International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 04 - Issue 07 || July 2018 || PP. 06-14

An Empirical Research on Chinese Stock Market and International Stock Market Volatility

Dan Qian[1], Wen-huiLi*

[1](Department of Mathematics and Finance,
Hunan University of Humanities Science and Technology Loudi , China/*corresponding

Abstract: This paper selects A-share Index of Shanghai Stock Exchange, Dow Jones Industrial Average, FTSE 100, and Nikkei 225 gains from June 7, 2010 to June 6, 2018, to make an empirical research on stock market volatility based on GARCH model. The results show that there is volatility clustering, durative and leverage effects in stock market. The volatility is largely affected by the past volatility, especially in Chinese stock market. Its influence reaches 0.948. The news had an asymmetric effect on the gains, in the United States, the United Kingdom, the Japanese stock market. "bad news" have a greater impact on the gains than the equivalent "good news." In general, A-share Index of Shanghai Stock Exchange volatility is bigger than the other three. The reason is that volatility has a certain correlation with the trend of the economy. Chinese GDP growth rate has always been in a higher position, which will lead to large fluctuations in the stock market.

Keyword: Shanghai A-share composite index, GARCH model, volatility

1. Introduction

Stock market volatility is a major issue in the modern financial field. China's stock market which is developinglately and immature, is larger than other mature capital markets. So that it is necessary to study the stock market volatilityto promote the development of the stock market.With the development of various mathematical statistics tools, the ARCH model technology has been continuously improved. At present, the GARCH model family is a widely used tool for measuring stock market volatility. The stock market is a barometer of the economy. That is to say the economic development of a country can affect the development of the capital market.

In view of the contemporary background, this paper makes use of the earnings data of China's stock market and three foreign economies since 2010, focusing on testing from multiple methods. (1) giving a brief description of the basic methods of volatility test, summarizing the key points of this paper with the existing research results; (2) explaing the data source and basic statistical characteristics; (3) using the optimal GARCH model for parameter estimation; (4) contacting the economic development of various countries analyzes and summarizing the volatility of the stock market.

2. Overview of Literature on Volatility Test Methods

The volatility of stock market prices is mainly reflected in the possibility that prices will deviate from expectations in the future. The greater the possibility that prices will rise or fall,will lead the greater the volatility of stocks.

Domestic scholars are very concerned about the volatility of China's stock market. Many documents have explored the characteristics of the volatility of stock markets in Shanghai and Shenzhen. Hou Qing, Mei Qiang and Wang Juan (2009) selected EGARCH and TGARCH models to capture the asymmetry of Shanghai stock market volatility, found that the volatility of the Shanghai Composite Index has obvious stage characteristics, and proposed government regulation measures for these characteristics. Liu Xuan and Feng Cai (2010) used GARCH and EGARCH models to empirically test the volatility and volatility of the Shanghai stock market from 2005 to 2008. The results show that the volatility has typical periodic characteristics and there is asymmetry of "leverage effect". ". Jiang Xiangcheng and Xiong Yamin (2017) used the GARCH model, TARCH model and EGARCH model to analyze the volatility of China's stock market, and found that the EGARCH model can better fit the fluctuations of the Shanghai and Shenzhen stock markets which have significant asymmetry.

Compared with the existing research results quoted above, this paper analyzes the volatility of China and international stock markets mainly about three characteristics: (1) Extending the time range from 2010 to the recent period, using the latest data,whichhas time-sensitive. (2) Using a variety of common methods in the research literature of recent years to analyze the stock market volatility, explaining the relation between the volatility of China's stock market and foreign stocksfrom multiple perspectives. (3) Analyzing and summarizing the economic situation of each country to promote the development of the capital market.

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3. Data Description and Feature Statistics Comparison

3.1 Data Description

In this paper, the stock index yield is calculated in logarithmic form, as follows: (3.1):

$$S_t = 100\% * (\ln P_t - \ln P_{t-1}) \qquad (3.1)$$

Among them, P_t as the closing level of the stock index on t trading day, the first-order difference is used in logarithmic form to eliminate some data interference factors, which is more stable than the percentage yield data, and convenient for modeling analysis. For the unified caliber, the data are all from the unified database (CSMAR Guotaian database), and the range of selected date is from June 7, 2010 to June 6, 2018, with a total of 1943 calendar days. This paper presents the stock market yield series in the following manner: Shanghai A-Share Composite Index (SZ), New York Dow Jones Stock Price Index (DJIA), London FTSE 100 Index (FTSE), and Tokyo Nikkei 225 Index (N225).

3.2 Descriptive statistics

(1) Spike Phenomenon

For the selected stock market index, the index is converted into the index return rate for descriptive statistics. The average yield, the standard deviation of the rate of return, the deviation, and the kurtosis are used to conduct comparative research. The Eviews10.0 software is used to analyze the results as for Table 1 shows.

Table 1 Basic statistical characteristics of each index yield series

	SZ	DJIA	FTSE	N225
Observations	1943	1943	1943	1943
MedianMean	0.064509	0.037605	0.016404	0.007508
Maximum	5.603612	4.653014	5.140443	7.426117
Minimum	-8.872906	-5.706205	-4.779414	-11.15343
Mean	0.011082	0.047698	0.021638	0.044550
Std.Dev	1.382330	0.879462	0.950898	1.341965
Skewness	-1.011491	-0.384512	-0.118786	-0.531326
Kurtosis	9.595212	7.754511	6.122587	8.774500
Jarque-Bera	3852.748	1877.972	793.9573	2790.964
Probability	0.000000	0.000000	0.000000	0.000000

As we cansee in Table 1, the Shanghai stock market has the largest median value, and the standard deviation is also the largest, while the New York stock market has the smallest standard deviation. The magnitude of the standard deviation reflects the volatility characteristics of the four index yield series to some extent. Observing the skewness index, we find that the distribution of the four index returns is left-biased, that means there is a long left tail. The left-biased situation of the Shanghai Stock Exchange's return rate series is the most obvious. In fact, beside the Shanghai Stock Exchange Index, the left-biased cases of the other three yield series are more obvious. A simple comparison result is:
$S_{SZ} > S_{N225} > S_{DJIA} > S_{FTSE}$ .Observing the kurtosis index, the kurtosis values of the four sequences are all greater than 3, and the degree of bulging of the distribution of the yield series is greater than the normal distribution, and the degree of bulging of the SSE index sequence is the most obvious. The simple size comparison result is $K_{SZ} > K_{N225} > K_{DJIA} > K_{FTSE}$. The JB statistic is quite large that indicate that the null hypothesis of rejecting the normal distribution which means that the rate of return does not follow the normal distribution. Although the rate of change of each yield series is different, it shows the characteristics of "thick tail" or "long tail" compared with the normal distribution of random variables.

(2) Fluctuating Aggregation

The yield curve is shown on the left side of Figure 1, and the random variable E is taken from the standard normal distribution on the right. Comparing the random distribution sequence characteristics of the normal distribution, we can observethat the SSE index sequence seems to have many "lumps", that is, the so-called fluctuations in the yield series have a significant "clustering" phenomenon. One of the main points in the picture is that the volatility occurs explosively; in the latter part of the sample interval, the market is relatively calm. It means that the rate of return often appears to be high or low for a certain period of time, and the volatility is continuous.

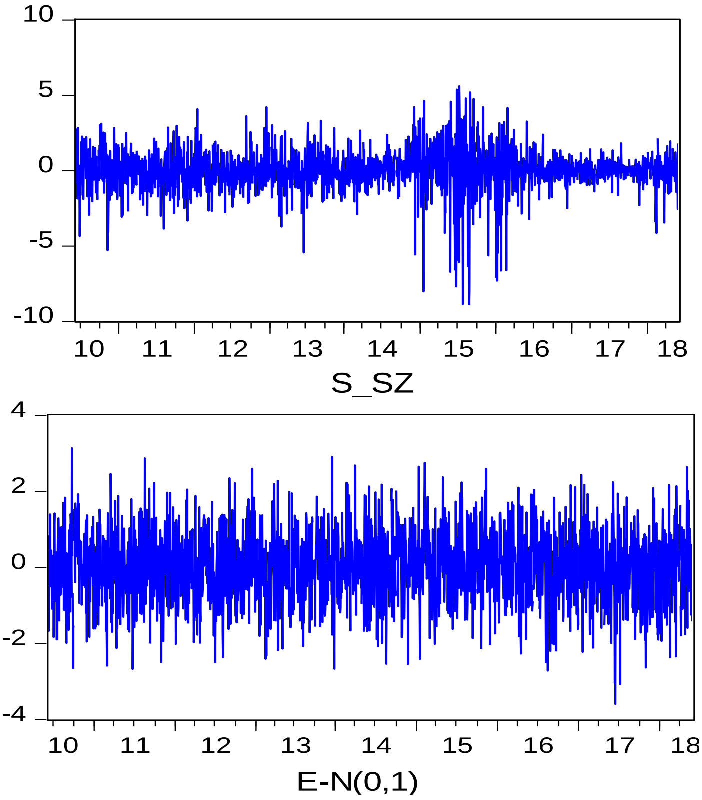

Figure 1 Comparison of the SSE Composite Index Yield Sequence and the Normal Distribution Random Variable

4. Model Establishment and Parameter Estimation

4.1 Data stationarity and correlation test

First, the four yield series are augmented by the ADF test to checkout the data stationarity. If the data is stable, the model can be modeled. The results are shown by EVIEWS as follows:

Table 2 Data stability checklist

Test values:	SZ	DJIA	FTSE	N225
ADF	-41.906	-46.314	-42.629	-45.460
1%level	-3.4335	-3.4335	-3.4335	-3.4335
5%level	-2.8628	-2.8628	-2.8628	-2.8628
10%level	-2.5675	-2.5675	-2.5675	-2.5675
Prob.*	0.0000	0.0001	0.0000	0.0001

The test statistic is much smaller than the critical value, that is to say the four yield series are stable, and there is no unit root.

A correlation graph was made using Eviews 10.0 to figure out the autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) of the four yield series. In general, if the autocorrelation coefficient or the partial autocorrelation coefficient is outside the confidence interval ±1.96×1/(T)1/2, it is statistically significant (where T is the number of observations). For example, the first three autocorrelation coefficients are 0.05, -0.03, and 0.005, and the first three partial autocorrelation coefficients are 0.05, -0.033, and -0.008, and the confidence interval is (-0.03988, 0.03988). It shows that under the 5% significance level, the autocorrelation coefficient and partial autocorrelation coefficient of the Shanghai Composite Index's return rate series decrease significantly.

The J-BQ statistic is calculated, and the obtained value and the corresponding P value result are shown in Table 3.

Table 3 Partial autocorrelation coefficients PACF and corresponding P values for each rate of return sequence

LAG	**SZ**		**DJIA**		**FTSE**		**N225**	
	PACF	**Prob**	**PACF**	**Prob**	**PACF**	**Prob**	**PACF**	**Prob**
1	0.050	0.028	-0.050	0.028	0.033	0.148	-0.032	0.163
2	-0.033	0.037	0.026	0.042	-0.034	0.124	0.006	0.359
3	0.008	0.084	-0.057	0.004	-0.042	0.046	0.002	0.562
4	0.061	0.007	0.017	0.006	-0.045	0.016	-0.044	0.213
5	0.008	0.013	-0.077	0.000	-0.020	0.023	-0.011	0.312
6	-0.065	0.001	-0.001	0.000	0.030	0.018	-0.017	0.369
7	0.039	0.001	-0.021	0.000	-0.029	0.024	0.027	0.329
8	0.044	0.000	-0.011	0.000	-0.043	0.011	-0.013	0.398

The autocorrelation test statistic of the four sequences is significant, indicating that there is autocorrelation in each lag period, that is,there are autocorrelation phenomena in the four sequences. This suggests that it may be appropriate to describe these four yield sequences using the AR(1)~AR(5) procedure.

4.2 Autoregressive model

According to the autocorrelation coefficient map, an autoregressive model is established to model each index. The results are as follows:

Table 4 Corresponding coefficient P value of each index autoregressive model

	SZ	DJIA	FTSE	N225
C		0.0075		
AR(1)	0.0003			0.0288
AR(2)				
AR(3)		0.0002	0.0079	
AR(4)	0.0000		0.0066	0.0339
AR(5)		0.0000		

Corresponding coefficients are tested to show that the model is suitable. In order to improve the model effect, the model is tested for ARCH effect and the ARCH model is established.

4.3 ARCH model

4.3.1 ARCH effect test

The daily rate of return of the stock price index shows the concentration of volatility, and the ARCH model can parameterize this feature well. A complete ARCH(q) model is:

$$y_t = \beta_1 + \cdots \beta_n x_{nt} + u_t, u_t \sim N(0, \sigma_t^2) \qquad (3.1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \ldots + \alpha_q u_{t-q}^2 \quad (3.2)$$

The modeling of volatility aggregation is represented by letting the conditional variance of the residual term σ_t^2 (see Equation 3.2) depend on the squared residual value of the previous terms. The ARCH effect test of the yield series was performed using Eviews10.0 software to check whether there is conditional heteroskedasticity. The results are shown in Table 5. The null hypothesis corresponding to the ARCH test is that $H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_P = 0$ there is no heteroscedasticity, ie there is no ARCH effect.

Table 5 Breusch-GodfreySerialCorrelationLMTest

	SZ	DJIA	FTSE	N225
F	60.7617	66.3814	39.1383	27.7586
Prob.F	0.0000	0.0000	0.0000	0.0000
Obs*R	263.3414	284.1266	178.2451	129.8927
Prob.	0.0000	0.0000	0.0000	0.0000

When the lag order is 5, the result F statistic and LM statistic (ie $T*R^2$ The number of observations multiplied by the multivariate correlation coefficient) is very significant, indicating that all four yield series have ARCH effect. Therefore, we can use the ARCH and GARCH models to describe the market index yield series.

4.3.2 Estimation of ARCH and GARCH Models

Four yield series were simulated by using ARCH, GARCH, TGARCH, and EGARCH models. According to the values of LogLikelihood, AIC and SC statistic of the four models, the fitting effect of each model can be compared, and the results are listed in Table 6.

Table 6 Comparison of fitting effects of each model

		Akaike-info-criterion	**Schwarzcriterion**	**Loglikelihood**
SZ	ARCH	3.119686	3.128289	-3027.775
	GARCH（1,1）	**3.119686**	3.128289	-3027.775
DJIA	ARCH	2.504278	2.510014	-2430.906
	GARCH（1,1）	2.311358	2.319961	-2242.484
	TGARCH(1,1)	**2.250979**	2.262450	-2182.826
	EGARCH(1,1)	2.251706	2.263177	-2183.532
FTSE	ARCH	2.678678	2.684413	-2600.336
	GARCH（1,1）	2.559013	2.567616	-2483.081
	TGARCH(1,1)	**2.495489**	2.506960	-2420.367
	EGARCH(1,1)	2.563356	2.571959	-2487.300
N225	ARCH	3.360329	3.366064	-3262.559
	GARCH（1,1）	3.277208	3.285812	-3180.808
	TGARCH(1,1)	**3.255015**	3.266486	-3158.247
	EGARCH(1,1)	3.276728	3.285331	-3180.341

New York Dow Jones Stock Price Index, London FTSE 100 Index, Tokyo Nikkei 224 Index three statistics, after adding the asymmetric term, the model's ability. of fitting is significantly improved, and the TGARCH model is better than the EGARCH model, whether a conditional variance explanatory variable is added to the mean equation or not. According to the AIC and SC statistic, the values of these two statistics of TGARCH are basically the smallest for the four yield series. Besides the SZ sequence, the EGARCH model and the TGARCH model cannot be used, and the mean equation and variance are used. None of the equations can pass the significance test. Considering the four yield series, the Shanghai Composite Index SZ uses the optimal GARCH model, while the New York Dow Jones Stock Price Index, the London FTSE 100 Index, and the Tokyo Nikkei 224 Index use the optimal TGARCH model. According to the above results, the model is selected and modeled by EVIEWS as follows:

(1) Estimate the SZ (Shanghai Composite Index) GARCH(1,1) model using Eviews, and the corresponding GARCH(1,1) system model is as shown in (3.3).

$$\begin{cases} y_t = u_t, u_t \sim N(0,\sigma^2) \\ \sigma_t^2 = 0.006 + 0.049u_{t-1}^2 + 0.948\sigma_{t-1}^2 \end{cases} \quad (3.3)$$

(2) DJIA (Dow Jones Industrial Average Index) is modeled by TGARCH (1,1) model. The coefficients of the variance equation are tested. According to the displayed results, the final model is expressed as:

$$\begin{cases} r_t = \varepsilon_t \\ \sigma_t^2 = 0.03\text{-}0.02\varepsilon_{t-1}{}^2 + 0.25\varepsilon_{t-1}{}^2 I_{t-1} + 0.86\sigma_{t-1}^2 \\ I_{t-1} = \begin{cases} 0 & \varepsilon_{t-1} > 0 \\ 1 & \varepsilon_{t-1} < 0 \end{cases} \end{cases} \quad (3.4)$$

(3) FTSE (UK FTSE 100 Index) is modeled using the TGARCH (1,1) model, and the final model is expressed as:

$$\begin{cases} r_t = \varepsilon_t \\ \sigma_t^2 = 0.03\text{-}0.03\varepsilon_{t-1}{}^2 + 0.20\varepsilon_{t-1}{}^2 I_{t-1} + 0.90\sigma_{t-1}^2 \\ I_{t-1} = \begin{cases} 0 & \varepsilon_{t-1} > 0 \\ 1 & \varepsilon_{t-1} < 0 \end{cases} \end{cases} \quad (3.5)$$

(4) N225 (Nikkei 225 Index) uses the TGARCH (1,1) model to figure the results. The coefficients of the variance equation pass the test. According to the displayed results, the final model is expressed as:

$$\begin{cases} r_t = \varepsilon_t \\ \sigma_t^2 = 0.08\text{+}0.043\varepsilon_{t-1}{}^2 + 0.15\varepsilon_{t-1}{}^2 I_{t-1} + 0.84\sigma_{t-1}^2 \\ I_{t-1} = \begin{cases} 0 & \varepsilon_{t-1} > 0 \\ 1 & \varepsilon_{t-1} < 0 \end{cases} \end{cases} \quad (3.6)$$

The ARCH effect test results of the above model are shown in Table7.

Table7 BreuschGodfreySerialCorrelationLMTest after ARCH modeling

	SZ	**DJIA**	**FTSE**	**N225**
F-statistic	0.741841	0.012747	0.851062	0.259125
Prob.F(5,1937)	0.3892	0.9101	0.3564	0.6108
Obs*R-squared	0.742322	0.12760	0.851566	0.259357
Prob.Chi-Square(5)	0.3889	0.9101	0.3561	0.6106

(1)Withthe ARCH test of the Shanghai Stock Index TGARCH (1,1) model, the associated probability is about 0.3889, significantly greater than 0.01, so there is no ARCH effect, indicating that the GARCH model (3.3) eliminates the conditional body variance. This model can fit the Shanghai Composite Index very well. among them, $\alpha + \beta = 0.049 + 0.948 < 1$ The fluctuation coefficient is close to 1, indicating that the conditional variance of the Shanghai Composite Index will be affected by the impact of external positive and negative information, signifying the impact of external favorable or bad news on the Shanghai stock market volatility will exist for a long time.

(2) DJIA (Dow Jones Industrial Average), British FTSE 100 Index, and Nikkei 225 Index were fitted to use the TGARCH model. At 5% significance level, all coefficients were tested. At the same time, the residual sequence passed the ARCH test, indicating that the TGARCH model eliminates the ARCH effect of the residual sequence and fits the sample data better. Among them, the US DJIA (Dow Jones Industrial Average) TGARCH asymmetric term coefficient is the largest estimate γ = 0.25, indicating that there is a significant asymmetric effect on the Dow Jones Industrial Average's yield volatility. The performance of “bad news” has a greater impact on the overall volatility impact of the US stock market than the equivalent “good news”. In the N225 (Nikkei 225 Index) fitting model (3.6), the asymmetry term coefficient γ =0.15. due to $\gamma > 0$,and γ Very significant, indicating that the Nikkei 225 index also has a “leverage effect”, specifically $\varepsilon_{t-1} \geq 0$ (good news), $I_{t-1} = 0$, the information will cause a 0.043 times impact on the Nikkei 225 index; $\varepsilon_{t-1} < 0$ (bad news), $I_{t-1} = 1$ At this time, it will cause an impact of 0.193 times.

5. Comparison of Volatility

Taking the conditional variance as an estimate of the volatility of the stock index's yield, the conditional variance sequence obtained by the GARCH model which is used to compare the volatility of the four yield series. Observing the conditional variance sequence obtained from the GARCH model in Figure 2.3.4.5, which is known in the data interval from 2014 to 2016. The Shanghai stock market and the London stock market are more volatile than the New York stock market and the Japanese stock market. The Shanghai stock market is the most volatile. The New York stock market and the London stock market are slower, the conditional variance is small, and the process of volatility has many similarities.

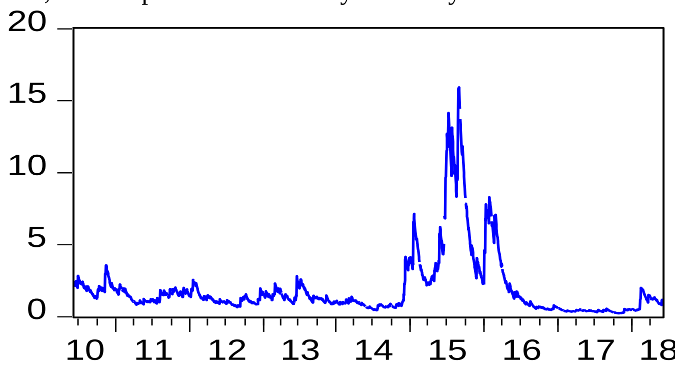

Figure 2 SSE index conditional variance sequence

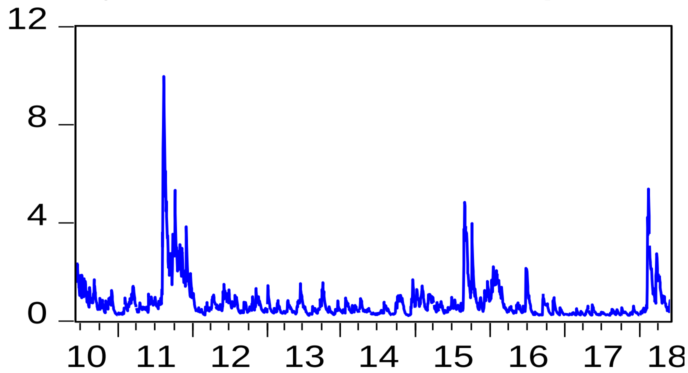

Figure 3 Dow Jones Industrial Index conditional variance sequence

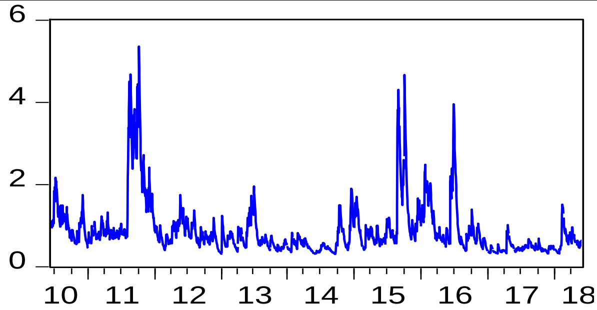

Figure 4 UK FTSE 100 index conditional variance sequence

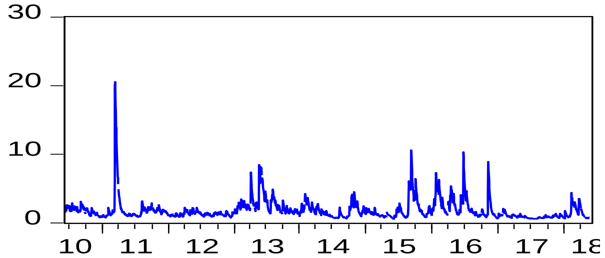

Figure 5 Nikkei 225 Index conditional variance sequence

In the time frame examined, the overall volatility of the Shanghai stock market was the largest, with the largest difference between the average and the highest point.

6. Further Analysis of High Volatility Causes

The volatility of Shanghai stock market represents the volatility of China's stock market in a certain sense. Therefore researchers are care about the reasons why China's stock market volatility is higher than the comparative foreign stock market during the period under investigation. In view of this, we briefly focus on the volatility of China, Japan, the United Kingdom and the United States on two important macroeconomic indicators from 2010 to 2018: total output growth rate and price level change rate. . Figure 6 shows the annual GDP growth rate at fixed prices, and Figure 7 shows the annual inflation rate based on consumer price CPI.

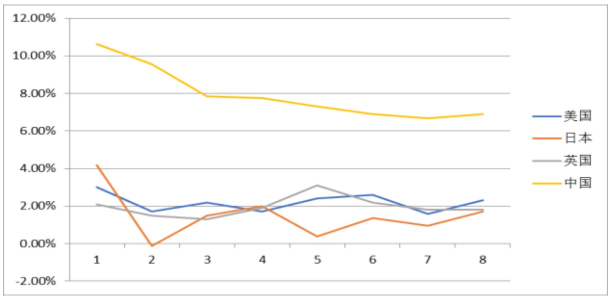

Figure 6 Annual GDP growth rate of GDP in each country

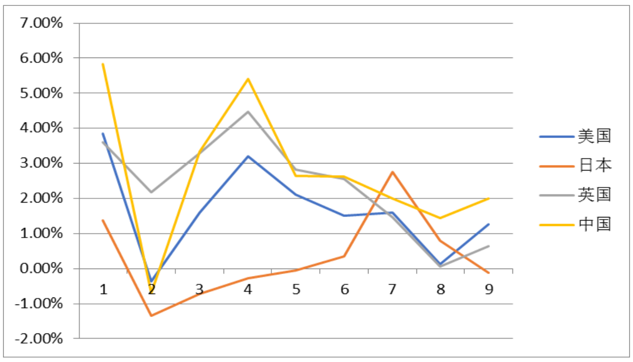

Figure 7 Rate of change in national price levels

We can see from Figure 6.7 that China's GDP growth rate has been a high level and CPI has a large fluctuation. When GDP growth is high, it will inevitably lead to inflation, which has a certain relationship with the risk of the stock market. In short, it is linked to four. The macroeconomic volatility of the economy during the period under review is difficult to conclude that China's stock market volatility is higher because China's macroeconomic volatility is higher. An extended implication of this conclusion is that people need to have a reservation about the popular saying that the stock market is a barometer of the national economy. The higher volatility of the Chinese stock market during the period under investigation is a problem that needs further explanation. It obviously that cannot be simply searched for from macroeconomic or external factors.

7. Summary

Through descriptive statistics and econometric analysis based on GARCH model family, this paper explains and compares the basic characteristics of the volatility of the SSE A share index, Dow Jones Industrial Index, FTSE 100 index and Nikkei 225 index yield series. The basic conclusion of this:

(1) The stock market volatility of China, the United States, the United Kingdom, and Japan are both clustered and persistent. The fluctuation of the market index in the current period is affected greatly by the past fluctuations of the market. The fluctuations of the market index of the four countries are 0.8. The above is caused by past fluctuations.

(2) The US, UK, and Japanese stock markets are asymmetric, that is to say“bad news” can have a greater impact on the market index than the equivalent “good news”.

(3) During the period of investigation, from June 2010 to June 2018, the overall volatility of the Shanghai stock market was higher than that of the three of other stock markets.

(4) There is a certain correlation between stock market volatility and basic economic trends. China's GDP growth rate keep the highest level comparing with the other three countries, and CPI volatility is also the largest. When GDP growth is high, it will inevitably lead to inflation, resulting in Chinese stock market. The fluctuations are large.

China's stock market is currently in the stage of “further regulation and development”. It should consider and respond to the high volatility of the stock market from the perspective of the institutional nature of domestic capital markets and its related fundamental issues.

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