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Quantile Connectedness of Uncertainty Indices, Carbon Emissions, Energy, and Green Assets: Insights from Extreme Market Conditions

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Abstract: In this study, we investigate the volatility spillover effects across uncertainty indices (Infectious Disease Equity Market Volatility Tracker (IDEMV) and Geopolitical Risk Index (GPR)), carbon emissions, crude oil, natural gas, and green assets (green bonds and green stock) under extreme market conditions based on the quantile connectedness approach. The empirical findings reveal that the total and directional connectedness across green assets and other variables in extreme market conditions is much higher than that in the median, and there is obvious asymmetry in the connectedness measured at the extreme lower and upper quantiles. Our findings suggest that the uncertainty caused by COVID-19 has a more significant impact on green assets than the uncertainty related to the Russia–Ukraine war under normal and extreme market conditions. Furthermore, we discover that the uncertainty indices are more important in predicting green asset volatility under extreme market conditions than they are in the normal market. Finally, we observe that the dynamic total spillover effects in the extreme quantiles are significantly higher than those in the median.

Keywords: green finance market; quantile connectedness; uncertainty; COVID-19; volatility spillover effects

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1. Introduction

Climate change has a significant impact on many facets of daily life, which has increased the public awareness of environmental protection issues and the concept of sustainable development. The Paris Climate Agreement and Sustainable Development Goals (SDGs) advocate for countries to reduce greenhouse gas emissions by shifting from using fossil energies to using clean energy sources. In this context, many investment and financing instruments have emerged in the financial market to support green and sustainable projects. Green bonds have attracted the attention of many policymakers, scholars, and investors since they were first introduced as the primary green financial instrument [1,2]. Green bonds have similar functions to conventional corporate bonds, with the exception that the proceeds from them are earmarked for environmentally friendly projects. Green bond issuance has increased gradually in the past few years. Although green bond issuance dropped in 2022, it was 28% higher in the first half of 2023 than in the same period of 2022 (USD 278.8 billion in the first half of 2023 and USD 218.1 billion in the first half of 2022) [3,4], indicating that market participants still have a positive attitude towards the green bond market. Furthermore, as the main green financial asset, clean energy stock plays an important role in providing finance to promote the development of clean energy industries and accordingly contributes to sustainable development. Green bonds and clean energy stock are becoming increasingly appealing to investors, as they present a good opportunity for investment diversification.

It is common knowledge that sudden events have an effect on financial markets. COVID-19 and the conflict between Russia and Ukraine have been the primary global crises in recent years, with significant effects on the development of the world economy. COVID-19 is a highly contagious, infectious disease that spread quickly around the world. COVID-19 has had a significant impact on the global economy since its outbreak [5,6], and it generated a sharp increase in uncertainty that led to dramatic fluctuations in the financial market. The economy and financial markets affected by COVID-19 are still quite vulnerable, although the global economy has gradually recovered. However, the eruption of the Russia–Ukraine war in February 2022 has increased the geopolitical risks and increased the fragility and instability of the global economic and financial system. The Russia–Ukraine war has had a significant influence on the energy industry, because Russia is the second-largest oil exporter in the world and has the most natural gas reserves. The soaring energy prices caused by the Russia–Ukraine war have increased countries' motivation to transition to clean energy. The influence of the Russia–Ukraine war on the energy market has been studied in the literature [7,8]; however, the impact on green finance markets is rarely discussed. It is crucial for investors and policymakers to comprehend how COVID-19 and the Russia–Ukraine war have affected green finance markets. As a result, investors can promptly modify and optimize their investment portfolios during turbulent periods, and policymakers will receive some insights to utilize when dealing with the next crisis.

Fossil fuel is the main source of greenhouse gas emissions, and the interconnection between fossil energy and clean energy in the financial market has been discussed in several studies [9,10]. Since clean energy and fossil fuels can be substituted for one another, it is reasonable that high fossil fuel prices would increase the demand for clean energy, thereby promoting the development of the clean energy industry and hastening the transformation of the low-carbon economy. Furthermore, a carbon emissions trading system has been proposed in order to reduce greenhouse gas emissions. This system allocates quantitative carbon emissions quotas to enterprises for use in controlling greenhouse gas emissions and allows companies to trade their respective carbon emissions balances. The effect of greenhouse gas emissions on global climate change and sustainable industries has been examined in some literature [11–14], particularly with an emphasis on international initiatives to combat climate change and guarantee sustainable growth in the future. It is worthwhile to investigate the connection between carbon markets, fossil fuels, and green financial assets, as this can provide a new perspective for green investment.

At present, the research on risk spillovers between green finance markets and other assets mainly focuses on the GARCH-type models [15,16] and the Diebold and Yılmaz [17] connectedness approach [10,18]. These methods can only estimate the average shock of the system, and the system shocks are not necessarily equal to the average shocks, so it is necessary to consider the spillover effects across assets in extreme cases. To address this research gap, Ando et al. [19] extended the Diebold and Yılmaz [17] connectedness approach with a quantile vector autoregression (QVAR) model, which can further measure the spillover effects across assets under different quantiles. Therefore, based on the quantile connectedness approach, the aim of this study was to illustrate the spillover effects between carbon emissions, fossil energies, the uncertainty indices of COVID-19 and the Russia–Ukraine war, and green finance markets in extreme market conditions.

The contributions of this study are as follows. First, we are the first to analyze the volatility spillover effects across green bonds, green stock, and uncertainty indices related to infectious diseases, the Geopolitical Risk Index, carbon emissions, crude oil, and natural gas, contributing to the existing literature. This research contributes to the understanding of the influence of the uncertainty index, Geopolitical Risk Index, carbon emissions, and energy on the connectedness of green assets. Second, the quantile connectedness approach was employed in this study to calculate the spillover effects across assets at the median, lower, and upper quantiles, which allowed us to illustrate the relationship between green assets and other assets under normal, extremely stable, and extremely volatile market conditions. Third, we compared the impact of COVID-19 and the Russia–Ukraine war on two different green assets: green bonds and green stock. Thus, this study contributes to highlighting the importance of global events in green finance markets.

The main results of this research are as follows. Firstly, we observed that the spillover effects across green assets, uncertainty indices, carbon emissions, and fossil energies are much higher under extreme market conditions than in the normal market; furthermore, the dynamic spillover effects exhibited obvious asymmetry in extremely stable and extremely volatile markets. Secondly, our analysis demonstrated that the uncertainty caused by COVID-19 contributed more spillovers to green assets than the uncertainty related to the Russia–Ukraine war in the various quantiles. Finally, we found that the dynamic total spillover effects in the lower and upper quantiles were much higher than those in the median, but the range of fluctuations in the extreme quantiles was slightly lower than that in the median.

The remainder of this paper is organized as follows. Section 2 outlines the literature review. Section 3 presents the methodology and data, and the empirical results are provided in Section 4. Section 5 concludes the paper.

2. Literature Review

Green finance assets can be utilized as diversified investments to increase the returns for market participants, in addition to financing firms and sustainable development projects. As a result, considerable attention and an increasing number of studies have recently been devoted to the green finance market. The main literature on the relationship between green assets and other assets can be roughly divided into the following aspects: the interconnections between green assets themselves [15,20,21] and those between green assets and other financial assets/commodities [22–24].

There is a substitutable relationship between fossil fuels and clean energy, so a large portion of research focuses on the connection between fossil fuels and green assets. For example, Kumar et al. [25] found that oil prices affect clean energy firms' stock prices by studying the relationship between oil prices, carbon prices, and clean energy indices. In addition, Xia et al. [26] showed the relatively high level of interdependence between fossil fuels and clean energy stock via a network approach.

Carbon emissions have also received much attention as a financial tool for the promotion of sustainable development. For instance, Jin et al. [27] analyzed the relationship between the green bonds, the VIX index, the commodity index, the energy index, and carbon futures through DCC-GARCH models and found the highest connectedness between carbon future returns and green bond returns. Similarly, Hammoudeh et al.'s [28] study also demonstrated the significant time-varying causality from the carbon emissions allowance price to green bonds. Dutta et al. [29] found a significant volatility linkage between European Union Allowance prices and European clean energy prices by employing a VAR-GARCH model.

COVID-19 has caused a rise in uncertainty in the financial market, and many studies show that COVID-19 has had a great impact on green finance markets [30–32]. For example, Liu et al. [33] investigated the impact of the COVID-19-related uncertainty index on renewable energy stocks, and they found the impact of COVID-19 on renewable energy stock returns and volatility to be more significant than that resulting from the global financial crisis. We employed the same uncertainty index as Liu et al. [33] to measure the uncertainty resulting from COVID-19. In addition, the conflict between Russia and Ukraine in 2022 significantly affected the energy market and caused a surge in geopolitical risks. In our study, we chose the Geopolitical Risk Index constructed by Caldara and Iacoviello [34] to represent the uncertainty caused by the Russia–Ukraine war. This index has been used in various research studies [35–37].

The existing research only investigates how COVID-19 or the Russia–Ukraine war has affected a particular class of green assets; it does not compare the impact of COVID-19 and the Russia–Ukraine war on different green assets. Secondly, to our knowledge, no studies to date have investigated the influence of fossil fuels and carbon emissions on clean energy stock and green bonds, so our research will fill this gap in the literature in this field. In this study, we further explore the impact of COVID-19, the Russia–Ukraine war, carbon emissions, and fossil energies on green assets in extreme market conditions using the quantile connectedness proposed by Ando et al. [19]. This method has been widely used to study the spillover effects across financial assets in different quantiles [38–40].

3. Methodology and Data

3.1. Data

To investigate the impact of carbon emissions, fossil energies, and uncertainty indices on green finance markets, we select the daily data of these indices between 10 January 2012 and 31 March 2023. All variables are listed in Table 1.

Table 1. Model variables.

Variable	Data
GB	Solactive Green Bond Index
GS	Standard & Poor Global Clean Energy Index
Oil	Brent Crude Oil
Gas	Henry Hub Natural Gas
Carbon	Carbon Emissions Futures
IDEMV	Infectious Disease Equity Market Volatility Tracker
GPR	Geopolitical Risk Index

For the green finance markets, we choose the Solactive Green Bond Index and the S&P Global Clean Energy Index to represent the performance of the green bond market and the green stock market, respectively. The Solactive Green Bond Index is a market-value-weighted index, and it comprises bonds that are defined as green bonds by the Climate Bonds Initiative. Although a number of indices, such as the Dow Jones Green Bonds Index, MSCI Green Bonds Index, and S&P Green Bonds Index, have been designed to measure the performance of the green bond market, the Solactive Green Bond Index is employed in our analysis as a proxy for the green bond market considering that these indices exhibit comparable characteristics and dynamics and a near-one correlation coefficient [41]. The S&P Global Clean Energy Index tracks the performance of 30 global companies, including clean energy production and clean energy production equipment and technology companies, which reflects the performance of the global green stock market. Carbon is proxied by the European Union allowance (EUA) futures from the European Union Emissions Trading System (EU ETS), which is the most active and largest-scale carbon emissions future trading market in the world. Fossil energy indices are measured using Brent Crude Oil and Henry Hub Natural Gas, which are the benchmark prices for oil and natural gas. All data on green assets, carbon, and fossil energy markets are unified to US dollars and downloaded from Bloomberg.

We consider the Infectious Disease Equity Market Volatility Tracker (IDEMV) and the Geopolitical Risk Index (GPR) to measure the infectious disease-related uncertainty and geopolitical uncertainty in this study, respectively. Some common uncertainty proxies have been created to measure economic uncertainty, such as the VIX, OVX, and EPU indices; however, these uncertainty indices ignore the economic impact of the pandemic and infectious diseases. This research employs the IDEMV index, which was constructed by Baker et al. [42]. It is a newspaper-based uncertainty index that reflects the volatility of the equity market due to infectious diseases. The daily data can be publicly accessed from http://policyuncertainty.com/infectious_EMV.html (accessed on 1 March 2024). The GPR was developed by Caldara and Iacoviello [34], constructed by tracking the news related to geopolitical events in newspapers, and is sourced from https://www.policyuncertainty.com/gpr.html (accessed on 1 March 2024).

Figure 1 displays the variations in the IDEMV index and GPR and the price fluctuations for green assets, carbon emissions, and fossil energies. In our sample period, it can be seen that the green bond and green stock prices dropped rapidly at the early stage of COVID-19 and then gradually increased and reached their peak in 2021. Thereafter, the green bond price fell drastically, while the green stock price maintained stable fluctuations after the price dropped to a certain extent after 2021. Notably, the prices of carbon, natural gas, and crude oil sharply fluctuated and reached their respective peaks during the Russia–Ukraine war in 2022. The GPR consistently exhibited strong volatility over the sample period, while the IDEMV only exhibited sharp fluctuations after COVID-19.

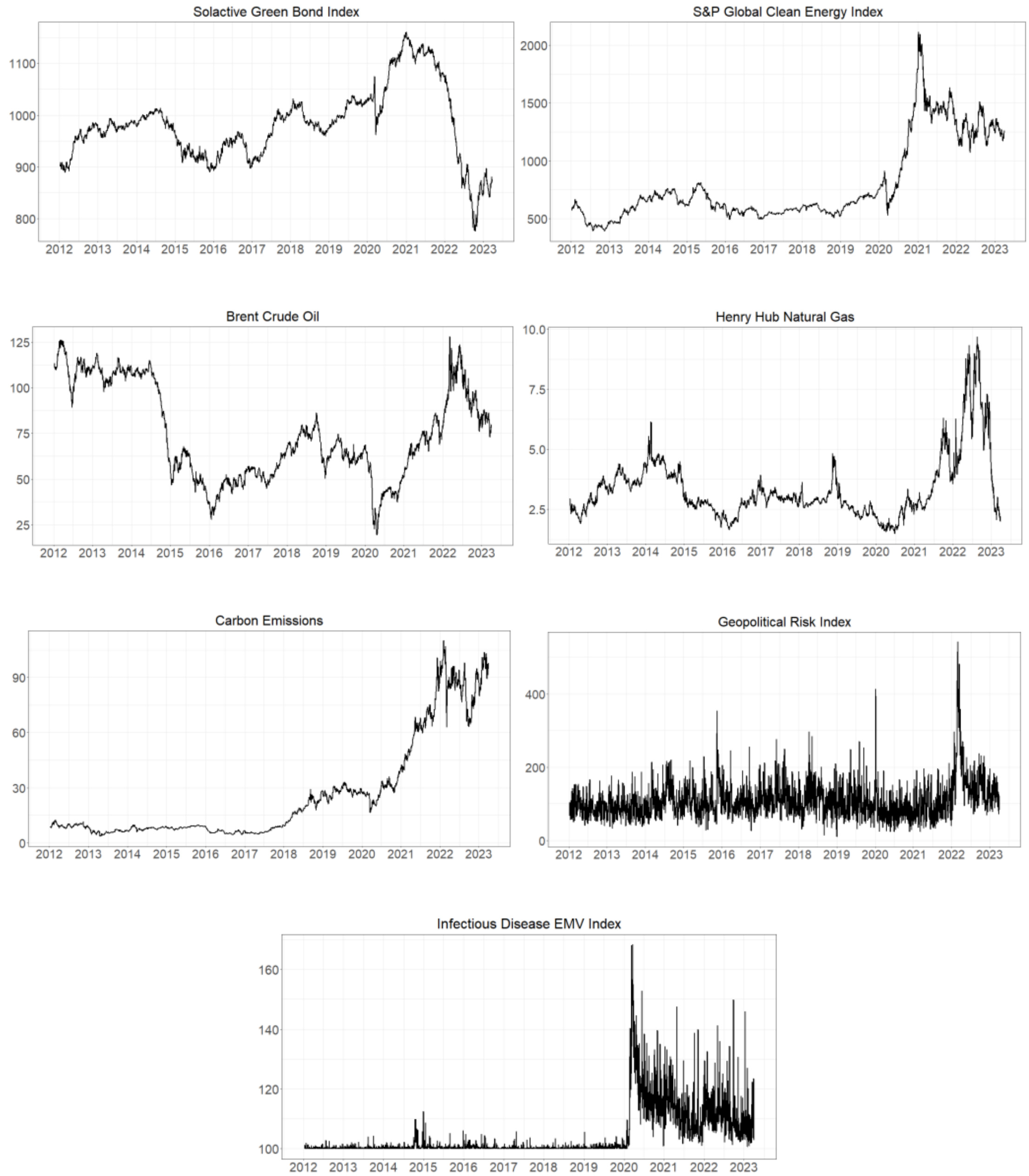


Figure 1. Time variations of variables.

We obtained the volatilities for the green assets, carbon emissions, and fossil energy indices by fitting the autoregressive–generalized autoregressive conditional heteroscedasticity (AR-GARCH) model. Table 2 provides the descriptive statistics and robustness test results for all variables. All variables are right-skewed and exhibit leptokurtic characteristics. In addition, the Jarque–Bera (JB) test results for all series allow us to reject the null hypothesis of normality at the 1% significance level. The Augmented Dickey–Fuller (ADF) unit root test results indicate that all variables are stationary at the 5% significance level.

Table 2. Descriptive variable statistics.

	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**JB**	**ADF**
			Volatility Series			
GB	0.000	0.000	2.729	11.284	11,497.979 ***	−2.022 **
GS	0.000	0.000	7.519	77.351	672,290.241 ***	−3.849 ***
Oil	0.001	0.001	6.300	51.232	290,323.386 ***	−6.576 ***
Carbon	0.001	0.001	6.998	79.565	707,783.123 ***	−7.247 ***
Gas	0.001	0.002	5.671	57.366	360,350.077 ***	−6.203 ***
			Uncertainty Index			
GPR	109.644	50.336	2.307	14.195	17,129.585 ***	−6.247 ***
IDEMV	104.351	8.303	2.848	13.409	16,449.114 ***	−10.170 ***

Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index; JB, Jarque–Bera test [43]; ADF, Augmented Dickey–Fuller unit root test [44]. ** and ***, rejection of null hypothesis at 5% and 1% significance levels, respectively.

3.2. Methodology

In this study, we analyzed the quantile volatility connectedness across green finance assets, carbon emissions, fossil energy, and the uncertainty indices by employing the quantile connectedness approach proposed by Ando et al. [19].

We first estimated the conditional volatility of green assets, carbon emissions, and fossil energy through a univariate GARCH (1, 1) model. Then, following Ando et al. [19], we constructed a quantile vector autoregression QVAR(p) with the variables and orders as follows:

$$y_t = c(\tau) + \sum_{j=1}^{p} B_j(\tau) y_{t-j} + e_t(\tau), t = 1, \cdots, T \tag{1}$$

where y_t represents a vector of n endogenous variables, t is the time, and $\tau \in (0,\ 1)$ denotes the quantiles. $c(\tau)$, $e_t(\tau)$ are the $n \times 1$ dimensional vector of intercepts and the error term at the quantile τ, respectively. $B_i(\tau)$ with $i = 1,\ \ldots, p$ denotes the $n \times n$ dimensional lag coefficient matrix at quantile τ.

To estimate the connectedness measures at every quantile, Equation (1) can be rewritten as an infinite-order vector moving average (MA) process:

$$y_t = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) e_{t-i}(\tau), t = 1, \cdots, T \tag{2}$$

where $\mu(\tau) = (I_n - B_1(\tau) - \cdots - Bp(\tau))^{-1} c(\tau)$, and

$$A_i(\tau) = \begin{cases} 0, i < 0 \\ I_n, i = 0 \\ B_1(\tau)A_{i-1}(\tau) + \cdots + B_p(\tau)A_{i-p}(\tau), i > 0 \end{cases}$$

Following Koop et al. [45] and Pesaran and Shin [46], we defined the generalized forecast error variance decomposition (GFEVD), with a forecast horizon H, as

$$\theta_{jk}^{H}(\tau) = \frac{\sigma(\tau)_{kk}^{-1} \sum_{h=0}^{H-1} \left(e_j' A_h(\tau) \sum e_k\right)^2}{\sum_{h=0}^{H-1} \left(e_j' A_h(\tau) \sum A_h(\tau)' e_j\right)} \tag{3}$$

$\theta_{jk}^{H}(\tau)$ represents the contribution of the k-th variable to the variance in the forecast error of the j-th variable at forecast horizon H. $\sum$ is the variance matrix of the error vector, and σ_{kk} is the k-th diagonal element of the $\sum$ matrix. e_j is a vector with a value of 1 for the j-th element and 0 otherwise.

Then, we normalized each entry of the variance decomposition matrix by its row sum as follows:

$$\overset{\sim H}{\theta}_{jk}(\tau) = \frac{\theta_{jk}^{H}(\tau)}{\sum_{k=1}^{N} \theta_{jk}^{H}(\tau)}, \text{ with } \sum_{k=1}^{N} \overset{\sim H}{\theta}_{jk}(\tau) = 1 \tag{4}$$

Following the Diebold and Yilmaz [17] framework, based on the GFEVD, various measures of connectedness at the τ-th conditional quantile can be defined as

$$CI_{j\leftarrow k}(\tau) = \overset{\sim H}{\theta}_{jk}(\tau) \tag{5}$$

$$To\_CI_{k\rightarrow \bullet}(\tau) = \sum_{j=1, j\neq k}^{N} \overset{\sim H}{\theta}_{jk}(\tau) \tag{6}$$

$$From\_CI_{\bullet \leftarrow k}(\tau) = \sum_{k=1, j\neq k}^{N} \overset{\sim H}{\theta}_{kj}(\tau) \tag{7}$$

$$Net\_CI_{k}(\tau) = To\_CI_{k\rightarrow \bullet}(\tau) - From\_CI_{\bullet \leftarrow k}(\tau) \tag{8}$$

$$NP\_CI_{jk}(\tau) = CI_{j\leftarrow k}(\tau) - CI_{j\rightarrow k}(\tau) \tag{9}$$

where $CI_{j\leftarrow k}(\tau)$ is defined as the pairwise directional risk spillover/connectedness from variable k to variable j at the τ-th quantile. $To\_CI_{k\rightarrow \bullet}(\tau)$ represents the directional spillover from variable k to all other variables in the system at the τ-th quantile, whereas $From\_CI_{\bullet \leftarrow k}(\tau)$ shows that the variable k receives directional spillovers from all other assets. $Net\_CI_{k}(\tau)$ represents the net connectedness of variable k at quantile τ. If $Net\_CI_{k}(\tau) > 0$, variable k can be considered a net receiver in the system, and this indicates that variable k receives more spillover from all other variables than it transmits to them in the system. If $Net\_CI_{k}(\tau) < 0$, variable k is seen as a net contributor in the system. $NP\_CI_{jk}(\tau)$ is the net directional connectedness between variable j and variable k at the τ-th quantile. If $NP\_CI_{jk}(\tau) > 0$, variable k dominates variable j in the system; otherwise, if $NP\_CI_{jk}(\tau) < 0$, variable k is dominated by variable j.

4. Empirical Findings and Discussion

4.1. Static Quantile Connectedness Analysis

4.1.1. Static Spillover Effects at the Median

From Table 3, Panel A, it can be seen that the total spillover effect of this system is only 10.35% at the median, indicating a low degree of connectedness among green assets and other variables in the normal market over the full sample. This article primarily focuses on the directional spillovers of green assets in order to better elucidate how uncertainties and other assets affect the green finance market. According to the median result (Panel A), green bonds receive the most spillover (13.87%) from green stock, followed by carbon (1.67%), oil (1.04%), the IDEMV (0.6%), gas (0.37%), and the GPR (0.26%). The green bonds transmit the most spillover (9.73%) to the green stock, followed by oil (8.6%), the IDEMV (2.57%), carbon emissions (1.69%), gas (0.19%), and the GPR (0.11%). This finding suggests that the impact of carbon emissions, fossil energies, and the uncertainty indices on green bonds and green stock is significantly lower than the mutual influences between green bonds and green stock in the normal market.

Table 3. Static volatility spillover.

Panel A: Volatility Spillover Measures at the Median (τ=0.5)								
τ = 0.5	GB	GS	Oil	Carbon	Gas	GPR	IDEMV	FROM
GB	82.17	13.87	1.04	1.67	0.37	0.26	0.60	17.83
GS	9.73	77.11	8.60	1.69	0.19	0.11	2.57	22.89
Oil	1.01	9.29	86.08	0.37	0.09	0.22	2.94	13.92
Carbon	1.48	2.02	0.31	95.80	0.15	0.22	0.02	4.20
Gas	0.65	0.13	0.23	0.21	98.02	0.08	0.68	1.98
GPR	0.41	0.36	0.37	0.80	0.53	97.26	0.27	2.74
IDEMV	0.95	3.60	3.96	0.12	0.24	0.05	91.08	8.92
TO	14.23	29.28	14.52	4.87	1.57	0.93	7.09	TCI: 10.35
NET	−3.60	6.39	0.60	0.66	−0.41	−1.81	−1.83	
Panel B: Volatility Spillover Measures at the Lower Quantile (τ=0.1)								
τ = 0.1	GB	GS	Oil	Carbon	Gas	GPR	IDEMV	FROM
GB	70.01	12.16	2.15	1.92	1.73	5.59	6.45	29.99
GS	10.92	64.13	8.58	1.95	0.69	3.71	10.03	35.87
Oil	2.20	10.14	76.08	0.65	0.48	2.49	7.96	23.92
Carbon	2.43	2.71	0.78	88.76	0.49	3.78	1.05	11.24
Gas	2.20	0.99	0.61	0.49	87.74	3.70	4.28	12.26
GPR	6.19	4.40	2.56	3.18	3.22	73.24	7.20	26.76
IDEMV	6.09	10.9	6.91	0.82	3.12	6.87	65.3	34.70
TO	30.02	41.29	21.58	9.01	9.74	26.13	36.97	TCI: 24.96
NET	0.03	5.41	−2.34	−2.23	−2.52	−0.63	2.27	
Panel C: Volatility Spillover Measures at the Upper Quantile (τ=0.9)								
τ = 0.9	GB	GS	Oil	Carbon	Gas	GPR	IDEMV	FROM
GB	25.17	28.95	13.05	4.60	4.71	7.96	15.56	74.83
GS	18.49	32.54	14.65	4.23	6.34	6.76	17.00	67.46
Oil	12.35	23.50	35.85	3.28	3.22	8.07	13.72	64.15
Carbon	13.13	22.29	8.90	34.91	4.60	7.60	8.57	65.09
Gas	11.70	8.99	2.44	2.12	55.34	4.67	14.73	44.66
GPR	7.86	6.53	2.75	2.81	3.28	60.27	16.50	39.73
IDEMV	13.70	14.64	5.00	2.55	9.35	6.42	48.34	51.66
TO	77.23	104.91	46.79	19.58	31.5	41.48	86.08	TCI: 58.23
NET	2.41	37.45	−17.35	−45.52	−13.16	1.75	34.43	

Note: This table displays the connectedness measures (expressed as a percentage) across variables based on the quantile connectedness approach (a QVAR model with a lag of 5 (BIC) and a 10-step-ahead forecast horizon). The *ij*-th entry presents the directional connectedness from market *j* to market *i*. TCI represents the total connectedness of the system. The "From" column exhibits the total connectedness received by one market from all other markets, whereas the "To" row reports the total connectedness transmitted from one market to all other markets. "Net" shows the net total connectedness (To–From) of market *i*, which determines the net transmitter (positive value) or net receiver (negative value) of the spillover in the system. GB, Solactive Green Bond Index. GS, Standard & Poor Global Clean Energy Index. Oil, Brent Crude Oil. Gas, Henry Hub Natural Gas. Carbon, Carbon Emissions Futures. IDEMV, Infectious Disease Equity Market Volatility Tracker. GPR, Geopolitical Risk Index.

According to the uncertainty indices, the IDEMV transmits much greater volatility spillover effects to the green bonds and green stock than the GPR, which implies that, in the normal market, an uncertainty index related to infectious diseases has a greater impact on the green assets than the geopolitical risk uncertainty. This finding is also supported by previous research [47,48], whose results indicate that the IDEMV has a significant impact on financial assets than the GPR. The IDEMV contributes more spillovers to the green stock than to the green bonds, while the GPR transmits more spillovers to the green bonds than to the green stock. This finding demonstrates that green bonds are more likely to be affected by extreme geopolitical events, while green stock reacts more violently to extreme events related to infectious diseases. Additionally, the GPR transmits fewer spillovers than other assets in both the green bond and green stock markets, suggesting that the influence of the GPR on green assets is lower than that of other assets.

Compared to fossil energies and the uncertainty indices, the green bond market is more susceptible to the impact of carbon emissions, as carbon emissions are the second-largest transmitter of green bond volatility spillovers. Oil transmits more spillovers to the green stock than carbon emissions, gas, and the uncertainty indices, suggesting that oil has a more significant effect on the green stock market than other assets. These results are also consistent with Xia et al. [26], who found that oil contributes more spillover to the green stock than carbon emissions and natural gas. In addition, oil contributes much more spillover effects to the green stock than to the green bonds, which indicates that oil has a more significant impact on the green stock than on the green bond market in the normal market. With the exception of the GPR, both the green bonds and green stock were rarely affected by natural gas during our sample period, which indicates that gas can be considered a hedge asset for green assets.

4.1.2. Static Spillover Effects at the Lower and Upper Quantiles

The estimated results of the spillover effects at the lower and upper quantiles are shown in Table 3, Panels B and C, which can help us to distinguish the performance of green assets in extremely stable and volatile markets.

In Table 3, Panels B and C evidence that the total spillover effects are 24.96% at the lower quantile and 58.23% at the upper quantile, which are significantly greater than the conditional median (10.35%). These results suggest that the interrelationship between green assets and other variables is closer in extreme market conditions, especially in an extremely volatile market, which is in line with previous research [49,50] on the market contagion, which demonstrated higher connectedness in the upper and lower quantiles. Furthermore, we observe obvious asymmetric tail interactions from the difference between the total and directional connectedness at the extreme lower and upper quantiles. Similar to the total connectedness, the directional connectedness rises significantly under extreme market conditions compared to those in the normal market.

With regard to the directional connectedness of green assets, the ranking of the spillover effects received by green bonds and green stock in the lower and upper quantiles is different from that at the median. This reflects the fact that, when the system is under extreme market conditions, the importance of the financial variables that affect the volatility of green assets changes. Thus, investors should promptly modify their investment strategies under different market conditions. Both in the lower and upper quantiles, green bonds and green stock are still the largest contributors to each other's volatility spillovers. This finding indicates that green stock and green bonds are not suitable for inclusion in the same investment portfolio, whether in the normal market or extreme market conditions.

In the upper quantile, the IDEMV index and GPR become the second- and fourth-largest contributors to the green bond and green stock spillovers, respectively. The IDEMV index is the second transmitter to green bond and green stock spillovers in the lower quantile, while the GPR moves up to become the third- and fourth-largest transmitter to green bonds and green stock, respectively. These results show that the contribution degree of the uncertainty indices to green asset volatility spillovers significantly increases both in the lower and upper quantiles in comparison to the median, indicating that the uncertainty indices play a more crucial role in predicting the green asset volatility in extreme market conditions than in the normal market. The findings are also consistent with previous research [51], which confirmed that the risk factor (GPR index) was a significant Granger cause for green bond market returns in the upper quantiles. Green bonds and green stock receive more spillover effects from the IDEMV index than from the GPR, both in the lower and upper quantiles, which is consistent with the median results. Meanwhile, the GPR transmits more spillovers to the green bonds than to the green stock, while the IDEMV index contributes more spillovers to the green stock than to the green bonds under extreme market conditions.

Both in the upper and lower quantiles, green bonds and green stock receive more spillovers from oil than from carbon emissions and natural gas, which indicates that green assets are more affected by oil in extremely stable and volatile markets. Natural gas has a greater impact on green assets than carbon emissions in the upper quantile, whereas carbon emissions have a greater impact on green assets in the lower quantile. This finding suggests that investors should pay more attention to changes in variables under different market conditions.

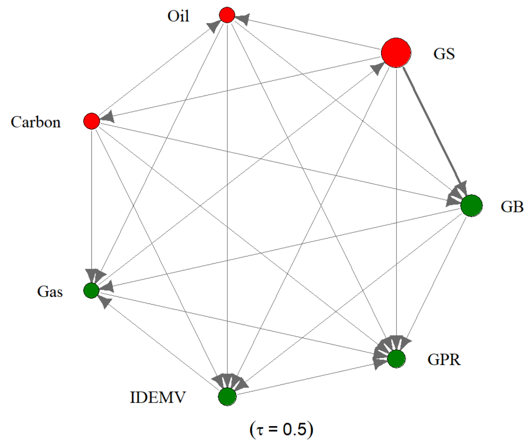
4.2. Network Analysis of Quantile Connectedness

Based on Table 3, Figure 2 displays the volatility network results at the median, lower, and upper quantiles, allowing us to clearly observe the direction and strength of the net pairwise spillovers between green assets and other variables at different quantile conditions, as well as the net transmitter and net receiver of the volatility system during our sample period.

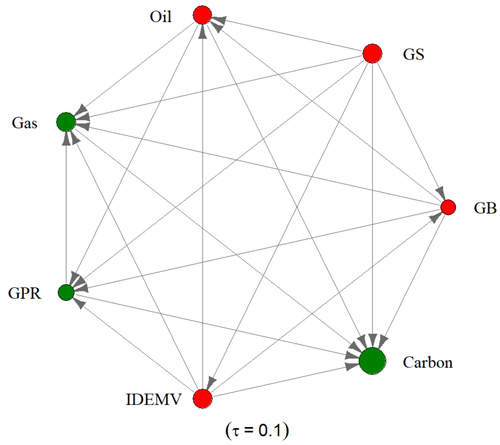
In Figure 2A, green stock, oil, and carbon emissions are the net transmitters of the volatility system, while green bonds, oil, natural gas, the IDEMV index, and the GPR are the net receivers. The thickness of the edges around the green bond and green stock nodes reflects the strongest net pairwise connectedness between green bonds and green stock. The direction of the edges around the green bond and green stock nodes shows that, with the exception of natural gas, green stock is the net pairwise transmitter for all assets. Green bonds are the net pairwise transmitter of natural gas, the IDEMV index, and the GPR, while they are the net pairwise receiver of green stock, oil, and carbon emissions.

Figure 2B,C show that the roles of each variable (net transmitter/receiver) in the system's volatility and the strength and direction of the net pairwise connectedness change in extreme market conditions. For example, green bonds and the IDEMV are the net receivers of the system in the median, while they become the net transmitters in the lower and upper quantiles. In addition, the size of the nodes at the upper quantile is larger than that of the nodes at the median and lower quantiles, suggesting the much higher transmission ability of the contributors in extremely volatile markets. We find that the arrow edge linked to each asset in the upper quantiles is thicker than in the median, which implies that the net pairwise connectedness across assets in an extremely volatile market increases.

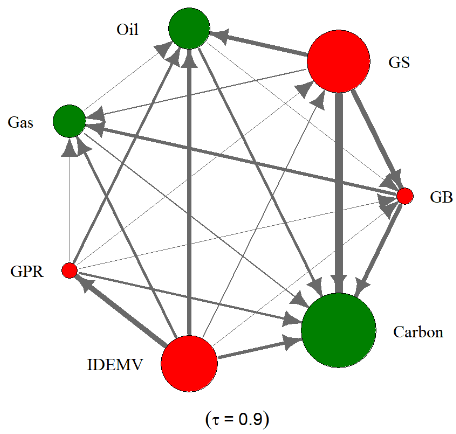
Notably, the IDEMV and GPR become the net transmitters of the system spillover in the upper quantile; meanwhile, these two indices are the net pairwise transmitters of all other assets, although this result is not observed at the median and lower quantile. This finding implies that the uncertainty indices transmit more spillovers to other assets than they receive from them in the upper quantile; thus, investors should be more alert to changes in the uncertainty indices in an extremely volatile market.



(**A**) Median



(**B**) Lower quantile



(**C**) Upper quantile

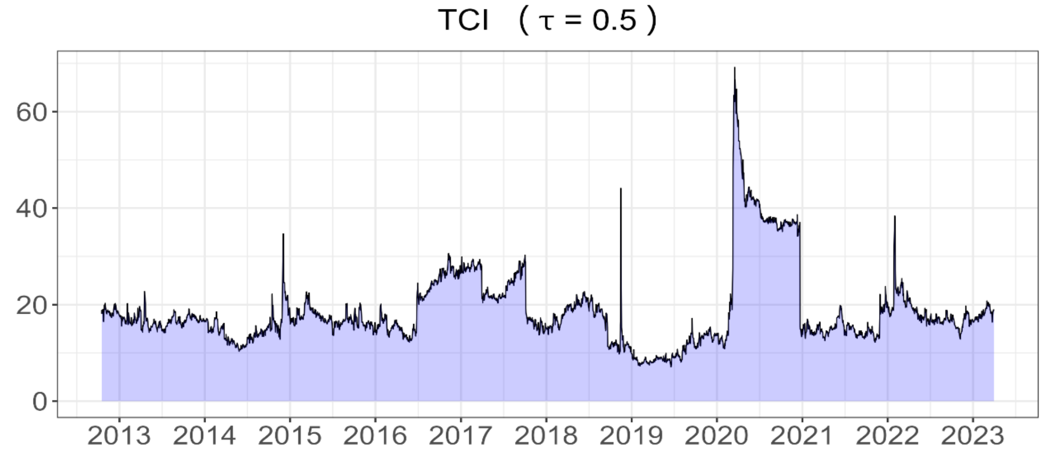
Figure 2. Volatility connectedness network plot at the median, lower, and upper quantiles. Note: The color of the nodes indicates whether they are net transmitters (red) or net receivers (green) of the system. The size of a node reflects the magnitude of its net connectedness. The edge arrow direction and edge thickness represent the direction and strength of the net pairwise connectedness between a pair of markets, respectively. GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

4.3. Dynamic Quantile Connectedness Analysis

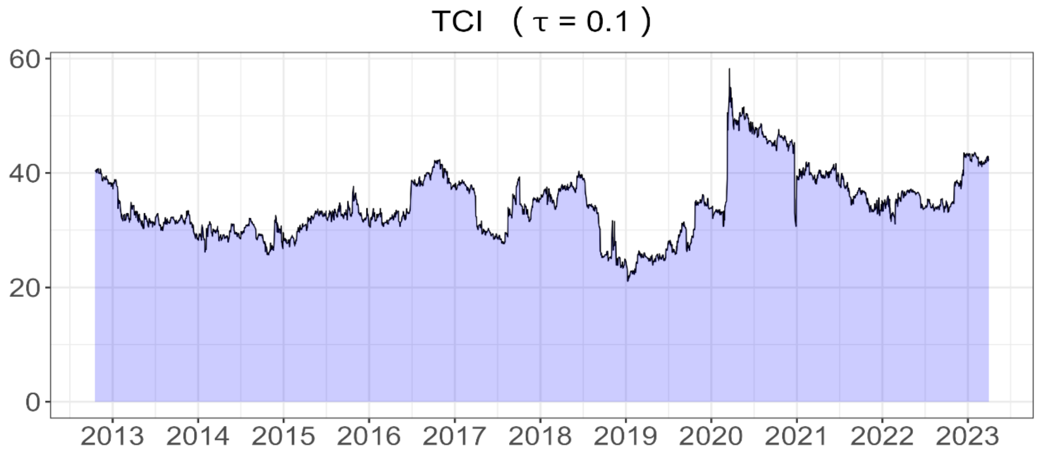
Thus far, this paper has analyzed the performance of static spillover effects across green assets and other variables in the full sample period. Now, we turn to the dynamic spillover effects across green bonds, green stock, the uncertainty indices, carbon emissions, and fossil energies at different quantiles.

4.3.1. Dynamic Total Spillover Measures at the Median, Lower, and Upper Quantiles

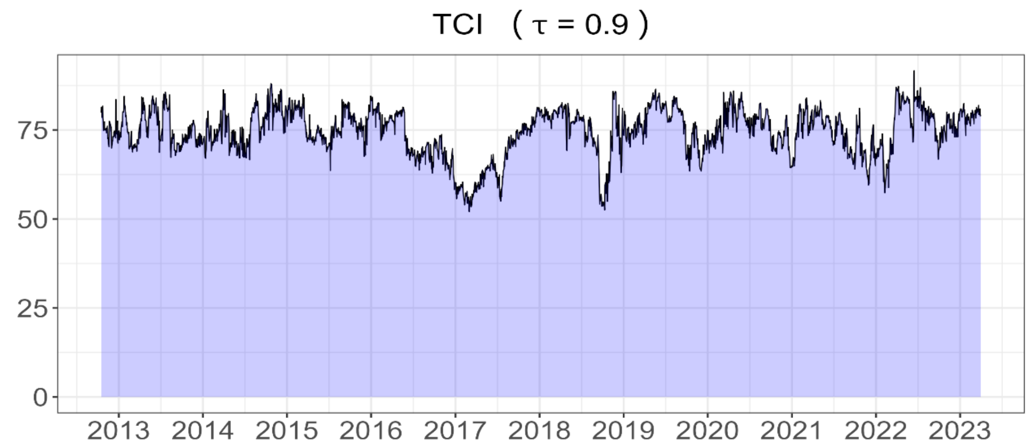
The results of the dynamic total spillover effects estimated at the median ($\tau = 0.5$), lower ($\tau = 0.1$), and upper ($\tau = 0.9$) quantiles are shown in Figure 3A–C, respectively. According to Figure 3A, the dynamic total spillover effects in the median range between 7% and 69% and vary considerably over time across our sample period. In particular, the dynamic total spillover effects exhibit a sudden and significant rise at several specific time points during our sample period. These spikes in the total spillover effects may be caused by sudden public events, such as the crude oil crisis in the period of 2014–2015; the COVID-19 pandemic, which has been ongoing since March 2020; the Russia–Ukraine war, starting in February 2022; and the surge in the natural gas price due to the United States' high demand in November 2018.



(**A**) Total spillover effects at the median (τ = 0.5)



(**B**) Total spillover effects at the lower quantile (τ = 0.1)



(**C**) Total spillover effects at the upper quantile (τ = 0.9)

Figure 3. Total spillover effects at the median, lower, and upper quantiles. Note: The dynamic spillover effects were captured using a 200-day rolling window based on a QVAR model with a lag of 5 (BIC) and a 10-step-ahead forecast horizon.

As shown in Figure 3A, it is worth noting that the dynamic total spillover effects suddenly increased and reached an unprecedented height (69%) in early March 2020, at the beginning of the spread of COVID-19. After this, the dynamic total spillover effects remained at a high level (over 40%) for over a month, indicating that, in the early stages of COVID-19, the inability to control the disease's spread quickly caused fear among the public, which caused severe fluctuations in the economic market. After the various response measures were taken against COVID-19, the dynamic total spillover effects decreased but still had higher spillover until the coronavirus vaccine was approved for use at the end of 2020. This finding implies that there was effective information transmission between green assets, the uncertainty indices, and other assets, as well as close connections between these assets, during the period of COVID-19. The dynamic total spillover effects rose and reached 38% at the start of the Russia–Ukraine war in February 2022, with a variation range of about 18%. The increases in the dynamic total spillover effects during the Russia–Ukraine war and in other extreme event periods are significantly smaller than the increases in the dynamic total spillover effects during the COVID-19 period, suggesting that, during our sample period, the shock of COVID-19 had a greater impact on the financial market, which is consistent with the previous literature [52,53].

Compared with the median, the dynamic total spillover effects are much larger at the lower and upper quantiles, as shown in Figure 3B,C, but the range of fluctuations is slightly lower, varying between 21% and 58% in the lower quantile and between 52% and 92% in the upper quantile. This reflects that the whole volatility system is particularly sensitive to extreme market conditions, especially in an extremely volatile market. It is worth noting that the fluctuation in the dynamic total spillover effects at the upper quantile shows a higher frequency than at the median and lower quantile, suggesting more frequent information exchange between green assets and other assets in an extremely volatile market. Likewise, we still observe a rise in volatility in the lower and upper quantiles in response to unexpected public events, confirming that extreme events still have pronounced impacts on the dynamic spillover effects between green assets and other variables under extreme market conditions.

4.3.2. Dynamic Net Directional Spillover Effects at the Median, Lower, and Upper Quantiles

Figures 4–6 present the dynamic net directional volatility spillover effects estimated at the median, lower, and upper quantiles for each variable. The positive value represents the asset playing the role of a net transmitter, while the negative value represents the net receiver of the system. It is obvious that, throughout time, the net directional spillover effects fluctuate between positive and negative values, showing that assets' functions are evolving.

At the beginning of COVID-19, we can find a large, positive spike or minus spike in the dynamic net spillover effects of all assets at the median, which indicates that major crises significantly increase net volatility spillovers. The increased net directional spillover caused by COVID-19 for all assets at the median is significantly larger than the increased net directional spillovers produced by the war, with the exception of gas, indicating that COVID-19 has a greater impact on the net volatility spillover of all assets than the Russia–Ukraine war. Interestingly, in most cases, the GPR is a net receiver of the volatility system.

We discovered that the strength and direction of the dynamic net spillover of one asset at various quantiles were different, indicating that the asset's role as a transmitter or receiver may alter depending on the market situation. At the lower and upper quantiles, the net spillover effects also increased, caused by the shock of the event. Similar to the performance of the dynamic total spillover effects, the net volatility spillover effects of all assets at the upper quantiles show higher-frequency fluctuations and higher volatility than the median and lower quantiles.

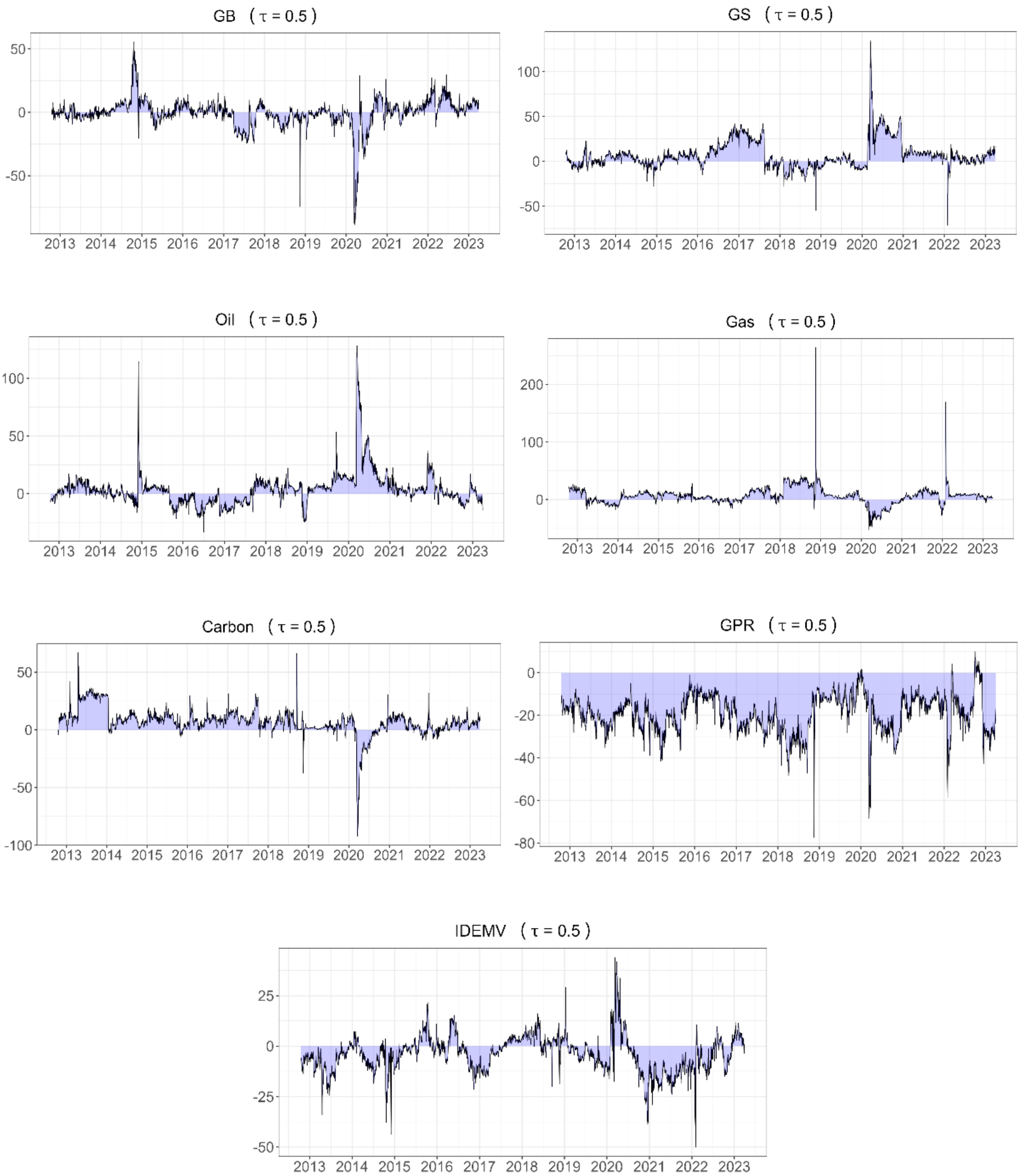


Figure 4. Net directional spillover effects at the median. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

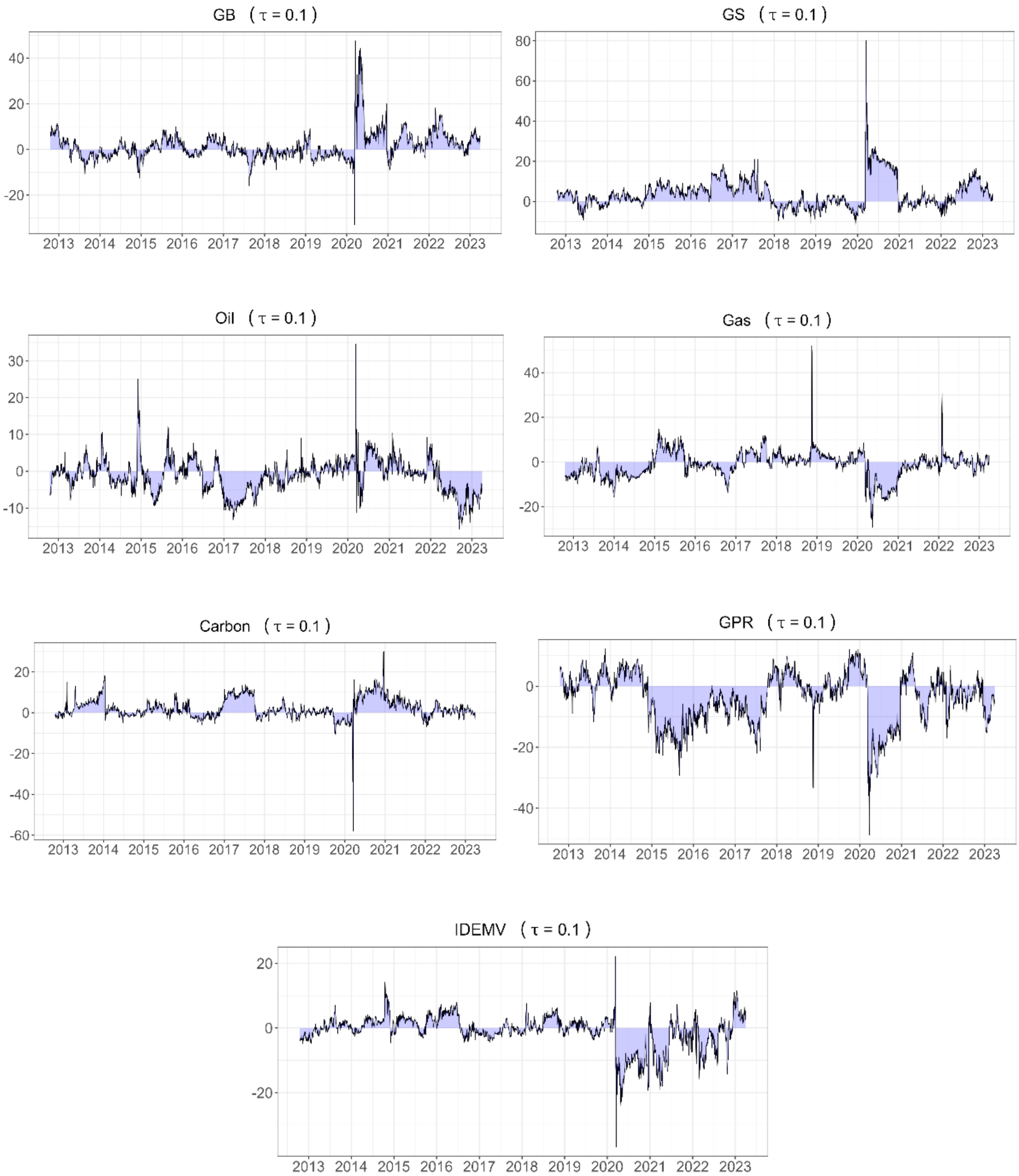


Figure 5. Net directional spillover effects at the lower quantile. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

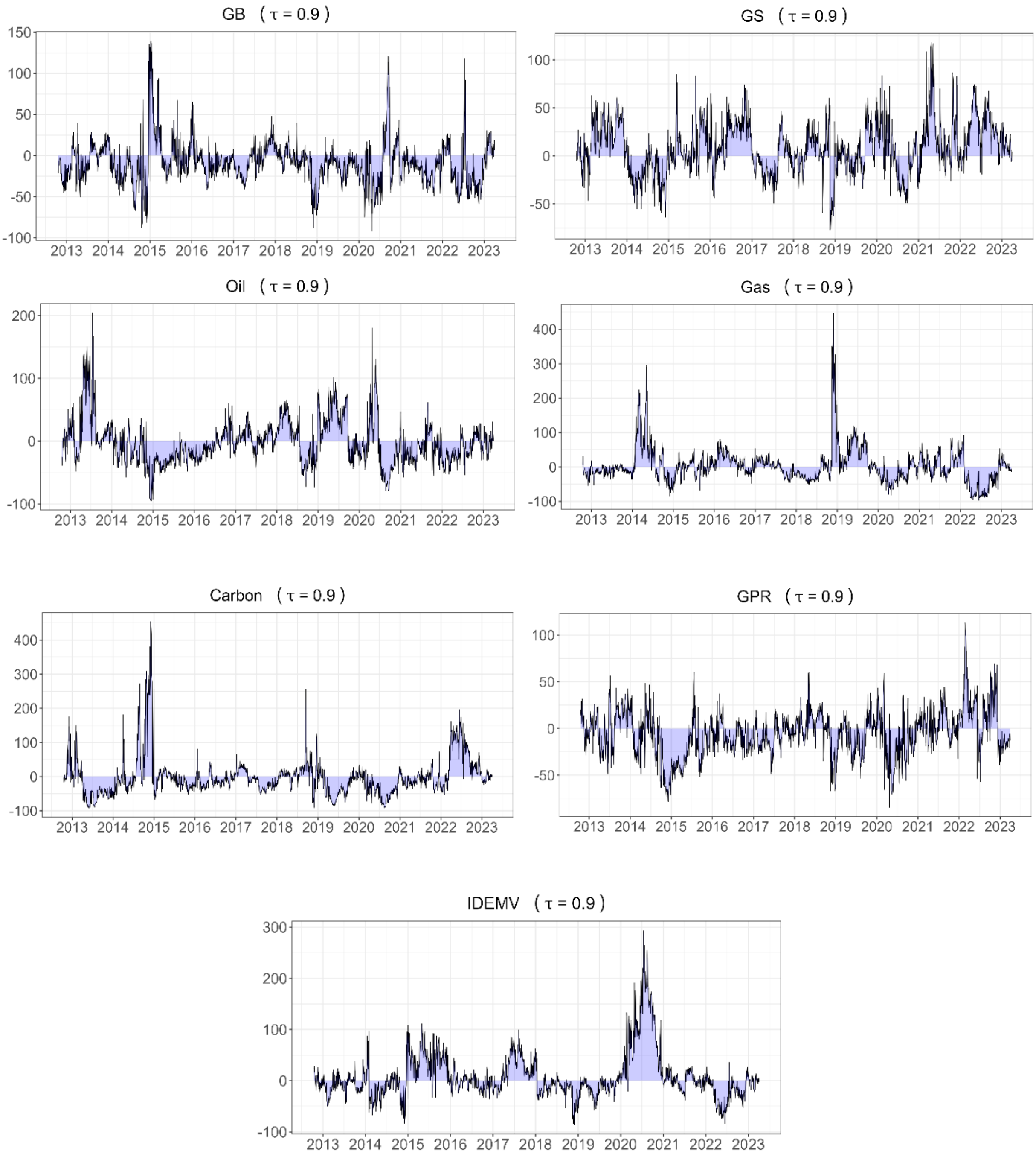


Figure 6. Net directional spillover effects at the upper quantile. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

4.3.3. Dynamic Net Pairwise Directional Spillover Effects at the Median, Lower, and Upper Quantiles

The net pairwise directional spillover effects between green finance markets and other markets at the median, lower, and upper quantiles are presented in Figures 7–9, respectively. The positive net pairwise spillovers indicate that the spillovers from GB/GS to other assets are higher than the spillovers from other assets to GB/GS. Similarly to the net directional spillover effects, the net pairwise spillover effects are time-varying in all types of markets at different quantiles. The intensity and direction of the net pairwise spillovers between other assets and green assets caused by various sudden events are different. In addition, all markets show a different dynamic net pairwise spillover at various quantiles. In addition, Figure 7 reveals that the IDEMV displays different characteristics regarding the net pairwise spillovers of the green bond and green stock markets, as a net contributor of green bonds and a net receiver of green stocks during the COVID-19 pandemic.

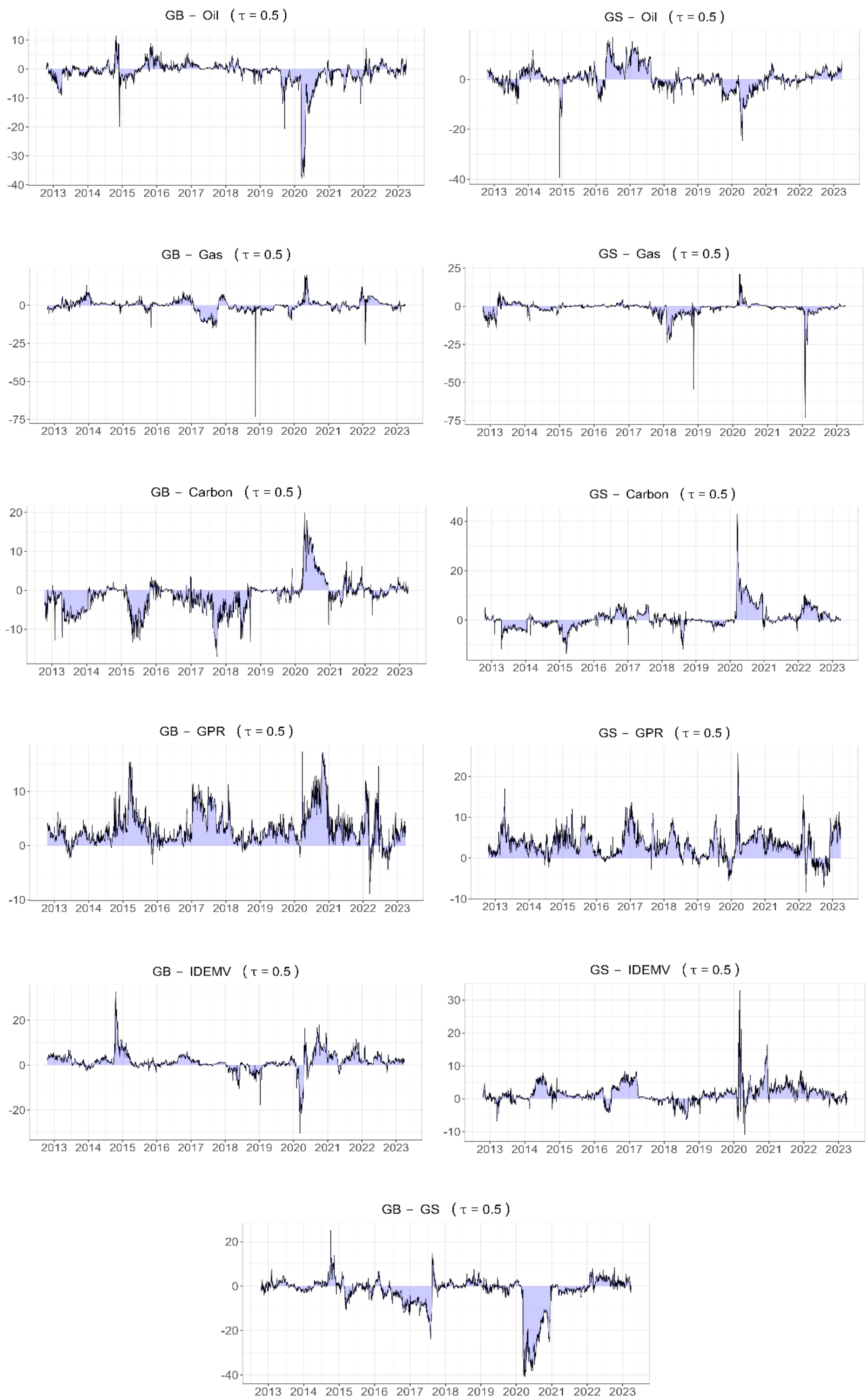


Figure 7. Net pairwise directional spillover effects between green assets and other assets at the median. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

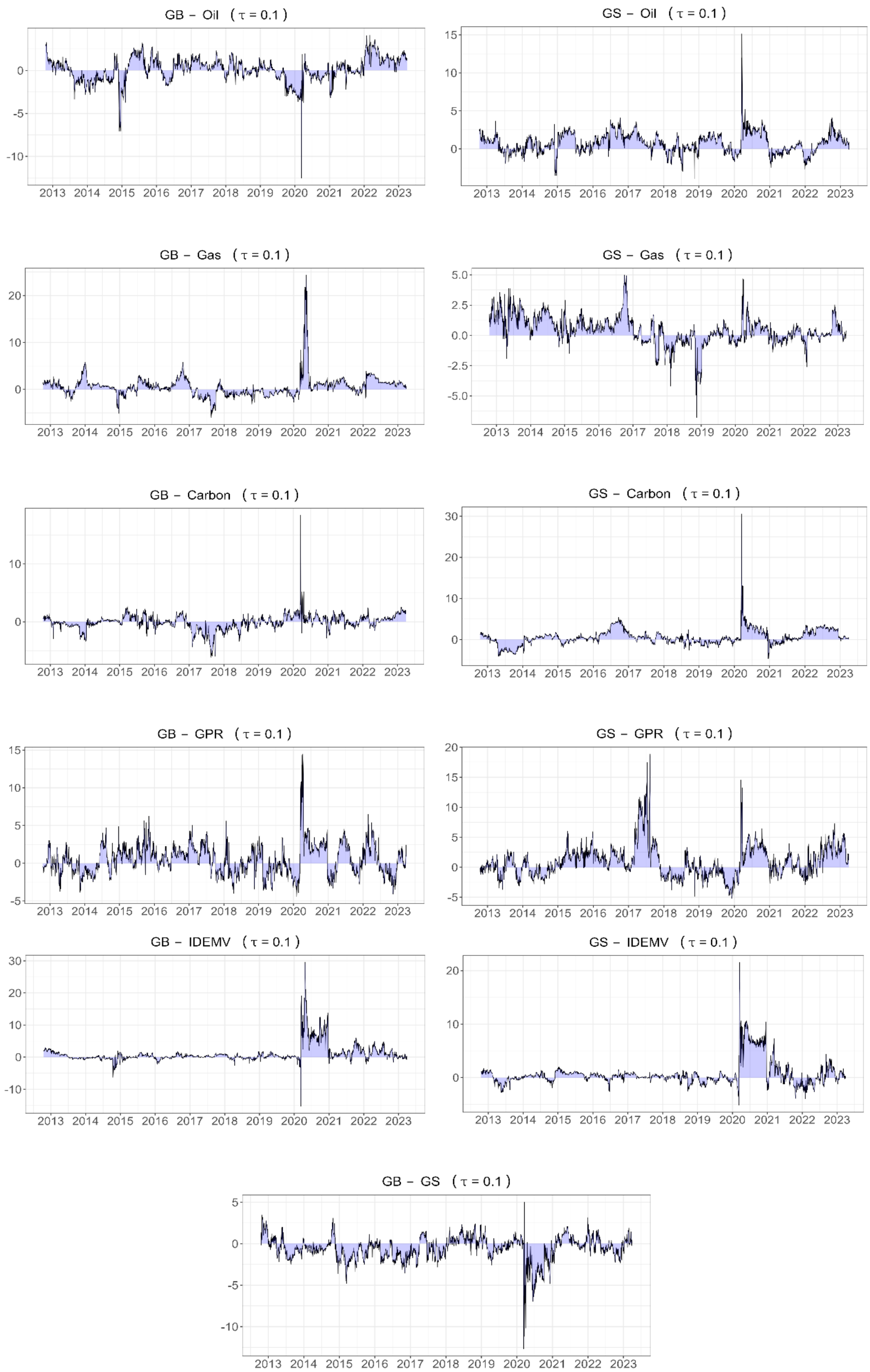


Figure 8. Net pairwise directional spillover effects between green assets and other assets at the lower quantile. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

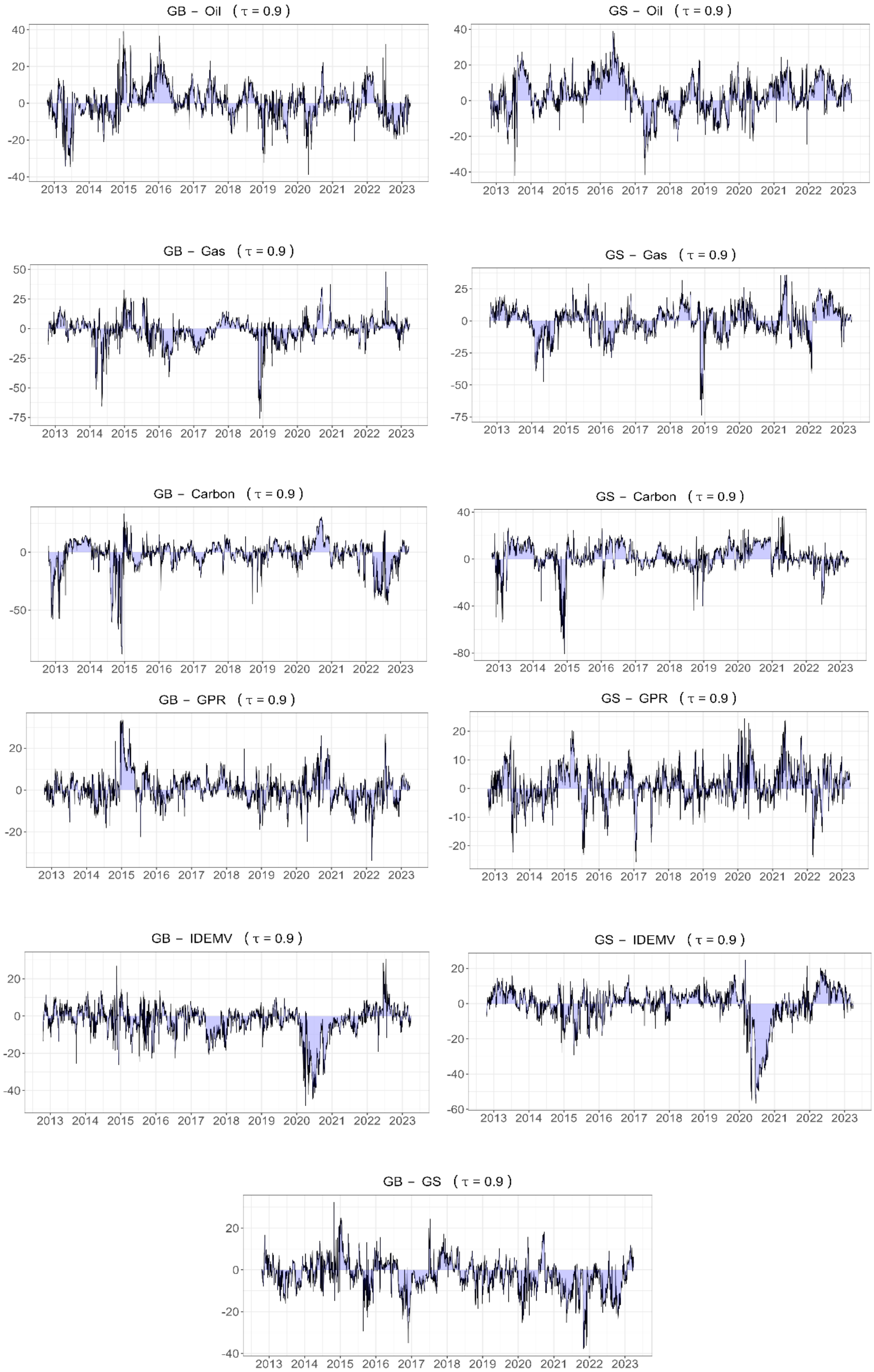


Figure 9. Net pairwise directional spillover effects between green assets and other assets at the upper quantile. Note: GB, Solactive Green Bond Index; GS, Standard & Poor Global Clean Energy Index; Oil, Brent Crude Oil; Gas, Henry Hub Natural Gas; Carbon, Carbon Emissions Futures; IDEMV, Infectious Disease Equity Market Volatility Tracker; GPR, Geopolitical Risk Index.

From Figure 9, we observe a rapid oscillation in the frequency of the net directional spillover effects between green assets and other assets, alternating between positive and negative values at the upper quantile. This indicates that the interaction between green assets and other assets is difficult to capture in the extremely volatile market. This finding also reflects that, in an extremely volatile market, investors should be careful to build a portfolio of green assets and other assets.

Except for the gas market, the net pairwise spillovers between assets and green assets at the median during COVID-19 was much higher than during the Russia–Ukraine war period. The net pairwise spillovers between gas and green assets at the median show a huge spike at the beginning of the Russia–Ukraine conflict, because Russia is a major exporter of natural gas, and the Russia–Ukraine war has led to a rapid increase in the price of natural gas. It is interesting to note that the net spillover effects between green assets and the GPR at the median are mostly positive, which implies that the spillovers from the GPR to green assets are smaller than those being received. This finding also suggests that the GPR cannot predict the stock volatility well in the normal market.

5. Conclusions

In this study, a quantile connectedness approach was employed to investigate the volatility spillover effects across carbon emissions, crude oil, natural gas, the uncertainty indices of COVID-19 and the Russia–Ukraine war, and green assets (green bonds and green stock) under extreme market conditions. Specifically, we applied the Infectious Disease Equity Market Volatility Tracker (IDEMV) to measure the uncertainty caused by COVID-19 and used the Geopolitical Risk Index (GPR) to represent the uncertainty of the Russia–Ukraine war, while we utilized two distinct categories for green assets: green stock and green bonds. In this study, we assumed that the connectedness estimated at the median, lower, and upper quantiles represented normal, extremely stable, and extremely volatile markets, respectively.

The main conclusions are summarized below.

The results concerning the static spillover effects reveal that the total and directional spillover effects across green assets and other variables in our sample when measured at the extreme quantiles are much higher than those at the median, which indicates that the interrelation between green assets and other variables is closer in extreme market conditions. This empirical finding is in line with previous research [49,50] on the market contagion, which demonstrated higher connectedness in the upper and lower quantiles. It also aligns with the results of Naeem et al. [40] and Khalfaoui et al. [54], who also examined the spillover effects between green markets and other markets (Bitcoin, the stock market, etc.). Their findings indicate that the spillover effects between green markets and other markets in extreme cases are significantly higher than those in normal cases.

The IDEMV contributes more spillovers to green assets than the GPR in the median and extreme quantiles, which implies that the uncertainty index caused by COVID-19 has a greater impact on green assets than the geopolitical uncertainty related to the Russia–Ukraine war under normal and extreme market conditions. This finding is confirmed by previous studies [47,48], which show that the IDEMV has a significant impact on financial assets than the GPR. According to the spillover contribution ranking of green assets, the ranks of both the IDEMV and GPR significantly increase in the lower and upper quantiles in comparison to the median, suggesting that the uncertainty indices are more effective in predicting green asset volatility in extreme markets than in the normal market.

In the normal market, green bonds are more affected by carbon emissions, and green stock is more susceptible to crude oil. In addition, both the green bonds and green stock are rarely affected by natural gas during our sample period, which indicates that natural gas can be considered a hedge asset for green assets. However, green bonds and green stock receive more spillovers from crude oil than from carbon emissions and natural gas in the lower and upper quantiles, which implies that green assets are more affected by crude oil in extremely stable and volatile markets.

The network analysis of green assets and other variables shows that the role of each variable (net transmitter/receiver) in the system's volatility and the strength and direction of the net pairwise connectedness change under different market conditions. This conclusion is also confirmed by Sharif et al. [55], who observed that the variables in the system exhibiting net spillover behavior varied across quantiles.

The dynamic spillover results indicate that the dynamic total spillovers in the lower and upper quantiles are much higher than those in the median, but the range of fluctuations in the extreme quantiles is slightly lower than that in the median. This suggests that the whole volatility system is particularly sensitive under extreme market conditions. This finding is also supported by the study of Long et al. [56], which examined the quantile connectedness between uncertainties and green bonds in the US, Europe, and China and discovered that the dynamic total spillover fluctuations in the extreme cases were relatively small. Our dataset included several periods of crisis, such as the crude oil crisis, COVID-19, the Russia–Ukraine war, etc. We noticed that these abrupt public events caused a spike in the dynamic total spillovers during our sample period, both in normal and extreme market conditions. During our sample period, the total spillover risk reached a high level in early March 2020 as a result of the financial shock due to the outbreak of COVID-19. Meanwhile, the shock of COVID-19 led to a significantly greater increase in the total spillovers of the system in the normal market than the increases brought about by the Russia–Ukraine war and other crises. This finding suggests that COVID-19 had a more significant effect on the green finance system than other crises during our study period, which is in line with prior research [52,53]. Moreover, we discovered that the fluctuation in the dynamic total spillover effects at the upper quantile exhibited a higher frequency than at the median and lower quantile, suggesting more frequent information exchange between green assets and other assets in an extremely volatile market.

Our empirical results have several implications for investors and policymakers. First, the connectedness across green assets and other assets increases under extreme market conditions and exhibits asymmetry at the lower and upper quantiles. As a result, investors and policymakers should pay attention to the changes in green assets and other assets in the normal market, as well as the interdependence of assets in extreme market conditions. Second, typically, when the correlation between green assets and other assets is weak, this implies that investors can benefit from interesting diversification opportunities by including green assets in their portfolios. Investors should exercise greater caution when changing their investment portfolios in an extremely volatile market, since the dynamic interaction between green assets and other assets is difficult to quantify in an extremely volatile market. Additionally, the hedging and safe haven potential of carbon emissions and natural gas against green assets can be exploited by investors in extreme volatility markets. Third, the spillover effects of the green assets contributed by uncertainty indices significantly increase under extreme market conditions, which indicates that policymakers should pay more attention to economic uncertainty changes and fortify the stability of green finance markets early on by enacting policies in response to extreme positive or negative events.

In the future, we should aim to broaden the scope of analysis to include more international economic indicators in order to provide a more global perspective on the financialization of green finance in the face of global events. Additionally, exploring the effects of other uncertainty indices on the green finance market is essential.

Examining the impact of other external shocks, like the Israel–Hamas conflict, with the analytical approach used in this study, remains an important area for future investigation.

Author Contributions: Investigation, T.L.; writing—original draft preparation, T.L.; writing—review and editing, Y.Z., W.Z. and S.H.; project administration, S.H.; funding acquisition, S.H. All authors have read and agreed to the published version of the manuscript.

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