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Study on the Volatility of CSI Index Returns 300 Based on GARCH Modeling

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Abstract

CSI 300 index reflects the overall dynamics of the stock market, covering about 60% of the market capitalization of the Shanghai and Shenzhen stock markets, this paper adopts the CSI 300 yield data from January 4, 2010-December 31, 2020, and analyzes its volatility by using the GARCH model, and the empirical results show that: there is an ARCH effect in the sequence of the CSI 300 yields; the GARCH (1, 1) model fits the change pattern of the CSI 300 yields, and is used to predict the future development trend of the index, which can provide the future investment direction for the relevant index investors, and also facilitate the government departments and the central bank to formulate the corresponding monetary policies. The GARCH (1, 1) model fits the change rule of CSI 300 yield and is used to predict the development trend of the index in the future, which can provide the future investment direction for the relevant index investors and facilitate the formulation of corresponding monetary policies by the government departments and the central bank.

Keywords

GARCH Model, CSI 300 Index Return, Leverage Effect, Volatility Aggregation

1. Introduction

The CSI 300 Index is an index jointly launched by the Shanghai and Shenzhen stock exchanges on April 8, 2005, designed to reflect the overall performance of the A-share market (Liu, Wang, & Wu, 2017). The CSI 300 Index aims to reflect the overall landscape and operational status of stock price fluctuations in China's securities market, serve as a benchmark for evaluating investment performance, and provide foundational conditions for index-based investing and index derivative innovation. The purpose and significance of this study is to establish a GARCH model using CSI 300 Index data from the past decade through the construction of a standardized financial data model. Using CSI 300 return data from January 4, 2010, to December 31, 2020, excluding non-trading days, this study employs Eviews 10.0 to analyze the volatility of returns on trading days using a generalized autoregressive conditional heteroskedasticity (GARCH) model. Through iterative data preprocessing and model refinement, the model is fitted to data variations, minimizing errors to a controllable range. Once successfully established, the model can forecast potential future trends of the CSI 300 Index. This enables the provision of investment recommendations to relevant investors (Chen, 2020), facilitates the advanced formulation of corresponding policies by government and banking regulators, and offers scholars a research methodology for analyzing the CSI 300 Index.

2. Empirical Analysis

2.1. Theoretical Analysis

The probability distribution of a smooth time series process is independent of the displacement in time. If an arbitrary set of random variables is taken from the sequence and the sequence is shifted forward h times, its joint probability distribution remains unchanged (Yu, 2022).

The first-order AR model, AR (1), is modeled as follows:

$$r_t = \alpha_1 r_{t-1} + w_t \quad (1)$$

When $\alpha_1 < 1$, the effect of the previous moment's fluctuation on the present moment's fluctuation will be smaller and smaller. Based on this, the covariance as well as the autocorrelation coefficient of this model calculated in this paper it is a fixed value, i.e., smooth at this point.

For higher-order AR models, this paper still uses a similar analytical approach (Guan, 2021), e.g., an AR (P) order model is as follows:

$$r_t = \sum_{i=1}^{p} \alpha_i r_{t-1} + w_t \quad (2)$$

According to the above model formula, when $\alpha_1, \alpha_2, \cdots, \alpha_i$ are all less than 1, then this sequence is considered to be smooth in this paper, however, if any of $\alpha_1, \alpha_2, \cdots, \alpha_i$ is greater than or equal to 1, then this sequence is considered to be not smooth.

To determine whether in the model is smooth, that is, to determine whether all are $\alpha_1, \alpha_2, \cdots, \alpha_i$ less than 1, this time to use the characteristic equation of the AR model:

$$1 - \alpha_1 x - \alpha_2 x^2 - \cdots - a_p x^p = 0 \quad (3)$$

There are p roots in this equation.

Going to test whether a particular AR series is smooth means testing whether one of the roots of that equation is greater than or equal to 1.

2.2. The Empirical Design Section Is as Follows

The equation form of the ARCH model is as follows:

Mean value equations: $y_t = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t$.

Variance model: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$.

The variance of ε_t in the above equation, which depends only on the interference term in the immediately preceding moments, is also the process of ARCH (1), and if the interference term to which it is subjected is generalized, the process of ARCH (q) is obtained as (Ji & Yang, 2021):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \tag{4}$$

In this equation, y_t represents the explained variable at moment t. ε_t is the momentary disturbance term, I_t is the set of information at moment t, and σ_t^2 is the conditional variance of ε_t. It is generally accepted that when ω is greater than 0, α_i is greater than 0, and $\sum \alpha_i$ is less than 1 ($i = 1, 2, \cdots, q$), this represents a smooth process of ARCH. In this model, ε_t obeys ARCH (q) process. And the ARCH model can reflect the volatility aggregation of the stock market (Tang & Ju, 2020).

The generalized autoregressive conditional heteroskedasticity model, i.e., GARCH model, which introduces its own lagged value in the decision model of the conditional variance σ_t^2 of the current period of ε_t, is defined as follows:

$$\varepsilon_t = e_t \sigma_t \tag{5}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 \tag{6}$$

The closer the value of the model coefficients in this model, i.e., $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j$, is to 1, the greater the volatility of the entire series. When the value is greater than 1, it indicates that the effects of this shock will persist and spread. When the sum of the values is less than 1, it means that the impact of the shock will gradually dissipate (Hu & Xing, 2022). The simplest GARCH model is the standardized GARCH (1, 1) model:

$$y_t = \beta_0 + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{8}$$

2.3. Data Sources and Pre-Processing

The data selected for this paper is the daily closing price of as a sample, and the source of the data is Invesco.com. CSI 300 for the CSI 300 index from January 4, 2010-December 31, 2020 after constant logarithmic difference processing of daily closing prices:

$$R_{t_i} = \ln y_{t_i} - \ln y_{t_i - 1} \tag{9}$$

where R_{t_i} represents CSI the return of with 3,002,676 data and y_{t_i} is the corresponding closing price data.

2.4. Descriptive Statistics Analysis

The mean value of the logarithmic return of CSI 300 index in the sample is 0.000145, the median is 0.000345, the maximum value is 0.064989, the minimum value is −0.091544, and the standard deviation is 0.014608. The skewness is −0.693074, and the kurtosis of left skewness of the series is 7.918043, which is bigger than the kurtosis of the normal distribution, which indicates that the distribution of the data shows the state of "sharp peak and thick tail" with left skewness. This indicates that the data distribution shows "sharp peaks and thick tails" with left skewness. At the same time, the JB normality test is conducted, and the final value of the statistic is 2910.015 and significant, which indicates that the distribution of CSI 300 index returns is significantly different from the normal distribution, according to which this paper carries out the next step of the smoothness test and so on.

2.5. The Process of Empirical Analysis

2.5.1. Smoothness and Unit Root Tests

The results of the unit root test for the variable *m* using Eviews 10 software are shown in the table below, and based on the graphs presented it can be observed that the original hypothesis is rejected at the 5% level of significance, i.e., the series is a smooth series with no time trend or random trend. The mean value modeling can be carried out (Liao, 2023). The specific results are shown in **Table 1**:

Table 1. Unit root test.

	ADF value	Coefficient P-value	Significance of the coefficient	Overall P*
R_t (c, t)	−50.36075	0.1739 (t)	insignificant	0.0000
R_t (c)	−50.33441	0.6241 (c)	insignificant	0.0001
R_t (none)	−50.33918	0.0000	significant	0.0000

2.5.2. Autocorrelation Test

Table 2. Autocorrelation test.

Serial number	AC	PAC	Q-Stat	Prob
1	0.026	0.026	1.8562	0.173
2	−0.034	−0.034	4.8925	0.087
3	0.021	0.022	6.0219	0.111
4	0.021	0.019	7.2489	0.123
5	0.014	0.014	7.7685	0.169
6	−0.067	−0.067	19.827	0.003
7	0.047	0.051	25.754	0.001
8	0.031	0.023	28.311	0.000
9	0.033	0.038	31.256	0.000
10	−0.019	−0.019	32.191	0.000

Continued

11	−0.024	−0.022	33.767	0.000
12	0.011	0.003	34.113	0.000
13	0.051	0.056	41.219	0.000
14	−0.053	−0.055	48.803	0.000
15	−0.008	0.002	48.975	0.000
16	0.035	0.023	52.264	0.000
17	0.01	0.006	52.515	0.000
18	−0.007	−0.003	52.646	0.000
19	0.006	0.017	52.759	0.000
20	0.062	0.049	63.199	0.000
21	0.025	0.023	64.878	0.000
22	−0.029	−0.026	67.217	0.000
23	−0.059	−0.056	76.533	0.000
24	−0.013	−0.016	76.968	0.000
25	0.027	0.020	78.886	0.000
26	−0.038	−0.034	82.801	0.000
27	−0.035	−0.026	86.201	0.000
28	0.057	0.047	94.992	0.000
29	0.019	0.003	95.924	0.000
30	−0.013	−0.001	96.43	0.000
31	−0.047	−0.035	102.53	0.000
32	−0.038	−0.043	106.49	0.000
33	0.046	0.039	112.34	0.000
34	0.005	0.014	112.42	0.000
35	−0.004	0.004	112.47	0.000
36	−0.007	−0.008	112.59	0.000

From **Table 2**, it can be seen that a large portion of the p-values are less than 0.05, and this paper concludes that there is serial autocorrelation. In the later modeling analysis is in this test a condition. And ACF and PACF are not obvious truncation and partial tail phenomenon, this paper can be considered that it is consistent with the establishment of model characteristics. ARMA (Liu & Qian, 2023).

2.6. ARMA Modeling

In this paper, we constructed and characterised an ARMA(p, q) volatility model for the Shanghai Composite Index, employing the first-order difference of the logarithmic difference of the CSI 300 Index. In order to ensure the efficiency of data utilization, from eight models are fitted for this purpose. During the fitting process ARMA (2, 2), ARMA (2, 1), ARMA (11, 2), ARMA (1), AR (2), AR (1), MA (2), MA (1). This paper found that only after the significance test ARMA (1, 1) and ARMA (2, 2) models passed the significance test for all coefficients. This paper then compares the AIC, SC, and HQC values to determine the final optimal model.

Table 3. Comparison of AIC, SC, HQC.

Mould	AIC	SC	HQC
ARMA (1, 1)	−5.618596	−5.614191	−5.617002
ARMA (2, 2)	−5.616713	−5.607903	−5.613525

As shown in Table 3, it can be observed that in ARMA (1, 1) model the AIC value is −5.618596 and SIC value is −5.614191, and in model the ARMA (2, 2) AIC value is −5.616713 and SIC value is −5.607903, and based on the judgement of the information criterion, this paper selects the model with smaller value as the optimal model.

From the above table, it can be observed that the ARMA (1, 1) model satisfies among the three information criteria the minimum, so finally chosen AIC and SIC ARMA (1, 1) is as the mean model. The autocorrelation test is performed the residual series of the model as LM test ARMA (1, 1) shown in Table 4:

Table 4. Model autocorrelation test.

Breusch-Godfrey Seral Correlation LM Test.			
F-statistic	0.072418	Prob.F (1, 2672)	0.7879
Obs*R-squared	0.072498	Prob.Chi-Square (1)	0.7877

From Table 4, it can be seen that the developed ARMA (1, 1) model passes the LM test and does not reject the original hypothesis at the level of significance, and the lag 10% same conclusion is obtained at order, and is therefore identified as the final mean model.

2.7. Test for Effect ARCH

The test for effect is to test whether the residual series are heteroskedastic and whether the residual squared series are correlated. The graphs of correlation coefficients and partial autocorrelation coefficients of the squared residual series show that there is a strong autocorrelation ARCH (Liu, Yang, & Shen, 2019).

The ARCH-LM test method and the results below further carried out are shown in Table 5.

From Table 5, the original hypothesis is rejected at the 5% level of significance, thus the model has ARCH effect.

Table 5. ARCH effect test.

Heteroskedasticity Test: ARCH			
F-statistic	91.689280	Prob.F (1, 2672)	0.0000
Obs*R-squared	88.713710	Prob.Chi-Square (1)	0.0000

2.8. GARCH Modeling

In this paper, we fit each order model, because p = 1, q = 1; the lag order should not be too large, so the highest lag order in this paper is 2nd order. After several attempts of GARCH (p, q) model, respectively, to establish normal distribution, generalized error distribution and GARCH (1, 1), GARCH (2, 2), GARCH (GARCH (1, 2), 2, 1) model, and ultimately finally determined to choose the generalized error distribution under the GARCH under the T-distribution (1, 1) model.

The inspection process is as follows:

In the GARCH (1, 1) model:

Table 6. GARCH (1, 1) model.

GARCH = C (3) + C (4) * RESID (−1)² + C (5) * GARCH (−1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR (1)	0.0183	0.9964	0.018439	0.9853
MA (1)	0.019647	0.994726	0.19752	0.9842
Variance Equation				
C	0.0001	3.9E−05	2.5948	0.0095
RESID (−1)²	0.0550	0.008038	3.500223	0.0005
GARCH (−1)	0.5999	0.105036	5.711617	0.0000
R-squared	0.0005	Mean dependent var		0.0001
Adiusted R-squared	0.0001	S.D. dependent var		0.0146
S.E. of regression	0.0146	Akaike info criterion		−5.4804
Sum aquared resid	0.5702	Schwarz criterion		−5.4693
Log likelihood	7332.315	Hannan-Quinn criter		−5.4764
Durbin-Watson stat	2.019693			
Inverted AR Roots	0.02			
Inverted MA Roots	−0.02			
Heteroskedasticity Test: ARCH				
F-statistic	0.6484	Prob. F (1, 2671)		0.4207
Obs*R-squared	0.6487	Prob. Chi-Square (1)		0.4205
Heteroskedasticity Test: ARCH				
F-statistic	8.2310	Prob. F (3, 2671)		0.0000

Continued

Obs * R-squared	40.6203	Prob. Chi-Square (3)	0.0000
Heteroskedasticity Test: ARCH			
F-statistic	7.8838	Prob. F (20, 2633)	0.0000
Obs*R-squared	76.8805	Prob. Chi-Square (20)	0.0000

In the GARCH (1, 1) model, all coefficients passed the significance test; however, higher-order ARCH effects were present and were therefore omitted.

In the T-GARCH (1, 1) model:

Table 7. T-GARCH (1, 1) model.

GARCH = C (3) + C (4) * RESID $(-1)^2$ + C (5) * GARCH (−1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR (1)	0.01499	1.5449	0.0096	0.9923
MA (1)	0.01598	1.5436	0.010354	0.9917
Variance Equation				
C	0.0021	0.000103	2.0647	0.0390
RESID $(-1)^2$	0.1500	0.070559	2.1258	0.0335
GARCH (−1)	0.5998	0.182038	3.2952	0.0010
T-DIST.DOF	19.79064	14.32650	1.3814	0.1627
R-squared	0.0006	Mean dependent var		0.0001
Adiusted R-squared	0.0002	S.D. dependent var		0.0146
S.E. of regression	0.0146	Akaike info criterion		−5.2907
Sum aquared resid	0.5701	Schwarz criterion		−5.2774
Log likelihood	7079.686	Hannan-Quinn criter		−5.2859
Durbin-Watson stat	2.0059			
Inverted AR Roots	0.01			
Inverted MA Roots	−0.02			

As shown in Table 7, the coefficient portion is not significant and is therefore omitted.

Under conditions of heteroskedasticity, namely in the EGARCH (1, 1) model:

Table 8. E-GARCH (1, 1) model.

GARCH = C (3) + C (4) * RESID $(-1)^2$ + C (5) * GARCH (−1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR (1)	−0.8838	0.0643	−13.7450	0.0000
MA (1)	0.9067	0.0577	15.7080	0.0000

Continued

Variance Equation				
C	0.0000	4.77E−07	2.5948	0.0095
RESID $(-1)^2$	0.0550	0.008038	6.8535	0.0000
GARCH (−1)	0.9401	0.007974	117.9038	0.0000
GEDPARAMETER	1.1639	0.039375	29.5616	0.0000
R-squared	0.0048	Mean dependent var		0.0001
Adiusted R-squared	0.0044	S.D. dependent var		0.0146
S.E. of regression	0.0145	Akaike info criterion		−5.9342
Sum aquared resid	0.5678	Schwarz criterion		−5.9210
Log likelihood	7940.0840	Hannan−Quinn criter		−5.9294
Durbin-Watson stat	1.9828			
Inverted AR Roots	−0.88			
Inverted MA Roots	−0.91			
Heteroskedasticity Test: ARCH				
F-statistic	0.6723	Prob. F (1, 2671)		0.4123
Obs*R-squared	0.6726	Prob. Chi−Square (1)		
Heteroskedasticity Test: ARCH				
F-statistic	0.6918	Prob. F (3, 2671)		0.5570
Obs*R-squared	2.0769	Prob. Chi-Square (3)		0.5566
Heteroskedasticity Test: ARCH				
F-statistic	0.5255	Prob. F (20, 2633)		0.9576
Obs*R-squared	10.553	Prob. Chi-Square (20)		0.9570
Heteroskedasticity Test: ARCH				
F-statistic	0.7248	Prob. F (25, 2633)		0.8364
Obs*R-squared	18.1760	Prob. Chi-Square (25)		0.8348

As shown in Table 8, All coefficients are statistically significant and pass the heteroscedasticity test. This paper concludes that the model can be used to fit the return volatility of the CSI 300 Index.

The final result obtained is: $\sigma_t^2 = 0.00000124 + 0.05559u_{t-1}^2 + 0.940159\sigma_{t-1}^2$.

In order to test the fit of the model, as shown in Table 6, the model is tested for the effects of ARCH.

Table 9. Heteroscedasticity test.

Heteroscedasticity test: ARCH			
F-statistic	0.6723	Prob. F (1, 2671)	0.4123
Obs * R-squared	0.6726	Prob. Chi-Square (1)	0.4121

As shown in **Table 9**, based on the results of the test, as well as **Table 6**, it is known that the model is no longer heteroskedastic.

3. Conclusion and Recommendations

This empirical study reveals the following findings: 1) Characteristics of the return distribution: The mean of the index returns approaches zero, exhibiting pronounced volatility. Its skewness is non-zero, with a kurtosis exceeding 3, indicating that the return series follows a non-normal distribution. The series displays sharp peaks and fat tails. The ADF test confirms the series' smoothness, while the LM test and GARCH (1, 1) model demonstrate significant ARCH effects, verifying the phenomenon of volatility clustering. Asymmetry effect analysis: Model comparisons reveal that both the CSI EGARCH (1, 1) and TGARCH (1, 1) models exhibit significant leverage effects on log-differenced returns. Negative news triggers substantially stronger volatility than positive news, closely reflecting investor behaviour patterns (Su, 2022). During market downturns, heightened risk aversion among investors leads to concentrated selling, amplifying volatility. Conversely, rising markets see increased risk appetite accompanied by underreaction. Concurrently, this study's interpretation of market mechanisms generating disorderly return fluctuations reflects the immaturity of China's securities market, manifested in: 1) a brief developmental history (officially launched in 2005); 2) an imperfect trading system; 3) a retail-dominated investor structure prone to excessive speculation; and 4) room for improvement in risk pricing mechanism effectiveness.

Based on this, corresponding regulatory policy recommendations are proposed: 1) Refine the information disclosure mechanism: enhance market transparency and establish a real-time data disclosure platform; 2) Optimise the regulatory framework: clarify the powers and responsibilities of regulatory bodies and establish cross-departmental coordination mechanisms (Wang, 2022); 3) Improve the risk pricing mechanism: define the division of responsibilities within the risk pricing mechanism and establish cross-departmental coordination mechanisms. 4) Cultivate institutional investors: guide long-term capital into the market through policies such as tax incentives to optimise the structure of market participants. Cultivating institutional investors: Guide long-term capital into the market through policies such as tax incentives, optimising the structure of market participants. Based on the above, we should strengthen the development of fundamental market systems and guide investor behaviour, which is the key pathway to promoting the healthy development of China's financial markets. Regulators need to seek a dynamic balance between risk prevention and market vitality, driving the securities market towards maturity.

This study utilises only daily closing data for the CSI 300 Index from 4 January 2010 to 31 December 2020, which inherently carries limitations (lack of intraday information, potential structural discontinuities, etc.). Future research is advised to construct quantitative trading strategies based on high-frequency data, such as intraday momentum strategies or mean reversion strategies. Empirical validation of these strategies' efficacy could further uncover intraday trading patterns and characteristics within the CSI 300 Index. Incorporating sector-level data (e.g., industry growth rates, sector profit margins) and firm-level data (e.g., financial statement metrics, corporate governance structures) pertaining to CSI 300 constituents would enrich subsequent investigations.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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