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Asymmetric Effects of Renewable Energy Markets on China's Green Financial Markets: A Perspective of Time and Frequency Dynamic Connectedness

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Abstract: This study investigates dynamic risk spillover effects between renewable energy markets and Chinese green financial markets from a time-frequency perspective by utilizing weekly data from two types of markets with a span from January 2010 to August 2022. The results show that the total spillover and net spillover effects vary widely across time. Short-run spillover is more dominant than long-run spillover. In most cases, green finance markets play the role of risk receivers in the system, while renewable energy markets are the main risk transmitters in the short run and the main risk spillover contributors in the long run. Finally, we determine that the hedging effect of green finance assets in the renewable energy market may decrease after the COVID-19 pandemic.

Keywords: renewable energy market; green financial market; time–frequency connectedness; hedging effect

MSC: 91B76

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1. Introduction

In recent years, global attention towards climate change and environmental conservation has escalated, prompting nations worldwide to adopt measures shifting towards sustainable energy and green finance sectors. Renewable energy, as an important part of the sustainable energy development strategy, is also the key to solving problems such as climate change and energy security, which have received more and more attention in recent years [1]. Renewable energy, including wind, solar, nuclear, etc., is regarded as an alternative to traditional fossil fuels. For instance, it has been found that investment in solar and wind energy will grow at an annual rate of 18%. The renewable energy market has been attracting a great deal of investment attention due to the rapid rise in clean energy technology and the placement of clean energy at the core of the new environmental protection policy [2]. In 2020, the global investment in renewable energy was USD 137 billion. The biggest contributor to the development of global clean energy was investment in the renewable energy market in the Asia–Pacific region [3].

As one of the world's largest energy consumers, China plays a crucial role in this transformative process. With robust governmental support and increased investments in renewable energy, China's renewable energy market is thriving. For instance, China has emerged as the world's largest market for wind and solar power generation. According to data from the International Renewable Energy Agency, in 2019, China added 28.5 gigawatts of wind power capacity and 30.1 gigawatts of solar power capacity, accounting for approximately 44% and 30% of the global newly installed capacity, respectively.

Simultaneously, the Chinese government actively promotes the development of green finance to support sustainable energy and environmental protection projects. According to the People's Bank of China, in 2019, China's green credit balance reached CNY 11.7 trillion, and green bond issuances amounted to 1.2 trillion yuan, representing year-on-year growth rates of 12.7% and 28.3%, respectively. These statistics indicate that China is rapidly becoming a significant player in the global green financial market and is increasingly influential in driving sustainable development initiatives.

Despite the rapid growth observed in both China's renewable energy and green finance markets, numerous unknown factors remain regarding the dynamic interplay between these two markets and their effects on each other. Specifically, there is a need to understand the asymmetric effects of the renewable energy market on the green finance market, wherein the impact of one market on the other may differ. The existence of such asymmetric effects could influence market stability and sustainability, underscoring the importance of conducting in-depth research in this area.

Therefore, this study aims to explore the asymmetric effects of the renewable energy market on China's green finance market from the perspective of time and frequency dynamic connectedness. By analyzing the variations and evolutions in this dynamic connection, we can gain a better understanding of the interrelationship between these two markets, providing deeper insights and guidance for China's sustainable development trajectory.

2. Literature Review

In recent years, renewable energy and related financial market assets have received lots of attention ([4–8]). Related topics include renewable energy ([9–11]), green bonds ([12–15]), clean energy stocks ([16–19]), etc. Most of them focus on the correlation between the renewable energy market and other markets.

Recently, some studies have focused on volatility spillovers among markets ([20–25]). For the renewable energy market, the positive impact of the energy market on renewable energy stock prices has been revealed through the VAR model and the linkage between the physical market and the financial market from a dynamic perspective [26]. There are weak linkages between green bonds, stock markets, and energy markets [27]. A weak link has also been found between green energy and financial markets by constructing a green energy index [28]. Many scholars believe that risk spillovers are derived from asset price fluctuations within the financial market ([20,29–31]). Moreover, some studies have found that there is a mutual volatility spillover between the energy market and other financial markets, which shows heterogeneity in the time and frequency domains ([32–35]).

For the hedging effect of the green financial market, it is suggested that the green financial market has a better hedging effect on the asset portfolio [36], which is consistent with the findings from [37]. However, some scholars hold little confidence in the hedging effect of green financial assets [38,39]. Those studies show evidence that the performance of green mutual funds is not satisfactory. The green bond market is independent of other markets and cannot effectively play the role of risk hedging, even becoming a risk exporter in the system. Therefore, the hedging effect of the green financial market remains to be examined, especially considering the impact of COVID-19 [40].

On the other hand, the spillover connectedness index of Diebold and Yilmaz [41] has been widely applied to the dynamic spillover effect between financial markets ([42–47]). Since the Diebold and Yilmaz (DY) method can only be used in the time domain, time and frequency dynamic connectedness were proposed by Baruník and Křehlík [48], which can simultaneously evaluate the magnitude and direction of time and frequency spillovers. At different time frequencies, the correlation between markets should be different, as agents with different preferences invest under different investment horizons. Therefore, the Baruník and Křehlík (BK) method has also been widely used recently ([49–51]).

As indicated above, the current literature focuses on the relationship between the green financial market and the traditional financial market and renewable energy. Our research aims to assess time and frequency dynamic connectedness among clean energy, Chinese renewable energy stocks, and green bonds by applying the BK model to investigate the hedging effect of clean energy on China's green financial assets.

3. Methodology

3.1. Barunik–Krehlik Framework

Based on the definition of generalized variance decomposition [41], Baruník and Křehlik extended it to the frequency domain and used the spectrum of the generalized variance decomposition to study the connectedness in the frequency domain and obtain time-varying results [48]. The generalized causal spectrum at frequency ω can be written as follows:

$$(f(\omega))_{k,j} = \frac{\Sigma_{j,j}^{-1}\left|\left(\Psi\left(e^{-i\omega}\right)\Sigma\right)_{k,j}\right|^2}{\left(\Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right)\right)_{k,k}}, \tag{1}$$

where $\left(f(\omega)\right)_{k,j}$ represents the contribution of the shock of variable k to the spectral of variable j at a given frequency ω, which is the causality within the frequency. On this basis, the weight function is introduced as follows:

$$\Gamma_j(\omega) = \frac{\left(\Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right)\right)_{k,k}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-i\lambda}\right)\Sigma\Psi'\left(e^{+i\lambda}\right)\right)_{k,k}d\lambda}. \tag{2}$$

Given a frequency band $d = (a,b)$, $a,b \in (-\pi,\pi)$, the generalized variance decomposition on the frequency band d is defined as follows:

$$(\Theta_d)_{k,j} = \frac{1}{2\pi}\int_d \Gamma_k(\omega)\Big(\Theta(\omega)\Big)_{k,j}d\omega. \tag{3}$$

The above Formula (3) can be further normalized to

$$\left(\widetilde{\Theta}_d\right)_{k,j} = \frac{(\Theta_d)_{k,j}}{\sum_j (\Theta_\infty)_{k,j}}, \tag{4}$$

where $(\Theta_\infty)_{k,j} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_k(\omega)\Big(\Theta(\omega)\Big)_{k,j}d\omega$, and $\left(\widetilde{\Theta}_d\right)_{k,j}$ is the connectedness of variable k to variable j on frequency band d. In addition, the overall connectedness on band d can be calculated as follows:

$$S_d^W = 100\cdot\left(1 - \frac{Tr\left\{\widetilde{\Theta}_d\right\}}{\sum\widetilde{\Theta}_d}\right), \tag{5}$$

where $Tr\{\cdot\}$ is the trace operator, and $\sum\widetilde{\Theta}_d$ is the sum of all elements of the matrix $\widetilde{\Theta}_d$. Given frequency d, the contribution to overall connectedness can be defined by weighting the internal metric.

$$S_d^F = S_d^W\cdot\frac{\sum\widetilde{\Theta}_d}{\sum\widetilde{\Theta}_\infty}. \tag{6}$$

S_d^F is the frequency connectedness over band d. It should be noted that the frequency connectedness separates the original connectedness into different parts, namely $\sum_{d_s} S_S^F = S$, where S is the total connectedness of Diebold and Yilmaz [41].

This method can measure the connectedness of market j on all other markets at frequency band d (To):

$$S_{j\to k,t}^d = \sum_{k=1,j\neq k}^n\left(\widetilde{\Theta}_d\right)_{k,j}. \tag{7}$$

It can also measure the connectedness received by market j from all other markets on frequency band d (From):

$$S^{d}_{j\leftarrow k,t} = \sum\nolimits_{k=1,j\neq k}^{n} \left(\widetilde{\Theta}_{d}\right)_{j,k}. \tag{8}$$

The net connectedness on band d is obtained as follows:

$$S^{d}_{j,t} = S^{d}_{j\rightarrow k,t} - S^{d}_{j\leftarrow k,t}. \tag{9}$$

3.2. DCC Model

We use the dynamic conditional correlation (DCC) model, proposed by Engle [52], to investigate the dynamic relationship between renewable energy markets and green financial markets. The ARMA-GJR-GARCH model is as follows:

$$r_t = c + \sum\nolimits_{i=1}^{p} \alpha_i r_{t-i} + \sum\nolimits_{j=0}^{q} \beta_j \varepsilon_{t-j}, \tag{10}$$

$$\varepsilon_t = \Sigma_t v_t, \tag{11}$$

$$\Sigma_t^2 = \Psi + \phi\varepsilon_{t-1}^2 + \eta\varepsilon_{t-1}^2 d_{t-1} + \Gamma\Sigma_{t-1}^2, \tag{12}$$

where r_t is the return of different markets, v_t is the white noise, and Σ_t^2 represents the conditional variance. $d_{t-1} = 1$ if $\varepsilon_t < 0$, otherwise $d_{t-1} = 0$.

The DCC model is as follows:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{13}$$

$$Q_t = \left(1 - \sum\nolimits_{m=1}^{M} a_m - \sum\nolimits_{n=1}^{N} b_n\right)\overline{Q} + \sum\nolimits_{m=1}^{M} a_m \tau_{t-m}\tau'_{t-m} + \sum\nolimits_{n=1}^{N} b_{nQ_{t-n}}, \tag{14}$$

where Q_t represents the covariance matrix, ${Q^*}_t$ is the diagonal matrix, and $\overline{Q}$ is the unconditional covariance for the standardized residuals. τ_{t-m} are the standardized residuals.

Finally, we conduct the portfolios for empirical analysis with the conditional variance and covariance calculated by the ARMA-GJR-GRACH-DCC model.

3.3. Data

As for the data on the renewable energy market, we use two data as proxies for the overall situation of clean energy in developed countries. The Wilder Hill Clean Energy Index (ECO) reflects the state of the U.S. renewable energy market, and the European Renewable Energy Index (REIX) reflects the European renewable energy market. For developing countries, we use the Mainland China New Energy Index (CNN), which is a good proxy for the state of clean energy in developing countries. The wind, photovoltaic, and nuclear energy markets represent the clean energies of China in detail. The data are from the Wind database.

The data are weekly frequencies from January 2010 to August 2022. Figure 1 shows the trends of all indices over the sample period. The raw data in this section are expressed as log differences. In general, some indices (CNN, wind, photovoltaic, and nuclear) experienced a pronounced fluctuation around 2015, all related to the Chinese market and may have been affected by the Chinese stock market crash in 2015. All indices show significant advances after 2021, which may be attributed to an increase in production demand during post-COVID-19 economic recovery. Figure 2 shows the returns trend of the indices. While they did not fluctuate a lot in the whole period, some of them fluctuated significantly around 2015, which corroborates our previous analysis.

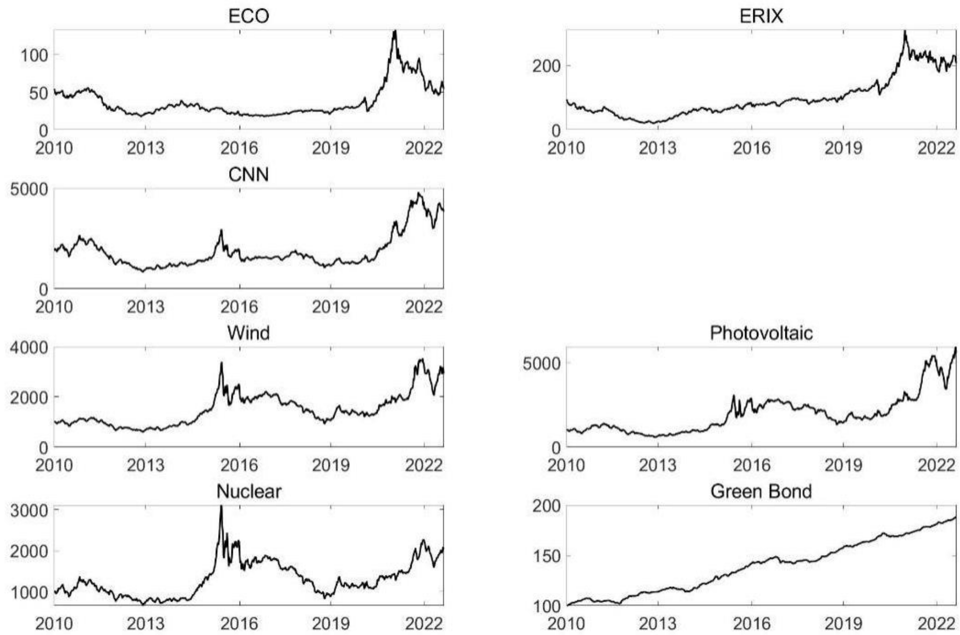

Figure 1. The index trends of renewable energy markets and green financial markets.

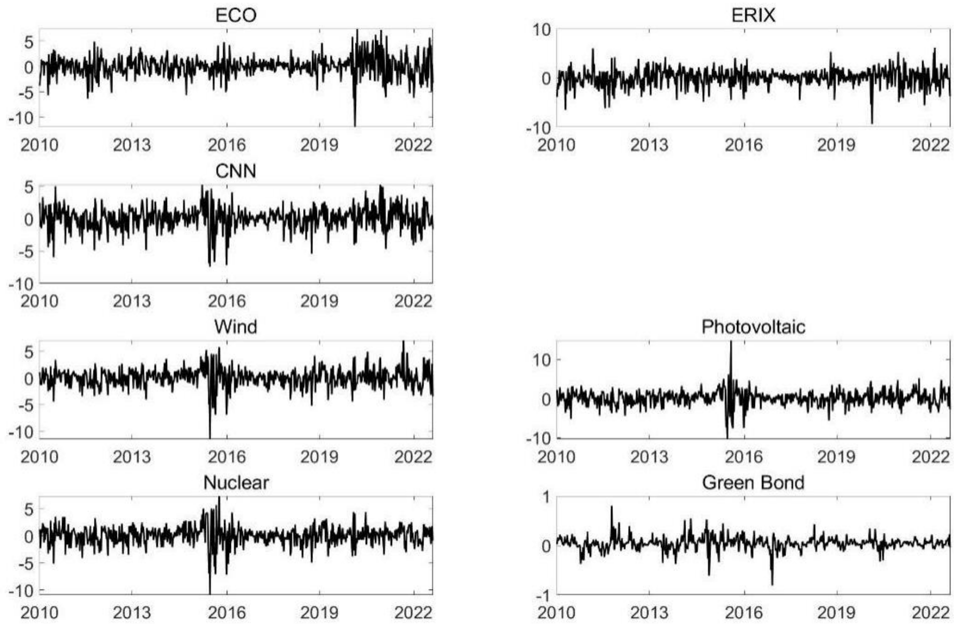

Figure 2. Returns trends of renewable energy markets and green financial markets.

Table 1 presents the descriptive statistics of all variables. The photovoltaic market has the highest maximum value of 14.8400, indicating significant positive returns at some point, while the ECO market has the lowest minimum value of −11.9193, indicating substantial negative returns. The photovoltaic market has a standard deviation of 1.9885, suggesting high volatility, while the green bond market has a standard deviation of 0.1316, indicating low volatility. Negative skewness (e.g., ECO, ERIX, and CNN) indicates that the distribution tails are longer on the negative side (left), while positive skewness (e.g., photovoltaic) indicates longer tails on the positive side (right). Higher kurtosis values indicate distributions with heavier tails and sharper peaks. The photovoltaic market has a kurtosis of 9.2536, suggesting a distribution with heavy tails and a sharp peak. All markets have high J–B test values, significant at the 1% level, indicating that the return distributions significantly deviate from normality. All markets show significant ADF test values at the

1% level, indicating that the return series are stationary. Overall, these statistics provide a comprehensive understanding of the characteristics of various renewable energy markets and China's green financial markets, covering aspects from average returns and volatility to distribution properties. The data indicate notable differences in the volatility and return distribution characteristics across different markets, particularly between the photovoltaic and green bond markets.

Table 1. Descriptive statistics of renewable energy markets and China's green financial markets.

	ECO	ERIX	CNN	Wind	Photovoltaic	Nuclear	Green Bond
Mean	−0.0001	0.0530	0.0472	0.0728	0.1159	0.0490	0.0423
Max	7.4541	6.1409	5.2281	7.0870	14.8400	7.3265	0.8027
Mini	−11.9193	−9.3372	−7.4162	−11.4976	−10.3534	−10.9154	−0.8062
S. D.	2.0960	1.8466	1.8208	1.8388	1.9885	1.7937	0.1316
Skew	−0.2693	−0.4967	−0.5188	−0.5363	0.0048	−0.6173	−0.2998
Kurt	5.4684	4.6132	4.4821	6.3211	9.2536	6.4719	9.5702
J–B	172.08 ***	96.76 ***	88.24 ***	328.35 ***	1054.28 ***	366.05 ***	1173.41 ***
ADF	−25.04 ***	−25.76 ***	−24.36 ***	−22.90 ***	−22.96 ***	−23.59 ***	−17.15 ***

Note: ECO, REIX, and CNN represent the renewable energy market of the US, Europe, and developing countries. The wind, photovoltaic, and nuclear energy markets represent the clean energies of China in detail. The Jarque–bera test is used to examine the normality of the series. ADF is the unit root test. *** denotes statistical significance at the 1% level.

Figure 2 shows a pairwise linear correlation. The result shows that the relationships between green financial assets are very similar. At the same time, the relationship between the renewable energy markets of developed and developing countries also shows a high correlation. In addition, the green finance market and the renewable energy market show a weak correlation, and this correlation is heterogeneous for different financial assets. For example, ECO has a weak positive correlation with Photovoltaic but a weak negative correlation with Nuclear, which is beneficial for our portfolio diversification. Figure 3 shows the pairwise linear dependence heat map.

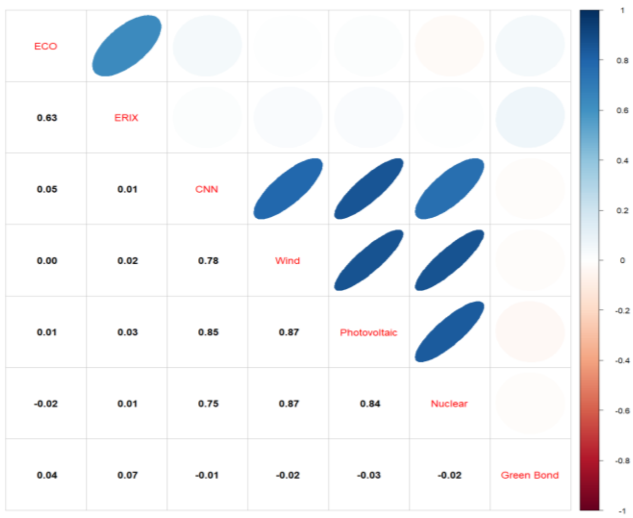

Figure 3. Pearson's correlation between renewable energy markets and green financial markets.

Table 2 shows the Johansen cointegration test results. We construct four models to explore the cointegration relationships between China's green finance market and the renewable energy market: Wind energy (WIND ECO ERIX CNN), photovoltaic energy (PV ECO ERIX CNN), nuclear energy (NUCLEAR ECO ERIX CNN), and bonds (BOND

ECO ERIX CNN). The Johansen cointegration test, including the trace test and maximum eigenvalue test, is employed, revealing significant long-term cointegration relationships across all models. This indicates stable long-term connections between the green finance markets, including wind energy, photovoltaic energy, nuclear energy, bonds, and the renewable energy market in China during the studied time series. To further analyze the dynamic relationships between variables, the BK model is utilized to differentiate between long-term and short-term spillover effects from a frequency-domain perspective. Through BK model analysis, a clearer understanding of the mutual influences of variables at different time frequencies is obtained. This comprehensive analysis sheds light on the impact mechanisms and transmission pathways between various green finance markets and the renewable energy market over different periods, providing crucial theoretical support and empirical evidence for research and policy formulation in related fields.

Table 2. Johansen cointegration test.

	WIND	**PV**	**NUCLEAR**	**BOND**
None	758.1335 ***	779.079 ***	755.5319 ***	692.3415 ***
At most 1	504.1855 ***	532.308 ***	504.5015 ***	445.6898 ***
At most 2	299.6901 ***	324.3131 ***	300.0749 ***	239.8589 ***
At most 3	131.8823 ***	129.5433 ***	123.3614 ***	103.9834 ***

Note:*** denotes statistical significance at the 1% level.

4. Empirical Results

4.1. Time–Frequency Dynamic Connectedness

Tables 3 and 4 show static connectedness results between renewable energy markets and China's green financial assets in the short and long run. The table presents the dynamic spillover effects among various indices, including ECO, ERIX, CNN, wind, photovoltaic, nuclear, and green bonds. The values represent the percentage of spillover from one index to another. In detail, the CNN index shows substantial spillover effects both received (from) and transmitted (to), indicating significant interaction with other indices. The CNN index has high volatility, with a notable amount of spillover received from other indices (10.93%) and transmitted to others (7.97%). The wind index exhibits strong spillover effects in both directions, particularly receiving spillovers from nuclear and transmitting to photovoltaic and CNN. It also shows significant volatility, receiving 9.26% of spillovers and transmitting 10.10%, indicating it plays a crucial role in the dynamic network. The nuclear index has a strong spillover effect, particularly towards photovoltaic energy and CNN, and also receives significant spillovers from other indices. The nuclear index's volatility is highlighted by its substantial spillover received (9.44%) and transmitted (9.39%), showing its central role in the network. The photovoltaic index is a net receiver in the short term but a significant contributor in the long term, transmitting substantial spillovers to other indices. Notably, the photovoltaic index demonstrates considerable volatility, with 9.52% spillover received and 10.60% transmitted, underlining its dynamic interaction within the market. As for ECO and ERIX, both indices primarily transmit spillovers to other markets, with ECO having a net positive spillover effect (1.09%) and ERIX being net negative (−0.35%). The green bond index mainly receives spillovers, indicating its stability and hedging attributes.

Table 4 shows the long-term results of connectedness. The total spillover effect is 47.85%, which is very close but smaller than the short-term spillover effect. Similar to the short-term, the contribution to the system from green stock assets is the most obvious. For renewable energy markets, the contribution of CNN is significantly improved compared with short-term results. On the other hand, photovoltaic energy is the main transmitter, followed by CNN, wind, and nuclear energy. In addition, the three green financial assets also receive the most spillover shocks, while the impact of green bond assets is only 0.71%. In terms of net spillover effects, renewable energy markets are the main net recipients, while green financial assets are the main net contributors. This result is quite different from that in the short term. Specifically, renewable energy markets (ECO,1.44%; ERIX, 1.39%; CNN, 0.73%) all play the role of a transmitter in the long run, while ECO is only a transmitter in the short run. In the long term, the relationship between the fluctuations of the green finance market and the renewable energy markets is similar to the short-term situation. The green finance market is mainly influenced by other markets, while its impact on other markets is relatively small.

Table 3. Connectedness between renewable energy markets and green financial markets in the short run.

	ECO	**ERIX**	**CNN**	**Wind**	**Photovoltaic**	**Nuclear**	**Green Bond**	**From**
ECO	35.96	13.18	0.04	0.05	0.10	0.03	0.20	4.25
ERIX	14.56	36.82	0.07	0.02	0.12	0.04	0.47	4.78
CNN	0.91	0.4	16.49	10.88	12.73	9.68	0.35	10.93
Wind	0.37	0.08	8.01	14.56	10.38	10.57	0.18	9.26
Photovoltaic	0.59	0.21	9.4	10.36	14.15	9.65	0.23	9.52
Nuclear	0.46	0.08	7.92	10.97	10.47	15.43	0.29	9.44
Green Bond	0.19	0.21	0.02	0.03	0.09	0.06	31.66	0.18
To	5.34	4.43	7.97	10.10	10.60	9.39	0.53	Total = 48.37
Net	1.09	−0.35	−2.96	0.84	1.08	−0.05	0.35	

Note: ECO, REIX, and CNN represent the renewable energy market of the US, Europe, and developing countries. The wind, photovoltaic, and nuclear energy markets represent the clean energies of China in detail. The values of From represent the amount of spillover that the index in the first column received from other indices. The values of To represent the amount of spillover that the index in the first row transmitted to other indices. Net is the net value after those two are offset. Total is the total spillovers between renewable energy markets and green financial markets in the short run.

Table 4. Connectedness between renewable energy markets and green financial markets in the long run.

	ECO	**ERIX**	**CNN**	**Wind**	**Photovoltaic**	**Nuclear**	**Green Bond**	**From**
ECO	32.25	13.97	0.25	0.01	0.07	0.13	0.08	4.12
ERIX	12.76	31.54	0.07	0.02	0.10	0.13	0.13	3.75
CNN	2.78	1.55	14.7	8.35	9.87	8.03	0.09	8.71
Wind	1.19	0.66	10.73	15.61	11.86	11.76	0.11	10.31
Photovoltaic	1.49	0.91	11.98	11.39	15.31	10.69	0.08	10.38
Nuclear	1.04	0.60	9.81	12.08	11.03	15.74	0.17	9.86
Green Bond	0.33	0.40	0.39	0.46	0.51	0.40	58.47	0.71
To	5.56	5.14	9.44	9.18	9.50	8.85	0.19	Total = 47.85
Net	1.44	1.39	0.73	−1.13	−0.88	−1.01	−0.52	

Note: ECO, REIX, and CNN represent the renewable energy market of the US, Europe, and developing countries. The wind, photovoltaic, and nuclear energy markets represent the clean energies of China in detail. The values of From represent the amount of spillover that the index in the first column received from other indices. The values of To represent the amount of spillover that the index in the first row transmitted to other indices. Net is the net value after those two are offset. Total is the total spillovers between renewable energy markets and green financial markets in the long run.

Therefore, from the perspective of time-varying spillovers, short-run risk spillover effects are more significant. Additionally, the total spillover effects of long-term and short-term volatility are shown in Figure 4. The short-term risk spillover effects are more significant in most cases, as indicated by the figure and description. Particularly, around 2020, the short-term spillover level reached its highest point. This could be related to specific market events or increased global economic uncertainty. Short-term spillover effects exhibit high dynamic changes, reflecting the market's sensitivity and quick reaction to sudden events in the short run. Although short-term spillover effects are more significant, there are periods when long-term spillover effects lead to short-term effects. For instance, around 2016, long-term spillover effects were ahead. Long-term spillover effects are relatively more stable, indicating the market's response to systemic risks and trends over a long time horizon. This stability might be influenced by structural changes or long-term policy impacts. Time-varying spillover effects show how spillover effects change over different periods. The figure illustrates that the dominance of short-term and long-term spillover effects varies over time. Further information on the time and frequency domains in the dynamic connectedness results can provide insights into spillover effects at different frequencies. While static results show the average effect, dynamic analysis can reveal details and fluctuations of spillover effects at specific times and frequencies.

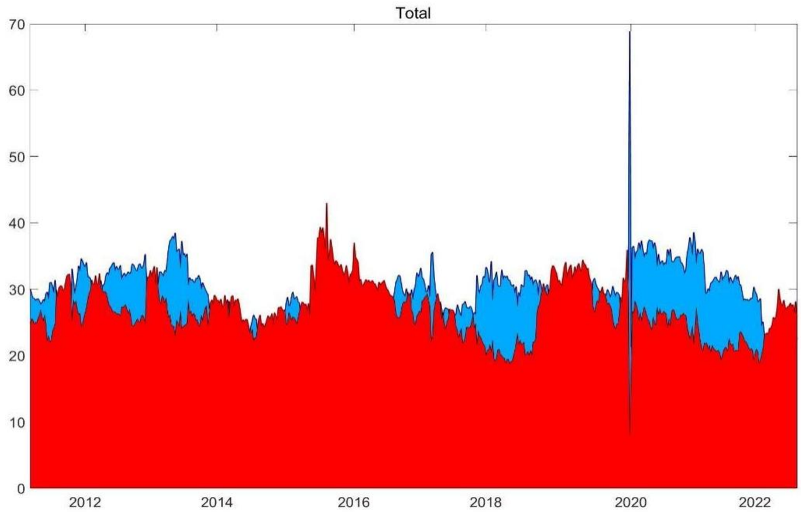

Figure 4. Total dynamic spillovers between renewable energy markets and green financial markets. Notes: The blue-colored area indicates the total spillover in the short term. The red-colored area reflects the spillover in the long term.

In summary, short-term spillover effects are generally more significant, especially during periods of market disruptions. Long-term spillover effects, while more stable, sometimes take the lead over short-term effects. Time and frequency domain dynamic analysis can provide a detailed understanding of market connectedness changes over different periods and frequencies.

Figure 5 shows the time-varying net spillover effect results. Most markets have a high net spillover effect in the system. For the net spillover of the renewable energy markets, ECO, ERIX, and CNN are the net recipients in the short run but net contributors in the long run. Specifically, the US renewable energy market (ECO) and China's renewable energy market (CNN) both show stronger net spillover effects. The spillover effects were more obvious around 2015 and 2020, and ECO turned into a net spillover contributor in the short term in 2020, which may be due to the shock of COVID-19 and fluctuations in the financial market.

Similar performances are observed in the net spillover of four different Chinese green finance assets. Firstly, wind energy, nuclear energy, and green bonds are the net spillover transmitters in the short term and the main contributors in the long term. Secondly, the net risk spillovers of all green financial instruments show strong volatility, reflecting great fluctuation of the asset price around 2015 and 2020, when the net spillover wind, photovoltaic, and nuclear energy reached the highest level.

However, we can still observe the time-varying volatility of net spillover effects in green financial markets. Specifically, green bonds were the main net receivers over the long term during the sample period, indicating their susceptibility to external shocks and internal factors within this system. In contrast, photovoltaic markets showed a lower net effect, demonstrating stability in both receiving and transmitting aspects. This further underscores photovoltaic energy stocks' strong hedging properties within portfolios. Overall, the dynamic net spillover transmission from renewable energy markets to the system is significant over the long term, while these markets are more susceptible to short-term impacts from financial markets. These findings align with the results of static connectivity analysis.

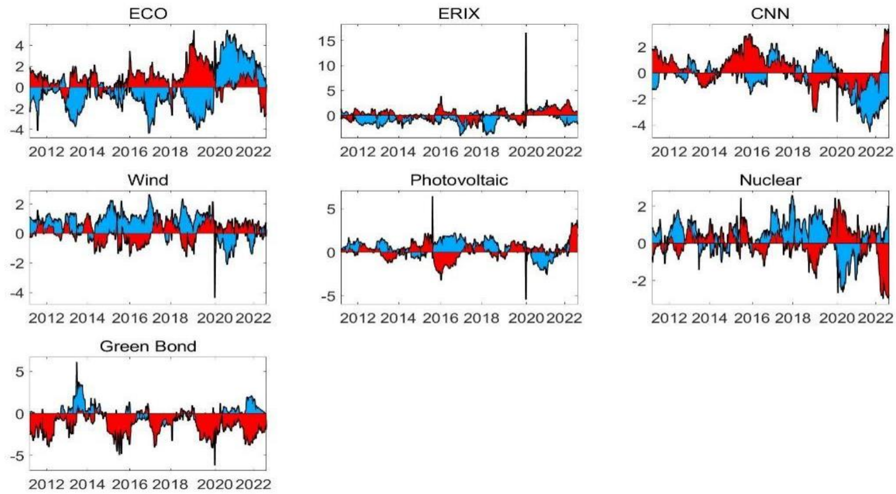

Figure 5. Total dynamic net spillovers between renewable energy markets and green financial markets. The blue-colored area indicates the total spillover in the short term. The red-colored area reflects the spillover in the long term.

To further discuss the pairwise spillover effect between different markets, we conducted network spillover structures of different markets in the short and long-run system, which are shown in Figures 6 and 7. It was noted in Figure 6 that wind and photovoltaic energy receive strong spillover effects from ERIX and CNN markets in the short term, and the green bond market is a weak receiver of risk spillovers within the system, which shows that the impact from renewable markets to green financial markets cannot be ignored in the short term. In other words, investors with green financial assets in their portfolio should pay attention to the spillovers from specific renewable energy markets. From Figure 7, we also note that in the long run, the green bond market turns into a strong receiver while it is a weak receiver in the short run. This spillover affects green bonds received not only from the renewable energy market but also from other green financial markets. The results also show that the spillover effect is obvious due to the linkage between green finance markets and new energy markets in the long term. In the long run, renewable energy markets remain a contributor to long-term spillover, although the spillover effects are weak between the renewable energy market and the green financial market. Specifically, the direction of the spillover effect is more manifested from the renewable energy market to the green finance market, which further leads to transmission inside green financial markets.

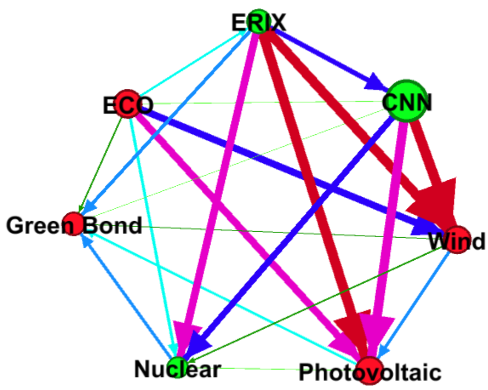

Figure 6. Net pairwise spillover network between renewable energy markets and green financial markets in the short run. Notes: A node of red (green) color indicates it is the most significant net transmitter (receiver) of spillover. The edge colors rank the strength of the pairwise directional spillover from red (strongest) to purple, pink, blue, light blue, and green (weakest). The edge arrow thickness also indicates the strength of the net pairwise spillover.

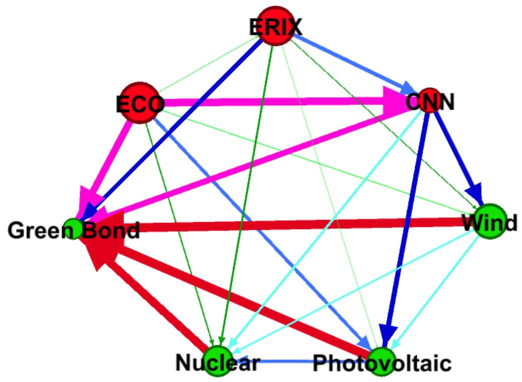

Figure 7. Net pairwise spillover network between renewable energy markets and green financial markets in the long run. See notes in Figure 6.

4.2. Hedging Effect

In this section, the DCC model is applied to conduct portfolios with renewable energy markets and green financial markets. By measuring the optimal portfolio weight, hedge ratio, and hedging effectiveness, we attempted to provide some investment advice for global investors at different times.

Firstly, assuming that investors have a portfolio with renewable energy and China's green financial markets, it is necessary to measure optimal portfolio weights to better apply cryptocurrencies to hedge risks. This can be defined according to the seminal work of [53]:

$$\omega_{rg,t} = \frac{h_{g,t} - h_{rg,t}}{h_{r,t} - 2h_{rg,t} + h_{g,t}}, with\ \omega_{rg,t} = \{0, if\ \omega_{rg,t} < 0\ \omega_{rg,t}, if\ 0 < \omega_{rg,t} < 1\ 1, if\ \omega_{rg,t} > 1, \tag{15}$$

where $\omega_{rg,t}$ is the optimal portfolio weight, and $h_{r,\ t}$ and $h_{g,t}$ are the conditional variance for renewable energy and green financial markets, separately. The optimal weight for the green financial market is $1 - \omega_{rg,t}$.

Secondly, we measured the hedging ratio β_{rg} [54] and calculated the minimum risk in our portfolio:

$$\beta_{rg,t} = h_{rg,\ t}/h_{g,t} \tag{16}$$

Then, we calculated the hedging efficiency by applying the hedging effectiveness (HE) index [30] to determine the differences between the benchmark portfolio and the optimal portfolio. We can define it as follows:

$$HE = 1 - \frac{Var_p}{Var_0}, \tag{17}$$

where Var_p and Var_0 are the variance of optimal portfolios and benchmark portfolios, respectively.

The sample was divided into pre-COVID-19 and post-COVID-19. More details about the results are shown in Table 5. We can determine some implications from the empirical results. Firstly, most of the optimal portfolios have a small weight except for green bonds, which suggests that the hedging effect can effectively be achieved with a small proportion of green financial assets in one portfolio. Most hedge ratios are positive, meaning that a short position in green finance assets can help hedge a long position in the renewable energy market. Secondly, the hedging effect of green financial assets is stronger than post-COVID-19, which proves that COVID-19 has changed the hedging effect of green financial assets and the economic and policy uncertainty brought by the COVID-19 pandemic to the financial market reduces the hedging efficiency of financial assets. Finally, the hedging effect varies in portfolios with different green financial markets, while the photovoltaic stock market has the best hedging effect followed by wind and green bonds. In other words, the risk of the portfolio with photovoltaics is more diversified.

Table 5. Optimal portfolios' weights, hedge ratios, and hedging effectiveness between renewable energy markets and green financial markets.

		Pre-COVID-19			Post-COVID-19			Full Sample		
		W_t	β_t	*HE* (%)	W_t	β_t	*HE* (%)	W_t	β_t	*HE* (%)
ECO	Wind	0.4798	0.0515	56.15%	0.6902	0.0503	32.37%	0.5227	0.0513	50.53%
	Photovoltaic	0.4447	0.0733	61.17%	0.6979	0.1097	26.29%	0.4964	0.0807	54.63%
	Nuclear	0.4827	0.0127	58.35%	0.7618	−0.0052	26.23%	0.5397	0.0091	53.82%
	Green Bond	0.9949	0.5083	−0.04%	0.9996	0.9522	0.60%	0.9958	0.5989	0.02%
ERIX	Wind	0.5225	0.0607	55.26%	0.5564	0.0319	39.73%	0.5294	0.0548	51.68%
	Photovoltaic	0.4883	0.0735	60.64%	0.5561	0.0658	33.64%	0.5022	0.0719	55.67%
	Nuclear	0.5244	0.0397	57.39%	0.6493	0.0246	27.21%	0.5499	0.0366	53.19%
	Green Bond	0.9976	0.7897	0.10%	0.9996	1.0992	−0.08%	0.9980	0.8529	0.08%
CNN	Wind	0.4843	0.8674	11.78%	0.5600	0.6125	19.60%	0.4997	0.8154	13.58%
	Photovoltaic	0.2815	0.8188	25.60%	0.5912	0.9150	3.82%	0.3447	0.8384	21.51%
	Nuclear	0.4847	0.8318	16.03%	0.6881	0.5720	5.03%	0.5262	0.7788	14.46%
	Green Bond	0.9912	−0.0712	2.03%	0.9960	−0.0948	0.20%	0.9922	−0.0760	1.88%

Note: *HE* represents the hedging effectiveness. W_t is the optimal portfolio weight. β_t is the hedge ratio, and *HE* represents the hedging effectiveness. The full sample set is divided into two parts due to the outbreak of COVID-19.

5. Conclusions

This paper analyzes the dynamic connectedness of the renewable energy market and the green finance market in both the time and frequency domains, dividing the data into pre-COVID-19 and post-COVID-19 periods to investigate how the pandemic affected portfolio hedging effects.

In the static analysis, we found that green finance markets play the role of contributors in the system, while renewable energy markets are the main receivers in the short run. However, in the long run, the roles reverse, with renewable energy markets becoming the primary spillover contributors. The dynamic connectedness results indicate that the short-term total spillover effect is stronger than the long-term in most cases, with net spillover effects significantly increasing during the 2015 stock market crash and the COVID-19 pandemic. Specifically, green bonds act as the main spillover receivers in the long term, while photovoltaic assets remain stable and exhibit hedging attributes. Network analysis revealed that wind and photovoltaic sectors receive strong net spillover from ERIX and CNN in the short term, while the long-term spillover effect between the renewable energy market and the green finance market is weak.

These findings have several important implications for hedging strategies and policy-making. For investors, the observed decrease in the hedging effect of green finance assets in the renewable energy market post-COVID-19 suggests a need to adjust the weight of these assets in their portfolios. Diversifying investments to mitigate risk exposure in times of market instability can improve portfolio performance.

For the public sector, understanding the connectedness between the renewable energy market and the green finance market provides crucial insights into systemic risks. Identifying the main risk receivers and transmitters can help policymakers develop targeted interventions to stabilize financial markets. This is particularly important for achieving Sustainable Development Goals, as stable financial markets are essential for funding renewable energy projects and other green initiatives.

Moreover, promoting stronger integration between renewable energy and green finance markets can enhance their resilience against future shocks. Governments could consider incentivizing the development of green financial products and encouraging investment in renewable energy sectors through subsidies, tax incentives, and supportive regulatory frameworks. These measures would not only contribute to market stability but also accelerate the transition to a sustainable economy.

Additionally, collaboration between the public and private sectors can be strengthened to address market vulnerabilities. For instance, creating public-private partnerships focused on green investments can attract more private capital into renewable energy projects, reducing the reliance on government funding alone.

In conclusion, the findings of this study highlight the dynamic interplay between the renewable energy market and the green finance market, emphasizing the need for adaptive strategies in portfolio management and policy-making. By leveraging these insights, both private and public sectors can better navigate market complexities, enhance financial stability, and contribute to sustainable development goals.

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