The Volatility Analysis of the CSI 300 Index Based on the GARCH Model

Yuntian Bai

School of Statistics and Mathematics
**Corresponding author. Email: Zhongnan University of Economics and Law*

ABSTRACT
Volatility can measure the quality of stocks and can be used in asset allocation and asset pricing to control the risks of stocks to a certain extent, so as to formulate reasonable investment strategies. Through the ARCH model, the GARCH model and the EGARCH model, this paper studies the volatility of the SSE 50 index to explore the stock price fluctuations in China's securities market and reflect the operation of my country's stock market. The study found that there is an obvious cluster effect in the volatility of the index, indicating a strong market speculation atmosphere, investors with short-term investment preferences, and less attention to stock value. Based on the analysis of the model, this paper forecasts the short-term volatility in the future and puts forward some reasonable suggestions.

Keywords: *SSE 50 index volatility; ARCH model; GARCH model; EGARCH model*

1. INTRODUCTION

In the context of the continuous acceleration of economic globalization, the financial market has greatly expanded, and a large amount of capital is flowing rapidly around the world, which also makes the financial market more volatile. According to Wang Yun's [1] collation of the financial crisis in the 20th century, the financial crisis since the 1980s can be divided into the following stages: the first stage was in the early 1980s worth more than $800 billion; the second stage was the bursting of a number of capitalist countries led by Japan in the 1990s; the third stage is the Thai currency reform in 1997, when the Thai baht fell sharply, and Thailand's economy quickly affected many countries in Asia, forming the Asian financial storm [2]; the fourth stage started in 2007 due to problems with subprime mortgages. Some financial institutions in the United States went bankrupt, leading up to large volatility in the US stock market. Eventually, it spread worldwide, causing the global financial crisis.

China's securities market has achieved rapid development under the background of financial globalization. On the one hand, the listed companies are increasing, and on the other hand, the market scale is increasing. The securities market and China's economic system promote and adapt to each other, and have gradually become an important part of China's national economy. At the same time, the increasing complexity of China's securities market also means that risk control is more important. In recent years, the COVID-19 pandemic has indirectly led to stock market volatility [3], which is also one of the risks facing China's stock market. Similarly, according to Ji Yu's study of China's stock market, it can be known that China's stock market is also affected by the world economic environment [4]. Some studies show that the volatility of China's stock index is much greater than that of mature developed countries, so how to fit the volatility more accurately and make more accurate predictions has become the focus of scholars' research. Better fitting of stock price fluctuations and more accurate predictions can not only improve the efficiency of securities trading, serve the real economy well, but also provide risk-related information for securities investors and provide a better reference for the formulation of investment strategies.

The Shanghai Composite 50 index comprehensively reflects the overall trend of China's securities market and reflects the operation of China's securities market.This paper analyzes the volatility sequence of Shanghai 50 according to the GARCH model and makes short-term predictions. The study of the volatility of the index can provide a correct reference for investment decisions and is also conducive to the study of the causes of the fluctuations. The research has the following significance: first, it is beneficial to improve and enrich the research theory of stock volatility in China; second, it explores the

Copyright © 2022 The Authors. Published by Atlantis Press International B.V.
This is an open access article distributed under the CC BY-NC 4.0 license -http://creativecommons.org/licenses/by-nc/4.0/.

characteristics of volatility in the Chinese securities market and provides a reference for investors.

2. LITERATURE REVIEW

Foreign research on volatility is earlier. As early as 1982, Engle proposed the ARCH model, whose variance is a function of time and can effectively solve the heterovariance problem. Therefore, it has been widely used in the financial field and laid the foundation for volatility research. In 1986, Bollerslev built the G ARCH model based on the A R C H model to better study the long-term correlation of volatility. Later volatility analyses were all based on the GARCH model.With the deepening of research, scholars gradually find the asymmetric phenomenon, that is, the fluctuation caused by negative information is always greater than that caused by positive information. In 1993, Engle and Ng studied asymmetric phenomena in the Japanese stock market.Subsequently, the model of the GARCH family has been widely extended and applied.

China studies volatility later than foreign scholars. In 1999, Ding Hua first used ARCH (1) and ARCH (2) models to analyze the [5] in Shanghai's securities market. In 2009, when he analyzed the CSI 300 index, he constructed the ARCH conditional mean equation, which was of great significance to [6] for risk control and financial market. Feng Yi, Sheng Lei and Yang Qingshan used the EGARCH model to study the volatility of The Chinese stock market. By using the GARCH family model, we found that EGARCH (1,1) had excellent fitting effect, and could also predict and analyze the change of yield of [7].

According to the above literature research, it is found that the GARCH model can effectively simulate the volatility of China Shanghai Composite 50 Index, which is conducive to investors' risk management and the administrative department's reasonable formulation of policies.

3. A BRIEF INTRODUCTION TO THE THEORETICAL MODEL

3.1. The ARCH model

3.1.1. Construction of the ARCH model

When studying the economic problems, it first needs to eliminate the deterministic non-stationary factors of the variables. Variables still appear most of the time that fluctuate slightly around the mean, but sometimes, fluctuation is greatly, which can be called the cluster effect. Cluster effects complicate many problems, while traditional time series measurement models mostly assume that the perturbation terms are independent and the variance is unchanged. Based on this dilemma, Engle constructs the ARCH model, and the variance in the model can indicate the change of fluctuations with time through heteroscedasticity.

$$\text{function:}\begin{cases} x_t = \beta_0 + \beta_1 x_{t-1} + \cdots + \beta_p x_{t-p} + \varepsilon_t \\ Var(\varepsilon_t) = h_t \\ h_t = \lambda_0 + \lambda_1 \varepsilon_{t-1}^2 + \cdots \lambda_q \varepsilon_{t-q}^2 \end{cases} \quad (1)$$

The model is called the ARCH (q) model. It can be seen from the model that the variance of the residual sequence is the conditional variance changing over time, which more accurately fits the sequence spot fluctuation characteristics. In this model, the mean of the residual sequence is zero, with heteroscedasticity 【$E(\varepsilon_t) = 0, Var(\varepsilon_t) = h_t$】. And the squared sequence of the residues has a correlation, Therefore, the current fluctuations can be expressed as a linear regression of the past fluctuations【$h_t = \lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2$】.

3.1.2. Constraints for the ARCH model parameters

(1). Non-negative variance: $Var(\varepsilon_t \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots) \geq 0$. The condition is equivalent to 【$\lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 \geq 0$】, which means【$\lambda_0, \lambda_1, \cdots, \lambda_q \geq 0$】.

(2). If we assume that $Var(\varepsilon_t) = \sigma^2$, then the expectation for the heteroscedastic function, and the results are as follows:

$$E[Var(\varepsilon_t \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots)] = E(\lambda_0 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2) \quad (2)$$

$$E[E(\varepsilon_t^2 \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots)] = \lambda_0 + \sum_{i=1}^{q} \lambda_i E(\varepsilon_{t-i}^2) \quad (3)$$

$$\sigma^2 = \lambda_0 + \sum_{i=1}^{q} \lambda_i \sigma^2 \quad (4)$$

$$\sigma^2 = \frac{\lambda_0}{1 - \sum_{i=1}^{q} \lambda_i} \quad (5)$$

Owing to $\sigma^2 \geq 0$, the parameters are satisfied: $0 \leq \lambda_i < 1, i = 1,2,\cdots,q$, and $\lambda_1 + \lambda_2 + \cdots + \lambda_q < 1$.

3.2. The GARCH model

In the ARCH model introduced in the previous section, it is not difficult to find that the heteroscedastic function is the moving average of q q in q, suitable for short-term correlations. For long-term autocorrelation, Engle's student, Tim Bollerslev, introduced the historical information in the ARCH model and constructed the GARCH model:

$$\begin{cases} x_t = f(t, x_{t-1}, x_{t-2}, \cdots) + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t \\ h_t = \lambda_0 + \sum_{j=1}^{p} \eta_j h_{t-j} + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 \end{cases} \quad (6)$$

Parameter satisfaction:

$$\begin{aligned} & 0 \le \lambda_i < 1, i = 1,2,\cdots,q \\ & 0 \le \eta_j < 1, j = 1,2,\cdots,p \quad (7) \\ & 0 \le \sum_{j=1}^{p} \eta_j + \sum_{j=1}^{q} \lambda_j < 1 \end{aligned}$$

The model focuses on two aspects of mean and volatility. First, the mean of the residual sequence is zero by extracting the deterministic information. The conditional heteroscedastic information in the residual sequence is again extracted so that the final white noise sequence. It is not difficult to see from the model structure that the ARCH model is a special case of the GARCH model.

Many empirical analysis results show that during the analysis of financial data, the GARCH model often works better and can more fully fit the characteristics of financial data.

3.3. The EGARCH model

In the financial market, there is a positive and a negative impact on the share price. Negative information often causes greater fluctuations and requires discrimination between heteroscedasticity functions of positive and negative shocks.

Nelson proposed the EGARCH model in 1991, which is one of the derived models to broaden and improve the GARCH model. Its structure is:

$$\begin{cases} x_t = f(t, x_{t-1}, x_{t-2}, \cdots) + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t \\ \ln h_t = \omega + \sum_{i=1}^{p} \eta_i \ln h_{t-i} + \sum_{j=1}^{q} \lambda_j g(e_{t-j}) \\ g(e_t) = \theta e_t + \gamma[|e_t| - E|e_t|] \end{cases} \quad (8)$$

The range of values is broadened by taking the logarithm of the heteroscedasticity function, so that there is no more need for a non-negative assumption of the parameters. And the newly added weighted perturbation function can be treated as asymmetric as follows.

$$\begin{aligned} g(e_t) &= \theta e_t + \gamma[|e_t| - E|e_t|] \\ &= \begin{cases} (\theta+\gamma)e_t - \gamma E|e_t|, e_t > 0 \\ (\theta-\gamma)e_t - \gamma E|e_t|, e_t < 0 \end{cases} \end{aligned} \quad (9)$$

In this formula, $E[g(e_t)] = 0; e_t \sim N(0,1); E|e_t| = \sqrt{2/\pi}$.

Usually take $\gamma = 1$, and the function $g(e_t)$ is abbreviated as:

$$g(e_t) = \begin{cases} (\theta+1)e_t - \sqrt{2/\pi}, e_t > 0 \\ (\theta-1)e_t - \sqrt{2/\pi}, e_t < 0 \end{cases} \quad (10)$$

4. EMPIRICAL RESEARCH

4.1. Descriptive statistical analysis

This paper uses the daily closing price data of Shanghai Composite 50 Index from January 4, 2005 to March 1, 2022, with a total of 4,084 data. And 3,168 valid data are obtained after data cleaning. The data comes from the choice of financial terminal. This paper represents the volatility of day t in r_t. The closing price y_t on day t satisfies the formula $y_t = y_{t-1} e^{r_t}$. Therefore, the log sequence of the closing price performs differential operation, expressed as:

$$r_t = \ln y_t - \ln y_{t-1} \quad (11)$$

The timing chart of the closing price is as follows:

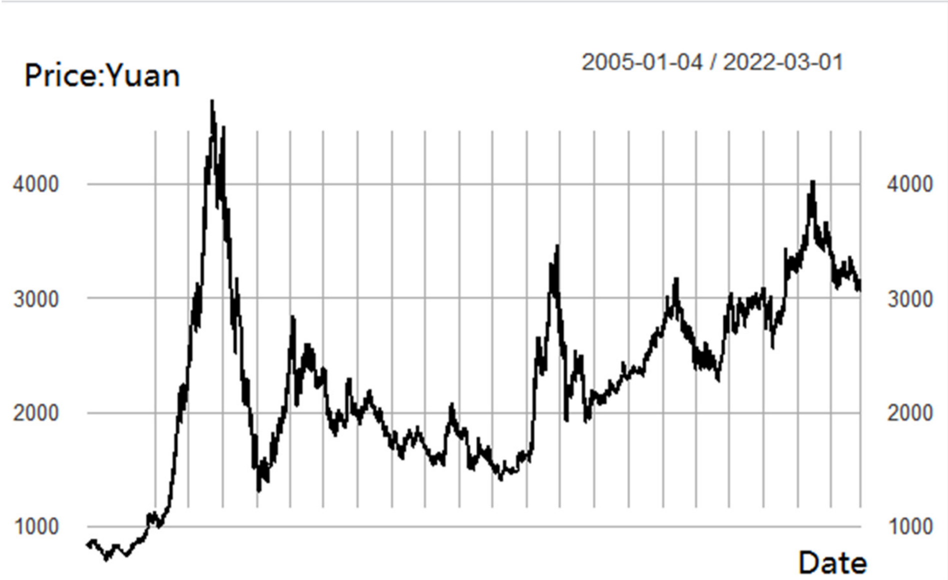

Figure 1. The timing chart of the closing price

The timing diagram shows that the sequence has a trend of continuous increasing and continuous decreasing alternately. The data has strong volatility, but the overall increasing trend, showing significant non-stationarity.

The timing diagram of the volatility obtained by making the first-order difference of the log yield is as follows:

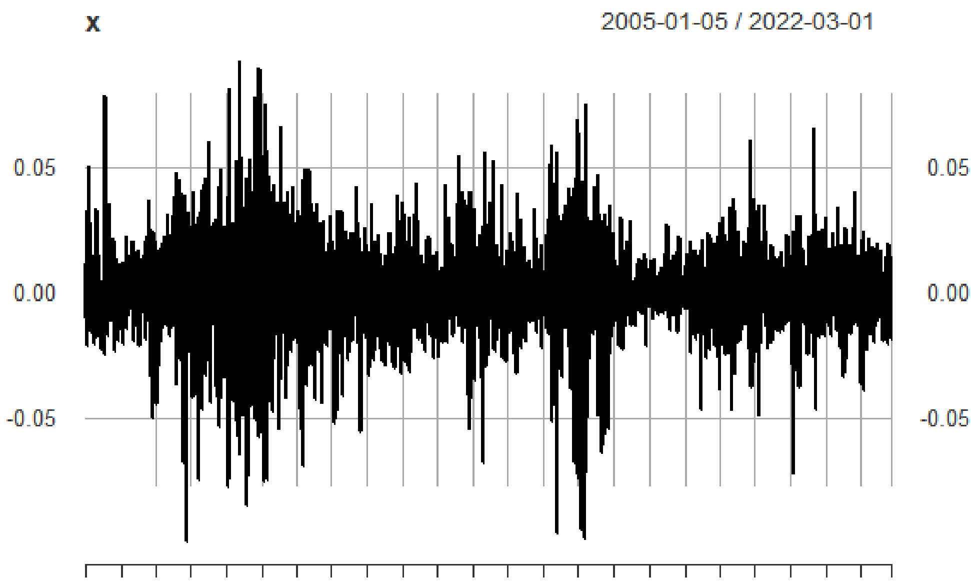

Figure 2. The timing diagram of the volatility

As can be seen from the sequence diagram, the sequence fluctuates slightly over a period of time. While in a period of time, there is a more obvious cluster effect of the volatility sequence.

4.2. Preprocessing of the second section of the time series

4.2.1. Stability test

For the processed time series presented above, a stationarity test is required before building a model analysis. Therefore, the ADF unit root test was performed first, and the results were obtained as follows:

Table 1. ADF test results table

Dickey-Fuller	Lag order	P-value
-14.151	16	0.01

The resulting ADF statistic is -14.151, and the test statistic, the null hypothesis of unit root in the logarithmic yield sequence is untenable, namely the data is stable.

However, the commonly used ADF test is effective in homogeneity of variance, but for heteroscedasticity, there is some degree of deviation, therefore, we use the nonparametric modified - Phillips-Perron test statistic [8] of the ADF test, which is more applicable to the stationarity test in heteroscedasticity.The inspection results are as follows:

Table 2. First Name

Dickey-Fuller	Truncation lag parameter	P-value
-64.025	10	0.01

The PP test shows that the value of the delayed order 10 statistics is equal to -64.0251, testing the statistic, which indicates that the volatility sequence can be regarded as a stationary sequence.

4.2.2. Pure random test

Although the stationarity of the volatility sequence has been determined, there is a unique sequence of white noise sequence, with zero mean, constant variance and zero covariance. It belongs to pure random sequence, which is obviously not satisfied with the needs of empirical analysis. Therefore, it needs to determine whether the volatility sequence is a white noise sequence, and the Ljung-Box test is used here [9].

In total, four sets of tests, successively lagging 6 to 24, gave the results as follows:

Table 3. Ljung-Box test

X-squared	df	P-value
35.567	6	$3.345X10^{-6}$
44.063	12	$1.49X10^{-5}$
64.004	18	$4.54x10^{-7}$
71.789	24	$1.168X10^{-6}$

It is worth noting that the LB test statistic is constructed under the assumption of satisfying the homogeneity of variance, and for the current heteroscedasticity situation, the LB statistic no longer follows the chi-square distribution. Although the P-value at this time is very small, we cannot make a hasty judgment, and we need to further investigate the size of the autocorrelation coefficient:

Table 4. Autocorrelation coefficient test

Lag	1	2	3	4	5	6	7	8
Coefficient	0.025	-0.020	0.028	0.046	-0.005	-0.057	0.031	0.008
Lag	9	10	11	12	13	14	15	16
Coefficient	0.008	0.006	0.023	0.026	0.038	-0.020	0.031	0.002
Lag	17	18	19	20	21	22	23	24
Coefficient	-0.005	0.021	-0.012	0.017	0.002	0.020	-0.011	0.007

It is not difficult to see that the correlation between the sequence values is very small, and the largest absolute value is $\rho_6 = -0.057$. Considering the LB test statistics and the autocorrelation coefficient comprehensively, the volatility sequence can be considered approximately as a pure random sequence.

4.2.3. ACF & PACF test

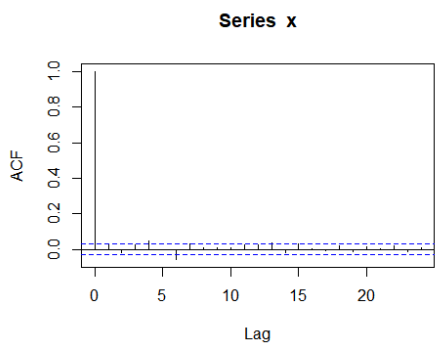

Figure 3. ACF test

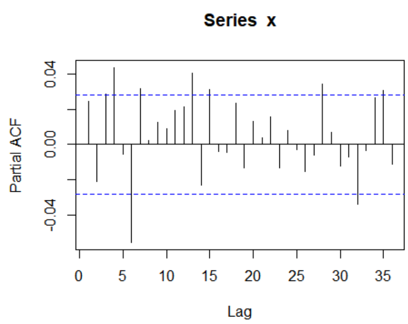

Figure 4. PACF test

Based on the autocorrelation coefficient and the partial autocorrelation coefficient, we built the ARIMA model to extract the mean information.

4.3. Empirical studies

4.3.1. The ARIMA model and the ARCH test

Based on the preprocessing of the time series in the second section, the ARIMA (a, b, c) model is established first. Since the volatility sequence is obtained from the log yield lag, b=1 is a=1, c=0, c = 0; a=0, c=1; a=c=0, the smallest AIC value is-26004.02, so the ARIMA (0,1,0) model is established here.

$$x_t = x_{t-1} + \varepsilon_t \quad (12)$$

The ARIMA (0,1,0) model is mainly used to extract the mean information, followed by a conditional heterovariance test for the volatility sequence, also known as the ARCH test.

The results of the ARCH test are as follows:

Table 5. Portmanteau-Q test

Lag	PQ	P value
4	481	0
8	829	0
12	1098	0
16	1387	0
20	1621	0
24	1896	0

Table 6. Lagrange-Multiplier test

Lag	LM	P value
4	3528	0
8	1520	0
12	959	0
16	696	0
20	549	0
24	430	0

The P-value of the lag of both Q and LM tests is zero, thus indicating a significant inhomogeneity of variance in this sequence, indicating a long-term correlation between the residual squared sequence.

4.3.2. Empirical analysis of the ARCH model

According to the description [10] for the ARCH model analysis in Time Series Analysis with R, the ARCH (4) model is first fitted to the volatility, and the parameter estimation results are obtained by using the maximum likelihood estimation method as follows:

Table 7. Maximum likelihood estimation parameter results

	Estimate	Std.Error	t value	Pr(>|t|)
omega	0.000114	0.000006	20.5831	0
alpha1	0.095886	0.019775	4.8540	0
alpha2	0.185716	0.022374	8.3006	0
alpha3	0.173454	0.023110	7.5056	0
alpha4	0.188914	0.023157	8.1578	0

Each parameter passed the significance test, and the fitted model was:

$$\begin{cases} x_t = x_{t-1} + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t, e_t \sim N(0,1) \\ h_t = 1.14\times 10^{-4} + 0.0959\varepsilon_{t-1}^2 + 0.1857\varepsilon_{t-2}^2 + 0.1735\varepsilon_{t-3}^2 + 0.1889\varepsilon_{t-4}^2 \end{cases} \quad (13)$$

The model has an AIC of-5.5069 and a BIC of-5.4993, indicating that the ARCH (4) model fits the volatility sequence of the Shanghai 50 index quite well.

4.3.3. Empirical analysis of the GARCH model

After completing the ARCH model estimation, the author then fitted the ARIMA (0,1,0) -GARCH (1,1) model to the volatility. Based on the conditional least squares estimation method, the parameter estimation results are as follows:

Table 8. Conditional least-squares method for parameter estimation

	Estimate	Std.Error	t value	Pr(>|t|)
omega	0.000001	0.000004	0.37056	0.710966
alpha1	0.065352	0.038419	1.70104	0.088935
beta1	0.931706	0.038375	24.27905	0.000000

Using the parametric significance test, it is found that the P-value of the constant term in the heteroscedasticity function was 0.71, significantly greater than the cutoff, so the constant term was not significant, and this parameter was removed.

The resulting fitted model is as follows:

$$\begin{cases} x_t = x_{t-1} + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t, e_t \sim N(0,1) \\ h_t = 0.0654\varepsilon_{t-1}^2 + 0.932h_{t-1} \end{cases} \tag{14}$$

It can be seen that the coefficient 0.065+0.932=0.997 is almost equal to 1, indicating that in the Chinese stock market, the impact of external factors on volatility at some point will be sustained.

The AIC of this model is -5.6142 and the BIC is -5.6096, compared to the AIC of the ARCH (4) model above.

The BIC values are smaller, indicating that the ARIMA (0,1,0) -GARCH (1,1) model fits the volatility sequence of the Shanghai 50 index well and is better than the ARCH (4) model.

4.3.4. Empirical analysis of the EGARCH model

Finally, the author fits the ARIMA (1,0,1) -EGARCH (1,1) model to the volatility, assuming that the sequence follows a normal distribution, and the equation for the EGARCH (1,1) model is:

$$\ln h_t = -0.0671 + 0.991\ln h_{t-1} - 0.0169(e_{t-1}) + 0.1465(|e_{t-1}| - E|e_{t-1}|) \tag{15}$$

The final model is:

$$\begin{cases} x_t = x_{t-1} + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t, e_t \sim N(0,1) \\ \ln h_t = -0.184 + 0.991\ln h_{t-1} + 0.1269e_{t-1}, e_{t-1} > 0 \\ \ln h_t = -0.184 + 0.991\ln h_{t-1} - 0.1634e_{t-1}, e_{t-1} < 0 \end{cases} \tag{16}$$

The AIC of this model is -5.6252 and the BIC is -5.6131, indicating that the EGARCH (1,1) model fits the volatility sequence of the Shanghai 50 index well and outperforms the ARCH (4) model and the GARCH (1,1) model.

4.3.5. Model optimization, selection and fitting test

(1). Model optimization and selection

Through the above output information, the AIC and BIC information of the EGARCH (1,1) model are minimal, so the EGARCH (1,1) model is relatively better in the above model fit.

(2). Distribution inspection

QQ plots and histograms of the residual sequence:

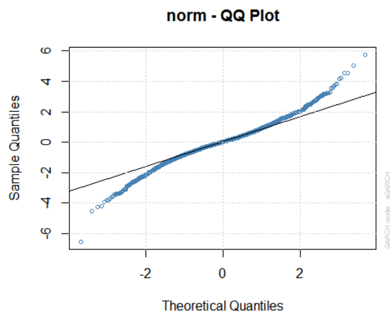

Figure 5. QQ plot

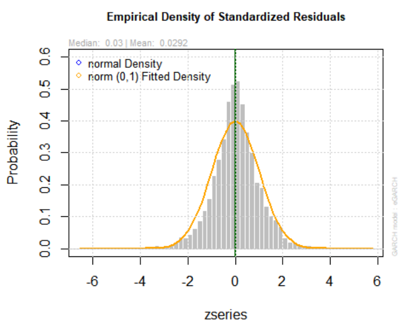

Figure 6. Histogram

In the graph on the left, it can be seen that the points near the sides deviate from the reference line, meaning that the sequence does not obey a normal distribution.The figure on the right also shows higher sequence observations than the standard normal curve, also indicating that the sequence does not obey a normal distribution.

The author tried to modify the distribution to t distribution, and the equation for the EGARCH (1,1) model is:

$$\ln h_t = -0.054 + 0.994 \ln h_{t-1} - 0.001(e_{t-1}) + 0.134(|e_{t-1}| - E|e_{t-1}|) \quad (17)$$

among, $E|e_{t-1}| = \sqrt{2/\pi}$.

The final model is:

$$\begin{cases} x_t = x_{t-1} + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t, e_t \sim N(0,1) \\ \ln h_t = -0.161 + 0.991 \ln h_{t-1} + 0.134 e_{t-1}, e_{t-1} > 0 \\ \ln h_t = -0.161 + 0.991 \ln h_{t-1} - 0.134 e_{t-1}, e_{t-1} < 0 \end{cases}$$

(18)

The model has an AIC of-5.6835 and a BIC of-5.6759, indicating the further improvement of the model fit under the assumption of the t-distribution.

Examination examining the QQ plots and histograms of the sequence shows that the QQ maps of the residual sequence are almost all on the normal reference line, and the t-distribution also better fits the features of the data spikes.

(3). Significance test of the model

Table 9. Significance test

Weighted Ljung - Box Test on Standardized Squared Residuals		
	statistic	p-value
Lag[1]	3.006	0.08294
Lag[2*(p+q)+(p+q)-1][2]	3.374	0.09118
Lag[4*(p+q)+(p+q)-1][5]	7.189	0.04665
Weighted Ljung - Box Test on Standardized Squared Residuals		
	statistic	p-value
Lag[1]	1.635	0.2011
Lag[2*(p+q)+(p+q)-1][5]	3.860	0.2720
Lag[4*(p+q)+(p+q)-1][9]	7.189	0.4511

Examination of the standardized residual sequence shows that the LB statistics, the model has fully extracted the information related to the mean. However, for the square sequence of standardized residues, the P value of the LB statistics of each order is greater than 0.05, that is, the model has adequately extracted the fluctuation-related information. The EGARCH (1,1) model is significantly established.

(4). Model prediction

The author transmits conditional heteroscedastic estimates for the next 3 periods, with standard deviation and 95% confidence intervals as follows:

Table 10. Model prediction results

K	Predicted value	Standard deviation	Lower limit of the 95% confidence interval	Upper limit of the 95% confidence interval
1	0.1447322	0.2313117	-0.4388977	0.4678442
2	0.1447322	0.4002806	-0.7700768	0.7990233
3	0.1447322	0.5654588	-1.0938258	1.1227724

5. CONCLUSION

In this paper, ARCH (4), GARCH (1,1) and EGARCH (1,1) models were constructed to analyze the yield sequence of Shanghai 50, and the feasible EGARCH (1,1) model was finally determined based on the comparison of AIC and BIC values.We show that the sequence does not obey the common normal distribution, and that the features of the data spikes are better fitted using the t-distribution. Among the three models, when the EGARCH (1,1) model was used, the higher fit and accuracy were better.This shows that the volatility is asymmetric, and the model coefficient can be found that the negative information will produce greater fluctuations. That is, there is a speculative phenomenon in the market, insufficient attention to the value of stocks, and more investors consider the speculative income rather than the income brought by value investment.

On the basis of the research and analysis, the paper makes the following suggestions. In the development of securities market, China should first make information open and transparent, provide information by establishing the corresponding mechanism, strengthen rational investment education and finally, enhance the securities market, heighten the risk management system, reinforce the legal system of securities market, and create a good investment environment.

The models selected in this paper are mainly based on historical data, and they analyze and interpret Shanghai 50 through the time series characteristics of volatility. However, there will be some differences between the forecast results and the realistic results. If the author wants to narrow the gap, he needs to select more indicators for comprehensive analysis, and establishes a more reliable model, so as to enhance the practicability and feasibility of the model. In the current field of finance and economics, there are many ways to simulate stock trend forecast, such as Monte Carlo simulation method, binary tree pricing model, etc., through a variety of simulation methods, combined with the GARCH model, can better predict the market, but also can predict the results of further test, the reliability of the model, this will be the future research direction in this paper.

REFERENCES

[1] Wang Yun, Zhang Xiao. The Definition and Analysis of Financial Security, Financial Risk and Financial Crisis. Times Finance, (13), 2021, pp. 91-94.

[2] Guan Tao, Han Huishi. Learn from international experience and lessons to cope with the pressure of local currency appreciation. China Securities Journal, 2005, pp. 1-5.

[3] Gao Xueyan. Causes and empirical analysis of China's stock market volatility. Co-Operative Economy & Science, (4), 2022, pp. 72-74.

[4] Ji Yu, Wang Lu, Hao Jianyang, et al. World Uncertainty Index and China Stock Market. Henan Science, vol. 39(10), 2021, pp. 1549-1556.

[5] Ding Hua. The ARCH phenomenon in the fluctuation of the stock price index. Quantitative & Technica Economics, (9), 1999, pp. 22-25.

[6] Tong Yumin. Stock market volatility-Evidence from the CSI 300 index. Finance&Economy, (3), 2009, pp. 81-83.

[7] Feng Yi, Sheng Lei, Yang Qingshan. Empirical Study on the volatility of Chinese Stock Market Based on EGARCH Model. Finance & Economy, (24), 2007, pp. 124-125.

[8] Tian Xingyu, Li Chuanjin. Pseudo-test of the PP test for heteroscedasticity time series. Statistics & Decision, (17), 2018, pp. 74-76.

[9] George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel and Greta M. Ljung, Time Series Analysis: Forecasting and Control, 5th Edition, John Wiley and Sons Inc., Hoboken, New Jersey, 2015, p. 712.

[10] Wang Yan. Time Series Analysis with R (The second edition), China Renmin University Press, Beijing, 2020.