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Study on the Volatility of New Energy Index Based on ARMA-GARCH Model

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ABSTRACT

New energy industry is an emerging industry in China with natural environmental protection attributes. However, new energy stock prices have fluctuated frequently in recent years, destabilising the market and affecting investment. Therefore, the article selects the daily closing prices of CSI New Energy Index from 1 August 2019 to 1 July 2024, and establishes a GARCH (1, 1) model through Eviews 13.0 to study the volatility of new energy stock prices in China. The results show that the new energy stock price return series has volatility aggregation and exhibits the characteristics of sharp peaks and thick tails.

KEYWORDS

New energy; GARCH model; Stock price

1. INTRODUCTION

With its renewable and less polluting qualities, new energy plays a significant role in China's energy supply system. It also effectively improves China's existing energy supply and demand situation and is essential for fostering sustainable economic growth. The idea of new energy is progressively gaining traction in the current global low-carbon energy transformation of the times, as is the enthusiasm for new energy industry investment. The development and application of new energy has emerged as the central tenet of the global energy transition strategy and the primary means of mitigating climate change.

In many nations around the world, the creation and use of new energy has emerged as a crucial component of energy transition strategies and a primary means of addressing climate change. The Chinese stock market's new energy sector, together with its associated upstream and downstream industries, has drawn a lot of interest from investors and is now one of their most sought-after areas. Researchers and investors are paying increasing attention to the CSI New Energy Index, which serves as the primary metric for assessing the overall performance of China's new energy sector. The new energy industry is developing rapidly against the backdrop of global energy transition and the fight against climate change, and its market performance and volatility have important research value for investors, policy makers and academics. How to reduce the investment risk and improve the investment returns of stocks in the new energy automobile industry has become an important research topic. An in-depth understanding of the price volatility of new energy automobile stocks and the driving factors behind it can also provide decision-making references for investors to open up investment channels, expand the range of choices for investment, and obtain the possibility of higher returns.

(1) Literature studies on ARMA-GARCH

Financial markets are particularly interested in characteristic studies like return and volatility, and one of the primary techniques for examining volatility in financial markets is time series analysis. Linear connections in time series data are mostly captured by traditional time series models including autoregressive (AR), moving average (MA), and autoregressive sliding average (ARMA) models. However, the traditional ARMA models have certain limitations when dealing with financial data because financial time series data are typically characterized by volatility aggregation, i.e., large fluctuations tend to be accompanied by large fluctuations and small fluctuations tend to be accompanied by small fluctuations. The autoregressive conditional heteroskedasticity (ARCH) model was developed by Engle (1982) as a solution to this problem. Bo and llerslev (1986) took the model further and proposed the generalized autoregressive conditional heteroskedasticity (GARCH) model.The GARCH model has been widely employed in the research of financial market volatility because it can capture the volatility aggregation properties in financial time series. studies of volatility. Since then, the number of tools available to study the volatility of returns on financial assets has gradually increased. Examples of these tools include the widely used Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, as well as its variants, the Exponential GARCH (EGARCH) model, the GJR-GARCH model, and others.

Many current scholars use ARMA models in combination with GARCH models. Huang Xuan (2018) and Yu Yue (2023) constructed ARMA-GARCH model to study the volatility of CSI 300 index return and return volatility and got the conclusion that the model is the optimal model to fit the volatility characteristics effectively; Shen Mingzheng (2023) and Yan Xiangyu (2024) and others studied the correlation between stock return and its influencing factors based on the ARMA-GARCH and VAR models and found that stock return and its influencing factors correlate with each other. The correlation between stock returns and their influencing factors was found to be significantly affected by industry and economic indices, with good impulse response performance, and both ARMA-GARCH and VAR models passed a series of robustness tests.

In addition, many scholars have carried out innovative research using GARCH models. raque (2017) and others use DCC-GARCH model to explore the inter-market dynamic correlation in depth; Li Zhuwei (2021) and others systematically study the risk spillover effect between internet finance and traditional finance based on Copula-ARMA-GARCH-CoVaR model. The results show that the level of risk spillover between financial industries changes over time, and the transmission of risk from Internet finance to traditional finance is more rapid.

(2) Research in the field of new energy stocks

Research on the stock index returns of the "new energy" sector has been conducted at two levels:

Sadorsky (2021) and Chen Menglong (2024) successively used the random forest model in machine learning algorithm to predict the stock price of new energy industry. The results show that the random forest model has high accuracy and practicality.

Second, an empirical analysis of the stock market is conducted based on the growth of the new energy business. Janda et al. examined the volatility association between the stock returns of US and Chinese clean energy businesses using the GARCH model. Xiong Hongjun et al. (2024) examined the dynamic correlation between the stock prices of Chinese new energy companies and airlines, pharmaceutical and health companies, agricultural companies, and non-ferrous metal companies using three multivariate GARCH models (CCC-GARCH, DCC-GARCH, and ADCC-GARCH). The findings indicate that non-ferrous metal firms have stronger stock market correlations, which investors may use as a key indication to forecast the stock returns of new energy companies.

In conclusion, the body of research on the analysis of the new energy stock market has been reviewed, and the ARMA-GARCH model's viability has been confirmed. However, the analysis and forecasting from the index's point of view remain inadequate, which has an impact on the evaluation of the new energy stocks' overall performance as well as their potential future trends. While earlier studies have concentrated on the influence of other variables or the relationship between different assets, this study forecasts and analyzes the CSI New Energy Index, focusing on China's new energy stock returns and their volatility correlations. At the same time, this paper focuses its research on Chinese new energy stocks, which gives the paper's conclusions a specific geographic and market context that is important for understanding the state of China's new energy stock market.

Specifically, the structure of this paper is arranged as follows : Firstly, the daily closing price data are preprocessed, and the daily return series are obtained by logarithmic differencing, and the smoothness test and related statistical test are performed. On this basis, an ARMA model is built to capture the linear characteristics of the daily return series, and then a GARCH model is introduced to capture the volatility aggregation characteristics to derive the best-fit model. Forecasting is carried out by the best-fit model, and the forecasting results of both dynamic and static forecasting methods are analysed to verify whether the model can forecast future asset price volatility.

2. RESEARCH METHODOLOGY AND MODEL DESIGN

2.1. ARMA Model

The autoregressive moving average (ARMA) model was developed in the 1970s by Box and Jenkins to investigate the volatility patterns present in the time series as a whole. In its general form, ARMA (p, q) combines the moving average (MA) and autoregressive (AR) models:

$$\mathrm{ARMA(p,q)}: \begin{cases} Y_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \\ \varphi_p \neq 0, \theta_q \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\epsilon^2, E(\varepsilon_t \varepsilon_s) = 0, s \neq t \\ E(Y_s \varepsilon_t) = 0, \forall\, s < t \end{cases} \qquad [10]$$

Where the moving average component's order (q), the autoregressive component's order (p), and the white noise series (ϵt) are represented by the parameters.

By modeling the current returns while taking historical returns and error terms into account, the ARMA model is able to reflect the linear connection present in the time series data.

2.2. GARCH Model

In order to capture the common volatility aggregation phenomenon (i.e., volatility aggregation, "sharp peaks and thick tails") in financial time series, Bollerslov extended the ARCH model in 1985 to capture the flat and volatile periods of the time series while combining the advantages of the ARCH model, and obtained the generalised autoregressive conditional heterogeneous variance model (GARCH model), whose general form is:

$$\begin{gathered} \varepsilon_t = \sigma_t \mu_t \\ \sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-1}^2 + \sigma_{j=1}^{q} b_j \sigma_{t-1}^2 \end{gathered} \qquad [14]$$

Where p represents the order of the autoregressive term in the GARCH (p, q) model and q represents the order of the ARCH term, which indicates the volatility of the model.

By modeling the current conditional variance and accounting for the squared past error and the previous conditional variance, the GARCH model is able to describe volatility clustering in time series data. The GARCH model has the benefit of being able to characterize changes in the conditional variance dynamically. It is especially well-suited for data that has volatility clusters. Financial time series data volatility may be accurately predicted by using volatility clusters, which are defined as long-term high or low volatility in the financial markets.

The purpose of the so-called ARMA-GARCH model is to distinguish between the variance and the mean in the model; that is, the residuals follow the GARCH model while the mean follows the ARMA model. This can more accurately describe and predict the risk in the financial market and make the results more accurate and reliable.

2.3. Data Source and Processing

The China Securities Market Research Centre (CSRC) created the CSI New Energy Index to represent the overall performance of Chinese equities in the new energy sector. With a particular emphasis on the return and volatility correlation of stocks in the new energy sector, the index sample is chosen from 50 stocks that are representative of the new energy sector, including solar energy, wind energy, energy storage, hydrogen energy, biomass, etc. As a result, the research object for this work is the CSI New Energy Index.

Since we can only obtain the data of the last 5 years on the CSI website, our study covers the timeframe from 1 August 2019 to 1 July 2024, with a total of 1,191 trading days of data. Subsequent data processing was performed using EVIEWS statistical software.

In order to ensure that the instability caused by the changes in the time series is eliminated as much as possible, the daily closing price time series data are logarithmically differenced to obtain the logarithmic return series of the new energy index: $r_{ydyl} = ln(P_t) - ln(P_{t-1})$

3. EMPIRICAL RESEARCH

3.1. Descriptive Analysis

In the linear plot of the logarithmic return series R of the CSI New Energy Index (Figure 1), a "clustering" phenomenon of return volatility can be observed: the index return series fluctuates sharply in the short term from the beginning of 2021 to the beginning of 2022, and then stays at a relatively low level from the middle of 2019 to the middle of 2020.

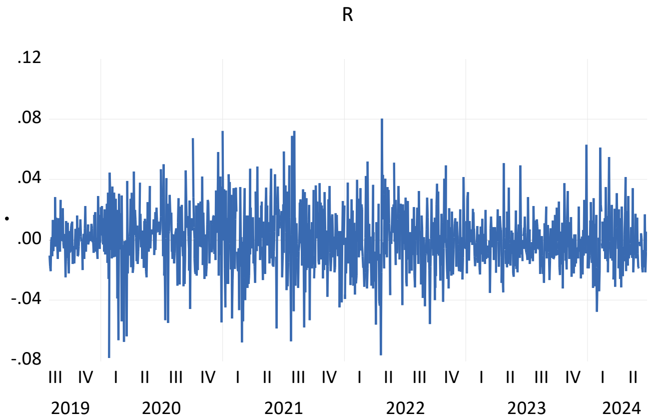


Figure 1. Time series chart of R

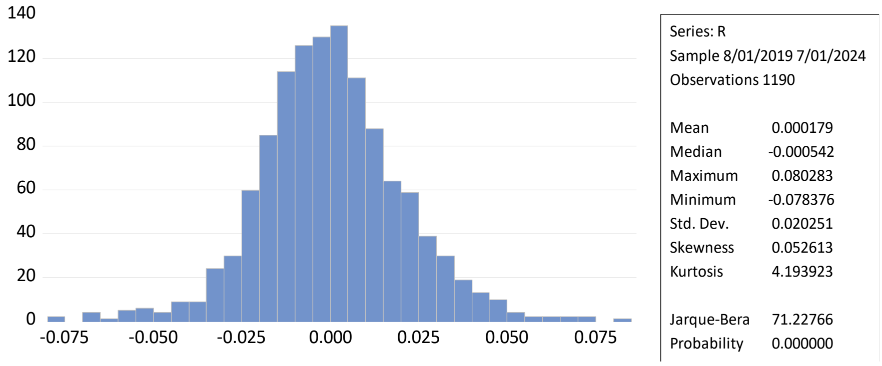


Figure 2. Histogram and stats

The descriptive statistics of the sequences are shown in Figure 2, which leads to three conclusions:

(1) Skewness is 0.05>0, and the sequence is right-tailed.

(2) Kurtosis is 4.19, which is higher than the peak 3 of normal distribution, and the sequence has the characteristic of "sharp peak and thick tail".

(3) Jarque-Bera statistic is 71.23, P-value is 0.000000, rejecting the assumption that the sequence obeys the normal distribution (normality test).

3.2. Stability Test

Due to the smoothness requirements of the model for the series, the series need to be tested for smoothness. The unit root test is typically used to determine how smooth the procedure is. Table 1 displays the findings. The sample period time series is smooth, as evidenced by the index logarithmic yield sequence ADF test result of -34.54792, which is smaller than the crucial value at the significance level of 1%.

Table 1. ADF test results

ADF	Critical value		
	1%	5%	10%
-34.54792	-3.435636	-2.863762	-2.568003

3.3. Autocorrelation Test and White Noise Test

The autocorrelation and partial autocorrelation coefficients of the series fall within two times the standard deviation, and the p-values corresponding to the Q-statistics are all greater than 0.05, indicating that the series does not have a significant correlation at a significant level of five percent. The 36th order lag is used in this paper. Additionally, it is evident that the series is white noise and does not fit the mean using an ARMA model.

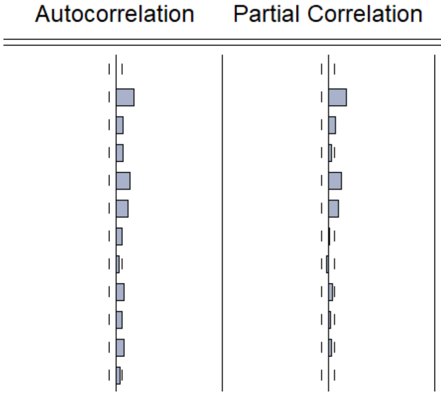
3.4. GARCH Model Building

On the basis of the selected ARMA not established, it is necessary to do the heteroskedasticity test of the residuals of the fitted model, i.e., ARCH effect test. There are two methods to test the ARCH effect: the LM method and the residual squared correlation plot test, where the second method is used. In this paper, the mean equation is set up in the following form:

$$R_t=c+u_t$$

To make the model fit better, Rt is de-meaned and its variation is given by Eq:

$$W_t=R_t-0.000179$$



	AC	PAC	Q-Stat	Prob
1	0.006	0.006	0.0371	0.847
2	0.173	0.173	35.781	0.000
3	0.066	0.066	40.934	0.000
4	0.067	0.038	46.263	0.000
5	0.144	0.127	71.222	0.000
6	0.116	0.103	87.407	0.000
7	0.060	0.015	91.757	0.000
8	0.037	-0.013	93.400	0.000
9	0.080	0.049	101.03	0.000
10	0.062	0.033	105.61	0.000
11	0.082	0.035	113.71	0.000
12	0.044	0.007	116.00	0.000

Figure 3. Correlogram

As can be seen in Figure 3, there is an ARCH effect since the series is autocorrelated and the p-value is 0 except for the first order lag. As a result, the GARCH model is established to obtain the GARCH (1, 1) model, as shown in Figure 4. The ARCH test is then conducted, and the results are displayed in Figure 5, with the p-value being greater than 0.05 indicating that there are no residuals containing the GARCH term and that the GARCH (1, 1) model can be used directly. This suggests that the article should use the GARCH model to further investigate the volatility of the new energy stock return series.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance Equation				
C	6.04E-06	2.25E-06	2.683450	0.0073
RESID(-1)^2	0.063715	0.011050	5.766022	0.0000
GARCH(-1)	0.923283	0.013163	70.14286	0.0000

Figure 4. GARCH (1, 1) results

F-statistic	1.529850	Prob. F(1,1187)	0.2164
Obs*R-squared	1.530455	Prob. Chi-Square(1)	0.2160

Figure 5. ARCH test results

3.5. Model Forecasting

Use GARCH (1, 1) model to predict the new energy index, because there is no ARMA model, so it can only be a static prediction step, through the data from 1 August 2019 to 1 July 2024 to predict the closing price on 2 July 2024. The prediction result is 1723.837 and the actual result is 1700.76, which is a good prediction, and the price index trend can be predicted in the coming day by this method.

4. CONCLUSION AND POLICY RECOMMENDATIONS

The research objective of this paper is to find a better fitting model to better explain the sharp peaks and thick tails characteristic of the yield series by analysing the statistical variable characteristics of the new energy stock price historical data. The conclusions of the empirical analysis are as follows:

(1) the new energy stock price series reflects obvious nonlinear characteristics, and in March 2021 and April 2022 the new energy stock price has two sharp declines. The stock price return over time shows continuous ups and downs and obvious volatility clustering. This volatility is continuous rather than intermittent.

(2) The CSI New Energy Index shows a general downward trend in the short term, and although it can only predict one step of the model, the model is able to accurately capture this volatility pattern.

(3) This paper does not use the ARMA model, which is slightly different from the traditional volatility fitting model, indicating that the new energy stock market has become more mature in recent years, with a stronger autocorrelation of stock prices, and further research is needed to use other models to better predict the stock price trend of the industry.

This paper puts forward relevant suggestions:

Firstly, policy support for new energy related listed companies should be further increased. With the state's strategic support for the new energy industry, related listed companies have ushered in a huge development opportunity. Therefore, the state should continue to strengthen the support for this industry through a variety of policy instruments.

In addition, new energy enterprises should be encouraged and guided to go out and co-ordinate green energy co-operation, so as to promote and help new energy enterprises to obtain the necessary funds and reduce their financing and operating costs.

Finally, scholars should continue to follow up on the forecasting and analysis of the new energy index, propose innovative methods and release the results in a timely manner to help investors reduce risks and help companies develop.

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