Wang & Tian, 2023).

At present, the demand for green capital is strong, with a severely deficiency of supply; thus, there exists a substantial financial gap. Therefore, it is crucial for China to develop green financing tools. Green bond is one of the most innovative and influential debt financing instruments, and has the dual characteristics of "green" and "bond". At the micro level, issuing the green bonds can expand financing channels for green projects and enterprises, and fill investment gaps (Wang & Xu, 2016). At the macro level, the continuous improvement of China's green bond market will contribute to the developing countries' sustainable evolution (Wang & Zeng, 2016).

The deepening reform of China's financial market system and the increasingly relaxed supervision of financial industry have led to more frequent interactions between financial sub-markets. However, high liquidity between financial markets also enhances risk. Once a sub-market has financial risks, the risk will spread rapidly to trigger a financial crisis. As a new type of global financial instrument, green bonds are bound to experience more diversified development and give birth to a variety of innovative financial products. Although it is an emerging market, it is becoming more and more closely related to other financial markets, which means that green bond prices and other financial asset prices are closely related to each other and influence each other. In the process of integration with China's traditional financial market, it is likely to accumulate certain risks and spillover risks.

In the current economic environment, China's economic development should not only pursue speed but also quality. Therefore, it is of great profound significance to promote green and sustainable economic transformation to solve China's economic and environmental problems. As China's financial market matures, the risks China faces are gradually emerging, which also tests the entire financial system. Preventing and controlling systemic risks has become an important topic in our economic activities. Therefore, exploring the spillover effect between China's green bond market (CGB) and traditional bond market for effective prevention and control of systemic risks is significant. We will focus on the traditional bond market and explore the interaction between the CGB and the traditional bond market. Studying mean, volatility and extreme risk spillover effects among financial markets has important practical value for promoting the CGB's progression, and provides a certain theoretical basis for issuers, investors, policy makers and regulators to help them adopt more effective policy measures.

2. Literature review

There are mostly two aspects to discuss green bond (GB) in the light of available literature. On the one hand, scholars have different views on the pricing differences between GB and ordinary bonds, which has discounts compared to regular bonds. On the other hand, for the economic impact of GB, most scholars are devoted to explore the stock market's reaction to the corporate green bond issuance (Lin et al., 2022).

Compared with traditional bonds, GB is used to finance specific investments which fail to pose additional risks to investors. Bonds tend to offer higher profitability, liquidity, and stability than bank to satisfy the most diversified investors (Ezuma et al., 2022). GB is relatively convenient in financing. For corporate investors, financing advantages are greater (Gianfrate, 2019), which help enhance corporate value. In addition, equity liquidity drives a significant enhancement in the yield of GB (Zhang et al., 2020), and investment performance advantage of GB diminishes over time (Kanamura, 2020).

Some scholars have taken the spread among the GB and traditional bonds, that is green bond premium, as the subject of study when discussing the pricing factors of GB. Partridge found that by 2018, the green premium in the U.S. secondary municipal bond market reached 50 basis points (Partridge & Medda, 2020). Nanayakkara deemed that GB in global capital markets trade at a premium of 63 basis points (Colombage & Nanayakkara, 2020).

Another scholar explores the reasons of "green premium". Through systematic literature review, MacAskill et al. (2021) found that the green premium variability for primary market is significant. Zerbib (2019) argued that GB is provided with a negative premium. The GB without third-party certification not only has no premium, but also has the risk of "greenwashing", and the credit spreads are significantly higher than ordinary bonds by 21 percentage points (Jiang & Fan, 2020; Qi & Liu, 2021). Social networks can submit useful information, and there are significant differences in the condition of investor sentiment on CB with different risk characteristics (Li et al., 2018). Investors' attention has different effects on the return and volatility of GB, and this relationship is time-varying (Pham & Huynh, 2020). The characteristics of GB will also affect the premium of GB. GB has certain advantages in issuing pricing, and the rating status of bond issuers and the government's invisible credit support will have different effects on GB spreads (Chen et al., 2021; Dou & Zhang, 2019; Gao & Ji, 2018).

In the study of the mean spillover effect, the most frequently used model by scholars is the VAR model, and on this basis, SVAR, MVAR and other models have been derived. Huynh (2021) studied the spillover risk effect of cryptocurrency market using VAR-SVAR and Granger causality. Gao & Li (2021) used the VAR model to predict error variance decomposition, calculated the DY spillover index to analyze the mean spillover effect between the GB and the traditional financial market. Liu & Wang (2018) used the MSVAR model to analyze the mean spillover effect of soybean futures between China and the United States. He (2017) verified that there is a mean spillover effect between the main board, the New Third Board and the GEM in the stock market through the VAR model. Naresh et al. (2017) used the VAR model to test the spillover between stock and commodity future markets.

The research on volatility spillover effects is becoming more and more mature. The research perspectives of scholars are diversified and there are two descriptions: One is to explore the volatility spillover effects within a financial market; and the other is to discuss the mutual spillover effect among different financial markets. Regarding the research methods, GARCH family models have been widely used because of their good modeling effect on volatility.

Zhou & Zhou (2006) used the multivariate GARCH model to analyze the volatility spillover effects of domestic and international crude oil markets, which proves that the direction of information transmission in the oil market is from the international market to the domestic market. Zhong et al. (2004) confirmed that there is an ability for the stock index future market to discover prices based on the modified EGARCH model. Yavas & Dedi (2016) studied the volatility spillover effects of German, British, Chinese, Russian and Turkish stock markets using the MARMA, GARCH, GARCH mean and EGARCH methods. Hu & Ma (2011) established the BEKK-MGARCH model to analyze the volatility spillover effect between the stock market and the bond market in different periods.

The CoVaR model is the main research method of extreme risk spillover effect, while with the widespread application of Copula, the combination of Copula and GARCH model, provides a new way of calculating CoVaR. Li & Fan (2011) measured the systemic risk premium of commercial banks in China using the CoVaR and quantile regression methods. The results showed that the systemic risk premium of state-owned banks is higher than that of joint-stock banks. When solving the problems related to systemic financial risk, Wairagu (2011) used the Copula function to quantitatively analyze the marginal contribution made by a particular financial institution to systemic financial risk, and also found that the correlation coefficient would affect the extreme risk spillover. With the wide application of Copula, its combination with the GARCH model provides a new idea for calculating CoVaR. Bai (2021) used the GARCH-DCC-Copula-CoVaR model to discuss the dynamic spillover effect of commercial banks on systemic risk of banks and their interdependence. Huang (2021) used the time-varying t-Copula model to study dynamic correlation and risk spillover heterogeneity between international oil prices and stock indexes of crude oil-related industries, with calculating %CoVaR to reflect the risk spillover intensity of international crude oil prices on Chinese oil-related industries. Some scholars have begun to calculate CoVaR by quantile regression. Zhu (2013) made a preliminary exploration of "Copula + Quantile". Kielmann & Manner (2022) combined the multivariate dynamic Copula model, quantile regression model based on D-vine and GAS Copula model to investigate the spillover effects between BRIC stock returns and different types of oil price shocks.

Currently, scholars' research mainly focuses on the spillover effect between GB and traditional financial market. Qin et al. (2019) constructed the MVMQ-CAViaR model to empirically analyze the tail risk spillover between low-carbon industry's stock market and the CGB, which found that the occurrence of labeled green bonds has changed dynamic process of one market shock affecting the tail risk of another market. There is a significant spillover effect between the assets of the GB and the traditional bond market, which leads to a significant hedging strategy, and the spillover effect is affected by the green labeling criteria (Tsoukala & Tsiotas, 2021). The volatility spillover effect between the two markets is bidirectional, showing a strong dynamic correlation, and the dynamic correlation coefficient fluctuates around the mean value (Reboredo et al., 2019; Wang, 2021).

Reboredo (2018) found that the GB is related to the corporate bond (CB) and the conventional bond (NB), and this relationship is time-varying. Moreover, as for the CB and NB, there is a significant influence of spillover effect for the GB. Through empirical analysis of the information transmission between GB and other assets, Su et al. (2022) found that there is a lack of preferences for green among the bond market's investors in China. It is the return and volatility of NB and CB that give impetus to GB; and there are different net spillover effects on different frequency scales for GB. Mensi et al. (2022) found that the connectivity between GB and the S&P 500 index is strengthened when a magnitude crash breaks out, and the spillover effect of government bonds were relatively less affected. The green energy and resource market has devoted significantly to the volatility spillover effect. Naeem et al. (2022) used the quantile connectivity method to conduct an empirical study and they found that the time-varying risk spillover is higher in the period of extreme high volatility, and there is a violent bidirectional risk spillover effect between GB and all assets except energy.

Overall, domestic and foreign scholars' research on GB mainly concentrate on theoretical research, and empirical analysis is relatively lacking, and the empirical research mostly focuses on the impact factors of GB pricing and GB spreads. From a macro perspective, there are fewer studies on the correlation between the GB and other financial markets, and they are in the process of continuous development and improvement. However, due to the late start of GB in China, there is little research on the law of development of China's bond market, especially on the degree of integration and risk linkage between it and traditional financial markets. Furthermore, in recent years, with the shortage of resources and the deepening environmental pollution, ecological problems have gradually become prominent. Developing green finance is an important way to build ecological civilization, indicating that China has elevated the concept of green financial development to a strategic level. At present, the majority of scholars have devoted to discuss mean spillover and volatility spillover, and the research on extreme risk spillover is shallow. In view of this, we establish VAR, DCC-GARCH and Copula-CoVaR models to study the China's spillover effect between the CGB and the traditional bond market from three perspectives: mean spillover, volatility spillover and extreme risk spillover, in order to provide new references and data support for issuers, investors, policy makers and regulators to take more effective policy measures.

3. Data and methodology

3.1. Data

At present, there are three principal indexes in CGB: China Bond China Climate-Aligned Bond Index, China Bond CIB Green Bond Index and China Bond Green Bond Index. The three indexes belong to the China Bond Wealth Index, and the green bonds listed on the interbank bond market, the Shanghai Stock Exchange and the Shenzhen Stock Exchange as samples. However, the sample size is diverse, and the volatility of the yield is also slightly different. China Bond Green Bond Index is the first batch of green bond index in China. It is compiled by China's official settlement agency. It is the green bond index with the longest history and the most influence in China, which can effectively represent the development of CGB. Moreover, it takes into account the mutual matching of different bond markets in the sample length. We select the GBI to represent the green bond market. For the traditional bond market, we regard the high-yield enterprise bond, corporate bond and conventional bond market as the proxy variables of the traditional bond market. Additionally, the China Bond High Yield Enterprise Bond Wealth Total Index (HYCB), the China Bond Treasury Bond Index (TBAI) and the China Bond Corporate Bond Index (EBAI) are selected as the proxy variables for the enterprise bond (HB), NB, and CB, respectively. The data in this article is obtained from the Wind database, which adopts index daily closing price, and the time interval is from 2016/5/9 to 2022/5/6. There are 1457 valid observation data for each market after excluding legal holidays and non-public trading days.

After obtaining the daily closing prices of the four market price indexes, we utilize the logarithmic difference operation method to calculate the four markets' logarithmic returns, while, r_gb、r_hb、r_nb and r_cb are used to represent the yields of green bond market, enterprise bond market, conventional bond market and corporate bond market, respectively. The results are shown in Table 1.

Figure 1. The time series graph of GB, NB, HB and CB.

Table 1. Descriptive statistics of market returns.

variable	Mean	Maximum	Minimum	Std.Dev.	Kurtosis	Skewness	J-Btest
r_gb	0.0174	0.8008	−0.8183	0.0803	23.1679	0.2125	32378
r_hb	0.0236	0.5562	−0.5527	0.0621	13.2491	0.2847	10773
r_nb	0.0144	0.3909	−0.5585	0.0550	9.6374	0.6196	5609.5
r_cb	0.0011	1.0538	−0.9505	0.1256	15.8382	−1.1160	15442

In the sample interval, the mean values of the four markets are positive, and the earnings performance of the HB is better than the other three markets. There is the smallest standard deviation for NB, which declares that the income fluctuation is the smallest with the strongest security. It can be found that the yields of GB, HB and NB are all right-skewed by examining the skewness index, while the CB has a left-skewed characteristic. Among them, the skewness of the CB is the highest and CGB is the lowest in deviation. Based on the kurtosis index, it can be found that there is a general phenomenon of leptokurtosis in the four markets. The J-B test of each market shows that the yield series of each market do not satisfy the normal distribution and have general characteristics of most financial time series.

The results in Table 2 indicates that the yield series of the four markets are all stationary on the basis of ADF statistics of each variable.

Table 2. ADF test results for each market return.

variable	ADF test	%1 threshold	%5 threshold	%10 threshold	Stationary
r_gb	−8.6346	−2.5659	−1.9410	−1.6166	Stationary
r_hb	−8.5242	−2.5659	−1.9410	−1.6166	Stationary
r_nb	−9.8269	−3.4328	−2.8625	−2.5673	Stationary
r_cb	−9,1778	−2.5659	−1.9410	−1.6166	Stationary

3.2. Methodology

According to the literature review, it is clear that the VAR model, VAR derivative model and Granger causality test are commonly used by scholars in the study of mean spillover effects. The GARCH family models have been widely utilized in the analysis of volatility spillover effects because of their good modeling of volatility. Nowadays, they mainly focus on multivariate GARCH models. When measuring extreme risks, CoVaR not only measures the risks faced by individual markets itself, but also takes into account the market contagion effect. The Copula function makes the establishment of marginal distribution very flexible. Therefore, the VAR model is used to analyze the mean spillover effect, the DCC-GARCH model is used to analyze the volatility spillover effect and the Copula-CoVaR model is used to discuss the extreme risk spillover effect.

3.2.1. The mean spillover effect model

We study the mean spillover effect between the two markets by constructing a binary VAR(P) model. The formula is as follows:

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \ldots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{2,t-1} + \ldots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-1} + \ldots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \ldots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{cases} \tag{1}$$

where p is the optimal lag order of the model, y1t, y2t are equation's two explained variables, the lag p values of y1t and y2t are the explanatory variables, y1, t-p and y2, t-p represent the lagged p-periods of y1t and y2t, while ε1t, ε2t are the perturbation terms, and β1i ,γ2i (i = 1,2,…,p) reflect the extent to which y1t and y2t are affected by their own prior period. γ1i (i =1,2,…,p) measures the influence of the lag term of y2t on y1t an, β2i (i =1,2,…,p) measures the influence of the lag term of y1t on y2t.

A VAR model with yt and xt as variables can be constructed for the reason that this section intends to verify whether there is a causal relationship between yt and xt. The specific equations are as follows:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_{1t} \tag{2}$$

Then, the null hypothesis that xt is not causal for yt is: H_0: $\beta_1=\beta_2=\ldots=\beta_p=0$

3.2.2. The volatility spillover effect model

The DCC-GARCH model considers that the correlation coefficient between series is a dynamic change rather than a fixed constant, which can better reflect the fluctuation influence among multiple series. Based on this advantage, we use the DCC-GARCH model to study the volatility spillover effect, which helps to better test the dynamic correlation between variables. Assuming that the time series yt presents a multivariate normal distribution structure with the mean of this multivariate normal distribution as μt, and the conditional covariance matrix as Ht, then the DCC-GARCH (1,1) model is expressed as follows:

$$\begin{gathered} y_t = \mu_t + \varepsilon_t \quad \varepsilon_t \mid F_{t-1} \sim N(0, H_t) \\ \varepsilon = H_{\mathrm{t}}^{\frac{1}{2}} \mu_{\mathrm{t}} \quad \mu_{\mathrm{t}} \sim N(0, I) \\ H_{\mathrm{t}} = D_t R_t D_t \end{gathered} \tag{3}$$

where, F_{t-1} denotes the set of all information before t − 1. μ_t, ε_t and u_t are N × 1 dimensional vectors, which represent the conditional mean, error term and normalized error term, respectively. In addition, R_t, H_t and D_t = diag ($h^{1/2}_{11,t}$, …, $h^{1/2}_{NN,t}$) are all N × N diagonal arrays, R_t represents the dynamic conditional correlation coefficient matrix, and H_t is the time-varying conditional variance-covariance matrix.

First, D_t is measured by calculating the time-varying conditional standard deviation of the univariate GARCH model. Then, the dynamic conditional correlation coefficient is calculated:

$$\begin{aligned} & h_{ii,t} = \omega + \alpha \varepsilon_{i,t-1}^2 + \beta h_{ii,t-1} \\ & R_t = diag(q_{ii,t}^{-1/2}, \ldots, q_{NN,t}^{-1/2}) Q_t diag(q_{ii,t}^{-1/2}, \ldots, q_{NN,t}^{-1/2}) \\ & Q_t = (q_{ij,t}) = (1 - \alpha - \beta)\overline{Q} + \alpha \mu_{t-1}{}' + \beta Q_{t-1} \end{aligned} \tag{4}$$

where Q_t and Q are N × N dimensional positive definite matrices, which represent the variance-covariance matrices of conditional and unconditional standardized residuals, respectively. Α and β represent non-negative shock and persistence parameters. Q_t and R_t will change over time as long as

$\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$ are satisfied, otherwise, the model converges to the CCC-GARCH model. In the DCC-GARCH (1,1) model, the dynamic correlation coefficient is:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{5}$$

3.2.3. The extreme risk spillover effect model

What seems extraordinary difficult is to model the joint distribution when the random variables with different marginal distributions are not independent of each other. Under this circumstance, the Copula function is a remarkably outstanding instrument to model its correlation between multiple random variables with known marginal distributions. The Copula function is widely used in the study of complex dynamic dependence between markets, and it is also mainly used to describe the correlation between variables. There are two common Copula functions: The elliptic copula function and Archimedean copula function. We focus on the binary Copula function.

(1) The binary normal Copula function

For the normal Copula function, the marginal distribution in the Copula function C(u,v) is a normal distribution. The expression of C(u,v) is as follows :

$$C(u,\upsilon,\rho) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(\upsilon)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(\frac{2\rho rs - r^2 - s^2}{1(1-\rho^2)}\right) drds \tag{6}$$

where $\phi^{-1}(\cdot)$ is the inverse function of the standard normal distribution function, and the parameter ρ denotes the correlation between $\phi^{-1}(u)$ and $\phi^{-1}(v)$. The normal Copula function has tail symmetry.

(2) The binary t-Copula function

What is notable is that the parameters to be estimated in the t-Copula function have degrees of freedom κ in addition to the correlation coefficient ρ. The expression of the t-Copula function is as follows:

$$C(u,\upsilon,\rho,\kappa) = \int_{-\infty}^{T_\kappa^{-1}(u)} \int_{-\infty}^{T_\kappa^{-1}(\upsilon)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(1 + \frac{r^2 + s^2 - 2\rho rs}{2\kappa(1-\rho^2)}\right)^{\frac{-(\kappa+2)}{2}} drds \tag{7}$$

where T (·) represents the t distribution function.

The VaR method is based on the quartile principle to represent the size of the risk. The mathematical expression of VaR is as follows:

$$P(\Delta\upsilon \le VaR) = \alpha \tag{8}$$

where Δv represents the value loss of a financial asset over a specific period, α is the confidence level, and VaR is the upper bound of possible loss.

Tsagkanos et al. (2022) used VaR based copulas to analyze the asymmetric risk spillover between GB and commodities. However, the deficiency of VaR method is that it only measures the risk level of a single market, and fails to take into account the common contagion effect between markets, which considerably reduces the risk assessment level of VaR method. Scholars proposed a new risk measurement method CoVaR based on VaR, trying to capture the risk spillover effects between financial institutions, while Girardi et al. (2013) adjusted the conditional events in CoVaR. They believe that more serious catastrophic events occur at the tail of the loss distribution compared to overly optimistic scenarios. The specific expression is as follows:

$$P(X^i \leq CoVaR^{i|j}_{\beta,t} \mid X^j \leq VaR^j_{\alpha,t}) = \beta \tag{9}$$

$CoVaR^{i|j}_{\beta,t}$ is the conditional risk of market i with respect to market j at moment t under the significant level β, which can be decomposed into the unconditional risk of market i itself and the risk spillover $\triangle CoVaR^{i|j}_{\beta,t}$ of market j to market i. Therefore, the downside risk spillover from market j to market i is expressed as follows:

$$\Delta CoVaR^{i|j}_{\beta,t} = \Delta CoVaR^{i|j}_{\beta,t} - VaR^i_{\alpha,t} \tag{10}$$

When the prices between markets are in different magnitudes, their VaR levels are also different, Therefore, further standardization is needed to obtain the risk spillover intensity from market j to market i:

$$\%\Delta CoVaR^{i|j}_{\beta,t} = \frac{\Delta CoVaR^{i|j}_{\beta,t}}{VaR^i_{\alpha,t}} \times 100\% \tag{11}$$

4. Empirical findings

4.1. Empirical analysis of mean spillover effect between green bond market and traditional bond market

4.1.1. Results of the Granger causality test

Table 2 confirms the yields of the traditional bond market and CGB have passed the ADF test, which ensures the stability of the time series. Therefore, we can carry out Granger causality test on the three market combinations of NB & CGB, CB & CGB and HB & CGB.

Table 3. Results for Granger causality test.

Null hypothesis	Lag order	χ^2	P value	conclusion
r_hb does not Granger cause r_gb	6	8.3197	0.3052	Fail to reject
r_gb does not Granger cause r_hb	6	27.7403	0.0002	Reject
r_nb does not Granger cause r_gb	5	10.5105	0.0327	Reject
r_gb does not Granger cause r_nb	5	61.1701	0.0000	Reject
r_cb does not Granger cause r_gb	6	2.6135	0.9562	Fail to reject
r_gb does not Granger cause r_cb	6	11.0820	0.0305	Reject

From Table 3, it can be known that for HB and CB, there is a unidirectional causality between CGB and the two bond markets; there is a bidirectional causality between NB and CGB. The above conclusions are consistent with the results of VAR parameter estimation.

4.1.2. Results of the VAR model

In line with the AIC and SC information criteria, the six-order lag is selected to construct the VAR model between the HB and CGB. The estimated results of the model are shown in Table 4.

The results of the VAR (6) model show that for autocorrelation, the yield of CGGB and HB have serial autocorrelation. In terms of mean spillover, CGB has an obvious negative explanatory effect on HB for two days. However, there is no obvious explanatory effect of HB on CGB. Therefore, there is a unidirectional negative mean spillover from CGB to the HB.

Table 4. Results for r_gb and r_hb.

	r_hb	r_gb		r_hb	r_gb
r_hb(−1)	1.0364**	−0.1179	r_gb(−1)	−0.2639***	1.4445***
t	29.3130	−2.4860	t	9.9620	40.6270
r_hb(−2)	0.0999	0.1796	r_gb(−2)	−0.2544***	−0.4434***
t	1.8970	2.5420	t	−6.0370	−7.8390
r_hb(−3)	−0.0745	−0.1345	r_gb(−3)	0.0101	0.1229
t	−1.4130	−1.8990	t	0.2350	2.1310
r_hb(−4)	−0.0307	0.0109	r_gb(−4)	−0.0477	−0.0759
t	−0.5830	0.1550	t	−1.1120	−1.3190
r_hb(−5)	0.1079	0.1048	r_gb(−5)	0.0073	−0.0034
t	2.0520	1.4850	t	0.1720	−0.0600
r_hb(−6)	−0.1416***	−0.0434	r_gb(−6)	0.0243	−0.0439
t	−4.1210	−0.9420	t	0.9010	−1.2130

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

In line with the AIC and SC information criteria, the optimal lag order of the VAR model between NB and CGB is five-order.

The VAR (5) model's result illustrates that in terms of autocorrelation, there is autocorrelation between the yields of NB and CGB. For mean spillover, there is an asymmetric bidirectional mean spillover between NB and CGB. Conventional debt plays a negative influence on CGB, which is affected by a positive influence. Furthermore, CGB has a greater impact on NB numerically.

Table 5. Results for r_gb and r_nb.

	r_nb	r_gb		r_nb	r_gb
r_nb(−1)	1.2845**	0.2228	r_gb(−1)	−0.1611	1.1178***
t	36.0980	11.0030	t	−2.5790	31.4280
r_nb(−2)	−0.3195***	−0.2212***	r_gb(−2)	0.2776**	−0.0423
t	−6.1680	−7.5060	t	2.8760	−0.7710
r_nb(−3)	0.0897	0.0384	r_gb(−3)	−0.1247	−0.0143
t	1.7000	1.2780	t	−1.2840	−0.2600
r_nb(−4)	−0.1010	−0.0746	r_gb(−4)	0.1519	0.0272
t	−1.9360	−2.5150	t	1.610	0.5070
r_nb(−5)	0.0319	0.0318	r_gb(−5)	−0.1312	0.0858**
t	0.8980	1.5720	t	−2.3210	−2.6670

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

The six-order VAR model is established for the HB and CGB using AIC and SC criteria for comprehensive judgment. As far as autocorrelation, there is a significant autocorrelation and non-white noise process between the two markets. For mean spillover, CGGB has a unidirectional negative impact on CB.

Table 6. Results for r_gb and r_cb market.

	r_cb	r_gb		r_cb	r_gb
r_cb(−1)	1.0364***	−0.1179	r_gb(−1)	0	1.4445***
t	29.3130	−2.4860	t	9.9620	40.6270
r_cb(−2)	0.0999	0.1796	r_gb(−2)	−0.2544***	−0.4434***
t	1.8970	2.5420	t	−6.0370	−7.8390
r_cb(−3)	−0.0745	−0.1345	r_gb(−3)	0.0101	0.1229
t	−1.4130	−1.8990	t	0.2350	2.1310
r_cb(−4)	−0.0307	0.0109	r_gb(−4)	−0.0477	−0.0759
t	−0.5830	0.1550	t	−1.1120	−1.3190
r_cb(−5)	0.1079	0.1048	r_gb(−5)	0.0073	−0.0034
t	2.0520	1.4850	t	0.1720	−0.0600
r_cb(−6)	−0.1416***	−0.0434	r_gb(−6)	0.0243	−0.0439
t	−4.1210	−0.9420	t	0.9010	−1.2130

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

4.1.3. Results of the model stability test

After estimating the unknown parameters of the VAR model, we plot the results of residual cumulative sum curves to test the systematic stability of the model. The linear graphs are as follows:

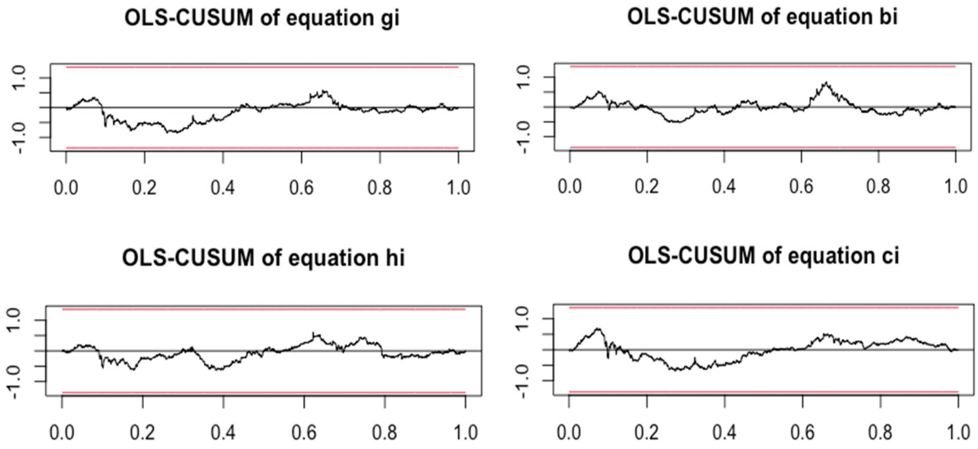

Figure 2. The linear graph of four markets.

The residual cumulative sum curves of the four market yields do not exceed the two red critical lines, indicating that there is a stability of the three sets of binary VAR models building r_gb with r_hb, r_nb and r_cb.

4.2. Empirical analysis of volatility spillover effect between the green bond market and traditional bond market

4.2.1. The establishment of the GARCH (1,1) model

The GARCH model parameter estimation is based on the AIC and SC criteria to clarify the optimal lag order of each yield series, and then the GARCH (1,1) model is established. From Table 7, the ARCH coefficients and GARCH coefficients of the four market yield series are statistically significant at 1% level and greater than 0. Moreover, $\alpha + \beta < 1$, which indicates that it satisfies the significance and stability conditions of the GARCH model, and proves that the modeling is robust and feasible. Furthermore, the sum of α and β is close to 1, which proves that the volatility of these four market yield series has strong aggregation and persistence.

Table 7. Results for GARCH (1,1).

	Constant	coefficient of ARCH(α)	coefficient of GARCH(β)
r_gb	0.0008***	0.4123***	0.5593***
	(4.649)	(7.324)	(10.884)
r_hb	0.0011***	0.1768***	0.5542***
	(4.316)	(4.228)	(6.123)
r_nb	0.0011***	0.1862***	0.7608***
	(3.343)	(4.987)	(16.230)
r_cb	0.0004***	0.4760***	0.4095***
	(7.071)	(7.508)	(7.390)

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

4.2.2. Parameter estimation of the DCC model

We construct a DCC model to obtain the dynamic correlation coefficients between the traditional bond market and CGB after the GARCH model. From Table 8, it can be found that DCC1 and DCC2 of the three market portfolios are statistically significant at a 1% level, and both greater than 0, and the sum is less than 1, which expresses that the significance and stability conditions of the DCC model are satisfied and proves that the modeling is robust and feasible. DCC1 between the three traditional bond markets and CGB are all in the range of 0.0008 to 0.0011 with little difference, which indicates that the volatility of the dynamic correlation coefficients between the three traditional bond markets and CGB is roughly equal. The DCC2 of the combination of NB yield and CGB yield is the largest, which declares the dynamic correlation coefficient between the two deviates from the normal correlation to a greater extent, showing a stronger trend in the graph.

Table 8. Results for DCC model.

	DCC1	DCC2	DCC1+DCC2
r_gb&r_hb	0.0008***	0.4123***	0.5593***
	(4.649)	(7.324)	(10.884)
r_gb&r_nb	0.0011***	0.8768***	0.8779***
	(4.316)	(4.228)	(6.123)
r_gb&r_cb	0.0011***	0.1862***	0.1873***
	(3.343)	(4.987)	(16.230)

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

4.2.3. Dynamic correlation analysis

We show the statistical characteristics of the dynamic correlation coefficients and plot the dynamic correlation coefficient diagrams between HB, NB, CB and CGB, respectively.

Table 9. Descriptive statistics of dynamic correlation coefficients.

	Minimum	Maximum	Mean
r_gb&r_hb	−0.0904	0.9861	0.6471
r_gb&r_nb	0.4353	0.9112	0.6457
r_gb&r_cb	0.1402	0.9924	0.7517

The range of dynamic correlation coefficient between the HB yield and CGB yield is between 0.4 and 0.8 from the Figure 3. Among the three sets of dynamic correlation, the value is small and most of the time positive. Therefore, the relationship between the two markets possesses a positive and weak volatility spillover effect.

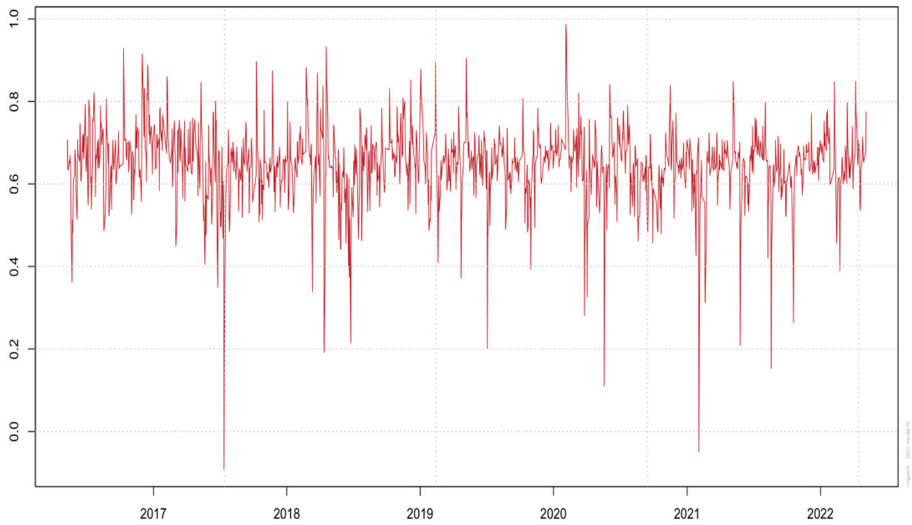

Figure 3. Dynamic relationship between r_hb and r_gb.

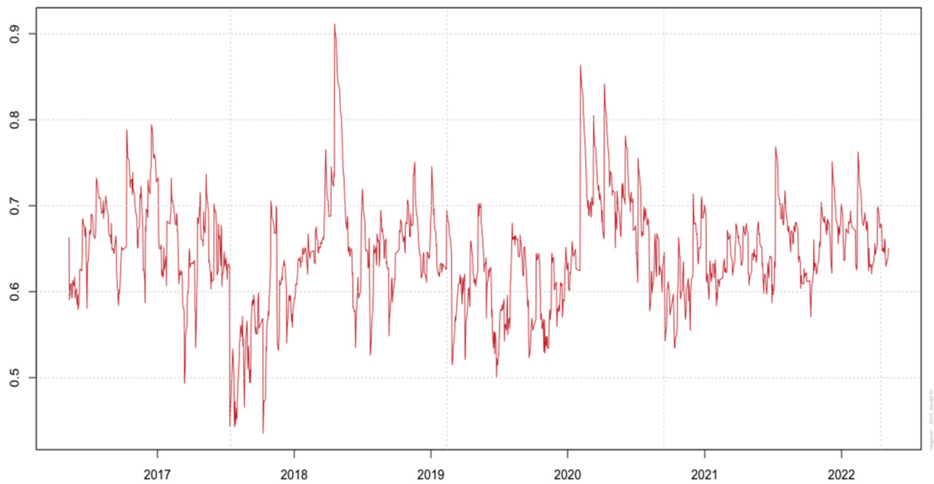

Figure 4. Dynamic relationship between r_nb and r_gb.

The yield correlation coefficient between the two markets is between 0.5 and 0.8 from Figure 4, which indicates that the relationship between them possesses a strong positive correlation and volatility spillover effect. In addition, in the first half of 2018 and 2020, the correlation between them reached a peak. At this time, there is a high degree of synergy, a large degree of volatility spillover and a large risk of allocation.

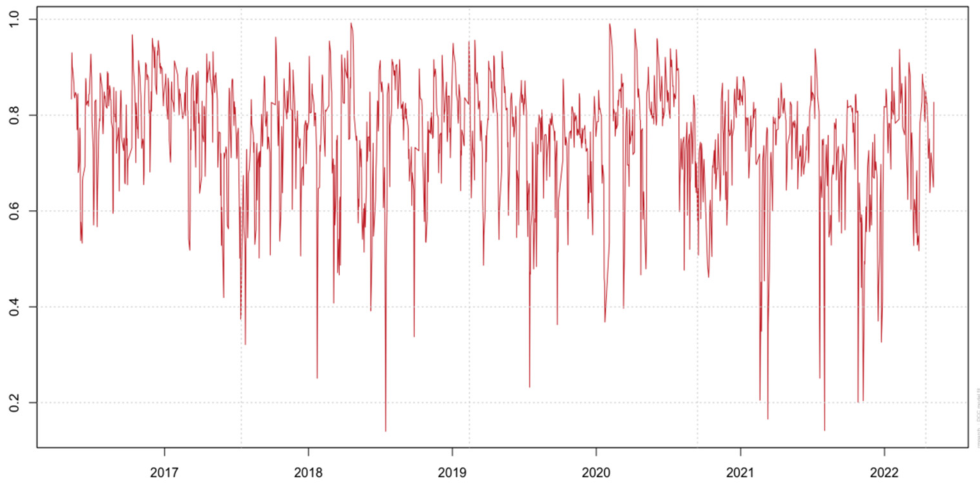

Figure 5. Dynamic relationship between r_cb and r_gb.

The coefficient between them is between 0.6 and 0.9, indicating that their relationship possesses a stronger positive correlation and volatility spillover effect from Figure 5. In addition, the coefficient fluctuates greatly over time, which illustrates that the volatility spillover effect is relatively unstable.

In a nutshell, the average value of the dynamic correlation coefficient among NB and CGB is the largest, indicating that this correlation between the two markets is the strongest, while the value among HB, CB and CGB is smaller, indicating that the correlation is weaker.

4.3. Empirical analysis of the extreme risk spillover effect between the green bond market and traditional bond market

4.3.1. Marginal distribution estimation

In order to select the optimal distribution, this paper fits the four bond markets' yields from Gaussian, Student-t, Skew Student-t, Ged and Skew-Ged distributions according to the log-likelihood value and information criterion. The maximum likelihood value and information criterion of GARCH (1,1) of each yield series under each distribution assumption are shown as follows:

Table 10. The fitting results of yield series.

Distribution	Goodness of fit	r_gb	r_hb	r_nb	r_cb
Student-t	AIC	−2241.656	−2427.686	−1223.579	−2845.977
	Log-likelihood	3.0696	3.3251	1.6711	3.8997
norm	AIC	−1939.099	−2214.332	−1112.48	−2667.289
	Log-likelihood	2.6554	3.0334	1.5199	3.6556
Ged	AIC	−2224.151	−2411.007	−1205.672	−2825.152
	Log-likelihood	3.0455	3.3022	1.6465	3.8711
Skew-t	AIC	−2241.749	−2435.992	−1223.802	−2845.993
	Log-likelihood	3.0783	3.3352	1.6801	3.9083
Skew-ged	AIC	−2224.401	−2415.642	−1206.369	−2826.307
	Log-likelihood	3.0445	3.3072	1.6461	3.8713

From Table 10, the fitting effects of Student-t and Skew-t are roughly equal, but both are better than the other distributions, with Skew-t distribution slightly better than Student-t distribution. Therefore, according to the criteria of this paper, the Skew-t distribution can be considered as the optimal distribution. We assume that all yield series obey Skew-t distribution, and establishes GARCH-Skew-t model as the marginal distribution of Copula joint distribution to make sure to fit Copula model and to compute CoVaR risk spillover accurately.

In the GARCH-Skew-t model parameter estimation of the four bond markets, the coefficients of ARCH (α) and the coefficients of GARCH (β) are both statistically significant at the 1% level and greater than 0 accompanied by a summation less than 1 as shown in Table 11, which indicates that the significance and stability conditions of the GARCH model are satisfied, proving that the model is robust and feasible. Moreover, the skewness parameter (η) and the degree of freedom parameter (ν) of the Skew-t distribution are also statistically significant at the 1% level, which proves that the Skew-t distribution is suitable for the GARCH model's residual distribution again.

Table 11. The fitting results of GARCH(1,1) under the Skew-t distribution.

	r_gb	r_hb	r_nb	r_cb
μ	0.0200	0.0314	0.0198	0.0031
	(8.8098)	(9.6331)	(5.8430)	(1.5098)
ω	0.0000**	0.0009**	0.0004**	0.0001**
	(3.4276)	(3.1156)	(2.4246)	(2.4053)
α	0.0254***	0.2901***	0.0918***	0.2365***
	(23.9653)	(3.1270)	(3.9852)	(3.4900)
β	0.9718***	0.5191***	0.8897***	0.7389***
	(159.1312)	(4.5860)	(34.0055)	(10.6590)
η	0.9861***	1.1112***	1.0261***	1.0064***
	(31.1209)	(27.6315)	(25.8812)	(28.1273)
ν	3.0413***	3.0334***	3.8586***	3.7020***
	(14.2022)	(10.9898)	(9.2521)	(9.9001)

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

4.3.2. Optimal Copula function selection

We utilize the binary Copula function to fit CGB and the traditional bond market. Based on AIC criterion, Copula function with the best fit is chosen to calculate CoVaR. Table 11 shows the specific AIC values of Copula.

From Table 12, the t-Copula function has the best fitting effect for the combination of CGB and HB. Regarding NB and CB, the SJC-Copula model has the best fitting effect among CGB and them. In Table 13, ρ and κ are parameters of t-Copula function, η and γ are parameters of SJC-Copula function.

Table 12. The fitting results of different Copula functions.

	Nomal	t-Copula	Clayton	Gumble	Frank	SJC-Copula
r_gb-r_hb	−570.86	−603.12	−434.19	−563.31	−499.18	−595.51
r_gb-r_nb	−550.23	−569.46	−434.61	−535.76	−435.57	−594.40
r_gb-r_cb	−924.04	−964.64	−737.38	−910.20	−797.14	−976.19

Table 13. Estimation results of optimal Copula.

	Optimal Copula model	ρ	κ	η	γ
r_gb-r_hb	t-Copula	0.58***	6.92***	——	——
r_gb-r_nb	SJC-Copula	——	——	5.76**	0.78***
r_gb-r_cb	SJC-Copula	——	——	6.53***	1.67***

Note: ***, **, and * indicate statistically significant at the 1%, 5% and 10% level.

4.3.3. Measurement of spillover effects

We adopt the combination of static and dynamic methods to measure the risk spillover characteristics of CGB and the traditional bond market using CoVaR, △CoVaR and %△CoVaR. The summation of risk spillovers is delegated by CoVaR; △CoVaR stands for the relative amount of risk spillover, which measures the net risk spillover between markets; and %△CoVaR is a standardized variable of risk spillover, which measures the contribution of risk spillover. Table 14 is the result of a bidirectional static risk spillover effect between CGB and the traditional bond market at 95% level.

Table 14. Static risk spillover between green bond market and traditional bond market.

Direction	Downside risk spillover		
	CoVaR	△CoVaR	%△CoVaR
r_gb→r_hb	−0.1906	−0.1222	198.32%
r_gb←r_hb	−0.2325	−0.1414	65.10%
r_gb→r_nb	−0.4101	−0.2302	32.30%
r_gb←r_nb	−0.2292	−0.1381	61.30%
r_gb→r_cb	−0.1591	−0.0921	60.20%
r_gb←r_cb	−0.2504	−0.1594	86.12%

First, as shown in Table 14, CoVaR and △CoVaR among the four markets are negative, and %△CoVaR is positive from the perspective of spillover direction, indicating that the relationship between the four markets possess a positive risk spillover effect. Second, with the point of spillover intensity, for the risk spillover effect between CGB and HB, the former contributes more to the latter's risk spillover; but for the risk spillover effect between CGB and NB and CB, the former contributes less to the latter's risk spillover. Finally, the risk spillover contributions of CGB to these three traditional bond markets are slightly different from the horizontal comparison of the market. CGB has the most violent risk impact on HB and the smallest contribution to the risk spillover of NB.

For the sake of portraying dynamic changes of the risk spillover among the four markets more clearly, this section plots time-varying graph of risk spillover, as follows: The black line indicates the traditional bond markets' unconditional risk value VaR, which means that the outside world does not involve them, and the red line indicates the CoVaR value of the HB, NB and CB under the green bond market's risky influence.

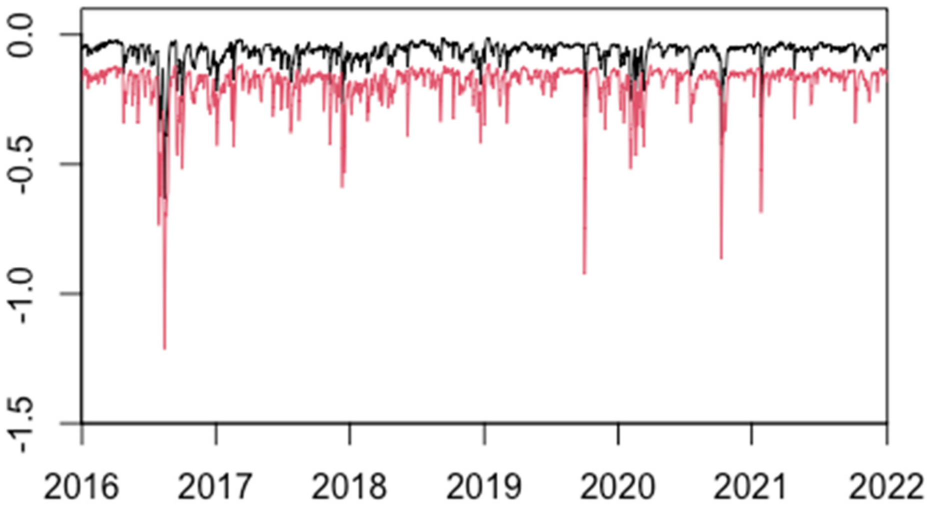

Figure 6. Dynamic risk spillovers from r_gb to r_hb.

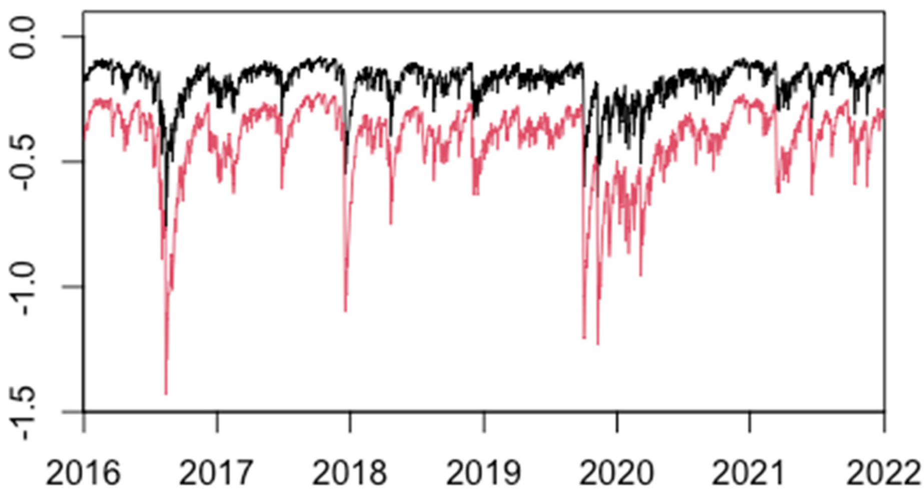

Figure 7. Dynamic risk spillovers from r_gb to r_nb.

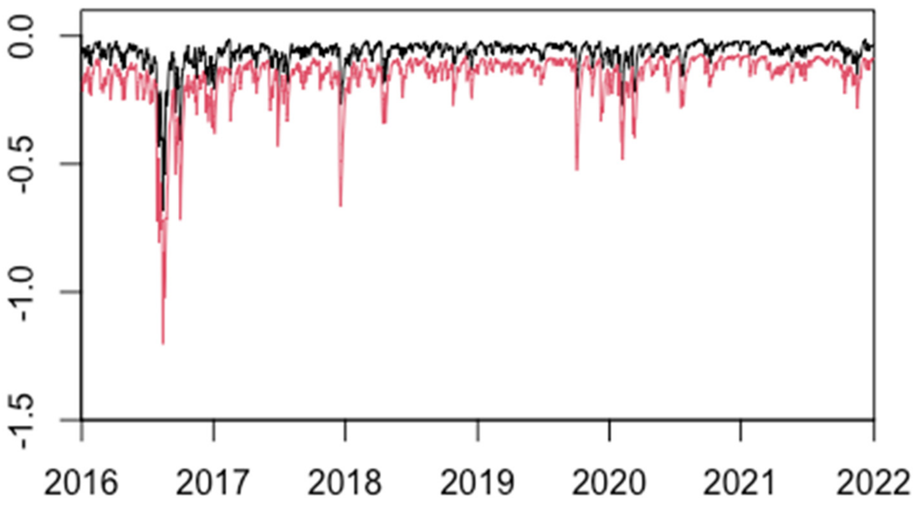

Figure 8. Dynamic risk spillovers from r_gb to r_cb.

It can be seen from figure 6 to figure 8 that the values of VaR and CoVaR among the traditional bond markets are time-varying. During the sample period, the absolute value of CoVaR is always smaller than VaR, which shows that a positive risk spillover effect of CGB on the traditional bond market will continue. What is worthy of remark is that the **△CoVaR** of CGB with the NB is larger than that with the HB, which manifests that the substitution effect between NB and CGB is higher.

5. Conclusions and recommendations

5.1. Conclusions

The daily closing price indexes of CGB, NB, CB and HB are selected in this paper to analyze the spillover effect among the four markets from May 9, 2016 to May 6, 2022. The specific conclusions are as follows:

First, there is a mean spillover effect among the four markets. Regarding mean spillover's direction, mean spillover from the CGB to HB and CB is unidirectional, while mean spillover between NB and CGB possess the bidirectional characteristics. When paying attention to the degree of mean spillover, CGB has the strongest spillover to NB, while HB and CB are less affected by the mean spillover of CGB.

Second, the relationship between the four markets is a certain linkage and positive volatility spillover. Thus, the largest volatility spillover with CGB is the conventional bond market. In contrast, the synergy between CGB and HB is low. The dynamic correlation coefficient between CGB and CB fluctuates greatly at times, indicating that the volatility spillover effect is relatively unstable.

Third, the relationship from the traditional bond market to CGB about risk spillover direction is positive. Obviously, CGB has a greater contribution to risk spillover of HB, while it contributes less to risk spillover of NB and CB. As far as dynamic action, the risk spillover from CGB to the traditional bond market fluctuates over time.

The empirical results of this paper are similar to Gao et al. (2021) previous research conclusions. At present, more theoretical studies are currently exploring the problems encountered in the development of CGB and the formulation of policies, and since green bonds started late in China and there are few existing literatures that use China as the research subject, we quantitatively analyze the spillover effects of CGB with the NB, HB and CB to provide a comprehensive familiarization of the risk correlation characteristics between CGB and the traditional bond market. In addition, the existing studies on spillover effects are from the perspective of mean and volatility. On this basis, we add research on extreme risk spillover, and reasonably use the Copula-CoVaR model to further explore and analyze the extreme risk spillover between CGB and traditional bond market as well as the correlation between them, which is conducive to reasonable risk prevention.

5.2. Recommendations

Through research and analysis, we found that the dynamic correlation and extreme risk spillover among the four markets are time-varying. During economic turbulence, such as the trade disputes between China and the United States in 2018 and the outbreak of the COVID-19 in 2020, the linkage and risk spillover among them have significantly enhanced. Therefore, investors need to show solicitude for the influence of major crisis events. When the market fluctuates violently, they should overcome panic, not blindly follow the crowd, and invest cautiously. Moreover, investors should increase their capacity to understand policy changes, learn to correctly view the fluctuations of the GCB and avoid irrational behavior. Investors should be aware of the correlation between GCB and related assets when formulating portfolio investment strategies, rationally allocate resources to enhance the accuracy and precision of investment decisions and maximize returns. Green bonds are a great diversification tool, so investors can consider adding green bonds to their portfolios.

In addition, the empirical results show that the information transmission between CGB and other markets is not smooth. The government's policy guidance can help the green bond market to build a favorable institutional framework, so it is necessary for the government to increase policy support for green bonds.

Use of AI tools declaration

All authors declare that we have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Bai J (2021) A Study of Systemic Risk Spillover Effects of Commercial Banks Based on GARCH-DCC-Copula-CoVaR Approach. *Huabei Financ,* 45–58.

Bhatnagar M, Taneja S, Özen E (2022) A wave of green start-ups in India—The study of green finance as a support system for sustainable entrepreneurship. *Green Financ* 4: 253–273. https://doi.org/10.3934/GF.2022012

Chen F, Zhang Y (2023) An Empirical Research on the Financial and Environmental R esults of Corporate Green Bond Issuance. *J Guangdong Univ Financ Econ* 38: 38–53+81.

Chen W, Huang L, Weng J (2021) Exploring the Pricing Advantages of Green Bond Issuance and Its Influencing Factors. *J Reg Financ Res*, 25–32.

Chen X, Zhang M (2022) China's Green Bond Market: Characteristics, Facts, Endogenous Dynamics, and Existing Challenges. *Int Econ Rev*, 104–133+107.

Colombage S, Nanayakkara K (2020) Impact of credit quality on credit spread of Green Bonds: a global evidence. *Rev Dev Financ* 10: 31–42.

Dou R, Zhang W (2019) The Effect of Green Factor on Bond Yield Spread——Based on PSM. *J Shanghai Lixin Univ Account Financ*, 47–57.

Ezuma REMR, Matthew NK, Ezuma R, et al. (2022) The perspectives of stakeholders on the effectiveness of green financing schemes in Malaysia. *Green Financ* 4: 450–473. https://doi.org/10.3934/GF.2022022

Gao X, Ji W (2018) Characteristics of Issuers and Credit Spread of Green Bond Issuance. *Financ Econ*, 26–36.

Gao Y, Li C (2021) Research on Risk Spillover Effect between Green Bond Market and Financial Market in China. *Financ Forum* 26: 59–69.

Gianfrate G (2019) Climate risks and the practice of corporate valuation.

Girardi G, Ergün AT (2013) Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *J Bank Financ* 37: 3169–3180. https://doi.org/10.1016/j.jbankfin.2013.02.027

He J (2017) An empirical study of spillover effects between Main Board, GEM and NSE. *China Manage Inf* 20: 110–112.

Hu Q, Ma L (2011) China's stock market and bond market Analysis of volatility spillover effect. *J Financ Res,* 198–206.

Huang Z (2021) The Impact of International Oil Price on the Stock Prices of Domestic Oil Related Industries—AnEmpiricalAnalysis Based on DCC-Copula-CoVaR.

Huynh TLD (2021) Does bitcoin react to Trump's tweets? *J Behav Exp Financ* 31: 100546. https://doi.org/10.1016/j.jbef.2021.100546

Jiang F, Fan L (2020) Green Premium or Green Discount?——A study based on China's green bond credit spreads. *Modernization Manage* 40: 11–15.

Kanamura T (2020) Are green bonds environmentally friendly and good performing assets? *Energ Econ* 88: 104767. https://doi.org/10.1016/j.eneco.2020.104767

Kielmann J, Manner H, Min A (2022) Stock market returns and oil price shocks: A CoVaR analysis based on dynamic vine copula models. *Empir Econ* 62: 1543–1574. https://doi.org/10.1007/s00181-021-02073-9

Kirithiga S, Naresh G, Thiyagarajan S (2017) Measuring volatility in the Indian commodity futures. *Int J Bonds Deriv* 3: 253–274. https://doi.org/10.1504/IJBD.2017.088545

Li Y, Wang Y, Deng W (2018) Investor Sentiment, Heterogeneity and the Credit Spread of Chinese Corporate Bonds. *Financ Trade Res* 29: 100–110.

Li Z, Fan L (2011) House Price Volatility, the Selection of Monetary Policy Instruments and the Stability of Macro-economy: Theory and Empirical Evidence. *Modern Econ Sci* 33: 13–20+122.

Lin T, Du M, Ren S, et al. (2022) How do green bonds affect green technology innovation? Firm evidence from China. *Green Financ* 4: 492–511. https://doi.org/10.3934/GF.2022024

Liu X, Wang S (2018) Research on mean spillover effect of Sino US soybean futures—— An Empirical Analysis Based on MSVAR Model. *Price: Theory Practice*, 99–102.

MacAskill S, Roca E, Liu B, et al. (2021) Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. *J Clean Prod* 280: 124491. https://doi.org/10.1016/j.jclepro.2020.124491

Mensi W, Shafiullah M, Vo XV, et al. (2022) Spillovers and connectedness between green bond and stock markets in bearish and bullish market scenarios. *Financ Res Lett* 49: 103120. https://doi.org/10.1016/j.frl.2022.103120

Naeem MA, Conlon T, Cotter J (2022) Green bonds and other assets: Evidence from extreme risk transmission. *J Environ Manage* 305: 114358. https://doi.org/10.1016/j.jenvman.2021.114358

Partridge C, Medda FR (2020) Green bond pricing: The search for greenium. *J Altern Invest* 23: 49–56. https://doi.org/10.3905/jai.2020.1.096

Pham L, Huynh TLD (2020) How does investor attention influence the green bond market? *Financ Res Lett* 35: 101533. https://doi.org/10.1016/j.frl.2020.101533

Qi H, Liu S (2021) Is there a Greenium in the Bond market of China? *Account Res*, 131–148.

Qin S, Wang X, Luo Y, et al. (2019) Spillover effects between the stock market and the green bond market in low-carbon industries—an analysis based on data before and after the emergence of labeled green bonds. *Wuhan Financ*, 67–72.

Reboredo JC (2018) Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energ Econ* 74: 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

Reboredo JC, Ugolini A, Chen Y (2019) Interdependence between renewable-energy and low-carbon stock prices. *Energies* 12: 4461. https://doi.org/10.3390/en12234461

Su T, Zhang ZJ, Lin B (2022) Green bonds and conventional financial markets in China: A tale of three transmission modes. *Energ Econ* 113: 106200. https://doi.org/10.1016/j.eneco.2022.106200

Tsagkanos A, Sharma A, Ghosh B (2022) Green Bonds and Commodities: A new asymmetric sustainable relationship. *Sustainability* 14: 6852. https://doi.org/10.3390/su14116852

Tsoukala AK, Tsiotas G (2021) Assessing green bond risk: an empirical investigation. *Green Financ* 3: 222–252. https://doi.org/10.3934/GF.2021012

Wairagu GP (2011) *The relationship between financial innovation and profitability of Commercial banks in Kenya.*

Wang Y (2021) Analysis of the Linkage Effect and Influencing Factors between the Green Bond Market and the Traditional Bond Market.

Wang Y, Tian Y (2023) Research on the Impact of the Issuance of Green Bonds on the Business Performance of Listed Companies. *China J Commerce,* 109–113.

Wang Y, Xu N (2016) The Development of Chinese Green Bonds and A Comparative Study of Chinese and Foreign Standards. *Financ Forum* 21: 29–38.

Wang Z, Zeng G (2016) International Green Bond Market: Current Situation, Experience and Enlightenment. *Financ Forum* 21: 39–45.

Yavas BF, Dedi L (2016) An investigation of return and volatility linkages among equity markets: A study of selected European and emerging countries. *Res Int Bus Financ* 37: 583–596. https://doi.org/10.1016/j.ribaf.2016.01.025

Zerbib OD (2019) The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *J Bank Financ* 98: 39–60. https://doi.org/10.1016/j.jbankfin.2018.10.012

Zhang Y, Wang Z, Tang Z, et al. (2020) Water Phase, Room Temperature, Ligand-Free Suzuki–Miyaura Cross-Coupling: A Green Gateway to Aryl Ketones by C–N Bond Cleavage. *Eur Org Chem* 2020: 1620–1628. https://doi.org/10.1002/ejoc.201901730

Zhong M, Darrat AF, Otero R (2004) Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. *J Bank Financ* 28: 3037–3054. https://doi.org/10.1016/j.jbankfin.2004.05.001

Zhou S, Zhou J (2006) A Study of Volatility Spillovers in Domestic and International Crude Oil Markets. *J China Univ Petroleum (Edition of Social Sciences)*, 8–11.

Zhu M (2013) Return distribution predictability and its implications for portfolio selection. *Int Rev Econ Financ* 27: 209–223. https://doi.org/10.1016/j.iref.2012.10.002