The fluctuation of stock market of "low carbon" enterprise and related policy impact

Fusen Shen*

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

*Corresponding author: 1532638869@qq.com

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Abstract: In this paper, under the policy environment of "carbon neutrality" and "carbon peak", the literature review is firstly conducted to describe domestic and international carbon trading and policy situation. Then, the closing price of the concept plate "CSI Mainland Low carbon Economy Theme index" represents the enterprise environment under the low-carbon environment. The GARCH model is used to study the volatility of the stock market. Then select economic uncertainty index and trade uncertainty index to represent the impact of policy factors, based on the GARCH-MIDAS model to analyze, finally draw a conclusion.

1. Introduction

President Xi Jinping set new targets for Reducing China's carbon emissions at a summit on climate ambitions on December 12.In September this year, Xi announced that China would "strive to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060", and further stated that "By 2030, China's carbon dioxide emissions per unit of GDP will drop by more than 65 percent compared with 2005.So as to achieve the emission reduction effect, the carbon trading market vigorous development, our country at present is mainly made of carbon cap-and-trade, to force a way for trading, so many enterprises in response to "carbon neutral" and "carbon peak" policy, start from the enterprise operation and the mode of production, energy saving and emission reduction of the corresponding stock market were also set up. Therefore, the research on related stocks is worthy of further study.

2. Literature review

Domestic and foreign scholars have carried out studies on carbon trading:

Domestic literature: Qi Tianyu, Yang Yuanzhe et al. [1] considered the impact of China's accession to the international Carbon Emission Trading System (ETS) dominated by Australia and the European Union on emission reduction and welfare of various countries based on three independent scenarios. Mo Jianlei [2] et al. studied the fluctuation of carbon price and analyzed the root of the fluctuation by combining carbon tax from the micro and macro perspectives. Diao Yunfei [3] et al. conducted a general empirical analysis of GARCH model in four places in China, analyzed the whole carbon trading market in China and put forward relevant suggestions.

Foreign literature: Boqiang Lin [4] conducted an efficiency analysis on the impact of ETS prices on energy consumption, carbon dioxide emissions and economy. Jennifer Morris[5] found the energy saving efficiency of CCS by considering the influence of CCS on the carbon price relative to other power generation methods on power generation efficiency.E. Marrasso[6] explored various energy utilization efficiencies from the perspective of the impact of carbon emissions and power generation efficiency on various energy efficiencies.

To sum up, the function of carbon emission permit is expounded macroscopically at home and abroad, but it is rarely specific to the fluctuation of a certain region, and the entity correlation is low.

There are also studies on the volatility of carbon price at home and abroad:

Domestic literature: Qian Chen and Xiaoyan Liu [7] etc. Research has shown that fluctuations in the long-term trend by the real economy running (such as economic growth, inflation, etc.), financial policies, such as monetary policy, regulation, market structure (e.g., investors, financial leverage, financial products), the influence of the short-term volatility is showed the characteristics of the mean reversion, It is more sensitive to policy news and emergencies in the market, such as the regulatory measures introduced by the stock market and the tightening of market liquidity, which will make the stock market fluctuate greatly in the short term. Lei Tian and Jianhao Lin [8] pointed out that economic policy uncertainty is an important embodiment of economic uncertainty and one of the two important sources of economic uncertainty.

Foreign literature: Adrian et al. [9] pointed out that the most important factor affecting the long-term trend of the stock market is still the economic cycle. When the economy is in recession, the economic system will face greater uncertainty, because the government will frequently introduce economic policies to stimulate output, promulgate regulatory measures to intervene in the market, affect market expectations and investor sentiment, so that the volatility of the stock market will significantly increase, and the stock market risk situation will also change. Rodrik et al. [10] studied the impact of market uncertainty on enterprise investment, and the results showed that increased uncertainty would make enterprise investment lag and increase enterprise cost.

To sum up, there are deep researches on the influence of policy factors and macro factors both at home and abroad.

3. Model is introduced

3.1 GARCH model

GARCH model, known as the generalized ARCH model, is an extension of the ARCH model and was developed by Bollerslev (1986). It is an extension of ARCH model, GARCH(P,0) model, which is equivalent to ARCH(P) model.

$$x_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \ldots + \beta_p x_{t-p} + u_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \lambda_1 \sigma_{t-1}^2 + \ldots + \lambda_p \sigma_{t-p}^2 + \alpha_1 u_{t-1}^2 + \ldots + \alpha_q u_{t-q}^2 \tag{2}$$

Equation (1) is called the conditional mean equation, and Equation (2) is called the conditional variance equation, which illustrates the variation characteristics of the conditional variance of time series. In addition, the above formula should satisfy:

$$\begin{aligned} &\alpha_0 > 0, \\ &\alpha_i \geq 0, i = 1, 2, \ldots q, \\ &\lambda_i \geq 0, i = 1, 2, \ldots p \\ &\mathbf{0} \leq \left(\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \lambda_i \right) < \mathbf{1} \end{aligned} \tag{3}$$

In addition, many empirical studies show that the yield distribution not only has the characteristic of peak and thick tail, but also the impact of yield residual on the yield is asymmetric. When the market is negatively impacted, the stock price falls and the conditional variance of return rate expands, leading to greater volatility of stock price and return rate. Conversely, as share prices rise, volatility falls. The decline in stock price leads to the decline in the value of the company's stock. Assuming that the company's debt remains unchanged, the company's financial leverage increases and the risk of holding the stock increases. So the effect of negative shock on conditional variance is also called leverage effect. Since the impact of positive and negative shocks on conditional variance in GARCH model is symmetric, the GARCH model cannot depict the asymmetry of conditional variance fluctuation of return rate.

3.2 GARCH-MIDAS model

When matching economic information and stock market volatility, due to the lag and low frequency of macroeconomic information, most existing methods focus on reducing the frequency of stock market data and constructing models with monthly or quarterly data. The estimation method that converts the daily data of the stock market into monthly data or quarterly data will lose the high-frequency effective information in the stock market, causing errors in parameter estimation and volatility prediction, and failing to evaluate the comprehensive impact of economic information on stock market volatility [11].Drawing on the research of Engle et al. [12], this paper constructs the GARCH-MIDAS model with exogenous variables to analyze the impact of economic uncertainty on stock market volatility. The return rate and volatility of stock market are set as follows:

$$\begin{aligned} r_{it} &= \mu_t + \sqrt{\tau_t g_{ii} \varepsilon_t}, \varepsilon_t | \ \Phi_{i-1,t} \sim N(0,1) \\ \sigma_{it}^2 &= \tau_t g_{i,t} \end{aligned} \tag{4}$$

Where $\Phi_{i-1,t}$ is the information set of the return rate on the i-1 day of the month T, volatility σ_{it}^2 is divided into long-term trend τ_t and short-term volatility $g_{i,t}$, short-term volatility follows GARCH (1, 1) model, namely:

$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{5}$$

Where, α > 0, β≥0, α+β < 1, the long-term trend is affected by uncertainty index X, τ_t in the specific form:

$$\tau_t = m + \theta_1 \sum_{k=1}^{n} \phi_{1k} \left(\omega_{11}, \omega_{12}\right) \mathrm{X1}_{t-k} + \theta_2 \sum_{k=1}^{K} \phi_{2k} \left(\omega_{21}, \omega_{22}\right) X\,2_{t-k} \tag{6}$$

Where, K is the maximum lag order of low-frequency variables, and the coefficients θ_1 and θ_2 are the long-term influence coefficients of X1 and X2 on volatility, respectively. $\theta_{\mathrm{k}}\left(\omega_1, \omega_2\right)$ is the weight function of Beta lag variable, in the form of:

$$\varphi_k\left(\omega_1, \omega_2\right) = \frac{(k/K)^{\omega_1 - 1}(1-k/K)^{\alpha_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1}(1-j/K)^{\omega_2 - 1}} \tag{7}$$

In order to ensure that the weight of lag variable is in attenuation form (the closer to the current period, the greater the influence on the current period), ω11=ω21=1 is generally fixed, and the attenuation speed of the influence degree of low frequency data on high frequency data is determined by the coefficients ω12 and ω22.At this point, the Beta weight function is simplified as:

$$\varphi_k\left(\omega_2\right) = \frac{\left((1-k/K)^{\omega_2 - 1}\right.}{\sum_{j=1}^{K} \left((1-j/K)^{\omega_2 - 1}\right.} \tag{8}$$

When estimating the maximum lag order K in the weight function, this paper uses the information of the past year to estimate the fitting effect of the weight coefficient. For daily and monthly data, K=36;If you have daily and quarterly data, K=12.In this paper, daily stock market return rate and monthly economic uncertainty index data are selected, so K=12.

According to the distribution function and model setting of return rate, the required parameters are obtained by maximum likelihood estimation, and the maximum likelihood function is:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\left[\log g_t(\Phi)\tau_t(\Phi) + \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)}\right] \tag{9}$$

3.3 Root error of prediction and absolute error of prediction

RMSE (root error of prediction) and MAE (absolute error of prediction) are selected for the accuracy of in-sample prediction with the addition of uncertain variables.

$$\begin{aligned} RMSE &= \frac{1}{T}\sum_{t=1}^{T}\left(\hat{\sigma}_t^2 - E_t\left(\sigma_t^2\right)\right)^2 \\ MAE &= \frac{1}{T}\sum_{t=1}^{T}\left|\sigma_t^2 - E_t\left(\sigma_t^2\right)\right| \end{aligned} \tag{10}$$

We assign $\hat{\sigma}_t^2$ to the conditional variance estimated by our model, and $E_t\left(\sigma_t^2\right)$ to the monthly volatility that serves as a proxy variable for the volatility. The smaller RMSE and MAE values, the smaller the difference between the predicted value and the actual value, and the better the prediction effect of the model.

4. Model is introduced

4.1 Descriptive statistics of the mainland low-carbon sector

This paper selects 488 daily closing price data of "CSI Mainland Low carbon Economy Theme Index" (000977.CSI) from December 28, 2018 to December 31, 2020 for analysis, representing the enterprise environment in a low carbon environment. The specific information of the sector is Table 1.

The time series plot of the daily closing price is shown in Figure 1. It can be seen that the daily closing price is approximately between 1000 and 2000, and gradually rises recently. In early 2020, due to the impact of the global COVID-19 epidemic, it drops slightly, but the impact is not significant, mainly because companies in the low-carbon sector have little contact with daily residents. Temporary shutdowns would not be much of a shock in a carbon-neutral, peak-carbon environment.

In the theory of time series, simple rate of return and logarithmic rate of return are generally used to describe the rate of return series. However, the daily data of carbon price used in this paper are continuous and compound, so logarithmic rate of return is used to describe the carbon price data of six stages, and logarithmic rate of return of carbon price is taken as the research object of this paper.

Daily rate of return is expressed as:

$$R(t) = ln(Pt\ \ / Pt-1) = ln(Pt) - ln(Pt-1) \tag{11}$$

The results are realized by MATLAB.

In order to better analyze the volatility of the rate of return series, this paper uses descriptive statistical indicators such as mean, maximum, minimum, standard deviation, skewness and kurtosis to analyze the basic characteristics of the daily volatility of the rate of return of carbon price in the two stages.The descriptive statistics of daily rate of return of two-stage carbon price are shown in Table 2.

It can be seen from table 2 that the average value of the closing price yield of the mainland low-carbon plate is close to 0 and greater than 0, indicating that the stock price shows an upward trend; In terms of standard deviation, the standard deviation of daily return of low-carbon stock price is very small and relatively stable; In terms of skewness, the skewness of the daily return of stock price is less than 0, showing an obvious left skew trend, indicating that its return is often lower than the average; In terms of kurtosis, the kurtosis of the daily return of stock price is obviously greater than 3, indicating that the distribution of the daily return of stock price is more concentrated. On the whole, the daily returns of the stock prices of the mainland low-carbon plates show the characteristics of peak and thick tail, and the JB test value is 1, indicating that the daily returns of the stock prices of the mainland low-carbon plates refuse to obey the assumption of normal distribution.

Table 1. Plate information

Index name	CSI Mainland Low carbon Economy Theme index		Index type	equity
Index code	000977.CSI		Base date	2010-06-30
Release date	2011-01-21		basic point	1000
Issuing agency	China Securities	Index Co., Ltd	Income treatment method	Price index
Performance benchmark	7		Number of components	50
Subordinate to the plate	The concept of plate		Weighted way	--
Index profile	The CSI Mainland Low-carbon economy Theme Index selects 50 low-carbon economy theme companies with high daily total market capitalization from the Shanghai and Shenzhen A-shares to form A sample stock to reflect the overall trend of low-carbon economy companies			

Table 2. Descriptive statistics of daily yield of closing price

Obs	mean	maximum	minimum	S.D.	skewness	kurtosis	JB test
488	7.0546e-04	0.0229	-0.0272	0.0070	-0.3089	5.0096	ans=1

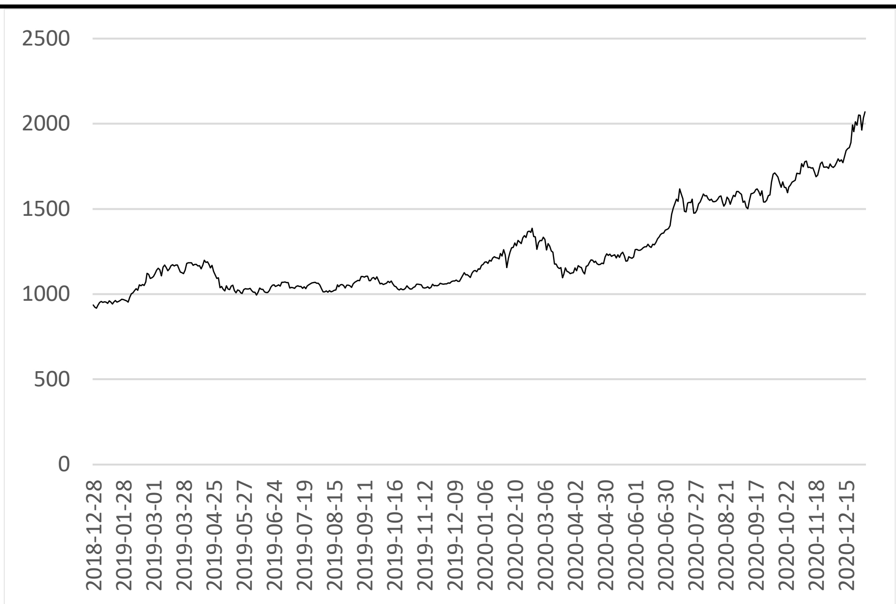

Figure 1. trend of daily closing price

4.2 Test the stability of daily return series

At present, there are many methods to test the stationarity of time series in theory, and the most commonly used methods are observation test and unit root test. The observation method test is mainly to roughly judge the stationarity of the time series by observing the time path graph of the time series. If the graph of the time series basically fluctuates up and down around its mean value and the fluctuation amplitude is similar, it is judged that the time series is stable; If the graph of the time series does not fluctuate around the mean value and shows an obvious upward or downward trend, it is judged that the series is non-stationary and further data processing is needed to make it stable. Compared with the observation method test which can only roughly judge the stationarity, the unit root test is more accurate and reliable because it uses statistics. The initial unit root test is generally completed by DF test. Later, with the deepening of research, higher-order time series have higher requirements for the test, Therefore, the ADF test extended by Dickey and fuller on the basis of DF test is widely used. This paper uses the ADF test to test the stability of the daily return of the stock price of the mainland low-carbon plate, and judges whether the data is stable through the "ADF test" function. The results show that the output results of "ADF test" function are all 1, indicating that the daily return series of stock prices of mainland low-carbon plates are stable series. See Figure 2. for the fluctuation trend of daily return series of stock price.

Figure 3 shows the calculation results of auto correlation and partial autocorrelation of daily return series of mainland low-carbon plate. It can be seen from Figure 3 that the autocorrelation lag order is 11 and the partial autocorrelation lag order is 11. Accordingly, the ARMA (11,11) model is established. The final prediction error FPE value of the model is 0.0005096 and the mean square error MSE value is 0.00004657.

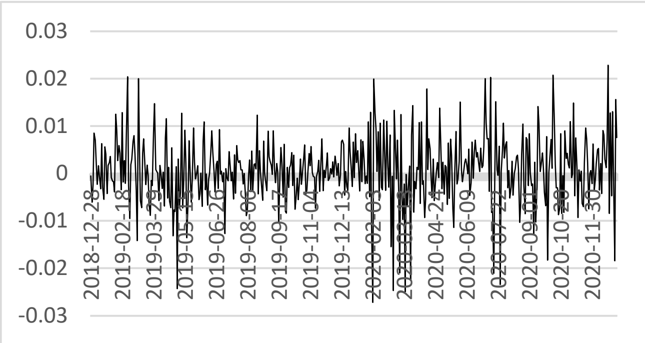

Figure 2. Daily yield trend

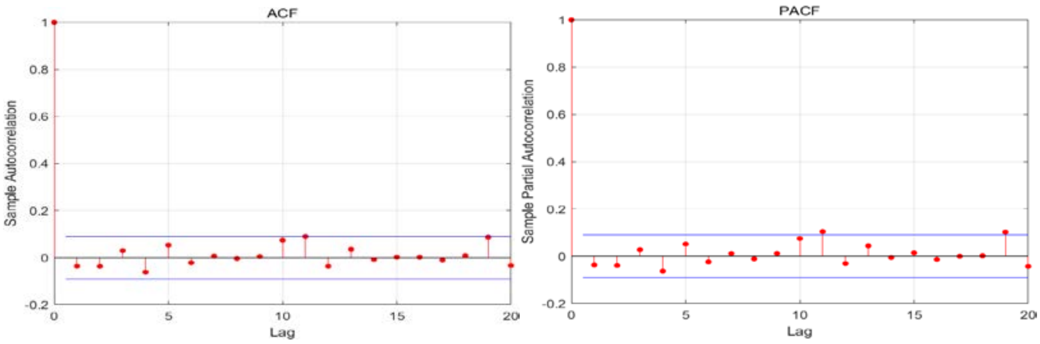

Figure 3. Autocorrelation and partial autocorrelation of daily return

4.3 Model diagnostic test

According to the ARMA (11,11) model of low-carbon daily rate of return in the mainland, the residual series are tested by white noise. If the residual sequence is not a white noise sequence, it means that there is still some valuable information in it, and the model needs to be further improved. This paper first uses the "resid" function to generate the residual sequence for this model, then uses the "lbqtest" function to test the autocorrelation of the residual sequence, uses the "archtest" function to test the arch effect of the residual sequence, and judges whether there is valuable information waiting to be mined in the daily return residual sequence of the stock price of the sector according to the program running results.

The output results of autocorrelation LBq test and arch effect test of ARMA (11,11) model are 1, indicating that the residual sequence has autocorrelation and arch effect, so the model needs to be improved accordingly. The residual series of the two-stage corresponding models are tested for arch effect with lag orders of 10, 15 and 20 respectively, and the output results are all 1, indicating that there is a high-order arch effect, namely GARCH effect, in the daily return series of stock price of low-carbon plate. Therefore, it is considered to further establish GARCH model.

4.4 Modeling and simulation of GARCH

GARCH model comes from the expansion of the constraints of arch model. The variance equation of GARCH model adds a time-delay structure to the variance equation of arch model, so as to solve the problem of insufficient parameter estimation efficiency of high-order arch model, which is more widely used in empirical research. For the stock price daily return series of this sector, GARCH (1,1), GARCH (1,2) and GARCH (2,1) models are established respectively. The results are shown in table 3.

By looking at the AIC value and BIC value, we can get that GARCH (1,1) is the most suitable. Therefore, this model is established. The GARCH term is 0.86655, indicating that the current variance still has an impact on the variance in the next period, and nearly 90% of the impact still exists in the next period; The sum of GARCH and arch is 0.97186. Less than 1 satisfies the parameter constraints and is very close to 1, indicating that the impact on the conditional variance is persistent, and the attenuation of volatility is slow. Once there is a large fluctuation, it is difficult to eliminate it in the short term, and the impact plays an important role in all forecasts in the future.

Table3. GARCH (1,1)

	Value	Standard Error	T Statistic	P Value
Constant	1.7578e-06	1.3783e-06	1.2753	0.20219
GARCH {1}	0.86655	0.027518	31.491	1.1686e-217
ARCH {1}	0.10531	0.022732	4.6327	3.609e-06

Table 4. GARCH (1,2)

	Value	Standard Error	T Statistic	P Value
Constant	3.6209e-05	6.4788e-06	5.5889	2.2854e-08
GARCH {1}	2e-12	0.14654	1.3648e-11	1
ARCH {1}	0.081569	0.048023	1.6985	0.089404
ARCH {2}	0.20426	0.057884	3.5288	0.0004174

Table 5. GARCH (2,1)

	Value	Standard Error	T Statistic	P Value
Constant	1.7841e-06	1.5358e-06	1.1617	0.24536
GARCH {1}	0.84042	0.5241	1.6036	0.10881
GARCH {2}	0.022585	0.47666	0.047382	0.96221
ARCH {1}	0.10864	0.048455	2.2422	0.024951

4.5 Monte Carlo simulation and prediction

Next, the "simulate" function is used to simulate the daily return series of stock price in the "mainland low-carbon" plate by Monte Carlo, and explore the fluctuation of the daily return series of stock price from the model. The number of Monte Carlo simulation paths is 500 and the number of phases is 100. The simulation results are shown in Figure 4. As can be seen from figure 4, the volatility of variance is large. With the increase of the number of periods, the volatility is greater, and the sample simulation results are similar, which shows that the relevant low-carbon enterprises have certain income fluctuations and need certain risk prevention.

Then, the 30 period Monte Carlo prediction based on 100 periods is run with the forecast function, and the results are shown in Figure 5. The red line is the prediction based on samples and the dotted line is the prediction without samples. It can be seen that the stock price may decline gradually in the next 30 periods and the fluctuation tends to be stable.

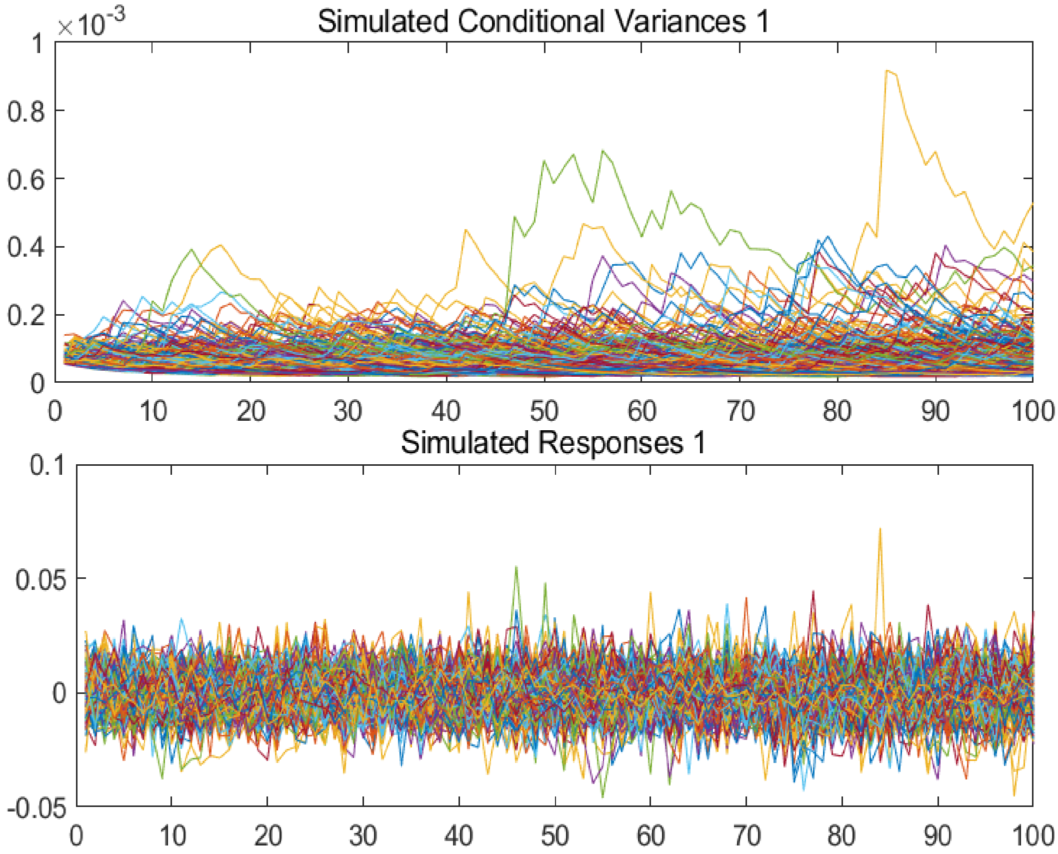

Figure 4. Simulation situation

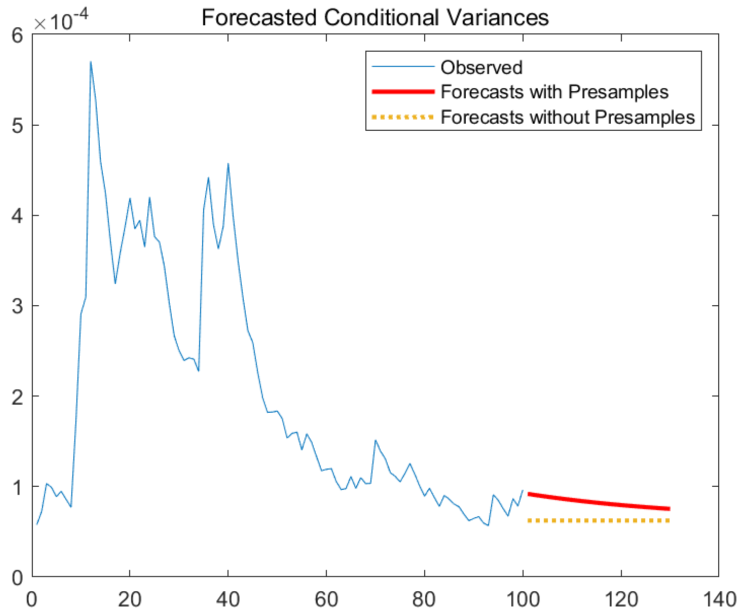

Figure 5. Forecast situation

4.6 Impact of policy uncertainty

This paper uses the stock daily closing price return (488 data) of the "CSI mainland low carbon economy theme index" from January 2, 2019 to December 31, 2020 and the indicators of economic policy uncertainty (EPU) and trade policy uncertainty (TPU) from 2019 to 2020. In order to calculate the GARCH-MIDAS model, the log return of daily closing price is multiplied by 100.

Figure 6 and figure 7 is the trend chart of EPU and TPU.It can be seen that EPU and TPU fluctuated greatly in the past two years, which may be due to the impact of the epidemic in the past year, supply side reform and counter cyclical conditions, resulting in policy instability.

Then, according to GARCH-MIDAS model, X1 is EPU and X2 is TPU.This paper is selected one year lag, so K=12.Table 6. shows the parameter results.It can be seen that the stock price returns of EPU and TPU to this sector are basically significant, indicating that economic policies and trade policies have a short-term volatility aggregation effect on stock prices. When observing the coefficient of "EPU TPU", it can be seen that $\theta 1$ is significant and negative, but the impact of a single EPU is not significant, indicating that trade policy will partially affect economic policy, and when the EPU is higher, the long-term component of stock price volatility in the next month will also decline. The impact of TPU is not significant, indicating that the change of trade policy has little impact on stock price volatility.

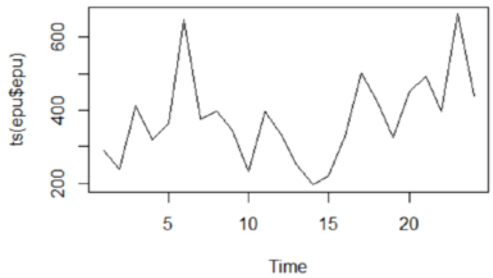

Figure 6. EPU trend chart

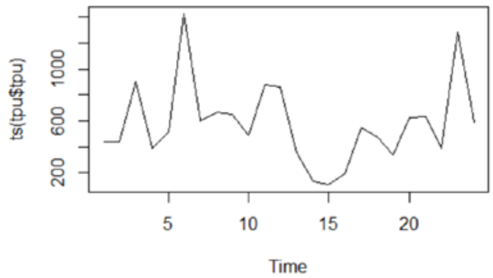

Figure 7. TPU trend chart

Table 6. Estimated results

	EPU	TPU	EPU+TPU
μ	0.109** (0.049)	0.110** (0.049)	0.116** (0.049)
α	0.074 (0.082)	0.062 (0.056)	0.053 (0.056)
β	0.769*** (0.127)	0.814*** (0.093)	0.845*** (0.129)
$\theta 1$	0.005 (0.007)		-0.010** (0.004)
$\omega 12$	1.551*** (0.574)		1.000 (0.7276)
$\theta 2$		0.003 (0.002)	0.0038 (0.0027)
$\omega 22$		2.334* (1.337)	2.5584* (1.5085)
m	-2.139 (2.615)	-1.684 (1.160)	1.3151 (1.3976)

The single factor weights of EPU (Figure 8) and TPU (Figure 9) can be obtained by calculating the weights according to the formula. It can be seen that EPU tends to 0 around the 12th period. According to $\theta 1 * \varphi_k(\omega_{12})$, the impact intensity of EPU lagging one month is -9.5%, indicating that the long-term component of stock price volatility of the next month will be reduced by 9.5% if EPU increases by 1%. It took 12 months for the long-term component to approach zero, indicating that the impact of economic policy on stock prices was largely eliminated. In terms of TPU, it can be found that the weight of TPU also tends to 0 after 12 months, indicating that the impact of trade policies on stock prices is eliminated after 12 months. Then according to $\theta 2 * \varphi_k(\omega_{22})$, the influence intensity of the lag period is 0.34%, indicating that a 1% increase in TPU will increase the influence of the long-term component of stock price volatility in the next month by 0.34%.

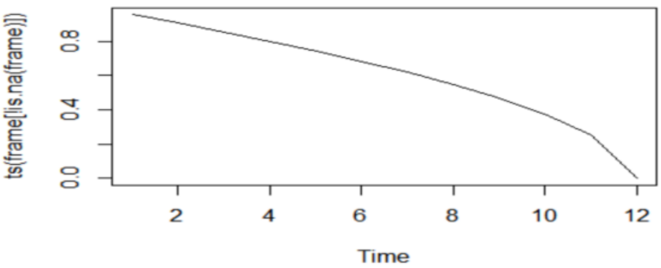

Figure 8.EPU weighted graph

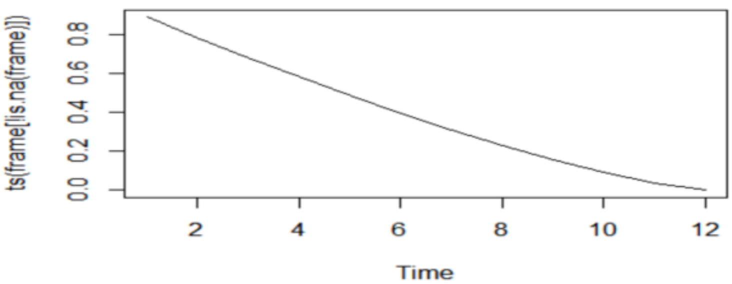

Figure 9.TPU weighted graph

4.7 In-sample fitting

Prediction and fitting with two-year data in the sample (figure 4.8), It can be seen that the fitting accuracy of double factor and single factor is good.

Table 7. Fitting results

	EPU+TPU	EPU	TPU
Rmse	1.0053	1.0052	1.0059
mae	0.7509	0.7482	0.7496

5. Conclusion

(1). The stock price of the "CSI mainland low carbon economy theme index" plate has a volatility aggregation effect. The impact of stock price is long-lasting, and the decline of volatility is slow. Once there is a large fluctuation, it is difficult to eliminate it in the short term.

(2). According to Monte Carlo prediction, the stock price may gradually and steadily decline in the next 30 days, which indicates that the Income Fluctuation of relevant low-carbon enterprises may begin to decline, but certain risk prevention is required.

(3). Economic and trade policies have a significant impact on the short-term fluctuations of stock prices in the "low-carbon sector", which may be due to the recent concepts of "carbon peak", "carbon neutralization" and relevant policies, resulting in the high sensitivity of relevant sectors to these policies.

(4). According to the weight functions of EPU and TPU, the long-term impact is eliminated only after 12 months, indicating that the long-term impact of the policy lasts for a long time. 5. Trade policy has little impact on stock price, and the weight slope is larger than that of EPU, indicating that the long-term impact of trade policy decreases rapidly. 6. The joint impact of economic policy and trade policy will strengthen the long-term impact of economic policy, although it is negative.

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