Green Bonds as Hedging Assets before and after COVID: A Comparative Study between the US and China

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Abstract: The COVID pandemic reveals the fragility of the global financial market during rare disasters. Conventional safe-haven assets like gold can be used to hedge against ordinary risks, but tail dependence can substantially reduce the hedging effectiveness. In contrast, green bonds focus on long-term, sustainable investments, so they become an important hedging tool against climate risks, financial risks, as well as rare disasters like COVID. The copula approach based on the TGARCH model is applied to estimate the joint distributions between green bonds and selected financial assets in both US and China. The quantile-based approach is also performed to offer a robustness check on tail dependence. The results show that all assets in the two countries have thick tails and tail dependence with time-varying features. The hedging effectiveness does decline during the COVID pandemic, but it is the hedging effectiveness against tail risks rather than against normal risks. It is argued that green bonds play a significant role in hedging against rare disasters especially in forex markets. It is also found that green bonds in the US and China converge in many aspects, suggesting a smaller cross-country difference than cross-asset difference.

Keywords: green bonds; hedging effectiveness; COVID

JEL: G110, G120

1. Introduction

The environment provides natural resources for and imposes limits on economic growth. Therefore, a sustainable growth must be an environment-friendly growth. In the face of intensifying environmental concerns, there is a thriving trend in both developed countries (Sarkodie, et al., 2021) and emerging economies (Song & Zhou, 2021) to achieve carbon-neutral growth by green energy-based innovations. Nevertheless, technological progress is not the only driver of sustainable growth. The finance-growth nexus (King & Levine, 1993; Beck et al., 2014; Zhang & Zhou, 2021) implies that green finance is needed to boost green growth (Yu et al., 2021). As a popular financing tool and investment vehicle, green bonds have gained an increasing attention in global financial markets (Taghizadeh-Hesary et al., 2021). According to World Bank and OECD, green bonds are defined as "fixed-income securities to exclusively develop eco-friendly and sustainable projects like renewable energy industries." The earliest green bonds were issued by the European Investment Bank in 2007 (Banga, 2018). Since 2008, the World Bank has issued over USD 13 billion equivalent in green bonds in 20 currencies (World Bank, 2021). In recent years, emerging economies like China have been actively in green bond issuance and management. In 2016, China issued more than one-third of the global green bond issuance (USD 81 billion), ranking the first in the world (Wang et al., 2019). A burgeoning green bond market provides financial capital for sustainable growth as well as alternative investment opportunities for investors.

In addition to its sustainability feature, green bonds also have a safe-heaven feature against tail risks (Jin et al., 2020; Yi et al., 2021). Specifically, during the COVID pandemic, the global financial markets underwent sharp downturns and volatile fluctuations (Uddin et al., 2021). Based on historical experience, financial crises due to epidemics are expected to be deeper but short-lived compared to the global financial crisis of 2009. For example, the Chinese stock market even grew by 20% during SARS in 2003. However, the crisis following the COVID pandemic seems to be much prolonged compared to past experience. In early stages of the outbreak in 2020, 30% of the worldwide stock market value evaporated within weeks, and that loss is yet to recover in mid-2021. Investors are forced to look for safe-heaven investment opportunities and hedging tools to diversify tail risks caused by rare disasters.

The pandemic causes abnormal fluctuations in financial markets and leads to failure of conventional hedging techniques. Campbell et al. (2002) find that benefits of diversification across asset classes substantially drop if the market experiences high volatility. This is because the distributional dependence among assets varies substantially in different quantiles. The tail dependence in rare disasters can be significantly different from mean dependence in normal times. For example, both cryptocurrencies and gold fail to provide safe-haven hedge against pandemic crisis (Kristoufek, 2020). Luckily, green bonds seem to provide a promising solution to this trouble. Evidence suggests that clean energy assets, especially green bonds, are great hedging tools in the US (Reboredo & Ugolini, 2020; Kuang, 2021). Han and Li (2020) find no risk spillovers between green bonds and stocks, suggesting that green bonds have outstanding diversification benefits for stock investors in China.

This paper is inspired by earlier studies in various countries but before the COVID pandemic. The existing literature either focus on the safe-heaven feature of green bonds in developed economies like the US and the EU (e.g., Abakah et al., 2021; Reboredo et al., 2020) or on non-hedging features of green bonds in China (e.g., Yi et al., 2021). We aim to provide updated evidence for the hedging capability of green bonds against rare disasters (or tail risks) using a comparative study of a representative developed economy (US) and emerging economy (China), before and after the pandemic. This research contributes to the empirical understanding of the role of green bonds in both US and China as a safe-heaven asset against tail risks. Evidence supports that green bonds have great potential to hedge against tail risks for traditional assets. We find that the financial markets in the two countries converge in many ways. The hedging effect of green bonds became slightly weaker for most assets after the pandemic but stronger for the forex market. The other contribution of this paper is its methodological discussion. The next section provides a comprehensive, systematic review of prevailing approaches adopted in the green literature.

2. Literature Review

As its name suggests, green bonds have two defining features. One is "green" and the other is "bond". Thus, the literature on green bonds is rolled out along these two dimensions. The green/sustainability literature highlights the effects on corporate social responsibility (Zhou & Cui, 2019) and corporate performance (Alonso-Conde & Rojo-Suarez, 2020). A consensus in this strand of green literature is that the sustainability nature of green bonds reaps the so-called "environmental benefit dividends" in line with the long-run direction of economic development and technological progress. This is effectively a micro-finance perspective into the long-run, fundamental factors of financial performance of green bonds. The bond/finance literature, on the other hand, accentuates the green bond risk premium (Diaz & Escribano, 2021). Many empirical studies find that green bonds enjoy higher yields, lower variance, and greater liquidity (Bachelet et al., 2019). Moreover, it is also found that green bonds have an asymmetric volatility feature—more responsive to positive shocks than negative shocks (Park et al., 2020). Therefore, it is argued that green bonds, or clean energy assets in general, can be a safe-haven tool to hedge against various risks (Xia et al., 2019; Kuang, 2021). This is more a macro-finance perspective into the short-run, cyclical factors of financial properties of green bonds.

Empirical studies usually employ multivariate time-serious models to capture the dynamic features of green bond markets. For example, Naeem et al. (2021) apply rolling window wavelet techniques to examine the time-varying features of correlation between green bonds and other assets. Park et al. (2020) adopt DCC-GARCH model to study the volatility spillovers between equity and green bond markets using the US data. Reboredo (2018) applies Copula models to study the tail dependence features and diversification benefits of green bonds. Reboredo and Ugolini (2020) use a structural VAR with heteroskedasticity to study interdependence between green bond and other financial assets. In the recent empirical literature (listed in **Table 1**), there are four trending approaches to studying co-movements between green bonds and other financial assets.

The first one is quantile-based approach, such as cross-quantilogram (Han et al., 2016; Naeem et al., 2021) and quantile autoregressive distributed lag (He et al., 2021). The advantage of quantile-based approach is that it can help identify the signs of the relationship not only at the mean but also at the tails of the complete distribution when the markets experience extreme decreases or increases. Therefore, it can deal with the so-called "asymmetric tail dependence", i.e., cases where two returns exhibit greater correlation during market downturns than market upturns (Erb et al., 1994; Ang & Chen, 2002; Patton, 2006). However, these models cannot accommodate complicated dynamics among assets such as volatility clustering.

To capture interdependence and volatility clustering at the same time, multivariate GARCH models (Engle, 2002) is an obvious choice. Therefore, it becomes the second trending approach in green bond literature (Maghyereh et al., 2019; Jin et al., 2020; Gao et al., 2021). However, GARCH-type models (e.g., CCC or DCC) are restrictive due to the linear specification among assets and the Gaussian assumption of the joint distribution (Wang et al., 2011).

To overcome these limitations, copula method (the third approach) is developed to relax the Gaussian restrictions while maintaining the rich interdependence feature. Copula method is influential in finance research for its flexibility in distributional assumptions, making it appropriate for explaining joint tail risks. Another advantage of copula method is its two-step procedure of estimating marginal and joint distributions. Therefore, it soon gains its popularity in green bond literature (Reboredo, 2018; Gong et al., 2019). Early copula methods assume constant parameters (e.g., Patton, 2004), but extensions like generalized autoregressive score solve this issue by introducing a dynamic copula (Patton, 2006).

Like other approaches, copula methods also have limitations. It focuses on the dependence of the variance-covariance matrix, leaving little to say on the dependence of the means. This is where a multivariate GARCH (MGARCH) model can be complementary. However, ordinary MGARCH model is unable to capture the time-varying feature of interdependence. In this regard, the time-varying parameter vector autoregressive (TVP-VAR) approach is appealing if the focus is on the evolution of the relationship between assets (Antonakakis et al., 2020). Compared with the copula method which can also capture time variation but only in the copula, TVP-VAR can capture time-varying features in both mean and variance-covariance matrices following a Bayesian interpretation (Pham & Nguyen, 2021). However, the drawback of TVP-VAR is that it cannot accommodate the fat-tail feature of returns documented in financial markets (Rietz, 1988; Barro, 2006). This is a critical limitation for our purpose because the focus of this paper is on tail risks and tail dependence.

Table 1 List of key literature

Literature	Period	Country	Method	Assets
Naeem et al. (2021)	2008-2019	US	cross-quantilogram	GBs, oil, gold, commodities
Park et al. (2020)	2010-2020	US	DCC-GARCH	GBs, stock
Reboredo (2018)	2014-2017	US	copula	GBs, bond, oil
Reboredo et al. (2020)	2014-2018	US, EU	wavelet	GBs, bond, stock, oil
Reboredo & Ugolini (2020)	2014-2019	US	SVAR	GBs, bond, stock, oil, forex
Maghyereh et al. (2019)	2001-2018	US	wavelet	GBs, oil, stock
Jin et al. (2020)	2008-2018	US	DCC-GARCH	GBs, stock, oil, commodities
Gao et al. (2021)	2015-2020	China	DCC-GARCH	GBs, stock, bond, forex
Yi et al. (2021)	2019-2020	China	event study method	GBs

To summarize, all four prevailing empirical approaches have their advantages and limitations. **Table 2** compares the key features of the four approaches in the recent green bond literature. It is arguable that the copula method is preferred to quantile-based method in terms of time variation modeling, and superior to TVP-VAR and multivariate GARCH in terms of tail dependence modeling. Therefore, this paper is going to adopt the copula approach, with the quantile-based approach to provide a complementary measure of the dependence among assets.

Table 2 Comparison of trending empirical approaches in green bond literature

Type	Mean Dependence	Tail Dependence	Fat Tail	Time-Varying
Quantile-Based	Yes	Yes	Yes	No
MGARCH	Yes	No	No	No
TVP-VAR	Yes	No	No	Yes
Copula	No	Yes	Yes	Yes

3. The Model

Returns of any assets, including green bonds, corporate bonds, stocks, oil index and dollar index, can be modeled in the following general form. The subscript g denotes green bonds, i denotes any other asset, and t is time. To be general, we allow both mean and volatility to change over time.

$$r_{gt} = \mu_{gt} + \xi_{gt}, \text{ where } \xi_{gt} \equiv \sigma_{gt}\epsilon_{gt} \tag{1)A}$$

$$r_{it} = \mu_{it} + \xi_{it}, \text{ where } \xi_{it} \equiv \sigma_{it}\epsilon_{it} \tag{1)B}$$

The mean component ($\mu_{\blacksquare t}$) of any asset ($\blacksquare = g, i$) can be modeled as an ARMA(p, q) process. To write the model in an elegant form, econometricians usually use polynomials of lag operator L, such as $\boldsymbol{\phi}(L;p) = \phi_1 L + \cdots + \phi_p L^p$ and $\boldsymbol{\psi}(L;q) = \psi_1 L + \cdots + \psi_p L^p$, to express the ARMA model:

$$\mu_{\blacksquare t} = \boldsymbol{\phi}(L;p)\mu_{\blacksquare t} + \boldsymbol{\psi}(L;q)\xi_{\blacksquare t} \tag{2}$$

Similarly, the volatility component ($\sigma^2_{\blacksquare t}$) of the model is assumed to exhibit a threshold generalized autoregressive conditional heteroskedasticity (TGARCH). The polynomials $\boldsymbol{\alpha}(L;m)$, $\boldsymbol{\beta}(L;n)$, and $\boldsymbol{\gamma}(L;s)$ are defined in a similar way for the GARCH(m), ARCH(n), and TARCH(s) terms.

$$\sigma^2_{\blacksquare t} = \alpha_0 + \boldsymbol{\alpha}(L;m)\sigma^2_{\blacksquare t} + \boldsymbol{\beta}(L;n)\xi^2_{\blacksquare t} + \boldsymbol{\gamma}(L;s)\xi^2_{\blacksquare t}|_{\xi_{\blacksquare t}<0} \tag{3}$$

Nothing is new up to this point. Equations (1)A, (1)B, (2) and (3) are time-series models widely applied in finance literature since 1980s. To extend this simple model, as we summarized in the literature section above, there are four directions. If the focus is on the tail dependence between ϵs, then we arrive at the quantile-based approach. If we are more interested in the mean dependence, then we have MGARCH. If the research embarks on the temporal variation of the dependence, then TVP-VAR is a good choice. If one wants to capture all features to a certain degree, then the copula approach is the optimal choice. Therefore, we will adopt the copula approach as the baseline in this paper.

In the copula approach, joint distributions between ϵ_{gt} and ϵ_{it} are obtained in two steps in the light of Sklar's theorem (1959). The theorem states that every multivariate cumulative distribution function (CDF) $F(\cdot)$ of a set of jointly distributed random variables (say, ϵ_{gt} and ϵ_{it}) can be expressed in terms of the marginal CDFs ($F_g(\epsilon_{gt})$ and $F_i(\epsilon_{it})$) and a copula function ($C(\cdot)$) to link the marginals:

$$F(\epsilon_{gt}, \epsilon_{it}) = C\left(F_g(\epsilon_{gt}), F_i(\epsilon_{it})\right) \tag{4}$$

Copulas provide a more complete description of dependence between two or more random variables than linear correlation coefficient (Patton, 2006). Thus, the copula approach deals with the interdependence between random variables via ϵs rather than via μs as opposed to MGARCH and TVP-VAR. The distributional dependence is therefore the core of the copula approach.

In the first step of the copula approach, marginal CDFs ($F_g(\epsilon_{gt})$ and $F_i(\epsilon_{it})$) can be separately estimated. This feature grants great flexibility in practice—the underlying marginals can have different distributions and/or different parameters, without having to conform with the restrictions if a multivariate distribution are directly applied to model the dependence of assets. In the green bond literature, it is well established that a Student's t distribution (with a fat tail) tends to be the most appropriate marginal distribution (Reboredo, 2018), so we are going to use t distributions for the marginals.

Turning to the second step of specifying copula models, we largely follow the classical approach developed by Patton (2006). The tail dependence of the lower and upper ends of marginal CDFs can be formulated as:

$$\tau_L = \lim_{x \to 0} \Pr\left(F_g(\epsilon_{gt}) \le x \middle| F_i(\epsilon_{it}) \le x\right) = \lim_{x \to 0} \frac{C(x,x)}{x} \tag{5}$$

$$\tau_U = \lim_{x \to 1} \Pr\left(F_g(\epsilon_{gt}) \ge x \middle| F_i(\epsilon_{it}) \ge x\right) = \lim_{x \to 1} \frac{1-2x+C(x,x)}{1-x} \tag{6}$$

The two tail dependence measures τ_L and τ_U describe the probability that both assets are in their lower or upper joint tails, i.e., during extreme events like the financial crisis and the COVID pandemic. There are many different copulas with different features of tail dependence. We discuss the most popular and relevant ones here.

- **Gaussian/Normal copula**. It does not allow for tail dependence of the underlying marginal distributions, so both tail dependence measures τ_L and τ_U are equal to zero. The dependence is simply measured by Pearson's correlation coefficient $-1 \leq \rho \leq 1$.
- **Student's t copula**. It has a fat tail, so tail dependence is possible. The symmetry of the t distribution implies an equal lower and upper tail dependence $\tau_L = \tau_U$ which depends on the two copula parameters, the correlation coefficient ρ and the degree of freedom ν.
- **Clayton copula**. It is an asymmetric distribution with greater lower tail dependence $\tau_L > 0$ than upper tail dependence $\tau_U = 0$. There is only one parameter of the Clayton copula $\vartheta \geq 1$, where $\vartheta = 1$ means independence.
- **Rotated Clayton copula**. It is the reverse of the Clayton copula, so it allows for positive upper dependence $\tau_U > 0$ but zero lower dependence $\tau_L = 0$. In practice, one can simply transform the data to swap the tails before estimation.
- **SJC copula**. It allows for asymmetric tail dependence $\tau_L \neq \tau_U$ and the two measures can be estimated directly.

In addition to the copulas described above, Gumbel copula is also popular, but it is close to Clayton copula. They, together with their rotated counterparts, are called the Archimedean copulas (Creal et al., 2011).

To capture time variation of copulas, an autoregressive conditional density in the spirit of Hansen (1994) is usually used. The advantage of this method relative to alternatives, regime switching method for example, is that it is more efficient and parsimonious in parameterization. Assume the time-varying parameters in copulas ($\theta_t \equiv \rho_t | \tau_{Lt} | \tau_{Ut}$) are summarized by an ARMA-type process (Patton, 2006).

$$\theta_t = \Lambda\left(a + b\theta_{t-1} + c\frac{1}{K}\sum_{k=1}^{K} H\left(\epsilon_{g,t-k}, \epsilon_{i,t-k}\right)\right). \quad (7)$$

In equation (7), $\Lambda(\cdot)$ is a logistic transformation to keep measures of tail dependence within defined domains. $H(\cdot)$ is product of normal quantile functions for normal copula, product of t quantile functions for t copula, absolute difference function for Clayton, Gumbel, and SJC copulas. According to Patton (2006), the length of lags $K = 10$ is chosen, which corresponds to 2 working weeks for daily data.

3. Results

Following the convention of the green bond literature, we select bond market, stock market, energy market, and forex market to study the dependence of green bond market. We will compare our results of a developed economy (US) with an emerging economy (China) which plays a significant role in green bond issuance.

3.1. Data Description

For the US, we use the daily data of Barclays MSCI green bond index (USGB) from Aug/2014 to Aug/2021. There are, of course, many alternative indices for green bonds, such as S&P Dow Jones green bond index, Solactive green bond index, and Bank of America Merrill Lynch green bond index. According to Reboredo (2018), different green bond indices share very similar patterns, so the choice of index does not matter much in our empirical results. The bond market is proxied by the 10-year US government bonds (USB). For the stock market in the US, we use Dow Jones index (USS). The forex market fluctuations are measured by the US dollar index (USF). As an important commodity related to green bonds, West Texas Intermediate (USO) crude oil index is used to measure changes of energy price in the US. It is preferred to Oil Brent Crude because the latter covers markets beyond the US.

For China, there are about ten representative green bond indices to choose from Jul/2014 to Aug/2021. We use the essential green bond index (CNGB) which meets the strictest criteria of green bonds in China and most countries in the world. The bond market in China is represented by the 10-year Chinese government bond index (CNB). The stock market in China is proxied by the Shanghai Security Exchange composite index (CNS). Fluctuations of forex market are measured by returns of USD/CNY exchange rate (CNF). China does not have a well-established domestic oil price index due to its net importing position as a price-taker in the international oil market. We use Brent oil price as a proxy of the international oil price that the Chinese market faces (CNO).

Table 3 reports descriptive statistics for daily returns of the abovementioned financial assets. The means of daily returns of all assets are close to zero and stationary according to ADF and KPSS tests, and they all have abnormal fat tails (kurtosis greater than 3 and JB tests are significant). Green bonds in both countries tend to be negatively correlated with fixed income markets and other assets, especially in China. The descriptive statistics in **Table 3** focuses on univariate properties of each asset. To visualize the dependence between assets, we plot scatter plots of selected assets against green bonds. **Figure 1**a shows the nonparametric joint distributions of assets in the US, while **Figure 1**b shows the counterparts in China. To facilitate comparisons over time, we use different colors to indicate pre-COVID and COVID samples. Plots of daily returns of these assets can be found in the Appendix. We can see some salient features from between-assets, cross-country, and over-time comparisons. First, there is a clear negative dependence between green bonds and the dollar index in the US, but the most salient negative dependence in China lies in the bond markets. It implies a different hedging role for green bonds in the two markets. Second, the distribution of green bonds in China tends to be more concentrated around its mean than those in the US, but green bonds in both countries enjoy lower uncertainty than other assets. In other words, the between-assets difference is smaller than the cross-country difference. Third, tail risks of most assets become more significant after the COVID pandemic, since the distributions become thicker in tails and flatter in peaks. One outstanding example is the oil price, which dropped to negative for the first time in history on 20th April 2020 due to the pandemic and the oil price war between Russia and Saudi Arabia. In contrast, green bonds do not have obvious change in terms of tail risks. Therefore, green bonds have great potential to be a safe-heaven asset resilient to rare disasters.

Table 3 Descriptive statistics for daily returns of financial assets in US and China

US	USGB	USB	USS	USF	USO	China	CNGB	CNB	CNS	CNF	CNO
Obs.	1830	1830	1830	1830	1830	Obs.	1799	1799	1799	1799	1799
Mean	0.0001	0.0001	0.0005	0.0001	-0.0018	Mean	0.0002	-0.0002	0.0004	0.0000	0.0002
Max	0.0222	0.4074	0.0938	0.0235	0.3766	Max	0.0097	0.0367	0.0576	0.0186	0.2102
Min	-0.0299	-0.2703	-0.1198	-0.0207	-3.0597	Min	-0.0089	-0.0568	-0.0849	-0.0099	-0.2440
SD	0.0036	0.0322	0.0111	0.0035	0.0834	SD	0.0010	0.0082	0.0140	0.0021	0.0261
Skew.	-0.7719	1.4912	-0.6993	0.2503	-28.76	Skew.	-0.0898	-0.2741	-0.9888	0.5941	-0.2613
Kurtosis	10.63	36.82	23.80	8.89	1.0E+03	Kurtosis	19.98	6.73	9.86	10.72	16.4785
JB	4.6E+03	8.8E+04	3.3E+04	2.7E+03	7.9E+07	JB	2.2E+04	1.1E+03	3.8E+03	4.6E+03	1.4E+04
ADF	-39.64	-43.50	-52.52	-45.85	-31.76	ADF	-26.38	-36.68	-40.44	-38.76	-41.88
KPSS	0.0524	0.0511	0.0192	0.0792	0.0638	KPSS	0.4125	0.1245	0.1316	0.1168	0.0726
Corr.	**USGB**	**USB**	**USS**	**USF**	**USO**	**Corr.**	**CNGB**	**CNB**	**CNS**	**CNF**	**CNO**
USGB	1					CNGB	1				
USB	-0.3792	1				CNB	-0.5265	1			
USS	-0.0078	0.3905	1			CNS	-0.0368	0.1294			
USF	-0.593	-0.0249	-0.2223	1		CNF	-0.0119	0.0395	-0.0433	1	
USO	0.0178	0.1074	0.1633	-0.0876	1	CNO	-0.0387	0.0299	-0.0016	0.0087	1

Table notes: The null hypothesis of the JB test is that the data come from a normal distribution. The null hypothesis of the ADF test and the KPSS test is that the data have a unit root. All hypotheses are rejected at 5% significance levels.

Figure 1a Scatter histograms of assets versus green bonds in US

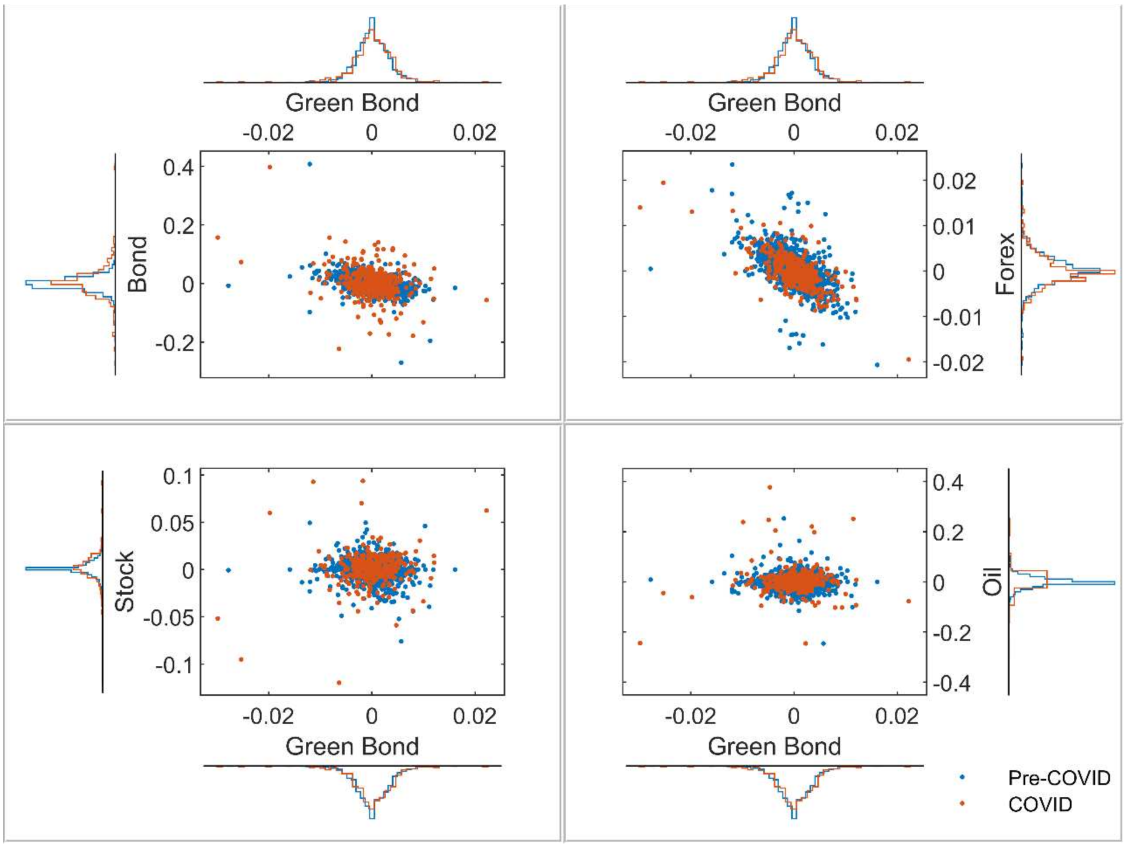
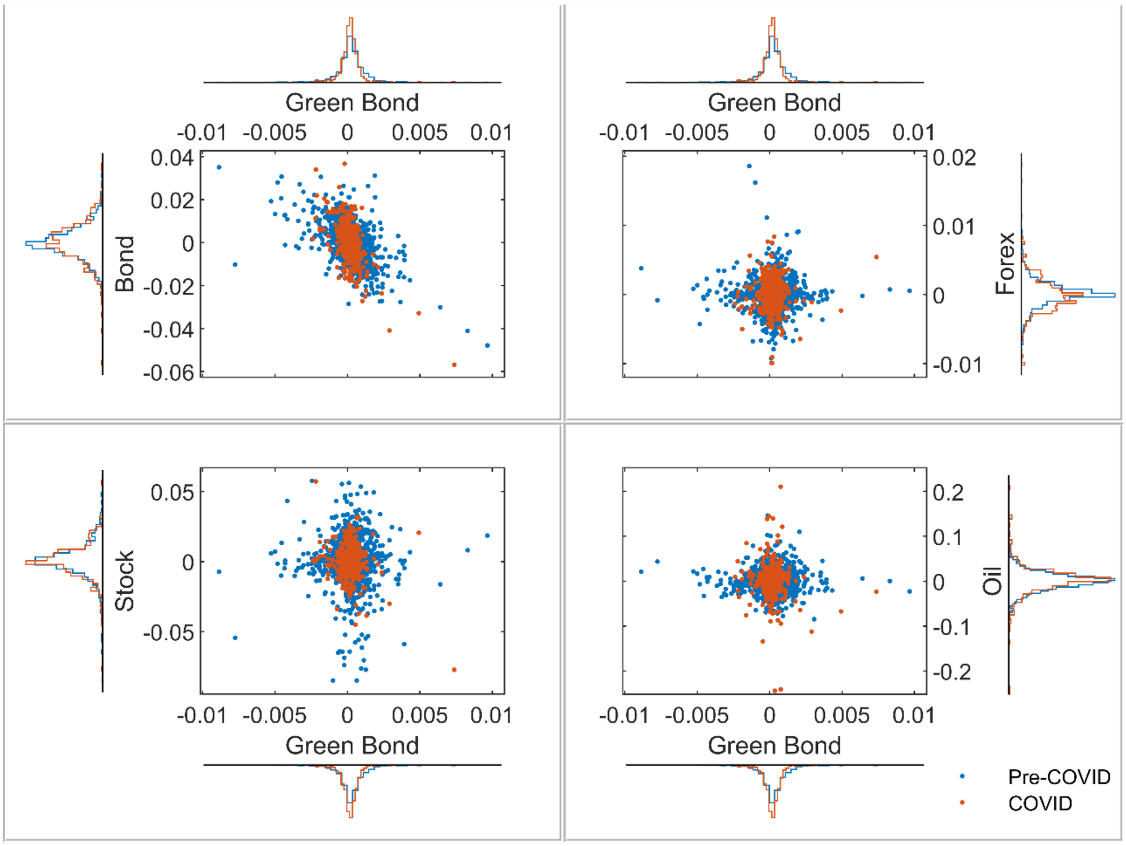


Figure 1b Scatter histograms of assets versus green bonds in China



To descriptively measure tail risks and tail dependence, the empirical literature develops metrics like Value at Risk (VaR), Conditional VaR (CoVaR), and Delta CoVaR (ΔCoVaR). Intuitively, VaR measures the loss of holding an asset if rare disasters with a specific probability (e.g., 5%) occur. In our case, it simply ranks historical (daily) returns of each asset and identify the return at the specific percentile. More generally, CoVaR is developed to estimate the possible loss under any conditions (Girardi & Ergün, 2013). The condition can simply be the downward risks below VaR of the asset per se or when other assets fall below their VaRs. Therefore, CoVaR provides a simple measure of tail dependence and risk spillover. Furthermore, ΔCoVaR represents the difference between the CoVaR of one asset (e.g., green bonds) under the distressed state of the other asset (e.g., stocks during the pandemic) and the CoVaR of the asset under the benchmark state (within 95% confidence intervals). The difference is usually divided by the benchmark CoVaR to show the marginal risk contribution of one asset vis-à-vis the overall risk of another asset (Shahzad et al., 2018).

Table 4 VaR, CoVaR, and ΔCoVaR of financial assets in US and China

	VaR at 5%		**CoVaR at 5%**		**ΔCoVaR**	
	Pre-COVID	COVID	Pre-COVID	COVID	Pre-COVID	COVID
USGB	-0.52%	-0.60%	-0.77%	-1.11%		
USB	-3.34%	-6.44%	0.28%	0.18%	19.631	5.879
USS	-1.45%	-2.19%	0.12%	-0.28%	33.808	-9.302
USF	-0.49%	-0.53%	0.47%	0.60%	109.112	26.948
USO	-3.87%	-6.02%	0.04%	0.02%	5.259	0.555
CNGB	-0.13%	-0.08%	-0.26%	-0.15%		
CNB	-1.28%	-1.50%	0.17%	0.13%	6.630	7.888
CNS	-2.09%	-1.86%	0.03%	0.08%	0.431	5.824
CNF	-0.33%	-0.35%	0.02%	0.03%	0.002	0.901
CNO	-3.67%	-4.75%	0.04%	0.05%	1.046	2.121

Table notes: The VaR columns are VaRs of different assets of the two countries at 5% percentiles. The CoVaR colums are the difference between the return of green bonds and the returns of other assets under stress conditions (defined as 5% percentiles). The USGB and CNGB rows are green bond VaRs conditional on green bond markets per se. Other rows are green bond VaRs conditional on other assets. The ΔCoVaR columns are ratios of return differences under stressed and normal states over the normal return.

As shown in **Table 4**, all the assets in the US experienced significant lower VaRs during the COVID compared to pre-COVID periods, apart from green bonds (USGB) and forex (USF). The difference in China seems less significant, especially for green bonds (CNGB) and forex (CNF) as well. It suggests that in both countries, green bonds and forex markets share an immune feature to COVID fluctuations.

In addition, the tail dependence between green bonds and other assets are qualitatively described by CoVaRs and quantitatively measured by ΔCoVaRs. It is obvious that the VaRs of green bonds in both countries have positive VaRs when other assets are in stressed states with only one exception (USS) during the COVID period. It suggests that green bonds have a great potential to hedge against tail risks for most assets.

Magnitude-wise, the hedging effect of green bonds (as quantified by ΔCoVaRs) drops in the US over the pandemic but rises in China. These observations will be formally tested by the copula approach.

3.2. Marginal Distributions

Estimation results of the marginal distributions outlined in equations (1)a, (1)b, (2), and (3) are presented in **Table 5**. The lag lengths are chosen according to AIC and BIC information criteria from the following ranges: $p, q \in \{0,1,2,3,4,5\},\ m, n, s \in \{0,1,2\}$.

Table 5 Estimation Results of Marginal Distributions

Mean	**USGB**	**USB**	**USS**	**USF**	**USO**	**CNGB**	**CNB**	**CNS**	**CNF**	**CNO**
AR(1) ϕ_1	-0.1239	0.0792	0.1208***	0.0448***		1.0151***		0.4015***	0.9069***	0.6866***
AR(2) ϕ_2	0.6235***	-0.0353	0.0206***	0.0426		0.3813***		-0.3046***		-0.68**
AR(3) ϕ_3	0.314*	-0.2377**		0.0414***		0.2819***		0.5373***		0.5724**
AR(4) ϕ_4	-0.7067***	0.7674***		0.042***		-0.9868***		-0.8682***		0.3638
AR(5) ϕ_5				0.0378***		0.3083***		-0.0438*		0.0385
MA(1) ψ_1	0.1585	-0.101	0.1212***	0.0416***		-0.5975***	0.1635***	-0.3928***	-0.8776***	-0.7225***
MA(2) ψ_2	-0.6175***	0.0651		0.0427*		-0.5934***	-0.0588**	0.3308***		0.7002**
MA(3) ψ_3	-0.3575**	0.2063*		0.0409***		-0.5511***		-0.5403***		-0.5835**
MA(4) ψ_4	0.6766***	-0.7853***		0.0412***		0.7368***		0.8548***		-0.3631
MA(5) ψ_5				0.0352***		0.0052				
Variance	**USGB**	**USB**	**USS**	**USF**	**USO**	**CNGB**	**CNB**	**CNS**	**CNF**	**CNO**
Constant α_0	0	0**	0***	0	0***	0	0*	0**	0	0***
GARCH(1) α_1	0.9276**	0.4314*	0.0186***	0.043	0.0279***	0.5118***	0.8866***	0.9032***	0	0.887***
GARCH(2) α_2	0	0.4653**		0.0418***					0.6611***	
ARCH(1) β_1	0.0796***	0.0491***	0.0144	0.015***	0.0437**	0.4287***	0.1017***	0	0.171***	0.0421**
ARCH(2) β_2				0.0151**				0.0942**	0.121**	
Leverage(1) γ_1	-0.0536**	0.1044***	0.0505***	0.0219	0.0778***	0.119	-0.0079	0.0457	0.0709	0.1123***
Leverage(2) γ_2				0.0212*				-0.0406	0.023	
DoF ν	5.0915***	7.6199***	0.3058***	0.3939***	0.1904***	2.5852***	5.2495***	3.8525***	3.8343***	4.981***
No. of Obs.	1830	1830	1830	1830	1830	1799	1799	1799	1799	1799
AIC	-15746.1	-8731.85	-12785	-15977.9	-8795.99	-21313.2	-12596.4	-11231.2	-17789.7	-8821.59
BIC	-15668.9	-8654.68	-12740.9	-15878.7	-8768.43	-21230.8	-12558	-11143.3	-17734.7	-8744.66

Table notes: significance level, 1% ***, 5% **, 10% *.

The mean equations of different assets have different lag lengths or different lengths of memory. Specifically, West Texas Intermediate (USO) crude oil index has no dynamic terms at all in the mean component. Turning to the volatility equations, all returns have significant GARCH and ARCH terms, indicating conditional heteroskedasticity or volatility clustering features. The leverage effects are also found for assets in both countries, which suggests that negative shocks tend to generate greater volatility.

To allow for thick tails, we assume Student's t distribution for marginal distributions. The estimated degrees of freedom confirm this hypothesis—a lower degree of freedom means a thicker tail. A t distribution converges to normal distribution if the degree of freedom is higher than 20. In our case, all estimated degrees of freedom are lower than 8, showing significant thick-tail features. Relatively speaking, green bonds in China tend to have lower degrees of freedom or greater tail risks.

3.2. Copula Functions

Based on the residuals of the marginal distribution models, we then estimate copulas of between green bonds and each asset. **Table 6** presents the estimation results of constant copula models with popular specifications.

Table 6 Estimation Results of Time-Invariant Copulas

		USB	USS	USF	USO	CNB	CNS	CNF	CNO
Normal	ρ	-0.400***	-0.054**	-0.597***	-0.01	-0.478***	-0.046*	-0.02	-0.004
	$\tau_L = \tau_U$	0	0	0	0	0	0	0	0
	AIC	-318.07	-3.374	-805.21	1.812	-466.4	-1.82	1.248	1.965
Student's t	ρ	-0.427***	-0.063**	-0.612***	-0.005	-0.457***	-0.050**	-0.02	-0.001
	DoF ν	4.423***	7.036***	4.041***	8.619***	4.375***	8.816***	99.99***	28.28***
	$\tau_L = \tau_U$	0.0144	0.0166	0.0059	0.0124	0.0126	0.0093	0	0
	AIC	-416.34	-36.7	-913.11	-19.51	-533.5	-19.864	3.539	2.103
Clayton	ρ	0.0001	0.0001	0.0001	0.0134	0.0001	0.0001	0.0001	0.0001
	τ_L	0	0	0	0	0	0	0	0
	AIC	2.099	2.001	2.166	1.639	2.132	2.014	2.01	2.007
Rotated	ρ	0.0001	0.0001	0.0001	0.0082	0.0001	0.0043	0.0001	0.0182
Clayton	τ_U	0	0	0	0	0	0	0	0
	AIC	2.096	2.007	2.16	1.875	2.128	1.962	2.005	1.438
SJC	τ_U	0	0***	0	0**	0	0***	0***	0
	τ_L	0	0***	0	0	0	0***	0***	0***
	AIC	49.982	8.261	74.253	4.551	59.776	8.082	8.798	5.983

Table notes: significance level, 1% ***, 5% **, 10% *.

For time invariant models, we estimate normal, student's t, Clayton, rotated Clayton, and SJC copula distributions to show robustness and to facilitate model selection. We report both correlation coefficients ρs as well as tail dependence measures τs, equation (5) and (6). Normal distribution has no tail dependence ($\tau_L = \tau_U = 0$), Student's t assumes symmetric tail dependence, which are positive for all assets ($\tau_L = \tau_U > 0$). This result implies that when there is a negative *rare* shock in some asset, it is likely that green bonds also undergo a negative *rare* shock. Be aware that tail dependence is not to be confused with correlation coefficient, which is a measure of linear dependence. In fact, most estimated ρs are negative ($\rho < 0$)—in normal times, if there is a negative shock to some asset, it is likely to have a positive shock to green bonds. In other words, the hedging effect of green bonds can differ between normal times and crisis times. Clayton copula assumes lower tail dependence ($\tau_L \neq 0$) but no upper tail dependence ($\tau_U = 0$), while rotated Clayton assumes the reverse, but none of them are significant. The SJC copula assumes asymmetric tail dependence, but the estimates are very small despite being significant. Using AIC as the model selection criterion, Student's t copulas stand out as the most efficient assumption for most assets apart from CNF and CNO in which normal distribution is preferred.

To visualize the estimated copulas, we use 3D mesh plots (**Figure 2**) to compare between assets and between countries. Starting with green bonds and "brown" bonds, the copulas of US and China are almost identical. Both copulas show tail dependence at lower and upper quantiles. Moving to green bonds and stocks, the two countries again share very similar shapes only with thicker tails (larger degrees of freedom). Next, the US dollar index still maintains a similar copula to bonds and stocks, while the copula for Chinese exchange rate is almost flat (with a degree of freedom close to 100), which means it is basically a normal copula. Turning to oil indices, the US and China share a similar shape but China has a flatter copula due to its weak position in the international oil market.

Figure 2 Copula distributions with Green Bond in US and China

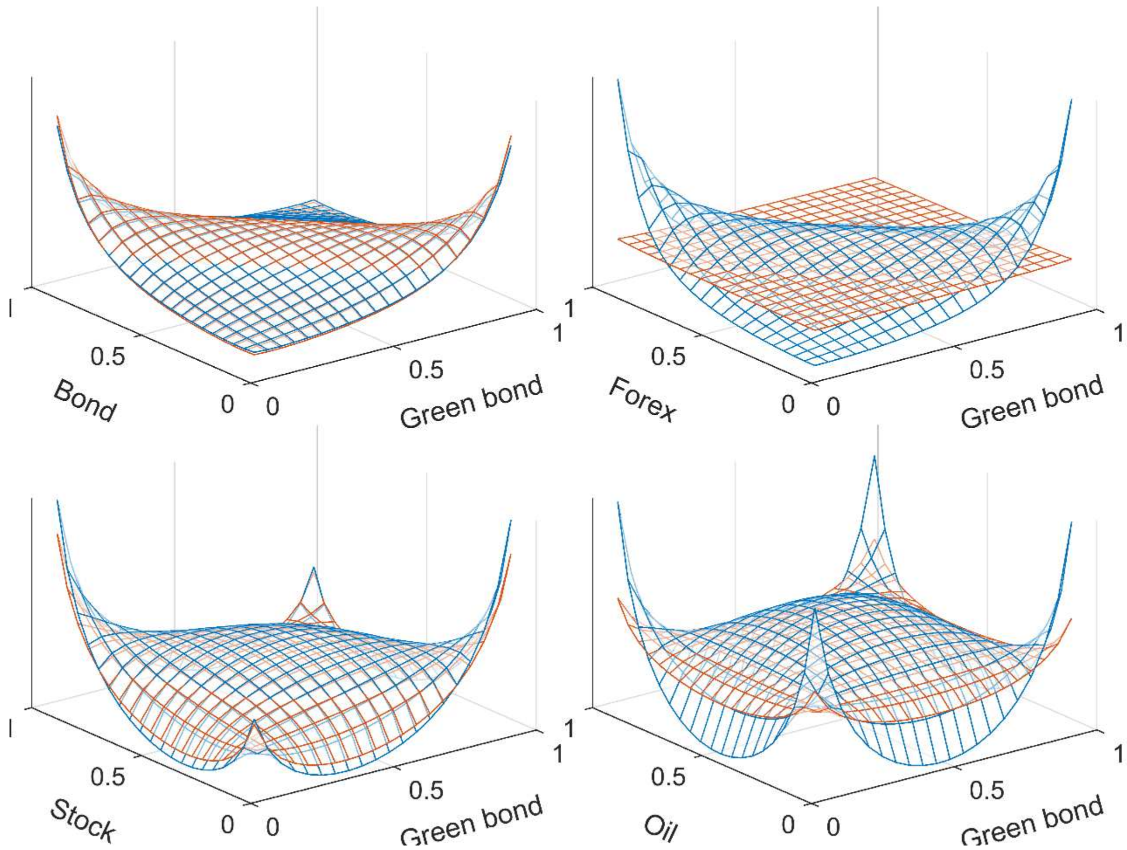


Figure notes: Blue mesh surfaces are copulas in the US, and red ones are copulas in China. The copulas are assumed to follow Student's t distributions.

If time-variation of copula functions is allowed, then correlation coefficient (ρ_t) and tail dependence (τ_{Lt}, τ_{Ut}) can change over time t. This dynamic feature is modeled by equation (7) following Reboredo (2018). Given that Student's t copula is the optimal choice, we focus on Student's t time-varying copulas, with normal time-varying copulas for CNF. We present the estimation results of time-varying copulas in **Table 7**. It is shown that time variation coefficients (a, b, c) are mostly significant.

To demonstrate time-varying features, correlation coefficients between green bonds and these assets are plotted in **Figure 3**. The fluctuations during the COVID pandemic become erratic. It is worth mentioning that, unlike the US, the correlation between green bonds and the forex market in China (i.e., USD/CNY currency pair, denoted as CNF) is stable throughout the sample period. Other asset markets in the US and China largely converge, especially in bond markets where the correlations are consistently negative for both countries.

Inclusion of time variation features imposes overparameterization costs, but the improved goodness of fit justifies a more sophisticated model according to the AIC information criterion. Comparing the AICs between **Table 6** and **Table 7**, most time-varying models are superior to time-invariant models apart from USB and CNS. The benefit of employing a time-varying model increases as the sample includes more pandemic observations. In fact, in an earlier run when only 2020 data are included, constant parameter models are favored. This finding suggests that the modelling choice can depend on data availability. Policymakers and decision-makers in the financial market should frequently update their models on new data arrival.

Table 7 Estimation Results of Time-Varying Copulas

		USB	USS	USF	USO	CNB	CNS	CNF	CNO
Normal	ρ	0.835***	-0.149	0.979***	0.684***	-0.98***	0.6717*	0.638	0.675
	a	-0.989***	-0.011	-0.236***	0.0017	-0.989***	-0.178*	-0.076	-0.031
	b	0.0319	0.051***	-0.079***	0.400***	-0.136***	0.077	0.3804**	-0.51***
	c	-0.388***	1.638***	2.013***	-1.996***	0.3321***	-1.93***	-1.97***	-0.675
	AIC	-313.09	-4.5049	-808.96	-6.5371	-471.92	2.148	2.398	-1.967
Student's t	ρ	0.357	-0.156	0.967	0.660	-0.98***	-0.599	0.018	0.654
	ν	4.484***	7.096***	3.964***	9.489***	4.468***	8.566***	99.81***	31.12***
	a	-1.906***	-0.012	-3.108***	0.004	-1.200**	-0.150	-0.078	-0.02
	b	0.031	0.047***	-0.091	0.274***	-0.05	0.139	0.3533***	-0.48***
	c	-2.411***	1.728***	-2.570***	-1.996***	-0.285***	-1.30***	-2.007***	-0.664***
	AIC	-412.46	-41.11	-914.79	-24.04	-535.37	-15.5094	4.2018	-1.5362

Table notes: significance level, 1% ***, 5% **, 10% *.

Figure 3 Time Variation of Correlations with Green Bond in US and China

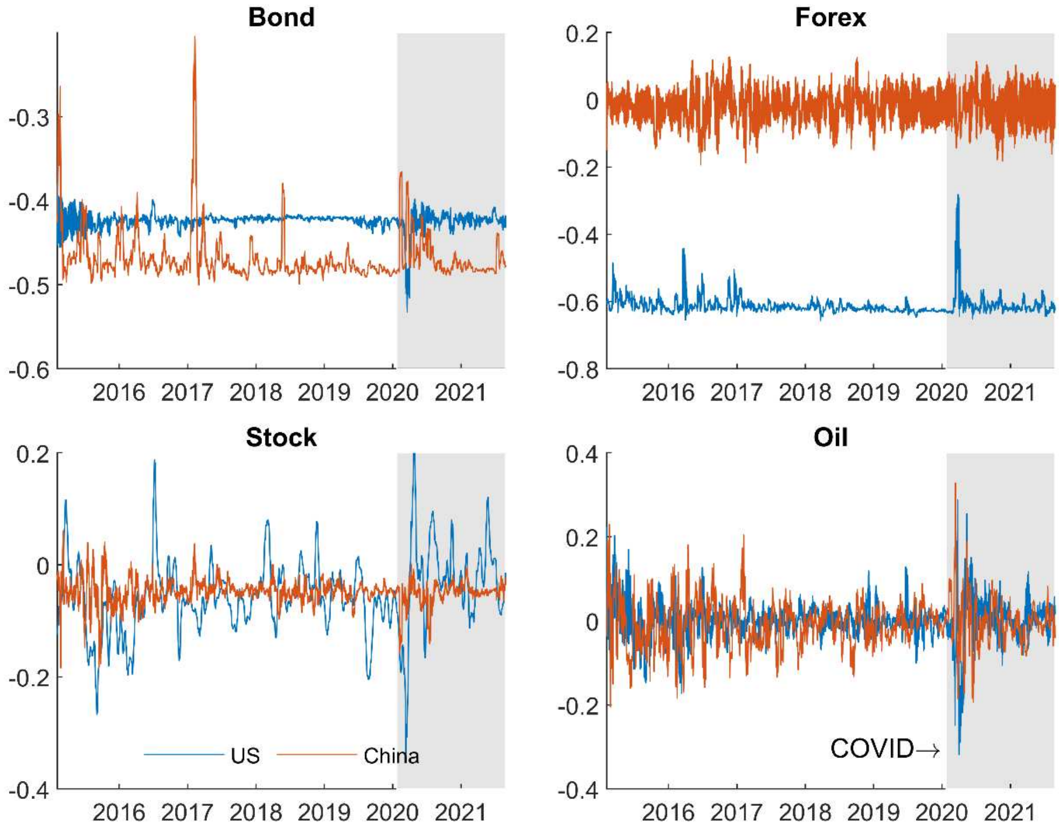


Figure notes: Blue lines are correlations of the US (left axes), and red ones are correlations of China (right axes). The shaded areas indicate the COVID pandemic (according to the WHO announcement).

3.3. Robustness

As shown in the previous section, estimated copulas display significant tail dependence. To provide a robustness check, we adopt two quantile-based measures to quantify the dependence of joint distributions between these assets and green bonds. The first measure is the quantile dependence, which calculates correlation coefficient within different quantiles (Patton, 2006). The second measure is the exceedance correlation developed by Ang & Chen (2001). A correlation at a given exceedance level is defined as the correlation between a pair of random variables when both rise or drop of more than a given number of standard deviations away from the means. It is a more flexible measure allowing for different degrees of dependence at different quantiles. The two measures provide a nonparametric alternative to copulas to describe the distributional dependence of chosen asset pairs. The advantage of the quantile-based approach, as discussed in the literature review, is that it can capture dependence in the entire joint distribution, not limited to the tails or means only. Also, it is nonparametric, so it is free from specification bias.

Figure 4 Quantile Dependence with Green Bond in US and China

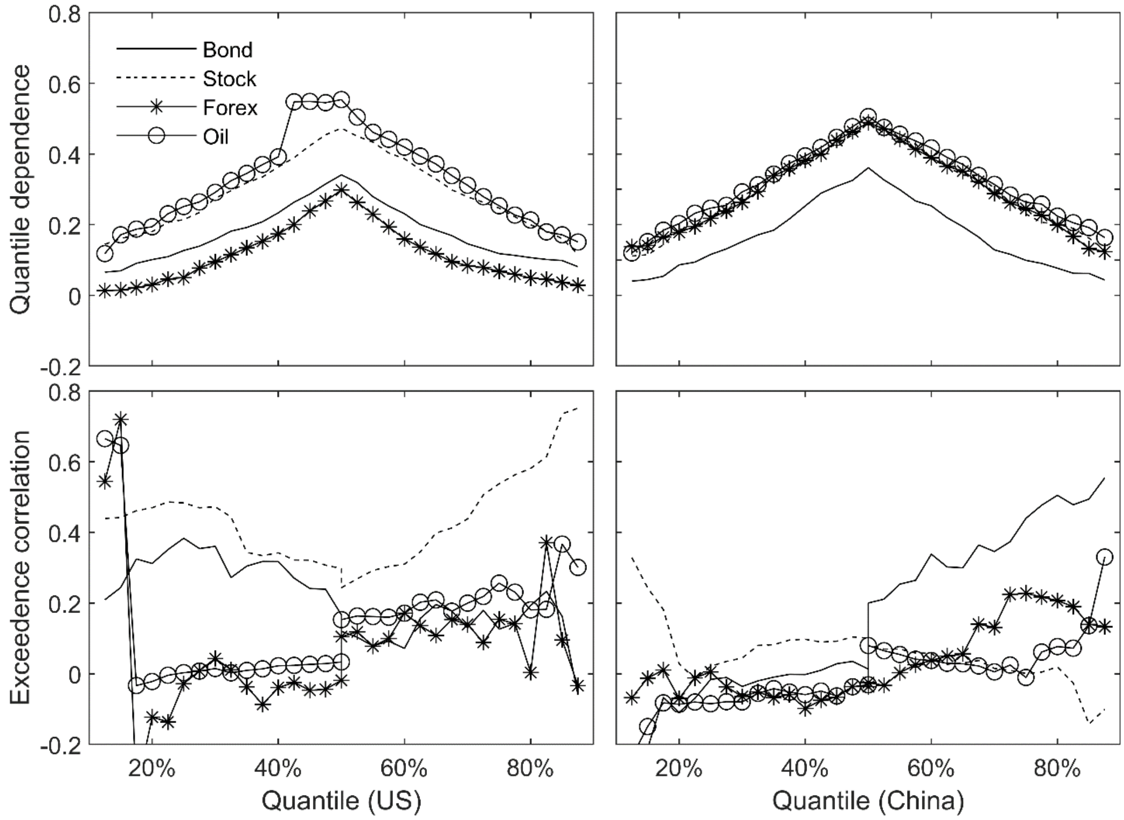


Figure 4 illustrates the two measures for the US and China. According to the quantile dependence (the upper two panels), the dollar index (forex) has the weakest tail dependence with green bonds in the US, followed by bonds, stocks, and oil. In China, by contrast, it is the bond market that has the weakest tail dependence. In terms of the exceedance correlation (the lower two panels), tail dependence is asymmetric for all assets in both countries. For example, in the US, the lower tail dependence of forex market and green bond market is 0.6, but the upper tail dependence is negative. This suggests that if there is a rare, bad shock, both markets tend to get hit, but if there is a rare, good shock, only one market is likely to receive it. This asymmetry is also observed in Chinese markets.

Compared with the estimation results in **Table 6**, tail dependence estimated in the copula approach and the quantile-based approach shares qualitative consistency. For example, the nonparametric quantile dependence (the upper panels) is mostly symmetric at tails in line with the symmetric feature of Student's t copulas. Exceedance correlations, however, are more erratic because it is based on stepwise exceedance and subject to small sample bias towards tails. This is an important drawback of nonparametric approaches since it does not leave noise processes out of the analysis. In contrast, the copula approach controls for dynamics in mean, so the results are more stable and reliable.

4. Discussion

The results show that the correlations between green bonds and other financial assets are significant, time-varying, and quantile-dependent. How can we make use of this information in investment practice? To evaluate the potential role of green bonds as safe-heaven assets to hedge against rare risks, it is common to calculate the optimal hedging weight (HW) and evaluate the hedging effectiveness (HE) of green bonds in a portfolio.

We follow Jin et al (2020) and adopt the Theory of Minimum Variance Heading Ratio (Johnson, 1960). Assume a portfolio is composed of an asset and a green bond index. The return of the hedged portfolio, r_{ht}, and its variance, $V(r_{ht})$, depend on the HW of green bond index (w_{gt}):

$$r_{ht} = (1 - w_{gt})r_{it} + w_{gt}r_{gt}. \tag{8}$$

$$V(r_{ht}) = (1 - w_{gt})^2 V(r_{it}) + w_{gt}^2 V(r_{gt}) + 2(1 - w_{gt})w_{gt}Cov(r_{it}, r_{gt}) \tag{9}$$

To minimize the variance of the hedged portfolio, take partial derivative of $V(r_{ht})$ with respect to w_{gt} to obtain the optimal HW (w_{gt}^*):

$$\frac{\partial V(r_{ht})}{\partial w_{gt}} = 0 \rightarrow w_{gt}^* = \frac{V(r_{gt}) - Cov(r_{it}, r_{gt})}{V(r_{it}) + V(r_{gt}) - 2Cov(r_{it}, r_{gt})}. \tag{10}$$

Note that if $w_{gt}^* > 0$, then the hedged portfolio contains a long position of green bonds. If $w_{gt}^* < 0$, then the portfolio is hedged by holding a short position of green bonds. Covariance and variance terms are conditional forecasts based on the estimated marginal distribution of TGARCH models described in subsection 3.2.

Figure 5 presents the time-varying optimal HW w_{gt}^* for the selected financial assets of the two countries. In the cross-country dimension, it is surprising that the correlations between green bonds and other bonds in the US and China are closely tracking each other, both before and after the COVID pandemic. It shows that the bond markets and green bond markets of the US and China are determined by similar factors such as monetary policy and green technological progress. In contrast, other markets such as stock and forex between the two markets significantly diverge (Guo & Zhou, 2021). In the over-time dimension, the COVID pandemic seems to reduce the correlations between financial assets and green bonds. It implies that the hedging role of green bonds is reduced during rare tail risks. Other influential events like the US-China trade war since 2018 and the oil price plunge in early 2020 may disturb the correlations temporarily but the influences are short lived.

Figure 5 Optimal Hedging Weights of Green Bonds in US and China

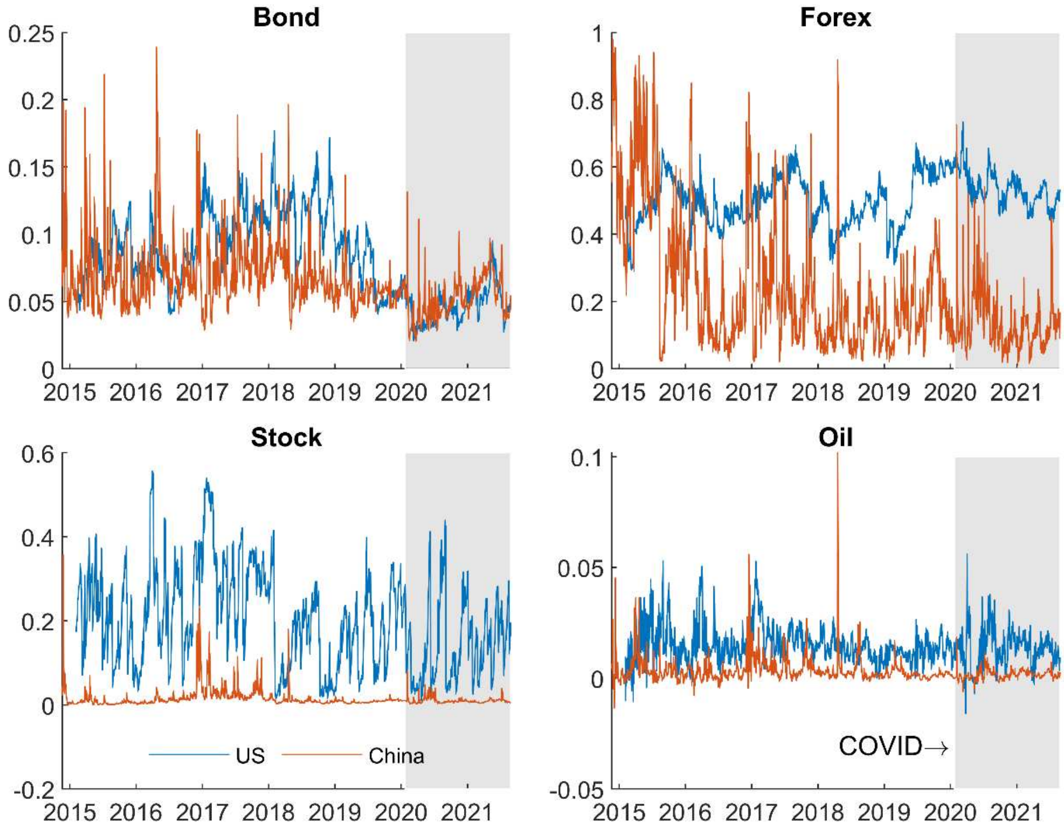


Figure notes: Blue lines are correlations of the US, and red ones are correlations of China. The shaded areas indicate the COVID pandemic (according to the WHO announcement).

From equation (10), it is straightforward that the diversification benefit of a hedged portfolio depends on the correlation between the underlying assets and the variances of them. To better quantify the diversification benefit of green bonds, it is useful to have a metric to summarize the hedging effect. Ku et al. (2007) propose a measure termed hedging effectiveness (HE) based on risk reduction:

$$HE \equiv \frac{V(r_{it})-V(r_{ht})}{V(r_{it})}. \tag{10}$$

Table 8 compares the optimal HWs and HEs of green bonds in the US and China, before and after the COVID pandemic. We can draw two important conclusions. On the one hand, the hedging effects of green bonds in China tends to be smaller than those in the US before the pandemic, but the gap becomes smaller or even reversed (e.g., bond market) since COVID. This indicates a fast development of green bonds in China relative to the US in recent years. In fact, China issued more than one-third of the global green bond issuance, ranking the first in the world (Wang et al., 2019). On the other hand, as a tail risk, the pandemic substantially reduced the hedging effects of green bonds with respect to bonds, stocks, and oil in both countries, but the hedging effects are still positive. It is worth pointing out that, despite smaller, this is unfair to compare HEs before and after the pandemic. It is because the HEs before the pandemic measure the hedging effect in normal times, while the HEs after the pandemic measure the hedging effect against tail risks. Specifically, the hedging effects in forex markets grow even stronger for both US and China since 2018, partly due to the exacerbating US-China trade war. Uncertainties in forex markets creates greater hedging capacity for green bonds in both countries.

Table 8 Hedging Weights and Hedging Effectiveness (pre-COVID VS. COVID)

		US		China	
		Pre-COVID	COVID	Pre-COVID	COVID
Bond	HW	9.13%	4.65%	6.97%	5.23%
	HE	18.65%	9.45%	14.24%	10.65%
Stock	HW	21.23%	14.75%	1.62%	1.03%
	HE	34.88%	25.30%	3.16%	2.05%
Forex	HW	50.16%	52.58%	26.88%	13.87%
	HE	**71.55%**	**74.15%**	**6.02%**	**23.76%**
Oil	HW	1.49%	1.35%	0.35%	0.17%
	HE	2.95%	2.69%	0.71%	0.34%

Table notes: HW = hedging weight, HE = hedging effectiveness.

To summarize, optimal HWs during the pandemic slightly dropped because of positive tail dependence between green bonds and other assets. However, it does not mean the hedging effect of green bonds in extreme times is weak. It is weaker compared to normal times. In fact, recent literature finds similar results for alternative hedging assets like Brent oil (Kang et al., 2021), gold (Salisu et al., 2021), and other precious metals (Mensi et al., 2021).

5. Conclusions

Green bonds provide financial capital for sustainable growth and a safe-heaven investment vehicle against financial shocks. It is well documented in the literature that, in normal times, hedging effectiveness of green bonds is significant in both developed countries like the US and emerging economies like China. However, evidence for the hedging effects during the COVID pandemic is still scanty.

To choose the most reliable method to address this research question, we critically review and comprehensively compare four prevailing approaches in the green finance literature. The copula approach is adopted for its flexibility and reliability in capturing tail dependence between assets. It is found that the pandemic does reduce the hedging effectiveness of green bonds with bonds, stocks, and oil, but boost the hedging effectiveness in forex markets. The behavior of green bonds in the US and China resembles each other, especially during the pandemic. There is a converging international green bond market in terms of both marginal distribution and copula function.

This paper offers new evidence for connectedness between conventional financial assets and green financial assets. It is important for portfolio management and risk diversification in both US and China, during both normal times and crisis times. Moreover, it also points some directions for policymakers. First, given the significant hedging effect of green bonds, governments should issue related regulations and industrial standards, which are recognized by international counterparts. International convergence of green bond standards can improve information disclosure and transparency, which can in turn strengthen the diversification function of green bonds for both developed and emerging economies. Second, resilience against rare disasters like climate risks and pandemic risks is the most important theme of the international community of our times, particularly after the COVID pandemic. Major economies like the US, the EU, and China adopt a sustainability strategy and support investment in green assets. It is an inevitable trend of an expanding international green bond market. However, as a safe-heaven asset, green bonds may be used by arbitragers and hot money in cross-border speculations. For emerging countries like China, it is advisable to develop off-shore institutional investors to hold long-term positions of green bonds. It can reduce the short-term shocks to the stability of green bonds market due to speculative activities in the forex market.

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Appendix: Daily returns of green bonds and other assets