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BITCOIN PRICE AND CHINESE GREEN BONDS: EVIDENCE FROM THE QARDL METHOD

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Abstract. This article primally explores the short-term fluctuation and long-term implications of the international Bitcoin price (BP) on the Chinese green bond (GB) market, within the sample period of 2014:M10–2023:M07. Bitcoin is the most important cryptocurrency and has a carbon-intensive feature, and its price suffers from great volatility and is closely related to the green finance market. Meanwhile, although China is the largest bitcoin mining state, it is pursuing a dual carbon target, which promotes its green bond market's development. Thus, it is valuable to investigate the influence of BP on GBs in China. Based on the quantile autoregressive distributed lag approach, this paper indicates that the positive and negative impacts of BP on the GB market are significant in the long-term but not apparent in the short-term. These results emphasize the importance for market participants to obtain a better understanding of how BP affects GB under various market circumstances. Implementing specific policies, such as regulatory mechanisms for Bitcoin trade, market-oriented reform for the bond market, and information disclosure, can alleviate shocks from BP and accelerate the development of the GB market.

Keywords: bitcoin price, green bond index, quantile auto-regressive distributed lag model.

JEL Classification: C22, E44, O11.

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1. Introduction

The Bitcoin market, as one of most important cryptocurrency markets, experienced rapid development, and its trading volume reached over 100 billion U.S. dollars in 2022 (Zhao & Zhang, 2023). More than 100,000 enterprises with approximately 10 million people participate in bitcoin transactions, and bitcoin's price has continued to rise after suffering several significant drops and finally exceeding $26,600 again in June 2022 (Salisu et al., 2023). The wide participation and high price of bitcoin play a significant role in global financial markets (Blasco & Corredor, 2022) but also raise concerns regarding the environment among policy-makers and supporters of greener energy sources (Goodkind et al., 2022; Hong & Zhang, 2023). Currently, the energy consumed by Bitcoin is approximately 110 Twh per year, accounting for 0.55% of the world's total energy consumption (Sharma et al., 2023). In addition, the bitcoin mining process is always accompanied by large emissions of CO_2, SO_2 and other pollutants. The carbon emissions generated by the mining process in 2021 were 22.9 million metrics, accounting for 8.5% of worldwide emissions in 2021 (Wu & Ding, 2023). In recent years, governments have gradually integrated environmental and social issues into their priority lists, and the global government has developed multiple strategies and instruments for achieving carbon reduction (Mahmood et al., 2021). Among these instruments, green finance, especially green bonds, can balance economic development and environmental protection, which attracts great attention (Duan et al., 2023). The issuance of green bonds rose from $0.8 billion when they were first introduced into global financial markets to $257.7 billion at the end of 2021 with 839 issuers. Thus, carbon-intensive Bitcoin and its subsequent environmental concerns may produce an obvious influence on the environmental protection-oriented green bond market. In addition, green bonds are not only an effective tool to mitigate the carbon footprint but also a crucial hedging tool against the risk from the enormous volatility of Bitcoin prices (Howson & De Vries, 2022).

This study focuses on the Chinese region because it plays a pivotal role in the global Bitcoin and green financial markets. First, China has a crucial position in the international Bitcoin market. There has been a considerable increase in the total number of Bitcoin full nodes in China. Particularly after March 2018, the utilization rate of Chinese Bitcoin nodes hit an unprecedented record of 17%, overtaking Germany and placing second behind the U.S. (Wang et al., 2019). Second, the high energy consumption of China's Bitcoin generates a large amount of carbon dioxide. Without any policy intervention, it is anticipated that China's annual energy combustion due to Bitcoin mining will reach 296.59 Twh in 2024, which will generate massive pollutants (Jiang et al., 2021). By 2024, the carbon emissions from the Bitcoin blockchain in China will reach 130.5 million tons per year, exceeding the combined annualized greenhouse gas emissions of the Czech Republic and Qatar (Liu et al., 2023). Third, the green financial products of China are diversified. Different from Western countries, which mainly focus on green financial innovation, China includes green investment, green credit, carbon finance and others (Qian & Yu, 2023). The scale of various products has also increased rapidly; for example, China created the world's largest green credit balance with 15.9 trillion RMB as of the end of 2021 (Guo et al., 2023). Regarding green bonds, China issued $37.4 billion in the first half of 2023, accounting for 13% of the global market share and becoming the second largest source of green volumes. Finally, China's green finance market shows great potential in reducing carbon emissions. The majority of the capital acquired by green finance is utilized for economic activities such as environmental restoration, climate change, resource conservation and high efficiency (Ran & Zhang, 2023). Their resource allocation role can promote the reduction of pollutants by sending incentive signals to green industries and warning signals to seriously polluting industries (Wang et al., 2023a).

This article concentrates on the long-term influence and short-term variation of the Bitcoin price (BP) on green bonds (GBs) in China through the quantile autoregressive distributed lag (QARDL) method and some robustness tests. The primary purpose is to explore the influencing mechanisms and clarify how BP affects GB and provide suggestions for promoting the development of the green bond market. The important results of our analysis are shown below. First, it is found that the long-term effect of BP on GBs is prominent in the majority of situations, and there are both positive and negative influences. Second, the statistical significance of short-term parameters is lower than that of long-term parameters across most quantiles, implying that temporary changes in policies and sudden events have a minor impact on GBs. Third, based on the rolling window analysis, this paper reveals that the long-term and short-term parameters between variables have time-varying properties. In other words, BP will produce disparate effects on GBs over time during the subsample periods.

The contributions of this study are as follows. First, the association between BP and GB has been analyzed in perspective with the realities in China. Excessive CO_2 emissions and energy consumption caused by bitcoin mining have triggered environmental concerns, resulting in an enormous need for green bonds to achieve harmonized development between economic and ecological optimization. However, the current literature focuses on bitcoin prices and green financial instruments in developed countries. China, the major bitcoin miner and green bond issuer, increasingly requires attention. Second, the framework of the influencing mechanism between BP and GB is preliminarily established, which is specific to China. The literature has analyzed the influencing channels in multiple aspects based on classic economic theory, such as hedges. However, these studies ignore that China has a relatively independent financial system and an immature green finance market. Thus, this paper is rooted in China's realities and tries to construct an analysis framework from the aspects of CO_2 emissions, energy consumption and energy prices. Third, the QARDL method performs better in capturing asymmetries from BP to GB in various quantiles, including long-term and short-term terms. Meanwhile, even if some particular variables do not meet the criteria for exogeneity, the unbiased parameter remains able to be evaluated. In addition, the approach is superior to ordinary least squares in addressing the issue of the error term's normality features, and it is frequently employed to evaluate financial data.

The remainder of this paper is organized as follows. Part 2 introduces the green finance function and practice and bitcoin's relationship with the environment and green assets. Part 3 presents the influencing mechanism of Bitcoin prices on green finance, including carbon emissions, energy consumption, and energy prices. Part 4 introduces the Quantile Auto Regressive Distributed Lag Model (QARDL) and its application advantages. Part 5 discusses the data resources and statistical descriptions of the variables. Part 6 presents the empirical analysis, subsample analysis, robustness test and further analysis. Part 7 summarizes the empirical results and offers conclusions and corresponding policy implications.

2. Literature review

2.1. Green finance function and practice

Green finance allocates capital reasonably through green investment, green credit, green insurance and various other tools, eventually realizing the coordinated development of the environment and economy (He et al., 2019; Ren et al., 2020). In light of this, the role of green finance in mitigating environmental degradation has been studied increasingly extensively. Zhu et al. (2020a) indicated that through the rational allocation of credit resources, green finance is conducive to achieving a win–win situation for economic development and environmental protection. Song et al. (2021) showed that green credit is a crucial component of green finance that aims to promote energy efficiency and create an eco-friendly economic structure. Guo et al. (2023) confirmed that the spatial spillover effect of green finance is beneficial for boosting energy utilization in local and surrounding regions and alleviating environmental degradation. Numan et al. (2023) justified that green finance encourages the shift of investment from the extensive usage of fossil energy to environmental protection that considers air quality and efficient green energy. Umar and Safi (2023) considered the OECD economies as the subject of study and indicated that there is a long-term association between green finance and environmental protection. Udeagha and Ngepah (2023) provided insight that green finance is a curial driving force for the environmental sustainability of BRICS economies.

Research on green finance and environmental development with carbon emissions as the bridge has also been highlighted. Zhang et al. (2021) found that modernizing industrial structures and advancing technology are the primary means through which green finance lowers carbon emission intensity. Guo et al. (2022) took China as a reference point and found that the negative direct impact of green finance on carbon emissions is noticeable, while the indirect influence is not apparent in the surrounding provinces. Mamun et al. (2022) expressed the view that green finance can considerably lower carbon dioxide in the short and long-term by improving energy efficiency and minimizing waste and pollution. Du (2023) also explained that the intensity of carbon emissions is negatively influenced by the short-term and long-term estimations of green finance of all quantiles, and the asymmetric effects have also been confirmed. Huang et al. (2023a) focused on China and identified that all components of green finance can obviously decrease the country's carbon footprint. Ran and Zhang (2023) also stated that the effectiveness of green finance in reducing China's carbon emissions is mainly reflected in developed and western regions. Sadiq et al. (2023) indicated that the increase in the issuance of green finance has augmented the funds earmarked for environmental initiatives, which are dedicated to mitigating carbon emissions. Tariq and Hassan (2023) believed that the popularization of green finance and clean energy contributes to environmental sustainability by cutting carbon dioxide emissions.

2.2. Bitcoin market and environment

The mining and trading process of Bitcoin consumes considerable energy, resulting in a serious carbon footprint. Thus, the influence of Bitcoin on environmental sustainability is drawing more attention worldwide. Mora et al. (2018) proposed that the emissions from Bitcoin mining will cause global warming to exceed 2 °C within three decades. Mohsin et al. (2020) demonstrated that a causal connection exists between environmental degradation and Bitcoin in the short and long term, and the connection is bidirectional. Mohsin (2021) presented that as the popularity of Bitcoin continues to grow, more coal and other fossil fuels need to be burned, ultimately posing an environmental risk. Erdogan et al. (2022) indicated that the demand for Bitcoin transactions will inevitably cause more energy consumption, which will exert a long-term influence on environmental pollution. Sarkodie et al. (2022) suggested that the technological drivers of Bitcoin will generate a large amount of carbon emissions, further producing a potential influence on global climate change. Hong and Zhang (2023) showed that Bitcoin trading places an enormous burden on Bitcoin mining, resulting in an extensive carbon footprint that is not conducive to environmental sustainability. Long et al. (2023) demonstrated that the dynamics of Bitcoin prices, including returns and volatility, are crucial factors driving carbon emissions and carbon prices. Qin et al. (2023) provided the insight that the price of Bitcoin has a positive impact on carbon emissions and energy consumption. Pagone et al. (2023) illustrated that the energy-intensive nature of Bitcoin's algorithm has resulted in its carbon footprint being approximately four times larger than the sum of all traditional currency forms, which has raised environmental concerns. Wu and Ding (2023) claimed that the process of Bitcoin mining relies heavily on fossil energy to provide electricity, leading to more pollutant emissions and exacerbating environmental issues.

2.3. Bitcoin market and green assets

Multiple studies have investigated the connection between Bitcoin and green assets. Symitsi and Chalvatzis (2018) showed that the return and volatility interactions between Bitcoin and green financial assets are unidirectional, while the shock effect was found to be bidirectional. Le et al. (2021) concluded that Bitcoin is a net contributor to volatility shocks, while green bonds are net recipients through time-frequency and spillover analyses. Naeem and Karim (2021) showed that the reliance between Bitcoin and green finance is time-varying and confirmed that the influence between them is indeed asymmetric. Pham et al. (2021) also revealed asymmetric spillover effects among green assets, fossil fuel investment and cryptocurrencies and proved that the effects are more pronounced during crisis periods. Goodell et al. (2022) shared the opinion that individual investors can consider investing more closely in green assets to diversify Bitcoin holdings. Khalfaoui et al. (2022) proposed that most green commodities seem to function as risk spillover transmitters, while Bitcoin is a net information recipient in the system. Duan et al. (2023) stated that the investment shelter effect of Bitcoin on green assets is remarkable, while it is slightly inferior to traditional assets. Huang et al. (2023b) showed that Bitcoin's investment shelter role in green assets strengthened after the outbreak of COVID-19, and green assets in turn consistently served as an effective hedging tool for Bitcoin. Khalfaoui et al. (2023) argued that changes in cryptocurrency volatility will affect the future fluctuation of green bonds across all market situations and periods. Sharma et al. (2023) found that Bitcoin is sensitive to the changes caused by the green economy and that there is a negative correlation between the two at most quantiles.

The existing literatures have widely discussed the function and practices of green finance, and bitcoin market and its relationship with environment and green assets. However, some improvements still need. Few studies directly investigate bitcoin price and green bond market, especially for China. Besides, the influencing mechanisms between bitcoin price and green bond is ambiguous. Finally, most literatures ignore the quantile– and time-varying dependent linkage between bitcoin price and green bond. Thus, this paper utilizes quantile ARDL model, and tries to reveal the clear influence from bitcoin price to China's green market, and provide the corresponding policy insights.

3. Theoretical basis and hypothesis development

The influence of Bitcoin on green finance can be explained by the following three potential mechanisms. First, Bitcoin market will stimulate green finance through carbon emissions. A large amount of energy would be needed in the process of Bitcoin mining, the majority of which originates from fossil fuels (Wu & Ding, 2023). As more individuals become interested in Bitcoin, there will be a greater demand for mining, resulting in higher carbon emissions (Corbet & Yarovaya, 2020). In addition, miners require adequate machine hardware to verify blockchain transactions in the trading process, which requires an enormous amount of electricity to make this process more effective (Truby et al., 2022). It is not difficult to find that the acquisition and usage of Bitcoin will generate considerable heat and carbon emissions, which has raised concerns about the environment (Hong & Zhang, 2023). Blockchain technology with a unique underlying mechanism has become an effective solution to reduce pollutants and solve environmental problems (Wu et al., 2023). Enterprises have to seek green financial instruments to raise funds for technology research and development, and financial institutions will also introduce more green financial products to support technological progress (Ran & Zhang, 2023).

Second, Bitcoin market will promote green finance through energy consumption. As the demand for Bitcoin increases, more miners need to employ powerful computers to improve the arithmetic speed and efficiency of operations (Sarkodie et al., 2022). This Bitcoin mining calculation process usually relies heavily on fossil energy such as coal and oil, which will inevitably lead to more energy consumption (Qin et al., 2023). Therefore, it is urgent to take measures to improve energy efficiency and ensure the sustainability of energy. Some Bitcoin mining enterprises have begun to explore more environmentally friendly and sustainable energy solutions, such as the usage of solar, wind power and other renewable energy sources (Bruno et al., 2023). Compared with traditional energy sources, hydro and wind have endless potential and can provide lasting energy for Bitcoin mining and trading, which means that the energy-intensive development model is gradually becoming green (Huang et al., 2023b). The development of renewable energy projects will undoubtedly increase the demand for green financial instruments, as they can provide enterprises with the necessary financial support and reduce financing costs (Zhao et al., 2023).

Finally, Bitcoin market will affect green finance through energy prices. In view of the fact that the mining machine needs energy to generate a hash to perform the appropriate calculation, the efficiency of these devices depends on electricity (Vries, 2019). Thus, the demand for electricity is proportional to the number of calculations per unit of energy, which also means higher electricity costs (Kristoufek, 2020). It is worth noting that electricity is supported by energy. Therefore, the profit of Bitcoin mining operation is dependent on the cost of energy. When energy prices are higher, the cost of Bitcoin mining is more expensive, which reduces profitability (Sarker et al., 2023). Therefore, under the incentive of cost-effectiveness, miners tend to pursue lower-cost energy. Compared with the marginal cost of fossil fuel energy production, the marginal cost of renewable energy is decreasing, which will increase the motivation of miners to switch to renewable energy (Malfuzi et al., 2020). Green finance is widely used as a crucial channel to address the financing challenges of renewable energy power generation projects (Sinha et al., 2023).

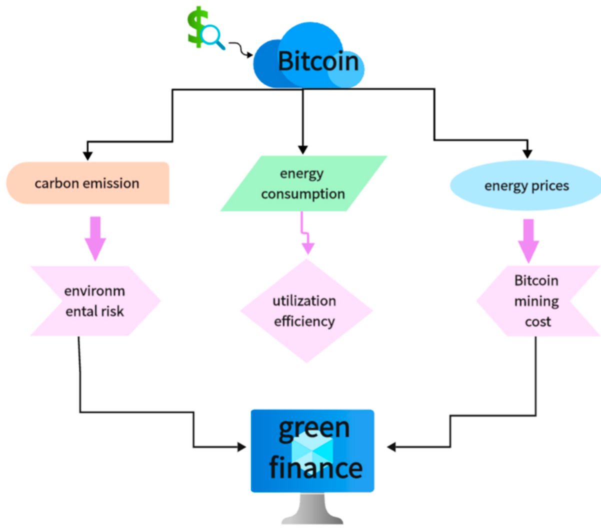

Figure 1. The influencing mechanism

In light of this discussion, this paper proposes Hypothesis I and presents the influence mechanism in Figure 1.

HI. *Bitcoin market can influence green finance.*

4. Methodology

Based on the idea of quantile cointegration (Koenker & Xiao, 2006), Cho et al. (2015) proposed the QARDL model. There are some advantages to employing the QARDL model to analyze how the price of Bitcoin affects the market for Chinese green bonds. First, it is a progressive and robust econometric framework that accurately represents asymmetry better than the conventional ARDL model (Abbass et al., 2022). Specifically, whether the effect of BP on GBs is asymmetric in diverse market situations can be captured by the QARDL model. Second, even if certain variables may fail to meet exogenous conditions, the QARDL model can achieve unbiased parameter estimates by incorporating lag components for both endogenous and exogenous variables (Ren et al., 2023). Moreover, this approach is more practical than ordinary least squares when resolving the challenge of the error term's normality feature. It presents obvious superiority in handling nonnormal data and is widely employed in financial, energy and environmental research (Xiang & Cao, 2023).

To better comprehend the OARDL approach, this article first presents the equation of the ordinary ARDL method with the variables of green bond (GB), bitcoin price (BP), economic policy uncertainty (EU), and oil price (OP), which is shown as follows:

$$\Delta GB_t = \alpha + \xi\left(GB_{t-1} - \beta_1 BP_{t-1} - \beta_2 OP_{t-1} - \beta_3 EU_{t-1}\right) + \sum_{j=1}^{p-1} \lambda_j \Delta GB_{t-j} + \sum_{j=0}^{q_1-1} \delta_{1,j} \Delta BP_{t-j} + \sum_{j=0}^{q_2-1} \delta_{2,j} \Delta OP_{t-j} + + \sum_{j=0}^{q_3-1} \delta_{3,j} \Delta EU_{t-j} + \varepsilon_t, \tag{1}$$

where Δ denotes the first difference operator and α and ε_t represent the intercept and error terms, respectively. ξ quantifies the rate of adjustment to the long-run equilibrium state. The lag order of the response variable and the regression variable is expressed by p and q, respectively. The long-term parameters are represented by β_i (i = 1, 2, 3), while the short-term parameters are denoted by λ and δ_i (i = 1, 2, 3). Furthermore, since the model specification covers the first-order difference terms of BP, OP and EU, all parameters in E (1) can be evaluated without endogeneity.

On the basis of Cho et al. (2015), this paper extends the ARDL (p, q) process to a context of quantile regression to obtain the QARDL (p, q) model, which is shown as follows:

$$\Delta GB_t = \alpha(\tau) + \xi(\tau)\left(GB_{t-1} - \beta_1(\tau)BP_{t-1} - \beta_2(\tau)OP_{t-1} - \beta_3(\tau)EU_{t-1}\right) + \sum_{j=1}^{p-1}\lambda_j(\tau)\Delta GBI_{t-j} + \sum_{j=0}^{q_1-1}\delta_{1,j}(\tau)\Delta BP_{t-j} + \sum_{j=0}^{q_2-1}\delta_{2,j}(\tau)\Delta OP_{t-j} + \sum_{j=0}^{q_3-1}\delta_{3,j}(\tau)\Delta EU_{t-j} + \varepsilon_t(\tau), \tag{2}$$

where α(τ), ξ(τ), $\beta_i(\tau)$ (i = 1, 2, 3), λ(τ) and δ_i (i = 1,2,3) are corresponding estimated coefficients at quantile τ.

This approach is superior to others because it comprehensively takes both long- and short-term effects into account, which depend on the different quantiles of the dependent variable. Thus, the QARDL model has been widely utilized in many fields, such as the stock market (Godil et al., 2020), resource sustainability (Wang et al., 2023b), the energy market (Du, 2023), environmental innovation (Alzakri, 2023) and green investment (Pang et al., 2022).

5. Data analysis

This paper employs the monthly data from 2013:M01 to 2023:M07. The price of Bitcoin was pushed up from $80 to $260 in early 2013 due to an influx of investors. BP also experienced dramatic fluctuations during the sample period, jumping 200 times in 2017 but sharply dropping within the next year and then rebounding again to exceed $10,000 in June 2019. During this time, the Chinese government committed to developing green finance. In 2015, the overall goal of "establishing a green financial system" was first proposed in the Overall Plan for the Reform of Ecological Civilization System. Subsequently, Guidance on Building a Green Financial System in 2016 outlined the essential tasks and particular strategies for establishing a green financial system.

The following variables are taken into account in this article. The first variable is bitcoin price (BP). The data are obtained from the Bloomberg Cryptocurrency Database, and have been widely employed in electricity consumption (Maiti et al., 2023) and climate policy uncertainty (Sarker et al., 2023). The Second variable is green bond (GB). This paper utilizes China's Green Bond Index, which can be obtained from Wind database, to measure the development of green bond market (Man et al., 2023). Some studies have explored the role of GBs in corporate environmental performance (Fan et al., 2023) and carbon emissions (Xu & Li, 2023). The third variable is economic policy uncertainty (EU). This paper employs the China's

Economic Policy Uncertainty Index, which is constructed by Hong Kong's South China Morning Post and obtained from http://policyuncertainty.com, to reflect uncertainties in China's economic policy (Lu et al., 2023). These data are downloaded from http://policyuncertainty.com. This index is extensively applied in technological innovation (Zhang et al., 2023) and geopolitical risks (Hoang et al., 2023). The last variable is oil price (OP). West Texas Intermediate (WTI) serves as a measure of this variable because it is the most significant and widely used crude oil pricing benchmark in the world, thus this paper uses WTI oil price, which is collected from U.S. Energy Information Administration (EIA), to measure the fluctuation of OP (Li et al., 2023a). This price has attracted the interest of many scholars in terms of energy prices (Wang et al., 2023c) and unemployment rates (Ahmed et al., 2023).

Figure 2 describes the trend of each variable. The tendency of GB is almost a straight and steady increasing line, reflecting the continuous support of banks, securities and other financial institutions and the government for it. The overall trend of OP is also comparatively steady aside from several noteworthy spots. OP fell into negative territory in April 2020 due to the outbreak of COVID-19 and the massive supply of oil from Saudi Arabia and Russia. Affected by the Russian-Ukrainian conflict in February 2022, OP experienced a strong increase and surpassed $100 per barrel. In contrast, EU shows dramatic volatility, which is mainly related to policy changes and political events. Examples include the G20 Summit held in 2016, the negotiations between China and the U.S. on the issue of trade friction in 2018 and the launch of the national carbon emissions trading market in 2021. BP has experienced multiple boom-bust cycles. The introduction of Bitcoin futures on the Chicago Board Options Exchange in December 2017 attracted a large number of investors, eventually leading to a

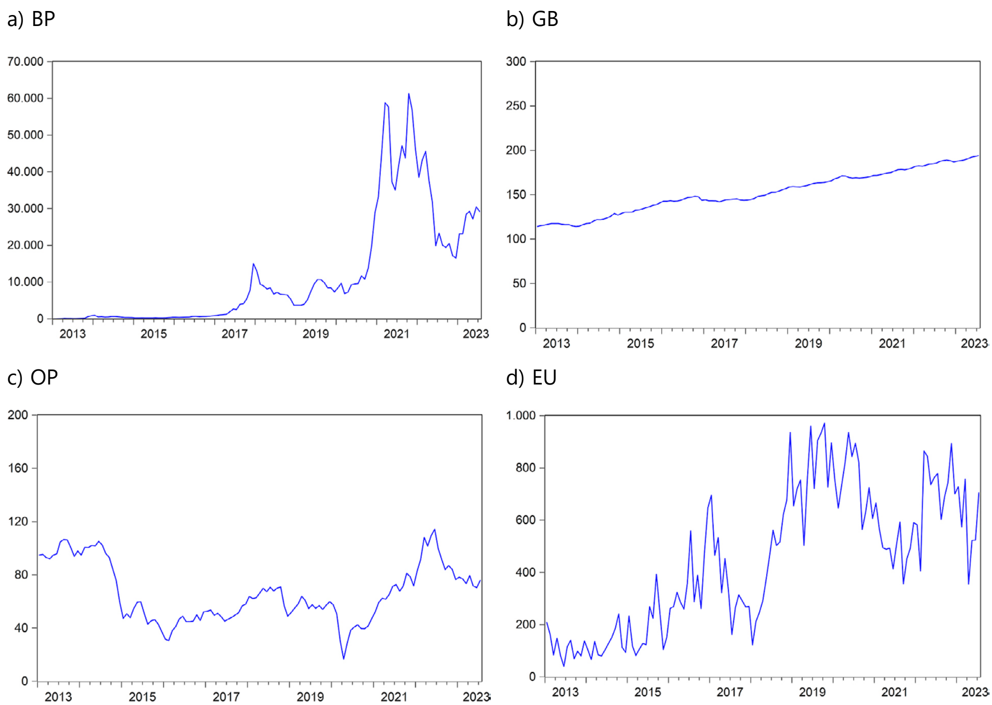

Figure 2. The fluctuating trend of BP, GB, OP and EU

peak of approximately $19,900. Subsequently, BP decreased, influenced by various policies, and dropped below $3200 in December 2018. More notably, BP presented a sharp upward trend in 2020, which was mainly due to the risk aversion of investors triggered by COVID-19 and the shortage in the supply of Bitcoin. The influx of a multitude of institutional investors in 2021 once again became a factor influencing BP's rise.

Table 1 presents the basic descriptive statistics of all variables. The mean values of BP, EU, GB, and OP are centered around 11648.190, 446.027, 152.456 and 66.261, respectively. Given that the skewness value of each variable is positive, they confirm right skewness. In terms of kurtosis, BP is 4.428, which means that it satisfies the leptokurtic distribution, while the values of the remaining variables are less than 3, which means that they possess platykurtic characteristics. In addition, the results of the Jarque-Bera test indicated that all variables have significant nonnormal distributions at least at the 10% level.

Table 1. Descriptive statistics

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J.-B
GB	152.456	148.252	194.004	114.219	23.281	0.004	1.918	6.375**
BP	11648.190	5403.303	61309.600	15.607	15475.100	1.536	4.428	60.736***
OP	66.261	60.790	114.285	16.699	21.981	0.377	2.171	6.646***
EU	446.027	452.149	970.829	40.403	268.844	0.204	1.800	8.496**

Note: *** and ** denotes significance at 1% and 5% levels, respectively.

6. Empirical analysis

6.1. Unit root test

Before moving to the QARDL model, there is one essential step: applying a unit root test to assess the order of integration. This article applies ADF (Dickey & Fuller, 1981), PP (Phillips & Perron, 1988) and KPSS (Kwiatkowski et al., 1992) to carry out unit root tests. As displayed in Table 2, the results of all variables accept the null hypothesis of ADF and PP that the time series has a unit root and reject the null hypothesis of KPSS that the time series is stable. This means that these variables are not stable in the level. Hence, to prevent any possible heteroscedasticity and guarantee the stationary of the series, BP, EU, GB and OP are all treated by first-order differential. As a result, all sequences are satisfied with stationarity, and the QARDL model can be processed at this time.

Table 2. Unit root test

	Level			First difference		
	ADF	PP	KPSS	ADF	PP	KPSS
GB	0.130	0.118	1.374***	–8.382***	–8.380***	0.065
BP	–1.696	–1.477	0.938***	–9.051***	–9.089***	0.051
OP	–2.227	–1.931	0.222***	–8.314***	–8.107***	0.143
EU	–1.953	–2.229	1.029***	–16.254***	–18.686***	0.053

Note: *** denotes significance at 1% level, respectively.

6.2. The QARDL analysis

Table 3 displays the empirical outcomes. With the purpose to keep consistency in research, we just clearly show the major linkage between BP and GB, and other parts are shown in Table A1 and A2 of Appendix. From the table, the range of quantiles (τ) covers 0.10th to 0.90th, and the increment is 0.1. With the exception of the lowest 0.10th quantile, $\xi(\tau)$ is positive and indeed statistically significant throughout other quantiles, which supports the reversion of green bonds toward their long-term equilibrium. Additionally, the deceive coefficient ξ changes at a rate of 0.043 at $\tau = 0.3$ and gradually decreases with increasing quantiles, eventually obtaining a minimum value of 0.023 at $\tau = 0.8$. The decline of coefficients with quantiles demonstrates that the linkage between GB and the other variables shows a weakening trend and is in the least significant state at the lowest quantile. More importantly, the long-term effect, represented by β_i (i = 1, 2, 3), and short-term effect, represented by δ_i (i = 1, 2, 3), are both captured at the same time. To highlight the research theme and provide consistent research, this paper focuses on discussing the effect of BP on the GB market.

Table 3. The QARDL results from BP to GB and GS

Quantile	Dependent variable GB		Dependent variable GS	
	Long-run estimate	Short-run estimate	Long-run estimate	Short-run estimate
	$\beta_1(\tau)$	$\delta_1(\tau)$	$\beta_1^*(\tau)$	$\delta_1^*(\tau)$
0.10th	0.051^{**} (0.019)	0.009^{**} (0.004)	0.149^{**} (0.063)	0.023^{***} (0.002)
0.20th	0.057^{***} (0.021)	0.011^{***} (0.001)	0.128^{**} (0.046)	0.012^{***} (0.003)
0.30th	0.042^{**} (0.016)	0.007^{**} (0.003)	0.179^{***} (0.046)	0.025^{***} (0.007)
0.40th	0.036^{**} (0.018)	0.008^{***} (0.002)	0.099^{***} (0.033)	0.027^{***} (0.005)
0.50th	0.045^{***} (0.016)	0.010 (0.013)	0.116^{**} (0.058)	0.022^{*} (0.012)
0.60th	0.090^{***} (0.028)	0.004 (0.011)	0.125^{**} (0.053)	0.002 (0.025)
0.70th	0.552^{***} (0.187)	0.021 (0.035)	0.111^{*} (0.060)	0.021 (0.028)
0.80th	0.095^{***} (0.025)	0.013 (0.024)	0.133^{**} (0.052)	0.016 (0.033)
0.90th	0.146^{**} (0.057)	0.017 (0.012)	0.139^{*} (0.070)	0.026 (0.040)

Notes: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively, Standard error is presented in parentheses.

It can be found from the table that $\beta_1(\tau)$ indicates that BP exerts a long-term positive influence on GBs at the significance level of 1% and 5%. The finding also reveals that BP and GB have long-term effects throughout the entire subsample, regardless of the bond market conditions (quantiles). BP increased from \$15 in 2009 to approximately \$30,000 in 2023, even though it suffered several significant price drops. Its rising popularity has attracted growing interest in Bitcoin globally (Ciaian et al., 2016), and more economic entities have joined this cryptocurrency market. Differing from traditional currencies, Bitcoin, relying on mining production, will bring obvious environmental damage through its intensive energy use (Bejan et al., 2023) and associated pollution emissions (Goodkind et al., 2022). BTC mining consumed 75.4 TWh of electricity in 2020, which exceeds Portugal (48.4 TWh) or Austria (69.9 TWh) in the same year. The dispute over Bitcoin mining has indeed continued, but an undeniable fact is that the overall amount of Bitcoin mining pools worldwide is expanding annually, from 850 in 2017 to 8630 in 2021, with China leading the way (Liu et al., 2023). By the end of 2020, China dominated over 75% of the worldwide Bitcoin blockchain operation (Jiang et al., 2021). Admittedly, China is likely to face serious environmental threats caused by the rising energy consumption associated with bitcoin mining (Qin et al., 2023). In recent years, China has sought a transformation in development mode and first announced the "Carbon Neutrality and Carbon Peak" targets. Therefore, green financing is becoming increasingly popular as the drive to save energy and cut emissions. Green finance can not only appeal to microeconomic entities to focus on environmental benefits but also cultivate new financing-investment channels. By the end of 2021, China had issued 1642 green bonds with a market value of 1727.685 billion RMB, up 43.91% and 33.19% year on year, respectively (Zheng et al., 2023). Enterprises can utilize the funds raised by green finance to upgrade obsolete equipment, innovate production technology and improve energy efficiency. Governments can also ease financial limitations and rationalize the allocation of resources for environmental projects and renewable energy infrastructure through green finance. Therefore, the green bond market attracts increasing attention from country, company and investors, and is able to positively respond to bitcoin price.

In addition, in Table 3, $\delta_1(\tau)$ demonstrates the short-term effect of BP on China's GB, and its values are positive and significant in lower quantiles, especially below the 0.40th quantile. The potential reason is that China green bond market is vulnerable to temporary shocks, such as policy changes, market mutation, and news events. When the Bitcoin price stays at a lower level and starts to increase, people's attention is gradually attracted. To obtain more profits, some enterprises will choose to increase bitcoin mining capacity, which brings increasing energy/electricity consumption and CO_2 emissions. At this time, awareness of environmental protection gradually wakes up, and investors pay attention to the environmental problems behind the price of bitcoin. They may anticipate that the nation will take measures to protect the environment and thus turn to the green bond market to pursue investing opportunities. China has embraced global investment, and the capital of domestic and foreign investors has made great contributions to expanding the country's green market (Li et al., 2023b). Thus, the green bond market is sensitive to the Bitcoin price when it stays at a low level and gradually causes public environmental concerns. However, the relationship between BP and GB becomes insignificant at higher quantiles. The potential reason is that the rapidly increasing bitcoin price would bring speculative arbitrage and other irrational investing behaviors, which triggers government and market concerns (Lee et al., 2022). For example, in 2021, China began to ban financial institutions and payment providers from processing bitcoin transactions, resulting in a decrease in BP and energy usage. The next potential reason is that Bitcoin's dramatically growing price offers investors additional investment options, which obviously influences the amount of investment in GBs (Goodell et al., 2022). Moreover, GBs are vulnerable to temporary development, policy incentives and major events, thus undermining the linkage with BP (Duan et al., 2023). For example, black swan events, such as the outbreak of COVID-19, the conflict of Russia-Ukraine, and China's green bond principle, affect China's green bond market in a short time via multiple channels (Xia et al., 2023).

6.3. Time-varying analysis

The QARDL model, as shown above, emphasizes the quantile-dependent relationship between BP and GB, which ignores the characteristics of time evolution. Thus, following Mensi et al. (2019), we re-estimate the QARDL model for capturing the time variations in different situations (quantiles) of BP on GBs in the case of China. Figure 3 displays the parameter's rolling quantile estimations for BP on GBs across the 0.25, 0.50, and 0.75 quantiles, together with its 95% confidence intervals. In particular, a specific market condition of Chinese GBs is associated with each quantile. A bear market is denoted by the 0.25 quantile, a normal market by the 0.50 quantile, and a bull market by the 0.75 quantile. Figure 3a–3c shows that in the full sample, $\beta_1(\tau)$ is positive and presents a time-varying pattern, with 95% confidence intervals.

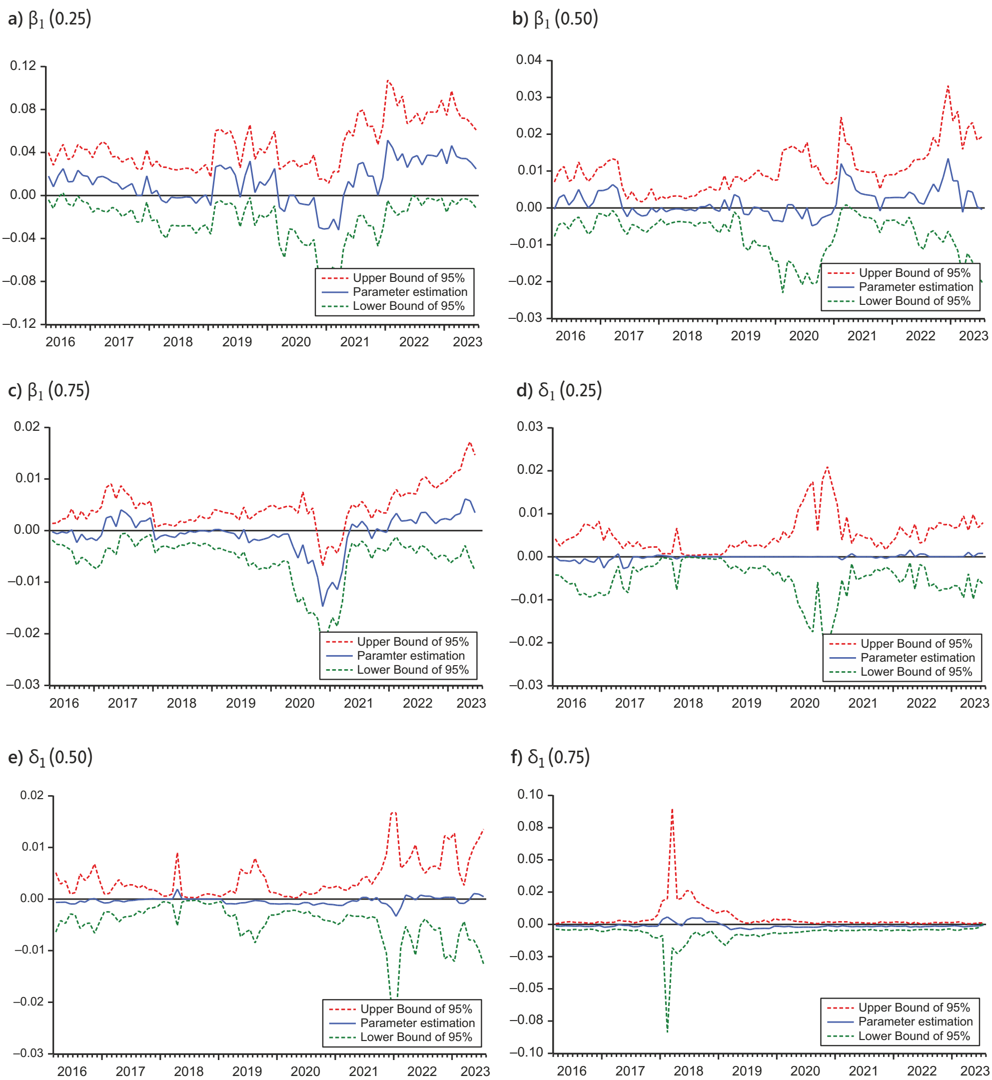

Figure 3. The time-varying estimation for long- and short-run parameters of BP

In approximately 2020–2021, there is a definite drop in the relevance of the rolling estimates. One possible reason is that BP exceeded $30,000 for the first time in 2021 and has displayed a volatile rising trend ever since. Investors' attention is drawn to the rising price, and speculative activities are sparked as a result, which decreases the funds invested in the GB market of China. Another potential argument is that when BP is getting more expensive, China attempts to take a series of measures to prevent damaging shocks from the bursting of cryptocurrency bubbles to the economy. In contrast, Figure 3d–3f shows that the parameter $\delta_1(\tau)$ is below zero and does not present significant time-varying volatility at different quantiles. These outcomes are consistent with the market trend for GBs, which indicates that long-term disruptions have a greater potential impact than short-term movements. Environmental governance, policy reforms and other long-term forces have a prominent impact on the development of GB. The "Dual Carbon" goals announced by China in 2020 have actively encouraged the establishment of a green, low-carbon and recycling-oriented economic system, which creates an enormous demand for GBs as a better financing tool. In contrast, speculative psychology, herding effects, unexpected events and other accidental factors will exert a large impact on the green bond market in the short-term.

7. Further analysis

7.1. Subsample analysis

The Wald test can recognize whether unknown structural breaks exist in a time series. Thus, it is utilized for scrutinizing the constancy of parameters. The corresponding statistics of the Wald test for β_1 and δ_1 are 5.671 and 8.970, and their *p*-values are 0.018 and 0.003, which rejects the null hypothesis and demonstrates that a structural break occurs. Furthermore, this paper utilizes the Zivot-Andrews test (Zivot & Andrews, 2012) for recognizing the structural break point in BP time series as the basis for the subsample analysis. According to the results, the structural break point is October 2020, which is basically consistent with Figure 3a–3c and the literature (Razmi & Razmi, 2023). Therefore, we choose 2020 as the cutoff point, and the results of the subsample analysis are shown below. In Table 4, we can observe that the parameters $\beta_1^{\Delta}(\tau)$ and $\delta_1^{\Delta}(\tau)$ become less significant after 2020. The potential reasons can be explained in the following aspects. The COVID-19 pandemic rapidly spread in 2020, and it led to prompt lockdown, travel restrictions and quarantine, which impacted the global economy, including China's green bond market (Wang & Zhang, 2021). However, bitcoin depends on the advantage of virtual transactions, and its price rapidly increases from 8000 US dollars in January 2020 to more than 60,000 US dollars in October 2021. This may disrupt the original relationship between GB and BP. In addition, in 2021, China begins to prohibit trading activities related to Bitcoin, which further exacerbates the deviations between GB and BP.

7.2. Robustness test

To ensure the robustness of the results, we redo the empirical process with alternative variables. First, China's green finance stock industry index (GS), coming from Wind database, is utilized to replace the green bond index, which covers firms in banking, environmental protection and other fields (Su et al., 2023). Second, different from the previous EU index, this

Table 4. The QARDL results from BP to GB before and after October 2020

Quantile	Before October 2020		After October 2020	
	Long-run estimate	Short-run estimate	Long-run estimate	Short-run estimate
	$\beta_1^{\dagger}(\tau)$	$\delta_1^{\dagger}(\tau)$	$\beta_1^{\Delta}(\tau)$	$\delta_1^{\Delta}(\tau)$
0.10th	0.087*** (0.020)	0.038*** (0.014)	0.026 (0.018)	0.016 (0.013)
0.20th	0.103*** (0.031)	0.041** (0.020)	0.023 (0.016)	0.011 (0.027)
0.30th	0.111*** (0.034)	0.057** (0.023)	0.019 (0.027)	0.010 (0.102)
0.40th	0.227** (0.098)	0.047** (0.019)	0.030 (0.119)	0.026 (0.095)
0.50th	0.331*** (0.114)	0.066*** (0.013)	0.045 (0.034)	0.030 (0.032)
0.60th	0.667*** (0.233)	0.103 (0.077)	0.117 (0.110)	0.041 (1.025)
0.70th	0.592*** (0.184)	0.129 (0.138)	0.228 (0.141)	0.132 (0.753)
0.80th	0.405* (0.225)	0.313 (0.264)	0.432 (1.042)	0.117 (0.123)
0.90th	0.519** (0.200)	0.202 (0.138)	0.246 (0.167)	0.093 (0.072)

Notes: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively, Standard error is presented in parentheses.

paper uses the new economic policy uncertainty (EU*) index, which is measured by two newspapers from mainland China, namely, Renmin Daily and Guangming Daily, and is obtained from http://www.policyuncertainty.com (Che et al., 2023). Third, the WTI oil price is replaced by a new oil price (OP*), which is the average price of the WTI, Brent and Dubai Fateh, and is collected from the International Monetary Fund (Wang & Liao, 2022). As shown in the column of GS in Table 3, $\beta_1^*(\tau)$ and $\delta_1^*(\tau)$ represent long-run and short-run influences from BP to GS. We find that long-run parameters are almost significant across quantiles, which is more obvious than the short-run counterpart. The results are consistent with former conclusions that GB is selected as the dependent variable. Furthermore, this paper discovers that the coefficients of $\beta_1^*(\tau)$ and $\delta_1^*(\tau)$ are larger than the coefficients of $\beta_1(\tau)$ and $\delta_1(\tau)$, which means that bitcoin prices have a larger influence on the green stock market. The potential reasons can be shown as follows. China's stock market consists of a higher percentage of individual retail investors and a lower percentage of institutional investors, which makes the market more susceptible to speculation and herding (Zhu et al., 2020b). More importantly, compared to the large-scale green bond market, the initial public offerings (IPOs) and refinancing of green enterprises in the green stock market are currently in early stages (Su et al., 2023). Therefore, the mentioned factors make green stock vulnerable to shocks from bitcoin price volatility.

7.3 Frequency domain analysis

Frequency domain analysis of the variable itself is attracting increasing attention (Hoque et al., 2023), which can provide more comprehensive results. Following Baruník and Křehlík (2018), the frequency fluctuations associated with variables are explored, and the corresponding results are shown in Figure 4. The frequency domain space is divided into high frequency (1 to 6 months) and low frequency (more than 6 months), and their spillover effects are investigated. In the figure, red and green shadows indicate directional overflow at high and

Figure 4. The frequency domain pairwise spillover

low frequencies, respectively. We observe that, compared to the relatively stable high-frequency spillover, the short-frequency spillover presents significant fluctuations and reaches a peak in 2021. In this year, some important things occurred in the bitcoin market. Bitcoin's market value exceeded $1 trillion for the first time, and per unit bitcoin exceeded $60,000 dollars in October 2021. Some famous companies, including Tesla, SpaceX, MicroStrategy, and others, and their management, such as Elon Reeve Musk, expressed optimism about Bitcoin. Tesla further announced an investment of $1.5 billion to purchase Bitcoin, which completely opened up the upward channel of Bitcoin. In addition, China, formerly the largest bitcoin mining country, officially prohibits bitcoin transactions, which causes a slight decrease in prices. However, the loss of computing power due to China's ban is rapidly compensated by other countries and regions, and the bitcoin market is rapidly restored and exceeds previous prices. The thriving market makes BP have a strong spillover effect on global financial instruments (Goodell et al., 2022), and China's green bonds are inevitably affected.

8. Conclusions and policy insights

This article examines the long-term dynamic impact and the corresponding short-term changes in Bitcoin prices on China's green bonds from the perspective of quartile and time-varying with the QARDL model. The full-sample results indicate that the interaction between BP and GBs indeed exhibits quantile sensitivity and time-varying dependence. Specifically, the short-term impacts of BP and GB are concentrated in the lower quartiles. One possible explanation is that the severe energy consumption and high emissions caused by bitcoin mining triggered environmental concerns and further expanded the development of the green bond market. In the upper quartiles, behaviors such as speculative arbitrage can better explain the connection between the two. In contrast, the long-term effect of BP on GBs is remarkable throughout the sample period, regardless of the quartile, which indicates that the effects of policy and environmental factors are often long-lasting.

Based on the empirical research, the paper makes the following implications. First, it is urgent to reduce the pollutants of bitcoin. Miners can replace the graphics processing unit (GPU) machine with more efficient devices, such as application-specific integrated circuits (ASICs), in the mining process to mitigate emissions. Carbon capture and storage technology can also be applied to restrain the spread of carbon emissions. Second, countries should vigorously develop renewable energy to provide power for Bitcoin. Renewable energy sources such as wind and solar energy are not only cleaner than fossil energy but also sustainable, which is a better choice to provide electricity for mining machines. It is desirable to promote the construction of hydropower, wind power and other bases, equipment manufacturing, operation and maintenance, and waste disposal to build a green closed-loop industrial supply chain for renewable energy. Third, making full use of the "green" feature of financial instruments such as green bonds. Policy-makers can utilize green bonds to rationally allocate resources to green energy and other environmentally friendly fields. Investors can take green bonds into account when they diversify their portfolios, thereby decreasing the financial risks caused by fluctuations in Bitcoin prices. Finally, transparent and stable policies are also essential. The policy changes caused by extreme conditions will increase economic uncertainty, which will cause volatility in bitcoin and green financial markets. Therefore, the government should be cautious and forward-looking in formulating relevant policies to ensure their execution and stability as much as possible.

In the future research, we can do further analysis in following aspects. On one hand, China has different green finance tools. When other markets, such as green credit, are mature, we can discuss the heterogeneous responses to bitcoin price. On the other hand, developed and developing exist differences, we can collect the balanced data for different countries, and carry out deep analysis.

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APPENDIX

Table A1. Results of QARDL for GB

Quantile	Constant	ECM	Long-term estimation			Short-term estimation			
(τ)	α(τ)	ξ(τ)	$\beta_1(\tau)$	$\beta_2(\tau)$	$\beta_3(\tau)$	λ(τ)	$\delta_1(\tau)$	$\delta_2(\tau)$	$\delta_3(\tau)$
0.10th	0.057 (0.117)	0.012 (0.031)	0.052** (0.019)	–0.072 (0.117)	–0.116*** (0.014)	–0.294** (0.133)	0.009** (0.004)	0.018*** (0.008)	0.015*** (0.003)
0.20th	0.077 (0.075)	0.038** (0.017)	0.057*** (0.021)	0.025 (0.181)	–0.113*** (0.018)	–0.245** (0.112)	0.011*** (0.001)	0.027** (0.011)	0.011** (0.005)
0.30th	0.008 (0.057)	0.043*** (0.014)	0.042** (0.016)	–0.081 (0.259)	–0.187*** (0.027)	–0.211** (0.096)	0.007** (0.003)	0.014** (0.006)	0.009*** (0.002)
0.40th	0.003 (0.050)	0.028** (0.013)	0.036** (0.018)	–0.209 (0.251)	–0.144** (0.063)	0.210 (0.133)	0.008*** (0.002)	0.014 (0.015)	0.013** (0.006)
0.50th	–0.027 (0.047)	0.027** (0.012)	0.045*** (0.016)	-0.113 (0.320)	–0.259*** (0.011)	0.226 (0.141)	0.010 (0.013)	0.012 (0.013)	0.020 (0.012)
0.60th	–0.033 (0.054)	0.033** (0.013)	0.090*** (0.028)	0.019 (0.318)	–0.107*** (0.014)	0.169 (0.093)	0.004 (0.011)	–0.011 (0.025)	0.023 (0.017)
0.70th	–0.050 (0.051)	0.032** (0.012)	0.552*** (0.187)	0.962 (0.571)	–0.269*** (0.068)	0.098 (0.104)	0.021 (0.035)	–0.012 (0.016)	0.018 (0.013)
0.80th	–0.078 (0.054)	0.023* (0.012)	0.095*** (0.025)	0.020 (0.154)	–0.116*** (0.023)	0.105 (0.112)	0.013 (0.024)	–0.015 (0.017)	–0.017 (0.022)
0.90th	0.136** (0.062)	0.025** (0.011)	0.146** (0.057)	0.055 (0.300)	–0.132*** (0.017)	0.166 (0.152)	0.017 (0.012)	–0.014 (0.019)	–0.014 (0.010)

Notes: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively, Standard error is presented in parentheses.

Table A2. Results of QARDL for GS

Quantile	Constant	ECM	Long-term estimation			Short-term estimation			
(τ)	$\alpha^*(\tau)$	$\xi^*(\tau)$	$\beta_1{}^*(\tau)$	$\beta_2{}^*(\tau)$	$\beta_3{}^*(\tau)$	$\lambda^*(\tau)$	$\delta_1{}^*(\tau)$	$\delta_2{}^*(\tau)$	$\delta_3{}^*(\tau)$
0.10th	–0.435 (0.734)	0.129*** (0.043)	0.149** (0.063)	–0.309 (0.293)	–0.118** (0.052)	–0.176*** (0.057)	0.023*** (0.002)	0.337*** (0.102)	0.127*** (0.032)
0.20th	1.117 (0.681)	0.153** (0.057)	0.128** (0.046)	–0.400 (0.251)	–0.170** (0.077)	–0.163*** (0.019)	0.012*** (0.003)	0.151** (0.071)	0.112*** (0.024)
0.30th	1.134 (0.707)	0.135** (0.058)	0.179*** (0.046)	–0.427 (0.652)	–0.422*** (0.138)	–0.174*** (0.041)	0.025*** (0.007)	0.136** (0.066)	0.102*** (0.021)
0.40th	1.076 (0.568)	0.146** (0.063)	0.099*** (0.033)	–0.429 (0.621)	–0.332* (0.169)	0.160 (0.095)	0.027*** (0.005)	0.070 (0.062)	0.124*** (0.019)
0.50th	0.733 (0.670)	0.177** (0.070)	0.116** (0.058)	0.534 (0.527)	–0.228* (0.116)	0.141 (0.092)	0.012 (0.025)	0.084 (0.060)	0.034 (0.019)
0.60th	0.608 (0.685)	0.169** (0.071)	0.125** (0.053)	0.456 (0.238)	–0.303** (0.144)	0.157 (0.094)	0.002 (0.025)	–0.111 (0.061)	0.017 (0.019)
0.70th	0.533 (0.634)	0.161** (0.067)	0.111* (0.060)	0.342 (0.233)	–0.324** (0.137)	0.142 (0.103)	0.021 (0.028)	–0.033 (0.067)	0.016 (0.021)
0.80th	1.017 (0.614)	0.153** (0.068)	0.133** (0.052)	0.156 (0.210)	–0.212** (0.082)	0.161 (0.124)	0.016 (0.033)	–0.018 (0.081)	–0.024 (0.025)
0.90th	1.233 (0.735)	0.152* (0.078)	0.139* (0.070)	0.291 (0.414)	–0.313*** (0.096)	0.159 (0.148)	0.026 (0.040)	–0.072 (0.096)	–0.029 (0.030)

Notes: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively, Standard error is presented in parentheses.