

Research Article

Correlation and Dynamic Volatility Spillover between Green Investing Market, Coal Market, and CO₂ Emissions: Evidence from Shenzhen Carbon Market in China

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With the continuous expansion scale of carbon market and the development of carbon trading mechanism, carbon emission right, as a new financial asset, is being brought into the category of asset allocation by more and more investors. As the burning of coal is the major source of carbon dioxide, China is facing serious ecological and environmental problems, which restrict the development of low-carbon economy. In order to reach the carbon dioxide emission reduction targets and promote the development of green investment market, the carbon market should be a good emission reduction measure. The correlation and dynamic volatility spillover among coal, carbon, and green investing markets are becoming a hot topic for current research. The paper applies both VAR-GARCH-DCC and VAR-GARCH-BEKK models to draw some significant conclusions. (1) The green investment market, coal market, and Shenzhen carbon market show obvious time-varying correlation, and the volatility of the green investment market is higher. (2) There is a bidirectional Granger causality between green investing and coal markets. (3) The investment portfolio and hedging mechanism of the market are established to reduce the risk and help investors obtain higher returns.

1. Introduction

In recent years, global climate and environmental problems have become increasingly serious. Low carbon and green development have become an important consensus for each country to seek new economic growth. As the world's largest emitter of greenhouse gases, our country is facing great pressure on emission reduction and has been actively involved in international carbon emission reduction activities. On September 22, 2020, China declared at the seventy-fifth UN General Assembly that "China will enhance its national independent contribution and adopt more effective policies and measures. CO₂ emissions will strive to reach a peak by 2030 and strive to achieve carbon neutralization by 2060" [1]. As a big greenhouse gas emission country, it is China's obligation and responsibility to reduce greenhouse gas emissions, and China has also made a commitment to reduce

greenhouse gas emissions. Whether out of social responsibility or to fulfill its commitments, it is imperative for China to implement a carbon trading mechanism to reduce carbon dioxide emissions in the future. In the wake of the rapid growth of China's carbon market, its relevance with the energy market is becoming closer and closer. The fluctuation of energy or carbon market caused by information shock is easily transmitted between the markets. Moreover, the spillover effect among carbon, energy, and green investment markets in China is not invariable. The degree of market fluctuation in different periods is different, and the intensity of the spillover effect should be different. Therefore, it is necessary to deeply investigate the time-varying fluctuation spillover characteristics among China's carbon market, energy market, and green investment market, which is of great practical significance for further promoting the rational formation of the internal price transmission

mechanism among three markets, preventing the rapid fluctuation of carbon price and promoting the stable operation of China's carbon trading system.

China's carbon neutralization target will promote the zero-carbon industry to become a new trend of long-term value investment. China will generate seven major investment fields and leverage 70 trillion green industry investment opportunities. It includes renewable resource utilization, energy efficiency improvement, end-to-end consumption electrification, zero-carbon power generation technology, energy storage, hydrogen energy, and digitization. By 2050, the market size of these seven major areas will reach nearly 15 trillion yuan in the same year and contribute 80% of the total emission reduction to China's zero-carbon emission. More than 80 percent of the emissions reduction is to be achieved from 2020 to 2050. In addition, China's zero-carbon transformation will create a large number of new jobs. Only emerging industries such as zero-carbon power, renewable resources utilization, and hydrogen energy will bring more than 30 million new jobs [2]. The rest of this paper is summarized as follows. The second part introduces the existing research results briefly. The third part constructs both VAR-GARCH-DCC and VAR-GARCH-BEKK models. In the fourth part, it introduces the data sources and processing process of carbon, coal, and green investment markets. In the fifth part, we discuss the results.

2. A Brief Literature Review

Many studies have confirmed the volatility and spillover effects of carbon and energy markets. Early studies mainly focused on the spillover effects between the EU carbon and energy markets. Albertola et al. used the method of multiple regression to test the structural mutation, and the results showed that energy prices, weather, and political decision-making factors were the main factors affecting the change of carbon prices [3]. Byun and Cho explored the volatility of the carbon market in Europe and added the energy market volatility to the carbon market volatility prediction equation for the first time, which shows that the fluctuation of Brent crude oil, coal, and power prices has a good prediction ability for the volatility of carbon price [4]. Liu and Chen fit the return series of carbon future market and energy future market through the FIEC-HYGARCH model and confirmed that there are volatility spillover and long-term memory effects among carbon and crude oil, coal, and natural gas market [5]. Rebredo analyzed the volatility spillover effect of the EU carbon and Brent crude oil market by constructing a multiple autoregressive conditional model. It is concluded that crude oil price fluctuation has a negative impact on EUA (European Union carbon emission quota) and that the price fluctuation has no significant ability to explain and predict. The results show that there is no volatility transfer mechanism between the two markets, so the prices of carbon emission futures and options should have less uncertainty [6]. Then, there are also some pieces of literature on the linkage between energy and carbon

markets. Hai Xiaohui and Yang Baochen applied the DCC-GARCH model in their research; they believe that, under the influence of macroeconomy, there is a positive correlation between carbon and coal, crude oil, and natural gas markets and the correlation coefficient of coal and natural gas prices to carbon price will fluctuate for a long time. The dynamic correlation coefficient of Brent crude oil price to carbon price fluctuates slightly [7]. Zhang and Sun explored the dynamic volatility spillover effect between the energy market and the EU carbon markets from positive and negative directions [8]. Theoretically, the burning of fossil energy is the main source of carbon dioxide, and industrial enterprises can transfer between different fuels (coal, oil, natural gas, etc.) through technology upgrading, which leads to the inherent correlation between fossil energy price and carbon market price [4, 5]. Some studies have found that the nexus between energy price and the first stage carbon price is weak, while the nexus between energy price and the second stage carbon price is strong [9]. Oberndorfer's research shows a significant positive nexus between the price of EUA and the stock market of power enterprises [10].

In view of the intuitiveness, simplicity, and stability of the DCC-MVGARCH model, many scholars at home and abroad use it to analyze the dynamic dependence between economic indicators or financial assets in order to dig out the internal mechanism of the economic phenomenon and formulate the optimal coping strategies. Demirel used studied the risk spillover effect and nexus between the four energy markets and the European carbon market and found that the risk transmission ranging from the energy market to the carbon market has obvious dynamic characteristics [11]. It is found that, compared with the EUA market, the Shenzhen carbon market does not have volatility information transmission with the energy market, but it does not exclude that, with the improvement of China's carbon market in the future, there will be a linkage between markets [12–16]. Some of the studies are shown in Table 1.

In summary, the existing literature provides useful inspiration for exploring the price fluctuation transmission mechanism of energy and carbon markets, but the above research that is mainly based on the GARCH model measures the volatility spillover effect through the significance of correlation coefficient, lacks the investigation of the time-varying and directional characteristics of spillover effect, and cannot describe the volatility spillover relationship between the carbon, coal, and green investment markets as a whole. This paper makes several contributions. Firstly, we selected daily data in China's carbon market, coal market, and green investment market as the research object and analyzed the dynamic correlation and spillover effects by using the VAR-GARCH-DCC and VAR-GARCH-BEKK models. Second, we further subdivided the spillover effects among carbon, coal, and green investment markets in China and investigated the dynamic characteristics of total spillover, directional spillover, and net spillover effects among the three markets. Third, we calculated the optimal portfolio and hedging ratio between different assets, which can provide useful investment suggestions for this study.

TABLE 1: Summary of related researches.

Literature	Methodology	Research contents	Year
Byun and Cho [4]	GARCH models	Carbon futures and energy volatilities	2013
Reboredo [6]	Multivariate conditional autoregressive	EU emission allowance and oil markets	2014
Xiaohui and Baochen [7]	DCC-MVGARCH	Energy market in phase II of the EU (ETS)	2014
Zhang and Sun [8]	BEKK-GARCH and DCC-MVGARCH models	Carbon prices and fossil energy prices	2016
Engle [11]	Multivariate generalized autoregressive conditional heteroskedasticity	Dow Jones industrial average and the NASDAQ	2003
Ulrich [14]	Equal-weighted portfolio	EU emission allowances and the stock market	2003
Cheng [16]	VAR(6)-GARCH(1, 1)-BEKK model	Financial markets	2010
Jie and Jie [17]	VAR model	Carbon emission spot prices	2018
Lin [18, 19]	BEKK-GARCH and DCC-MVGARCH models	Carbon, coal, and new energy stock markets	2019
Salisu [20]	VARMA-BEKK-AGARCH approach	Oil price and US stock	2015
Meng-Shan Z [21]	Analysis of provincial panel data	Carbon emission and green finance	2019

3. Methodology

In econometric research, scholars use the VAR model to analyze the autocorrelation of time series, the relationship between time series and the impact of dynamic shocks on variables [17]. In this paper, we first use the vector autoregressive (VAR) model to determine the spillover effect of market returns, then use the Granger causality test to determine the causality of market returns, and build the VAR model with optimal lag orders. Engle first proposed using the arch model to capture the volatility characteristics of time series [18, 19]. Bollerslev improved the model and proposed the GARCH model, which solved the problem of many lag periods [22]. For the study of volatility spillover effect among financial markets, the most common method used by scholars at home and abroad is the multivariate GARCH model [23-26]. Li et al. found that the multivariate GARCH model can cover multiple factors affecting the market at the same time and provide more information so as to more comprehensively describe the volatility spillover effect between multiple markets [27]. Then, they test the volatility spillover effect of each market by the GARCH model. The mean equation of the model tests the price spillover effect between markets, while the variance equation tests the volatility spillover effect. In our study, the dynamic correlation and spillover effect of coal, green investment, and carbon markets are studied by using both the VAR- (*Vector autoregressive*-) GARCH- (*generalized autoregressive conditional heteroscedasticity*-) DCC (*dynamic conditional correlation*) model and the VAR-GARCH-BEKK (*Baba, Engle, Kraft, and Kroner*) model.

3.1. Price Spillover of Conditional Mean. We construct the p -order VAR model for the three groups of market returns and take it as part of the mean equation. The formula can be expressed as follows:

$$R_{i,t} = \beta_0 + \beta_1 \sum_{j=1}^{t-1} R_{1,t-j} + \beta_2 \sum_{j=1}^{t-1} R_{2,t-j} + \beta_3 \sum_{j=1}^{t-1} R_{3,t-j} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ represents the returns of the three markets at time t ; $R_{1,t-j}$ and $R_{3,t-j}$ represent the lagged returns of three markets. Whether the coefficient β is 0 depends on the result of the Granger causality test; $\varepsilon_{i,t} = (\varepsilon_{i,t}^1, \varepsilon_{i,t}^2, \varepsilon_{i,t}^3)$ represent the error term of the mean value equation of two-market returns. Then, (1) can be simplified as

$$R_{i,t} = \beta_0 + \sum_{g=1}^3 \beta_g \sum_{jh=1}^3 R_{h,t-jh} + \varepsilon_{i,t}. \quad (2)$$

According to the VAR model, we can know the correlation between the returns, and the Granger causality test can show the directivity of the mean spillover effect. We use the DCC-GARCH and BEKK-GARCH models to analyze the dynamic correlation and volatility spillover in the two markets. And the conditional variance equations of the models are different.

3.2. VAR-GARCH-BEKK. In order to study the transmission mechanism of return volatility, this paper studied the spillover effect of return volatility by using multiple GARCH (MGARCH, also known as VGARCH) models. The basic form of the MGARCH variance equation is shown as follows:

$$\text{vech}(H_t) = C_0 + \sum_{j=1}^q A_j \text{vech}(H_{t-j}) + \sum_{i=1}^p B_i \text{vech}(\varepsilon_{t-i}, \varepsilon'_{t-i}), \quad (3)$$

where the notation $\text{vech}(H_t)$ represents $N(N+1)/2 \times 1$ vector composed by $N \times N$ matrix. ε_{t-i} is the residual vector of the mean equation. H_t represents the conditional variance-covariance matrix of ε_t . C_0 , A_j , and B_i represent the coefficient matrix of constant, GARCH term, and ARCH term, respectively. Since the estimation result of (3) easily leads to negative coefficients A_j and B_i , it is necessary to satisfy the positive definite covariance matrix. In our study, the BEKK model proposed by Engle and Kroner is used to solve the above problem [17]. The variance equation is shown in

$$H_t = C'C + B'\varepsilon_{t-1}\varepsilon'_{t-1}B + A'H_{t-1}A + D'I_{t-1}\varepsilon_{t-1}\varepsilon'_{t-1}D, \quad (4)$$

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix},$$

$$C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix},$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix},$$

$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix},$$

$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix}.$$

(5)

In the bivariate case, H_t in the formula is the conditional variance-covariance matrix of market volatility. In (5), h_{11} , h_{22} , and h_{33} represent the conditional variance of the three series; h_{12} , h_{21} , h_{23} , h_{31} , and h_{32} represent the conditional covariance among the series. For the fluctuation of a market, its fluctuation mainly comes from two aspects: one is the fluctuation and covariance of self and the other, and the other is the absolute residual of self and the other and their interaction. Therefore, for a market, as long as its influence from the other side is not significant, its fluctuation only depends on its own previous fluctuation and the influence of the previous absolute residual; that is, there is no spillover effect of other markets on the market. In model (4), h_{11} is the conditional variance of the carbon market in China, and h_{22} and h_{33} denote the conditional variance of the coal market and green investing market, respectively. h_{ij} is the conditional covariance of market i and market j . The model can be used to investigate the first moment relationship (mean spillover) and the second moment relationship (volatility spillover) between markets.

3.3. VAR-GARCH-DCC. DCC-GARCH model is also called the dynamic conditional correlation model [18]. In the model, r is the time series of n observation samples; r_t is the vector of $n \times 1$; standard normal distribution is with the covariance matrix of H_t . The formula is expressed as follows:

$$r_t = \mu_t + e_t,$$

$$\mu_t = E\left(\frac{r_t}{F_{t-1}}\right),$$

$$e_t \sim N(0, H_t),$$

$$H_t = D_t R_t D_t,$$

$$D_t = \begin{pmatrix} \sqrt{h_{t1}} & & \\ & \ddots & \\ & & \sqrt{h_{tm}} \end{pmatrix},$$

$$R_t = (Q_t^*) Q_t (Q_t^*)^{-1},$$

$$Q_t = \left(1 - \sum_{m=1}^M \alpha_m - \sum_{n=1}^N \beta_n\right) \bar{Q} + \sum_{m=1}^M \alpha_m z_{t-m} z'_{t-m} + \sum_{n=1}^N \beta_n Q_{t-n},$$

$$z_t = D_t^{-1} e_t,$$

$$\bar{Q} = T^{-1} \sum_{m=1}^M u_t u'_t.$$

(6)

In the formula, μ_t is the conditional mean; e_t is residual; D is the diagonal matrix formed by conditional standard deviation; R_t is a dynamic correlation coefficient matrix; z_t is obtained by standardizing the residuals e_t ; \bar{Q} is the unconditional square error of standard residuals; α_m and β_n are the parameters (m and n denote lag orders). That is to say, α and β indicate the influence of previous shocks and dynamic conditional relations on the dynamic conditional relations in the current period [19].

4. Variables and Data Sources

4.1. Variable Selection. Our research studies the dynamic correlation and volatility spillover among the green investment market, coal market, and carbon market. In China, the carbon market is composed of 8 pilot units, which is still in the imperfect stage. This paper focuses on the stable and safe operation of the Shenzhen carbon market. So in our research, we make use of daily price data of Shenzhen carbon market as a proxy for carbon market, CSI Green Investing Index as the proxy for Green Investing Index, and steam coal future price as the proxy for coal market ranging from September 26, 2013, to December 10, 2020. Therefore, after

preliminary data processing, a total of 1611 observations were retained in the study. We use the following formula to get returns:

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right). \quad (7)$$

RGIS, RCOAL, and RCARBON represent the daily closing price. The description of variables is shown in Table 2.

4.2. Data Set. In China, there are eight pilot markets. Shenzhen carbon trading market is the earliest and the most active. In our research, we chose carbon price in Shenzhen's carbon market began to trade on June 18, 2013. The cumulative trading volumes in Shenzhen's carbon market were up to 44,550.477 thousand tons, and the total turnover of the market reached over 11.3129 yuan so far.

Shenzhen's carbon market is relatively more market-oriented and is the first carbon market pilot in China, with less data missing on quota trading day and relatively good continuity, and the first carbon market with turnover exceeding trillion [20, 28]. Since 2013, the trading scale of Shenzhen's carbon emission trading market has obvious growth. Compared with other markets, the price of the carbon market in Shenzhen is relatively stable, which can objectively reflect the supply and demand balance of the carbon emission trading market. The carbon subsidy price is a key factor reflecting China's carbon market [19]. As a result, in our research, the trading price of Shenzhen's carbon market is chosen as the index of China's carbon market.

At present, in China, the energy consumption structure mainly based on coal will not change in a short time. Shenzhen carbon market included 636 control units, covering power, water, gas, and manufacturing industries. With the gradual improvement of market mechanism and the gradual presentation of emission reduction effect, Shenzhen continues to strengthen the construction of carbon trading system, further expand the coverage of carbon trading, and expand the industry coverage to public transport, airport, and wharf industries. At present, there are 811 control units in Shenzhen's carbon market. In view of the importance of coal in China's energy market, this paper deeply studies the dynamic relationship and spillover effect among green investment, coal, and carbon markets. China's Zhengzhou Commodity Exchange launched the steam coal future contract on September 26, 2013. The steam coal is the coal used as the power raw material, which is mainly used for thermal power generation. Because the emission control enterprises in the Shenzhen carbon emission trading market are mainly hydropower, transportation, and construction, this paper selects the contract price of steam coal futures to represent the coal price.

Green investment is a new investment mode to adapt to economic and social development. This new investment mode follows the requirements of sustainable development, conforms to the consistent standards of low-carbon economic development, and aims to realize the virtuous cycle of

ecosystem, low emission, low consumption, sustainable development of economy and society, and maintain the harmony between man and nature. The development of the green industry is inseparable from financial support. However, for a long time, due to the low rate of return on investment, single financing channel, and high financing cost of the green industry, there is a shortage of investment in the green industry and an incentive mechanism to encourage green investment. Ma Jun (Chief economist of the Research Bureau of the people's Bank of China) [29] believes that, in order to do a good job in the environmental protection industry, it is not enough to rely only on financial investment, and we must attract social funds through financial innovation. China urgently needs to establish a financial system to encourage green investment, covering capital market, bank credit, insurance, and other financial fields. Particularly, considering the importance of direct financing, it is suggested that listed companies should be required to disclose environmental protection-related information and establish a green stock index in the future. Due to the substitution effect of green energy on traditional energy, we believe that there is a certain relationship between the green investment market and the carbon market or coal market. The green income of the stock index of China Securities Green Investment is relatively high, and there is no significant representation of environmental risk. Shanghai and Shenzhen A shares, as sample stocks, reflect the overall performance of green investment theme companies. The index takes June 29, 2012, as the base date, the adjusted market value of all sample stocks after the close of that day as the base period, and 1000 points as the base point.

Firstly, the stocks ranking in the last 20% of the average daily turnover in the sample space in the past year are excluded; secondly, according to the green income and environmental risk information of listed companies, the companies with high green income and no significant environmental risk are selected as the green investment theme to be selected; finally, according to the ranking of the average daily market value of A shares in the past year from high to low, the top one that selected 300 shares constitutes the sample stock of CSI green investment stock index.

4.3. Description of Data. We selected 1601 observations ranging from September 26, 2013, to December 10, 2020. From Figure 1, we can see the price fluctuation trend of the carbon market, steam coal future contracts, and CSI Green Investing Index.

Since its launch on June 18, 2013, the price of the carbon market in Shenzhen has risen steadily, and it is basically stable between 60 and 90 yuan at the present stage. The scarcity value of the right to use greenhouse gas emission space is more and more brought into the decision-making behavior by the government and individuals. This price incentive mechanism promotes the adjustment of energy structure and optimization of industrial structure in Shenzhen and finally promotes the development of low-carbon economy in Shenzhen. On the whole, the period from September 26, 2013, to December 26, 2015, fluctuated

TABLE 2: Variable description.

Category	Variable	Content	Data sources
Green investing market	GIS	CSI Green Investing Index (closing price)	WIND (available at http://www.wind.com.cn/)
Coal market	COAL	Steam coal future contract price (closing price)	WIND (available at http://www.wind.com.cn/)
CO ₂ emissions	CARBON	Shenzhen carbon price (closing price)	https://www.cerx.cn

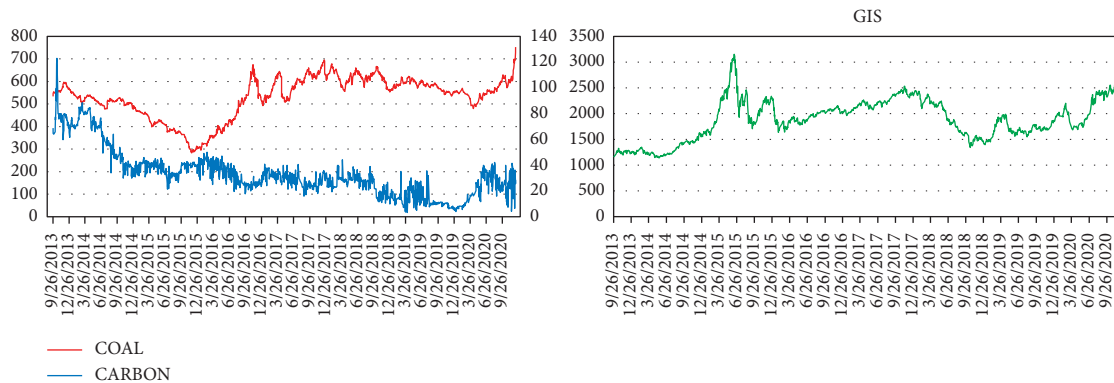


FIGURE 1: Price trends of the Shenzhen carbon market, coal market, and CSI Green Investing Index.

greatly. Due to the low volume of quota trading, the price of carbon trading fell sharply during this period. We can see the trend of coal prices from Figure 1. In recent years, due to the serious overcapacity of domestic coal, affected by imported coal, coal prices have continued to fall. In November 2015, as the Chinese government announced policies to reduce overcapacity in the coal industry, coal prices began to rise and peaked in October 2016. At the end of 2016, in order to alleviate the problems of coal supply and coal price, the Chinese government issued a series of policies to increase the number of days of coal production, which made the coal price decline. However, the Chinese government has not stopped the pace of reducing excess capacity, and the coal industry continues to reduce excess capacity, which makes coal prices rise again. At present, the price of coal is between 550 and 700 yuan/ton. We can see the price trend of the green investing market from Figure 1. Since September 2013, the green investment index has risen rapidly and reached its peak in June 2015. Since June 2015, the green investment index has been rising slowly, showing the characteristics of average recovery. After 2018, the green investment index is relatively stable.

The rate of return is an index reflecting the change of price fluctuation. The return series has many excellent statistical characteristics, and the price series is more suitable for the inspection and analysis of econometric. In order to reduce the volatility of time series data and eliminate heteroscedasticity, this paper does logarithmic processing on the original data.

Table 3 shows the return data for the three markets. Table 3 shows that the average is smaller than its standard deviation of the series, but the mean value and median of all return series are nearly 0. The Std. Dev (standard deviation) of the Shenzhen carbon trading market is 0.246616, which indicates that the market fluctuation is the most severe. When the return has a thick tail, the kurtosis of each series is more than three, and the negative skewness coefficient

TABLE 3: Descriptive statistics.

	RCARBON	RCOAL	RGIS
Mean	-0.00055	0.000214	0.000517
Median	-0.000732	0.000	0.001399
Maximum	1.963503	0.114399	0.058925
Minimum	-1.789769	-0.15544	-0.099137
Std. Dev.	0.246616	0.014475	0.017925
Skewness	0.04929	-1.157113	-0.820549
Kurtosis	17.40322	21.0647	6.682545
Jarque-Bera	13830.83	22112.61	1083.623
Probability	≤ 0.001	≤ 0.001	≤ 0.001
Sum	-0.879282	0.342389	0.827617
Sum Sq. Dev.	97.25	0.335015	0.513758
Observations	1600	1600	1600

indicates that the left tail of the three returns is longer than the right tail. From JB statistics, we can see that the normality hypothesis is rejected. It means that the return series used in this research obey the nonnormal distribution. The GARCH model can solve this problem. Furthermore, if the time series shows a volatility clustering effect, the return series is considered to be an autoregressive conditional heteroscedasticity process [30].

From Figure 2, it can be seen that all yield series have a volatility aggregation effect, which indicates that we need to consider the GARCH model to study the correlation and volatility spillover among the three markets in our research.

As shown in Table 4, the unconditional correlation coefficient of the return series shows that the carbon market in Shenzhen is positively correlated with the coal market. The Shenzhen carbon market has a negative relationship with the green investing market, and the green investment market is positively correlated with the coal market. The test results also show that, in the three markets, the absolute values of the correlation coefficients are a bit small. Because of the late start of China's carbon emission trading market, there is no national unified carbon market, only regional

market. In this study, only the Shenzhen carbon market is selected, so the impact of the carbon market on the other two markets is limited.

In this paper, ADF and PP tests are used to test the stationarity of the three series, and the test results are shown in Table 5. From the results of the ADF and PP test, the return series of the three markets are stable, which can be studied by the VAR-GARCH-BEKK and VAR-GARCH-DCC models.

5. Empirical Results

5.1. Analysis of Empirical Results

5.1.1. Empirical Results of the VAR-GARCH-DCC Model. The dynamic correlations and spillover effects between the carbon, coal, and green investing markets were estimated based on empirical methods. In this paper, we use the VAR-GARCH-DCC model to study the dynamic correlation among the three markets.

The empirical results of the VAR-GARCH-DCC model are shown in Table 6. The empirical results can be elaborated from three aspects. In the first part, the return and influence of the two markets are explained by the conditional mean equation. The second part is to analyze the conditional variance equation of two-market fluctuation through empirical research. The third part is the dynamic correlation effect between the two markets.

It can be seen from Table 6 that there is a negative correlation between the rate of return of the Shenzhen carbon market and the lagging rate of return, and the correlation degree of the coal market is the same. The lagged return of the carbon market in Shenzhen also has a significant negative impact on the return of the green investment market. The reason is that the rise of Shenzhen's carbon market price forces companies to buy quotas in the short term to make up for the shortage instead of enhancing green investment, which reduces the total green investment. Additionally, the lagged return of the green investing market and the current return of the coal market have a negative relationship. From this, we can see that the power generation and heating that rely too much on coal will face the problems of reducing coal supply and increasing energy use costs in the future.

In our model, we use the GARCH effects γ to measure long-term persistence and the ARCH effects σ to measure short-term persistence of the market. The estimation coefficient on conditional variance equation γ and terms and conditions σ is significant at the level of 1%. The values of γ are higher than values of σ , which shows that the model fits well, and the long-term sustainability of the three markets is stronger than the short-term sustainability of the three markets. Also, $\gamma + \sigma$ is the duration of the fluctuation present, and the sum of γ and σ is close to 1.

In the DCC model, the parameter α indicates the influence degree of the standard residual error of a lag period on the dynamic correlation coefficient. The closer the parameter β is to 1, the stronger the persistence of the correlation among variables. On the value of DCC parameters,

the impact of the coal market, Shenzhen carbon market, and green investment market on DCC has no short-term sustainability. From Table 6, the values of DCC parameters ($\beta = 0.726235$) are statistically significant at 1% confidence level and close to one. This shows that the impact of the coal market, Shenzhen carbon market, and green investment market on DCC has significant long-term sustainability.

In the above models, α with low values and β with the high values indicate that the correlation process rejects the shocks and obeys the mean reversion process. In addition, if the residual of the two variables increases or decreases at the same time, the correlation will rise. If the residuals of the two variables change in the opposite direction, the correlation will decline. In the three models, the coefficients of these models are positive, and the sum of them is less than 1. The volatility persistence ($\alpha + \beta = 0.987697$) of the coal market and the green investing market is much higher.

Three dynamic conditional correlation coefficient graphs are obtained by calculation. It can be seen from Figure 3 that there are dynamic correlations between Shenzhen carbon and coal markets, between Shenzhen carbon market and green investment market, and between coal market and green investment market.

The descriptive statistics of dynamic conditional correlation coefficients of the three models are given in Table 7. From the mean value of dynamic correlation, the mean value of the correlation coefficient between the Shenzhen carbon market and coal market is 0.18753, and the mean value of the correlation coefficient with the green investment market is 0.11657. Overall, China's carbon market is highly correlated with the coal market and green investment market.

The dynamic conditional correlation coefficient of the Shenzhen carbon market and coal market is between 0.47215 and 0.53614, with an average of 0.18753, indicating that there is a positive correlation between the market returns of the two markets. Our empirical result is different from the results of Lin and Chen [19] and Gou [28]. However, the coefficient between the two markets fluctuates greatly in a certain period, which indicates that the dynamic relationship between the two markets has changed under the impact. The coefficients of dynamic conditional correlation between the returns of the Shenzhen carbon market and green investment market fluctuate between -0.69547 and 0.4786 , and the mean and median of the coefficients are 0.11657 and 0.12576. Our results are different from those of Zhu and Cheng [21]. Their research results show that the higher the level of green finance, the lower the carbon emissions, but the impact coefficient is not high, indicating that the impact of the development of green finance on carbon emissions is limited. The reason for this empirical result may be that China has not yet established a unified carbon trading market, and the carbon quotas among the pilot sites cannot be circulated. As a result, the carbon trading price in the pilot sites is only formed by the supply and demand of quotas in the province (city), and the linkage with the national green investment has not been fully reflected.

The dynamic conditional relationship coefficient between the coal market and green investment market return varies from -0.35241 to 0.49867 . The mean value of the

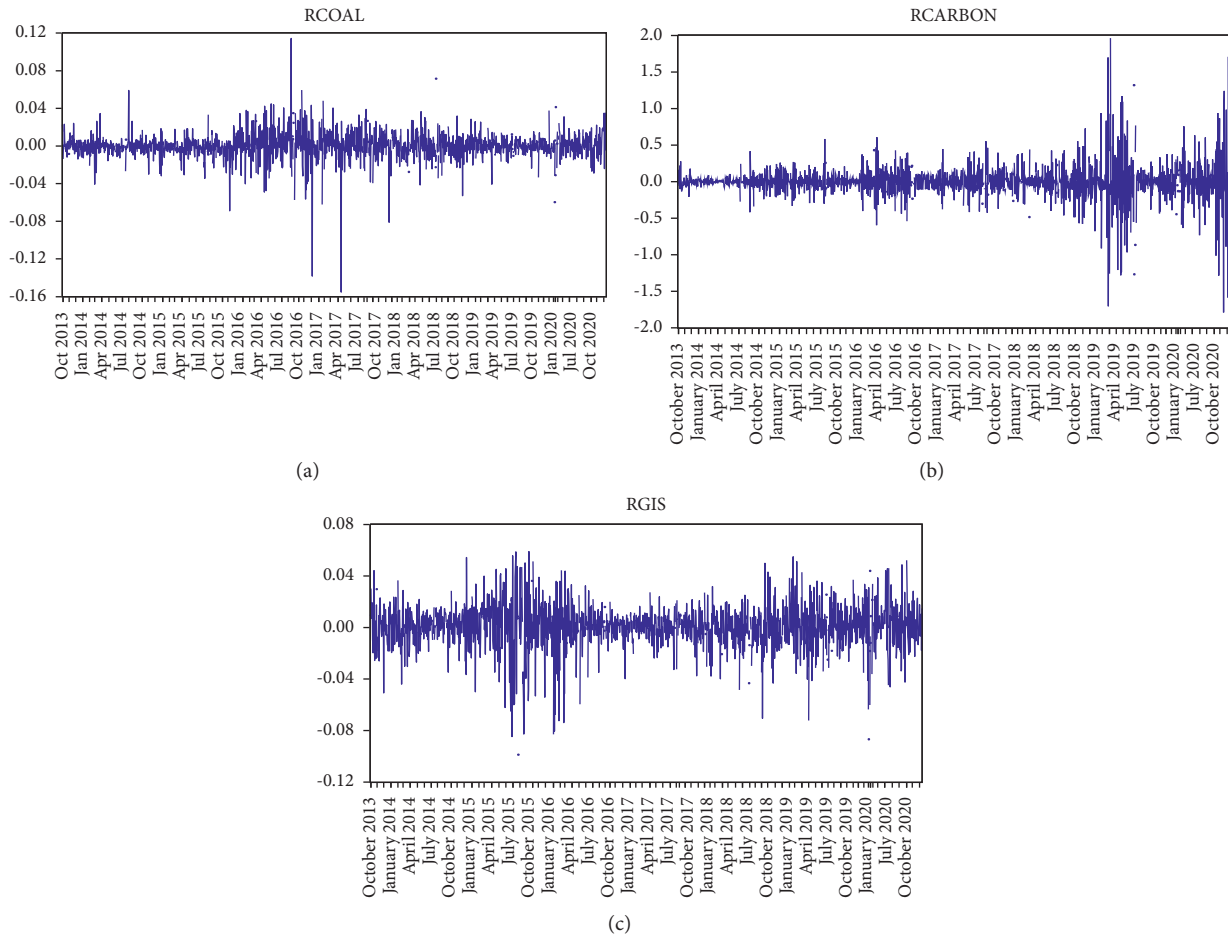


FIGURE 2: Returns of carbon, coal, and green investing market. (a) RCOAL. (b) RCARBON. (c) RGIS.

TABLE 4: Coefficients of unconditional correlations.

	RCARBON	RCOAL	RGIS
RCARBON	1.0000		
RCOAL	0.0020	1.0000	
RGIS	-0.0156	0.0557	1.0000

TABLE 5: Stationarity test.

	ADF	p value	PP	p value
RCARBON	-135.7365	0.0001	-25.7225	≤0.001
RCOAL	-43.2457	≤0.001	-43.1157	≤0.001
RGIS	-37.3876	≤0.001	-37.4462	≤0.001

estimated coefficient is -0.1347 , which indicates that the correlation between the returns of the two markets is negative. Coal is the most important fuel in China’s energy consumption structure, so it is reasonable that there is a negative correlation between the coal market and the green investing market. The results show that the dynamic conditional correlation coefficient, to a certain extent, reveals the possibility of diversification of investment in the three markets.

5.1.2. Empirical Results of the VAR-GARCH-BEKK Model. In order to investigate the interaction among the carbon market, coal market, and green investment market return series, this paper makes the Granger causality test on three-time series. The results of the test are shown in Table 8.

In this paper, the test results of three variables show that, at the significance level of 10%, two original hypotheses are rejected. They are as follows: (1) carbon market is not the Granger cause of coal market; (2) green investment market is

TABLE 6: Results of VAR-GARCH-DCC.

	RCARBON and RCOAL		RCARBON and RGIS		RCOAL and RGIS
<i>Mean equation</i>					
μ_1	-0.001283 (0.132)	μ_1	-0.00923 (0.327)*	μ_2	-0.00623 (0.213)***
μ_2	-0.00684 (0.054)**	μ_3	0.00657 (0.089)**	μ_3	-0.00684 (0.0607)***
φ_{11}	-2.138525 (1.231)	φ_{11}	-2.138525 (0.063)	φ_{22}	0.037338 (0.214)
φ_{12}	-2.159664 (0.217)	φ_{13}	-8.319055 (0.0321)	φ_{23}	-2.159664 (0.053)*
φ_{21}	-0.560726 (0.113)**	φ_{31}	-0.560726 (0.064)*	φ_{32}	-0.016865 (0.0441)
φ_{22}	0.736867 (0.962)	φ_{33}	2.205697 (0.0523)	φ_{33}	0.736867 (0.0201)
<i>Variance equation</i>					
ω_1	0.981338 (0.0041)*	ω_1	0.451378 (0.032)	ω_2	0.666592 (0.0402)
ω_2	0.991044 (0.653)**	ω_3	0.939264 (0.041)*	ω_3	0.991044 (0.0917)
σ_1	0.300446 (0.003)***	σ_1	0.32046 (0.291)***	σ_2	0.13211 (0.0708)***
σ_2	0.23937 (0.117)***	σ_3	0.17164 (0.0029)***	σ_3	0.39287 (0.0618)***
γ_1	0.699554 (0.342)***	γ_1	0.67954 (0.0014)***	γ_2	0.86789 (0.0931)***
γ_2	0.76063 (0.0314)***	γ_3	0.82836 (0.0102)***	γ_3	0.60713 (0.0405)***
<i>DCC</i>					
α	0.059116 (0.021)		-0.02263 (0.002)***		0.03635 (0.073)**
β	0.726235 (0.003)***		0.84315 (0.0102)***		0.951347 (0.0902)***
<i>Model diagnostics</i>					
AIC	11.347		10.578		7.652
SBC	10.289		11.483		7.349
LOG - L	663.631		509.754		489.371

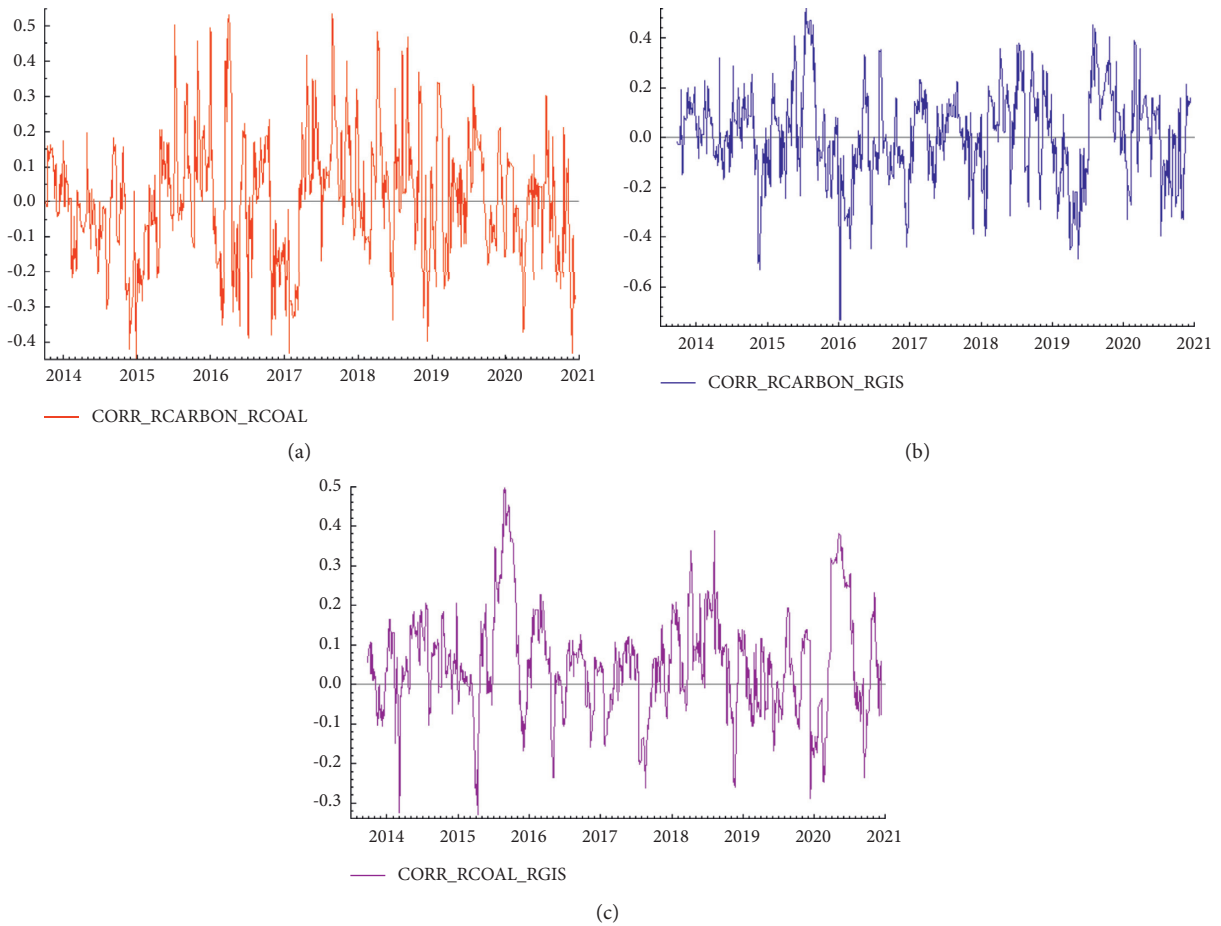


FIGURE 3: The trend of dynamic conditional correlation. (a) The dynamic conditional correlation between carbon and coal market returns. (b) The dynamic conditional correlation between carbon market returns and green investing market. (c) The dynamic conditional correlation between coal and green investing market.

TABLE 7: Descriptive statistics of dynamic conditional correlation coefficient.

	Mean	Median	Maximum	Minimum
RCARBON and RCOAL	0.18753	0.3871	0.53614	-0.47215
RCARBON and RGIS	0.11657	0.12576	0.4786	-0.69547
RCOAL and RGIS	-0.1347	0.24157	0.49867	-0.35241

TABLE 8: Granger causality test of each variable.

Null hypothesis	F-statistic	Prob.
RCOAL does not Granger cause RCARBON	1.16183	0.003132
RCARBON does not Granger cause RCOAL	1.04853	0.3507
RGIS does not Granger cause RCARBON	0.80593	0.4469
RCARBON does not Granger cause RGIS	4.35699	0.013
RGIS does not Granger cause RCOAL	0.3574	0.003574
RCOAL does not Granger cause RGIS	0.6229	0.006229

not the Granger cause of carbon market. Therefore, the following understanding can be formed:

First, from the long-term trend, the coal market has a long-term impact on the carbon market.

Second, although the carbon market is the Granger cause of the green investment market, the green investment market is not the Granger cause of the carbon market.

Third, there is a bidirectional Granger causality between the green investing market and the coal market.

Since the Granger causality test is based on F-test, its basic idea is to observe whether the fitting effect of the equation can be significantly improved when the lag variables of other variables are added to the VAR equation. Granger causality test reflects the interaction between variables, but it cannot reflect the interaction between variable fluctuations.

Engle [31] research finds that, due to the existence of investment in the capital market, the capital market has a "cluster effect" and "leverage effect," and the market price fluctuation has an arch effect. In order to further study the asymmetric spillover effects among the three markets, this paper selects the VAR-GARCH-BEKK model. The test results of the model are shown in Table 9. The test results were divided into two parts. The first part analyzes the return and impact effects among the three markets by conditional means. The second part analyzes the volatility spillover effect among the three markets by using the conditional variance equation. The regression result of the conditional variance equation is the most important part of the BEKK model. Next, we will discuss the regression results.

Table 9 shows the volatility spillover test results among the carbon market, coal market, and green investing market. a_{ij} (ARCH effect) is the impact of the arch effect of interaction between two variables on the future collaborative volatility relationship, and b_{ij} (GARCH effect) is the impact of volatility persistence of interaction between two variables on the future volatility of two variables.

Hypothesis 1. $a_{ij} = b_{ij} = 0$ means that there is no one-way volatility spillover effect between market i and market j ;

Hypothesis 2. $a_{ji} = b_{ji} = 0$ means that there is no one-way volatility spillover effect between market j and market i ;

Hypothesis 3. $a_{ij} = b_{ij} = a_{ji} = b_{ji} = 0$ means that there is no bidirectional volatility spillover effect between market i and market j .

In the carbon trading market and coal market model established in this paper, the estimated coefficients a_{11} and a_{22} are significantly different from zero at the significance level of 10%, which indicates that the returns of the carbon market and coal market have an obvious ARCH effect. The estimated coefficients b_{11} and b_{22} are significantly different from zero at the significance level of 5%, which indicates that the returns of the carbon market, coal market, and green investment market have an obvious GARCH effect. Some foreign studies have found that the coal market has a significant volatility spillover effect on the European carbon market [21, 22]. To some extent, since China has not established a unified carbon trading market, there are only eight pilot projects, so the market structure, mechanism, and other aspects are not perfect, and there are big problems. As a modern emerging market, the domestic carbon market has started late and has not become an important investment target for investors. In addition, due to the low quota price, the impact of Shenzhen's carbon market on the coal market is limited.

In the model of the Shenzhen carbon market and green investment market, our results show that there is no two-way volatility spillover effect between the two markets. In our opinion, we believe that there is no spillover effect between the Shenzhen carbon market and the green investment market for two reasons.

(1) We choose the carbon trading prices to be traded in the Shenzhen carbon market, whereas the green investing market is calculated by selecting the stock price of companies with high green income and no significant environmental risk according to the green income and environmental risk information of listed companies. In addition, some of these companies with the theme of green investment are included in the Shenzhen carbon market, so the impact of Shenzhen's carbon emission trading quota price on the green investment market price is limited. (2) In

TABLE 9: Result of VAR-GARCH-BEKK.

RCARBON and RCOAL		RCARBON and RGIS		RCOAL and RGIS	
<i>Mean equation</i>					
μ_1	-0.01273 (0.26135)	μ_1	-0.0509 (0.25922)	μ_2	-0.0305 (0.27552)**
μ_2	-0.0053 (0.35938)*	μ_3	0.00643 (0.35246)	μ_3	0.0533 (0.32760)
φ_{11}	0.010201 (0.5751)***	φ_{11}	0.012224 (0.582)***	φ_{22}	0.01162 (0.33225)**
φ_{12}	0.0092 (0.27494)	φ_{13}	0.043 (0.31702)	φ_{23}	-0.03 (0.30974)*
φ_{21}	0.002055 (0.50908)	φ_{31}	0.001968 (0.50344)**	φ_{32}	0.001076 (0.20767)
φ_{22}	0.956149 (0.11603)**	φ_{33}	0.951874 (0.91175)	φ_{33}	0.983258 (0.13096)
<i>Variance equation</i>					
c11	-0.002174 (0.27319)**	c11	-0.001529 (0.26176)*	c22	-0.00037 (0.33547)
c21	-0.000542 (0.36423)**	c31	0.00062 (0.35488)	c32	0.000485 (0.36799)
c22	-0.519903 (0.33807)	c33	-0.530391 (0.034748)	c33	-0.047379 (0.29016)
a11	-0.212557 (0.31370)*	a11	-0.218972 (0.31678)***	a22	0.012045 (0.29399)**
a12	-0.095003 (0.20385)	a13	-0.06267 (0.16469)	a23	0.008294 (0.18608)*
a21	-0.072353 (0.21289)**	a31	-0.004474 (0.18009)	a32	0.027269 (0.16421)**
a22	-0.1597 (0.12903)**	a33	0.04408 (0.16024)***	a33	0.029829 (0.18451)***
b11	0.001891 (0.12015)***	b11	0.000229 (0.17213)**	b22	-0.009958 (0.19778)*
b12	-0.041182 (0.32738)	b13	0.029175 (0.26872)	b23	0.032983 (0.27957)**
b21	0.005892 (0.33386)	b31	0.005515 (0.27617)**	b32	0.007928 (0.28708)**
b22	0.00997 (0.42935)**	b33	0.012253 (0.41784)	b33	0.001154 (0.39647)***
d11	-0.000103 (0.22818)	d11	-0.000054 (0.025246)**	d22	-0.033 (0.14093)
d12	0.001656 (0.39981)**	d13	0.00039985 (4.198)*	d23	0.01062 (0.46787)***
d21	0.967074 (0.80048)***	d31	0.95 (0.16799)*	d32	0.983225 (0.57755)
d22	0.254474 (0.26736)	d33	0.282485 (0.19618)**	d33	0.17114 (0.23108)
<i>Diagnostics</i>					
AIC	9.351	10.871	7.762		
SBC	9.475	10.139	7.941		
LOG-L	5185.165	4842.467	8767.354		

reality, the price of carbon emissions trading is also affected by energy prices, financial markets, and policies. The impact of the green investment market on the Shenzhen carbon market is limited.

In the model of the green investment market and coal market, there is a two-way volatility spillover between the two markets. As we all know, as a part of the energy market, the domestic coal market plays an equally important role in China's energy market as international crude oil plays in the world's energy market. The estimated coefficients a22 and a33 are significantly different from zero, which indicates that green investment and coal market returns have an obvious arch effect.

5.2. *Optimal Portfolio.* The importance of the volatility spillover effect between the two markets lies in that investors' assets in both markets are unstable and vulnerable to risk and uncertainty. The key of market trading is to determine the optimal hedging ratio, in other words, the number of future contracts that should be hedged for a specific spot market risk position. This paper establishes the optimal portfolio weight to determine the optimal quantity and hedging ratio of each market. The optimal holding weight of the two assets can be expressed as follows [32]:

$$w_{i,j,t} = \frac{h_t^{ii} - h_t^{ij}}{h_t^{jj} - 2h_t^{ij} + h_t^{ii}}$$

$$w_{i,j,t} = \begin{cases} 0 & \text{if } w_{i,j,t} < 0, \\ w_{i,j,t} & \text{if } 0 \leq w_{i,j,t} \leq 1, \\ 1 & \text{if } w_{i,j,t} > 1, \end{cases} \quad (8)$$

$$\beta_{i,j,t} = \frac{h_t^{ij}}{h_t^{ii}}$$

where $w_{i,j,t}$ is the weight of the asset j in a one CNY portfolio of asset i and asset j at time t . The weight of the asset i is $1 - w_{i,j,t}$. h_t^{ij} is the conditional covariance between asset i and asset j .

Based on the estimation results of the VAR-GARCH-BEKK model, this paper calculates the optimal hedging ratio of the carbon market and coal market. It can be seen from Table 10 that the optimal weight of the carbon market is 79.65%, and that of the coal market is 20.35%. The optimal hedging ratio of the carbon market is 35.18%; that is, shorting 0.3518 yuan coal market can hedge 1 yuan long position in the carbon market.

TABLE 10: Hedging ratio.

Optimal ratio	RCARBON and RCOAL	RCOAL and RCARBON
$\omega_{ij,t}$	0.7965	0.2035
$\beta_{ij,t}$	0.3518	0.1469

6. Conclusion

Based on the VAR-GARCH-DCC and VAR-GARCH-BEKK models, this paper empirically studies the dynamic correlation and volatility spillover effect among the Shenzhen carbon market, coal market, and green investment market. Besides, there is a certain dynamic correlation among the carbon trading market, coal market, and green investment market, but the financial function is still not comprehensive enough. This also shows that as a new financial market form, the carbon market has defects in its market structure, mechanism, and function, and the rationality, complexity, and effectiveness of its market mechanism are also controversial. Based on the empirical study, we can draw some important conclusions:

- (1) In the VAR-GARCH-DCC model, the parameters representing the persistence of the correlation are significant and close to 1 in all models, which indicates that the long-term persistence of the correlation among the volatility of returns in the carbon market, coal market, and green investment market is very high. Among them, the sustainability between the green investing market and the coal market is the highest, followed by the carbon market and green investing market, while the sustainability between the carbon market and coal market is relatively low.
- (2) In the three groups of dynamic conditional correlation coefficient graphs, the correlation coefficient of return fluctuation between the carbon market, coal market, and green investing market has obvious time-varying characteristics. To some extent, the time-varying characteristics of the correlation coefficient between the carbon market and the coal market are related to the fluctuation of coal price. The correlation coefficient between the two markets is higher, while the coal price is lower. In the same period, the correlation coefficient of the coal market in green investing market also has obvious time-varying characteristics.

Due to the volatility spillover effect between the carbon market and the coal market, the establishment of the portfolio and hedging mechanism of the two markets can reduce the trading risk and provide a better asset allocation strategy. With the gradual establishment and improvement of China's carbon market, there are dynamic links and volatility spillover effects between carbon and coal markets. The relationship between the coal market, carbon market, and green investment market may be highlighted or even strengthened.

In summary, the contribution of our research is to help the government, investors, and other relevant personnel

understand the dynamic correlation and spillover effects among carbon, coal, and green investment markets and help them formulate investment strategies and improve the yield. Investors should pay attention to the relationship among the fluctuation of the carbon market, coal market, and green investing market and reduce the risk of asset portfolio through reasonable asset allocation. At the same time, as the relationship among the fluctuation of carbon, coal, and green investing markets is time-varying, it is necessary to constantly adjust the allocation proportion of asset portfolio, actively carry out risk management, and obtain a higher risk-adjusted income.

Data Availability

The daily data used to support the findings of this study have been deposited in the Wind Database in China.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

All authors read and approved the final manuscript.

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References

- [1] 2020, https://weibo.com/ttarticle/p/show?id=2309404570757316346170#_loginLayer_1618985959052.
- [2] J. Chen, Y. Jiang, S. Li et al., *Zero-Carbon Investing: Opportunities from China's Carbon-Neutrality Goal*, RMI and Investment Association China, Beijing, China, 2021.
- [3] E. Alberola, J. Chevallerier, and B. Chèze, "Price drivers and structural breaks in European carbon prices 2005-2007," *Energy Policy*, vol. 36, no. 2, pp. 787-797, 2008.
- [4] S. J. Byun and H. Cho, "Forecasting carbon futures volatility using GARCH models with energy volatilities," *Energy Economics*, vol. 40, pp. 207-221, 2013.
- [5] H. Liu and Y. Chen, "A study on the volatility spillovers, long memory effects and interactions between carbon and energy markets: the impacts of extreme weather," *Economic Modelling*, vol. 35, pp. 840-855, 2013.
- [6] J. C. Reboredo, "Volatility spillovers between the oil market and the European Union carbon emission market," *Economic Modelling*, vol. 36, pp. 229-234, 2014.
- [7] H. Xiaohui and Y. Baochen, "The dynamic relationship between the European union's emission trading scheme and energy market," *Resources Science*, vol. 36, pp. 1442-1451, 2014.
- [8] Y. J. Zhang and Y. F. Sun, "The dynamic volatility spillover between European carbon trading market and fossil energy market," *Journal of Cleaner Production*, vol. 112, pp. 2654-2663, 2016.
- [9] Y. M. Wei, L. C. Liu, Y. Fan et al., "China energy report," *Carbon Emission Research*, Science Press, Beijing, China, 2008.

- [10] O. Ulrich, "EU Emission Allowances and the stock market: evidence from the electricity industry," *Ecological Economics*, vol. 68, pp. 1116–1126, 2009.
- [11] B. Mehmet, R. Demirer, S. Hammoudeh, and D. K. Nguyen, "Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk," *Energy Economics*, vol. 54, pp. 159–172, 2016.
- [12] C. Li, W. T. Ma, and B. Wang, "Research on spillover effect within financial markets," *The Journal of Quantitative and Technical Economics*, vol. 27, pp. 3–19, 2010.
- [13] J. Cui, J. Huang, and K. Li, "Research on the relationship between Carbon Emission spot Prices, Energy prices and the dow jones index of China based on VAR," *On Economic Problems*, vol. 7, pp. 27–33.
- [14] D. D. Wang and D. T. Yang, "Driving factors of China's carbon emission rights' price—based on data of guangzhou carbon emissions exchange," *Journal of Capital University of Economics and Business*, vol. 5, pp. 87–95, 2018.
- [15] M. Lu and Y. Q. Cang, "Grey correlation analysis on energy prices and carbon price in China," *Environmental conformity Assessment*, vol. 10, pp. 88–92, 2018.
- [16] Z. H. Wang and Y. Hu, "An empirical analysis of the factors affecting the carbon price in China," *Industrial Technology & Economy*, vol. 37, pp. 128–136, 2018.
- [17] R. F. Engle and K. F. Kroner, "Multivariate simultaneous generalized ARCH," *Econometric Theory*, vol. 11, no. 1, pp. 122–150, 1995.
- [18] B. Lin and J. Li, "The spillover effects across natural gas and oil markets: based on the VEC-MGARCH framework," *Applied Energy*, vol. 155, pp. 229–241, 2015.
- [19] B. Lin and Y. Chen, "Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: a case of Beijing CET market in China," *Energy*, vol. 172, pp. 1198–1210, 2019.
- [20] G. H. Hua, H. Y. Wu, K. Zhou, and X. Q. Ma, "Policy orientation, market openness and jump behaviors: study of China's regional carbon emission market," *Systems Engineering*, vol. 35, no. 10, pp. 37–45, 2017.
- [21] M. S. Zhu and M. M. Cheng, "On correlation between carbon emission and green finance development: analysis of provincial panel data in China from 2008 to 2018," *Journal of Wuhan Business University*, vol. 33, no. 5, pp. 58–61, 2019.
- [22] T. Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, vol. 31, no. 3, pp. 307–327, 1986.
- [23] A. A. Salisu and T. F. Oloko, "Modeling oil price-US stock nexus: a VARMA-BEKK-AGARCH approach," *Energy Economics*, vol. 50, pp. 1–12, 2015.
- [24] H. Chen, Z. X. Liu, Y. P. Zhang, and W. You, "The linkages of carbon spot-futures: evidence from EU-ETS in the third phase," *Sustainability*, vol. 12, no. 6, pp. 1–18, 2020.
- [25] A. Jain and P. C. Biswal, "Dynamic linkages among oil price, gold price, exchange rate, and stock market in India," *Resources Policy*, vol. 49, pp. 179–185, 2016.
- [26] Y. J. Lee, N. W. Kim, K. H. Choi, and S. M. Yoon, "Analysis of the informational efficiency of the EU carbon emission trading market: asymmetric MF-DFA approach," *Energies*, vol. 13, no. 9, pp. 1–14, 2020.
- [27] C. Li, W. T. Ma, and B. Wang, "Learning effect, change of inflation target and the formation of inflation expectation," *Economic Research Journal*, vol. 10, pp. 39–53, 2011.
- [28] W. J. Guo, "Factors Impacting on the Price of China's Regional Carbon Emissions Based on Adaptive Lasso Method," *China Population, Resources and Environment*, vol. 25, no. S1, pp. 305–310, 2015.
- [29] http://pinglun.youth.cn/ll/201509/t20150915_7117518.htm.
- [30] W. H. Chan and J. M. Maheu, "Conditional jump dynamics in stock market returns," *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 377–389, 2002.
- [31] R. F. Engle, "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models," *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 339–350, 2003.
- [32] K. F. Kroner and V. K. Ng, "Modeling asymmetric movements of asset prices," *Review of Financial Studies*, vol. 11, pp. 844–871, 1998.