

# Empirical Study on Volatility of Stock Returns in China

## --Based on ARCH Model

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### Abstract

China belongs to developing countries, capital market imperfections, stock prices often fluctuate. Based on the CSI 300 index as the starting point, from 2006 to 2017 study on fluctuation of the ARCH model data, designed to yield study on volatility of Chinese stock market increase theory and practice. Statistics on the CSI 300 index yields description and analysis of volatility clustering, sequence found there is a marked spike heavy-tailed, starboard and volatility clustering. ADF test shows the data are stable. ARCH effects tests discovered the CSI 300 index yields the ARCH effect is obvious. TAR model is established and the asymmetry of the EGARCH model Shanghai and Shenzhen 300 index, found that there is significant asymmetry effect. According to the results of the empirical analysis, combined with the current situation of China's stock market, corresponds to the proposed policy recommendations.

### Keywords

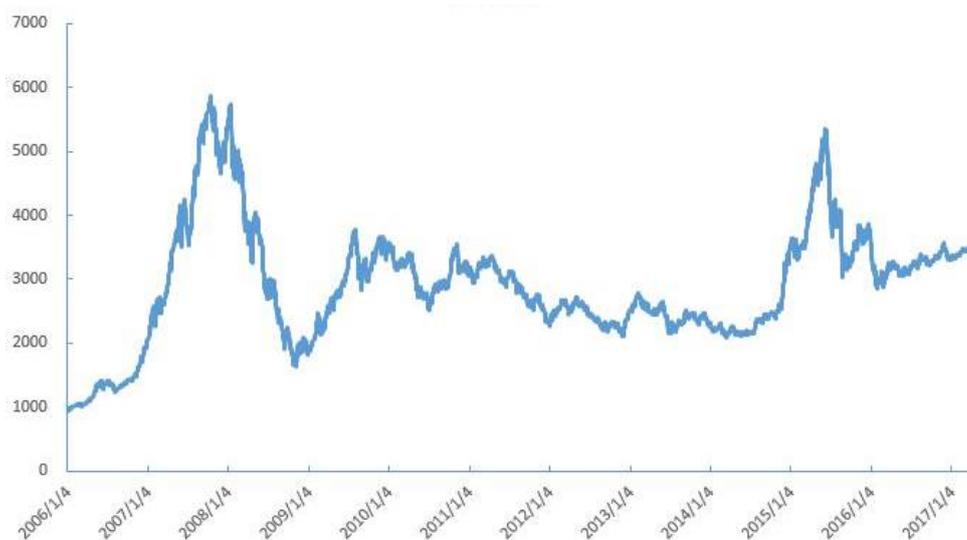
The CSI 300 index yields; ARCH Model; Volatility.

## 1. INTRODUCTION

### 1.1. Research Background

The stock market, also known as the equity market, is an important part of the financial market and plays a pivotal role in the entire financial system. As early as the early 17th century, Amsterdam in the Netherlands formed the prototype of the stock exchange. After the early stock market experienced a relatively free development, relevant laws and regulations were gradually established, and the development of the stock market has achieved a new process. After 1970, with the further opening of the economy and global liberalization of trade, the stock market has achieved rapid development on a global scale. The role of stocks in corporate finance, resource allocation and risk management has become more prominent.

In the early 1990s, China established the Shanghai Stock Exchange and the Shenzhen Stock Exchange, and the Chinese securities market began its development. In October 2009, with the listing of the GEM, the framework of China's multi-level capital market system was basically completed. In 2010, the margin financing and stock index futures business was launched one after another, and the capital market has a two-way trading mechanism. After 2012, the sub-financing and securities lending business was launched one after another, and the new three-board market was further liberalized. The development of China's securities market has made new breakthroughs. The securities industry has become an important industry to promote China's national economic growth. While the scale of securities investment is growing, it also brings great instability to the securities market. We selected data from 2731 days from January 4, 2006 to March 30, 2017 to plot the overall trend of the CSI 300 Index during the sample period.



**Figure 1.** Overall trend of the Shanghai and Shenzhen 300 Index (price index)

Source: Shanghai Stock Exchange

From Figure 1, we can see that from January 4, 2006 to March 30, 2017, the CSI 300 stock index fluctuated significantly. Since the second half of 2006, the Shanghai and Shenzhen stock markets have entered a period of rapid growth. Since 2008, due to the impact of the global financial crisis, the Shanghai and Shenzhen 300 Index fell sharply, the stock index fluctuated between 2000-4000 points, and continued until 2015. Since July 2014, the stock market has ushered in a new round of bull market, and the stock index continues to rise. Until July 2015, the stock index plummeted. The overall chart of the Shanghai and Shenzhen 300 Index reflects its violent fluctuations.

## 1.2. Significance

The stock market has always been filled with great uncertainty, and stock prices are constantly changing. Volatility means income and risk. Moderately volatile markets can have a positive impact on the economy, promote market capital flows, and investors can profit from it. Excessive changes are not conducive to market investment and increase risk. China is a developing country, the capital market is still not perfect, various financial forces are complicated, and the stock price often has large fluctuations. It is difficult for investors to correctly judge the market situation, which leads to increased risks. Since the launch of the stock index futures in 2010, the stock market has become more volatile.

In view of the current development of China's financial market, the social and economic environment is becoming more and more complex, and there are more and more factors affecting stock price changes. By studying it, we can provide concrete solutions for a series of economic reforms in China. This is not only related to the income level of Chinese investors, but also closely related to the stability of financial markets. This paper studies the volatility of China's Shanghai and Shenzhen stock markets based on the ARCH model. The ARCH model can well describe the volatility of stock indices. It helps investors understand the market operation, grasp the direction of the market, accurately determine the risks in the actual operation process, and make more rational investment behavior.

## 1.3. Domestic and Foreign Literature Review

### 1.3.1 Foreign literature review

As early as the 1960s, Mandelbrot (1963) [1] found that the fluctuations have a certain concentration. Engle (1982) [2] first proposed the ARCH model and related derived models.

Bollerslev (1986) [3] extended Engle's ARCH model into a GARCH model, which we often call the generalized autoregressive conditional heteroskedastic model. Then in 1993, Engle and Ng (1993) [4] discovered market asymmetry. This asymmetry is mainly manifested in the following conditions: when the market is in a down situation, the volatility will react more quickly to the market; and when the market is in a rising situation, the volatility will react more slowly. This is also known as the "leverage effect."

Subsequently, Danielson (1994) [5] found that for the daily data of the S&P 500 index from 1980 to 1987, the EGARCH model has better performance than the ARCH and GARCH models, and the fitted data is more versatile. Reliability. Zakoian (1994) [6] and Singleton (2001) [7] both used the GARCH model family to fit the stock market's rate of return and proved that the fluctuations are asymmetric. In the study of volatility accuracy, Basel and Valentina (2005) [8] studied the volatility of the S&P500 index through the GARCH model and found that if the information is symmetrical, the GARCH model can more accurately explain the volatility of the index. . The model of asymmetric GARCH is more suitable for the case of information asymmetry.

### 1.3.2 Domestic literature review

China's research on volatility is relatively rare. With the development of the market, relevant research is gradually increasing. As early as 1999, Ding Hua (1999) [10] established the ARCH model, and analyzed the ARCH phenomenon in the A-share index of Shanghai Stock Market in China. Zhou Shaozhen and Chen Qianli (2002) [11] proved through empirical analysis that there is indeed a GARCH effect in China's stock market. Liu Jinqun and Cui Chang (2002) [12] selected the Shanghai Composite Index and the Shenzhen Composite Index as the research objects, and used the GARCH model for empirical tests. It was found that these two markets did have significant leverage effects. Later, Kong Huaqiang (2006) [13] proved that both the SSE 180 Index and the Shenzhen 100 Index have ARCH effects. The EGARCH model is used to fit the exponential fluctuation characteristics of the two capital markets. Chen Yan, Han Lilei (2009) [14] used the ARCH model (ie, the autoregressive conditional heteroscedasticity model) to conduct empirical research on the Shanghai and Shenzhen 300 stock indexes with the daily rate of return. The results show that the fluctuation of yield has a strong and obvious agglomeration. And they also found that another model, the EGARCH model, can better fit the fluctuations in the rate of return.

He Hongxia (2010) [15] used the GARCH model to conduct an empirical analysis of the Shanghai and Shenzhen 300 Index. The results of the study indicate that there are significant conditional heteroscedasticity of fluctuations during the sample period. However, no stock price fluctuations were found to be affected by the asymmetry. Zhang Yan (2011) [16] used the GARCH model to empirically study the impact of CSI 300 stock index futures on spot volatility. Sun Deshan, Korea Tao, and Qian Cheng (2012) [17] conducted an empirical analysis of the futures market. By establishing the ARCH model, we analyze the fluctuation law of the total turnover of futures, and think that the data fitted by the TARARCH model will be better.

The structure of the article is as follows: The first part is the introduction, the research background and research significance are put forward, and the literature review is carried out. The second part is the theoretical model, which introduces the definitions and formula expressions of the ARCH model, GARCH model, TARARCH model, EGARCH model used in this paper. The third part is the data selection and statistical analysis, which explains the variable selection and data source, and makes a statistical description and volatility agglomeration analysis of the Shanghai and Shenzhen 300 index yield series. The fourth part is the empirical analysis. Firstly, the Eviews6 measurement analysis software is used to test the stability of the sample data (using the ADF test method). Then the ARCH effect test was carried out. The volatility of the Shanghai and Shenzhen 300 Index was tested by establishing the ARCH model and the GARCH model. Then the TARARCH model and the EGARCH model were established to test the asymmetry

of the Shanghai and Shenzhen 300 Index. The fifth part is the policy recommendations, which combines the conclusions of the above empirical analysis and proposes relatively reasonable policy recommendations.

## 2. THEORETICAL MEASUREMENT MODEL

### 2.1. ARCH Model

The autoregressive conditional heteroskedastic model (Autoregressive Conditional Heteroscedasticity Model) was first proposed by Engle (1982) [2]. Bollerslev (1986) [3] extended the ARCH model to the Generalized ARCH Model—the generalized autoregressive conditional heteroskedastic model we often refer to. In a study analysis, Engle found that the variance stability of the disturbance term is usually poor. To solve this problem, Engle proposed the autoregressive conditional heteroscedasticity model in 1982, the ARCH model.

Consider a regression model with k variables:

$$y_t = \gamma_0 + \gamma_1 x_{1t} + \cdots + \gamma_k x_{kt} + \mu_t \quad (1)$$

Assuming that all information is public at time t-1, we can write the distribution of  $\mu_t$ :

$$\mu_t \sim N[0, \alpha_0 + \alpha_1 \mu_{t-1}^2]$$

$\mu_t$  follows a normal distribution. The expression of the ARCH(1) procedure is as follows :

$$\text{var}(\mu_t) = \sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 \quad (2)$$

The conventional ARCH model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \mu_{t-2}^2 + \cdots + \alpha_p \mu_{t-p}^2 \quad (3)$$

### 2.2. GARCH Model

Since the ARCH model requires  $\alpha_i$  non-negative condition to ensure the conditional variance  $\sigma_t^2$  is always positive. In reality, it is often difficult to do it accurately. So we introduce a generalized autoregressive conditional heteroscedasticity model, which is usually said GARCH model.

In the GARCH (1, 1) model:

$$y_t = x_t \gamma + u_t \quad (4)$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (5)$$

Where  $x_t$  is a 1\*(k+1) dimensional exogenous variable vector and  $\gamma$  is a (k+1)\*1 dimensional coefficient vector. The model contains the following three functions:

- (1) Constant term:  $\omega$
- (2)  $u_{t-1}^2$  (ARCH item)
- (3) Forecast variance of the previous period:  $\sigma_{t-1}^2$  (GARCH item)

(1,1) in the GARCH(1,1) model refers to the GARCH term with order 1 and the ARCH term with order 1. The higher-order GARCH model is denoted as GARCH (q,p) and is expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i u_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (6)$$

In this equation, (q, p) refers to the GARCH term with order q and the ARCH term with order p.

### 2.3. TARARCH Model

The TARARCH model, the threshold autoregressive conditional heteroscedasticity model, was proposed by Zakoian (1990) [6]. The model of TARARCH can be expressed as:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \gamma u_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \quad (7)$$

Where  $d_{t-1}$  is a nominal variable. When  $u_{t-1} < 0$ ,  $d_{t-1} = 1$ , in other cases,  $d_{t-1} = 0$ . As long as  $\gamma \neq 0$ , there is an asymmetrical effect.

In the model of (2-7),  $\gamma u_{t-1}^2 d_{t-1}$  is called the TARARCH term. The symmetry effect is reflected by the coefficient  $\gamma$ .  $\sigma_t^2$  depends on the previous  $u_{t-1}^2$  and  $\sigma_{t-1}^2$  sizes. When  $u_{t-1} > 0$ , it means good news. When  $u_{t-1} < 0$ , it indicates a bad message. The impact of good or bad news is completely different. Good news can cause an impact of  $\alpha$ ; bad news will bring the impact of  $\alpha + \gamma$ . When  $\gamma$  is not equal to zero, an asymmetrical effect can be considered. If  $\gamma > 0$ , the effect of the impact is considered to be an increase in the fluctuation. When  $\gamma < 0$ , the result is that the fluctuation is reduced.

The more general TARARCH model is as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i u_{t-i}^2 + \sum_{k=1}^r \gamma_k u_{t-k}^2 d_{t-k} \quad (8)$$

### 2.4. EGARCH Model

The EGARCH (Exponential GARCH) model was proposed by Nelson (1991) [9]. The conditional variance is expressed as:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left| \frac{u_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}} \quad (9)$$

This model can be used to detect leverage effects. We can use the value of  $\gamma$  to determine if the data has a leverage effect. When  $\gamma \neq 0$ , it is considered that there is a certain asymmetry. And if  $\gamma = 0$ , it means that it is symmetrical.

The higher order EGARCH model is:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{u_{t-i}}{\sigma_{t-i}} - E\left(\frac{u_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{k=1}^r \gamma_k \frac{u_{t-k}}{\sigma_{t-k}} \quad (10)$$

### 3. DATA SELECTION AND STATISTICAL ANALYSIS

#### 3.1. Variable Selection and Data Source

This paper selects the daily rate of return of the CSI 300 stock index as a variable. The Shanghai and Shenzhen 300 Index is jointly compiled by the Shanghai and Shenzhen Stock Exchanges and covers most of the high quality and high liquidity stocks in the A shares. And the use of scientific programming techniques, the selection of constituent stocks has strict standards. The index covers the market conditions of all walks of life and has excellent representation. There are two ways to get the return on the stock price index. One is the simple rate of return, which is the ratio of the daily closing price to the previous day's closing price. Its expression is:

$$R_t = (P_t - P_{t-1}) / P_{t-1} \tag{11}$$

Another method is the logarithmic rate of return, whose expression is:

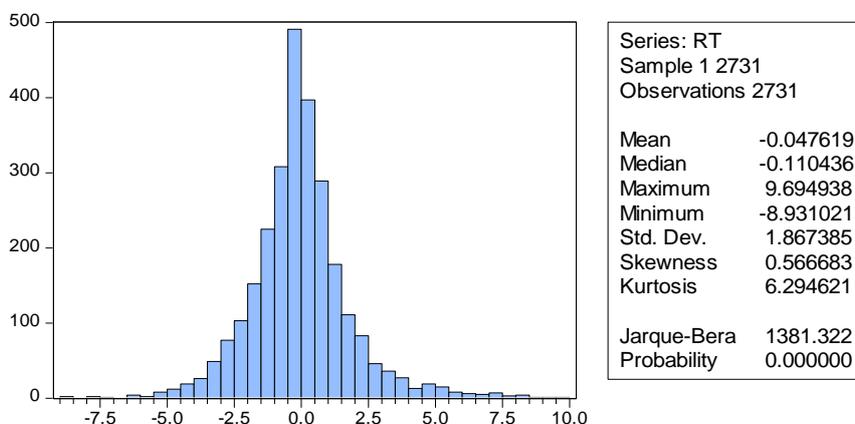
$$R_t = 100 * \ln(P_t/P_{t-1}) \tag{12}$$

Among them,  $P_t$  is the closing price of the stock index at time t, and  $P_{t-1}$  is the closing price of the stock index at time t-1.

Since the CSI 300 Index is a time series, it is easy to cause unevenness. Therefore, the logarithmic rate of return is used as a variable for subsequent testing. This paper selects the time span from January 4, 2006 to March 30, 2017, and contains data for 2731 trading days as a sample. All data comes from the Shanghai Stock Exchange. Based on the ARCH model, this paper conducts an empirical study on the stock price index of China from the basic statistical characteristics of the stock index of Shanghai and Shenzhen 300 stock indices.

#### 3.2. Statistical Description of the Shanghai and Shenzhen 300 Index Yields

In order to have a preliminary understanding of the volatility characteristics of the Shanghai and Shenzhen 300 Index, we first operate in Eviews6, and obtain the basic statistical characteristics of the Shanghai and Shenzhen 300 Index's return rate over the entire sample interval.



**Figure 2.** Statistical chart of the yield of the Shanghai and Shenzhen 300 Index

Analysis of the data in Figure 2 shows:

(1) The yield skewness is 0.566683, which is greater than 0, indicating that the heavy tail is on the right and is rightward.

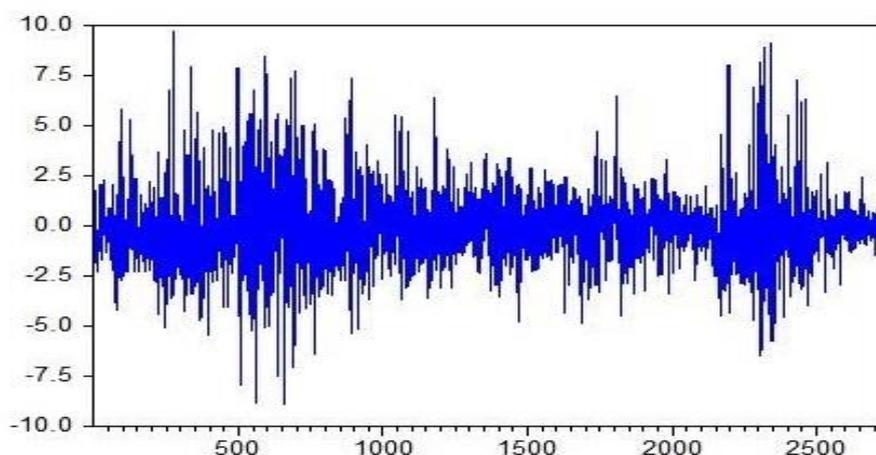
(2) The kurtosis is 6.294461, which is greater than 3. Compared with the normal distribution, the sequence of the yield of the Shanghai-Shenzhen 300 Index is steeper and has a thick tail phenomenon, and the sequence distribution has a long right tail.

(3) The P value of the J-B statistic is very close to zero. The hypothesis that the rate of return sequence obeys a normal distribution can be rejected at a certain level of significance.

From the statistical analysis of the Shanghai and Shenzhen 300 index yields, the yield series has obvious "spikes and thick tails". The reason why the index rate of return has such a characteristic may be due to the irrational decision-making caused by the asymmetry of information, which causes large fluctuations in prices. On the other hand, it may be due to the excessive attention of investors, that it is possible to judge the trend of future stock returns by analyzing the fluctuation of historical rate of return, so as to make investment decisions.

### 3.3. Analysis of Volatility Aggregation of Shanghai and Shenzhen 300 Index Yield

In order to further understand the volatility characteristics of the Shanghai and Shenzhen 300 index yields, we use EViews6 software to generate a time series chart of the Shanghai and Shenzhen 300 index yields to observe whether it has volatility agglomeration. Volatility agglomeration means that financial time series returns tend to be accompanied by large fluctuations after large fluctuations, followed by smaller fluctuations followed by smaller fluctuations.



**Figure 3.** Time series of the Shanghai and Shenzhen 300 index yields

As can be seen from Figure 3, the CSI 300 index fluctuates relatively in some time periods (such as between 1400 and 1600 and between 2000 and 2100 observations), and the fluctuations are relatively large in some time periods. (such as between 400 and 600 and between 2,300 and 2,400 observers). This shows that the fluctuation of the rate of return has its special agglomeration.

In summary, we can find that the Shanghai and Shenzhen 300 index yield series have obvious peak thick tail, right bias and volatility clustering. And the data does not obey the normal distribution and does not meet the assumptions of the traditional least squares method. If the OLS model (least squares method) is used to fit the exponential rate of return, there will be some bias, resulting in inaccurate results. Therefore, we need to use other models to empirically analyze the volatility of yields to get more accurate predictions.

## 4. EMPIRICAL TEST

### 4.1. Stationarity Test

Since the traditional model is no longer suitable for the Shanghai and Shenzhen 300 Index, the ARCH model suitable for the data characteristics of this paper is used to empirically analyze the yield series. The ARCH model can better characterize the volatility of stock indices. The empirical test using the ARCH model must first ensure that the yield series is stable. If the data is not stable, it may lead to regression results that are not credible, and is a kind of pseudo-regression. Therefore, it is necessary to conduct a stationarity test before modeling. The following uses the Augmented Dickey-Fuller Test in the EViews6 metrology software to determine whether the yield series is stable.

**Table 1.** ADF test results

Testing method	T statistic	1% threshold	Conclusion
ADF test	-50.660***	-3.433	smooth

Note: \*\*\*indicates a 1% significance level; \*\*indicates a 5% significance level; \*indicates a 10% significance level.

Looking at the T statistic in Table 1, we can see that the absolute value of 50.660 is much larger than the critical value of 3.433 for the corresponding significance level (1% significance level). So we can think that the yield series does not have a unit root at the 1% significance level. The results of the ADF test indicate that the sequence is stationary and can be used to build an ARCH model.

### 4.2. ARCH Effect Test of Shanghai and Shenzhen 300 Index Yield

From the statistical histogram of the Shanghai and Shenzhen 300 index yields, it can be seen that the sequence does not conform to the assumption of the traditional normal distribution, and there may be an ARCH effect, so the ARCH effect test is performed.

#### 1. Determine the lag order

The first step is to determine the lag order of the autoregression before performing the test. The regressions were performed on the lags 1, 2, 3, 4, and 5, and the results are shown in Table 2.

**Table 2.** AIC Values and F Statistics for Phase 5 Regression

Order	AIC value	F statistic
1	4.087132	2.570324
2	4.087354	2.629454
3	4.088134	1.432874
4	4.083591	14.83417
5	4.089305	0.143368

When determining the lag order, we need to judge based on the AIC value and the F statistic. Observing the data in Table 5-2, it can be seen that the AIC value and the F statistic are optimal when the lag phase 4 is used. So the lag order is chosen to be 4, and the corresponding regression equation is:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 r_{t-3} + \beta_4 r_{t-4} + u_t \quad (13)$$

## 2. Residual sequence autocorrelation test

After determining the lag order, the autocorrelation of the residual sequence is tested first. The autocorrelation coefficient of the residual term is derived from EViews6.

**Table 3.** Autocorrelation test of residuals

Order	Autocorrelation	Partial correlation	Q statistic	Incidental probability
1	0.029	0.029	2.2224	0.136
2	-0.024	-0.025	3.8532	0.146
3	0.019	0.020	4.8095	0.186
4	-0.001	-0.003	4.8112	0.307
5	0.004	0.005	4.8624	0.433
6	-0.063	-0.063	15.568	0.016
7	0.027	0.031	17.550	0.014
8	0.010	0.004	17.799	0.023
9	0.004	0.008	17.846	0.037
10	0.007	0.006	17.998	0.055

From the Q statistic and P value in Table 3, we can judge that there is no significant autocorrelation in the residual term after regression. The autocorrelation test of the squared residual term is then performed.

**Table 4.** Autocorrelation test of residual squared term

Order	Autocorrelation	Partial correlation	Q statistic	Incidental probability
1	0.168	0.168	77.206	0.000
2	0.150	0.126	138.94	0.000
3	0.175	0.138	222.60	0.000
4	0.157	0.101	289.70	0.000
5	0.118	0.051	327.62	0.000
6	0.140	0.075	381.46	0.000
7	0.153	0.083	445.18	0.000
8	0.142	0.067	500.47	0.000
9	0.085	-0.000	520.43	0.000
10	0.151	0.077	582.91	0.000

Observing the data in Table 4, it can be found that the autocorrelation of the squared residual term is very significant. This shows that there is a high-order ARCH effect in the residual sequence, and we use the ARCH model for empirical analysis.

## 3. Perform heteroscedasticity test on residuals

The residual of the sequence linear regression was tested by heteroscedasticity (using the BP test) to determine its ARCH effect.

**Table 5.** Results of heteroscedasticity test

Heteroskedasticity Test			
F statistic	24.02231	Probability	0.0000
LM test statistic	23.82987	Probability	0.0000

The test results of heteroscedasticity show that the corresponding probability of F statistic and LM test statistic are less than 0.05, so the original hypothesis is rejected, indicating that there is obvious heteroscedasticity in the yield series. The above tests show that the data is suitable for fitting with the ARCH model.

#### 4.3. Establish An ARCH Model to Test the Volatility of the Shanghai and Shenzhen 300 Index

The above analysis shows that the data does not meet the assumptions of the traditional least squares method. If the OLS model is used to fit the exponential rate of return, there will be some bias, resulting in inaccurate results. The ARCH model can better describe the volatility of the stock index, so we use the ARCH model to empirically analyze the volatility of the yield to obtain more accurate predictions. The ARCH model was built using EViews6 software and the results were estimated as follows:

**Table 6.** ARCH model estimation results

variable	coefficient	Standard deviation	Z statistic	Probability
Constant term	-0.031698	0.034444	-0.920270	0.3574
R(-4)	0.062069	0.014203	4.370060	0.0000
Constant term	2.785939	0.063140	44.12319	0.0000
ARCH item	0.204443	0.021431	9.539493	0.0000
goodness of fit	0.005243	AIC value		4.038497
Adjusted goodness of fit	0.004878	SC value		4.047167
Likelihood value	-5502.490	DW value		1.942195

The result is expressed as:

$$R_t = -0.031698 + 0.062069R_{t-4} + u_t$$

$$(0.034444) \quad (0.014203)$$

$$\sigma_t = 2.785939 + 0.204443u_{t-1}^2$$

$$(0.063140) \quad (0.021431)$$

Because the conditional heteroscedasticity of the Shanghai and Shenzhen 300 index yield is obvious, it is very suitable to use the ARCH model to fit the change of yield. The model can reflect the volatility change law of China's stock market return rate, and its analysis results have higher accuracy.

#### 4.4. Establish A GARCH Model to Test the Volatility of the Shanghai and Shenzhen 300 Index

Although the ARCH model has the advantage of well describing the undulating heteroscedasticity, there are too many residual lags. Compared with the ARCH model, the advantage of the GARCH model is that the low-order GARCH model can be used to represent the high-order ARCH model, which makes the identification and estimation of the model easier. The GARCH model is built using EViews6 software. The results are as follows:

**Table 7.** GARCH model estimation results

variable	coefficient	Standard deviation	Z statistic	Probability
Constant term	-0.044293	0.025457	1.739903	0.0819
R(-4)	0.027465	0.019361	1.418612	0.1560
Constant term	0.008548	0.003442	2.483261	0.0130
ARCH item	0.055711	0.004625	12.04684	0.0000
GARCH item	0.944045	0.004284	220.3551	0.0000
goodness of fit	0.003288	AIC value	3.809895	
Adjusted goodness of fit	0.002922	SC value	3.820733	
Likelihood value	-5189.792	DW value	1.940492	

The result is expressed as:

$$R_t = -0.044293 + 0.027465R_{t-4} + u_t$$

$$\begin{matrix} (0.0819) & (0.1560) \\ \sigma_t = 0.008548 + 0.055711u^2_{t-1} + 0.944045\sigma^2_{t-1} \\ (0.0130) & (0.0000) & (0.0000) \end{matrix}$$

From the results of the GARCH model estimates in Table 7, it can be found that all the coefficients in the  $\sigma_t$  equation pass the significance test. This significant reaffirmation has shown that the yield fluctuations described above have a certain agglomeration. Since the sum of the ARCH coefficient and the GARCH coefficient is  $0.999756 < 1$ , it is in accordance with the assumptions, indicating that the conditional variance of the Shanghai-Shenzhen 300 index logarithmic yield is stable. The sum of the coefficients of the ARCH and GARCH terms is very large, and is close to one. This shows that the random impact energy continues to affect the conditional variance. This test results show that historical data plays an important role in predicting future development.

From the time series, the Shanghai and Shenzhen 300 index yields show significant volatility agglomeration. Volatility agglomeration means that financial time series returns tend to be accompanied by large fluctuations after large fluctuations, followed by smaller fluctuations followed by smaller fluctuations. The holding period of the Shanghai and Shenzhen 300 Index assets is usually very short, and the shortening of the holding period makes the transactions frequent. A large number of market participants made trading transactions on the same day, and frequent trading activities made assets highly liquid. This high liquidity is also a major cause of index fluctuations.

#### 4.5. Establishing A TARCh Model to Test the Asymmetry of the Shanghai and Shenzhen 300 Index

Although both the ARCH model and the GARCH model can better deal with the problem of heteroscedasticity and can effectively eliminate the peak and tail of the yield series, it is difficult to describe the bias of the yield distribution. To this end, the TARCh model is built in EViews6 to address the bias of the yield distribution. The TARCh model results are estimated as follows:

**Table 8.** TARCh model estimation results

variable	coefficient	Standard deviation	Z statistic	Probability
Constant term	-0.048234	0.026680	-1.807872	0.0706
R(-4)	0.026640	0.019429	1.371140	0.1703
Constant term	0.007407	0.003285	2.254458	0.0242
ARCH item	0.050745	0.005164	9.826731	0.0000
TARCh item	0.007861	0.006507	1.208059	0.2270
GARCH item	0.945659	0.004236	223.2326	0.0000
goodness of fit	0.003208	AIC value		3.810339
Adjusted goodness of fit	0.002842	SC value		3.823345
Likelihood value	-5189.397	DW value		1.940445

The result is expressed as:

$$R_t = -0.048234 + 0.026640R_{t-4} + u_t$$

(0.0706)                      (0.1703)

$$\sigma_t^2 = 0.007407 + 0.050745u_{t-1}^2 + 0.007861u_{t-1}^2d_{t-1} + 0.945659\sigma_{t-1}^2$$

(0.0242)                      (0.0000)                      (0.2270)                      (0.0000)

In this model, the TARCh item describes the leverage effect. Since the coefficient of the TARCh term is  $0.00786 \neq 0$ , there is an asymmetrical effect. When there is a "good news", there is a shock of 0.050745. When there is a "bad news", it will bring a shock of 0.058606 ( $0.050745 + 0.007861$ ). The impact of bad news is much bigger. Through empirical analysis, it is found that there is a significant leverage effect on the yield of the Shanghai and Shenzhen 300 Index. The same level of "bad news" has brought the impact of the CSI 300 Index far stronger than the impact of the same level of "good news". The bad news is more volatile than the good news.

#### 4.6. Establish an EGARCH Model to Test the Asymmetry of the Shanghai and Shenzhen 300 Index

The EGARCH model is built below to test the asymmetry of the Shanghai and Shenzhen 300 Index. The EGARCH model can use the value of  $\gamma$  to determine whether the data has a leverage effect. The results of the EGARCH model in EViews6 are estimated as follows:

**Table 9.** Estimation results of EGARCH model

variable	coefficient	Standard deviation	Z statistic	Probability
Constant term	-0.044022	0.026865	-1.638637	0.1013
R(-4)	0.026988	0.018593	1.451553	0.1466
C(4)	-0.087133	0.006667	-13.06913	0.0000
C(5)	0.124960	0.009263	13.48950	0.0000
C(6)	0.000613	0.004921	0.124561	0.9009
C(7)	0.994182	0.001715	579.8151	0.0000
goodness of fit	0.003244	AIC value		3.806752
Adjusted goodness of fit	0.002878	SC value		3.819757
Likelihood value	-5184.506	DW value		1.940468

The result is expressed as:

$$R_t = -0.044022 + 0.026988R_{t-4} + u_t$$

$$\log(\sigma^2_t) = \begin{matrix} (0.1013) & (0.1466) \\ -0.087133 + 0.124960 \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| - 0.000613 + 0.994182 \log(\sigma^2_{t-1}) \\ (0.0000) & (0.0000) & (0.9009) & (0.0000) \end{matrix}$$

The results show that there is also a significant leverage effect in the EGARCH model. The fluctuations caused by the same bad news and good news are different. In the EGARCH model, the value of  $\alpha$  is 0.124960, and the estimated value of its asymmetrical term  $\gamma$  is 0.000613. When  $u_{t-1} > 0$  (good news), the impact consists of  $\alpha + \gamma = 0.124960 + (-0.000613) = 0.124347$ . When  $u_{t-1} < 0$  (a bad news), the magnitude of the impact is  $\alpha + \gamma = 0.124960 + (-0.000613) \cdot (-1) = 0.125573$  times. The empirical analysis of the EGARCH model also shows that the leverage effect is widespread in the Shanghai and Shenzhen 300 index yields.

The empirical results of the TARCH model and the EGARCH model show that the Shanghai and Shenzhen 300 index yields have obvious leverage effect. This may be due to the special trading system of the CSI 300 Index. The CSI 300 Index implements a T+0 trading system that allows for both short-selling and long-term trading. Another reason may be that investors have the psychology of irrational investment. Investors' lack of response during the rising process and overreaction in the downturn are the main reasons for the asymmetric market volatility. At the same time, due to the imperfect risk management system, some investors are easily driven by interests and use legal loopholes to conduct speculation. Such violations will disrupt market order, create unfair competition and cause market volatility.

## 5. POLICY SUGGESTION

### 5.1. Strengthening Rational Investment Education

China's current financial market belongs to the category of emerging markets, the market system is imperfect, the laws and regulations are incomplete, and the information is asymmetrical. The vast number of retail investors in the market lack the concept of rational investment and follow the trend. Therefore, government departments should strengthen the rational investment education for market investors and correctly guide investment. Further improve the conditions for investors to enter the market, evaluate and classify the risk tolerance of investors, open up suitable financial products for different investment entities, promote rational investment, and control risks from the source.

### 5.2. Improve the Information Disclosure System

Listed companies are an important part of the financial market. On the one hand, they are the demanders of funds. They raise funds needed for operation through listing. On the other hand, listed companies are also suppliers of funds and participate in market investment. Whether the information of listed companies can be fully disclosed will directly affect the investment decisions of investors, thus affecting the stability of the entire financial market. Improve the information disclosure system, ensure the sharing of basic information, create a fair and open investment environment for investors, give full play to the role of the market, avoid insider trading, and maintain market stability.

### 5.3. Improve the Risk Management System

As a place for market transactions, the Exchange has the responsibility and obligation to supervise market participants to ensure the normal conduct of transactions. Through the improvement of the daily limit system and the margin system, a series of risk management measures are taken to protect the legitimate rights and interests of investors and prevent

market turmoil caused by excessive speculation. The exchange shall regulate the behavior of all parties to the transaction and form a benign trading environment.

#### 5.4. Promoting the Construction of the Rule of Law in the Market

China's financial market started late, and relevant laws and regulations are still not complete. Investors are easily driven by interests and use legal loopholes to speculate. This behavior will seriously disrupt the normal operating order of the securities market and cause market volatility. Government departments should accelerate the construction of the rule of law in the securities market, have clear legal norms for all aspects of market behavior, prevent market fluctuations caused by imperfect laws and regulations, and improve the effectiveness of management.

#### REFERENCES

- [1] Mandelbrot, Benoit. The Variation of Certain Speculative Prices [J]. *Journal of Business*, 1963, 36(4): 115-130.
- [2] Engle, Robert. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of UK Inflation [J]. *Econometrica*, 1982, 50(7): 203-224.
- [3] Bollerslev, Tim. Generalized regressive conditional heteroskedasticity [J]. *Journal of Econometrics*, 1986, 31(8): 307-327.
- [4] Engle, Robert and Ng, Victor. Measuring and Testing the Import of News on Volatility [J]. *Journal of Finance*, 1993, 48: 1022-1082.
- [5] Danielsson, J. Stochastic volatility in asset prices: estimation with simulated maximum likelihood [J]. *Econometrics*, 1994 (64): 375-400.
- [6] Zakoian, JM. Threshold Heteroskedastic Models [J]. *Journal of Economic Dynamics and Control*, 1994(18): 931- 955.
- [7] Singleton, KJ. Estimation of affine asset pricing models using the empirical characteristic function [J]. *Journal of Econometrics*, 2001 (102): 111-141.
- [8] Awartani, Basel and Valentina, Corradi. Predicting the Volatility of the S&P-500 Stock Index via GARCH Models: the Role of Asymmetries [J]. *International Journal of Forecasting*, 2005 (1): 167-183.
- [9] Nelson, Daniel. Conditional Heteroskedasticity in Asset Returns [J]. *A New Approach Econometrics*, 1990, 59(11): 347-370.
- [10] Ding Hua. ARCH Phenomenon in Stock Price Index Fluctuation [J]. *Quantitative Economics and Technology Economics Research*, 1999(9): 22-25.
- [11] Chen Qianli, Zhou Shaoqi. Research on the Volatility of Shanghai Stock Index's Return [J]. *Quantitative Economics & Technology Economics Research*, 2002(6): 122-125.
- [12] Liu Jinqun. Cui Chang. An Empirical Analysis of the Return and Volatility of China's Shanghai and Shenzhen Stock Markets [J]. *Economic Research (Quarterly)*, 2002(1): 885-898.
- [13] Kong Huaqiang. Financial market volatility model and municipal research [D]. *Capital University of Economics and Business*, 2006.
- [14] Chen Yan. Han Lilei. An Empirical Study on the Volatility of the Revenue of the Shanghai and Shenzhen 300 Indexes [J]. *Financial Economics*, 2009(14): 70-72.
- [15] He Hongxia. Research on Volatility of China's Stock Market Price——GARCH Family Model Based on Shanghai and Shenzhen 300 Index [J]. *Journal of Hetian Teachers College*, 2010(03): 10-12.

- [16] Zhang Yan. Empirical Research on China's Stock Index Futures and Spot——Based on Shanghai and Shenzhen 300 Stock Index Futures [J]. Value Engineering, 2011 (11): 126-128.
- [17] Sun Deshan, Qian Cheng, Guo Tao. Application of GARCH Model in China's Futures Market Forecasting [J]. Journal of Liaoning Normal University, 2012(03): 4-6.
- [18] Li Wei. Comparative study of VAR estimation models in Chinese stock market under long memory conditions [D]. Xiangtan University, 2008.
- [19] Zhao Li. Analysis of the Volatility of the Shanghai and Shenzhen 300 Index Yield Based on GARCH Model [D]. Chengdu University of Technology, 2013.