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The Impact of the COVID-19 Pandemic on the Connectedness between Green Industries and Financial Markets in China: Evidence from Time-Frequency Domain with Portfolio Implications

Jing Deng [1], Jingxuan Lu [1], Yujie Zheng [1], Xiaoyun Xing [1,*], Cheng Liu [2] and Tao Qin [1]

[1] School of Economics and Management, Beijing Forestry University, Beijing 100083, China
[2] Research Centre for the Two Mountains Theory and Sustainable Development, Beijing Forestry University, Beijing 100083, China
* Correspondence: xyxing@bjfu.edu.cn

Abstract: To achieve sustainable economic growth, a significant amount of private capital must be invested in green industries. However, risk management in the green industry stock market has drawn much attention recently due to the uncertainty and high risk present in this market. By applying the spillover index model of Diebold and Yilmaz, the frequency-domain spillover approach developed by Baruník and Křehlík, and the dynamic conditional correlation (DCC) model, this paper focuses mainly on the heterogeneity of the volatility spillovers among six green industry equities and other financial assets in China, under various market economy situations. Based on the empirical results obtained in this paper, we find that the green industry stock markets have the least impact on the gold and energy futures markets. Additionally, based on asymmetric analyses, it can be concluded that the green bond market has experienced the smallest shocks from the six green industry stock markets. By utilizing frequency-domain analyses, the energy futures market experiences the least amount of volatility from green stocks. Additionally, the COVID-19 pandemic affects the interconnectedness of markets. Prior to the COVID-19 pandemic, energy futures were the most suitable portfolio instrument for green industry stocks. When the COVID-19 pandemic occurred, however, gold proved to be the most advantageous portfolio asset. The research findings of this paper demonstrate the impact of COVID-19 on the selection of the best investment instruments for green industry stocks, which is beneficial for reducing the investment risk of green financial market participants and increasing the demand for green stock markets, while also providing practical advice for environmentally conscious investors and policymakers.

Keywords: green industries; financial markets; risk spillovers; portfolio management; COVID-19 pandemic; variance decomposition

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1. Introduction

With its rapid industrialization and modernization, China has achieved both economic growth and financial development targets [1], succeeding in becoming the world's second-largest economy [2]. However, from the perspective of energy consumption, China still ranks the first and is currently the largest carbon emitter worldwide [3]. To address ecological imbalances and environmental pollution in China, the proposal to develop green industries emphasizing energy conservation, low pollution, and low emissions has been widely recognized. Meanwhile, under the carbon neutrality commitment, affected by investor sentiment and profitability, investors will favor green companies, which leads to more capital inclined to green industries and promotes their sustainable development [4]. Compared with developed countries, whose green industry advancement relies on market leadership, China's green sector development is driven mainly by the government. According to the forecast of the National Climate Strategy Center, CNY 3 to 4 trillion must be invested in green industries each year to achieve carbon emission reduction targets (the data can be obtained from China's Policies and Actions for Addressing Climate Change (2020), available at http://www.ncsc.org.cn/yjcg/cbw/, accessed on 6 September 2022). Nevertheless, due to fiscal budget constraints, the government can provide only approximately 10–15% of the funds needed for green investments. As a result, a large amount of private capital must be invested in green industries.

In this context, in 2019, China published the "Green Industry Guidance Catalogue" (see https://en.ndrc.gov.cn/policies/, accessed on 6 September 2022). Based on the country's economic and social development state, industrial stage, resources, and ecological environment features. The catalog divides China's green industries into six major sectors—namely, the energy conservation and environmental protection industry (EPI), clean production industry (CPI), clean energy industry (CEI), ecological environment industry (EEI), green infrastructure industry (GII), and green service industry (GSI)—and puts forward the key points of green industry development. The document is of great significance for clarifying the boundaries of green industries, establishing a national unified green standard system, and guiding funds to focus on the most critical green industries and projects.

There are two basic types of private capital investment modes, namely, indirect financing modes such as green credit and direct financing modes such as green bonds and stocks. In comparison to green credit and bonds, the green stock market is always characterized by higher investment risk [5,6], leaving investors with difficult options. By 2020, the scale of China's green credit stock was close to CNY 12 trillion, making the country first in the world on this indicator, and the cumulative quantity of green bond issuance had reached CNY 1.15 trillion, putting China second globally. However, the amount of financing obtained by green companies through the stock market is less than 10 percent of that secured through the bond market, indicating that China's green industry is still in its infancy, and few funds are invested directly in the form of green stocks. Therefore, given the massive gap in private investment in China's green industries, it is crucial for green stock investors to study risk management strategies that provide them with advice for reasonable asset allocation and combinations, thus reducing portfolio risk and ultimately promoting green development [7].

To the best of our knowledge, the research on risk management in the green stock market considers mainly the global clean energy market as a representative case. In addition, in terms of portfolio choices, frequently considered assets include crude oil [8–10], gold [11], the volatility index (VIX) [5], nonferrous metals [12], the carbon price index [13], and coal [14]. With the advancement of the green bond market, several investigations have concluded that the performance of green bonds is weakly associated with that of stocks and clean energy in general [15–20], which suggests that green bonds might have the potential to be used as a portfolio instrument for risk diversification by clean energy shareholders. Since green bonds and stocks of green industries both offer environmental benefits from emission reduction, environmentally friendly investors are more likely to add green bonds to their green stock portfolios than other assets [20]. Due to their higher average yield than traditional bonds [21], green bonds are considered a stable and sustainable investment for long-term projects, making them favored among green investors [18].

Since China has issued the "Green Industry Guidance Catalogue", which classifies green industries into six broad categories (including not only the generally perceived clean energy industry but also other green industries, namely, the energy conservation and environmental protection industry, clean production industry, ecological environment industry, green infrastructure industry, and green service industry), how to manage the risks of these green industries is a concern for environmentally conscious investors and policymakers. However, little attention has been paid to exploring the most suitable safe-haven assets for green industries other than the clean energy industry. In addition, there is evidence that uncertainty in market spillovers is becoming more pronounced and that system connectedness increases significantly under extreme conditions [22–24]. The COVID-19 epidemic, one of the most destructive global events in recent years, triggered a global economic crisis and led to extreme market conditions, ranking among the most significant crisis events in history. Moreover, in recent decades, as the concept of green economy has become increasingly popular around the globe, the influence of COVID-19 on the relationship between green financial markets and conventional financial markets has become increasingly prominent. In light of the COVID-19 crisis, it is also essential to conduct an analysis of the risk management of various green industry stocks.

With these considerations in mind, this paper employs the data on China's green bond and green stock markets from 2016 to 2022, aiming to address the following questions. What is the correlation between green industry stocks and other financial assets? Which asset performs the best as a portfolio instrument to manage the stock market risks of different green industries? How has the COVID-19 pandemic affected the portfolio choices of green stock investors? The main contributions of this paper can be summarized as follows. First, this paper applies the spillover index model of Diebold and Yilmaz [25] to explore the volatility spillover relationship between China's six major green industry stock markets and other financial markets. We find that the energy futures market receives the fewest shocks from the EPI, CPI, EEI, and GII, while the gold market receives the fewest shocks from the CEI and GSI. Second, this paper illustrates asymmetric connectedness by decomposing the series of returns into positive and negative returns, then calculating their volatility, respectively, and finds that the shocks received from the six green industry stock markets to the green bond market are the lowest. Third, by employing the frequency-domain spillover approach developed by Baruník and Křehlík [26], this paper analyzes the frequency-domain connectedness in their volatility and obtains the difference in spillovers across different periods. Fourth, this paper divides the sample into three stages: before, during, and after the COVID-19 outbreak. The dynamic spillover results further show the dynamic differences in the correlation between green stocks and other markets. Finally, through portfolio weights analysis, it is found that in the full sample period, pre-COVID-19 period as well as post-COVID-19 period, energy futures is the most suitable portfolio tool for green industry stocks, while the occurrence of crisis events makes gold to be the best portfolio instruments.

This paper focuses on the risk spillover effect between China's green industry stocks and other financial markets under different market conditions, particularly the COVID-19 epidemic, in order to provide effective recommendations for environmentally friendly investors and policymakers to reduce the risks of investing in the green stock market and to stimulate the demand for the development of China's green industry.

2. Literature Review

2.1. Portfolio Diversification of Green Stock Markets

The literature on the risk management of green stocks mainly takes the global clean energy markets as representative cases. In terms of combining clean energy and traditional energy commodities such as oil, the existing investigations analyze the correlation relationships between these assets through vector autoregression (VAR) under the causality framework. For instance, the authors of [27] find that clean energy stock prices are significantly affected by oil prices. Furthermore, the authors of [28] employ the generalized autoregressive conditional heteroskedasticity (GARCH) model and concludes that a portfolio of clean energy stocks and oil futures is appropriate, where oil futures act as a hedge against the risk of clean energy stocks. Ref. [29] applies three indices of global renewable energy stocks and three clean energy sectoral indices to represent renewable energy markets and concludes that oil markets offer limited hedging opportunities for clean energy investors. Additionally, the authors of [30] discover that the clean energy index can provide a profitable hedging opportunity in combination with crude oil futures. Moreover, the authors of [31] argue that compared with long-term investors, short-term investors could use oil as a hedge for renewable energy investments to achieve portfolio volatility reductions. Ref. [32] finds that under bearish market conditions, investors should increase their clean energy investment to hedge against high negative oil returns.

As the above-mentioned literature review would suggest, scholars pay attention mostly to clean energy markets and seldom consider stocks of other green industries. Additionally, the current research rarely examines the differences in portfolios and risk management strategies across different green industries. With these considerations, this paper studies the relationship between a variety of green industry subsectors and low-risk financial assets to develop effective diversification strategies.

2.2. The Effect of Green Bonds on Green Stock Markets

With the rapid development of the green bond market, there is a growing body of literature investigating the relationship of spillovers between the stock markets of the six green industries and the green bond market. Ref. [33] notes that although green bonds and green stocks share common climate-friendly characteristics, there is hardly any evidence about the relationship between these two assets. The results of [20] indicate a negligible relationship between green bond and clean energy market performance, which means that these assets can be combined into portfolios under normal circumstances. In addition, the authors of [34] find that extreme upside or downside risks in the clean energy market are transmitted to the green bond market, with downside risk exerting a greater spillover effect. Ref. [35] explores the relationship between green bond indices and clean energy indices during the COVID-19 pandemic, concluding that this relationship was often stronger than usual during the pandemic period. To establish a more synthetic measure for the green stock market, the authors of [19] employ not only the clean energy index but also the green building index, the green transportation index, and the global water index. In doing so, the authors of [19] argue that green stocks and green bonds are relatively unconnected under normal market conditions but that the connectedness becomes stronger during periods of extreme market volatility. These preceding studies primarily study the relationship between green stocks and other markets, with little attention paid to distinctions in portfolio choices with other traditional safe-haven assets.

Additionally, in the literature, green stocks are often represented by global indices such as the NASDAQ OMX Green Economy family, MSCI Global Environment, and Dow Jones Sustainability World Index. Due to the considerable investment demand and policy support in China, the associations with the stock market performance of China's six green industries are worth discussing. To the best of our knowledge, few studies have yet been conducted based on data for China. Nevertheless, there are several exceptions. Ref. [36] uses Chinese data from 2015 to 2020 and finds that the green bond market is affected by unidirectional risk spillovers from green stocks, industrial stocks, and industrial commodities. Ref. [14] examines the static and dynamic connectedness between China's carbon, traditional energy commodities (oil and coal), new energy and materials markets, and finds that China's carbon market is more correlated with energy markets. This paper uses the CSI Green Economy family of indices to represent the stock markets of China's six green industries and focuses on not only the differences in risk diversification between green bonds and other assets with respect to green stocks but also the coordinated movement of green industry stock prices at the subsector level and the heterogeneous volatility of low-risk financial assets.

2.3. The Effect of Special Conditions on Green Stock Markets

Crisis events and negative market impacts in one market may spill over into other markets in different ways, making the special conditions in the green stock market critical for investors. First, only a few papers have included asymmetric volatility, especially the asymmetry in volatility of China's green financial markets, in the study of risk management. Ref. [37] identifies that the contribution of fossil energy price changes to renewable energy returns has a strong time-varying pattern and that the total connectedness of the positive return network slightly outweighs that of the negative return network. Similarly, the authors of [18] report that green bonds exhibit asymmetric volatility and behave differently from the stock market. Meanwhile, recent studies show that market spillovers are stronger during bear market periods than during normal or bullish periods [38–40], which is crucial for investors. From this perspective, this paper applies data on China's green stock markets and compares the performance of green bonds and traditional safe-haven assets under negative returns on green stocks to explore the viability of portfolios under asymmetric risk.

Second, regarding crisis situations, the authors of [11] observe that gold has a positive impact on clean energy stock returns in extreme cases. Ref. [33] examines the dependence between green financial products and traditional asset classes during various crisis situations and conclude that during turbulent periods, the relationship between green and traditional asset classes is frequently stronger than that during the entire sample period. Ref. [41] examines the nature of the time-varying market risk of investment in green stocks across the US, Europe, and the Asia-Pacific region during the periods of two recent global crises and find that for the Asia-Pacific green stocks, there is no spillover from the local market. The COVID-19 pandemic is an extreme crisis and a source of systemic risk (Sharif et al., 2020) that is regarded as one of the most disruptive global events since the Great Depression and the 2008 global financial crisis (GFC) [42]. Ref. [43] finds that due to the impact of the COVID-19 pandemic, volatility spillovers between global financial markets have increased. Ref. [44] further proves stronger effects on the connectedness of the COVID-19 outbreak than of the financial crisis. Ref. [45] finds that the return spillover effects between oil and agricultural products have been more pronounced during the COVID-19 pandemic than in normal times. The authors of [42] discover that during the COVID-19 period, the connectedness between climate-friendly investments and traditional stocks may have been augmented. Ref. [14] observes a strengthened connectedness between carbon, traditional energy, and new energy stocks after the outbreak of COVID-19. According to [19], the performance of green bonds and green stocks has been more closely linked during the COVID-19 pandemic.

The COVID-19 crisis has undoubtedly negatively impacted the stability of global financial markets [46], and investors and portfolio managers are facing unprecedented challenges in the face of this catastrophic event. In this context, this paper employs the [25] spillover approach to analyze the connectedness between green stocks and bonds and other safe-haven assets. To investigate the impact of the COVID-19 emergency on the correlation between markets, this paper further subdivides the sample into three periods: before, during, and after the COVID-19 outbreak. Moreover, by conducting the portfolio weights analysis, this paper studies the portfolio weight and its effectiveness between green stocks and other financial markets under different market conditions. In doing so, this paper captures the respective spillovers under the circumstances of downside risks and provides suggestions for investors and policy implications specific to the different periods of the COVID-19 pandemic.

3. Theoretical Research and Practical Implications

3.1. Mechanism between Green Stocks and Other Financial Markets

According to modern portfolio theory, when there is a strong correlation between financial markets, there is a significant trend of changes in the same direction or opposite direction between financial assets, so the decentralized investment strategy cannot play a risk aversion role when the market plummets. Conversely, if the correlation between financial markets is low, the impact of abnormal fluctuations in one market on other markets is limited. The systemic risk can be avoided by diversifying an investor's investment portfolio in order to increase their overall income.

Currently, as a result of the development of economic globalization and the improvement of financial deepening, the interaction between financial markets is intensifying, and there is a certain degree of market integration, resulting in a more complex correlation between markets due to the price linkage mechanism. Regarding the green bond market, green industry stocks and green bonds have developed rapidly over the past few years, becoming an integral part of the green financial system and the primary green asset allocation component for financial institutions. As an important lever for low-carbon enterprises to obtain financial support, when the green bond market is generally good, investors expect that the low-carbon industry stock market will also strengthen under the influence of economic fundamentals, forming a linkage effect between markets. As far as the traditional stock market is concerned, there is a convergence of ups and downs between the traditional stock market and the green stock market, meaning that when the green stock market is in crisis, the risk impact will be transferred significantly to the highly correlated traditional stock market, resulting in a high correlation between markets. Concerning the gold market, as a unique precious metal commodity, gold possesses the triple attributes of commodity, currency, and finance on the gold market. As a traditional hedge asset, it possesses the currency attribute and the ability to hedge, and is less vulnerable to the risk associated with other markets. It can also provide risk diversification for green stock investments. For the energy futures market, the relationship between the energy futures market and the financial market is gradually strengthened as the financial characteristics of energy increase. As an essential basic means of production, energy has a rigid demand in social and economic development, and its price fluctuations impact the real economy, influencing the performance of the stock market and forming a risk spillover relationship between markets. Based on the above analyses, this study proposes Hypothesis 1.

Hypothesis 1. *There is a correlation between the green stock market and other financial markets, and different financial assets have varying risk impacts on green stocks. Diversified investment strategies may reduce the investment risk of green industries.*

Based on the aforementioned research assumptions, this paper also incorporates traditional hedge assets gold, energy futures with weak correlation with the stock market, emerging green bonds, and traditional stocks with high-risk characteristics into the research system, analyzes their differential impact on green industry stocks. Moreover, this paper explores the most appropriate hedge assets in the green stock market, so as to provide effective recommendations for green industry stock investors to effectively invest in the green stock market.

3.2. Impact Mechanisms of Asymmetric Risks, Special Events, and Different Frequency Domains

According to the investor sentiment theory, positive and negative market information will elicit different responses from investors, with the risk spillover resulting from negative market information typically being greater. When the price of the green stock market falls as a result of negative information, investors tend to increase their risk perception and aversion to uncertainty, adjust their portfolios, and demand higher risk premiums, thereby increasing the risk of the market. In a negative income environment, the green stock market consequently has a greater spillover effect. Nonetheless, unexpected events may also directly contribute to a decline in investor sentiment, thereby exacerbating market risk. As a significant special event in recent years, the COVID-19 epidemic has a significant effect on the economy as a whole. Consequently, the impact of the epidemic will have a multiplier effect on the market for the green industry. In addition, when investors in green stocks establish portfolios in various markets, they will pay close attention to the portfolio's components with varying cycle lengths and use expected utility for asset valuation. Therefore, the market's cyclical factors will generate heterogeneous shocks, resulting in varying short- and long-term spillover effects in the green stock market. Based on this, this paper proposes Hypothesis 2.

Hypothesis 2. *China's green stock market demonstrates an asymmetric risk spillover effect. Sudden special events will exacerbate the risk spillover effect in the market, and the risk spillover effects vary depending on the cycle frequency.*

According to the aforementioned research hypotheses, it is possible to conclude that the correlation between the green stock market and other financial markets varies based on market conditions, and that portfolio management is more important in extreme market conditions. When allocating assets, investors should not only consider single-period investment decisions, but also pay more attention to dynamic portfolio selection, as investors' investment behavior is frequently long-term. This paper then offers effective recommendations for investors' long-term dynamic risk management.

4. Methodology

4.1. Time-Domain Spillover Index Model of Diebold and Yilmaz

Spillovers are a widely employed characterization of interdependence and connectedness in a dynamic system that measures the transmission of information across assets or markets. The time-domain spillover index model is constructed based on the generalized version of the variance decomposition of forecast errors of a VAR system proposed by [47,48], which provides a practical framework to quantify the magnitude and direction of spillover effects across different time scales. Although several methods have been proposed to estimate return and volatility spillovers [5,9,29,49,50], the Diebold–Yilmaz (DY) approach [25] has become popular for researchers and has many merits over other previously developed spillover measurement techniques.

Compared to the conventional model, the DY spillover index model offers the following benefits: first, it eliminates the results' dependence on the lag order. It can also determine the net disseminator of risk spillovers and the role mechanism of various assets in the transmission of market information. In addition, when combined with rolling window technology, we can calculate the dynamic spillover index and track the dynamic changes of the market spillover effect.

Initially, the p-order VAR model of covariance stability can be mathematically described as

$$V_t = \sum_{i=1}^{p} \psi_i R_{t-i} + \varepsilon_t, \tag{1}$$

where V_t represents the n-dimensional variance sequence, ψ_i is the $n \times n$ coefficient matrix, and $\varepsilon \sim (0, \sum)$ is a vector of independently and identically distributed disturbances with zero and $\sum$ covariance matrix. The moving average expression of V_t is given by

$$V_t = \sum_{i=1}^{p} A_i \varepsilon_{t-i}, \text{ with } A_i = \psi_1 A_{i-1} + \psi_2 A_{i-2} + \cdots + \psi_p A_{i-p}, \tag{2}$$

where A_i is the $n \times n$ coefficient matrix of the vector moving average (VMA), while A_0 is the $n \times n$ identity matrix that satisfies $A_i = 0$ for $i < 0$. In addition, the generalized forecast error variance decomposition can be written as

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum\limits_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum\limits_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}. \tag{3}$$

In Equation (3), θ_{ij} represents the contribution of the jth variable of the system to the variance of forecast error of the element i, and σ_{jj} represents the standard deviation of the error term of variable j. Notably, e_i is an $N \times 1$ vector, with one as the ith element and zero otherwise. Additionally, $\sum$ represents the covariance matrix of the vector of errors ε. Given that $\sum_{j=1}^{N} \theta_{ij}(H) \neq 1$, a normalization of Equation (3) can thus be obtained as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum\limits_{j=1}^{N} \theta_{ij}(H)}. \tag{4}$$

Obviously, we find that Equation (4) can be applied to estimate pairwise connectedness from j to i at time horizon H. In addition, in Equation (4), we must, respectively, have

$$\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N, \tag{5}$$

$$\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1. \tag{6}$$

Accordingly, the total spillover index, the directional spillover index, and the net spillover index can be derived. First, we add up the influence of the cross-variance share in the error variance to construct the total spillover index, which can be given by

$$TSI(H) = \frac{\sum\limits_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{1}{N} \sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H) \times 100. \tag{7}$$

Specifically, the total spillover index explains the proportional contribution of the spillover effect between N markets and the total forecast error variance and averages the off-diagonal elements. In relation to Equation (7), the closer the values of $TSI(H)$ are to 1, the stronger the connections across the variables in the VAR system. Through the generalized VAR model, the DY spillover index model can be further employed to quantify the size of the directional spillover effect between different markets. Consequently, the spillover index from market i to j and that from market j to i can be expressed as

$$DSI_{i\leftarrow j}(H) = \frac{\sum\limits_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100, \tag{8}$$

$$DSI_{j\leftarrow i}(H) = \frac{\sum\limits_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100. \tag{9}$$

Furthermore, we use the net spillover index to measure the net spillovers of a single market to all other markets, based on which we can deduce which market may act as the risk receiver and which as the risk transmitter. Specifically, the net spillover index can be given by

$$NSI_{ij}(H) = DSI_{j\leftarrow i}(H) - DSI_{i\leftarrow j}(H). \tag{10}$$

In Equation (10), a positive $NSI_{ij}(H)$ suggests that market i is a net transmitter of shocks. Nevertheless, a negative $NSI_{ij}(H)$ might imply that market i is a net receiver of shocks.

4.2. Frequency-Domain Spillover Method of Baruník and Křehlík

As a supplement to the Diebold and Yilmaz index quantifying the spillover effect in the time domain, the authors of [26] propose a methodology to analyze the connectedness in the frequency domain. Under this framework, the directional spillovers are decomposed across different frequencies (e.g., the short term, medium term, and long term). We consider a frequency response function including Ψ_h that captures the coefficients of the Fourier transform, with $i^2 = -1$, given by

$$Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega}\Psi_h, \tag{11}$$

where ω denotes the frequency. Thus, the generalized causation spectrum over frequencies, $\omega \in (-\pi, \pi)$, can be defined as follows:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-i\omega}\right)\Sigma\right)_{j,k}\right|^2}{\left(\Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right)\right)_{j,j}}, \tag{12}$$

where $\Psi(e^{-i\omega})$ represents the Fourier transformation of the impulse response function Ψ and $(f(\omega))_{j,k}$ is the proportion of the spectrum of the jth variable at frequency ω based on the shocks in the kth variable. To obtain a natural decomposition of the original generalized forecast error variance decomposition (GFEVD) into frequencies, we can simply weight $(f(\omega))_{j,k}$ by the frequency share of variance of the j variable, where the weighting function is given by

$$\mathrm{H}_j \equiv \frac{\left(\Psi\left(e^{-i\omega}\right)\sum\Psi'\left(e^{+i\omega}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-i\lambda}\right)\sum\Psi'\left(e^{+i\lambda}\right)\right)_{j,j}d\lambda}. \tag{13}$$

As shown in Equation (13), it represents the jth variable power at the given frequency ω, which must satisfy sums of the frequencies to a constant value of 2π. It should be noted that the Fourier transform of the impulse response is a complex valued quantity, although the generalized spectrum is the squared coefficient of the weighted complex numbers, hence producing a real valued quantity. Therefore, we can obtain a frequency band as $d = (a, b) : a, b \in (-\pi, \pi), a < b$, and the GFEVD on a specific frequency band d is computed as

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int_d^{\infty} H_j(\omega)(f(\omega))_{j,k}d\omega. \tag{14}$$

Moreover, the generalized variance decomposition is scaled under the frequency band as follows:

$$\left(\tilde{\theta}_d\right)_{j,k} = (\theta_d)_{j,k} / \sum_k (\theta_\infty)_{j,k}. \tag{15}$$

In the following analysis, we consider three frequency bands: 1∼5 days (the short term), 5∼30 days (the medium term), and 30 or more days (the long term). These frequency bands also correspond to different horizons from an investment perspective.

4.3. DCC-GARCH Model

The dynamic conditional correlation (DCC) model estimates the correlation matrix directly by utilizing the standardized residuals which reduces the number of parameters to be estimated and makes inferences regarding the hedging effectiveness. Traditional models, such as the COPULA function, have considerable difficulties in defining dependency structures above two dimensions when describing time-varying dependencies because of the multiple parameters and increasing computational complexity. DCC-GARCH, on the other hand, can be utilized to represent the volatility spillovers between various financial time series as well as the high-dimensional dynamic correlation between them. The advantage of this is that it eliminates the requirement to comprehend the distribution of model errors in order to estimate model parameters consistently. Therefore, to find effective diversified portfolio tools for green industry stocks, this paper uses the dynamic conditional correlation multivariate GARCH model (DCC-GARCH model) from [51] to calculate the dynamic conditional correlation coefficient series between two assets.

The DCC-GARCH model is implemented in two steps. Firstly, the univariate GARCH process of each asset return series is estimated. Secondly, the parameters of the dynamic correlation structure are estimated by the standardized residual of the obtained conditional variance. From a bivariate perspective, the DCC process is as follows:

$$\mathrm{r}_t = \mu_t + \omega r_{t-1} + \varepsilon_t, \tag{16}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t. \tag{17}$$

In Equation (16), r_t is a matrix of logarithmic returns for the commodity implied volatility and clean energy stock indexes, μ_t designates a matrix of fixed parameters, r_{t-1} indicates potential serial correlation, ε_t indicates the noise term, and z_t indicates that the error term follows the Student-t distribution. Moreover, $H_t^{\frac{1}{2}}$ refers to the matrix of conditional volatilities. The covariance matrix is expressed as:

$$H_t = D_t R_t D_t, \tag{18}$$

$$D_t = diag(\sqrt{h_{t'}^i}\sqrt{h_t^j}), \tag{19}$$

where $h_{t'}^i$ and h_t^j are the conditional volatilities of asset of the i market and the j market, respectively. D_t is a diagonal of time-varying standard deviations and R_t is the conditional correlation matrix of the standardized returns. It is expressed as:

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}, \tag{20}$$

where Q_t is the time-varying conditional correlation of residuals. According to the authors of [51], Q_t is defined as:

$$Q_t = (1-a-b)\bar{Q} + a z_{t-1} {z'}_{t-1} + b Q_{t-1}, \tag{21}$$

where a and b are non-negative scalar parameters, $\bar{Q}$ refers to the matrix of unconditional correlations for the standardized innovations z_t.

In order to further analyze the dynamic portfolio, the conditional variance and covariance estimates extracted from the above DCC-GARCH model are used to calculate the dynamic optimal portfolio weight, hedge ratio and hedge effectiveness. At time t, the optimal weight ratio of asset j in the portfolio of "asset i/asset j" of each unit is:

$$w_{ij,t} = \frac{\Sigma_{ii,t} - \Sigma_{ij,t}}{\Sigma_{ii,t} - 2\Sigma_{ij,t} + \Sigma_{jj,t}}, \tag{22}$$

where $w_{ij,t}$ refers to conditional covariance between asset i and asset j at time t, $\Sigma_{ii,t}$ and $\Sigma_{jj,t}$ are the conditional variances of asset i and asset j at time t, respectively. When the market does not allow short selling, there are restrictions on $\Sigma_{ij,t}$:

Therefore, at time t, the optimal weight proportion of asset i in the portfolio of "asset i/asset j" of each unit is $1 - w_{ij,t}$. Further, we refer to the method of Antonakakikis et al. (2020b) to evaluate the time-varying effectiveness of portfolio and hedging, as follows:

$$HE_i = 1 - \frac{\mathrm{var}(r_p)}{\mathrm{var}(r_i)}, \tag{23}$$

where $\mathrm{var}(r_p)$ represents portfolio variance and $\mathrm{var}(r_i)$ refers to variance of asset i. HE_i indicates that asset i is the percentage of variance reduction of hedging positions. The higher the value, the more risk reduction.

4.4. Asymmetric Spillover Measure

To examine the asymmetric spillovers among green stocks, green bonds and other financial assets, this paper follows the common decomposition approach in [52–54] and decomposes the returns series into negative and positive returns to construct the asymmetric connectedness network. Specifically, the negative returns series are calculated as follows:

$$r^{-} = \begin{cases} r_i, \text{ if } r_i < 0, \\ 0, \text{ otherwise} . \end{cases} \tag{24}$$

In Equation (24), r_i represents the overall returns series. The positive returns series are given as follows:

$$r^{+} = \begin{cases} r_i, \text{ if } r_i > 0, \\ 0, \text{ otherwise} . \end{cases} \tag{25}$$

In the following analysis, we should note that we focus mainly on the differences between the spillovers calculated based on the total returns and those based on the negative ones.

5. Data Description

5.1. Data

To investigate the connectedness among China's six green industry stock markets, green bond market and several other conventional financial markets, this paper utilizes the data of the daily closing prices of the corresponding assets. The sample period ranges from 1 January 2016 to 24 June 2022, with the initial date of this sampling period determined by the availability of data on the green bond market in China. The data used in this paper come mainly from the Wind database and China Securities Index Co., Ltd.

Table 1 describes the variables used in the analysis. This study determines six categories of green industries according to *the green industry guidance catalogue*, considers the degree of match between the index and green industry companies, and then selects representative market segments under each category. Finally, this paper selects the green indexes of various industries in Wind Green Economy family, including the *Energy Saving Lighting Concept Index* and the *Charging Pile Concept Index* under the Energy Conservation and Environmental Protection Industry (EPI), the *Air Governance Concept Index* and *the Wastewater Treatment Concept Index* under the Clean Production Industry (CPI), the *Power Concept Index* and the *Pv Concept Index* under the Clean Energy Industry (CEI), the *Smart Agriculture Concept Index* and the *Forest Industry Index* under the Ecological Environment Industry (EEI), the *Building Energy Efficiency Concept Index* and *Intelligent Transportation Concept Index* under the Green Infrastructure Industry (GII), and the *Contract Energy Management Concept Index* under the Green Service Industry (GSI). The *ChinaBond Green Bond Index* (CGB) (although there are several other green bond indices, e.g., the *ChinaBond China Green Bond Select Index* and the *ChinaBond China Climate-Aligned Bond Index*, they all belong to the *ChinaBond index*, the volatility difference of which is less than 0.0015) is used as a proxy for the green bond market. For the sake of comparison, we further introduce several traditional assets to test their safe-haven characteristics, namely, the *China Securities Index 300* (HS300), *SHFE Aurum Commodity Index* (AU), and *China Securities energy futures composite index* (EF).

Table 1. Descriptions of variables.

Primary Market	Secondary Market	Index	Abbreviation
Green Stock Market	Energy Conservation andEnvironmental Protection Industry	Energy Saving Lighting Concept Index	EPI1
		Charging Pile Concept Index	EPI2
	Clean Production Industry	Air Governance Concept Index	CPI1
		Wastewater Treatment Concept Index	CPI2
	Clean Energy Industry	Power Concept Index	CEI1
		Pv Concept Index	CEI2
	Ecological Environment Industry	Smart Agriculture Concept Index	EEI1
		Forest Industry Index	EEI2
	Green Infrastructure Industry	Building Energy Efficiency Concept Index	GII1
		Intelligent Transportation Concept Index	GII2
	Green Service Industry	Contract Energy Management Concept Index	GSI
Green Bond Market	Green Bond	ChinaBond Green Bond Index	CGB
Traditional Stock Market	General Stock	China Securities Index 300	HS300
Safe-Haven Asset Market	Gold	SHFE Aurum Commodity Index	AU
Energy Market	Energy Futures	China Securities Energy Futures Composite Index	EF

5.2. Trend of Market Index Returns

Figure 1 displays the trend of China's green industry as well as the results from other financial market indexes. The yield of the standard stock market index and the green stock market index both exhibit noticeable long-term volatility. Financial markets, such as the ones for gold and green bonds, exhibit less volatility in comparison, indicating greater stability and the potential for usage as a diversified risk management tool for green stocks. The yield of each market significantly changed at the same time when the COVID-19 epidemic broke out in early 2020, indicating that the occurrence of crisis events will exacerbate the anomalous oscillations in market returns.

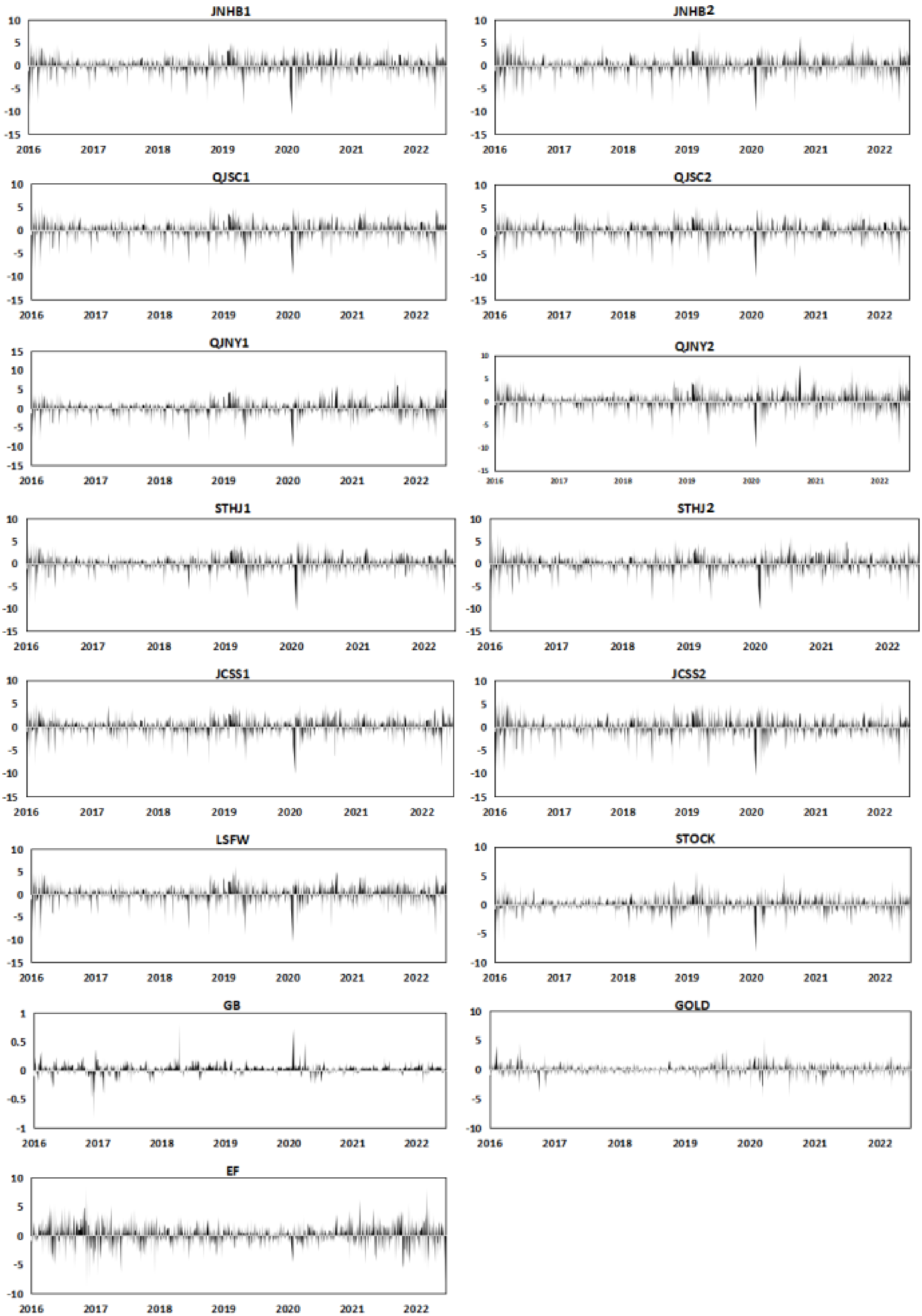


Figure 1. Time series diagram of different market returns.

6. Empirical Results

6.1. Preliminary Analysis

Table 2 reports the descriptive statistics for submarket returns. As shown in Table 2, the average returns of all markets are close to 0, and the fluctuation ranges are similar. From the kurtosis and skewness coefficients, it can be seen that the kurtosis of all returns series is high, indicating that they show leptokurtic distributions. Additionally, the returns of markets are negatively skewed, Furthermore, the Jarque–Bera test rejects the null hypothesis of normal distributions. In terms of the augmented Dickey–Fuller (ADF) test and the Phillips and Perron (PP) test, the results clearly show that all return series have stationarity at the 1% significance level. Finally, based on Akaike information criterion (AIC), this paper determines that the optimal lag order of VAR model with volatility spillover effect is 1 according to the criterion of minimum information value.

6.2. Static Spillover Connectedness

Table 3 reports the description of the static spillover index for the volatility of the six green industry stock markets, green bond market and major traditional financial markets. Specifically, the diagonal of the matrix demonstrates the proportion of risk carried by each submarket. The off-diagonal row sums (termed “From”) and column sums (termed “To”) show the entire directional connectedness from and to the corresponding market, respectively. Moreover, the bottom right corner presents the total connectedness. In general, we may safely conclude that approximately 73.79% of the forecast error variances can be attributed to volatility spillovers, indicating high interdependence between the volatility of the various markets. With respect to directional connectedness, this paper focuses mainly on green industry stock markets, and special attention is paid to their risk spillovers with other markets.

First, a strong correlation among green stocks can be observed in Table 3, and the traditional stocks are strongly connected as well. Specifically, the spillovers from the green industry stock markets to the general stock markets are 8.97%, 6.42%, 8.44%, 7.01%, 5.57%, 6.66%, 8.78%, 7.80%, 7.88%, 8.00%, and 7.51%, which are all greater than those from the general stock markets. The results indicate that the development of China’s green industry is still in its infancy and that the stock markets of this industry are more volatile than the general stock market. Moreover, the return spillovers of green industry stocks to green bonds, gold, and the energy futures market appear to be relatively weaker. Notably, the shocks transmitted from the six green industry stocks to green bonds are, without exception, significantly lower than the volatility spillovers transmitted from the green industry to the traditional stock market, indicating that green bonds and green stocks have different return characteristics. Therefore, investors are advised to consider green bonds as fixed-income investments and green stocks as equity investments.

Moreover, as seen in Table 3, the spillover effect of green stocks on energy futures and gold is weak. We further find that there is heterogeneity in the volatility spillover effect of different green industry stocks, among which, the energy futures market receives the fewest shocks from the EPI, CPI, EEI, and GII, while the gold market receives the fewest shocks from the CEI and GSI.

Table 2. Summary descriptive statistics.

	EPI1	EPI2	CPI1	CPI2	CEI1	CEI2	EEI1	EEI2	GII1	GII2	GSI	CGB	HS300	AU	EF
Mean	−0.0022	−0.0021	−0.0085	−0.0331	0.0156	0.0413	−0.0143	−0.0321	0.0228	−0.0240	0.0199	0.0168	0.0151	0.0348	0.0996
Median	0.0700	0.1000	0.1000	0.0600	0.0800	0.1100	0.0600	0.0800	0.1200	0.0600	0.1400	0.0200	0.0500	0.0300	0.1100
Maximum	5.7500	7.6100	5.3500	5.3900	9.3300	7.8700	5.2100	6.6600	5.1300	6.4900	6.1800	0.8000	5.7800	5.4000	8.1700
Minimum	−10.8100	−10.4400	−9.6800	−10.2200	−10.3600	−10.2600	−10.5500	−10.2800	−10.1400	−10.5200	−10.5600	−0.8200	−8.2100	−4.8100	−8.6000
Std.Deviation	1.8219	1.9508	1.7271	1.6721	1.8873	1.8959	1.6114	1.8412	1.6983	1.9323	1.8087	0.0817	1.2471	0.8349	1.7353
Skewness	−0.8291	−0.6900	−0.9165	−0.8751	−0.4129	−0.5600	−0.9021	−0.8022	−0.8225	−0.8285	−1.0356	−0.4673	−0.6737	−0.0882	−0.3013
Kurtosis	6.5911	6.4032	6.7140	6.7482	6.6558	6.1228	7.7485	6.5796	6.3977	6.7573	7.4203	23.4844	7.4842	7.8138	5.3293
Jarque-Bera	1025.47 ***	883.93 ***	1124.26 ***	1121.54 ***	920.64 ***	721.38 ***	1691.19 ***	1008.50 ***	933.98 ***	1105.22 ***	1561.80 ***	27,559.22 ***	1436.91 ***	1520.81 ***	379.40 ***
ADF	−38.57 ***	−40.30 ***	−39.22 ***	−39.98 ***	−40.06 ***	−39.23 ***	−37.72 ***	−37.82 ***	−38.81 ***	−38.81 ***	−39.31 ***	−16.43 ***	−40.85 ***	−39.43 ***	−40.58 ***
PP	−38.57 ***	−40.27 ***	−39.22 ***	−39.98 ***	−39.99 ***	−39.18 ***	−37.69 ***	−37.84 ***	−38.81 ***	−38.80 ***	−39.26 ***	−27.53 ***	−40.92 ***	−39.74 ***	−40.58 ***

Notes: Jarque–Bera tests for the null hypothesis of a normal distribution. ADF tests the estimates of the augmented Dikey–Fuller (1979) unit roots tests. *** denotes significance at the 1% levels.

Table 3. Total volatility spillover matrix.

	EPI1	EPI2	CPI1	CPI2	CEI1	CEI2	EEI1	EEI2	GII1	GII2	GSI	CGB	HS300	AU	EF	FROM
EPI1	11.67	8.23	9.73	7.83	5.72	7.27	8.68	6.92	9.04	9.31	8.61	0.18	6.69	0.1	0.02	88.33
EPI2	9.42	11.7	9.36	7.95	6.39	8.04	8.38	6.67	8.48	8.4	9.28	0.13	5.66	0.1	0.06	88.3
CPI1	9.33	8.26	11.93	9.44	5.93	6.32	8.86	7.31	8.57	8.44	8.61	0.15	6.69	0.13	0.04	88.07
CPI2	8.61	7.99	10.45	11.82	6.16	6.21	9.09	7.36	8.86	8.11	8.47	0.24	6.38	0.15	0.1	88.18
CEI1	8.05	8.48	8.28	7.44	12.92	9.97	8.64	6.26	7.71	6.95	8.79	0.17	6.18	0.03	0.14	87.08
CEI2	9.17	8.5	8.31	6.98	7.97	12.88	8.44	6.62	8.07	7.64	8.81	0.1	6.35	0.04	0.12	87.12
EEI1	8.97	7.86	9.21	8.17	6.19	6.83	12.7	7.59	8.18	8.28	8.28	0.35	7.11	0.2	0.07	87.3
EEI2	8.65	7.67	9.39	8.08	5.94	6.53	9.29	13.18	7.91	8.11	7.67	0.19	7.2	0.13	0.06	86.82
GII1	9.39	7.99	9.29	8.65	5.93	6.95	8.77	7.3	11.48	8.48	8.8	0.18	6.62	0.09	0.05	88.52
GII2	10.09	8.2	9.34	7.99	5.87	6.85	8.73	7.2	8.53	11.88	8.58	0.19	6.42	0.09	0.03	88.12
GSI	9.22	8.74	9.32	8.14	6.73	7.58	8.68	6.72	8.74	8.17	11.49	0.15	6.21	0.06	0.07	88.51
CGB	3.84	2.57	2.93	3.74	2.02	1.81	3.24	2.63	3.03	3.74	2.6	63.22	3.48	0.49	0.66	36.78
HS300	8.97	6.42	8.44	7.01	5.57	6.66	8.78	7.8	7.88	8	7.51	0.36	16.34	0.18	0.06	83.66
AU	1.19	1.07	1.2	1.13	0.34	0.33	1.98	1.22	0.57	1.13	0.19	0.24	1.82	86.4	1.2	13.6
EF	0.12	0.36	0.2	0.39	1.35	0.59	0.53	0.21	0.35	0.21	0.36	0.12	0.18	1.49	93.56	6.44
TO	105	92.33	105.46	92.94	72.12	81.94	102.11	81.81	95.9	94.97	96.56	2.75	76.97	3.28	2.68	1106.82
NET	16.67	4.03	17.39	4.76	−14.97	−5.17	14.81	−5.01	7.38	6.85	8.06	−34.04	−6.69	−10.32	−3.75	73.79

Notes: This table is based on vector autoregressions of order 1 (as determined by the Akaike information criterion) and generalized variance decompositions of 10-day-ahead forecast errors.

6.3. Asymmetric Spillover Analysis

In this subsection, we conduct asymmetric spillover analysis by decomposing the returns into positive and negative returns and calculating volatility, respectively. Since investors are more susceptible to bad news, we mainly analyze the differences between the overall system and the negative system. As we compare the results shown in Tables 3 and 4, we can generally conclude that the total connectedness in the negative returns system (72.62%) is not greater but in fact lower than that in the overall system (73.79%).

First, we are concerned about the spillover relationship between green industry stock markets and traditional stock markets. In the negative volatility system, the green industry stocks are still strongly correlated with the traditional stock market.

Second, we concentrate on the connectedness between the green industry stock markets and the green bond market. To be specific, we can observe from Table 4 that the shocks received from the six green industry stock markets to the green bond market are the lowest, which is significantly lower than the total spillover index in the overall system.

Table 4. Total spillover matrix for negative volatility.

	EPI1	EPI2	CPI1	CPI2	CEI1	CEI2	EEI1	EEI2	GII1	GII2	GSI	CGB	HS300	AU	EF	FROM
EPI1	10.64	8.3	8.15	8.36	7.79	8.36	8.08	7.6	9.27	8.34	8.24	0.01	6.65	0.03	0.18	89.36
EPI2	8.68	10.38	8.89	9.03	7.58	7.83	8.27	7.93	8.33	8.84	8.56	0	5.53	0.01	0.13	89.62
CPI1	8.12	8.54	9.96	9.19	7.54	7.39	8.82	8.3	8.31	8.91	9	0	5.81	0.01	0.1	90.04
CPI2	8.39	8.59	9.05	10.52	7.88	7.42	8.27	8.44	8.58	8.44	8.53	0	5.7	0.01	0.17	89.48
CEI1	8.61	8.04	8.16	8.52	11.07	9.29	7.69	7.85	8.64	7.52	8.01	0.01	6.28	0.01	0.29	88.93
CEI2	8.86	8.05	7.96	8.02	9.01	11.27	7.6	7.7	8.77	7.62	7.79	0.01	7.06	0.01	0.26	88.73
EEI1	8.21	8.07	9	8.57	7.27	7.08	10.73	8.63	8.03	8.8	9.04	0.01	6.46	0	0.11	89.27
EEI2	8.05	7.99	8.54	8.93	7.58	7.46	8.71	11	8.22	8.57	8.18	0.02	6.48	0	0.26	89
GII1	9.2	8.05	8.39	8.48	8.02	8.35	7.75	7.67	11.25	7.86	8.47	0.02	6.26	0.02	0.22	88.75
GII2	8.6	8.56	9.09	8.67	7.07	7.14	8.88	8.34	8.04	10.79	8.99	0	5.74	0.01	0.08	89.21
GSI	8.4	8.18	9.22	8.64	7.48	7.45	8.96	7.98	8.65	8.89	10.52	0.01	5.52	0.01	0.08	89.48
CGB	0.14	0.06	0.02	0.02	0.06	0.02	0.01	0.02	0.08	0.08	0.09	98.5	0.04	0.16	0.71	1.5
HS300	8.4	6.9	7.1	7.36	7.75	8.29	7.97	8.03	8.1	7.22	7.02	0.01	15.58	0.01	0.25	84.42
AU	0.31	0.29	0.35	0.16	0.24	0.41	1.08	0.56	0.29	0.35	0.41	0.32	0.69	94.48	0.07	5.52
EF	1.44	1.01	1.03	1.48	2.06	1.3	0.94	1.65	1.42	0.69	1.09	0.01	1.45	0.41	84.04	15.96
TO	95.42	90.62	94.94	95.44	87.34	87.79	93.05	90.69	94.73	92.14	93.43	0.43	69.66	0.69	2.92	1089.29
NET	6.05	1	4.9	5.96	−1.59	−0.94	3.78	1.69	5.99	2.93	3.94	−1.08	−14.76	−4.84	−13.04	72.62

Notes: This table is based on vector autoregressions of order 1 (as determined by the Akaike information criterion) and generalized variance decompositions of 10-day-ahead forecast errors.

Third, from the results shown in Table 4, we can see that when green stocks fall, the spillover effect of each green stock market on gold decreases, and the result is no more than 0.6%, that is, gold is relatively less affected by the decline of green stock market.

Finally, the spillover effect of each green stock market on energy futures is stronger than that of the overall spillover in the negative volatility system, even more than 2%, indicating that energy futures are vulnerable to the fluctuation spillover effect of green stocks in the downwind direction.

6.4. Frequency-Domain Spillover and Network Connectedness

The connectedness between the stock markets of the six green industries and other financial markets could vary across different frequency domains. Based on the frequency domain decomposition spillover index model proposed in [26], the original sequence frequency domain is decomposed into high frequency and low frequency, where the frequency band of high frequency is 3.14 to 0.63, representing the period of 1 to 5 days, the frequency band of intermediate frequency is 0.63 to 0.10, representing 5 to 30 days, and the frequency band for low frequencies is 0.10 to 0, representing 30 or more days.

Figure 2 demonstrates the network connectedness among markets at different frequencies. In Figure 2, the green node represents a receiver, while the red node represents a transmitter. The edge colors rank the strength of the pairwise directional connectedness from blue (strongest) to purple, pink, and light yellow (weakest). Additionally, the arrow thickness reflects the strength of the pairwise directional connectedness. Figure 2a illustrates the pairwise directional connectedness during the whole sample period, echoing the results in Table 3. It is noted that there are reasonably solid pairwise spillovers between similar markets. For instance, strong connectedness can be observed between green stock markets and traditional stock markets. These findings suggest that the time-domain spillovers seem to be more relevant to the classification of markets.

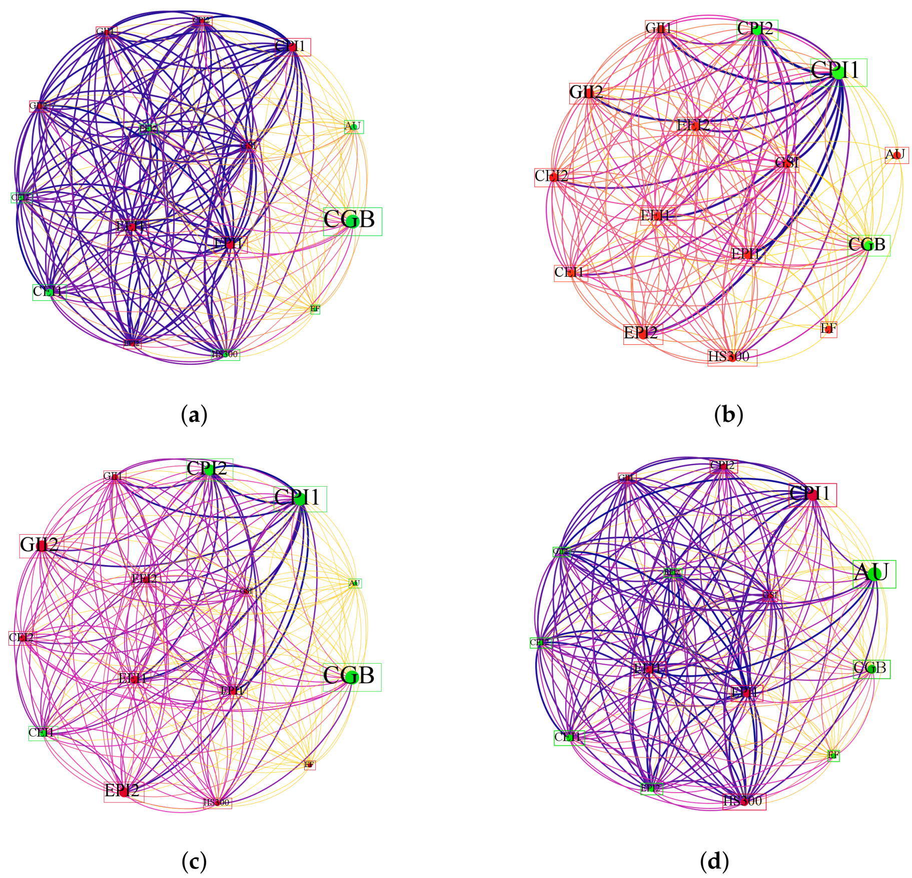


Figure 2. Network connectedness. (**a**) The whole sample period; (**b**) 26 March 2018 to 31 December 2019; (**c**) 1 January 2020 to 31 December 2020; (**d**) 1 January 2021 to 5 November 2021.

By comparing Figure 2a,c,d, we can see that in the long term, the connectedness between the stock markets of the six green industries and traditional stocks market is the largest, and in the short run, the connectedness of variables in the system decreases, which can be explained by the fact that the information transmission is more rapid in the long term than in the intermediate and the short term.

6.5. Dynamic Spillover and the Impact of COVID-19

Considering the time-varying characteristics of the return spillover index, we further estimate the volatility spillover movements between the stock markets of the six green industries and other financial markets using a rolling time window. The forecast horizon is 10 and the window width is 200. Figure 3 plots the total volatility spillovers estimated by the rolling-window analysis. It is evident that around January 2020, the volatility spillover indices experienced an abnormal rise. The COVID-19 pandemic might be the major cause of the 2020 fluctuations that negatively affected global stock markets. In turn, the negative emotions caused by the abnormal fluctuations in the financial markets further strengthened the dynamic spillovers in the corresponding submarkets. Since the effects of the epidemic have gradually diminished in China, the correlation between markets has gradually returned to the normal level. This further verifies that major emergencies in various financial submarkets are highly contagious.

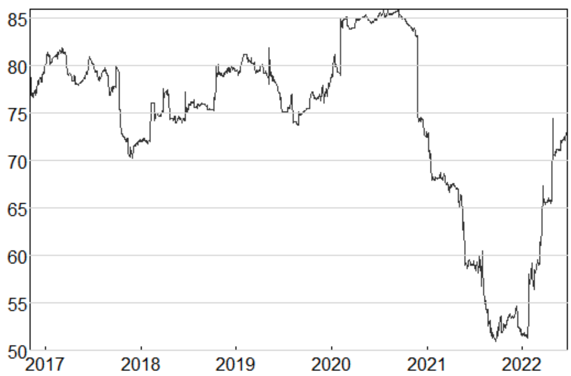


Figure 3. Rolling-window estimation of total connectedness.

In addition, to further investigate the impacts of the COVID-19 pandemic, the sample period is subdivided into three subperiods: the pre-COVID-19 period (1 January 2016 to 31 December 2019), the COVID-19 period (1 January 2020 to 30 September 2020), and the post-COVID-19 period (1 October 2020 to 24 June 2022). (On December 31, 2019, Wuhan Municipal Health Commission reported a cluster of cases of novel pneumonia, which was eventually identified as Coronavirus disease 2019 (COVID-19) by the WHO. Therefore, the start date of the COVID-19 is therefore assumed to be December 31, 2019, and the COVID-19 epidemic period is defined as the daily data from January 1 to September 30, 2020.) The selection of the subperiods is based on Figure 2, and then, we calculate the directional spillovers in the pre-COVID-19, COVID-19, and post-COVID-19 periods. This may provide some detailed insights into spillover effect transmission trends across the markets under investigation. As shown in Tables 5–7, the total connectedness is 73.76%, 83.99%, and 64.99% in the three periods, respectively. The total spillovers increase, which could be explained by the stronger market interaction following the COVID-19 outbreak.

More specifically, from Table 5 it can be concluded that before COVID-19 the spillovers of green stocks to energy futures were the smallest. According to Table 6, during the COVID-19 pandemic, not only did the total connectedness increase, but the spillover effect of green stocks on green bonds and energy futures has also increased significantly. In contrast, the volatility spillover effect between green stocks and gold is relatively low. Moreover, gold exerted the least impact on other markets.

Table 5. Spillover matrix in pre-COVID-19 outbreak.

	EPI1	EPI2	CPI1	CPI2	CEI1	CEI2	EEI1	EEI2	GII1	GII2	GSI	CGB	HS300	AU	EF	FROM
EPI1	10.4	7.98	9.18	7.3	8.06	8.76	8.62	7.79	8.18	8.31	8.68	0.01	6.59	0.1	0.04	89.6
EPI2	8.78	10.54	8.71	7.74	8.12	9.16	8.57	7.91	7.99	7.87	8.76	0	5.74	0.07	0.01	89.46
CPI1	8.8	7.82	10.7	8.58	7.84	8.18	8.69	7.92	8.34	7.79	8.42	0.01	6.76	0.13	0.02	89.3
CPI2	8.13	7.88	9.54	10.79	7.94	8.36	8.23	8.04	8.4	7.58	8.57	0.01	6.38	0.13	0.03	89.21
CEI1	8.59	8.3	8.6	7.72	9.53	9.06	8.44	8.13	8.31	7.52	9.09	0.01	6.6	0.06	0.02	90.47
CEI2	8.83	8.68	8.58	7.55	8.52	10.19	8.4	7.86	8.21	7.71	8.69	0	6.67	0.09	0.02	89.81
EEI1	8.74	8.02	8.86	7.35	8.06	8.54	10.83	8.24	7.89	7.64	8.58	0.01	7.05	0.15	0.02	89.17
EEI2	8.42	7.88	8.82	7.61	7.95	8.38	8.93	11.24	8.03	7.43	8.16	0	7.08	0.06	0	88.76
GII1	8.48	7.93	8.88	8.07	8.2	8.62	8.26	8.09	10.09	7.65	9.02	0.01	6.62	0.08	0.01	89.91
GII2	9.38	8.16	8.8	7.54	7.98	8.53	8.48	7.74	8.05	10.02	8.67	0.01	6.51	0.12	0.01	89.98
GSI	8.58	8.04	8.6	7.83	8.34	8.54	8.69	8.02	8.23	7.59	10.79	0	6.65	0.07	0.04	89.21
CGB	1.98	1.36	1.54	2.06	1.27	1.12	1.12	0.9	1.36	2.42	1.56	79.95	0.95	0.37	2.05	20.05
HS300	8.46	6.58	8.45	6.96	7.65	8.07	8.17	8.15	7.79	7.22	8.05	0	14.26	0.17	0.02	85.74
AU	0.7	0.8	0.97	0.76	0.26	0.63	1.58	0.26	0.6	0.56	0.31	0.22	1.68	89.83	0.85	10.17
EF	0.7	0.17	0.43	0.35	0.61	0.64	0.58	0.16	0.23	0.41	0.23	0.02	0.4	0.65	94.41	5.59
TO	98.6	89.61	99.96	87.42	90.78	96.59	96.75	89.22	91.62	87.69	96.8	0.31	75.66	2.24	3.13	1106.4
NET	8.99	0.16	10.66	−1.78	0.32	6.78	7.59	0.46	1.71	−2.29	7.58	−19.73	−10.08	−7.93	−2.45	73.76

Notes: This table is based on vector autoregressions of order 1 (as determined by the Akaike information criterion) and generalized variance decompositions of 10-day-ahead forecast errors.

Table 6. Spillover matrix during-COVID-19 outbreak.

	EPI1	EPI2	CPI1	CPI2	CEI1	CEI2	EEI1	EEI2	GII1	GII2	GSI	CGB	HS300	AU	EF	FROM
EPI1	10.52	7.46	9.6	8.78	5.82	6.08	5.83	5.05	10.14	10.2	8.14	2.77	9.01	0.04	0.56	89.48
EPI2	9.58	9.74	9.17	7.96	6.31	7.73	5.64	4.23	9.81	9.38	9.55	1.8	8.23	0.02	0.84	90.26
CPI1	9.39	7.37	11.57	9.37	5.41	4.94	6.44	5.85	9.99	9.47	7.7	2.82	8.89	0.02	0.77	88.43
CPI2	8.5	6.84	9.93	10.7	6.25	4.96	7.43	5.25	10.37	8.74	7.84	3.43	8.85	0.08	0.82	89.3
CEI1	8.01	7.57	7.89	7.6	9.58	8.67	6.53	5.74	8.92	7.9	8.82	2.31	8.96	0.35	1.13	90.42
CEI2	8.83	7.75	7.61	7.15	7.69	10.14	6.81	5.4	8.99	8.46	9.26	1.84	8.29	0.19	1.6	89.86
EEI1	8.02	6.53	8.03	7.98	6.89	5.74	10.77	6.01	8.27	9.11	8.21	4.49	9.19	0.1	0.67	89.23
EEI2	8.13	6.26	9.08	6.97	6.86	6.19	6.82	12.03	7.74	9.64	6.4	2.49	10.08	0.89	0.42	87.97
GII1	8.87	6.8	9.28	9.6	5.93	5.46	6.72	5.05	12.49	8.73	8.46	3.09	8.85	0.03	0.63	87.51
GII2	9.83	7.31	8.82	7.5	6.29	6.72	6.75	5.33	8.11	11.94	8.09	3.21	9.48	0.12	0.49	88.06
GSI	9.06	7.87	8.67	8.4	6.28	6.97	6.5	4.34	10.48	8.79	10.36	3.28	8.08	0.06	0.86	89.64
CGB	7.35	5.16	7.62	7.22	6.22	4.5	7.31	5.6	7.59	7.99	7.43	15.82	9.05	0.17	0.99	84.18
HS300	8.6	6.62	8.79	7.11	6.65	6.11	6.22	6.64	7.88	9.59	7.29	3.92	13.71	0.47	0.4	86.29
AU	5.53	1.24	2.08	0.5	0.21	1.1	1.91	1.96	0.52	5.28	2.46	10.04	2.02	63.28	1.89	36.72
EF	6.11	6.17	5.92	4.62	5.32	7.25	5.74	4.14	6.73	6.58	7.02	1.79	5.02	0.13	27.45	72.55
TO	115.82	90.96	112.5	100.76	82.12	82.42	86.65	70.58	115.54	119.85	106.67	47.29	114.01	2.67	12.06	1259.91
NET	26.34	0.7	24.07	11.46	−8.3	−7.43	−2.57	−17.39	28.03	31.79	17.03	−36.89	27.71	−34.05	−60.49	83.99

Notes: This table is based on vector autoregressions of order 1 (as determined by the Akaike information criterion) and generalized variance decompositions of 10-day-ahead forecast errors.

Table 7. Spillover matrix in post-COVID-19 outbreak.

	EPI1	**EPI2**	**CPI1**	**CPI2**	**CEI1**	**CEI2**	**EEI1**	**EEI2**	**GII1**	**GII2**	**GSI**	**CGB**	**HS300**	**AU**	**EF**	**FROM**
JNHB1	18.26	6.52	12.19	8.99	0.56	3.74	10.12	3.9	12.23	11.79	6.37	0.01	5.27	0.03	0.02	81.74
JNHB4	12.08	17.51	12.52	8.16	1.85	5.37	8.97	2.35	9.35	7.56	9.04	0.02	5.08	0.06	0.08	82.49
QJSC1	11.12	6.61	19.83	14.37	1.43	1.69	11.24	5.29	6.64	7.31	6.83	0.07	7.37	0.07	0.16	80.17
QJSC2	9.84	4.84	15.46	19.94	2.19	1.44	13.86	5.53	7.81	6.9	5.77	0.08	6.14	0.09	0.11	80.06
QJNY1	4.65	6.28	7.42	8.52	30.92	13.14	13.06	1.04	3.46	2.4	4.92	0.72	2.82	0.07	0.59	69.08
QJNY2	13.53	5.83	8.22	6.33	4.99	24.86	9.89	1.81	8.05	5.35	6.62	0.75	3.59	0.13	0.06	75.14
STHJ1	10.03	4.32	11.86	13.11	1.16	2.22	25.11	4.43	9.07	7.03	5.37	0.25	5.23	0.62	0.17	74.89
STHJ3	9.73	3.19	11.36	10.43	1.26	1.51	11.19	24.07	6.46	9.03	4.31	0.02	6.88	0.47	0.09	75.93
JCSS1	13.23	5.62	10.39	10.29	0.92	3.03	11.93	5.03	16.91	11.08	5.39	0.04	6.05	0.02	0.08	83.09
JCSS2	13.41	4.84	10.47	8.56	1.06	2.48	7.91	5.66	12.47	22.57	5.5	0.16	4.87	0.02	0.01	77.43
LSFW	11.63	8.13	12.83	9.31	2.61	4.47	11.44	3.35	8.06	7.34	14.67	0.13	5.55	0.21	0.29	85.33
GB	0.11	0.13	0.72	2.3	0.49	0.83	0.49	0.09	0.45	0.55	0.88	92.09	0.24	0.56	0.07	7.91
STOCK	8.92	3.56	7.59	5.71	0.41	2.33	10.08	3.94	7.53	8.27	4.34	0.2	34.55	2.17	0.42	65.45
GOLD	0.24	0.5	0.32	0.06	0	0.62	1.02	0.45	0.14	0.69	1.13	5.16	1.4	84.8	2.36	14.09
EF	0.71	1.9	0.58	0.07	3.78	0.65	0.53	2.25	0.04	0.06	0.87	0.03	0.52	8.97	79.04	20.96
TO	119.22	62.26	121.92	106.21	22.71	43.52	121.74	45.12	91.75	85.35	67.35	7.62	61.02	13.5	4.49	974.87
NET	37.49	−20.23	41.75	26.15	−46.37	−31.62	46.85	−30.82	8.66	7.93	−17.99	−0.29	−4.43	−1.71	−16.47	64.99

Notes: This table is based on vector autoregressions of order 1 (as determined by the Akaike information criterion) and generalized variance decompositions of 10-day-ahead forecast errors.

6.6. Portfolio Weights Analysis

To deepen our understanding further on the investment implications of our study, we report in Table 8 the summary statistics of the bilateral portfolio weights (weight) and portfolio effectiveness (HE) of the first and second assets, in which weight refers to the proportion of safe-haven assets in the investor's portfolio and HE indicates how much risk can be reduced adding risk averse assets to the portfolio. The greater the HE value, the stronger the effectiveness of the portfolio. Table 8 reports the statistics for the whole sample period and sub period, including pre-COVID-19 period, COVID-19 period, and post-COVID-19 period.

Table 8. Bilateral portfolio weights and effectiveness.

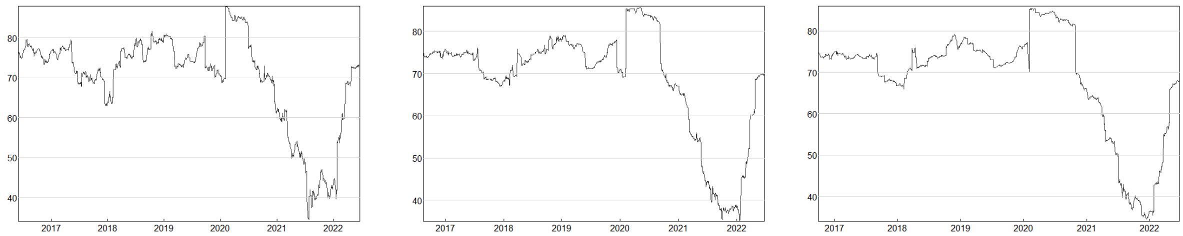
	Whole Period		Pre-COVID-19 Period		COVID-19 Period		Post-COVID-19 Period	
	Weight	HE (%)	Weight	HE (%)	Weight	HE (%)	Weight	HE (%)
JNHB1/GB	0.9964	1.75	0.9968	0.59	0.9912	7.86	1.0000	0.29
JNHB2/GB	0.9966	1.74	0.9969	0.61	0.9919	6.66	1.0000	0.46
QJSC1/GB	0.9962	1.90	0.9968	0.58	0.9905	6.03	1.0000	0.62
QJSC2/GB	0.9957	2.04	0.9973	0.49	0.9887	7.46	1.0000	0.34
QJNY1/GB	0.9960	2.05	0.9963	0.68	0.9913	6.46	1.0000	0.60
QJNY2/GB	0.9961	1.86	0.9961	0.67	0.9927	5.56	1.0000	0.26
STHJ1/GB	0.9959	1.57	0.9963	0.49	0.9930	3.95	1.0000	0.27
STHJ2/GB	0.9966	1.45	0.9968	0.59	0.9922	5.46	1.0000	0.18
JCSS1/GB	0.9951	2.18	0.9955	0.90	0.9915	5.74	1.0000	0.33
JCSS2/GB	0.9968	1.63	0.9975	0.52	0.9913	6.86	1.0000	0.32
LSFW/GB	0.9958	4.37	0.9960	0.78	0.9901	7.38	1.0000	0.43
JNHB1/GOLD	0.7993	23.00	0.8105	23.73	0.7852	18.79	0.7944	23.56
JNHB2/GOLD	0.8194	20.60	0.8254	22.15	0.7855	18.65	0.8406	17.21
QJSC1/GOLD	0.7811	25.71	0.8007	25.66	0.7090	24.48	0.7883	25.03
QJSC2/GOLD	0.7686	27.63	0.7999	25.98	0.6746	28.39	0.7504	30.22
QJNY1/GOLD	0.8033	22.42	0.7961	25.65	0.7561	21.22	0.8658	14.10
QJNY2/GOLD	0.8082	21.35	0.7938	25.29	0.7907	17.90	0.8707	13.18
STHJ1/GOLD	0.7521	27.21	0.7631	29.28	0.7392	20.63	0.7426	26.71
STHJ2/GOLD	0.8062	21.38	0.8025	24.25	0.7915	14.96	0.8262	18.82
JCSS1/GOLD	0.7785	1.41	0.7967	25.94	0.7412	27.46	0.7668	26.95
JCSS2/GOLD	0.8123	21.75	0.8359	21.55	0.7601	19.93	0.7866	23.80
LSFW/GOLD	0.7924	23.67	0.8007	25.24	0.7240	24.63	0.8256	18.57
JNHB1/EF	0.5412	39.85	0.5209	43.66	0.8503	7.28	0.3939	54.30
JNHB2/EF	0.5759	37.03	0.5475	40.44	0.8487	7.58	0.4704	50.91
QJSC1/EF	0.5181	40.91	0.5107	43.24	0.7415	14.71	0.3866	54.41
QJSC2/EF	0.5044	42.54	0.5124	42.78	0.6881	21.07	0.3514	59.62
QJNY1/EF	0.5586	37.35	0.5004	43.95	0.8273	8.49	0.5388	42.58
QJNY2/EF	0.5576	37.78	0.4932	45.02	0.8786	5.56	0.5223	44.43
STHJ1/EF	0.4614	45.86	0.4461	48.77	0.7586	14.61	0.2926	61.57
STHJ2/EF	0.5452	36.89	0.5090	42.53	0.8618	5.12	0.4217	47.36
JCSS1/EF	0.5141	41.23	0.5034	42.97	0.7730	13.56	0.3653	57.72
JCSS2/EF	0.5650	38.11	0.5727	38.03	0.7802	13.71	0.3781	58.46
LSFW/EF	0.5351	39.34	0.5117	42.66	0.7690	13.31	0.4315	51.03

Notes: This table summarizes the results of the optimal portfolio weights and the corresponding effectiveness.

During the whole sample period, the HE value of EF is the largest, which means that incorporating EF into the portfolio of green industry stocks can effectively reduce investment risk, namely, EF is the most suitable tool for diversified portfolio of green industry. At the same time, the weight proportion of almost all hedging assets is greater than 50%, which means that investors should hold more green bonds, gold and energy futures than green industry stocks, so as to reduce the risk of green stock investment. Specifically, in the portfolio of green stocks and energy futures, the average optimal weight of EPI2 and EF is the highest, which is 0.5759, indicating that for the portfolio of CNY 100, CNY 57.59 will be invested in EF, and the remaining CNY 43.41 will be invested in EPI2.

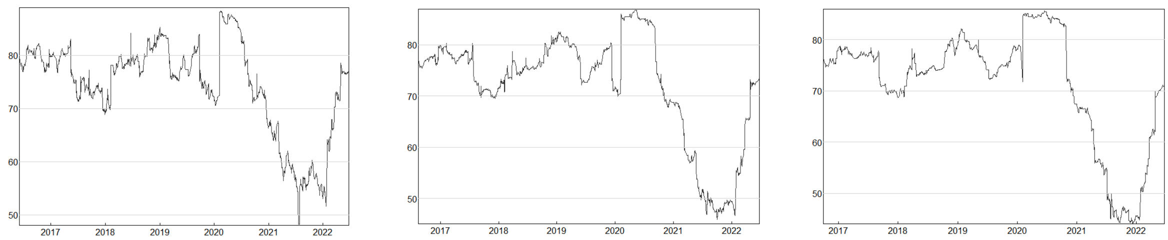
6.7. Robustness Checks

To further verify the robustness of the above-mentioned results, we change the H-step-ahead forecasting period to 2 and 5 days and adjust the rolling windows to 100 to 180 days. Figures 4 and 5 show the time-varying spillover graphs of the total spillover index under different forecast horizons and rolling window size combinations. It can be observed that there are comparable trends, indicating that the main empirical results are robust.



(**a**) (**b**) (**c**)

Figure 4. Robustness checks by applying the 2-day forecast horizon: (**a**) 100-day rolling windows; (**b**) 150-day rolling windows; (**c**) 180-day rolling windows.



(**a**) (**b**) (**c**)

Figure 5. Robustness checks by applying the 5-day forecast horizon: (**a**) 100-day rolling windows; (**b**) 150-day rolling windows; (**c**) 180-day rolling windows.

7. Discussion

Using the spillover index model of Diebold and Yilmaz and the frequency-domain spillover approach developed by Barun'ik and Kvrehl', this paper aims to examine the risk spillovers and the asymmetric connectedness between the green industry stock markets, green bond market, and other traditional financial markets in China. Using rolling time windows, this paper captures the dynamic risk spillovers between six green industry stock markets and other financial markets and investigates the impact of COVID-19. In addition, the DCC-GARCH model is used to analyze the optimal portfolio tool for green industry stocks under various market economy conditions. The following is a summary of the key findings of this paper.

First, this paper demonstrates through a static spillover analysis that the correlation between the six green industry stocks and various financial markets varies. Specifically, for EPI, CPI, EEI, and GII, the energy futures market experiences the fewest shocks, whereas the CEI and GSI have the smallest effect on the gold market's volatility.

Second, by decomposing the returns into positive and negative returns and calculating volatility, this study concludes that under the downside risk of the green stock market, the spillover effects between green stocks and green bonds are the smallest.

Third, using the frequency-domain spillover approach developed by Barun'ik and Kvrehl' and demonstrating network connectedness, this paper concludes that the correlation between green industry stocks and other financial assets fluctuates over time. In addition, a segmented analysis is used to examine the impact of the COVID-19 pandemic on the volatility spillover effect of stocks in the six green industries. In this regard, the final conclusion of this paper is that the spillovers of green stocks to energy futures were smallest prior to COVID-19. During the COVID-19 outbreak, gold experienced the fewest shocks. The spillover effects between the green stock market and other financial markets are heterogeneous in the post-COVID-19 era.

8. Conclusions, Implications, and Limitations

A considerable amount of private capital must be invested in green industries in order to achieve sustainable economic growth. As the primary source of direct financing, investors who hold a substantial number of equity assets are exposed to relatively high risk. In order to reduce the investment risk of participants in the green financial market and stimulate the demand for the green stock market, this paper focuses on the impact of the COVID-19 epidemic on the dynamic risk spillover and the selection of optimal investment tools between China's green industry stock market and other financial markets, and offers effective recommendations for environmentally friendly investors and policymakers.

First, static spillover results indicate that the correlation between green stocks, gold, and energy futures markets is relatively weak. Therefore, investors can construct diversified portfolios of green stocks using the two asset classes. In order to maximize the benefits of each market and to achieve the coordinated development of the green industry and other financial markets, policymakers should simultaneously consider the differences in the relevance between markets. Moreover, when the green industry stock market presents downside risks, investors should increase their green bond holdings and decrease their energy futures holdings. Moreover, the risk contagion between markets is stronger over the long term, so environmentally conscious investors should diversify the investment risk of long-term financial assets appropriately.

Second, based on the results of different stages of time under the influence of the COVID-19 epidemic, investors should invest more in the energy futures market prior to the epidemic, i.e., during periods of relative economic stability. When the epidemic and other crises occur, investors should reduce their investments in energy futures and green bonds, but increase their investments in the gold market to ensure the security of their assets and mitigate the negative impact of crisis events on their investments. Policymakers should thoroughly consider the impact of extraordinary events and market fluctuations on the risk contagion of the green industry, and provide support for the effective risk management of China's green industry by establishing an effective risk early warning mechanism.

In future research, if the data can be subdivided and quantified more precisely, and if the time interval can be extended, more precise and timely conclusions and policy recommendations will be obtained. Concerns for future research include, for instance, further analysis of the impact of sudden crisis events, such as the Russian–Ukrainian war, on green industries, as well as research on more detailed green industry markets and more diverse financial markets, so as to more effectively promote the development of various types of green industries.

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