International Journal of Technical Research and Applications e-ISSN: 2320-8163,
www.ijtra.com Special Issue 13 (Jan-Feb 2015), PP. 56-60

SUDDEN CHANGES IN VOLATILITY IN CHINESE STOCK MARKET

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Abstract—**This study analyzed the return series of Chinese stock market by using GARCH model without sudden changes and re-examined the impact of sudden changes in volatility persistence in Chinese stock market by using GARCH model with sudden changes. We detected sudden changes in volatility by using the iterated cumulative sums of squares (ICSS) algorithm. Our findings indicated that the investor psychology was still green in Chinese stock market and the Chinese stock market still had high speculation and risk. In addition, we also found that the ignorance of sudden changes in volatility would overestimate volatility persistence in stock markets.**

Index Terms—**Sudden changes, volatility persistence, ICSS algorithm, GARCH model, Dummy Variable.**

I. INTRODUCTION

In financial market, the characteristics of time series data is often unstable and the volatility means the uncertainty of returns on assets, which is often used to measure the risk of assets. Specifically speaking, larger fluctuations will be relatively gathered in a certain time period, while smaller fluctuations will be relatively gathered in another time period. Many economists[1-2] have established a variety of models to predict volatility, especially the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with the time-varying feature which is the most commonly used volatility model in this field. Because the GARCH model can effectively capture the phenomenon of fluctuations aggregation and heteroskedasticity characteristics in volatility of return on assets.

Accordingly, we also used Auto-regressive and Moving Average (ARMA) model and conducted some tests to estimate the return series to confirm whether there was ARCH effect or not. We detected that the volatility of return series of Shanghai Composite Index had the characteristic of cluster, which meant that the volatility of the stock market in the past had an effect on the volatility in the following time. Besides, this phenomena can be explained by trading behavior which is to seriously chase price. It is obvious that the investor psychology is immature in Chinese stock market. Certainly, this situation is fit for the national conditions of China as it is only thirty four years for Chinese stock market, so the mechanism also is seriously unsound.

Then, we adopted the GARCH model to explain this return serious. We found that the historical volatility information had a persistent impact on volatility of stock returns, although the impact was hard to eliminate in short term, which also revealed that Chinese stock market was featured with high speculation and risk.

As corresponding to domestic and global economic events, the infrequent sudden changes or regime shifts have impact on the volatility of stock returns. Because the sudden changes in economy and its fundamentals, are important components of managing market risk and uncertainty, building investment portfolios, and pricing derivative securities[3].Therefore, it is important to estimate the impact of sudden changes in volatility. Nevertheless, the GARCH model does no good for detecting sudden changes. In other words, it can't make a relative good estimation on volatility persistence[4]. In order to overcome this problem, Inclán and Tiao[5] designed a method, called iterated cumulative sums of squares (ICSS) algorithm, to identify the time points of sudden changes. On the top of this, many economists[6-9] adopted the generalized autoregressive conditional heteroskedasticity (GARCH) class models to document the effects of sudden changes on volatility. As a result, these studies all supported the notion that to ignore sudden changes would overestimate the persistence of volatility in stock markets.

This study adopted the GARCH model to evaluate the return series and re-examined the impact of sudden changes on volatility persistence in shanghai composite index, or SCI for short. The principal objectives of this study mainly consist of four parts. First of all, to estimate the return series to confirm whether there is ARCH effect or not through the ARMA model and some tests. Secondly, to explain this return serious through the GARCH model. Thirdly, to discover the points of sudden changes through the ICSS algorithm. The fourth one is to examine whether the inclusion of sudden changes in the GARCH model can reduce the coefficients of volatility persistence or not.

The reminder of the paper is organized as follows: Part 2 is about the introduction of ICSS algorithm and GARCH model; Part 3 is about the description of the characteristics of the sample date; Part 4 is about the presentation of the results of the empirical study; and Part 5 is about some concluding remarks.

II. METHODOLOGY

Following Inclán and Tiao[5], this study used ICSS algorithm to identify sudden changes in volatility, and then took the points of sudden changes into the univariate GARCH(1,1) model to estimate as dummy variable.Besides, we also estimated the GARCH(1,1) model without sudden change dummies. Therefore, this part was mainly made of three sections as follows.

1. ICSS algorithm.

The ICSS algorithm was used to detect discrete sub-periods of changing stock return volatility. Popularly speaking, the ICSS algorithm was to identify the points of sudden changes in variance of a time series.

It supposes that when a sudden change occurs as a result of a sequence of financial events, the variance of a time series will from stationary state to unstable state; and then the variance comes back to stationary state until another market shock happens. This process is repeated over time, generating a time series of observations with an unknown number of changes in variance.

Let $\{\varepsilon_t\}$ denote an independent time series with a zero mean and an unconditional variance marked σ_t^2. The variance is given by σ_i^2, i=0,1,2,...,N_T, where N_T is the total number of variance changes in T observations, and $1<k_1<k_2<k_3<\ldots<k_{N_T}<T$ are the change points. The variance over N_T intervals is defined as follows:

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1<k<k_1 \\ \sigma_1^2, & k_1<k<k_2 \\ \vdots & \\ \sigma_{N_T}^2 & k_{N_T}<t<T \end{cases} \quad (1)$$

A cumulative sum of squares is utilized to determine the number of changes in variance and the point in time at which each variance shift occurs. The cumulative sum of squares from the first observation to the k^{th} point in time is expressed as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \text{where } k=1,\ldots,T \quad (2)$$

Define the statistic D_k as follows:

$$D_t = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \text{ where} D_0 = D_T = 0 \quad (3)$$

and C_T is the sum of squared residuals from the whole sample period. Note that if no changes in variance occur, the D_k statistic will oscillate around zero (if D_k is plotted against k , it will resemble a horizontal line). However, if one or more changes in variance occur, then statistic values drift up or down from zero. Significant changes in variance are detected using the critical values obtained from the distribution of D_k under the null hypothesis of constant variance. If the maximum absolute value of D_k is greater than the critical value, the null hypothesis of homogeneity can be rejected.

Define k^* as the value at which $max_k|D_k|$ is reached; if $max_k\sqrt{(T/2)}\,|D_k|$ exceeds the critical value, then k^* will be used as the time point at which a variance change in the series occurs. The term $\sqrt{(T/2)}$ is required for the standardization of the distribution. Following Inclán and Tiao (1994), the critical value of 1.358 is the 95th percentile of the asymptotic distribution of $max_k\sqrt{(T/2)}\,|D_k|$. Therefore, upper and lower boundaries can be established at ± 1.358 in the D_k plot. A change point in variance is identified if it exceeds these boundaries. However, if the series includes multiple change points, the D_k function alone will not detect change points at different intervals. Inclán and Tiao (1994) thus modified the algorithm that employs the D_k function to search systematically for different change points in the series. This is accomplished by evaluating the D_k function over different time periods, determined by breakpoints, which are identified by the D_k plot.

2. GARCH(1,1) MODEL

Following the seminal work of Engle[1] considers the return series y_t and the associated prediction error $\varepsilon_t = y_t - E_{t-1}[y_t]$, in which $E_{t-1}[y_t]$ is the expectation of the conditional mean on the information set at time $t-1$. The GARCH(1,1) model of Bollerslev is as follows:

$$y_t = \mu + \sum_{i=1}^{b} p_i y_{t-i} + \sum_{j=1}^{c} q_j u_{t-j} + u_t \quad (4)$$

$$u_t = z_t\sqrt{h_t}, \quad z_t \sim N(0,1) \quad (5)$$

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} \quad (6)$$

Where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, which ensures that the conditional variance (h_t) is positive, and $(\alpha+\beta) < 1$ are introduced for covariance stationarity. In the GARCH model, the sum of α and β quantifies the persistence of shocks to conditional variance. A common empirical finding is that the sum of α and β is quite close to one, thereby implying that shocks are infinitely persistent, corresponding to an integrated GARCH (IGARCH) process.

3. *Multiple sudden changes with GARCH model*

In an effort to asses the impact of sudden changes on volatility, sudden changes should be incorporated into the standard GARCH model. Following the study of Agguhioarwal Inclán and Leal[6], we modify above GARCH (1,1) with multiple sudden changes that were identified via the ICSS algorithms, as follows:

$$y_t = \mu + \sum_{i=1}^{b} p_i y_{t-i} + \sum_{j=1}^{c} q_j u_{t-j} + u_t \quad (7)$$

$$u_t = z_t\sqrt{h_t}, \quad z_t \sim N(0,1) \quad (8)$$

$$h_t = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha u_{t-1}^2 + \beta h_{t-1}, \quad (9)$$

in which $D_1 \cdots D_n$ are dummy variables that take a value of one from each point of sudden change of variance onwards, and take a value of zero elsewhere.

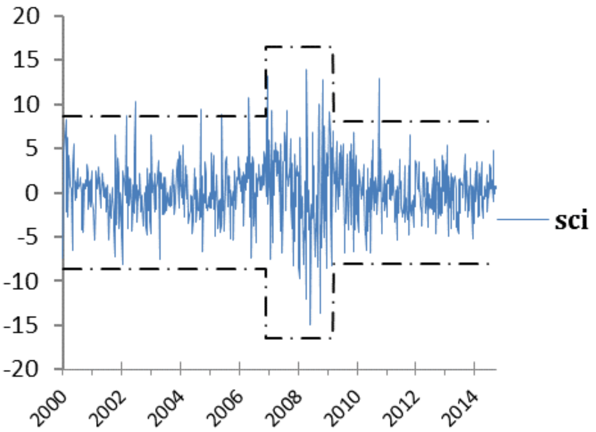
III. DATE AND DESCERIPTIVE STATISTICS

This study used the Friday closing price of shanghai composite index(SCI) from January 7, 2000 to October 10, 2014. If there is a Friday holiday, we would use the last day of this week of trading as the stock price. And this date was provided by netease finance, which was famous for supporting financial information for consumers.

For getting the time series of returns, we used the logarithmic method to all sample indices as follows. $r_t = 100 \times \ln(p_t/p_{t-1})$ for $t = 1,2,\cdots,T$, where r_t

is the returns for each index at time t, p_t is the current price, and p_{t-1} is the price from the previous day.

Figure 1. Shows the dynamic of returns of SCI.



NOTES: Dotted lines denoted ± 3 standard deviations. The ICSS algorithm estimated sudden change points.

From this figure, we found that it was difficult for us to judge whether it was a stationary time series. In order to document this time series in a stationary process, we have conducted a unit root test.

Table 1 shows the results of the unit root test for this time series of SCI returns and the descriptive statistics. As you can see, Panel A of Table 1 shows the results of three types of unit root test for each of the sample returns: the augmented Dickey-Fuller (ADF), Phillips-Peron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS). The null hypothesis of the ADF and PP tests is a time series that contains a unit root, whereas the KPSS test has the null hypothesis of a stationary process. As shown in Panel A, large negative values for the ADF and PP test statistics reject the null hypothesis of a unit root, while the KPSS test statistic does not reject the null hypothesis of stationary at a significance level of 1%. Thus, both return series are a stationary process.

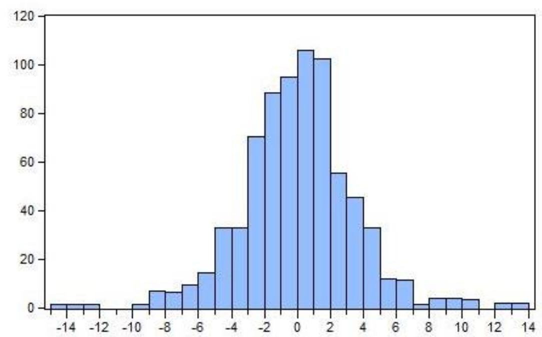
TABLE 1. Descriptive statistics and unit root tests.

SCI	
Panel A: unit root tests	
ADF	-26.09533***
PP	-26.49189***
KPSS	0.093815
Panel B: descriptive statistics	
Mean	0.060667
Median	0.130604
Maximum	13.94474
Minimum	-14.89794
Std.dev.	3.367629
Skewness	0.097286
Kurtosis	5.110621
Jarque-bera	138.3341 [0.000000]
Panel C: diagnosic tests	
Q(24)	54.423 [0.0000]
$Q_s(24)$	278.59 [0.0000]
LM-RACH(10)	6.784288 [0.0000]

NOTES: P-value are in brackets; standard errors are in parentheses. The LM-ARCH(10)[F statistics] test statistic checks for remaining ARCH sffects in estimated residuals. The Ljung-Box test statistics check for the serial correlation of squared residual series. *, ** and *** indicate statistics are significant at the 10%, 5% and 1% level, respectively.

Besides, as shown in Panel B of Table 1, the means of this time series are quite small, and the corresponding standard deviations are substantially higher. Based on these points, we inferred that the distribution of this time series was not normal incorporate with the value of skew, kurtosis, and Jarque-Bera tests. In order to illustrate the distribution of this return series intuitionally, figure 3 offers the graph of distribution of this time series. Look at this graph, we found that the distribution of this return series featured leptokurtosis and fat-tail and this phenomenon often appeared in the financial return series caused by the arch effect.

FIGURE 2. Shows the distribution of this time serious.



In addition, we use the ARMA model and do some tests to confirm whether there is a ARCH effect in this serious time. As you can see in the table 1, the values of Q (24) is relatively larger value. Incorporate with the value of P, we considered that there was a feature of autocorrelation in this return series. Besides, we also detected the ARCH effect by using the ARCH-LM test. As a result, we found that it was good for us to use the GARCH model to estimate the persistence of volatility of SCI.

Finally, we found that the volatility of return series of Shanghai Composite Index had the characteristic of clustering. It means that the volatility of this stock market in the past had an effect on the volatility for the future. It shows that the investor psychology is not mature in Chinese stock market.

IV. RESULTS OF THR EMPIRICAL STUDY

1. Sudden changes in conditional variance.

ICSS algorithm calculates the standard deviations among change points to identify the number of sudden changes. Combined with the figure1, we can visually explain the point of sudden changes. The time periods of sudden changes in volatility detected by ICSS is also shown by table 2. Look at figure 1 and table 2, we detected that the sudden changes in volatility were related to global economic events, such as global financial crisis in 2007. Therefore, we found that it was helpful to detect the sudden changes by connecting with the global economic.

TABLE 2. Sudden change points estimated by ICSS algorithm

NUMBER OF SUDDEN CHANGE POINTS	TIME PERIOD	STANDARD DEVIATION

2	7 JANUARY 2000 —1 DECEMBER 2006	2.872468
	2 DECEMBER 2006 — 20 MARCH 2009	5.517369
	21 MARCH 2009 — 10 OCTOBER 2014	2.708748

NOTE: Time periods were detected by the ICSS algorithm.

2. The selection of GARCH model.

Before estimating the volatility model, we have to use the Auto-regressive and Moving Average(ARMA) model to remove the autoregressive of this return series for analyzing the volatility accurately. In other words, we have to use the right ARMA model to remove the short memory of this return series. There is no doubt that it is very important to choose the compatible lag with ARMA model. But we don't hope to use the high lag in the ARMA model. Just as someone[10] mentioned that if we used the high lag to estimate in this model, we would probably remove the long memory.

For these points, this study detected the lags from the combination of n=0,1,2,3 and s=0,1,2,3 based on the GARCH(1,1) model. We also adopted the laws of HQC (Hannan-Quinn Criter) to choose the best ARMA-GARCH (1,1) model as follows.

TABLE 3 The results of HQC value in ARMA-GARCH

MODEL	(b , c)	Without dummies	With dummies
ARMA(b,c)-GARCH(1,1)	b=0,c=0	5.140794	5.120370
	b=0,c=1	5.144590	5.123410
	b=0,c=2	5.146672	5.124551
	b=0,c=3	5.147161	5.125450
	b=1,c=0	5.139934	5.120941
	b=1,c=1	5.135348	5.118338
	b=1,c=2	5.140463	5.125529
	b=1,c=3	5.145029	5.127446
	b=2,c=0	5.141802	5.120142
	b=2,c=1	5.137188	5.121090
	b=2,c=2	***5.132247***	***5.118234***
	b=2,c=3	5.137357	5.129130
	b=3,c=0	5.143023	5.120673
	b=3,c=1	5.143755	5.125442
	b=3,c=2	5.140035	5.121801
	b=3,c=3	5.149107	5.121961

NOTES: the inclined number is the best one in these results.

Look at table 3, we can find that ARMA (2,2)-GARCH(1,1) is the best one among these choices.

3. ESTIMATION OF ARMA(2,2)-GARCH(1,1)

TABLE 4. The estimation results of ARMA(2,2)-GARCH(1,1)

	ARMA(2,2)-GARCH(1，1) WITHOUT DUMMIES	ARMA(2,2)-GARCH(1，1) WITH DUMMIES
PANEL A: ESTIMATION RESULTS		
μ	0.056523	0.047795
AR(1)	1.229524***	1.200235***
AR(2)	-0.878936***	-0.848809***
MA(1)	-1.211359***	-1.175804***
MA(2)	0.907162***	0.874340***
ω	0.154116*	1.120301***
α	0.058837***	0.051869**
β	0.926139***	0.803869***
D_1		3.395887**
D_2		-0.123070
$\alpha+\beta$	0.984976	0.855738
PANEL B: DIAGNOSIC TESTS		
Log-likelihood	-1876.133	-1867.194
AIC	5.112981	5.094151
$Q^2(24)$	19.479[0.491]	17.188[0.641]
LM-ARCH(10)	0.566659[0.8417]	0.510964[0.8830]

NOTES: P-value are in brackets; standard errors are in parentheses. The LM-ARCH(10)[F statistics] test statistic checks for remaining ARCH sffects in estimated residuals. The Ljung-Box test statistics check for the serial correlation of squared residual series. *, ** and *** indicate statistics are significant at the 10%, 5% and 1% level, respectively.

This study is mainly aimed to consider the sudden changes in using GARCH model instead of the asymmetry of volatility of return series. Therefore, we won't think about using the GJR-GARCH model or EGARCH model.

Look at the estimation results of panel A in this table. We can know that AR (1), AR (2), MA (1), MA (2) are significant at the 10%, 5% or 1% level. But The others are not significant at any levels. Hence, we can't take these variables into the GARCH model for describing the return series better.

TABLE 5. The estimation results of ARMA(2,2)-GARCH(1,1)

	ARMA(2，2)-GARCH(1，1) WITHOUT DUMMIES	ARMA(2，2)-GARCH(1，1) WITH DUMMIES
PANEL A: ESTIMATION RESULTS		
AR(1)	1.228462***	1.190216***
AR(2)	-0.877662***	-0.839448***
MA(1)	-1.210219***	-1.164312***
MA(2)	0.906024***	0.864403***
ω	0.154881*	1.356963**
α	0.058813***	0.058297**
β	0.926089***	0.758659***
D_1		4.348650**
$\alpha+\beta$	0.984902	0.816958
PANEL B: DIAGNOSIC TESTS		
Log-likelihood	-1876.257	-1867.519
AIC	5.110604	5.089603
$Q^2(24)$	19.210[0.508]	16.846[0.663]
LM-ARCH(10)	0.561872[0.8455]	0.524567[0.8735]

NOTES: P-value are in brackets; standard errors are in parentheses. The LM-ARCH(10)[F statitics] test statistic checks for remaining ARCH sffects in estimated residuals. The Ljung-Box test statistics check for the serial correlation of squared residual series. *, ** and *** indicate statistics are significant at the 10%, 5% and 1% level, respectively.

According to the table 5, we can know that every coefficient is almost significate at the 1% level. Additionally, the coefficients of ARCH term and GARCH term are larger than zero and the sums of this two coefficients is close to 1. Based on the sums of this two coefficients, we found that the historical volatility information had a persistent impact on volatility of stock returns and that the impact was hardly eliminated in short term, which meant that Chinese stock market shows highly speculative and risky feature.

Except that, we can also know that the squared standardized residual can't be against the scale hypothesis on the basis of the values. In other words, the return series is independent. From the values of LM-ARCH (10), we knew that the ARCH effect did not exist in this model. That was to say, there was no problem in using this GARCH model to describe the return series.

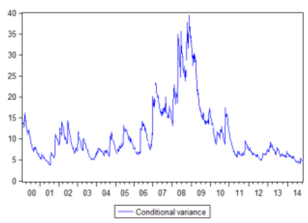
At last, according to the laws of AIC and LOG-LIKELIHOOD, we thought the GARCH model with dummies as better than the GARCH model without dummies in demonstrating this return series. Therefore, this return series can be described by this GARCH model as bellow.

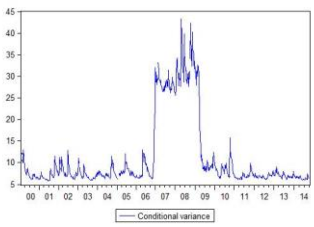
GARCH estimation with sudden changes

$$y_t = 1.190216\, y_{t-1} - 0.839448\, y_{t-2} - 1.164312\, u_{t-1} + 0.864403\, u_{t-2} \quad (10)$$

$$h_t = 1.356963 + 0.058297\, \varepsilon^2_{t-1} + 0.758659\, h_{t-1} + 4.348650\, D_1 \quad (11)$$

Look at the table 5, we found that the value of α and β without dummies was larger than the value of these two parameters without dummies. By following papers of these economists[6-9], we detected that ignoring sudden changes on volatility would overestimate the persistence of volatility. In order to reflect this point more directly, we show the graph of the conditional variance of this two kinds of GARCH models[1] as follows.





V. Conclusion

In this study, we found that the distribution of this return series in Chinese stock market featured leptokurtosis and fat-tail. This phenomenon often appears in the financial return series. So we used ARMA model and conducted some tests to estimate the return series to confirm whether there was ARCH effect or not. We detected that the volatility of return series of Shanghai Composite Index had the characteristic of clustering, which meant that the volatility of this stock market in the past had an effect on the volatility for the future. And this phenomena can be explained by trading behavior. As a result, it was shown that the investor psychology was immature in Chinese stock market. Certainly, this situation is fit for the national conditions in China that Chinese stock market just has undergone for only thirty four years and the mechanism was seriously unsound.

Then, we used the GARCH model to explain this return series and found that the historical volatility information had a persistent impact on volatility of stock returns. And the impact was hardly eliminated in short term, which meant that Chinese stock market had a high speculation and risk.

Therefore, we come to conclusion that the development of Chinese stock market is still immature. So the government should adopt this method to simulate, analyze and forecast the risk in Chinese stock market and should draft corresponding policies to improve market supervision ability. Moreover, investors should also use the volatility rules in stock market to avoid risk as much as possible.

Finally, we also detected sudden changes by using the ICSS algorithm and incorporated these sudden changes to the global economic events. We found that the identification of sudden changes in volatility was largely related to the global economic events, like the global financial crisis occurred in 2007. So we take sudden changes as dummy variable into GARCH(1,1) model . By comparing the results of estimation between two kinds of models[2], we draw the same conclusion that ignoring sudden changes in volatility will overestimate volatility persistence in stock markets.

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[1] Two kinds of models: GARCH model with sudden changes and GARCH model without sudden changes.

[2] Two kinds of models: GARCH model with sudden changes and GARCH model without sudden changes.