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WHAT CAUSES THE RETURN AND VOLATILITY SPILLOVER IN CHINESE GREEN FINANCE MARKETS? A TIME-FREQUENCY PERSPECTIVE

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Abstract. This paper analyzes both return and volatility spillovers between green bonds, green stocks, clean energy, and carbon markets from April 28, 2014, to May 31, 2024, using the time-frequency connectedness methodology. Further, determinants of these spillovers are examined from perspectives of economic fundamentals (macroeconomics, inflation, and rate), market contagion (market volatility and investor sentiment), and uncertainties (EPU, CPU, GPR, and the COVID-19 pandemic) with the linear regression and quantile regression methods. Our investigation demonstrates that return and volatility spillovers exhibit significant crisis jumps during periods of financial turmoil. During most periods, both return and volatility spillovers occur predominantly in the short run. Second, green bonds and carbon markets show safe-haven characteristics as net risk recipients. Furthermore, economic fundamentals, market contagion, and uncertainty factors exhibit obvious impacts on both green finance market spillovers, albeit in differing magnitudes and directions. Notably, both return and volatility spillovers in the short and long run are determined by economic fundamentals, market contagion, and uncertainty variables. What's more, these factors exhibit stronger interpretations of extreme return spillovers. These findings pose significant ramifications for risk mitigation and portfolio diversification for investors and authorities throughout Chinese green finance markets.

Keywords: return spillovers, volatility spillovers, China's green finance markets, economic fundamentals, market contagion, uncertainty.

JEL Classification: C58, G10, G14, G15.

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1. Introduction

Recent years have witnessed tremendous climate change, environmental deterioration, and the greenhouse effect. As an important component of the financial system, green finance contributes directly to projects aimed at reducing carbon emissions and promoting clean energy adaptation and has become an essential means for achieving green development. Green finance markets have exhibited a >100% yearly growth, and it is expected to mean they shall make up almost a third of worldwide investments until 2025 (Naeem et al., 2022). Consequently, green finance markets may possess several benefits, such as risk management and portfolio diversification during economic and financial turmoil periods. In particular, as the highest global carbon emitter, China is dedicated to promoting green financial activities to mitigate the pressure of carbon emission reduction, environmental degradation, and green development, and has made remarkable achievements in green finance development. Specifically, by 2023, Chinese green bonds grew fast and have emerged as key engines driving the swift development of international green bonds. Green stocks are also an essential source of green finance to boost green development, whose market size continues to grow. In addition, the Chinese carbon market became operational in July 2021 and is anticipated to grow into the largest carbon market globally. More importantly, given commodities financialization, the investment attribute of clean energy is increasingly prominent and has obvious portfolio diversification and safe-haven characteristics relative to other assets (Çelik et al., 2022). Therefore, clean energy is regarded as an integral component of green finance markets for China in this study.

Furthermore, financial integration accelerates market interactions, resulting in cross-market risk contagion and transmissions within financial systems. Especially for green finance markets, its green attribute represents the generally consistent involvement groups of green finance (comprising investors, regulators, and other market participants). Based on this development, the interaction among Chinese green finance markets is intuitively appealing as these markets have distinctive fundamental properties that enable them to cope with disturbances and readjust to economic unpredictability. Some researchers have confirmed significant differences between the spillovers of returns and volatility across financial markets in a dynamic path (Billah et al., 2022; Kao et al., 2024). However, it is unknown how green finance market spillovers will react to these financial and economic stresses and uncertainties. Therefore, an in-depth investigation of the transmission of returns and volatility in the Chinese green finance markets, as well as the impacts of the economy, finance, and uncertainty factors on those spillovers, provides an innovative viewpoint for investors, legislators, and regulators on improving asset al.ocation and risk mitigation.

Nevertheless, some issues need to be addressed in the very relevant literature. Prior research on return and volatility spillovers in Chinese green finance markets remains insufficient. Second, despite the recent development of literature, there appears to be no work on a thorough analysis of the determinants of green finance market spillovers. Moreover, the multidimensional analysis of returns and volatility in time-frequency areas, is somewhat limited. This study investigates Chinese green finance market spillovers on return, volatility, and time-frequency dimensions to tackle previous research gaps. We further explore various variables that contribute to these spillover effects during normal and extreme market circumstances using the linear regression and Quantile regression (QR) methods.

This study brings four distinct contributions to current research. Firstly, we focus on spillovers in Chinese green finance markets, advancing our knowledge of the relationship across finance markets. Second, this study explores the overall, net directional, and net pairwise spillover effects in terms of return and volatility, as well as across different time horizons and frequencies. Furthermore, by using the time-frequency connectedness technique, this study validates that both return and volatility spillovers exhibit large crisis leaps and vary across different frequency domains. Third, we confirm the diverse patterns of the impacts of economic fundamentals, market contagion, and uncertainties determinants on Chinese green finance market spillovers across return and volatility, in addition to short- and long-term frames. What's more, this study indicates that economic fundamentals, market contagion, and uncertainty factors exhibit stronger interpretations for the extreme return spillovers.

The remaining parts are arranged according to the following: Section 2 offers literature review. Section 3 outlines the approaches. Section 4 describes the data. Section 5 displays the discussions. Section 6 concise conclusion and implications.

2. Literature review

This investigation involves three aspects of present studies. Firstly, most works concentrate on spillover effects between green and traditional finance markets (Wen et al., 2024; Zeng et al., 2024). Several researchers verified the time-varying spillovers and hedging effects across green investments and other financial markets from the perspective of the global market (Mensi et al., 2023; Zhou et al., 2023). Due to the common energy attributes, spillovers between renewable energy and brown energy have been documented in many research (Zhang et al., 2023a; Lei et al., 2024). For instance, Liu et al. (2023) investigated the asymmetrical and time-varying effects between clean energy and crude oil and verified the net volatility receiver role of oil in clean energy (Tan et al., 2021). Ding et al. (2023) identified minimal volatile correlations between renewable-energy securities and fossil fuels.

Another body of research investigates the spillovers within global green financing markets (Dogan et al., 2022; Naeem et al., 2023). Scholars have affirmed the significant changing characteristics of spillover effects among green finance markets (Khalfaoui et al., 2022; Zhang et al., 2023b). Some researchers examined spillovers between green bonds, green equities, and renewable energy from perspectives of return or volatility (Lorente et al., 2023), and clarified that green bonds tend to bear risks (Tian et al., 2022). Carbon markets function as shock transmitters among sustainability-related financial indexes (L. Pham et al., 2022).

In addition, uncertainty around the world has sparked significant interest among scholars in the factors that drive financial market spillovers. The macro economy and investor sentiment are important determinants of market spillovers (Charfeddine et al., 2022; Feng et al., 2023). Moreover, studies asserted the substantial influence of investor sentiment and market volatility indices on both return and volatility spillovers in related markets (Jia et al., 2022; Pham & Cepni, 2022). Numerous studies have further examined the various impacts of these drivers during extremely market circumstances, including EPU, the COVID-19 pandemic, GPR, and CPU (Chen et al., 2024; Mignon & Saadaoui, 2024).

To summarize, despite extensive research on the linkages among green bonds, clean energy, and carbon markets in view of the international finance markets, there appears to be a shortage of concern with Chinese green finance market spillovers. An in-depth analysis of both returns and volatility spillovers in Chinese green finance markets from over time and frequency domains is quite limited. Second, previous research has claimed that both economic and financial factors, as well as various uncertainties (EPU, CPU, GRP, and COVID-19), exhibit obvious influences on finance market spillover effects, while more studies can yet be conducted. Moreover, there is a scarcity of literature detailing the asymmetrical patterns of these impacts during moments of extreme market conditions. Consequently, our study aims to address these research gaps.

3. Methodology

3.1. Spillover connectedness in time and frequency domains

Various approached are available for exploring these topics. The time-frequency connectedness method based on the TVP-VAR model is more suitable for the sample data of this study and aligns with the research theme. Therefore, this study applies the connectedness technique introduced by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) based on the TVP-VAR method to examine Chinese green finance market spillovers in the time-frequency domain. The TVP-VAR model for order one is formulated as:

$$y_t = \beta_{1t} y_{t-1} + \beta_{2t} y_{t-2} + \ldots + \beta_{pt} y_{t-p} + \in_t, \quad \in_t \sim N(0, \Sigma_t), \tag{1}$$

where y_t, y_{t-1}, and $\in_t$ are $Z \times 1$ dimensional vectors of green finance markets series. The time-varying variance-covariance matrix Σ_t and time-varying VAR coefficients $\beta_{it}(i = 1, \ldots, p)$ are dimensional metrics. Then, using the $Z \times Z$ matrix lag-polynomial $\beta(L) = \left[I_Z - \beta_{1t} L - \ldots - \beta_{pt} L^p\right]$ with I_Z identify matrix, $\beta(L) y_t = \in_t$. Subsequently, following the Wold representation theorem, equation (1) can be formulated as: $y_t = \Psi(L) \in_t$, where $\beta(L)$ matrix of infinite lag polynomials can be computed recursively from $\beta(L) = \left[\Psi(L)\right]^{-1}$. Since $\Psi(L)$ includes an infinite number of lags, it is approximated by Ψ_l computed at $l = 1, \ldots, L$ horizons.

The L-step-ahead Generalized Forecast Error Variance Decomposition (GFEVD) $\tilde{\varphi}_{ijt}(L)$ may be assessed the impact of shocks in market j on market i:

$$\varphi_{ijt}(L) = \frac{(\Sigma_t)^{-1}_{jj} \sum_{l=0}^{L} ((\Psi_l \Sigma_t)_{ijt})^2}{\sum_{l=0}^{L} (\Psi_l \Sigma_t \Psi'_l)_{ii}}; \tag{2}$$

$$\tilde{\varphi}_{ijt}(L) = \frac{\varphi_{ijt}(L)}{\sum_{k=1}^{Z} \varphi_{ijt}(L)}. \tag{3}$$

According to normalization, $\sum_{i=1}^{Z} \tilde{\varphi}_{ijt}(L) = 1$ and $\sum_{j=1}^{Z} \sum_{i=1}^{Z} \tilde{\varphi}_{ijt}(L) = Z$. Referring to Karim et al. (2022), L is set to be 10. The total directional connectedness to others (TO) is expressed as:

$$TO_{it}(L) = \sum_{i=1, i \neq j}^{Z} \tilde{\varphi}_{jit}(L). \tag{4}$$

The total directional connectedness from others (FROM) can be clarified as:

$$FROM_{it}(L) = \sum_{i=1, i \neq j}^{Z} \tilde{\varphi}_{ijt}(L). \tag{5}$$

The net total directional connectedness (NET) can be computed by:

$$NET_{it}(L) = TO_{it}(L) - FROM_{it}(L). \tag{6}$$

If $NET_{it}(L) > 0$, market i appears as the net spillover transmitter to other variables. Then, the overall connectedness index (TCI) can be computed as follows:

$$TCI_t(L) = Z^{-1} \sum_{i=1}^{Z} TO_{it}(L) = Z^{-1} \sum_{i=1}^{Z} FROM_{it}(L). \tag{7}$$

Furthermore, Baruník and Křehlík (2018) and Chatziantoniou et al. (2021) take the frequency response function $\Psi(e^{-i\omega}) = \sum_{l=0}^{\infty} e^{-i\omega l} \Psi_l$, with $i = \sqrt{-1}$. ω represents frequencies. Then, the spectral density of y_t at frequency ω can be calculated as the Fourier transform of TVP-VMA (∞):

$$S_y(\omega) = \sum_{l=-\infty}^{\infty} E\left(y_t y'_{t-l}\right) e^{-i\omega l} = \Psi(e^{-i\omega l})\Sigma_t \Psi'(e^{i\omega l}). \tag{8}$$

The frequency GFEVD may be normalized as follows:

$$\varphi_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1} \left| \sum_{l=0}^{\infty} (\Psi(e^{-i\omega l})\Sigma_t)_{ijt} \right|^2}{\sum_{l=0}^{\infty} (\Psi(e^{-i\omega l})\Sigma_t \Psi(e^{i\omega l}))_{ii}}; \tag{9}$$

$$\tilde{\varphi}_{ijt}(\omega) = \frac{\varphi_{ijt}(\omega)}{\sum_{k=1}^{Z} \varphi_{ijt}(\omega)}. \tag{10}$$

$\tilde{\varphi}_{ijt}(\omega)$ depicts the spectrum's part of market j_{th} at specific frequency ω is impacted by j_{th} market changes. Formally, there is a frequency range $d = (a,b) : a,b \in (-\pi,\pi)$, $a < b$. The GFEVD on frequency range d is formulated as: $\tilde{\varphi}_{ijt}(d) = \int_a^b \tilde{\varphi}_{ijt}(\omega) d\omega$. The connectedness of green finance markets at frequency range d may be formulated as:

$$TO_{it}(d) = \sum_{i=1, i \neq j}^{Z} \tilde{\varphi}_{jit}(d); \tag{11}$$

$$FROM_{it}(d) = \sum_{i=1, i \neq j}^{Z} \tilde{\varphi}_{ijt}(d); \tag{12}$$

$$NET_{it}(d) = TO_{it}(d) - FROM_{it}(d); \tag{13}$$

$$TCI_t(d) = Z^{-1} \sum_{i=1}^{Z} TO_{it}(d) = Z^{-1} \sum_{i=1}^{Z} FROM_{it}(d). \tag{14}$$

3.2. Determinants of spillover effects

The main determinants of financial market spillovers can be summarized as the economic fundamentals, market contagion, and uncertainty aspects.

(1) Economic fundamental determinants.

Following the findings of Charfeddine et al. (2022), economic fundamentals can impact the green finance market spillovers by influencing the business activities (macroeconomy) and expected cash flows (monetary policy). Economic circumstances may influence green finance market spillovers by changing finance market operations. The composite index method is used to calculate the Chinese macroeconomic climate index (*ME*), which is based on a number of indicators that reflect the current state of the economic cycle, including GDP components and employment[1]. By taking into account industry productions, employment, investment, consumption, and exports in a comprehensive manner, as well as showing notable effects on financial risks, the ME can accurately reflect the direction and extent of the Chinese economy (Yu & Zheng, 2022). The monthly year-on-year CPI growth rate (*CPI*) indicates inflation that is closely tied to stock market volatility (Abbas et al., 2019), and may increase the risk

[1] https://www.stats.gov.cn/zs/tjws/tjfx/202301/t20230101_1903945.html.

of contagion in the financial market (Huang et al., 2024). Moreover, the yield to maturity on 10-year Treasury bonds (*RATE*) is a proxy for monetary policy and closely pertains to financial risks. In general, Lower interest rates can reduce the risk contagion effect of traditional finance markets (Huang et al., 2024).

(2) Market contagion determinants

When investors are more optimistic, stable asset prices contribute to weaker market spillovers (Fang et al., 2018). The CICSI index (*CICSI*) developed by Yi and Mao (2009) is employed to quantify Chinese investor sentiment. Moreover, according to Zheng and Liu (2018), market spillover is an increasing function of market volatility. The weighted mean volatility for four green finance markets by monthly turnover is utilized to signify the market volatility (*MV*) (Jiang et al., 2022).

(3) Uncertainty determinants

Scholars have confirmed the influences of EPU, CPU, and GPR on financial market spillovers (Elsayed et al., 2022; Wang et al., 2023a; Wu & Liu, 2023). For instance, CPU can decrease the spillovers among green assets, the EPU and GPR show mixed influences on financial market spillovers (Pham et al., 2024; Xiong et al., 2024). Notably, these impacts may diverge in the short and long run (Man et al., 2024). Moreover, the COVID-19 pandemic (*COVID-19*) significantly impacted financial markets, as highlighted by Wang et al. (2023b). A dummy variable is used to symbolize the COVID-19 epidemic. The period of Chinese COVID-19 occurrence (December 2019 to January 2023) is labeled as 1, while the rest of the observations are labeled as 0. Consequently, a linear regression model was employed to analyze the impact of various variables on Chinese green finance market spillovers as follows.

$$\begin{aligned} C_t = {} & \sigma_0 + \sigma_1 ME_t + \sigma_2 CPI_t + \sigma_3 RATE_t + \sigma_4 MV_t + \sigma_5 CICSI_t + \sigma_6 EPU_t + \\ & \sigma_7 CPU_t + \sigma_8 GPR_t + \sigma_9 COVID-19_t + \rho_t, \end{aligned} \tag{15}$$

where C_t represents the logarithm of return and volatility spillovers in green finance markets, including the overall, short-term, and long-term spillovers. ρ_t is the error term.

3.3. Quantile regression designs

The QR method introduced by Koenker and Bassett (1978) enables to examine the non-linear effects of multiple factors on risk spillovers (Lee, 2021). A quantile regression model in the paper is constructed as follows:

$$\begin{aligned} C_t^{\theta} = {} & \varsigma_0^{\theta} + \varsigma_1^{\theta} ME_t + \varsigma_2^{\theta} CPI_t + \varsigma_2^{\theta} RATE_t + \varsigma_4^{\theta} MV_t + \varsigma_5^{\theta} CICSI_t + \varsigma_6^{\theta} EPU_t + \\ & \varsigma_7^{\theta} CPU_t + \varsigma_8^{\theta} GPR_t + \varsigma_9^{\theta} COVID-19_t + \upsilon_t, \end{aligned} \tag{16}$$

where ς_0^{θ} is the coefficients of determinants on the spillovers at the θ_{th} quantile and is measured using multiple values θ within (0, 1).

4. Data and descriptive statistics

4.1. Green finance markets

The Chinese green finance markets in this paper include green bonds, green stock, clean energy, and carbon markets. China Bond-China Green Bond Net Price Index (GB) is utilized to represent green bonds. Considering Lin et al. (2018), the China Securities Environmental

Protection Industry Index (GS, code 000827) is selected to reflect green stocks. Closing prices of Hubei carbon allowances (CM) can be utilized as a proxy for the carbon market. Following Wang et al. (2021), clean energy can be identified via the China New Energy Index (CE, code 399412). For the sake of consistency and availability, the daily dataset covers from April 28, 2014, to May 31, 2024, and was obtained from the Wind database. The daily return series of green finance markets can be calculated as follows: $R_t = \ln(P_t / P_{t-1})$ (P_t denotes the daily closing price.). Regarding market volatility, according to Zhu et al. (2024), daily volatility V_t can be computed by the GARCHSK model[2]. Moreover, the Bai-Perron structural test indicated the absence of structural breakpoints in the Chinese green finance market series[3].

Table 1. Descriptive statistics for return and volatility series of Chinese green finance markets

	Mean	Median	Max	Min	Std. dev	Skewness	Kurtosis	JB	$Q^2(20)$	ADF
					Return					
GB	0.000	0.000	0.011	–0.009	0.001	0.120**	22.079***	48490.202***	222.882***	–10.790***
GS	0.000	0.001	0.068	–0.125	0.018	–0.772***	4.557***	2302.017***	768.970***	–12.753***
CE	0.000	0.001	0.073	–0.123	0.020	–0.686***	3.712***	1557.781***	667.160***	–12.761***
CM	0.000	0.000	0.111	–0.197	0.028	–0.250***	4.795***	2311.205***	595.818***	–14.228***
					Volatility					
GB	0.000	0.000	0.000	0.000	0.000	2.394***	25.483***	66837.219***	999.791***	–10.712***
GS	0.000	0.000	0.001	0.000	0.000	3.454***	18.882***	40190.899***	11897.033***	–7.031***
CE	0.000	0.000	0.001	0.000	0.000	5.266***	41.107***	179023.082***	3222.678***	–7.807***
CM	0.001	0.001	0.001	0.001	0.000	30.605***	1037.743***	107435429.407***	1392.570***	–12.936***

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (The following tables are the same).

Table 1 reports the statistical descriptions. Intuitively, the return of the carbon market exhibits the largest standard deviations. The return series for green stocks, clean energy, and the carbon market endure slightly negative skewness values, indicating significant losses during undesirable market scenarios. Positive skewness values of green finance market volatility confirm the presence of possible incidents. The JB (Jarque-Bera) test detects anomalous numbers across both return and volatility sequences, indicating a departure from normal distributions. The Ljung-Box (Q^2) statistics indicate the return and volatility clustering of most green finance market series. Moreover, all series exhibit stationarity.

4.2. Determinants of return and volatility spillovers

With data availability, sample intervals for the regression models are from May 2014 to September 2023. The detailed descriptions are summarized in Table 2 as follows.

[2] Since the realized volatility method diminishes data frequency and affects the accuracy of empirical results, the GARCHSK model preserves the original data frequency and does not affect empirical analysis. Therefore, we choose the GARCHSK model to assess the volatility of the green finance markets. Besides, due to limited space, the detailed GARCHSK model is delineated in Appendix.

[3] Due to limited space, the findings of the Bai-Perron structural test are not presented here. If you need them, you can request them from the author.

Table 2. Description of the determining factors

Category	Variables	Name	Definition	Sources	Type
Economic Funda-mental	ME	Economic growth	The macroeconomic climate index compiled by the National Bureau of Statistics monthly.	CSMAR	Loga-rithmic
	CPI	Inflation	Chinese year-on-year monthly CPI growth rate.	CSMAR	%
	RATE	Basic rate	Yield to maturity on 10-year Treasury bonds.	CSMAR	%
Market contagion	MV	Market volatility	The weighted average volatility of four green finance markets by monthly turnover.	Manual calculation	%
	CICSI	Investors sentiment	Constructed by Yi and Mao (2009).	CSMAR	Index
EPU		Chinese economic policy uncertainty	Estimated by Davis et al. (2019) using two mainland Chinese newspapers: the Renmin Daily and the Guangming Daily.	http://www.policyuncertainty.com/	Loga-rithmic
CPU		Climate policy uncertainty	CPU, developed by Gavriilidis (2021).		Loga-rithmic
GPR		Geopo-litical risk	Introduced by Caldara and Iacoviello (2022), and utilizes media stories to gauge worldwide conflicts.		Loga-rithmic
COVID-19		COVID-19 Pandemic risk	As described above.	Manual calculation	Dummy variable

Note: CSMAR and CEI refer to the China Stock Market & Accounting Research Database and the China economic information network database, respectively.

5. Empirical findings

5.1. Dynamic spillover analysis

Within this study, short-term spillovers refer to frequency spillovers lasting 1-3 months, while long-term spillovers relate to frequency spillovers lasting more than 3 months.

(1) Total spillovers

As shown in Figures 1–2, in time domains, return and volatility spillover effects fluctuated around 0% to 60% and experienced dramatic shifts, especially during the Chinese stock market collapse in 2015–2016 and the COVID-19 pandemic. These findings are inconsistent with that of Naeem et al. (2022). As depicted in Figure 1, the most notable decrease in the overall return spillovers during 2014 can be related to the opening of the Hubei carbon market in April 2014. Then, since 2015, the total return spillover in green finance markets has remained at 30% and fluctuated continuously. Subsequently, the return spillover increased dramatically to 50% in early 2020 and varied between 20% and 50% during 2020. These results contrast with earlier investigations that indicated the COVID-19 pandemic had financial consequences, resulting in large spillover effects (Bouri et al., 2021; Karim et al., 2022). Probable reasons are as follows. Green finance markets mostly focused on green industries that have been slightly susceptible to the COVID-19 epidemic. Second, the implementation of multidimensional green finance policies improves the green finance market mechanism, hence mitigating the green finance market spillover to some degree.

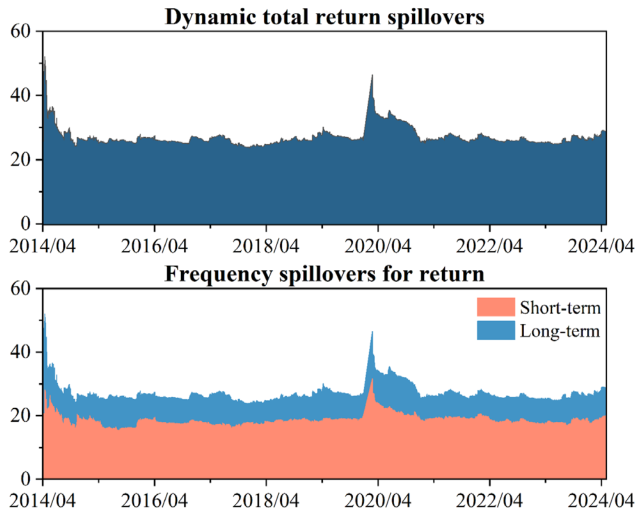

Figure 1. Dynamic total return spillovers in Chinese green finance markets

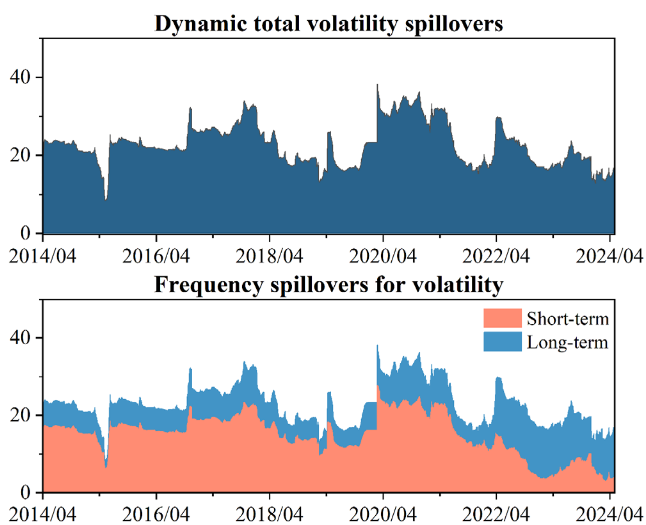

Figure 2. Dynamic total volatility spillovers in Chinese green finance markets

Figure 1 also portrays the frequency spillover as short-term and long-term parts. Comparable with preceding results, the short-term spillover recognizes consecutive rises and falls tied to challenging situations. The surge over 2020 illustrates the COVID-19 pandemic. Moreover, short-run spillover effects dominated long-run spillover effects. The monthly outcomes align with daily conclusions from Tian et al. (2022), which signifies that temporary interconnections are greater over lasting spillovers resulting from uncertainties and sudden changes throughout the economy. Likewise, investors respond quicker to unanticipated events compared to regular market-driving factors.

Figure 2 illustrates the volatility spillover dynamics. Compared to the return spillovers, the volatility spillovers during the period of 2014–2015 are relatively stable. Subsequently, there was an obvious decline ranging from 25% to 5% during 2015, which points to the catastrophic collapse in Chinese stock markets during 2015. During this period, with the booming trend since 2014 and highly leveraged funds allocation in the market, there was a serious market valuation bubble in Chinese stock markets, causing a rapid change of volatility spillover in green financial markets via assets price linkage and investor attention channels. Since 2018, volatility spillovers in green finance markets have dropped around 10–20% during 2018–2020. Similarly, the volatility spillover surged to 40% over 2020–2021, reflecting the serious impacts of the COVID-19 pandemic. Furthermore, long-run volatility spillover effects outweigh short-run volatility spillover effects, in accordance with the conclusions proposed

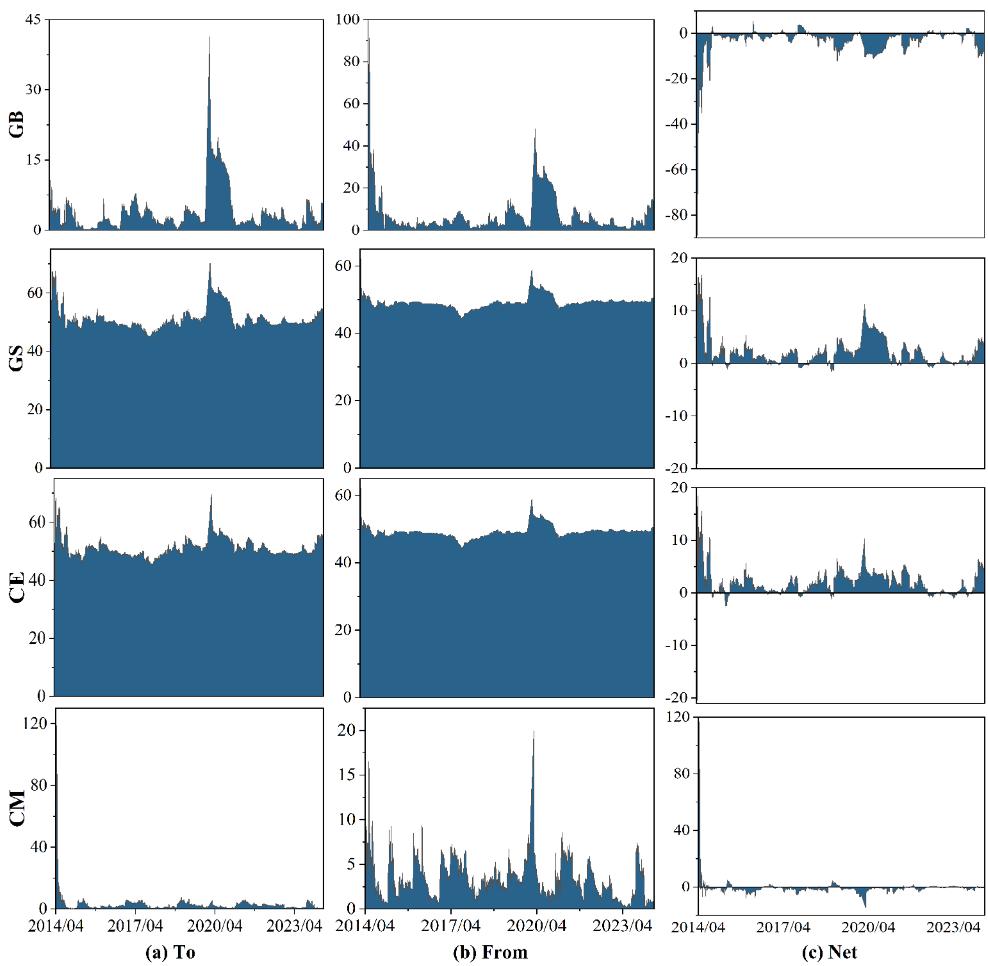

Figure 3. Dynamics of directional return spillovers (%)

by Naeem et al. (2022). Mensi et al. (2021) also endorsed that market volatility is mostly a long-term phenomenon marked by apparent jumps over time.

(2) Net directional spillovers

As depicted in Figures 3–4, these noticeable variations across each form of overall directional spillover signal substantial connections between economic and political uncertainties and the value swings of green assets. Nevertheless, each market's role in net spillover transmitters or net spillover receivers inevitably shifted both before and after different shocks. As for return spillovers, the green stock and clean energy market configure positive spillovers, implying that directional spillover effects from green stock and clean energy to other green finance markets are stronger than those in opposite directions. Green stock and clean energy seem net shock transmitters, while green bonds and carbon market are net return spillover receivers of the most time. In disagreement with Chen et al. (2022) and Tian et al. (2022), green stock and clean energy markets may bring substantial diversity benefits, safeguarding investors' assets from unforeseen losses.

Figure 4 depicts the time-varying directional volatility spillovers. Similar to return spillovers,

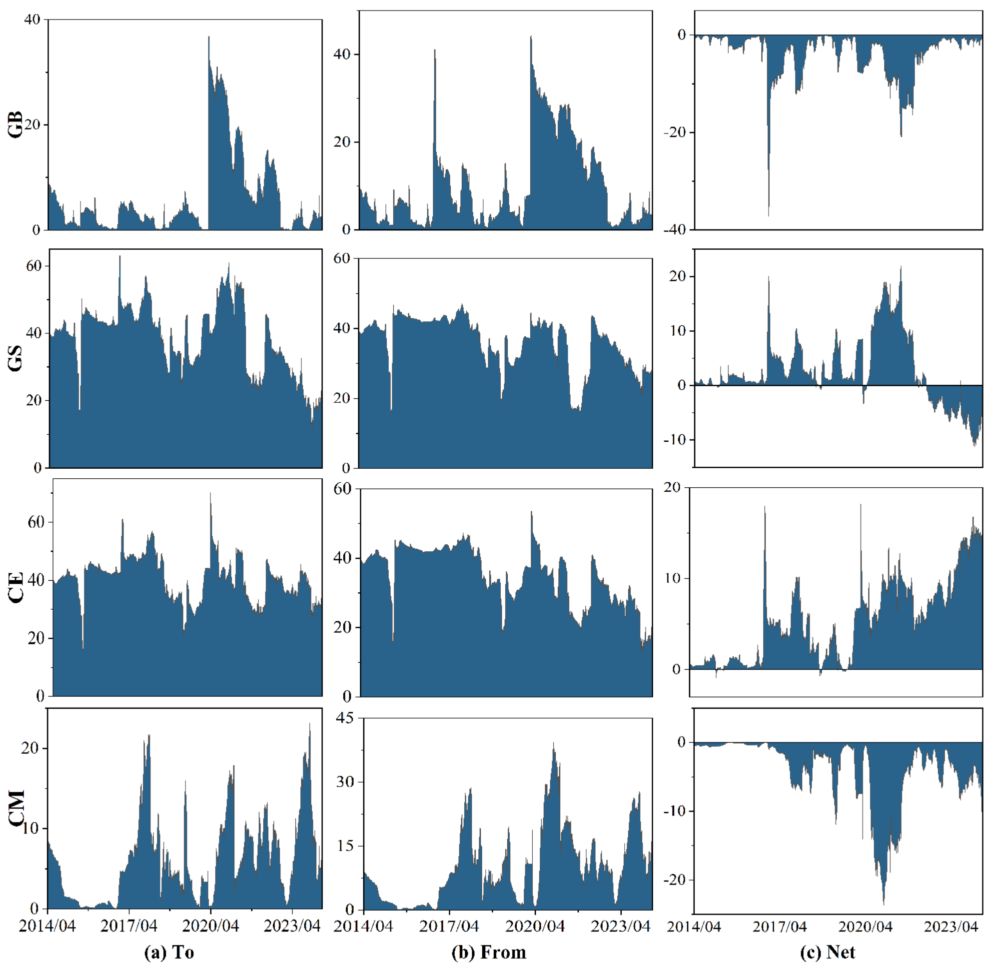

Figure 4. Dynamics of directional volatility spillovers (%)

the clean energy market mostly transferred volatility spillover effects into other green finance markets. Jumps and troughs within green finance markets during 2015, 2017–2018, and 2020–2022 denote the Chinese stock market crash, the Sino-U.S. trade friction, and the COVID-19 pandemic. Green bonds and the carbon market received volatility spillovers from green stock and clean energy markets, which mirrored the safe-haven along with diversifying benefits properties of green bond and carbon markets over shock periods.

The directional spillovers in frequency domains are depicted in Figure 5 and Figure 6. Generally, shocks drastically shift investor anticipations and bring spillover uncertainty. When confronted with shocks, return spillover variations are primarily motivated by short-term spillovers, whilst long-term components are generally steady. Particularly, short-term return spillovers in green bonds possess predominant influences. However, long-term

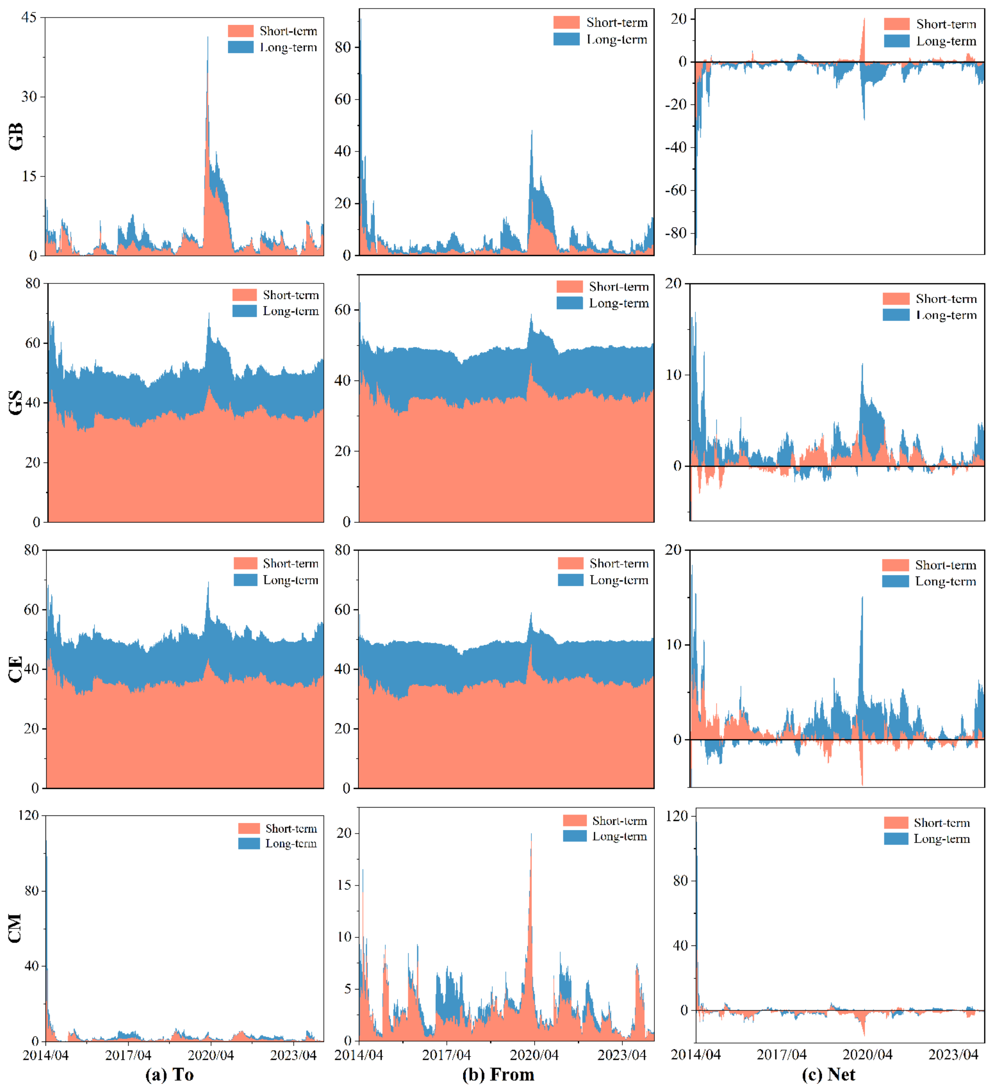

Figure 5. Directional return spillovers in time-frequency domain (%)

return spillovers in green stock, clean energy, and carbon markets are predominant. During the period of 2015, 2017–2018, and 2020–2022, the Chinese stock market crash, the Sino-US trade friction, and the COVID-19 pandemic witnessed a rapid rise (fall) within the short-run net return spillovers for green financial markets. The time-frequency patterns of net return spillover effects across green bonds, green stock, and clean energy markets also display notable variations. As shown in Figure 6, volatility spillover variations are mainly motivated by long-term spillovers. This indicates that the spread of risks in financial markets typically takes place through the gradual buildup of risks over a lengthy. Similarly, the directional volatility spillovers in green stocks and clean energy demonstrate significant divergences.

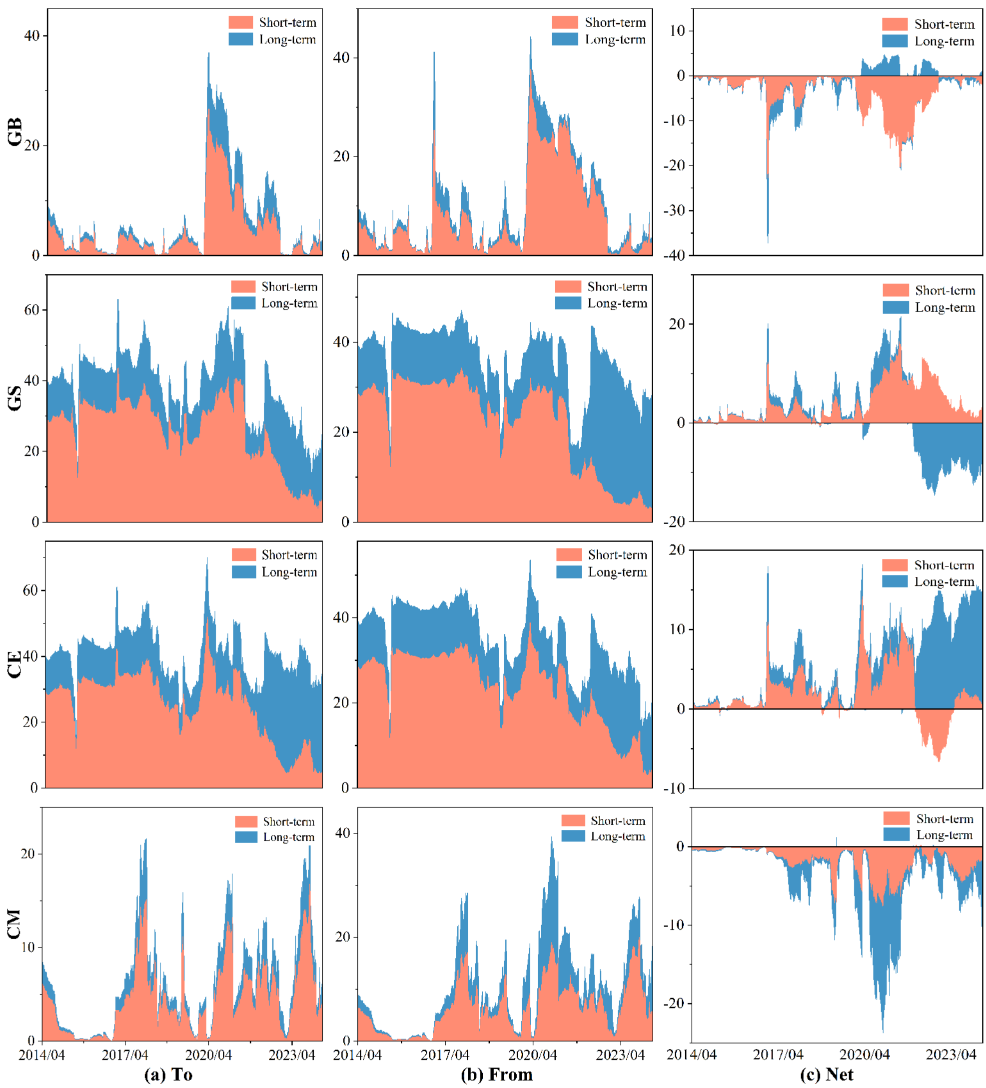

Figure 6. Directional volatility spillovers in time-frequency domain (%)

5.2. What drives the spillovers

(1) Linear regression

The following part explicitly assesses the influences of economic fundamentals, market contagion, and uncertainty factors on Chinese green finance market spillovers. The empirical results are summarized in Table 3 as follows. To start with, both economic fundamental (*ME*, *CPI*, and *RATE*), market contagion (*MV* and *CICSI*), and uncertainty (*EPU*, *CPU*, and *COVID-19*) factors have notable influences on Chinese green finance market spillovers, although both extent and trajectory of these effects vary. The influence of *COVID-19* is relatively slight, which corresponds to the findings of dynamic spillovers.

Within the temporal dimension, the negative impacts of *ME* on the return spillovers verify the "Cash Flow Expectation Effect" theory. This suggests that economic growth primarily represents the steady operation of enterprises and then forms optimistic investor expectations, thus reducing finance market spillovers. Specifically, when economic development is booming, the increases in the aggregate demand and the trade volume improve the enterprises' profitability, causing optimistic expectations of market investors. Thus, the finance market is relatively steady. These findings affirm the conclusion of Arfaoui et al. (2023). On the contrary, *ME* presents positive effects on volatility spillovers, implying that economic growth may increase volatility spillovers. Moreover, by the "Discount Rate Effect" theory, *RATE* is a positive determinant of both total return and volatility spillover effects. This indicates that increases in the basic rate enhance the return spillovers of green finance markets. Furthermore, given the positive coefficient of *CICSI*, increasing investor sentiment can amplify the volatility spillovers in Chinese green finance markets. This is feasible because that optimistic investor may actively invest in green assets, triggering asset price fluctuations and increases in green finance market spillover effects.

What's more, in contrast to earlier findings (Akyildirim et al., 2022; L. Pham et al., 2022), uncertainty variables, such as *CPU*, present negative influences on both return and volatility spillovers in Chinese green finance markets. The facts indicate the risk level of the Chinese green finance sector is decreasing owing to the rising climate policy uncertainty. This aligns with the findings of Pham et al. (2024) regarding *CPU* and green asset spillovers. The reason is that *CPU* can influence the idiosyncratic return and volatility of an individual green finance market, potentially leading to significant negative effects on green finance market spillovers, referred to as the idiosyncratic channel (Pham et al., 2024). In other words, while green asset return often escalates with an increasing *CPU* index, the rising *CPU* might correlate with a reduction in green finance market spillovers. Moreover, another possible explanation is that the *CPU* has intensified the risk contagion within traditional financial markets. *EPU* has contrary impacts on return and volatility spillovers in Chinese green finance markets. Furthermore, the emergence of the COVID-19 epidemic may also increase return and volatility spillovers in Chinese green finance markets. Notably, *MV* shows negative impacts on green finance market spillovers, contrasting with conclusions of Akyildirim et al. (2022). However, the diminishing impact of *GPR* on green finance market spillovers coincides with the findings of Wang et al. (2023a) and Gao and Liu (2024), implying that with the deceleration of asset integration by investors may, heightened macroeconomic risk factors, may provoke investor apprehension and reduce spillovers among financial assets.

Table 3. Determinants of the total return and volatility spillovers

	Variables	Return spillovers			Volatility spillovers		
		Total	Short-term	Long-term	Total	Short-term	Long-term
Economic Fundamental	ME	-1.402^{***} (0.000)	-0.586^{***} (0.000)	-1.536^{***} (0.000)	1.302^{***} (0.000)	3.057^{***} (0.000)	-1.776^{***} (0.001)
	CPI	0.001 (0.943)	0.005 (0.418)	–0.010 (0.115)	0.028^{***} (0.000)	0.150^{***} (0.000)	-0.216^{***} (0.000)
	RATE	0.051^{**} (0.045)	0.034^{*} (0.052)	0.041 (0.340)	0.114^{***} (0.000)	0.281^{***} (0.000)	–0.065 (0.149)
Market Contagion	MV	-0.048^{***} (0.000)	-0.034^{***} (0.001)	0.022^{**} (0.029)	-0.032^{***} (0.000)	–0.032 (0.496)	-0.086^{***} (0.008)
	CICSI	0.011 (0.444)	–0.002 (0.804)	0.028 (0.144)	0.031^{***} (0.000)	0.110^{**} (0.015)	-0.194^{**} (0.035)
Uncertainty	EPU	0.032^{**} (0.035)	0.026^{*} (0.056)	0.084^{***} (0.000)	-0.074^{***} (0.000)	-0.209^{***} (0.006)	0.073 (0.163)
	GPR	-0.229^{***} (0.000)	-0.069^{***} (0.007)	-0.166^{***} (0.000)	-0.111^{***} (0.000)	-0.224^{**} (0.041)	0.242^{*} (0.090)
	CPU	–0.020 (0.237)	–0.010 (0.552)	-0.085^{***} (0.000)	–0.004 (0.511)	–0.091 (0.269)	0.041 (0.542)
	COVID-19	0.137^{***} (0.000)	0.119^{***} (0.000)	–0.008 (0.825)	0.252^{***} (0.000)	0.339^{***} (0.001)	0.395^{***} (0.000)
	C	10.582^{***} (0.000)	5.743^{***} (0.000)	9.745^{***} (0.000)	-2.382^{***} (0.000)	-10.052^{**} (0.012)	9.190^{***} (0.000)
R^2		0.733	0.711	0.547	0.418	0.362	0.525
Adjusted R^2		0.710	0.685	0.506	0.368	0.306	0.483

For multiple frequency domains, economic fundamentals, market contagion, and uncertainty factors are all key determinants of short-term and long-term spillovers. These influence effects highlight comparable structures within the time domain. For instance, *ME*, *MV*, and *GPR* negatively impact return spillover effects over a short-term horizon. *RATE*, *EPU*, and *COVID-19* positively influence return and volatility spillovers in the short run. However, economic fundamentals and market contagion factors show different impacts on return and volatility spillovers over the long run. For instance, *MV* presents positive impacts on return spillovers in the long run. Compared to the coefficient of total and short-term spillovers, *ME*, *CICSI*, and *GPR* have a contrary influence on volatility spillovers in the long term. What's more, it should be noted that volatility spillovers serve as forms of risk transmission. Market contagion factors can determine the volatility spillovers across different frequencies. In light of the similar results confirmed by Zhao et al. (2021) and Sun et al. (2022), we can again intuitively emphasize that green finance market spillovers co-move with general finance and economic factors, while the direction varies.

(2) Quantile regression

The existence of spillover effects inspires us to further investigate various variables affecting green finance market spillover effects throughout down and up markets (0.05th and 0.95th quantiles). The influence of economic fundamentals, market contagion, and uncertainty factors on green finance market spillovers at extreme quantiles is readily apparent. However, the effects of these indicators differ in terms of direction and statistical significance.

Table 4. Determinants of the total return spillovers at extreme quantiles

	Variables	0.05			0.95		
		Total	Short-term	Long-term	Total	Short-term	Long-term
Economic Fundamental	ME	–0.074*** (0.003)	0.282*** (0.001)	–0.080 (0.698)	–1.030*** (0.000)	–1.039*** (0.000)	–2.083* (0.050)
	CPI	0.008*** (0.000)	0.012*** (0.002)	0.030*** (0.002)	0.031** (0.010)	0.021*** (0.004)	–0.009 (0.912)
	RATE	–0.046*** (0.000)	–0.043*** (0.000)	–0.151*** (0.000)	0.112*** (0.002)	0.079*** (0.000)	0.439*** (0.000)
Market Contagion	MV	–0.003 (0.524)	–0.015*** (0.006)	0.009 (0.505)	–0.009 (0.507)	–0.013 (0.190)	–0.024 (0.620)
	CICSI	0.025*** (0.000)	0.003 (0.612)	0.056*** (0.000)	–0.033** (0.034)	–0.057*** (0.000)	0.001 (0.982)
Uncertainty	EPU	0.029*** (0.000)	0.058*** (0.000)	0.014 (0.473)	–0.006 (0.797)	–0.012 (0.416)	–0.087** (0.035)
	GPR	0.000 (0.971)	–0.056*** (0.000)	0.104*** (0.002)	–0.166*** (0.000)	–0.150*** (0.000)	–0.267* (0.050)
	CPU	–0.021*** (0.001)	–0.031*** (0.004)	–0.055** (0.032)	–0.016 (0.621)	–0.012 (0.521)	–0.091 (0.269)
	COVID-19	0.007 (0.105)	0.040*** (0.000)	–0.110*** (0.000)	0.195*** (0.000)	0.236*** (0.000)	0.203** (0.032)
	C	3.627*** (0.000)	1.771*** (0.000)	2.438** (0.012)	8.577*** (0.000)	8.310*** (0.000)	12.706** (0.013)
R^2		0.302	0.476	0.244	0.559	0.617	0.409
Adjusted R^2		0.241	0.430	0.178	0.521	0.584	0.358

Table 4 summarizes divergent results for the determinants of return spillovers at extreme quantiles. In the time domain, except for *MV*, *GPR*, and *COVID-19*, other variables contribute to return spillovers in the green finance market at the 5th quantile. Therein, *CICSI* demonstrates positive impacts on the return and volatility spillovers at 0.05 quantile, revealing that optimistic investor sentiment may increase the spillover effects in green financial markets during extreme downturn periods. One possible explanation is that optimistic investors tend to decrease their changes to their green portfolios. Likewise, the return spillovers are positively driven by *CPI* and *EPU* during extremely lower shock periods. On the contrary, *ME*, *RATE*, and *CPU* negatively affect the return spillovers at the 5th quantile. However, at the 95th quantile, *RATE*, *MV*, and *GPR* are influencing the return spillovers negatively, which aligns with the outcomes observed in normal market situations. These results also accord with Mensi et al. (2022)' outcomes. As for different frequency dimensions, the impacts of most variables on both immediate and prolonged return spillovers are comparable to their impact from the perspective of time, with few exceptions. For instance, *ME* positively impacts the short-run return spillovers at an extremely upper quantile.

Table 5 summarizes QR outcomes for the determinants of volatility spillovers at extreme quantiles. Economic fundamentals, market contagion, and uncertainty factors exhibit different patterns of obvious impacts on the volatility spillovers at extreme quantiles. Notably, the effect of economic foundations and market contagion factors on volatility spillovers is more pronounced in the lower quantile compared to the higher quantile. This emphasizes that market volatility spillovers are more susceptible to economic and financial disturbances during turbulent periods. Within the time domain, market contagion and uncertainty indices mainly influence the volatility spillovers in the 5th quantile, while volatility spillover effects in the 95th quantile are primarily driven by economic fundamentals and uncertainty factors. The positive coefficients of *ME* and *CPI* suggest that economic development may increase risk spillovers in the green finance market under upside market trends. Furthermore, at the extremely upper quantiles, *GPR* negatively impacts volatility spillovers while *CPU* and *COVID-19* positively influence volatility spillovers.

Table 5. Determinants of the total volatility spillovers at extreme quantiles

	Variables	0.05			0.95		
		Total	Short-term	Long-term	Total	Short-term	Long-term
Economic Fundamental	ME	2.914*** (0.000)	7.094*** (0.000)	2.441*** (0.000)	0.109 (0.561)	–0.083 (0.683)	-0.342 (0.324)
	CPI	–0.007 (0.717)	0.255*** (0.000)	–0.099*** (0.000)	0.037*** (0.000)	0.048*** (0.000)	-0.035** (0.027)
	RATE	0.048 (0.381)	0.278** (0.046)	–0.036 (0.124)	0.226*** (0.000)	0.233*** (0.000)	-0.107** (0.010)
Market Contagion	MV	–0.163*** (0.000)	–0.242*** (0.001)	–0.140*** (0.000)	0.008 (0.507)	0.019 (0.143)	-0.074*** (0.001)
	CICSI	–0.057** (0.044)	0.182** (0.013)	–0.124*** (0.000)	0.011 (0.339)	0.063*** (0.000)	-0.160*** (0.000)
Uncertainty	EPU	–0.223*** (0.000)	–0.563*** (0.000)	–0.155*** (0.000)	0.013 (0.488)	–0.026 (0.185)	0.217*** (0.000)
	GPR	0.062 (0.401)	0.087 (0.645)	0.185*** (0.000)	–0.160*** (0.000)	–0.261*** (0.000)	-0.242*** (0.000)
	CPU	0.103* (0.067)	–0.061 (0.665)	0.046* (0.057)	0.119*** (0.000)	0.092*** (0.000)	0.018 (0.669)
	COVID-19	0.164*** (0.002)	0.222* (0.090)	0.124*** (0.000)	0.179*** (0.000)	0.153*** (0.000)	0.237*** (0.000)
	C	–10.059*** (0.000)	–28.716*** (0.000)	–9.347*** (0.000)	2.062** (0.019)	3.319*** (0.001)	4.376*** (0.007)
R^2		0.334	0.532	0.279	0.376	0.305	0.348
Adjusted R^2		0.275	0.491	0.216	0.322	0.245	0.291

Turning to the frequency domains, the influence of economic fundamentals, market contagion, and uncertainty variables on volatility spillovers demonstrates distinctive patterns across multiple frequency domains and quantiles. Only *CPI* influences short-run and long-run volatility spillover effects at the 5th and 95th quantiles. *CICSI* positively affects volatility spillover effects at both the lowest and highest quantiles. These results further confirm the conclusion of Kodres and Pritsker (2002) and Ngene (2021). Furthermore, we also examined the impacts of these factors on return and volatility spillovers among green finance markets across various quantiles (from 0.05 to 0.95, with an interval of 0.05). The results are summarized in Appendix, Figure A1, revealing that: at different quantiles, the influences of different determinants on return and volatility spillovers exhibit a heterogeneous pattern of variation. As quantiles increase, the coefficients of *ME*, *CICSI*, and *GPR* transition from positive to negative, indicating a tendency of decreasing volatility, while the coefficients of the other variables present an upward variation pattern, shifting from negative to positive.

5.3. Robustness tests

For the validity of the conclusions, the robustness tests have been performed from two different perspectives. First, sample period replacement. The 2015–2016 Chinese stock market crisis exerted tremendous influences on green financial sectors. This major event shock may affect the findings. Therefore, sample data spanned between March 2014 and June 2016 was excluded. Table 6 displays the empirical findings and verify the preceding conclusions. Second, alternative lags in the TVP-VAR model. We evaluate various time lags (2, 3, and 4). The estimation outcome is outlined in Table 7. Likewise, these determinants play an important role in green finance market spillovers.

Table 6. Robustness tests with sample period replacement

	Variables	Return spillover		Volatility spillover	
		Coefficients	P value	Coefficients	P value
Economic Fundamental	ME	–1.735***	0.000	–2.511***	0.006
	CPI	–0.016	0.317	–0.053	0.326
	RATE	0.078*	0.081	0.232	0.135
Market Contagion	MV	–0.055***	0.003	–0.271***	0.000
	CICSI	0.047**	0.032	0.153**	0.043
Uncertainty	EPU	–0.007	0.775	–0.035	0.695
	GPR	–0.221***	0.000	–0.707***	0.000
	CPU	–0.013	0.513	–0.340***	0.000
	COVID-19	0.130***	0.000	0.350***	0.000
	C	12.180***	0.000	19.425***	0.000
R^2		0.769		0.769	
Adjusted R^2		0.740		0.740	

Table 7. Robustness tests with alternative lags in TVP-VAR model

	Variables	Lag length = 2		Lag length = 3		Lag length = 4	
		Return	Volatility	Return	Volatility	Return	Volatility
Economic Fundamental	ME	–0.739*** (0.000)	–0.393*** (0.000)	–0.824*** (0.000)	–0.551*** (0.000)	–0.908*** (0.000)	-0.575*** (0.000)
	CPI	0.010*** (0.000)	0.001 (0.750)	0.010*** (0.000)	0.010*** (0.000)	0.009*** (0.000)	0.015*** (0.000)
	RATE	–0.001 (0.556)	0.239*** (0.000)	0.003 (0.203)	0.254*** (0.000)	0.004 (0.100)	0.256*** (0.000)
Market Contagion	MV	0.008*** (0.000)	–0.033*** (0.000)	0.006*** (0.000)	–0.035*** (0.000)	0.007*** (0.000)	-0.032*** (0.000)
	CICSI	0.045*** (0.000)	0.094*** (0.000)	0.051*** (0.000)	0.087*** (0.000)	0.051*** (0.000)	0.087*** (0.000)

End of Table 7

	Variables	Lag length = 2		Lag length = 3		Lag length = 4	
		Return	Volatility	Return	Volatility	Return	Volatility
Uncertainty	EPU	0.036*** (0.000)	–0.094*** (0.000)	0.034*** (0.000)	–0.070*** (0.000)	0.048*** (0.000)	-0.064*** (0.000)
	GPR	–0.091*** (0.000)	–0.099*** (0.000)	–0.110*** (0.000)	–0.093*** (0.000)	–0.115*** (0.000)	-0.106*** (0.000)
	CPU	–0.010*** (0.000)	–0.059*** (0.000)	–0.013*** (0.000)	–0.057*** (0.000)	–0.009*** (0.000)	-0.059*** (0.000)
	COVID-19	0.023*** (0.000)	0.137*** (0.000)	0.012*** (0.000)	0.095*** (0.000)	0.002 (0.444)	0.078*** (0.000)
	C	6.913*** (0.000)	5.405*** (0.000)	7.434*** (0.000)	5.906*** (0.000)	7.764*** (0.000)	6.037*** (0.000)
R^2		0.549	0.325	0.522	0.294	0.530	0.302
Adjusted R^2		0.504	0.256	0.474	0.223	0.482	0.231

6. Conclusions

Our research provides new insights into both return and volatility spillovers of the Chinese green finance markets in time-frequency domains. We further examine the role of economic fundamentals, market contagion, and uncertainty factors prominently underpinning these spillovers using daily data from April 28, 2014, to May 31, 2024. The outcome reveals that China's green finance market spillovers have been exceptionally susceptible to macroeconomic, financial, and social incidents. Nearly all return and volatility spillovers happen over the immediate future. Moreover, both green bonds and the carbon market become the net risk receivers due to the dynamics of net directional spillovers. Green stocks and clean energy perform different roles in market spillovers over time. On the other hand, the obvious impacts of economic fundamentals, market contagion, and uncertainty factors on return market spillovers vary in magnitude and direction. Furthermore, these determinants have strong interpretations for the extreme spillovers.

For market investors, green portfolio strategies need to be continuously monitored and timely altered to minimize losses, as the spillover patterns in green finance markets vary drastically in response to economic and financial shocks. Further, green bonds and carbon markets are net recipients of spillover effects about return and volatility, which mirrored the safe-haven and diversification properties of green bonds and carbon markets throughout the shock period. Therefore, the green bond and carbon market are highly suggested to be included in green portfolios to mitigate the risks associated with other green assets. What's more, investors must concentrate on key indicators, including macroeconomic and climate policies, and adjust portfolios according to market spillover fluctuations.

For the regulatory authorities and policymakers, active risk prevention and market isolation measures should be taken to slow down the transmission from general market risks to green financial markets. Moreover, the significant divergences in the frequency domains between return and volatility spillover effects hint that some targeted regulatory policies can be implemented to integrate green finance markets. Lastly, indirect risk management of green finance markets can also be applied through economic and monetary policies, which aim to promote high-quality economic development.

This article exclusively examines Chinese green finance markets, resulting in limited findings. Moreover, there is a scarcity of study concerning the relationship between green finance and emerging financial markets. Consequently, subsequent investigations on this topic may encompass the spillover effects between green finance and new financial markets, and ascertain the varied influences of these aspects on such spillover impacts.

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Author contributions

R.Y. L conceived the study and were responsible for the design and development of this manuscript. L. C was responsible for data collection. R.Y. L and Y.T. F were responsible for data interpretation. R.Y. L wrote the first draft of the article. L.Y. H reviewed and edited the article.

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APPENDIX

As for return series R_t, assuming that the conditional mean follows the AR (1) process, then the AR(1)-GARCHSK($p_1, q_1, p_2, q_2, p_3, q_3$) model can be expressed as:

$$\begin{cases} R_t = \mu_t + \varepsilon_t = a_1 R_{t-1} + h_t^{1/2}\eta_t \\ h_t = \alpha_0 + \sum_{i=1}^{q_1} \alpha_{1i}\varepsilon_{t-i}^2 + \sum_{j=1}^{p_1} \alpha_{2j} h_{t-j} \\ s_t = \gamma_0 + \sum_{i=1}^{q_2} \gamma_{1i}\eta_{t-i}^3 + \sum_{j=1}^{p_2} \gamma_{2j} s_{t-j} \\ k_t = \delta_0 + \sum_{i=1}^{q_3} \delta_{1i}\eta_{t-i}^4 + \sum_{j=1}^{p_3} \delta_{2j} k_{t-j} \end{cases}, \quad \text{(A1)}$$

where μ_t represents conditional mean of return. ε_t is the error term. $h_t^{1/2}$ is the conditional standard deviation. η_t is the standardized residual term, satisfied $\eta_t \sim (0,1)$. a_1 denotes coefficients of return R_{t-1}. $\varepsilon_t \mid I_{t-1} \sim D(0, h_t, s_t, k_t)$, I_{t-1} indicate the information set time t-1. $D(0, h_t, s_t, k_t)$ is a Gram-Charlier distribution including variance (h_t), skewness (s_t), and kurtosis (k_t). γ_0 and δ_2 are constant coefficients. γ_1 and δ_2 are coefficients of standardized new information η_t. γ_2 and δ_2 are coefficients of skewness and kurtosis.

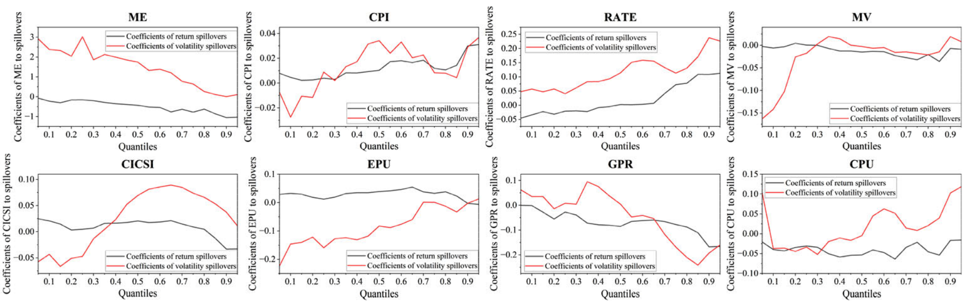

Figure A1. Coefficients of economic fundamentals, market contagion, and uncertainty on return and volatility spillovers