

Mixed uncertainty information and volatility in the green bond market based on a new two-regime GARCH-MIDAS extension model

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Abstract

Purpose – This study pioneers a novel two-regime Generalized Autoregressive Conditional Heteroskedasticity–Mixed Data Sampling (GARCH-MIDAS) extension model to disentangle the dual dynamics of traditional drivers and mixed uncertainty indicators in green bond market volatility. Unlike conventional single-regime frameworks, our approach uniquely integrates macroeconomic fundamentals, financial market conditions, and bond performance with multidimensional uncertainty indices (economic policy, geopolitical risks, and market volatility) through a regime-switching mechanism.

Design/methodology/approach – This paper applies the GARCH-MIDAS model to analyse the data. First, traditional and uncertainty variables are incorporated into the single-regime GARCH-MIDAS model to study their impact on the green bond market's long-term components. Second, the two-regime GARCH-MIDAS model is implemented to study the combined impact of traditional and uncertainty factors at different frequencies on the green bond market.

Findings – Our findings suggest that uncertainties have a lasting influence on the green bond market. The results also indicate that traditional factors are still the leading drivers of the green bond market. Notably, the two-regime model captures more information than the benchmark GARCH-MIDAS model.

Research limitations/implications – While this paper advances understanding of China's green bond market, three limitations warrant attention. First, the reliance on nationally specific indicators necessitates regional calibration for global applications given divergent policy frameworks. Second, the monthly frequency of uncertainty indices may understate persistent low-frequency shocks, while the 2018–2023 sample period's concurrent crises (trade tensions and the COVID-19) could amplify measured uncertainty effects. Third,

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although we incorporate multidimensional uncertainties (economic policy, geopolitical, financial), other sector-specific factors, such as climate technology risks remain unexplored.

Originality/value – The first marginal contribution of this paper is the construction of a multidimensional indicator system for the green bond market that integrates traditional factors and uncertainty variables. The second marginal contribution lies in effectively addressing the problem of varying data frequencies in the green bond market and other indicator systems by constructing the GARCH-MIDAS model, thereby avoiding information loss or result distortion caused by converting data of different frequencies to the same frequency. The third marginal contribution is the extension from the original single-regime model to a two-regime model, which links traditional indicator variables with uncertainty variables, addresses the limitations of single-regime models in explaining multiple variables, and examines the combined impact of traditional and uncertainty variables on the green bond market.

Keywords Green bonds, Uncertainty information, Mixed data, Green finance, GARCH-MIDAS

Paper type Research article

1. Introduction

Green bonds have become a pivotal instrument in sustainable finance, broadening investment channels and reallocating capital toward green economic development (Naeem, Farid, Ferrer, & Shahzad, 2021). Understanding their volatility drivers is therefore critical for enhancing market efficiency and advancing climate goals (Wang, Wang, Cheng, & Shi, 2024). Recent global uncertainties—from the COVID-19 pandemic to geopolitical tensions—have amplified green bond market volatility, which often exceeds that of traditional bonds (Xia *et al.*, 2022). Traditional macroeconomic indicators alone cannot fully capture these dynamics. Brandt and Gao (2019) offers new approaches to quantify policy and geopolitical uncertainties using big data, yet the relationship between such uncertainties and green bond movements remains complex and underexplored.

Methodologically, prior studies often rely on conventional models that require frequency alignment, causing information loss and estimation bias (Ghysels & Marcellino, 2016). Mixed-data approaches such as MIDAS preserve original frequency structures and improve estimation accuracy (Silvestrini & Veredas, 2008). Accordingly, we adopt the GARCH-MIDAS framework (Conrad & Kleen, 2020; Kristjanpoller & Minutolo, 2016) to jointly assess traditional and uncertainty factors. Our extended two-regime GARCH-MIDAS model outperforms the single-regime benchmark and captures richer volatility information, as detailed below.

The first marginal contribution of this paper is the construction of a multi-dimensional indicator system for the green bond market that integrates traditional factors and multi-dimensional uncertainty variables. Existing studies typically examine either traditional factors (Xia *et al.*, 2022) or single-type uncertainty factors such as EPU (Pham & Nguyen, 2022), but rarely both. Our comprehensive system enables a more systematic analysis of green bond market drivers, addressing the limitation of single-factor or partial-factor approaches.

The second marginal contribution lies in effectively addressing the problem of varying data frequencies by constructing the GARCH-MIDAS model. Traditional models require same-frequency data, and frequency conversion often causes information loss or estimation distortion (Ghysels & Marcellino, 2016; Silvestrini & Veredas, 2008). While Wang, Ma, Liu, and Yang (2020) applied GARCH-MIDAS to stock volatility forecasting, they did not extend it to green bond drivers nor consider the joint frequency effects of traditional and uncertainty factors. Our application preserves raw data integrity and improves estimation reliability.

The third marginal contribution is the extension from the original single-regime model to a two-regime model, which links traditional indicator variables with uncertainty variables. Existing single-regime studies (Wang *et al.*, 2024; Kim, Dong, & Yoon, 2024) cannot capture interactive effects between the two factor types. Although Conrad and Kleen (2020) theoretically demonstrated the superiority of multi-regime models, they did not apply it to green bonds. Our two-regime GARCH-MIDAS model handles mixed-frequency data and

incorporates a regime-switching mechanism, allowing us to examine both the individual and combined impacts of traditional and uncertainty factors on green bond volatility.

The remainder of this paper proceeds as follows. [Section 2](#) reviews the literature on uncertainty–green bond relationships and the GARCH-MIDAS model, identifying research gaps. [Section 3](#) outlines the single-regime and two-regime GARCH-MIDAS specifications and model evaluation criteria. [Section 4](#) describes the data, variable selection, transformation methods, and summary statistics. [Section 5](#) reports empirical results, covering single-regime analysis, two-regime analysis with combined uncertainty and traditional variables, and model comparisons. [Section 6](#) extends the analysis to the COVID-19 period. [Section 7](#) concludes with policy implications and discusses limitations and future research directions.

2. Literature review

2.1 Uncertainty and green bonds

The popularity of green bonds has grown steadily since 2013 ([Flammer, 2021](#)). They fund advanced technological projects to mitigate the negative effects of industrialisation ([Bhutta, Tariq, Farrukh, Raza, & Iqbal, 2022](#)). Investor support, such as positive social media posts, can influence preferences and increase green bond returns ([Zerbib, 2019](#); [Piñeiro-Chousa, López-Cabarcos, Caby, & Šević, 2021](#)). Financial market shocks affect green bonds, but spillovers to other markets remain limited due to the green bond market's relatively small scale ([Reboredo & Ugolini, 2020](#)).

Following the 2008 financial crisis, “uncertainty” gained prominence in academic research. Financial turmoil and rising uncertainty are key drivers of economic shocks ([Stock & Watson, 2012](#)). [Baker, Bloom, and Davis \(2016\)](#) developed the EPU index using text-search methods, [Caldara and Iacoviello \(2022\)](#) constructed the GPR index, and the CBOE introduced the VIX to measure market uncertainty ([Chung & Chuwonganant, 2014](#)).

A growing literature explores uncertainty's correlation with green bonds, which show time- and state-varying dependency on uncertainty ([Pham & Nguyen, 2022](#)). Economic uncertainty can amplify green bond mispricing ([Wang, Li, & Ren, 2022](#); [Cai, Fu, & Kerestecioglu, 2023](#)). During high EPU periods, green bonds serve as hedging and safe-haven assets ([Doğan, Trabelsi, Tiwari, & Ghosh, 2023](#); [Karim, Lucey, Naeem, & Yarovaya, 2024](#)). Geopolitical risks and climate policy uncertainty also affect green finance and stock markets ([Wu & Liu, 2023](#); [Tang, Chen, Sarker, & Baroudi, 2023](#); [Su, Zhang, & Lin, 2022](#)). Financial uncertainty shapes volatility trends, while monetary policy uncertainty curbs speculation ([Rudkin, Qiu, & Dłotko, 2023](#); [Baydaş, Elma, & Pamučar, 2022](#)). Cultural uncertainty further influences green bond issuance ([Mertzanis & Tebourbi, 2024](#)). However, most studies focus on selected uncertainty types, often overlooking traditional economic factors. Thus, integrating uncertainty indicators into the traditional economic framework is essential for a comprehensive understanding of green bond market drivers.

2.2 The GARCH-MIDAS mixed data model

Studying the relationship between uncertainty and green bonds using traditional econometric models presents several challenges. On the one hand, these models assume that explanatory and dependent variables share the same frequency ([Ghysels & Marcellino, 2016](#)). In practice, however, the Green Bond Index is typically published daily, while uncertainty indicators such as the EPU and GPR are compiled monthly. To cope with such mixed frequencies, traditional methods convert data via weighting or iteration, but these conversions often cause information loss or estimation uncertainty ([Silvestrini & Veredas, 2008](#)). On the other hand, conventional models are limited in characterizing long-term volatility components in green bonds ([Ghysels, Sinko, & Valkanov, 2007](#)), although exogenous predictors can improve forecasting accuracy ([Xia et al., 2022](#)). This study aims to overcome these problems by integrating traditional indicators, uncertainty variables, and the green bond market into a coherent framework.

Mixed-frequency data can better identify causality between variables than uniform-frequency methods. [Engle, Ghysels, and Sohn \(2013\)](#) proposed the GARCH-MIDAS model based on the MIDAS framework, which decomposes conditional total variance into a long-term component and a short-term component. However, the standard GARCH-MIDAS remains a single-regime model and cannot incorporate multiple mixed-frequency indicators simultaneously, limiting its empirical applicability ([Fang, Lee, & Su, 2020](#)).

Existing studies predominantly employ single-regime specifications ([Wang et al., 2024](#); [Kim et al., 2024](#)), failing to capture interactions between conventional and uncertainty drivers. Building on [Conrad and Kleen's \(2020\)](#) theoretical proof of multi-regime superiority, we develop a two-regime GARCH-MIDAS framework that pairs conventional indicators with uncertainty shocks without forcing frequency alignment—a critical advancement given the mixed-frequency nature of our dataset.

Based on the above problems and research challenges, the chief contributions of this paper are as follows.

Firstly, it builds a multi-dimensional indicator system for the green bond market. The traditional indicator system adds multi-dimensional uncertainty variables like economic, geopolitical, and financial market uncertainties to comprehensively analyse green bond market drivers and key factors.

Secondly, this paper effectively addresses varying data frequencies in the green bond market and other index systems by constructing the GARCH-MIDAS model. In the empirical analysis, the single-regime model is used to analyse the impact of each indicator variable on the green bond market and fully capture the effective information in the indicator system. This model avoids information loss or results distortion by changing different frequency data to the same frequency data.

Finally, the analysis is extended by developing a two-regime model from the original single-regime model. This model links traditional indicator variables with uncertainty ones, addressing the limitations of single-regime models in explaining multiple variables. It aids in studying the combined impact of traditional and uncertainty variables on the green bond market by analysing its impact mechanism.

[Figure 1](#) provides this paper's research framework:

3. Model method

This paper applies the GARCH-MIDAS model to analyse the data ([Engle et al., 2013](#)). Firstly, traditional and uncertainty variables are incorporated into the single-regime GARCH-MIDAS model to study their impact on the green bond market's long-term components. Secondly, the two-regime GARCH-MIDAS model ([Conrad & Kleen, 2020](#)) is implemented to study the combined impact of traditional and uncertainty factors with different frequencies on the green bond market.

3.1 The single-regime GARCH-MIDAS model

Our modeling strategy adopts a phased approach to ensure methodological rigor. We first establish baseline relationships using the single-regime GARCH-MIDAS specification, where each predictor individually interacts with green bond volatility through [Equations \(4\)](#). This foundational analysis not only validates data compatibility but also identifies dominant drivers for regime specification. The subsequent two-regime extension in [Equations \(8\)](#) operationalizes [Conrad and Kleen's \(2020\)](#) multi-regime theory by combining the most influential conventional and uncertainty variables identified in Phase 1, effectively creating an integrated system where macroeconomic fundamentals and uncertainty shocks jointly sculpt volatility patterns.

The GARCH-MIDAS model is a mixed frequency model divided into short-term and long-term fluctuations. The short-term fluctuations are used to describe the changes in the

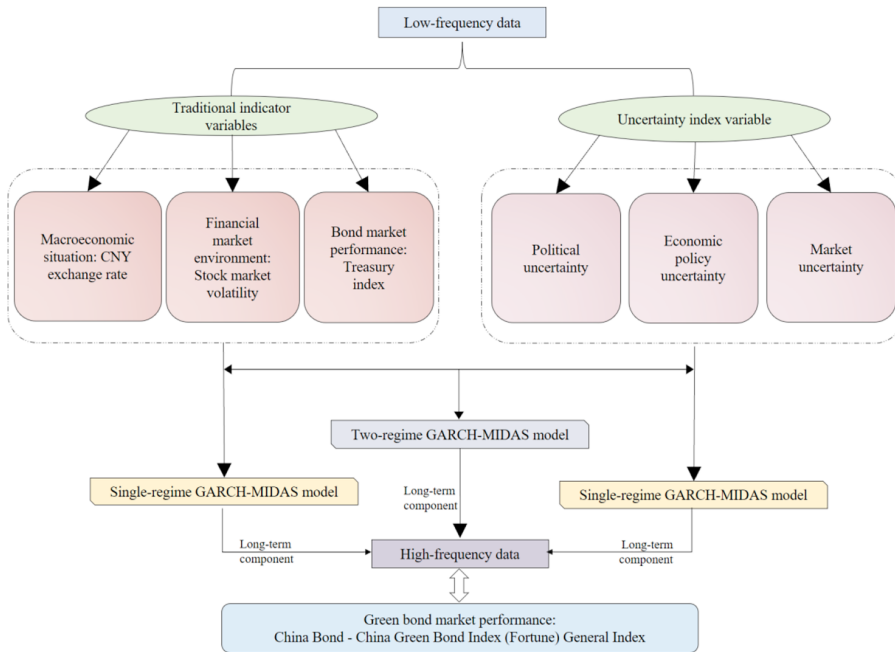


Figure 1. The research framework

conditional variance over time. The long-term fluctuations capture the long-term volatility of factors using low-frequency data. Within the GARCH-MIDAS model, $r_{i,t}$ is the return sequence of the i th day of the t th month, satisfying:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}} \varepsilon_{i,t}, i = 1, 2, \dots, N_t, t = 1, 2, \dots, T, \quad (1)$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0, 1), \quad (2)$$

Where N_t represents the number of valid days in the t th month, $\Phi_{i-1,t}$ represents the valid information in time period $i - 1$ within the t th month, and μ is the unconditional mean. In Equation (1), the conditional variance $\delta_{i,t}^2 = \tau_t g_{i,t}$, where $g_{i,t}$ represents the short-term component, is generally composed of high-frequency uncertainty factors. τ_t represents the long-term component, which is usually composed of low-frequency factors with long-term trends, such as macroeconomic conditions.

According to Conrad and Kleen (2020), green bond data is characterised by peaks and thick tails. Thus, this paper sets the short-term component $g_{i,t}$ as the GJR-GARCH (1,1) process:

$$g_{i,t} = \left(1 - \alpha - \frac{\gamma}{2} - \beta\right) + (\alpha + \gamma I_{\{\varepsilon_{i-1,t} < 0\}}) \frac{\varepsilon_{i-1,t}^2}{\tau_t} + \beta g_{i-1,t}, \quad (3)$$

Where α is the ARCH term, β is the GARCH term, $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta + \gamma/2 < 1$.

The conditional variance is non-negative, and its long-term component τ_t is characterised by the MIDAS model. This paper adopts its logarithmic form:

$$\log(\tau_t) = m + \theta \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) X_{t-k}, \quad (4)$$

Where K is the maximum lag order, X_{t-k} is the volatility of the relative lag k period, and $\varphi_k(\omega_1, \omega_2)$ is the weight function. This paper selects the Beta polynomial function as the weight function, that is:

$$\varphi_k(w_1, w_2) = \frac{[k/(K+1)]^{w_1-1} \times [1 - k/(K+1)]^{w_2-1}}{\sum_{j=1}^K [j/(K+1)]^{w_1-1} \times [1 - j/(K+1)]^{w_2-1}}, \quad (5)$$

$$\sum_{k=1}^K \varphi_k(\omega_1, \omega_2) = 1. \quad (6)$$

[Engle et al. \(2013\)](#) simplified the above Beta weight function by setting $\omega_1 = 1$. Additionally, [Conrad and Kleen \(2020\)](#) found that setting ω_1 to 1 is the optimal choice for model parameters. Therefore, the above formula can be simplified to:

$$\varphi_k(\omega) = \frac{[1 - k/(K+1)]^{w-1}}{\sum_{j=1}^K [1 - j/(K+1)]^{w-1}}. \quad (7)$$

This paper combines daily and monthly data to determine the maximum of lag order K . The optimal value for K is set to 36, while the uncertainty indicator variable is set to 12. These choices are based on the research conducted by [Engle et al. \(2013\)](#) and [Conrad and Kleen \(2020\)](#).

3.2 The two-regime GARCH-MIDAS model with an uncertainty index

This paper incorporates traditional indicator variables into the two-regime GARCH-MIDAS model, adding uncertainty indicator variables to analyse the common roles of traditional and uncertain factors in the green bond market. The rationale for adopting a two-regime specification is twofold. First, green bond markets are inherently sensitive to shifts in policy regimes and investor sentiment. Periods of elevated uncertainty may fundamentally alter the transmission channels through which traditional macroeconomic factors and uncertainty indicators affect volatility, compared to tranquil periods. Second, a single-regime model imposes a constant relationship between predictors and the long-term volatility component over the entire sample period. This assumption may mask heterogeneous effects that are only detectable when allowing for regime-dependent parameters. For instance, a single-regime θ captures an average effect that may appear weak or insignificant, whereas a two-regime framework can reveal that the effect is strong and significant in one regime but offset or even reversed in another. Such a distinction has direct implications for risk management and policy timing, as investors and regulators face fundamentally different market conditions across regimes.

[Equation \(4\)](#) presents a model of the impacts of green bonds on a single-regime indicator when it is expanded into a two-regime model to incorporate an uncertain indicator variable. The model is as follows:

$$\log(\tau_t) = m + \theta^T \sum_{k=1}^{K^T} \varphi_k(w_1^T, w_2^T) Tro_{t-k} + \theta^U \sum_{k=1}^{K^U} \varphi_k(w_1^U, w_2^U) Un_{t-k}, \quad (8)$$

Where T is the traditional influencing factor, and U is the uncertainty factor.

The single-regime model only examines how one explanatory factor affects green bond market volatility. In contrast, the extended model adds two factors to the research framework, allowing for a deeper investigation into the combined effects of traditional indicators and uncertainty indicator variables on the green bond market, building upon the original model's foundation.

3.3 Model evaluation criteria

This paper presents the concept of the variance ratio (VR) to evaluate the long-term component's impact on the overall variance within the model. It is outlined as follows:

$$VR = \frac{\text{var}(\log \tau_t)}{\text{var}(\log \tau_t g_{i,t})}, \quad (9)$$

The VR value determines the power of the explanatory variable on the explained variable. The larger the VR, the greater the impact on the explained variable and the more it reflects the causal relationship between the two.

In addition, this paper also introduces the Gaussian quasi-likelihood loss function (QLKE) to evaluate model performance, which is defined as follows:

$$QLIKE(\delta_t^2, h_t) = \frac{\delta_t^2}{h_t} - \ln\left(\frac{\delta_t^2}{h_t}\right) - 1, \quad (10)$$

In Equation (10), $\delta_{i,t}^2 = \tau_i g_{i,t}$ is the total of the model conditions, and $h_t = (\sum_{j=1}^K r_{t-j}^2)/K$ is the realization of the volatility. This paper uses the QLIKE value to compare the fitting advantages of single-regime and two-regime GARCH-MIDAS models. For extreme abnormalities, the results of QLIKE will be more stable than those of the mean square error (MSE) (Patton, 2011). When the QLIKE value is lower, the better the fitting effect of the model and the more reliable the fit.

4. DATA sources

This paper takes China's green bonds as an example and selects the ChinaBond-China Green Bond Index (GBI) to measure the development status of its green bond market and use it as the explained variable. In selecting traditional indicator variables, this paper uses the Onshore CNY Exchange Rate (CNY) as the indicator variable of China's macroeconomic conditions, the China Treasury Bond Index (TBI) to measure bond market performance, and the Stock Market Volatility (SMV) of CITIC Securities, one of the most representative Chinese stock markets, to reflect the financial market environment. The selection of these traditional indicators is grounded in their established roles in China's financial system. CNY serves as a key barometer of China's macroeconomic conditions and external economic balance, and fluctuations in the exchange rate directly affect cross-border capital flows and financing costs for domestic bond issuers, which is particularly relevant for green bonds given the growing participation of international investors in China's green bond market. TBI represents the risk-free benchmark in China's fixed-income market, and as green bonds compete with treasury bonds for investor capital, movements in TBI reflect shifts in investor risk preferences and the relative attractiveness of green bonds as an asset class. SMV captures the overall sentiment and

uncertainty in China’s equity market, which often spills over into the bond market through portfolio rebalancing and risk-off behavior. Together, these three indicators provide a comprehensive representation of the macroeconomic, bond market, and financial market conditions that shape the investment environment for green bonds in China. Furthermore, this paper selects the Global Economic Policy Uncertainty Index (GEPU), the US Economic Policy Uncertainty Index (US_EPU), the China Economic Policy Uncertainty Index (China_EPU), the Geopolitical Risk Index (GPR), and the CBOE Volatility Index (VIX) as indicator variables for uncertain information. We also incorporate traditional indicator variables and uncertainty indicators into the mixing model framework and pre-process data.

First, the GBI indicator data is transformed as follows to obtain the yield sequence:

$$r_{i,t} = \frac{P_{i,t} - P_{i-1,t}}{P_{i-1,t}} \times 100, \tag{11}$$

Secondly, the logarithmic difference method is used for the VIX, and the absolute value of the difference is obtained for the other uncertainty indicators to reflect changes in uncertainty. At the same time, the remaining traditional indicator variables are subjected to corresponding difference processing. The data in this paper are mixed, in which the explained variables are high-frequency data, and the explanatory variables include daily and monthly data. The data timeframe spans January 2010 to November 2023. Table 1 shows the information and explanation of this paper’s data and sample sources.

A descriptive statistical analysis of variables was performed before the empirical analysis, and Table 2 presents the results after pre-processing the data. By observing the data in the table, it is found that the skewness values of all variables are greater than zero, indicating that these variables are right-skewed. Meanwhile, in the results, the kurtosis value of GBI is greater than 3, indicating that this index variable has leptokurtic and fat-tailed characteristics. In addition, all variables pass the ADF inspection, Arch inspection, and Jarque-Bera test at a 1% level, indicating that these sequences are stable and are typical financial time sequences, such as non-positive and autocorrelation.

Table 1. Data and samples sources

Index	Variable	Data source description	Frequency
Green bond market	GBI	ChinaBond-China Green Bond Index Source: Wind Database	Daily
Traditional indicator variables	CNY	USD/CNY exchange rate (onshore RMB) Source: Wind Database	Daily
	TBI	China Treasury Bond Index Source: Wind Database	Daily
	SMV	CITIC Securities Stock Market Volatility Source: Wind Database	Monthly
Uncertainty indicator variables	GEPU	Baker <i>et al.</i> (2016) constructs a global Economic Policy Uncertainty Index based on an automatic text search Source: http://www.policyuncertainty.com/	Monthly
	Country EPU	Baker constructs the US and China Economic Policy Uncertainty Index based on an automatic text search Source: http://www.policyuncertainty.com/	Monthly
	GPR	Caldara constructs a Geopolitical Risk Index based on the frequency of relevant words in major newspapers and papers Source: http://www.policyuncertainty.com/	Monthly
	VIX	The Chicago Board of Trade’s Volatility Index is based on the real-time prices of options on the S&P 500® Index Source: https://cn.investing.com	Daily

Table 2. Descriptive statistical analysis

Variables	Mean	StdDev	Min	Max	Skewness	Kurtosis	ADF	ARCH	Jarque-Bera
GBI	0.023	0.202	−2.006	2.222	0.594	17.507	−11.382***	236.040***	44388.000***
CNY	0.008	0.408	−1.214	1.284	0.520	1.313	−9.428***	3199.700***	404.890***
TBI	1.539	1.176	−1.680	6.333	0.239	1.422	−9.162***	3194.800***	325.310***
SMV	0.055	1.875	−4.690	12.740	1.993	13.087	−11.477***	3222.300***	26982.000***
GEPU	26.502	25.642	0.111	138.185	1.877	4.083	−10.796***	3146.300***	4435.700***
US_EPU	38.478	36.145	0.191	209.588	2.202	6.182	−8.848***	3197.000***	8306.000***
China_EPU	91.070	78.174	1.027	457.759	1.512	3.197	−10.260***	3178.100***	2791.100***
GPR	15.817	18.751	0.061	127.812	2.986	11.590	−8.148***	3263.900***	24503.000***
VIX	−0.013	1.138	−2.925	4.060	0.468	0.885	−14.369***	3154.500***	239.840***

Note(s): *** represents that the null hypothesis is rejected at a 1% significance level

Figure 2 charts the time sequence of all interpreted variables. Analysis of the curve trend in the diagram shows that the green bond market has fluctuated in the past ten years. These fluctuations are particularly obvious from 2015 to 2020. Notably, uncertainty indicators have risen due to the COVID-19 epidemic. International financial markets were greatly impacted, especially regarding economic policies, increasing fluctuations and risk. In addition, the geopolitical risks in various countries have risen in recent years, such as military conflicts in Russia and Ukraine, Pakistani conflicts, and international trade conflicts such as the Sino-US trade war. These risks have undoubtedly exacerbated the pressure of global inflation. Studying the development trends and influencing factors of green bonds in high volatility periods is essential for green financial transformation.

5. Empirical results and analysis

First, this section uses the single-regime GARCH-MIDAS model for regression analysis. Next, it introduces uncertainty indicators based on traditional variables for the two-regime GARCH-MIDAS regression. The following is a brief overview of this section. Section 5.1 presents the fitting outcomes of the single-regime GARCH-MIDAS model and analyses the green bonds' volatility under various indicator variables. Section 5.2 incorporates traditional and uncertainty indicator variables into the GARCH-MIDAS model for a two-regime analysis. Section 5.3 compares and analyses the results of the single-regime model with those of the two-regime model.

5.1 The single-regime analysis of green bond driving factors

Table 3 shows the fitting results of adding each indicator variable to the single-regime GARCH-MIDAS model. The results show that parameters α and β are significant and satisfy $\alpha + \beta + \gamma/2 < 1$, indicating that the model conditions are met.

This paper focuses on parameter θ , which reflects the influence of long-term component τ_t on conditional differences. In the traditional indicator variables, according to the results displayed in Table 3, the θ parameters of the remaining indicators are significant, except for CNY. The θ parameters of CNY are negative, showing that fluctuations in the CNY exchange rate adversely affect the green bond market. The CNY exchange rate reflects the future trend of macroeconomic conditions to a certain extent. The depreciation of the RMB can trigger capital outflows, reducing the capital supply in the green bond market, negatively impacting the entire

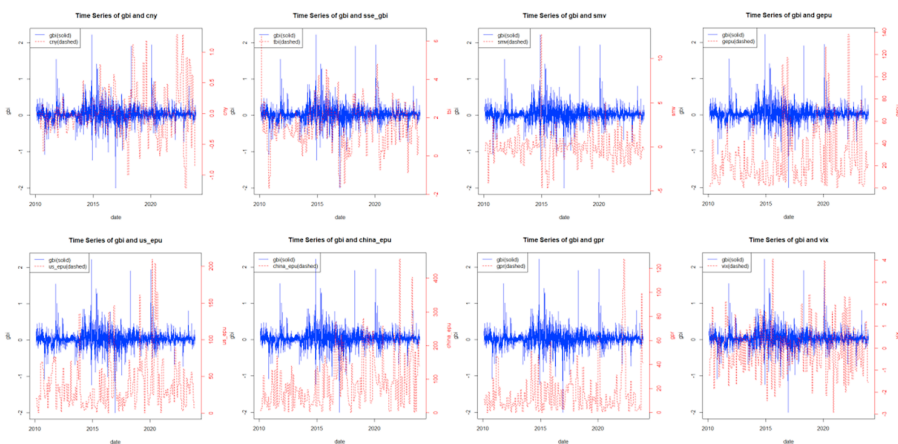


Figure 2. Time series charts

Table 3. The single-regime GARCH-MIDAS

		μ	α	β	γ	m	θ	w_2	LLH	BIC	VR(X)
Traditional indicator variables	CNY	0.025*** (0.004)	0.281** (0.118)	0.743*** (0.106)	-0.076* (0.062)	-1.724* (0.902)	-1.708 (1.272)	9.992** (3.970)	757.507	-1459.909	26.074
	TBI	0.027*** (0.003)	0.236** (0.119)	0.767*** (0.115)	-0.035 (0.047)	-2.908*** (0.838)	0.590*** (0.210)	25.192*** (9.010)	864.286	-1673.255	37.640
	SMV	0.025*** (0.004)	0.341*** (0.100)	0.695*** (0.089)	-0.080* (0.076)	-0.562 (0.906)	1.386** (0.638)	1.032*** (0.221)	1024.303	-1992.473	18.883
Uncertainty indicator variables	GEPU	0.027*** (0.004)	0.286** (0.133)	0.601*** (0.161)	-0.055 (0.110)	-0.995** (0.506)	0.076*** (0.024)	1.000* (0.605)	904.440	-1753.451	32.552
	US_EPU	0.025*** (0.004)	0.307* (0.405)	0.726*** (0.247)	-0.096* (0.293)	-0.230 (2.707)	0.038* (0.021)	1.000 (2.387)	947.924	-1840.320	26.804
	China_EPU	0.024*** (0.004)	0.377** (0.200)	0.629*** (0.129)	-0.140* (0.159)	-0.799 (1.056)	0.019*** (0.005)	1.000** (0.510)	768.431	-1481.757	25.401
	GPR	0.027*** (0.005)	0.306* (0.164)	0.714*** (0.119)	-0.102 (0.114)	0.066 (1.406)	0.145 (0.126)	1.000 (0.892)	795.995	-1437.351	16.725
	VIX	0.026*** (0.003)	0.281*** (0.095)	0.725*** (0.088)	-0.048* (0.056)	-2.035* (1.067)	1.668** (0.831)	9.012*** (2.380)	884.2696	-1713.222	28.577

Note(s): Values in parentheses indicate the standard deviation. *, ** and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively

bond market and thus triggering fluctuations in the green bond market. In addition to the CNY, TBI and SMV positively affect green bond market fluctuations. Compared to other bonds, treasury bonds are safer. When TBI rises, investors may shift from other bond markets to traditional bonds, in which situation the demand for green bonds will decrease and market volatility increase. The rise in stock market volatility reflects the increase in uncertainty within the financial market, impacting the issuance and pricing of environmentally friendly bonds. The stock and bond markets compete in the flow of funds and investors will look for a relatively secure shelter when the stock market risk increases. At this point, investors will shift from the bond market, including green bonds, to more conservative investment instruments, resulting in less trading volume in the green bond market and increased volatility.

Table 3 presents the model-fitting results of the uncertainty indicator variables. As shown in the table, except for the Geopolitical Risk Index (GPR), the θ parameters of the remaining indicators are significant. That is, the impact on the green bond market is significant. According to the content in the Table 3, the Global Economic Policy Uncertainty Index (GEPU) and the country's Economic Policy Uncertainty Index (US_EPU, China_EPU) have a notable positive impact on green bond market fluctuations, and a rising EPU will increase the volatility of this market. Economic policy uncertainty reflects the instability of the macroeconomic environment and may directly or indirectly impact the principal issuer of green bonds, investors, and the market environment. Meanwhile, policy adjustments often accompany a rise in economic policy uncertainty, which may affect green bond financing costs and project approval. Furthermore, as the uncertainty surrounding worldwide economic policies escalates, abrupt swings in the short-term green bond market could trigger ripple effects across international markets, intensifying instability.

Table 3 also presents the model-fitting results of GPR and VIX. According to the parameter value of θ , increasing GPR and VIX augment green bond market volatility, with VIX having a notable positive effect. The rise in GPR means that the political stability of related regions and the focal country has decreased, and economic and social risks have increased. Furthermore, geopolitical risks may lead to fiscal deficit and economic weakness. In this case, the government can adopt a tightening policy and increase bond interest rates to respond to economic risks, directly affecting the country's bond market. The VIX is also known as the "Investor Panic Index", an important indicator for evaluating future risks. A rise in VIX is often accompanied by increased market uncertainty, which may originate from many aspects, such as geopolitical and macroeconomic risks. The higher the VIX, the greater the market expectations, meaning that the uncertainty of the future market increases, enhancing the instability of the green bond market.

In addition, Table 3 presents the VR values of each fitting model. The VR value represents the impact of the extended-term element within the model on the overall variance. The larger the VR value, the greater the contributions of the variable to total volatility, and the more it can explain the volatility of the green bond market. Generally, traditional and uncertainty indicator variables have explanations similar to those of the green bond market. On average, traditional indicator variables are more advantageous than uncertain ones, especially the VR value in the GARCH-MIDAS-TBI model, which is 37.640%, the largest of all VR values. Traditional indicators are the primary driving force behind fluctuations in the green bond market, although the impact of uncertain indicators should not be overlooked.

Existing studies have explored the drivers of green bond market volatility from multiple perspectives. Xia *et al.* (2022) focused on the impact of traditional macroeconomic indicators and financial market variables on green bond volatility, confirming the leading role of factors such as macroeconomic conditions and financial market environment in shaping green bond market fluctuations, which is consistent with our finding that traditional indicators like TBI and SMV are significant drivers of green bond market volatility. Pham and Nguyen (2022) examined the influence of economic policy uncertainty on the green bond market, revealing that economic policy uncertainty has a non-negligible impact on market stability, which aligns with our result that GEPU, US_EPU, and China_EPU have significant positive effects on

green bond market volatility. These commonalities validate the reliability of our research framework in capturing core drivers of the green bond market.

Our results further refine the understanding of traditional factor impacts by identifying the heterogeneous contribution of different macroeconomic and market indicators, a detail not fully addressed in prior studies. For instance, [Reboredo and Ugolini \(2020\)](#) noted the link between financial market conditions and green bond price dynamics but did not quantify the relative importance of specific financial indicators. Our findings show that TBI has the highest VR value among traditional variables, meaning treasury bond market performance contributes more to green bond volatility than CNY exchange rate or stock market volatility. This phenomenon arises because treasury bonds, as low-risk fixed-income assets, directly compete with green bonds for investor capital — when TBI rises, investors shift to safer treasury bonds, reducing green bond demand and amplifying volatility. In contrast, CNY exchange rate fluctuations only indirectly affect green bonds through capital outflow pressures, while SMV impacts are mitigated by the partial segmentation of green bond markets from general stock market sentiment, explaining their lower contribution to volatility.

Another key result — the insignificant impact of GPR on green bond volatility, distinct from the significant effects of EPU and VIX — adds new insights to existing literature. [Caldara and Iacoviello \(2022\)](#) highlighted the broad impact of geopolitical risks on financial markets, but our study shows this effect does not extend strongly to green bonds. This is because green bonds are closely tied to long-term environmental policy goals and project cash flows, which are less sensitive to short-term geopolitical shocks. Unlike general bonds or equities, green bond investors often have longer investment horizons and prioritize environmental returns, making them less likely to adjust positions in response to temporary geopolitical tensions. Additionally, governments often maintain or strengthen green policy commitments during geopolitical uncertainty to sustain long-term sustainable development, providing a buffer that weakens the transmission of GPR to green bond markets. This explains why GPR's θ parameter is not significant, while EPU and VIX remain impactful.

5.2 Two-regime analysis under uncertainty and traditional variable combinations

Uncertainty and traditional indicators are combined in a two-regime GARCH-MIDAS model to study their joint impact on green bond market instability. The fitting results of the two-regime model parameters are shown in [Table 4](#).

The results in [Table 4](#) show that the parameters for α and β are all significant, demonstrating that the fluctuations in the green bond market have strong sustainability. Simultaneously, the results meet $\alpha + \beta + \gamma/2 < 1$, showing that the stability of the model is ensured and the conditions for model parameters are satisfied. During the model estimation outcomes, the parameters for γ are negative, indicating non-symmetrical volatility in the green bond market, and its response to sharp news is greater than to good news. In the case of incomplete and effective markets and information asymmetry, negative news and conflicts will be regarded as a more important signal. Therefore, investors will be more inclined to adopt a cautious or risk-averse strategy when facing these risks.

Panel A of [Table 4](#) presents the two-regime GARCH-MIDAS model after the two combinations of GEPU and traditional variables. The model parameter θ^{Un} shows that the combination of GEPU and the traditional variable is significantly positive, indicating that GEPU exerts a notable positive impact on fluctuations within the green bond market. This is the same as the result obtained by the single-regime model. The findings explain that an increase in global economic policy uncertainty will exacerbate the volatility of the green bond market, and this effect is stable in the long term. The impact of each model's coefficient θ value indicates that the effects of fluctuations in each variable in the two-regime model on the green bond market have diminished compared to the single-regime model. However, for the contributions of the total difference, the VR value of the GEPU two-regime model increased more than the VR value of the traditional monocular model. This information indicates that

Table 4. The two-regime GARCH-MIDAS

	μ	α	β	γ	m	θ^{Tra}	w_2	θ^{Un}	w_2^{two}	VR(X)
<i>Panel A: Results of the two-regime GARCH-MIDAS based on traditional indicators and GEPU</i>										
CNY	0.028*** (0.003)	0.280** (0.120)	0.615*** (0.136)	−0.033 (0.093)	−0.888* (0.538)	−1.253 (0.988)	9.683** (4.125)	0.076*** (0.018)	1.000*** (0.315)	54.767
TBI	0.027*** (0.010)	0.264*** (0.060)	0.587*** (0.056)	−0.007 (0.071)	−1.658*** (0.422)	0.329*** (0.090)	35.642** (17.926)	0.074*** (0.011)	1.000*** (0.161)	67.513
SMV	0.027*** (0.004)	0.280** (0.131)	0.603*** (0.171)	−0.048** (0.099)	−1.140** (0.504)	0.490* (0.389)	2.787** (1.151)	0.073*** (0.024)	1.000 (0.619)	52.737
<i>Panel B: Results of the two-regime GARCH-MIDAS based on traditional indicators and US_EPU</i>										
CNY	0.029*** (0.008)	0.332*** (0.061)	0.689*** (0.028)	−0.095* (0.065)	0.639 (1.138)	−2.639*** (0.519)	6.197** (2.379)	0.065*** (0.008)	1.000*** (0.082)	62.301
TBI	0.029*** (0.008)	0.242*** (0.052)	0.639*** (0.040)	−0.003 (0.058)	−1.589*** (0.336)	0.324*** (0.088)	33.482* (13.215)	0.052*** (0.005)	1.000*** (0.093)	69.941
SMV	0.030*** (0.101)	0.290*** (0.084)	0.579*** (0.051)	−0.046* (0.086)	−1.093*** (0.341)	1.034*** (0.373)	1.800*** (0.466)	0.053*** (0.007)	1.000*** (0.098)	60.272
<i>Panel C: Results of the two-regime GARCH-MIDAS based on traditional indicators and China_EPU</i>										
CNY	0.028** (0.012)	0.264*** (0.062)	0.657*** (0.051)	−0.032 (0.074)	−0.709 (0.538)	−1.297* (0.680)	13.640 (10.207)	0.023*** (0.004)	1.000*** (0.318)	56.297
TBI	0.026 (0.101)	0.189*** (0.042)	0.781*** (0.026)	−0.018 (0.049)	−2.749*** (0.678)	0.574*** (0.177)	26.477** (10.984)	0.011*** (0.004)	1.000* (0.610)	54.137
SMV	0.024 (0.101)	0.265 (0.449)	0.763*** (0.024)	−0.071 (0.057)	−1.150 (2.565)	−1.852** (0.907)	1.000*** (0.306)	0.001 (0.004)	9.815** (4.202)	52.258
<i>Panel D: Results of the two-regime GARCH-MIDAS based on traditional indicators and GPR</i>										
CNY	0.028*** (0.008)	0.295*** (0.034)	0.758*** (0.018)	−0.109** (0.046)	−1.999 (3.177)	−3.031*** (0.617)	7.136*** (2.766)	0.116*** (0.036)	1.000*** (0.278)	28.680
TBI	0.027*** (0.009)	0.245*** (0.049)	0.755*** (0.024)	−0.034* (0.057)	−2.683*** (0.926)	0.597*** (0.206)	25.410*** (9.017)	0.020 (0.030)	1.814*** (0.365)	38.363
SMV	0.027*** (0.003)	0.251** (0.109)	0.746*** (0.130)	−0.037 (0.048)	−2.582*** (0.716)	0.895* (0.539)	3.173*** (0.748)	0.014 (0.009)	31.47*** (0.492)	33.688

(continued)

Table 4. Continued

	μ	α	β	γ	m	θ^{Tra}	w_2	θ^{Un}	w_2^{two}	VR(X)
<i>Panel E: Results of the two-regime GARCH-MIDAS based on traditional indicators and VIX</i>										
CNY	0.27*** (0.003)	0.295*** (0.105)	0.712*** (0.092)	−0.056 (0.062)	−2.077 (1.456)	4.577* (2.503)	1.000** (0.435)	1.534** (0.683)	9.745*** (2.187)	34.295
TBI	0.026*** (0.004)	0.279*** (0.090)	0.733*** (0.080)	−0.053 (0.054)	−1.324 (1.768)	−0.341 (0.907)	2.926*** (0.937)	2.769*** (1.022)	8.746*** (2.925)	31.171
SMV	0.027*** (0.008)	0.289*** (0.052)	0.706*** (0.027)	−0.037 (0.060)	−2.207** (0.977)	0.597 (0.526)	3.659** (1.517)	1.627** (0.779)	9.356*** (2.412)	34.369
Note(s): Values in parentheses indicate the standard deviation. *, ** and *** indicate $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively										

global economic policy uncertainty has a complementary relationship with traditional variables. Including the two simultaneous interpretations of the model can better interpret the long-term fluctuations of the green bond market.

Panels B and C present the fitting results of the two-regime models after combining US_EPU and China_EPU with traditional variables respectively, on a pairwise basis. Compared with the traditional variable impact coefficient, whether US_EPU or China_EPU, the impact coefficient θ^{Tra} in the two-regime model is lower than the traditional variable θ in a single-regime model. In terms of variance contribution, the VR value of the two-regime model is considerably greater than that of the single-factor model. It is worth noting that the impact coefficient θ^{Un} of the uncertainty variable in the US_EPU two-regime model is larger than the impact coefficient θ in the single-factor model, showing that the combination with traditional variables enhances the explanatory power of US_EPU regarding the impact of green bond market volatility. In the China_EPU two-regime model, the combination with SMV reduces the influence coefficient value of uncertainty variables, and θ^{Un} is no longer significant. Nevertheless, the combination of China_EPU and CNY increases the influence coefficient θ value of the uncertain variable. That is, the explanation of China_EPU is enhanced when combined with CNY. This reveals that the influence of China's economic policy uncertainty on the fluctuations of the green bond market is significant.

Panel D shows the fitting results of the two-regime models formed by combining GPR with each of the traditional variables pairwise. The remaining θ^{Un} has become unpredictable due to the combination of GPR and CNY in the model results. The traditional variable impact coefficient θ^{Tra} in the combination of GPR, CNY, and TBI significantly increases compared to the θ^{Tra} in the single-regime model. This shows that the combination of traditional variables and GPR has weakened the influence of GPR and highlights the dominant role of traditional variables in green bond market fluctuations. In addition, the variance ratios of each two-regime model are greater than that of the GPR single-regime model, which is similar to the conclusion drawn previously. What's different in Panel E compared with the previous ones is that, in the two-regime model of the VIX and TBI combination, the impact coefficient θ^{Un} of the uncertainty variable is significantly greater than the impact coefficient in the VIX single-regime model. This indicates that the combination with the traditional variable has enhanced the impact of the uncertainty factor VIX on the volatility of the green bond market.

Our two-regime model results further complement and extend the understanding of green bond market drivers compared to prior studies, particularly in revealing the interactive effects of traditional and uncertainty factors. [Conrad and Kleen \(2020\)](#) theoretically demonstrated the superiority of multi-regime models in capturing volatility dynamics but did not apply this framework to green bond markets or examine the joint impact of dual factor types. Our findings show that when traditional variables are combined with uncertainty indicators, the VR values of the two-regime model are generally higher than those of single-regime models. This phenomenon occurs because the two-regime framework captures the complementary relationship between traditional and uncertainty factors: traditional variables reflect the fundamental supply-demand and capital flow dynamics of the bond market, while uncertainty factors amplify or mitigate these dynamics by shaping investor risk perception. For example, when US_EPU rises, the sensitivity of investors to TBI fluctuations increases — they are more likely to shift from green bonds to treasury bonds amid policy ambiguity, leading to a greater combined impact on volatility than either factor alone.

Another notable result from the two-regime analysis is the asymmetric adjustment of traditional and uncertainty factor coefficients, which has not been reported in existing literature. When combining China_EPU with CNY, the θ^{Un} becomes more significant than in the single-regime China_EPU model, while combining China_EPU with SMV reduces θ^{Un} 's significance. This discrepancy arises from the different transmission channels of uncertainty factors through traditional variables. CNY exchange rate fluctuations are closely linked to China's macroeconomic policy orientation — when China_EPU increases, exchange rate volatility amplifies the uncertainty of green bond issuer financing costs, strengthening the impact of

China_EPU on market volatility. In contrast, SMV reflects broader financial market sentiment, which may overlap with the information content of China_EPU, leading to a partial offset of their respective impacts. This finding highlights that the influence of uncertainty factors on green bonds is not fixed but depends on the type of traditional factor they interact with, a nuance that single-regime models or studies focusing on isolated factors cannot capture.

The above results and analysis demonstrate the following. ① The traditional variables θ^{Tra} and uncertain variable θ^{Un} obtained by traditional and uncertainty indicators remain significant. ② The variance in the two-regime model is generally higher than the VR value in the single-regime model. These conclusions show that compared with the single-regime model, the two-regime model can integrate information from traditional and uncertainty factors, and the complementary effect of the two variables improves the explanatory power of green bond market fluctuations. The above conclusions further confirm that the uncertainty indicator variables affect the long-term fluctuations driving the green bond market.

To assess the value added by the two-regime extension, we compare its performance against the single-regime benchmark along two dimensions. First, in terms of explanatory power, the VR values of the two-regime models consistently exceed those of their single-regime counterparts across nearly all variable combinations (Tables 3 and 4). For example, the VR increases from 37.64% in the single-regime TBI model to 67.51% in the two-regime TBI-GEPU combination, indicating that the two-regime framework captures a substantially larger portion of long-term volatility. Second, and most importantly, the two-regime model reveals asymmetric roles of predictors across states that are completely hidden in the single-regime specification. Specifically, we find that uncertainty factors such as US_EPU and VIX exert stronger impacts when paired with traditional variables in the two-regime framework, while GPR's influence becomes weaker or insignificant when combined with certain traditional indicators. These cross-regime differences are not merely quantitative but qualitative. They suggest that the driving forces of green bond volatility are state-dependent, and that the effectiveness of policy interventions or hedging strategies should be calibrated to the prevailing regime. Thus, the two-regime model does not simply add parameters. It provides a materially different and more nuanced understanding of the underlying volatility dynamics.

5.3 Comparison of the results of the single-regime and two-regime models

The value in the single-regime model represents the influence of different variables on green bond market fluctuations. In the two-regime model, θ is divided into θ^{Tra} and θ^{Un} , respectively, representing the impact of traditional and uncertainty variables in fluctuations. To analyse green bond market drivers under different models, this paper compares θ values using combination diagrams.

Figures 3 and 4 show the traditional and uncertainty variable θ values under the single-regime model for the full sample interval. Among the conventional variables, CNY negatively impacts green bond volatility, most notably from SMV. Among the uncertainty variables, China_EPU minimally impacts green bond volatility, while VIX has the biggest impact.

Figures 5 and 6 add two-regime model fitting coefficients based on the full sample interval single-regime model θ value and use the column diagram to represent the distributions of traditional and uncertainty variables. By comparing the impact coefficients of the single-regime models, it is found that, except for CNY in Figure 5, the impact coefficients of other two-regime models all show a decreasing trend. Moreover, most of the models in Figure 6 also exhibit this characteristic. The influence coefficients of the variables in each combination method of the two-regime model are similar to the influence coefficient directions of the variables in the single-regime model, which is even more evident in Figure 6.

To compare the differences in the impacts of different variables on green bond volatility across different time dimensions, this paper divides the entire data interval into three dimensions (2010–2014, 2015–2019, and 2020–2023), and compares the impact coefficients with the results of the entire sample interval as the benchmark. Figures 7 and 8 present the

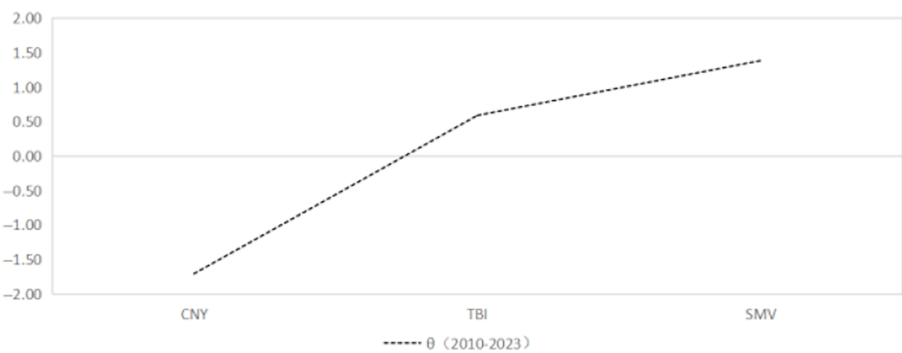


Figure 3. The θ values of traditional variables

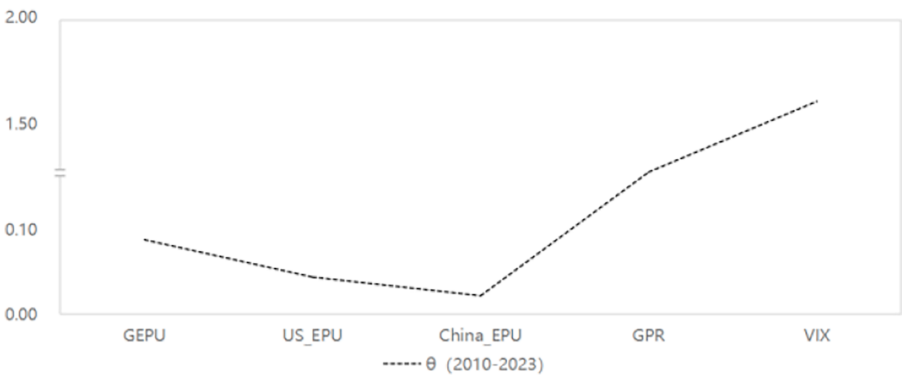


Figure 4. The θ values of uncertainty variables

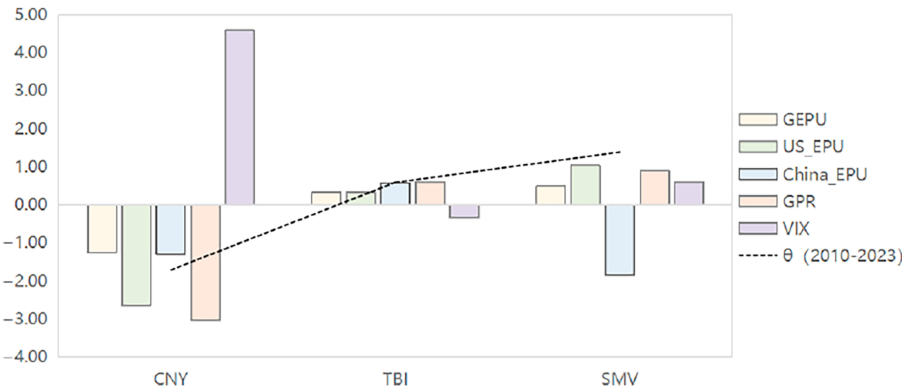


Figure 5. The θ^{Tra} values of traditional variables

combined coefficients of traditional and uncertainty variables in different sample intervals. During each time interval, the impact of variables on green bond volatility remains stable, with CNY and TBI having a more significant effect in shorter periods than the entire sample

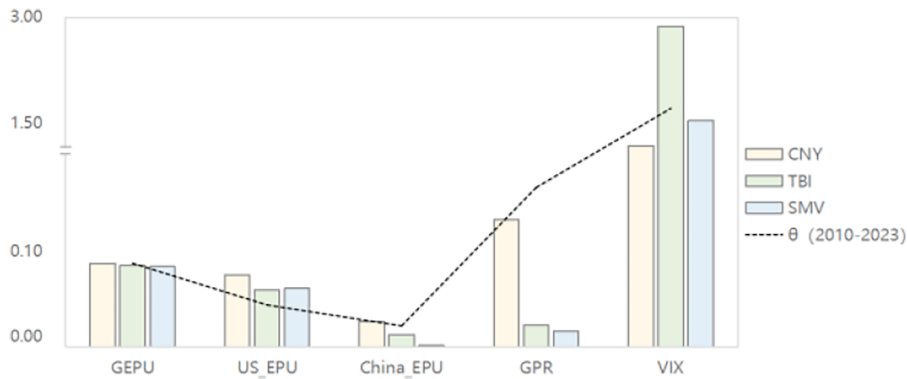


Figure 6. The θ^{Un} values of uncertainty variables

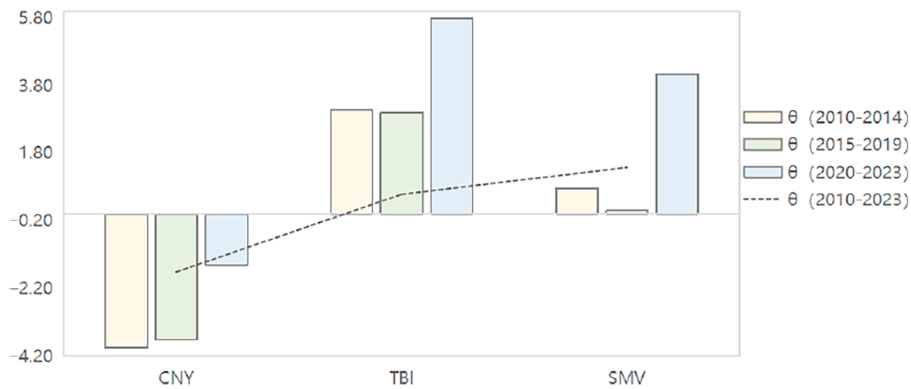


Figure 7. Traditional variable θ values with different intervals

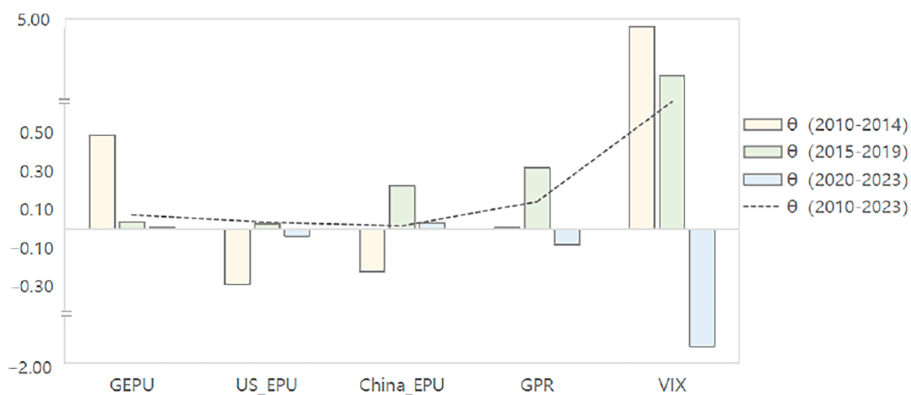


Figure 8. Uncertainty variable θ values with different intervals

interval. For uncertainty variables, green bond fluctuations differ from variables depending on the year, but, in general, the impact direction of various variables will not change significantly. Furthermore, this paper compares the influence coefficients of the two-regime model over different year intervals, along with the influence coefficients of the single-regime and two-regime models across the full sample interval. As many models correspond to different variable combinations in this paper, the traditional variable coefficients are based on the combination of VIX and traditional variables as an example, as shown in Figures 9 and 10, respectively. Observation shows that the impacts of different factors on green bonds vary to different degrees in different intervals, which is caused by the differences in the risk levels across different time dimensions.

6. Analysis of green bond market drivers in the context of COVID-19

This paper uses data from after 2019 to further test the empirical results. Since 2019, various extreme high-risk events such as COVID-19, international trade frictions, and regional conflicts have been common, resulting in a period of high fluctuation and uncertainty. Therefore, this paper estimates the single- and two-regime GARCH-MIDAS using data after 2019 to examine the influence of the green bond market during periods of significant volatility.

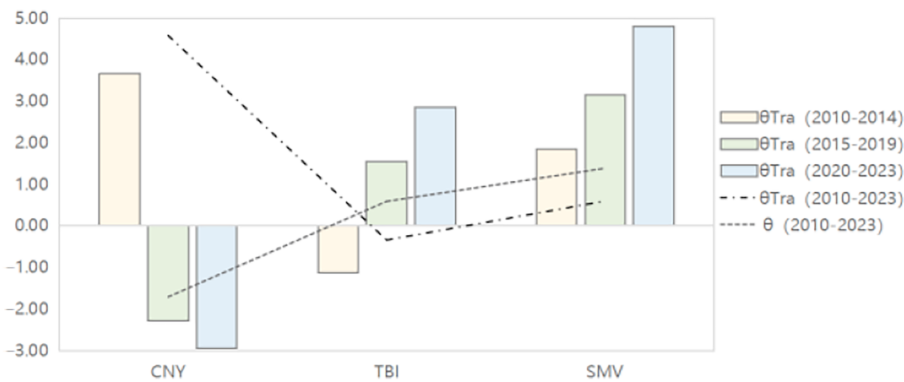


Figure 9. Traditional variable θ^{Tra} values with different intervals

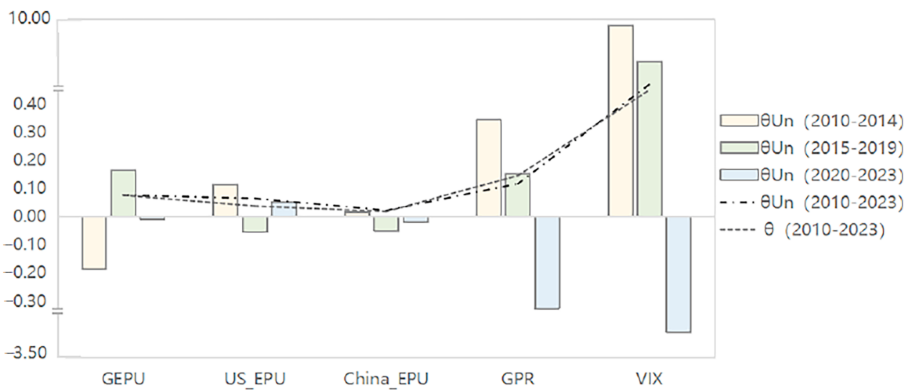


Figure 10. Uncertainty variable θ^{Un} values with different intervals

6.1 The single-regime GARCH-MIDAS model under the epidemic background

The fitting results of a single-regime GARCH-MIDAS model are shown in Table 5. The parameter estimation value of the full sample interval in Table 5 shows that most of the impact coefficients of the uncertainty variables are not significant. Meanwhile, uncertainty variables' influence on green bond market fluctuations has weakened, indicating challenges in capturing market changes during periods of high volatility. Although factors become more complex at this time, global economic policy uncertainty and geopolitical risks remain key drivers in the green bond market. Furthermore, comparing traditional variables' impact across intervals shows that while CNY's θ value decreased, it never reached significance at 5%. However, the intensity of TBI and SMV significantly increased. This indicates that traditional variables' influence on green bond market fluctuations significantly increased during high volatility, becoming a key driver, further confirming traditional factors as the primary drivers of green bond market volatility.

Our findings on the enhanced influence of traditional variables during the epidemic period align with some post-crisis financial market theories but also provide green bond-specific insights not covered in prior studies. Naeem *et al.* (2021) noted that conventional financial assets become more sensitive to macroeconomic fundamentals during high-volatility events like COVID-19, and our results extend this observation to green bonds — specifically, the VR value of SMV reaches 57.867% in the post-2019 single-regime model, significantly higher than its full-sample VR value, while TBI remains a key driver with stable impact intensity. This phenomenon occurs because the epidemic heightened investors' risk aversion and focus on asset safety. As SMV rises amid market turbulence, investors' demand for safe-haven assets intensifies, leading to more pronounced capital flows between stock and green bond markets, thus amplifying SMV's impact on green bond volatility. In contrast, Pham and Nguyen (2022) only examined pre-epidemic EPU impacts and did not capture this crisis-driven shift in traditional factor importance, while our post-2019 analysis reveals that traditional variables (rather than uncertainty factors) become the core volatility drivers during extreme events — likely because uncertainty factors were already at elevated levels during the epidemic, making their marginal impact less prominent compared to the more volatile traditional market indicators.

6.2 The two-regime GARCH-MIDAS model under the epidemic background

Table 6 shows the two-regime model of the interval section after 2019. After careful consideration of the effects of CNY and various uncertainty variables on the fluctuations of the green bond market, the parameters θ_{Tra} are found to be significantly negative, which aligns with the findings of the single-regime model. The coefficient θ^{Tra} is significantly positive and compatible with the findings of the single-regime model when combining US_EPU, TBI, and SMV to examine green bond market fluctuations. Furthermore, the variance ratio of the two-regime model ratio is greater than that of the single-regime model, which confirms the conclusions of the full sample model. Considering the impact coefficients of China_EPU and TBI, θ^{Un} is significantly positive and smaller than the China_EPU monocular model, which is consistent with the results of the full sample interval model mentioned earlier. The influence coefficient of VIX and traditional variable θ^{Tra} are also significant based on the influence direction of the single-regime model. Therefore, the model results in the high fluctuation period after 2019 are similar to those from the full sample period.

Our two-regime model results during the post-2019 epidemic period further uncover the strengthened interactive mechanism between traditional and uncertainty factors, which differs from the relatively stable interaction patterns observed in the full-sample analysis. Wang *et al.* (2024) explored the relationship between uncertainty and green bond markets using a single-regime model but did not capture how crisis events reshape the joint impact of dual factor types. Our findings show that in the two-regime combination of TBI and US_EPU, the VR value reaches 80.496% — far higher than the post-2019 single-regime VR values of TBI and

Table 5. The single-regime GARCH-MIDAS (since the 2019 epidemic)

		μ	α	β	γ	m	θ	w_2	LLH	BIC	VR(X)
Traditional indicator variables	CNY	0.031*** (0.005)	0.226 (0.209)	0.068 (0.071)	0.298 (0.342)	−4.054*** (0.380)	−1.499 (1.291)	6.243 (4.815)	393.506	−743.884	42.983
	TBI	0.029** (0.015)	0.827*** (0.229)	0.244 (0.245)	−0.164 (0.751)	7.900 (11.492)	5.792 (7.312)	1.567*** (0.401)	390.875	−738.621	22.835
	SMV	0.032*** (0.005)	0.176 (0.168)	0.076 (0.077)	0.308 (0.297)	−4.099*** (0.295)	4.141** (2.791)	1.569** (0.687)	399.679	−756.231	57.867
Uncertainty indicator variables	GEPV	0.031** (0.013)	0.364 (0.257)	0.047 (0.198)	0.182 (0.291)	−4.616*** (0.310)	0.012** (0.005)	11.917 (47.957)	396.799	−750.469	56.844
	US_EPV	0.032*** (0.005)	0.196 (0.209)	0.051 (0.084)	0.211 (0.335)	−3.106** (1.233)	−0.035 (0.033)	7.363*** (1.164)	392.309	−741.491	33.771
	China_EPV	0.032*** (0.005)	0.180 (0.203)	0.060 (0.091)	0.279 (0.343)	−8.008*** (2.286)	0.033* (0.021)	1.000*** (0.358)	391.902	−740.675	33.637
	GPR	0.033*** (0.004)	0.182 (0.140)	0.085 (0.091)	0.243 (0.286)	−2.505* (1.468)	−0.080 (0.072)	2.476 (1.942)	406.838	−770.548	72.857
	VIX	0.034*** (0.005)	0.163 (0.206)	0.051 (0.084)	0.309 (0.359)	−4.338*** (0.253)	−1.611 (2.147)	3.215*** (0.261)	391.648	−740.168	23.424

Note(s): Values in parentheses indicate the standard deviation. *, ** and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively

Table 6. The two-regime GARCH-MIDAS (since the 2019 epidemic)

	μ	α	β	γ	m	θ^{Tra}	w_2	θ^{Un}	w_2^{two}	VR(X)
<i>Panel A: Results of the two-regime GARCH-MIDAS based on traditional indicators and GEPU</i>										
CNY	0.031*** (0.005)	0.197 (0.175)	0.066 (0.064)	0.308 (0.322)	-3.803*** (1.241)	-1.353 (1.142)	6.580* (3.880)	-0.008 (0.041)	5.854*** (1.817)	41.828
TBI	0.032*** (0.004)	0.146 (0.183)	0.450*** (0.061)	0.274 (0.303)	-1.231 (2.516)	-1.073*** (0.205)	1.000 (0.692)	-0.044 (0.081)	3.706*** (1.334)	28.203
SMV	0.031*** (0.012)	0.285 (0.269)	0.142 (0.235)	0.252 (0.293)	-9.745*** (2.744)	4.015 (4.147)	2.334* (1.342)	0.168* (0.091)	1.282 (0.991)	68.619
<i>Panel B: Results of the two-regime GARCH-MIDAS based on traditional indicators and US_EPU</i>										
CNY	0.026*** (0.010)	0.254*** (0.093)	0.787*** (0.056)	-0.084 (0.113)	-0.847 (4.725)	-25.057** (10.023)	1.000*** (0.207)	0.052 (0.042)	1.453 (1.034)	77.335
TBI	0.028*** (0.008)	0.304*** (0.100)	0.765*** (0.051)	-0.142 (0.151)	-5.165 (7.202)	7.496* (4.267)	5.155* (3.063)	-0.172 (0.115)	2.339* (1.427)	80.496
SMV	0.031*** (0.005)	0.221 (0.146)	0.082 (0.084)	0.280 (0.296)	-2.709 (1.907)	5.463** (2.576)	1.233*** (0.261)	-0.033 (0.044)	1.700*** (0.448)	63.649
<i>Panel C: Results of the two-regime GARCH-MIDAS based on traditional indicators and China_EPU</i>										
CNY	0.029*** (0.004)	0.674 (0.853)	0.540 (0.484)	-0.616 (0.502)	-1.043 (3.962)	-8.114 (11.605)	1.000** (0.469)	-0.019 (0.050)	2.407* (1.308)	34.667
TBI	0.033*** (0.005)	0.346*** (0.098)	0.703*** (0.088)	-0.113 (0.096)	-8.924** (3.865)	3.872 (2.526)	11.021*** (3.003)	0.004** (0.002)	2.987 (7.312)	86.294
SMV	0.032*** (0.005)	0.167 (0.175)	0.072 (0.068)	0.316 (0.296)	-2.417 (3.061)	4.331 (2.938)	1.659*** (0.654)	-0.014 (0.027)	1.000 (0.960)	60.089
<i>Panel D: Results of the two-regime GARCH-MIDAS based on traditional indicators and GPR</i>										
CNY	0.027*** (0.008)	0.165 (0.236)	0.790*** (0.077)	-0.201 (0.231)	1.490 (2.502)	-5.408*** (1.995)	5.768*** (1.432)	-0.326** (0.128)	1.252*** (0.271)	70.749
TBI	0.028*** (0.007)	0.467*** (0.089)	0.667*** (0.064)	-0.281** (0.112)	-18.002* (10.391)	11.500 (7.620)	3.381*** (1.184)	-0.107 (0.101)	3.163 (2.530)	84.607
SMV	0.033*** (0.004)	0.182 (0.142)	0.083 (0.088)	0.024 (0.285)	-2.535* (1.487)	-0.025 (0.083)	34.580*** (11.970)	-0.077 (0.072)	2.599 (2.189)	73.883

(continued)

Table 6. Continued

	μ	α	β	γ	m	θ^{Tra}	w_2	θ^{Un}	w_2^{two}	$\text{VR}(\text{X})$
<i>Panel E: Results of the two-regime GARCH-MIDAS based on traditional indicators and VIX</i>										
CNY	0.031*** (0.005)	0.181 (0.145)	0.087 (0.095)	0.371 (0.317)	−4.114*** (0.356)	−2.952* (1.661)	2.768*** (0.743)	−3.404* (1.808)	3.057*** (0.406)	63.508
TBI	0.033*** (0.005)	0.295 (0.324)	0.445 (0.783)	0.045 (0.372)	0.240 (1.846)	2.861** (1.155)	1.000*** (0.351)	2.616 (3.468)	1.111** (0.449)	19.750
SMV	0.031*** (0.004)	0.188 (0.134)	0.084 (0.085)	0.329 (0.297)	−4.204*** (0.288)	4.805** (2.470)	1.260*** (0.234)	−2.519 (1.889)	3.159*** (0.474)	70.322
Note(s): The values in parentheses indicate the standard deviation. *, ** and *** indicate $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively										

US_EPU — and this combined contribution is also more prominent than in the full-sample two-regime model. This phenomenon stems from the epidemic's amplification of policy uncertainty and fixed-income market competition. During the crisis, US_EPU surged due to pandemic response policy adjustments, while investors sought safety in treasury bonds, making TBI fluctuations more sensitive to policy uncertainty. As a result, the interaction between TBI and US_EPU creates a volatility synergy that exacerbates green bond market fluctuations — an effect that single-regime models or studies ignoring crisis contexts fail to identify. Additionally, in the combination of SMV and China_EPU, the θ^{Tra} remains significant and positive, while θ^{Un} weakens slightly compared to the full sample. This is because SMV, as a high-frequency indicator, more timely reflects epidemic-induced market panic, partially overriding the impact of monthly China_EPU data, highlighting the time-sensitive nature of factor interactions during extreme events.

6.3 Model effect evaluation

This paper uses the QLIKE loss function to assess the model's fitting performance. The results are shown in Table 7. Panel A and B present the QLIKE value corresponding to the full sample and high volatile intervals in single and two-regime GARCH-MIDAS models. Overall, whether a full sample interval or a high volatility range, the QLIKE statistics of the two-regime GARCH-MIDAS model are generally lower than the single-regime GARCH-MIDAS model. This means that compared to monocular factor models, two-regime models have better expression. It also demonstrates that combining traditional and uncertainty indicators to analyse their joint impact on green bond market fluctuations provides a more comprehensive understanding than using a single variable.

Based on the above analysis, the two-regime GARCH-MIDAS model is more effective than the traditional single-regime GARCH-MIDAS model. In interpreting the fluctuations in the green bond market, traditional variables play a leading-driven role, and the uncertainty

Table 7. QLIKE statistics

	The single regime	GEPU&Tra	US_EPU&Tra	China_EPU&Tra	GPR&Tra	VIX&Tra
<i>Panel A: Full sample interval</i>						
CNY	0.081	0.101	0.087	<i>0.074</i>	<i>0.034</i>	<i>0.080</i>
TBI	0.093	0.097	0.099	<i>0.079</i>	<i>0.038</i>	0.116
SMV	0.197	<i>0.102</i>	<i>0.101</i>	<i>0.072</i>	<i>0.057</i>	<i>0.039</i>
GEPU	0.101					
US_EPU	0.096					
China_EPU	0.052					
GPR	0.027					
VIX	0.064					
<i>Panel B: High volatility interval (2019–2023)</i>						
CNY	0.308	<i>0.308</i>	0.336	<i>0.294</i>	<i>0.297</i>	0.310
TBI	0.308	<i>0.306</i>	<i>0.035</i>	<i>0.018</i>	<i>0.025</i>	<i>0.308</i>
SMV	0.307	0.309	0.308	<i>0.307</i>	<i>0.304</i>	0.309
GEPU	0.309					
US_EPU	0.306					
China_EPU	0.307					
GPR	0.305					
VIX	0.307					

Note(s): The italic area marks the results of the two-regime model with lower QLIKE values than the one-factor model

variables also contain rich explanation information. Therefore, it is necessary to consider traditional and uncertainty variables.

To summarize, the single-regime GARCH-MIDAS model offers a parsimonious and computationally efficient framework for capturing the long-term impact of individual predictors on green bond volatility. Its main strength lies in its simplicity and interpretability, making it suitable for identifying the dominant drivers in a straightforward manner. However, its primary limitation is the implicit assumption that the relationship between predictors and volatility remains constant over time, which may oversimplify the underlying dynamics and mask state-dependent heterogeneity. In contrast, the two-regime GARCH-MIDAS model relaxes this constancy assumption by allowing the impact of traditional and uncertainty factors to vary across two endogenously determined states. This flexibility enables the model to capture asymmetric and complementary effects that are entirely hidden in the single-regime framework. The empirical results demonstrate that the two-regime model consistently yields higher VR values and lower QLIKE statistics, indicating superior explanatory power and better in-sample fit. Nevertheless, this enhanced performance comes at the cost of increased model complexity and parameter proliferation, which may pose estimation challenges in smaller samples or with a larger set of predictors.

Overall, the choice between the two specifications depends on the research objective. For a general understanding of the average effects of key drivers, the single-regime model provides a useful baseline. For a more nuanced analysis that accounts for regime-dependent dynamics and interactive effects between traditional and uncertainty factors, the two-regime model offers substantial value added, particularly in the context of green bond markets characterized by frequent policy shifts and varying investor sentiment.

7. Conclusions and policy recommendations

7.1 Main conclusions

This paper uses traditional influencing factors to construct a multi-dimensional index system for green bond market fluctuations. It utilises a single-regime GARCH-MIDAS model with mixed data to study green bond market drivers and introduces uncertain index variables with traditional indicators to build a two-regime model for further study. Through empirical research, the following conclusions are drawn:

First, macroeconomic indicators have varying effects on green bond volatility, but conventional indicators remain the main drivers of market fluctuations. The long-term effects of uncertainty indicators on green bond market volatility cannot be ignored. Furthermore, intensified economic policy uncertainty and geopolitical risks will increase green bond market volatility.

Second, factors have varying degrees of differences and structural changes, resulting in the volatility of the green bond market in different time dimensions. Amidst heightened market volatility, the influence of conventional factors on green bond market fluctuations has notably escalated, with economic policy uncertainty and geopolitical risks continuing to serve as key catalysts for volatility in the green bond market at such times.

Third, the mixed data model allows multiple variables to be studied simultaneously. The model evaluation results demonstrate the superiority of the two-regime GARCH-MIDAS model. By incorporating both traditional and uncertainty variables, it outperforms the single-regime model in both expressiveness and explanatory power.

7.2 Policy recommendations

Drawing on these key findings, this study presents a set of actionable policy suggestions for investors, regulators, energy firms, and policymakers, rooted in the volatility trends of the green bond market and the associated risk mitigation strategies.

For investors, our results indicate that traditional macroeconomic and bond market indicators remain the dominant drivers of green bond volatility. In the single-regime model, the VR value of TBI reaches 37.64% and that of SMV reaches 18.88%. This suggests that investors should continue to monitor conventional financial market conditions as primary signals for portfolio adjustment. At the same time, the two-regime analysis reveals that uncertainty factors such as US_EPU and VIX exert significantly stronger impacts when combined with traditional variables. The θ^{Un} value reaches 2.769 in the TBI-VIX combination, compared with only 1.668 in the single-regime VIX model. This finding implies that during periods of elevated uncertainty, investors should pay particular attention to the interaction between policy shocks and bond market conditions. Practically, investors can adopt China's approach of pairing traditional bond metrics with geopolitical risk dashboards, which is similar to the EU's Sustainable Finance Disclosure Regulation, to enhance cross-regime portfolio adjustments.

For green bond market regulators, our model comparison demonstrates that the two-regime GARCH-MIDAS framework consistently yields higher VR values and lower QLIKE statistics than the single-regime benchmark across nearly all variable combinations. This indicates that volatility dynamics are state-dependent and cannot be adequately captured by a constant-parameter model. This provides empirical justification for establishing dynamic early-warning mechanisms that adjust according to prevailing market regimes. Regulators should integrate mixed-frequency analysis into risk monitoring systems, as our results show that low-frequency uncertainty indicators such as monthly EPU and GPR jointly shape long-term volatility together with high-frequency market data such as daily GBI and VIX. This approach, mirroring China's Green Finance Reform Pilot Zones framework, can help preemptively identify systemic risks before they materialize.

For energy enterprises, our findings show that during the post-2019 high-volatility period, the impact of SMV on green bond volatility increased substantially. The VR value rises from 18.88% in the full sample to 57.87% after 2019, reflecting heightened investor sensitivity to stock market turbulence during crises. This suggests that firms issuing green bonds should time their issuance strategies according to stock market conditions and incorporate uncertainty buffers into bond terms. Our two-regime results further indicate that GPR's influence becomes weaker or insignificant when combined with certain traditional indicators, implying that geopolitical risks may be partially hedged by strong macroeconomic fundamentals. Chinese solar firms have practiced linking bond terms to regional GPR levels, which offers a replicable model for global peers to manage such risks.

For policymakers, our evidence confirms that economic policy uncertainty has a significant and persistent positive impact on green bond volatility across both regimes. In the single-regime model, the θ values for GEPU, US_EPU, and China_EPU are 0.076, 0.038, and 0.019 respectively. This underscores the need for consistent and transparent policy frameworks to avoid unnecessary uncertainty that could destabilize green finance markets. Furthermore, our COVID-19 period analysis reveals that traditional factors become even more dominant during extreme events, suggesting that policy interventions should focus on stabilizing macroeconomic fundamentals as the first line of defense. Domestically, China's tiered risk-response system provides a template for central banks to stabilize green markets during crises by activating liquidity support when volatility exceeds historical norms. Internationally, promoting the hybrid model of blending traditional indicators with real-time uncertainty metrics through platforms such as the ASEAN+3 Bond Market Forum could help standardize climate-resilient financing across jurisdictions.

7.3 Limitations and future research directions

While this paper advances understanding of China's green bond market, three limitations warrant attention. First, the reliance on nationally-specific indicators necessitates regional calibration for global applications given divergent policy frameworks. Second, the monthly

frequency of uncertainty indices may understate persistent low-frequency shocks, while the 2018–2023 sample period's concurrent crises (trade tensions, COVID-19) could amplify measured uncertainty effects. Third, although we incorporate multi-dimensional uncertainties (economic policy, geopolitical, financial), other sector-specific factors like climate technology risks remain unexplored.

Future research should validate findings through cross-country comparisons and integrate higher-frequency uncertainty metrics to enhance temporal resolution. Expanding investigations to sector-specific uncertainties and employing structural break analysis could further refine volatility regime identification across heterogeneous risk environments.

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