Uncertainties drive the green bonds dance: two pioneer markets perspective

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Abstract: Motivated by the lack of studies related to the uncertainties driving the green bond markets, we aim to fill this gap by discussing the effects of three uncertainty indicators in different market states. In specific, we applied the cross-quantilogram method to detect quantile dependences and utilize the quantile causality test for robustness as well as capture the predictive causalities. To understand the heterogeneities between developed and developing markets in uncertainty transmission, this paper mainly focused on the two pioneer markets (the USA and China), as representatives. The results show that uncertainties are important drivers for the green bonds dance but they would play different roles in different nations. The most influential uncertainty determinant of USA green bonds is financial uncertainty while China is economic policy uncertainty. Additionally, the impact on green bond returns would vary at different market states, and green bond volatilities may respond abnormally to extreme increasing changes of the uncertainties. These findings imply the financial characteristics and the inside heterogeneities between different markets of green bonds. Eventually, the corresponding great investment implications and policy significances are discussed in detail in the concluding section.

Keywords: Uncertainties; Green bonds; Quantile; USA and China; Risk management

JEL Classification: E60, G10, G19

Data Availability Statement

The dataset used in this study will be made available on request

Abbreviations

UGBI: Green bonds index of United States (return series)

CGBI: Green bonds index of China (return series)

UGBIV: Green bonds index volatility of United States

CGBIV: Green bonds index volatility of China

UVIX: The CBOE VIX index of United States (return series)

CVIX: The CBOE VXFXI index of China (return series)

AEPU: The economic policy uncertainty of the United States (return series)

CEPU: The economic policy uncertainty of China (return series)

OVX: The CBOE OVX index (return series)

1. Introduction

The severity of climate warming is gaining global consensus (Dunne et al., 2013), many countries have therefore proposed ambitious carbon neutral targets. The climate-resilient economy therefore has received the common attention of the government, international organizations, and the public (Liu and Lin, 2017; Lin and Jia, 2019). This background brought new green financial opportunities for individuals and institutional investors, in particular, green bonds with lower overall environmental risks have been widely sought after (Tolliver et al., 2019; Sartzetakis, 2020). Green bonds allow features and mechanisms similar to conventional fixed-income corporate bonds (Reboredo and Ugolini, 2020), which both issue bond certificates to investors and promise to pay interest at a certain rate and repay the principal. The main difference is, green bonds have much stricter "use of proceeds" criteria, the raised funds are limited to environment-friendly projects, such as carbon emissions reduction, biodiversity protection, clean transportation, etc. Thus, green bonds are recognized as an appropriate financial instrument for the transition to a climate-resilient economy (Ng and Tao, 2016; Banga, 2019). It can not only attract investment in environment-friendly projects through monetary incentives but also promote changes in financial orientation and compress the investment space of high-pollution fossil energy projects.

In fact, with the increasing awareness of environmental protection and decarbonization, this new financial asset has been receiving extensive attention from global investors, especially within the sustainability-oriented financial community. According to the statistics of the Climate Bond Initiative, the total amount of global green bond issuance reached 170.9 billion dollars in 2018 and such a scale is expected to further expand to 350 billion dollars after 2020. Consequently, it is vital to understand green bonds such as financial features, return and volatility drivers, or risk transmission mechanisms, which would provide investors with necessary reference information and help policy-makers apply this new asset in the carbon-neutral process. Such reality needs have made green bonds become the main research topic among financial scholars.

Although some empirical studies investigate (1) the unique financial properties of green bonds by comparing them with the conventional bonds and (2) the complex correlation characteristics between this asset and other financial assets, less is known about the driving roles of macro external uncertainties on the green bond market oscillations. Uncertainty is always an important factor likely to affect the behavior of investors, such as financial trends, future economic policies, and the potential effects of correlated market changes (Lin and Su, 2020). The mainstem verified channel of uncertainty transmitting to real finance is that uncertainty induced panics affecting the investors' emotion and behaviors (Popp and Zhang, 2016; Al-Yahyaee et al., 2019). This may cause both recessions or risk premiums on financial assets, which rely on the assets' safe-haven characteristics (Al-Yahyaee et al., 2019). Meanwhile, uncertainty would affect investment decisions through future government policies, eventually shocks to financial markets (Kang and Ratti, 2013; Naifar and Hammoudeh, 2016). Different assets would always have distinct responses to uncertainty changes (Berger and Uddin, 2016; Lin and Su, 2020). With the financial nature of green bonds, assuming that driven effects exist from uncertainties to this market is reasonable. Furthermore, the green bond is an emerging asset, it is important that uncovering the driving roles of uncertainties to outline its financial properties and provide some guidelines for increasing investors with green preference. Thus, this study aims to fill this knowledge gap.

We choose three kinds of appropriate indicators to measure uncertainty induced from different sources, they are VIX implied volatility index, EPU index, and OVX crude oil volatility index. These indicators have always been unutilized as the representative proxies to measure macro uncertainties (Jones and Olson, 2015; Gozgor et al., 2016; Ji et al., 2018; Al-Yahyaee et al., 2019; Sarwar and Khan, 2019). The VIX implied volatility index collects the "risk-neutral" expected stock market variance that can be termed as the financial or equity uncertainty. The news based EPU indices capture the uncertainty associated with spikes in government regulatory and fiscal policies, thus treated as policy-induced uncertainty, it would affect the behavior of financial agents and lead to delays or adjustments in their investment decisions. For the crude oil volatility index, OVX is based on oil options' implied volatility and represents the investors' sentiment on the crude oil market performance, thereby effectively measuring the crude oil uncertainty.

One issue worth noting when studying green bonds is that there may be some potential heterogeneities between markets in developing and developed nations. Previous studies have found that new financial assets in developing countries usually have poor supporting systems and cumbersome market integration steps, which bring them different risk exposure from developed countries (Ariss, 2010; Ali et al., 2017). Moreover, a shred of more direct evidence is Banga (2019), which indicates that developing countries may be troubled by the balance between economic development priorities and the mandates of decarbonization, such institutional barriers lead to the development and financial features of green bond compounded. Follow this guideline, Wang et al. (2020) have detected the debt and stock market reaction to green bond issuance in developing countries, via China as the research setting. Thus, we conduct empirical research based on two representative pioneer markets, the USA and Chinese green bonds, aiming to obtain a comprehensive understanding and provide some summarized features for green bond markets in different nations.

In parallel, following the previous related studies (Phan et al., 2018; Kang et al., 2019; Das and Kannadhasan, 2020), financial assets are always asymmetrically affected by uncertainties, and green bonds often show asymmetric characteristics in their cross-market relations too. Thus, we mainly use the cross-quantilogram (Han et al., 2016) and causality in quantiles methods (Balcilar et al., 2016) as our main methodologies to study the driven effects of uncertainty on green bonds and the predictive causality between the two. Both methods are econometric models based on quantile regression, which can effectively capture the asymmetric relationships between variables under different quantile states. It is worth noting that the cross- quantilogram model can both consider the quantiles of the independent variable and the dependent variable; the corresponding results may help us analyze the market's response to uncertainty shocks under different risk scenarios.

This article confirms the asymmetric driving effects of three uncertain factors on the green bond markets, and uncover the heterogeneous features among developed and developing countries. The discussions on green bond return and volatility may provide investors and policy-makers with sufficient information and assistance. In sum, we contribute to the domain of green bonds in the following aspects: (1) With the empirical study on how the uncertainties affect the green bonds return and volatility, we uncover the driven effects and some safe-haven characteristics, these results fill the knowledge gap of this new area and provide some significant implications for risk aversion of green bonds.

(2) This study employs a thorough research framework based on three uncertainty indicators and the two pioneer markets, thereby obtaining the conditions about the heterogeneities. (3) The methodologies utilized in this research allow us to obtain the asymmetric effects of uncertainties, this would improve the theoretical significance of the formulation of government policies and investors' investment decisions.

The remaining parts of this paper have been organized as follows. Section 2 introduces the literature review. Section 3 is concerned with the data set and variables discussed for this study. Section 4 describes the methodologies. The fifth section analyzes the main results of empirical investigation. In the last section, we discuss the main conclusions and summarize some implications.

2. Literature review

As mentioned above, this article aims to investigate how the macro uncertainty factors drive the US and Chinese green bond markets. Thus, we have divided the review into two parts according to the antecedent and outcome variables: the studies on green bonds and the driving effects of uncertainties.

2.1 Green bonds

As a young but essential financial asset, the existing literature on green bonds is increasing and focuses particularly on two fields, the green or financial nature, and cross-market linkages. Pham (2016) conduct a pioneer quantitative systematic study of the green bond by applying a multivariate GARCH model and comparing it with the conventional bonds. He provides an efficient analysis idea for this research domain, the followers usually detect the characteristics of green bonds by comparing them with conventional bonds. Some researchers make such comparisons and capture the differences between the two in terms of risk premium, issuance profitability, etc. For instance, Karpf and Mandel (2017) find green bonds may induce higher yields than conventional bonds due to their special credit characteristics. Baker et al. (2018) investigate this difference from the perspective of "green" attributes, indicating lower yields of green bonds. Then, Zerbid (2019) performs a matching method, followed by a two-step regression procedure, to estimate the yield deviation between a green bond and a counterfactual conventional bond. Its results also suggest that the yields of green bonds are lower than that of conventional bonds. Additionally, the stock positive responses of shareholders to green bonds issuance in USA and EU are uncovered by Baulkaran (2019) and Tang and Zhang (2020), Wang et al. (2020) thereby shift focus to developing countries, they suggest Chinese stocks have similar rises of profits after issuing green bonds.

A growing body of literature on green bonds pays particular attention to its cross relations with other financial assets or instruments. An early example of this issue is Reboredo (2018), which concentrates on the co-movement, diversification, and price spillover effects between green bonds and financial markets (corporate and treasury bonds, stock, and energy commodities), via the copula models. This research finds corporate and treasury bonds always have close co-movements with green bonds but equity and energy markets do not. Then, Broadstock and Cheng (2019) study the determinants of correlation patterns between green and black bond markets, illustrating the crucial roles of macroeconomic variables. In some more recent papers, many complex relationships between green bonds and other assets have been emphasized. Huynh et al. (2020) focus on the linkages among several emerging financial assets containing green bonds, Liu et al. (2020) devotes to the risk spillovers between green bonds and clean energy stocks, and

Reboredo et al. (2020) expand the sample country from the USA to other regions like Europe, gaining the connectedness networks in the frequency domain. Besides, Pham and Huynh (2020) capture the links between investor attention and green bonds return (volatility) series. Regrettably, there are no investigations directly related to the research issues of this article that exploring the driving roles or links of macro uncertainties on green bonds, thereby displaying a significant knowledge gap in the literature.

2.2 The driving roles of uncertainties

An important strand of the recent research in finance contents that uncertainty should matter for the financial markets' performance (Naifar and Hammoudeh, 2016; Lin and Su, 2020b). Financial market uncertainty that usually proxied by Chicago Board Options Exchanges (CBOE) VIX obtains the most insights in this area. Antonakakis et al. (2013) show that the U.S. stock market returns are negatively affected by financial uncertainty via the DCC model. Sarwar (2014) then finds a strong negative contemporaneous relation between VIX changes and European stock returns and presents some asymmetric characteristics. Furthermore, other assets may also display a similar dependence on the VIX that has been widely examined (see, Kang et al., 2019 (bonds), Silvennoinen and Thorp, 2013 (commodities), Balcilar et al., 2017 (gold), etc.).

After Baker et al. (2016) developed a set of economic policy uncertainty (EPU) index, there is a lot of literature paying attention to its key roles in finance. For instance, Li (2017) tested the hypothesis that China's economic policy uncertainty (EPU) commands a positive equity premium and found that there may be miss valuation co-movements in the stock market when the economic policy is in an uncertain state. EPU can always drive multiple aspects of the financial system, including the return (Bonaime et al., 2018; Yang et al.,

2019) and volatility (Su et al., 2019) and there are always some asymmetric and nonlinear features in such effects. You et al. (2017) and Al-Yahyaee (2020) verify this fact based on the quantile and tail dependence methods, respectively. When comparing different economies for the impact of the EPU on the domestic financial market, it can be found that the driven roles of EPU might have some heterogeneous characteristics (Demir and Ersan, 2017).

Additionally, oil market uncertainty is always revealed as an important source of uncertainty for fossil fuel-related assets, such as energy futures (Gong and Lin, 2018; Nikkinen and Rothovius, 2019), clean energy stocks (Dutta, 2017; Ahmad et al., 2018). OVX appears to be a superior indicator to measure this uncertainty and is widely utilized in the previous literature whose financial influence also displays the asymmetric format as other uncertainties (Kocaarslan et al., 2017; Xiao et al., 2018;). Among all the related literature, there is only one study that combined the green bonds and uncertainties. Broadstock and Cheng (2019) detects the roles of VIX and EPU on the time-varying relations between black and green bond prices but neglect the direct information transmit on green bonds return and volatility.

Overall, we can find the research blank of uncertainty driving the green bonds from both the perspectives of uncertainty and green bonds literature. Combinedly considering the importance of such knowledge in investing and promoting green bonds, it is necessary to focus on this issue. Our research idea came into being. Reviewing the existing literature, we could conclude the uncertainty always produce an asymmetric impact on financial assets and different effects may exist in the cross-connections of green bonds across market states. This guides us to employ the nonlinear model in empirical studies. Meanwhile, the literature in the field of driving roles of uncertainties also provides the rationale to concentrating on the heterogeneities between different countries. Based on the above study facts, we eventually construct our research frameworks (See Appendix Figure 1).

3. Data and Variables

3.1 Data sets

This study contains two original data sets, green bonds and uncertainty indices. Following Reboredo et al. (2020), we track the price performance of USA green bonds by Bloomberg Barclays MSCI US Green Bond Index. This index contains bonds that use proceeds for green projects (such as pollution prevention and decarbonization), thereby are consistent with the Green Bond Principles. To measure the overall financial performance of Chinese green bonds, we use the ChinaBond Green Bond Index, compiled by the Chinese official settlement agency, China Central Depository & Clearing Co., Ltd. (CCDC). This index also consists of bonds with the green certification or which meets the green principles, thus always be treated as a representative benchmark for Chinese green bonds.

Previous contents have stated that this paper concentrated on three kinds of uncertainty factors derived from different sources, including financial uncertainty, economic policy uncertainty, and oil uncertainty. These uncertainties are reflected by the respective price indices. Specifically, for the US and China cases we take, respectively, the following uncertainty indices:

Financial uncertainty: The stock market volatility index (VIX) is a key measure of stock market expectations of near-term volatility, which always be proved to be a leading uncertainty factor driving the evolution of financial assets (see, Al-Yahyaee et al., 2019;

Stolbov and Shchepeleva, 2020). Thus, we respectively use the CBOE VIX and CBOE VXFXI to measure the USA and Chinese financial or stock market uncertainty. The CBOE VIX extracts the implied volatility of S&P 500 index options while CBOE VXFXI measures the expectation of 30-day volatility of the China ETF. It should be noted that their impacts on financial assets (like equity, fixed-income bonds, commodity futures, etc.) have both been detected by various literature, this provides the rationale of us utilizing these indices.

(2) Economic policy uncertainty (EPU): For the indices of EPU, Baker et al. (2016) develop a famous set of indices to reflect the economic policy uncertainty of different countries. The index of the USA can effectively measure the actual situation and would be applied in this research, but there are some backward for its index of China. Specifically, US-EPU is based on newspaper archives from Access World New's NewsBank service that contains over 1000 newspapers, while the index for China only captures the information of the South China Morning Post (SCMP), an English newspaper in Hong Kong. Thus, the Chinese EPU index constructed by Baker et al. (2016) is far less accurate than the USA index. It will be sensitive to news related to Hong Kong and may cause some bias from editorial policies or preferences of this only specific newspaper. Moreover, this index lacks a daily assessment of Chinese economic policy uncertainty. To overcome these defects, Huang and Luk (2020) collected the related information from 10 mainland Chinese newspapers to construct a new index of Chines economic policy uncertainty in a similar way to Baker et al. (2016) and generated it from daily data. Considering the advantages of this higher frequency index and the improvement of the new Chinese EPU index, the economic policy uncertainty of the USA and China applied in this research are respectively

measured by the indices of Baker et al. (2016) and Huang and Luk (2020)[1].

(3) Oil market uncertainty: green bonds that are limited to using proceeds to environmental and low-carbon projects would always display some close links with the traditional fossil fuel energies (Huynh et al., 2020; Liu et al., 2020). Due to such conditions in line with the financialization of crude oil (Silvennoinen and Thorp, 2013; Ma et al., 2019), we introduce the crude oil market uncertainty in our estimation. Moreover, financialization has brought crude oil a worldwide market characteristic, thus we applied one measurement to represents the overall global crude oil market uncertainty that would influence both the USA and China, that is, the CBOE OVX index. This index is the most influential proxy of crude oil market uncertainty and always produces influence on financial assets (see, Dutta et al., 2020; Lin and Su, 2020; He et al., 2020).

This paper applied the daily data of the above indices which were collected from Bloomberg, DataStream, Wind, and CBOE databases. The sample covers from October 15, 2014 (the launch date of Bloomberg Barclays MSCI US Green Bond Index) to September 30, 2020. The variables are transformed into natural logarithmic form for empirical purposes that is $R_t = ln\ (P_t/P_{t-1}) \times 100$ where P_t denotes the value of the index at date *t*. Since we not only focus on how the uncertainties drive the green bond yields but also the cases of volatilities. To obtain the volatility series, we conduct the estimation of the GARCH (1,1) model based on the green bonds return series so that we could obtain the same daily frequency data of green bonds volatilities (Engle and Bollerslev,

[1] The data for USA and Chinese EPU index are obtained from www.policyuncertainty.com website and https://economicpolicyuncertaintyinchina.weebly.com website

1986; Abbas et al., 2019; Fasanya and Akinbowale, 2019; Liu and Gong, 2020).

3.2 Statistic proprieties

Prior to the main empirical estimation, we conduct a descriptive summary of variables. The corresponding results have been displayed in Table 1. This table shows some basic statistical results about the mean, median, standard deviation, minimum value, and maximum value. We could find that UGBIV has the highest daily average returns while CEPU displays the largest standard deviations. The skewness coefficients signify the green bonds return series are negatively skewed and all other sequences are positively skewed, and the kurtosis test results show some fat-tailed distribution. Additionally, to ensure the suitability of the causality test, we provide the unit root properties of the variables from the ADF test. The results suggest that all the time series are stationary.

Table 1 The Descriptive Statistic Results for Time Series

	UCBI	CGBI	UGBIV	CGBIV	UVIX	CVIX	AEPU	CEPU	OVX
Mean	0.021	0.021	0.084	0.013	0.010	-0.002	0.083	-0.076	0.011
Median	0.020	0.022	0.049	0.006	-0.435	-0.312	-0.313	-2.085	-0.294
Minimum	-3.326	-0.818	0.018	0.003	-34.105	-28.785	-185.874	-182.432	-31.032
Maximum	1.511	0.844	2.008	0.358	76.825	36.577	321.562	211.188	36.621
Stdev	0.291	0.104	0.146	0.025	8.554	6.000	50.695	51.693	6.232
Skewness	-1.581	-0.184	7.485	7.493	1.350	0.991	0.292	0.144	0.790
Kurtosis	19.177	14.402	70.420	75.997	7.723	4.742	1.890	0.512	3.900
ADF	-11.834***	-9.111***	-5.881***	-7.434***	-12.661***	-12.959***	-15.330***	-17.211***	-11.304***
Observations	1458	1458	1458	1458	1458	1458	1458	1458	1458

Note: *** indicates significance at the 1% levels.

Additionally, we perform a BDS test (Brock et al., 1996) to verify the existence of the nonlinearity in the linkages between uncertainties and green bonds. This test is applied to the residuals obtained from the VAR (1) model. The test results are presented in Table 2. According to this table, the null hypothesis of i.i.d. residuals at various embedding dimensions (m) is rejected strongly at the highest level of significance, which provides evidence, there are apparent nonlinear relationships between all three kinds of uncertainties and green bonds. This conclusion holds for both the USA and China. Thus, ignoring the non-linear associations in markets may lead to some bias or incorrect findings, this also provides us with the rationality of utilizing nonlinear, non-parametric approaches to detect the driven effects.

Table 2 BDS Non-Linearity Test

Markets	Dimension(m)	$\varepsilon^{***}(1)$	$\varepsilon^{***}(2)$	$\varepsilon^{***}(3)$	$\varepsilon^{***}(4)$
UGBI-UVIX	2	10.457***	12.049***	12.529***	11.273***
	3	12.504***	13.819***	14.118***	12.806***
	4	13.679***	15.036***	15.179***	13.806***
	5	15.342***	16.269***	15.922***	14.512***
CGBI-CVIX	2	12.500***	14.670***	14.360***	13.347***
	3	15.257***	16.379***	15.213***	14.066***
	4	18.734***	17.975***	15.802***	14.412***
	5	22.621***	19.389***	16.143***	14.544***
UGBI-UCPU	2	10.874***	12.039***	12.952***	12.054***
	3	13.429***	13.866***	14.510***	13.603***
	4	15.353***	15.296***	15.621***	14.622***
	5	17.525***	16.507***	16.261***	15.222***
CGBI-CCPU	2	12.527***	14.615***	14.437***	13.700***
	3	15.257***	16.225***	15.249***	14.463***
	4	18.949***	17.754***	15.805***	14.755***
	5	23.415***	19.167***	16.108***	14.791***
UGBI-OVX	2	10.673***	11.914***	12.038***	10.775***
	3	12.717***	13.745***	13.826***	12.530***
	4	14.031***	15.029***	15.067***	13.712***
	5	15.683***	16.199***	15.888***	14.490***
CGBI-OVX	2	13.820***	14.266***	13.847***	13.307***
	3	16.728***	15.968***	14.876***	14.138***
	4	20.664***	17.523***	15.506***	14.516***
	5	25.550***	18.985***	15.909***	14.638***
UGBIV-UVIX	2	16.353***	17.153***	18.656***	18.680***
	3	18.868***	17.632***	18.657***	18.303***
	4	21.170***	18.087***	18.312***	17.890***
	5	23.354***	18.264***	17.968***	17.479***
CGBIV-CVIX	2	19.010***	16.008***	15.839***	12.331***
	3	19.757***	15.905***	15.911***	12.253***
	4	20.424***	15.889***	15.873***	12.070***
	5	21.331***	16.079***	15.977***	12.159***
UGBIV-UCPU	2	18.075***	17.618***	18.738***	15.837***
	3	19.316***	17.761***	18.640***	16.515***
	4	20.344***	17.773***	18.295***	16.604***
	5	21.241***	17.614***	17.878***	16.463***
CGBIV-CCPU	2	18.780***	17.064***	14.536***	9.477***
	3	19.398***	16.788***	14.728***	9.830***

	4	20.058***	16.773***	14.904***	10.101***
	5	20.864***	16.806***	15.060***	10.356***
UGBIV-OVX	2	15.320***	17.003***	18.501***	17.749***
	3	17.065***	17.511***	18.501***	17.487***
	4	18.889***	17.932***	18.220***	17.127***
	5	20.958***	18.308***	17.950***	16.773***
CGBIV-OVX	2	15.644***	14.326***	15.067***	12.402***
	3	15.380***	14.070***	15.098***	11.999***
	4	15.229***	13.834***	14.886***	11.731***
	5	15.272***	13.827***	14.668***	11.531***

4. Methodology

4.1 Cross quantilogram model

As a model-free method, the Cross-quantilogram model was firstly introduced by Linton and Whang (2007) and developed into a multivariate version by Han et al. (2016), which has a good ability to measure the quantile dependence and directional predictability between two-time series. Compared with other methods for measuring correlation, the Cross-quantilogram method can effectively capture the properties of a joint distribution but don't require moment conditions for time series, thereby avoiding restrictive parametric assumptions and assumption of finite moments. Further considering this model could measure dependences of two-time series under different quantile states, we employ it in this study. The key to using this method is to ensure that all variables in the model follow a stationary stochastic process. The specific steps are as follow:

First, suppose y_t and x_t are two stationary time series variables, where $y_t = (y_{1t},y_{2t})^{\mathrm{T}} \in \mathbb{R}^2$, $x_t = (x_{1t},x_{2t})^{\mathrm{T}} \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$, and $x_{it} = [x_{it}^{(1)},\ldots\ldots,x_{it}^{(d_i)}]^{\mathrm{T}} \in \mathbb{R}^{d_i}$ with $d_i \in \mathbb{N}$ for $i = 1,2$. The conditional distribution function of the series y_{it} given x_{it} with density function can be described by $F_{y_i|x_i}(\cdot\,|x_{it})$, thus the corresponding conditional quantile function is $q_{i,t}(\tau_i) = \inf\{v{:}F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}$ for $\tau_i \in (0, 1)$, $i = 1,2$.

Based on the Han et al. (2016), the quantile-hit or quantile-exceedance process is a good measure of serial dependence between two events $y_{1t} \leq q_{1,t}(\tau_1)$ and $y_{2,t-k} \leq q_{2,t-k}(\tau_2)$, which is formulated as $\{1[y_{it} \leq q_{i,t}(\cdot)]\}$ for $i = 1,2$. Thus, the cross-quantilogram will be the function of this quantile-hit process as in the following manner:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))]}{\sqrt{E[\psi^2_{\tau_1}(y_{1,t} - q_{1,t}(\tau_1))]}\sqrt{E[\psi^2_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_2))]}} \tag{3}$$

for $k = 0, \pm 1, \pm 2, \ldots$, which indicates the number of lead-lag periods to time t. Where $\psi_\alpha(u) \equiv I[u < 0] - a$.

The serial dependence between the two-time series is captured by $\rho_\tau(k)$. To estimate this term based on observations $\{(\boldsymbol{y}_t, \boldsymbol{x}_t)\}_{t=1}^{\mathrm{T}}$, a linear quantile regression model should be constructed for simplicity. Let $q_{i,t}(\tau_i) = x_{it}^{\mathrm{T}}\beta_i(\tau_i)$ with a $d_i \times 1$ vector of unknown parameters $\beta_i(\tau_i)$ for $i = 1,2$. Thus, the original problem can be transformed into estimating the parameters $\beta(\tau) \equiv [\beta_1(\tau_1)^{\mathrm{T}}, \beta_1(\tau_1)^{\mathrm{T}}]^{\mathrm{T}}$, which could be obtained from the following minimization procedure.

$$\hat{\beta}_i(\tau_i) = \arg\ min \textstyle\sum_{t=1}^{T} \varrho_{\tau_i}(y_{it} - x_{it}^{\mathrm{T}}\beta_i) \tag{4}$$

for $\beta_i \in \mathbb{R}^{d_i}$, where $\varrho_a(u) = u(a - 1[u < 0])$.

During the process of estimation, one may be interested in testing the null hypothesis that conditional correlations are not different from zero. Also based on Han et al. (2016), we applied the Box-Ljung test in this paper.

$$\hat{Q}_\tau^{(p)} = T(T+2)\sum_{K=1}^{p} \frac{\hat{\rho}_\tau^2(k)}{T-k} \tag{5}$$

Given that the asymptotic distribution of cross-quantilogram contains noise, Han et al. (2016) employ the stationary bootstrap of Politis and Romano (1994) to obtain the denoise statistic results, this paper follows this procedure and run 5000 times repetitions. To make the estimated quantile dependence more intuitive, we construct several heat maps to visualize the results. The heat map can realize the comprehensive display of the three dimensions through horizontal, vertical, and color changes, thereby effectively capturing the degree and structure of the dependence relationship between the two variables under different quantile conditions. Considering the differences in the dependence relationship under general market conditions and extreme market conditions, this paper considers 11 quantile states (0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95). Therefore, each heat map includes a total of 121 cells, and the color scale indicates the strength of the dependence relationship.

4.2 Causality in quantiles method

Since the relationship between the uncertainties and the green bond markets exhibits potentially nonlinear characteristics from Table 2, classical linear Granger causality tests may not effectively measure the causal impact between variables. Thus, we use the nonparametric quantile causality method proposed by Balcilar et al. (2016) to detect the causality-in-quantiles between variables. Compared with the standard causality test, this methodology can find the nonlinear causal impacts by considering the different states of the market, and robust to possible regime shifts and jumps in the dataset. Note that this method merged and improved the causality test approaches of Jeong et al. (2012) and Nishiyama et al. (2011), and it can be constructed by the following steps. At first, we set the quantile-based causality as: x_t does not cause y_t in the θ quantile regarding the lag vector $\{y_{t-1},\ldots, y_{t-p}, x_{t-1},\ldots,x_{t-p}\}$ if

$$Q_\theta\{y_t|y_{t-1},\ldots, y_{t-p}, x_{t-1},\ldots,x_{t-p}\} = Q_\theta\{y_t|y_{t-1},\ldots, y_{t-p}\}$$

(6)

In contrast, x_t does cause y_t in the θ quantile regarding the lag vector $\{y_{t-1},\ldots, y_{t-p}, x_{t-1},\ldots,x_{t-p}\}$ if

$$Q_\theta\{y_t|y_{t-1},\ldots, y_{t-p}, x_{t-1},\ldots,x_{t-p}\} \neq Q_\theta\{y_t|y_{t-1},\ldots, y_{t-p}\}$$

(7)

Based on Jeong et al. (2012), in the above equation, $Q_\theta = (y_t| \cdot)$ represents the θ-th conditional quantile of y_t, which is dependent on *t*. The range of t is restricted between 0 and 1, corresponding to the possible quantile distributions.

Then, we can extend the above test to a higher moment condition by formulating Eq (6) and (7). However, there may be a common complication that arises in the *k*th moment (Syed et al., 2018), to solve this problem, the nonparametric Granger quantile causality approach of Nishiyama et al. (2011) is introduced. Accordingly, the final higher hypothesis of the causality-in-quantiles is defined as:

$$H_0{:}P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad \text{for k} \in \{1,2,\ldots K\} \text{ is the order}$$

(8)

$$H_0{:}P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad \text{for k} \in \{1,2,\ldots K\} \text{ is the order}$$

(9)

Where $Y_{t-1} \equiv (y_{t-1},\ldots,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},\ldots,x_{t-p})$ and$Z_t = (X_t,Y_t)$. $F_{y_t|Z_{t-1}}(y_t| \cdot)$ is a conditional distributional function of y_t and presumed to be completely continuous.

Since the causality in variance could reveal the volatility nexuses, we can detect the quantile causality of volatility by measuring the causality in the second moment state. In other words, setting k = 2 in formulas (3) and (4), the causality in variance (volatility) can be obtained.

5. Empirical results

5.1 Results for Cross-quantilogram

Figure 1 illustrates how the uncertainties drive the USA green bonds under different quantile states. The one-day-ahead dependence (one day lag) of green bonds on uncertainties could be efficiently captured from this estimation. To construct the heatmap, the Box-Ljung test is used for statistical significance, and all insignificant relationships have been set to zero. Figure 1 includes six sub-heatmaps indicating the presence of cross-quantilogram dependence between USA green bonds and uncertainties. The upper part and the lower part respectively represent the uncertainty-driven changes in U.S. green bond returns and volatility; three uncertainties display differentiated effects, their results are placed from left to right, correspondingly representing cases of financial uncertainty, economic policy uncertainty, and oil market uncertainty. Moreover, in each heatmap, the horizontal axis indicates the quantiles of the returns or volatility, while the y-axis corresponds to a quantile of the uncertainties.

For the case of return series, the effects of UVIX and OVX display a similar pattern that it mainly remains in the area that combines the lower to mid quantiles of green bonds (0.05–0.50) with the mid to upper quantiles of uncertainties (0.50–0.90). A significant negative influence is found for the cases of the two uncertainties, and such effects would be getting larger with the rise of uncertainties, as evidenced by the gradually darkened color in heatmaps. In contrast, the changes of UEPU would positively drive the USA green bonds returns, though which could be only observed during the bull market state (0.6-0.8). This implies that the uncertain shocks of financial and oil markets would be the crucial risk factors that driving the downside yields while changes in economic policy uncertainty may drive the green bond more profitable in some certain circumstances due to its fixed-income features.

Cross-quantilogram dependence estimates show that there are more statistically significant parameters when detecting the effects on volatility series. What stands below such differences between the results of return and volatility is, uncertainties would more likely drive the USA green bonds to dance through affecting its volatility than directly on the return. From Figure 1, the UVIX and OVX still show more driving effects than UEPU, similar to situations of returns series. No matter when the volatility of the green bond is bullish or bearish, UVIX and OVX might always play the leading roles, while the changes of UEPU will hardly affect the green bonds variance except for few extreme cases. Some asymmetric characteristics could be confirmed, the uncertainties under rising and falling trends would produce differentiated impacts on green bonds volatility. Specifically, areas in various shades of red running from the north-west corner of these heat maps to the north side reveal that UVIX and OVX could positively drive the volatility of the green bonds in bearish states, especially when the uncertainties change dramatically; meanwhile, if the UVIX and OVX are in the bearish state (0.05-0.45), green bonds volatility would always negatively dependent on them. The economic or financial story behind this asymmetric relationship is “financial contagion” and the “flight to quality” effect (Cheuathonghua and Padungsaksawasdi, 2019; Afonso and Kazemi, M., 2020). Since green bond has become an optional asset in diversification, the huge increases of financial uncertainty would guide a capital flight from risky assets to safe-havens. Financial turmoil consequently induces the risk contagion to green bonds thereby rising its volatility, while crude oil as another financialized energy market could also bring similar effects through this mechanism.

However, when the financial and oil market uncertainties are under the bearish stages, the risk shocks may not hastily change investors' forecast future uncertainty bearish. Investors' lowly speculative and hedge activities eventually result in the green bonds volatility decrease.

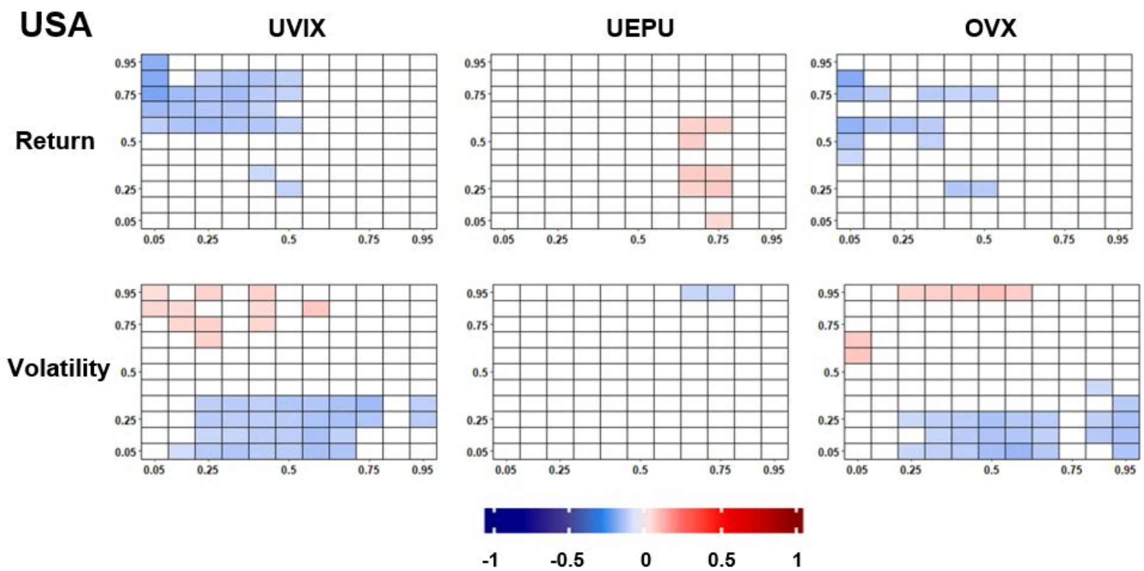

Figure 1 Cross-quantilogram Estimation Results of USA

Figure 2 illustrates the driven effect of uncertainties on Chinese green bonds. This figure also includes six sub-heatmaps and have the same arrangements as in Figure 1. Similarly, this figure displays the one-day-ahead cross-quantilogram dependence of Chinese green bonds on uncertainties and the statistically insignificant linkages were set as zero, according to the Box-Ljung test.

Analysis by returns series of Chinese green bonds revealed that CVIX and OVX have similar driving roles. They both provide negative effects when uncertainties and green bond yields are simultaneously bearish, while the positive facilitation on green bond returns might be observed if the uncertainties upward change extremely. This illustrates that the driven effects of uncertainties are not always immutable, uncertainty factors in extreme bullish states will display different influence from those in general states. The situation of CEPU provides further evidence. When CEPU is bearish, the change in CEPU is always positively correlated with green bond yields in the bull market, which is consistent with the results of the USA green bonds. However, Chinese green bonds have a unique feature that they would negatively rely on extremely bullish economic policy uncertainty. In other words, uncertainties drive the returns of the USA and Chinese green bonds to dance in a similar pattern but stupendous rises in uncertainties may induce some different responses of the latter. This implies that the Chinese green bond market has relatively weaker safe heaven capabilities than the USA markets for the extreme macro uncertainty risk.

On the other hand, the uncertainties' driven role on the volatility of Chinese green bonds shows completely different results from the United States. The presented dependence structure shows that the changes of CVIX and OVX carry no or little information in driving the Chinese green bonds volatility, while the CEPU always has a significant impact on it under the various quantile states. Asymmetry could also be observed in the results of volatility. CEPU under the low to medium quantiles (0.05-0.6) always positively drives green bonds volatility but significant negative movements occur if the CEPU sharply changes. This result is another evidence of Chinese green bonds sensitive to the extreme uncertainty risk.

As we conduct an in-depth comparison of the results in Figure 2 to Figure 1, we find that the differences between the USA and China are their distinct safe heaven properties for extreme uncertainties and their main driving uncertainty factors. Chinese green bonds are more dictated to the policy-induced economic uncertainty, while the financial market uncertainties are the crucial factors driving the USA green bonds. Such circumstances are more likely to occur in the impact on volatility. There are two possible explanations or implications for this result. Firstly, due to the early development, good openness and relatively complete market supporting construction, the US green bonds market has a more effective integration with the general financial market, while the latecomer green bonds market formed in China has not been effectively integrated with the mature financial system, exhibiting a lower volatility dependence on financial uncertainty. Additionally, the Chinese green bonds market is still mainly promoted by the government so that more sensitive to economic policy uncertainties than the US market, which is consistent with the reality that China's green bond issuers are mainly state-owned enterprises (banks) and local government financing platform[2]. Additionally, the effects of OVX on the two nations' green bonds might reveal the different status of crude oil in traditional fuel consumption. Though the OVX will affect China's green bond returns through financial risk contagion on some occasions, the coal consumption-based energy consumption structure determines that the Chinese green bond market has a weaker correlation with crude oil-induced uncertainty than the US market.

[2] Information sourced from ChinaBond: https://www.chinabond.com.cn/cb/cn/yjfx/zybg/20200629/154731622.shtml.

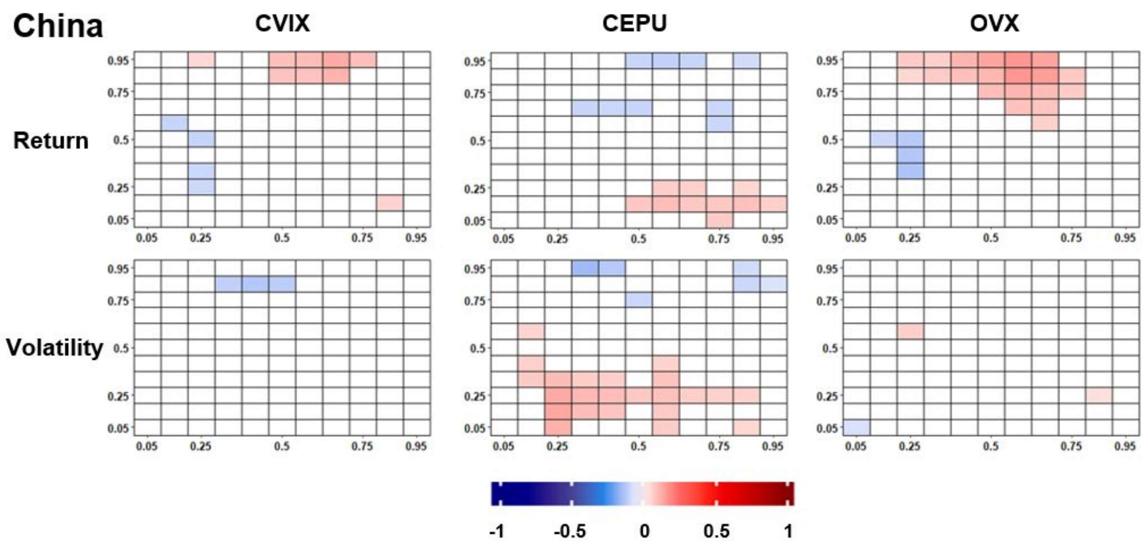

Figure 2 Cross-quantilogram Estimation Results of China

5.2 Results for Causality in quantiles

After establishing the cross-quantilogram dependences from three macro uncertainties to green bonds, the process of our main empirical research performs the causality-in-quantile model to confirm the robustness and investigate the predictive causalities in variables. As described in the Methodology, this model can be subdivided into causality-in-mean and causality-in-variance for different moment conditions, and different quantiles in the dependent variable distribution are used to represent the state of markets. We set the quantiles from 0.1 to 0.9 with an interval of 0.05 corresponding to the previous cross-quantilogram estimation. These quantiles can classify the green bond markets into different states, namely normal market (average market), bullish (good market) and bearish (bad market) corresponding to the 50th (average), 90th (higher), and 10th (lower) quantiles, respectively.

The results of the nonparametric causality-in-quantiles between uncertainties and the USA or Chinese green bonds are presented in Figure 3 and Figure 4, respectively. Note that these figures have both two rows where the upper sub-graphs indicate the results of returns, the lower sub-graphs present the case of volatility (measured as return variance). In this figure, the 10% critical value is represented by the orange lines, while the gray lines indicate the 5% critical value.

Firstly, as for the case of the US, the estimated causality in quantiles reveals that the most results from cross-quantilogram estimation are robust. For example, Both UVIX and OVX are the causes of green bonds return in a bearish market, while UEPU is more likely to affect the green bonds return in a bull market. This asymmetric characteristic is consistent with the previous results from the cross-quantilogram method. Meanwhile, as shown in the more standard inverted U-shaped curves, the predictive causality of uncertainties on green bonds volatility is also the evidence that uncertainties drive the US green bonds through affecting volatility, and such effect would mostly be asymmetric across different quantile states.

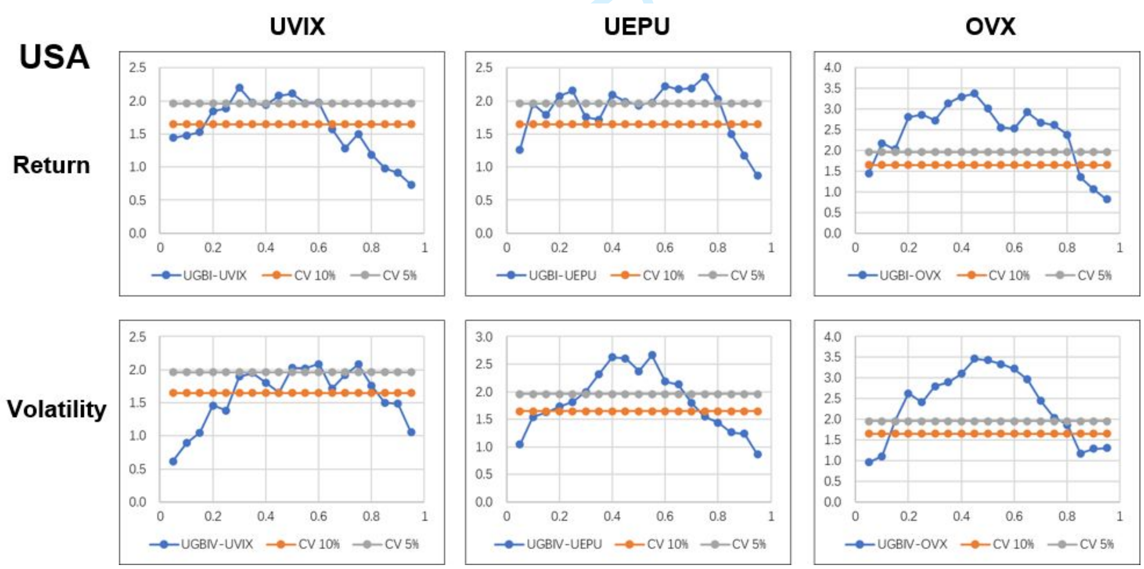

Figure 3 Quantile Causality from Uncertainties to Green bonds of USA

For China, the estimated causality static value of financial uncertainty (CVIX) and oil market uncertainty (OVX) also display a lower level than the case of the US, confirming the robustness of the results in cross-quantilogram estimation on China. Meanwhile, the CEPU still display as the most influential factor on Chinese green bonds. Especially for the volatility, it shows the rejection of the no causality hypothesis in the quantiles ranging from 0.25 to 0.85 at a significance level of 5%, while the other two uncertainties even have few causal impacts on Chinese green bonds volatility. This further confirms that achieving neutrality to the policy-induced risk is crucial to ensure the stability of the Chinese green bond market. Meanwhile, the weak integration with the conventional financial market has also indirectly led to the fact that Chinese green bonds have a better safe-haven capability to normal uncertainty shocks than U.S. green bonds.

All in all, the empirical results based on the causality in quantiles method provide robust evidence for the driving roles of uncertainties to green bonds in two pioneer nations. The possible rationale behind such results is, the relatively developed US green bond has become a widely accepted financial asset with more green priority investors, thus more dependent on the uncertainty induced from overall financial conditions; while the Chinese green bond mainly promoted by government forces, the boom in trading volume accorporates the weak integration with the general financial market, which eventually lead to close relations with policy-induced uncertainty.

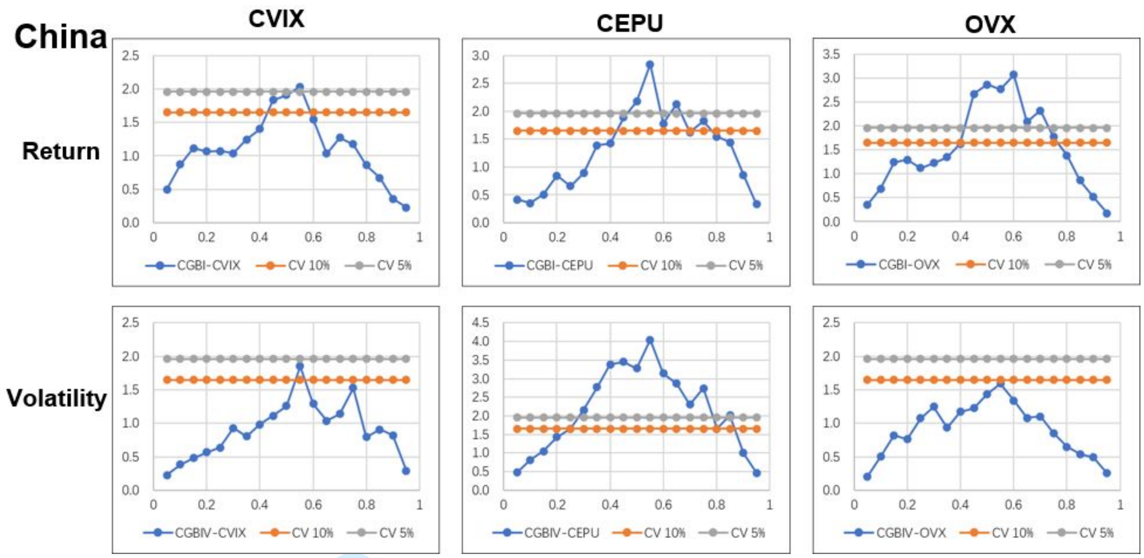

Figure 4 Quantile Causality from Uncertainties to Green bonds of China

6. Conclusion and implications

The seriousness of climate change and the efforts on carbon neutrality are gradually gaining global recognition (Lin and Du, 2015; Shahbaz et al., 2019). The existing facts prove that green finance is a good channel to promote clean and low-carbon development (Lin and Zhu, 2019). It can not only attract investment in environmental protection projects through monetary incentives but also promote the transformation of the financial industry to reduce the investment space of high-pollution fossil energy projects. In this context, with relatively low environmental risks and large financing needs, green bonds are developing rapidly, especially getting popular within the sustainability-oriented financial community.

The capital allocation critically depends on the profitability and the risk-adjusted performance of assets (Gaganis et al., 2015; Paltrinieri et al., 2020). As green bonds are developing into a prosperous new investment field, uncovering the drivers is crucial for investors to scrutinize and price the risks in green bonds. Macro uncertainties are always the important factors affecting the financial assets through risk exposure, thus considerable studies tend to examine the impact of it. However, reviewing the previous researches, we find the well-established literature that little attempted to develop an in-depth investigation of green bonds for this issue.

Consequently, we extend the emerging literature by exploring how macro uncertainties drive the green bonds dance. To obtain the potential heterogeneous characteristics in different nations, we analyze from the perspective of the two pioneer markets, the USA and China. They are representatives for developed and developing markets. There are three correlated uncertainty factors considered in this research, financial (equity market) uncertainty, economic policy uncertainty, and oil market uncertainty, respectively reflecting the financial system-induced, policy-induced, and traditional fossil fuels induced risks. With the possible nonlinear association between examined variables indicated by the theoretical analysis and BDS test, we applied two quantile-based methodologies to conduct the main empirical study, cross-quantilogram and quantile causality methods. They could obtain the dependence and causality structures between variables across quantile states and even understand the driving roles of uncertainties under different conditions.

Applying the estimation to high-frequency daily data for more than 5 years, we obtain the results indicate that (i) Uncertainties are important determinants of green bonds but they would play different roles in different nations. The USA green bonds market is more sensitive to financial uncertainty while Chinese green bonds would be mainly driven by the economic policy uncertainty, this implies the differences of these two markets in the fields of market maturity, the participation of green investors, and market forces. (ii) The driving roles of these uncertainties would vary at different market states of green bonds, displaying some asymmetric characteristics in the impact mechanism. For instance, financial and oil market uncertainties determine the USA green bonds return at the bearish and normal market but won't affect the bullish market. The quantile states of uncertainties will also have similar asymmetric features. China could be treated as a safe-haven of financial and oil market risks in most cases, but it will lose such function facing extreme upward uncertainties. (iii) With the inclusion of both return and volatility, our results outline a comprehensive picture of how the uncertainties drive the green bonds. The impacts of uncertainties on the profitability of green bonds are closely related to the state of the market, while the impact on volatility is more dependent on the state of the uncertainty itself.

The findings of this study offer meaningful insights into the green bond markets, thus providing valuable implications for both investors and policymakers. For green bond investors, they must make an efficient assessment of the market states of green bonds when they combined them in a portfolio to gain diversification benefits. Since the green bond does not perform its safe-haven role to financial and oil uncertainties in a bearish market condition, the investors need to allocate more capital to investment vehicles that exhibit no or a negative correlation with green bonds in a market downturn. Hedgers or financial institutions with multinational investment demands need to pay careful attention to macro uncertainties and treat developing and developed markets in different investment strategies. Since Chinese green bond returns may depend on the extreme rising uncertainties, adequate design of pre-emptive measures and risk management plans would be vital before include Chinese green bonds into the portfolios. For policymakers, the safe-haven capabilities and potential hedge roles of green bonds illustrate further benefits to develop this green financial mean. They need to construct more aggressive and thorough schedules for cultivating green bonds. The green bonds volatilities have different correlations with bearish and bullish uncertainties, the policymakers in a fresh green bond market could build a system to monitor the uncertainties and apply interventions to prevent excessive volatility when appropriate. Besides, the results for two pioneer markets imply the differences in cultivating green bonds between developed and developing countries. The developing countries (In this paper, China) rely more on government showdown tasks or direct market participation of state-owned assets to achieve green bonds market scale expansion, which makes them more slowly integrate with the general financial system and always be sensitive to policy-induced uncertainty. Thus, developing countries like China should pay more attention to stimulating market vitality in promoting green bonds. They need to guide investors to favor green, and erect sound supporting financial systems to accelerate its integration with conventional financial markets, thereby achieving a substantial and efficient development of green bonds.

Data Availability Statement

The dataset used in this study will be made available on request

Appendix

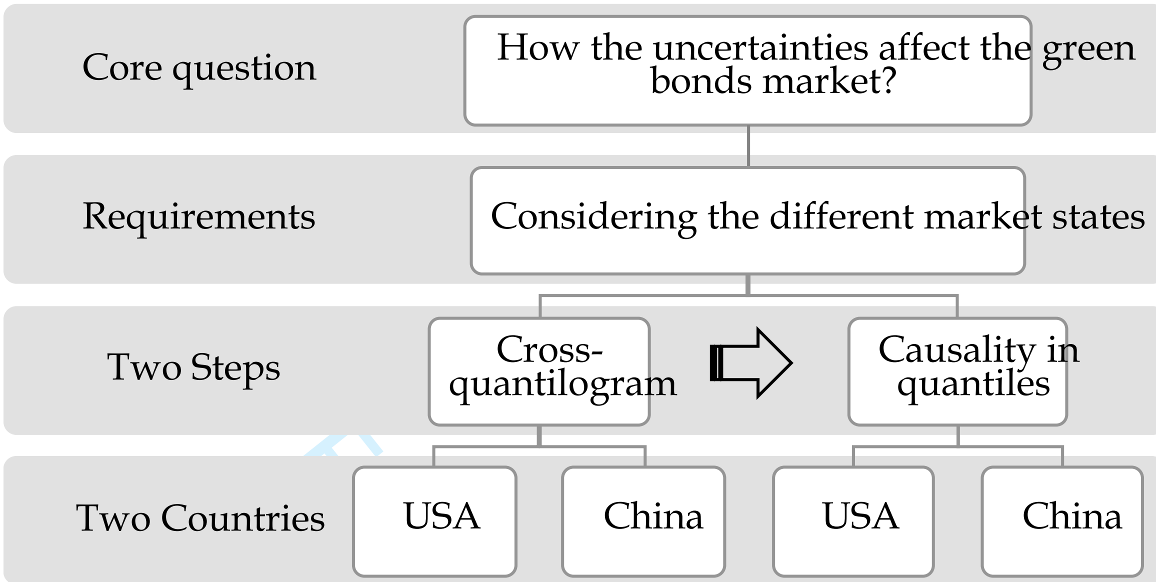

Figure A1. The research framework of this research (Graphic abstract)

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