Research on the Volatility of China's Stock Market Returns Based on GARCH Model-Taking CSI 300 Index as an Example

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Abstract. The volatility of yields reflects the degree of risk in the market, and at the same time the volatility of yields is viewed as a measure of information, and high volatility is generally accompanied by large market information shocks. Therefore, it is particularly important to study the volatility of China's stock market returns so as to find out where the problems lie. In this paper, the CSI 300 index is taken as the research object, and a total of 2,671 daily closing prices from 4 January 2013 to 29 December 2023 are taken as the sample, and the GARCH family model is used to analyse this sample data, so as to derive the volatility characteristics of the CSI 300 index and to make static forecasts.

Keywords: CSI 300 index; volatility; GARCH family model.

1. Introduction

1.1. Background of the topic and significance of the study

1.1.1 Background to the selection of topics

Prior to the launch of CSI 300 Index on 8 April 2005, there existed independent composite indices and constituent indices in Shanghai and Shenzhen stock exchanges, which were highly recognised by investors but lacked the standard of indices that could reflect the overall market trend in China. The CSI 300 Index, jointly issued by the Shanghai and Shenzhen stock exchanges and compiled by CSI, is able to reflect the overall trend and operation of China's securities market, filling the gap of China's lack of cross-market indices and meeting the market demand. As an evaluation standard of market performance, it has become one of the wind vane to observe the trend of the whole market. The launch of the index further improves the existing index system of the market, and also lays a solid foundation for capital market indexed investment and index derivatives innovation.[3] The index was launched to further improve the market's existing index system and lay a solid foundation for capital market indexed investment and index derivative innovation.

All along, the research on the volatility characteristics of stock market prices and the development trend of stock market yields has been a hot topic in the industry. Yield is a major important indicator for measuring the price of financial assets, and its volatility can well describe the volatility of asset prices. Domestic and foreign scholars in the study of yield volatility, usually using the establishment of yield volatility model to analyse and forecast the series. This research can be traced back to the 1960s, and long-term research can be found that there are volatility clustering and peak-thick tail ARCH characteristics in the data. Then, the general time series model fitting the volatility of the data has the problem of insufficient accuracy. After Bollerslev (1986) proposed the GARCH model, the model has been widely used and developed to date, the study of short-term volatility based on the GARCH family of models has gained acceptance in the academic community[2] .

Therefore, this paper adopts the closing price of each trading day from 4 January 2013 to 29 December 2023 in total 2671 data as the original data, and uses the GARCH model to test the volatility change of CSI 300 daily return, hoping that it can find out the characteristics of the volatility of the CSI 300 and analyse the reasons.

1.1.2 Significance of the study

Volatility is a fundamental characteristic of securities markets and implies the creation of risks and returns. A certain degree of volatility is conducive to promoting the development of the real economy, thus enabling market participants to benefit from it. Therefore, the study of the volatility of China's stock prices is of practical significance in the following aspects:

(1) For investors, the magnitude and frequency of price fluctuations are important references for investors when investing. Through the CSI 300 Index, investors can understand the overall trend of the stock market and price movements, and based on this, make reasonable estimates of the future situation, so as to effectively arrange investment decisions.

(2) For fund-raisers, since the stock price is closely related to the operation of the listed company, the fluctuation of the stock price in turn reflects the operation of the company. Based on the analysis of the volatility of the stock market, the fund-raisers can find out the deficiencies in the operation in time and take measures to improve them, so as to promote the sustainable and healthy development of the listed company.

(3) For policy makers, through the study of stock price volatility, the government can formulate a series of reasonable and effective policy measures to improve the market order, reduce the negative impacts of stock price volatility on society, and ensure the healthy development of the securities market.

1.2. Research ideas

In this paper, the GARCH model is used to study the volatility of CSI 300 index returns, and the research ideas are described below:

The first chapter is the introduction. Firstly, it introduces the background of the selected topic and the significance of the study, shows the theoretical and practical significance of the study, and explains that the study has certain necessity.

The second chapter is the theoretical model. In order to study the problem, it is necessary to apply theoretical knowledge correctly, so as to obtain theoretical support and persuasive conclusions. In the theoretical model, the ARCH model and GARCH model are mainly described, and the definitions and characteristics of the models are introduced, and the broader forms of the models (TGARCH and EGARCH) are introduced to deal with the deficiencies in the models.

Chapter 3 is the empirical analysis. In this paper, after selecting the closing price of each trading day of CSI 300 index from 4 January 2013 to 29 December 2023 as the original data, a total of 2,671 data samples were collected, and using the Eiews8 software, an empirical analysis of the GARCH family model was carried out, including descriptive statistical analysis, ADF smoothness test, autocorrelation test of the return series, ARCH effect test, based on the test results, a relatively reasonable and realistic GARCH model was established.

Chapter 4 is devoted to conclusions. A series of conclusions are drawn from the above analyses.

2. Theoretical Modelling

2.1. ARCH Modelling

ARCH model is also known as Autoregressive Conditional Heteroscedasticity Model, whose main core is the moment t of the ε is affected by the magnitude of the squared error at the moment (t-1), i.e., it is a function of the variance ($=\sigma^2$) is affected by the magnitude of the squared error at moment (t-1), i.e., it is dependent on the magnitude of the squared error of ε_{t-1}^2 of the[1] .

$$Y_t = \beta_0 + \beta_1 X_{1t} + \Lambda\Lambda + \beta_k X_{kt} + \varepsilon_t \tag{1}$$

Suppose that at the moment (t-1), under all information conditions, there is more than one of its interferences, and the distribution of its interference terms is:

$$\varepsilon_t \sim (0, \ (\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)) \tag{2}$$

That is, ε_t follows a normal distribution with 0 as the mean and ($\alpha_0+\alpha_1\varepsilon_{t-1}^2$) as the variance. Since the variance of ε_t in (2) will just depend on the disturbance term at that moment in the prior period, it is an ARCH(1) process. However, generalising the disturbance term to which it is subjected, the ARCH (p) process is:

$$Var(\varepsilon_t) = \sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \Lambda\Lambda + \alpha_p\varepsilon_{t-p}^2 \tag{3}$$

If there is no autocorrelation present in the error variance, there is $H_0: \alpha_1 = \alpha_2 = \Lambda = \alpha_p = 0$. At this point, $Var(\varepsilon_t) = \sigma_t^2 = \alpha_0$, the result is the case of homoskedasticity in the error variance. Engle has used the following regression to test the hypothesis of the above dummy:

$$\hat{\varepsilon}_t^2 = \hat{\alpha}_0 + \hat{\alpha}_1\varepsilon_{t-1}^2 + \hat{\alpha}_2\varepsilon_{t-2}^2 + \Lambda\Lambda + \hat{\alpha}_p\varepsilon_{t-p}^2 \tag{4}$$

Where $\hat{\varepsilon}_t$ is the OLS residuals obtained from our estimation in the original regression model (1).

Bollerslev (1986) will expand and improve the ARCH model, proposed GARCH, and through a series of in-depth research, empirical analysis shows that the GARCH model can have a better grasp of the analysis of financial market data.[7] The characteristics of financial data have been fully embodied, and has been respected and widely used.

The simplest GARCH model is the standardised GARCH (1, 1) model:

$$y_t = x_t\gamma + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

The mean equation for a function of one exogenous variable and with an error term is given in (5). It is called the conditional variance because σ^2 is the predicted variance and is based on information from the previous moment, it is called the conditional variance. The conditional variance equation given in (6) is a function of the ARCH term, and the GARCH term:

(i) Mean value: ω ;

(ii) The information on volatility from the prior period can be measured by the lag of the squared residuals of the mean equation: ε_{t-1}^2 (ARCH term);

(iii) The forecast variance of the previous period: σ_{t-1}^2 (GARCH term).

The first term "1" in parentheses in GARCH (1, 1) refers to the GARCH term of order 1, and the second term "1" in parentheses refers to the ARCH term of order 1. A special form of the GARCH model is the ordinary ARCH model, which is the conditional variance equation without lagged forecast variance specification. The special form of the GARCH model is the normal ARCH model, i.e., the conditional variance equation without the lagged forecast variance specification.

2.2. GARCH Modelling

Engle and Ng plotted the asymmetric information curve under the influence of good news and the combination of information curve under the influence of bad news, and determined that the asymmetric effect is the basic manifestation of the market's response to shocks in financial markets, and that this asymmetric effect forms the "leverage effect" in financial markets, which is an important factual feature of many financial assets, i.e., the volatility response is much stronger and more rapid in a market downturn than in a market upturn. This asymmetric effect creates a "leverage effect" in financial markets, which is also an important factual feature of many financial assets, i.e., volatility reacts much more strongly and quickly when the market is falling than when the market is rising, and the TGARCH model and the EGARCH model are the two main models describing such asymmetric shocks.

(1) TGARCH model

The TGARCH or Threshold ARCH model was introduced independently by Zakoian.J.M (1990) and Glosten, Jafanathan, Runkle (1993). This model is a good simulator of the "leverage effect" in financial markets and has conditional variance of the form:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \tag{7}$$

Where, when $\varepsilon_t < 0$, $d_t = 1$; otherwise $d_t = 0$.

In this model, good news ($\varepsilon_t > 0$) and bad news ($\varepsilon_t < 0$) have completely different impacts on the conditional variance: good news has a shock to one; bad news has a shock to$\alpha + \gamma$ the shock. We say that there is leverage if$\gamma > 0$, we say that there is leverage; if$\gamma \neq 0$, then the information is asymmetric. The TGARCH term in the model, the leverage term (γ) is described by the (RESID<0)*ARCH(1) term in the output.

(2) EGARCH model

The premise of the linear GARCH model assumes that the fluctuations caused by positive and negative shocks of equal absolute value are the same, i.e., the conditional variance is the same, and the final response should be a symmetrical and equal fluctuation of returns caused by positive and negative shocks of equal absolute value. But in reality, especially in the financial market, the absolute value of equal positive and negative shocks caused by the volatility is often different, because in the stock market often reacts to the stock price decline is much larger than the rise, and the downward process to be more violent, more volatile. Obviously, the asymmetry of volatility in the stock market to not be explained by the previous linear GARCH model, Nelson (1991), on the other hand, proposed the EGARCH or exponential (Exponential) GARCH model. However, the symmetric conditional variance function is not yet fully accurate, especially in the case of the negative correlation between the return on prior assets and market volatility at the time of debt. To avoid this and to complete the non-negative assumptions on the parameters, he based the GARCH model on the conditional variance was specified:

$$\log(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{8}$$

On the left side of the equation is the logarithm of the conditional variance, which means that the leverage effect is not quadratic but exponential, so the predicted value of the conditional variance must be non-negative. It is possible to test whether the leverage effect exists by assuming that $\gamma<0$. If $\gamma\neq 0$, then the impact is non negative. The lever effect term (γ) is denoted in the output as RES/SQR[GARCH] (1).

The advantage of this model is that the data of the conditional variance is the logarithmic form of σ_t^2, so the variance σ_t^2 is a positive number greater than 0, so there is no need to add other restrictions to the formula. Since the parameters in the model have no constraints, the final solution process is simpler and more flexible.

3. Empirical analysis

3.1. Sample Data Selection and Statistical Description

(1) Data Selection

In this paper, the closing price of each trading day of CSI 300 index from 4 January 2013 to 29 December 2023 is used as the original data, with a total of 2,671 data samples, the data is obtained from Flush iFinD, and Pt is used as the CSI 300 index of the t-th day.

In the study of stock market volatility, the daily return of CSI 300 is used as the examining variable, in order to reduce the error, the natural logarithmic treatment of the daily return, i.e., the daily return of CSI 300 is expressed as the logarithmic first-order difference of the closing indices of the two adjacent days, and then the return is calculated by the formula:

$$r_t = \log(P_t) - \log(P_{t-1}) \tag{9}$$

Follow-up data processing was performed using EVIEWS8 statistical software.

(2) Descriptive statistical analysis

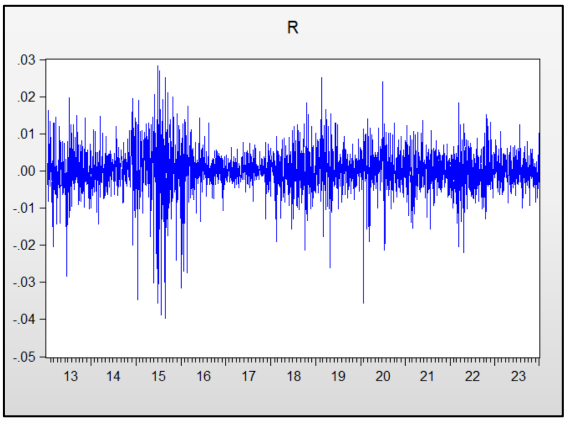


Fig. 1 Time series plot of log returns of the CSI 300 Index

As can be seen from Fig. 1, the CSI 300 index return fluctuates up and down around 0, and the index return series fluctuates sharply in the short term from the beginning of 2015 to the beginning of 2016, and the return series fluctuates at a low level in the short term from the middle of 2016 to the end of 2017, so that the overall series has the obvious "clustering" phenomenon. " phenomenon.

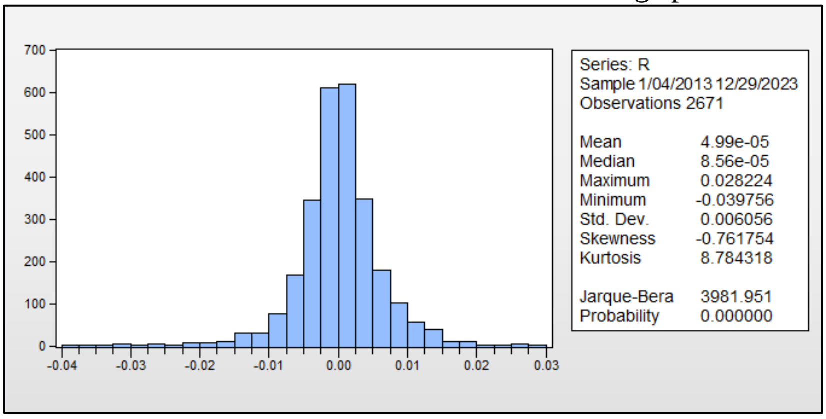


Fig. 2 Descriptive statistics of CSI 300 index returns

From Fig. 2, we can see that the standard deviation of the logarithmic return series of CSI 300 index is 0.006056, with a skewness of -0.761754, and a kurtosis of 8.784318, which is much higher than the kurtosis value of 3 of the normal distribution. The return r_t has the characteristic of a sharp peak and a thick tail. The JB statistic is 3981.951 with a p-value of 0.000000, therefore rejecting the assumption of a normal distribution.

3.2. Stability test of CSI 300 index return series

The most commonly used method in the smoothness test is the unit root method proposed by two American statisticians, D. A. Dickey and W. A. Fuller, in the 1970s, which is the method to determine whether the autocorrelation coefficient is equal to one. After nearly 30 years of academic research, this method was finally summarised as the ADF test, i.e. Augmented Dickey-Fuller (ADF) test.

From the descriptive statistics analysis above, it can be seen that the yield series fluctuates around the mean and there is no trend. Therefore, an ADF unit root test with an intercept term and no trend term is performed on the series with the following results:

Table 1. CSI 300 Index Returns ADF Test Results

		t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		-50.02709	0.0001
Test critical values:	1% level	-2.565828	
	5% level	-1.940942	
	10% level	-1.616620	

From the results of ADF test, the Mackinnon critical values of unit root test at 1%, 5% and 10% significance levels are -2.565828, -1.940942 and -1.616620 respectively, and the value of t-test statistic is -50.02709, which is smaller than the corresponding critical value and corresponds to a p-value of 0.0001, thus rejecting H_0 , indicating that the CSI 300 index return series is a smooth series.

3.3. ARCH effect test

(1) Selection of the lag order and establishment of the mean value equation

The time series model is used in this paper, so the lag order of the autoregression of the return should be chosen first. The mean equations of CSI 300 index returnsr_t The mean equations of the CSI 300 index all take the following form:

$$r_t = C_0 + \sum_{i=1}^{n} C_i r_{t-1} + \varepsilon_t \tag{10}$$

Table 2. Autoregressive Lag Order Selection

Lag	P-value
1	0.0479
2	0.4585
3	0.3016
4	0.1241
5	0.7709
6	0.0018
7	0.0372
8	0.1610
9	0.1806
10	0.4386
11	0.0567

According to the p-value, it can be seen that lag 6 is optimal, so lag 6 is chosen, then the equation can be written as:

$$r_t = C_0 + C_1 r_{t-1} + C_2 r_{t-2} + C_3 r_{t-3} + C_4 r_{t-4} + C_5 r_{t-5} + C_6 r_{t-6} + \varepsilon_t \tag{11}$$

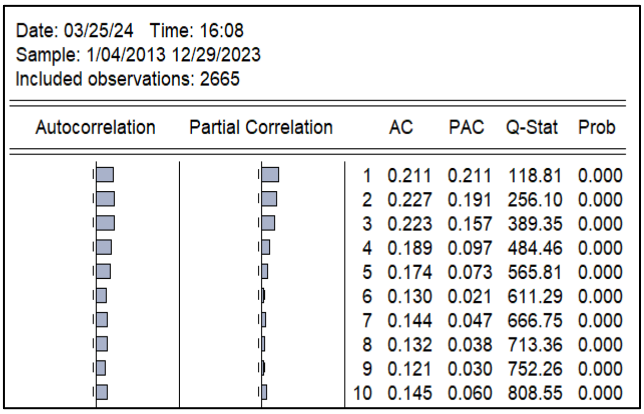
(2) Autocorrelation test for residual series

Date: 03/26/24 Time: 14:53
Sample: 1/04/2013 12/29/2023
Included observations: 2671

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.032	0.032	2.7530	0.097
		2	-0.035	-0.036	6.0386	0.049
		3	0.003	0.005	6.0571	0.109
		4	0.038	0.037	9.9942	0.041
		5	-0.009	-0.011	10.215	0.069
		6	-0.073	-0.070	24.358	0.000
		7	0.030	0.034	26.812	0.000
		8	0.054	0.046	34.674	0.000
		9	0.030	0.030	37.127	0.000
		10	-0.028	-0.022	39.257	0.000

Fig. 3 Autocorrelation coefficients AC and PAC values for the residual term of CSI 300 index returns

As can be seen in Fig. 3, there is a sixth-order higher-order autocorrelation in the residual term of the CSI 300 index return.


Date: 03/25/24 Time: 16:08
Sample: 1/04/2013 12/29/2023
Included observations: 2665

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.211	0.211	118.81	0.000
		2	0.227	0.191	256.10	0.000
		3	0.223	0.157	389.35	0.000
		4	0.189	0.097	484.46	0.000
		5	0.174	0.073	565.81	0.000
		6	0.130	0.021	611.29	0.000
		7	0.144	0.047	666.75	0.000
		8	0.132	0.038	713.36	0.000
		9	0.121	0.030	752.26	0.000
		10	0.145	0.060	808.55	0.000

Fig. 4 Autocorrelation coefficients of the squared residuals of the CSI 300 index returns AC and PAC values

As can be seen in Fig. 4, there is significant autocorrelation in the squared residuals of the CSI 300 index returns.

(3) ARCH-LM Test on residuals (lagged 6th order)

Table 3. Results of ARCH-LM Test on the residuals of CSI 300 index

F-statistic	124.0800	Prob. F (1, 2662)	0.0000
Obs*R-squared	118.6430	Prob.Chi-Square (1)	0.0000

An ARCH-LM test is performed on the residuals of a linear regression of a series, where the F statistic is tested for the joint significance of the squared residuals across all lags. The Obs*R^2 statistic is the LM test statistic, which is the number of observations T multiplied by the test regression R^2. Given the significance level α = 0.05 and degree of freedom 10, the value of LM is 118.6430 greater than the given value of 18.307, and the accompanying probability P is 0.0000, which is less than 0.05, rejecting the original hypothesis, indicating that there is a significant heteroskedasticity phenomenon in the yield series, and the residuals have a strong ARCH effect, so this paper adopts the GARCH model to fit CSI 300 index yield variation of the data is reasonable.

3.4. Empirical evidence of the GARCH family of models

1. Volatility study of CSI 300 index returns

Table 4. GARCH (1, 1) model estimation results

Dependent Variable: HS300
Method: ML-ARCH (Marquardt)-Normal distribution
Sample (adjusted): 1/15/2013 12/29/2023
Included observations: 2665 after adjustments
Convergence achieved after 15 iterations
Presample variance: backcast (parameter=0.7)
GARCH=C(3)+C(4)*RESID(-1)^2+C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000130	8.74E-05	1.490202	0.1362
HS300 (-6)	-0.040164	0.01975	-2.031072	0.0422
Variance Equation				
C	2.86E-06	6.10E-08	4.691836	0.0000
RESID(-1)^2	0.078690	0.004657	16. 89735	0.0000
GARCH (-1)	0.916758	0.004413	207.7608	0.0000

R-squared	0.004057	Mean dependent var	4.66E-05
Adjusted R-squared	0.003683	S.D. dependent var	0.006053
S.E. of regression	0.006041	Akaike info criterion	-7.665095
Sum squared resid	0.097199	Schwarz criterion	-7.654048
Log likelihood	10218.74	Hannan-Quinn criter.	-7.661098
Durbin-Watson stat	1.931093		

$$r_t = 0.00013 - 0.040164\gamma \tag{12}$$

(1.490202) (-2.031072)

$$\sigma_t^2 = 2.86 * 10^{-6} + 0.078690\varepsilon_{t-1}^2 + 0.916758\sigma_{t-1}^2 \tag{13}$$

(4.691836) (16.89735) (207.7608)

Log likelihood=10218.74, AIC=-7.665095, SC=-7.654048

It can be seen that in the conditional variance equation of CSI 300 index return, both the ARCH and GARCH terms are highly significant, and this significance indicates that the volatility of the return series has the characteristic of clustering. The sum of the ARCH and GARCH terms of CSI 300 index returns is 0.995448, which is less than 1 and meets the constraints on the parameters. However, since the sum of the two coefficients, 0.995155, is very close to 1, it proves that the impact of the shock on the conditional variance is not transient but a persistent process, and it can be inferred that the shock plays an important role in the future prediction by the feature, and therefore the GARCH (1, 1) is a smooth process.

2. A study of asymmetry in return volatility of the CSI 300 index

(1) TGARCH model estimation

Table 5. TGARCH model estimation results

Dependent Variable: HS300				
Method: ML-ARCH (Marquardt)-Normal distribution				
Sample (adjusted): 1/15/2013 12/29/2023				
Included observations: 2665 after adjustments				
Convergence achieved after 20 iterations				
Presample variance: backcast (parameter=0.7)				
GARCH=C(3)+C(4)*RESID(-1)^2+C(5)*RESID(-1)^2(RESID(-1)<0)+ C(6)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000114	9.06E-05	1.263781	0.2063
HS300 (-6)	-0.039135	0.019759	-1.980654	0.0476
Variance Equation				
C	3.05E-07	6.23E-08	4. 889279	0.0000
RESID(-1)^2	0.073898	0.006937	10. 65196	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.011126	0.007766	1.432652	0.0398
GARCH (-1)	0.915229	0.004620	198.1047	0.0000
R-squared	0.004052	Mean dependent var	4.66E-05	
Adjusted R-squared	0.003678	S.D. dependent var	0.006053	
S.E. of regression	0.006042	Akaike info criterion	-7.664663	
Sum squared resid	0.097199	Schwarz criterion	-7.651406	
Log likelihood	10219.16	Hannan-Quinn criter.	-7.659866	
Durbin-Watson stat	1.931269			

$$r_t = 0.000114 - 0.039135\gamma \tag{14}$$

(1.263781) (-1.980654)

$$\sigma_t^2 = 3.05 * 10^{-7} + 0.073898\varepsilon_{t-1}^2 + 0.011126\varepsilon_{t-1}^2 d_{t-1} + 0.915229\sigma_{t-1}^2 \tag{15}$$

(4. 889279) (10. 65196) (1.432652) (198.1047)

Log likelihood=10219.16, AIC=-7.664663, SC=-7.651406

As shown in equation 15, the estimated coefficient value of $\varepsilon_{t-1}^2 d_{t-1}$ is 0.011126, with a p-value of 0.0398, which is significantly positive, indicating the existence of asymmetric effects. At the same time, it indicates that the volatility of CSI 300 Index has a "leverage effect", and the volatility caused by negative news is much larger than that caused by equally strong positive news.

(2) EGARCH model estimation

Table 6. EGARCH model estimation results

Dependent Variable: HS300
Method: ML-ARCH (Marquardt)-Normal distribution
Sample (adjusted): 1/15/2013 12/29/2023
Included observations: 2665 after adjustments
Convergence achieved after 27 iterations
Presample variance: backcast (parameter=0.7)
LOG(GARCH)=C(3)+C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1)))+C(5)*RESID(-1)/@SQRT(GARCH(-1))+C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.47E-05	8.87E-05	0.955057	0.3395
HS300 (-6)	-0.039726	0.020000	-1.986249	0.0470
		Variance Equation		
C (3)	-0.254331	0.023773	-10.69831	0.0000
C (4)	0.177710	0.009228	19.25844	0.0000
C (5)	-0.009244	0.005854	-1.579150	0.0135
C (6)	0.988290	0.002258	437.6386	0.0000
R-squared	0.004175	Mean dependent var		4.66E-05
Adjusted R-squared	0.003801	S.D. dependent var		0.006053
S.E. of regression	0.006041	Akaike info criterion		-7.661157
Sum squared resid	0.097187	Schwarz criterion		-7.647901
Log likelihood	10214.49	Hannan-Quinn criter.		-7.656360
Durbin-Watson stat	1.931400			

$$r_t = 8.47 * 10^{-5} - 0.039726\gamma \tag{16}$$

(0.955057) (-1.986249)

$$\log(\sigma_t^2) = -0.254331 + 0.177710\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.009244\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + 0.988290\log(\sigma_{t-1}^2) \tag{17}$$

(-11.84297) (18.82741) (-2.469106) (397.3750)

Log likelihood=10214.49, AIC=-7.661157, SC=-7.647901

As shown in Equation 17, the estimated coefficient of $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is -0.009244 with a p-value of 0.0135, which is significantly negative, indicating that there is a significant leverage effect on the CSI 300 index returns during the sample period.

3.5. Forecast of CSI 300 Index based on GARCH model

Static forecasts were made using the GARCH model with a modelling interval of the closing price of each trading day from 4 January 2013 to 30 December 2022 and a forecast interval of 3 January 2023 to 29 December 2023.

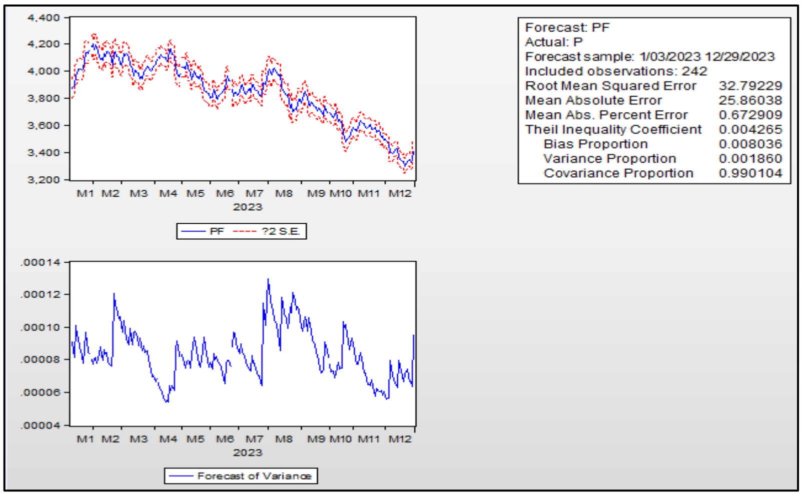


Fig. 4 CSI 300 Index Forecasts

As can be seen in Fig. 4, the Theil coefficient is 0.004265, indicating that the prediction is accurate.

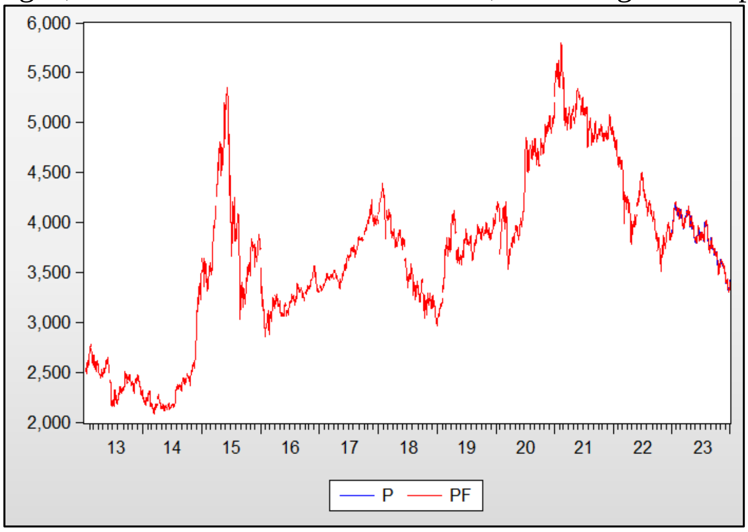


Fig. 5 CSI 300 Index Return Forecast and Real Value Fitting Curve

As can be seen from Fig. 5, the prediction results have a certain degree of accuracy, and the predicted part is highly overlapped with the real part, so the GARCH model can reflect the real situation of the data well by capturing the fluctuating information and has considerable predictive ability.

4. Conclusion

A series of analyses in the previous section leads to several conclusions:

1. GARCH model can be applied to China's stock market. Because the volatility of CSI 300 index has heteroskedastic characteristics, so this paper applies the GARCH family model can reflect the volatility change rule of China's stock market returns, and its analysis and research results have a certain degree of accuracy.

2. CSI 300 index returns there is a clear "cluster" phenomenon, and the distribution of the sequence shows the characteristics of the thick tail of the sharp peaks, there is a clear GARCH effect, the past fluctuations over time on the future impact of the gradual weakening.

3. Through the establishment of TGARCH and EGARCH models, it is found that there is an obvious leverage effect on the return of CSI 300 index. The impact of the same degree of "bad news" on the CSI 300 index is much stronger than the same degree of "good news" on the CSI 300 index, and the volatility generated by the negative news is greater than the volatility generated by the positive news. This is mainly due to the fact that China's CSI 300 Index adopts a T+0 trading model, which allows investors to make long and two-way trades or short trades in the market, thus generating a large number of irrational speculative behaviours, and a number of investors will also avoid losses, which in turn causes fluctuations in the rate of return.

4. The static prediction results show that the GARCH model has a certain predictive ability for China's CSI 300 index.

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