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Abstract

This paper investigates volatility switching in the Shanghai Stock Exchange (SSE hereafter,) using several recently developed techniques. They can be categorized into CUSUM type tests and Markov-Switching ARCH models. By detecting and dating switches with these models, we are able to show the volatility dynamics in SSE. Investigating the events in SSE around the switching date suggests that regulation improvements significantly reduce the volatility of the underlying market. Furthermore, the empirical results show that outliers can have significant impact on the conclusion and thus should properly be removed.

JEL: **G15, G18**

Keyword: **Volatility switching; CUSUM test; Markov-Switching ARCH; Shanghai Stock Exchange; Outlier**

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1 Introduction

Modelling stock market volatility has been one of the most actively discussed topics in empirical finance. Some asset pricing models, such as the CAPM (Capital Asset Pricing Model), and the Black-Scholes Option Pricing Model use the volatility of asset returns as a key input factor. Despite the huge success of such models, the standard modelling techniques with regard to volatility, such as the ARCH and GARCH models, have some fundamental flaws. It is often assumed that the parameters of such models are constant over time, but, applied to data with a long time series, this assumption may be violated. Among others, Lamoureux and Lastrpes (1990) argue that there may be a high persistency of shocks in the GARCH model because of occasional shifts in the parameters: thus, a more appropriate model should be chosen which would allow parameters to shift in the estimation.

According to the current literature, there are basically two types of technique used in analyzing the shifts in volatility models. One of them is the CUSUM type of tests. Some earlier work such as Inclan and Tiao (1994) uses a centered cumulative sum of squares to detect changes in volatility. Their methods have been applied to the volatility of the series rather than to any underlying models. Kokoszka and Leipus (1998) and Kokoszka and Leipus (2000) also use the idea of CUSUM but apply it to shifts in an ARCH process. Lee et al. (2003) further extend the basic idea to the GARCH(1,1) model. All of these techniques are to be used for detecting and dating a single break. An additional important contribution by Inclan and Tiao (1994) is to develop an ICSS (iterated cumulative sum of squares) algorithm to deal with multiple breaks, which can be extended to other techniques mentioned above. Due to their simplicity, CUSUM techniques have been widely used. However, according to Andreou and Ghysels (2002), these tests often have low power in small samples. Therefore it is necessary to make sure of a sufficiently large sample size, say, over 500 observations. Furthermore, Franses and van Dijk (1999) suggest that the existence of outliers is also important and can affect the results significantly. Thus correcting for outliers before the test is necessary.

Another method of modelling occasional shifts in volatility models is to incorporate the features of Markov-switching into ARCH models. Cai (1994) developed such an approach by taking into account occasional shifts in the asymptotic variance of the Markov-ARCH process. Hamilton and Susmel (1994) proposed another Markov-switching ARCH model (MSARCH hereafter), and claim that the model offers a better fit to data and hence provides better forecasts. It is possible to generalize this idea to the GARCH model and also extend it to the MSGARCH model. However, the path dependent problem, which requires the entire history of the state variables for the MSGARCH conditional variance, makes this estimation unfeasible. Several studies have proposed other ways of solving the problem, for example Dueker (1997), Chaudhuri and Klaassen (2001) and Bauwens et al. (2007). They use either an approximation of some of the most recent states (such as in Dueker, 1997), or the Bayesian method (as in Bauwens et al., 2007). Although these models claim to improve the forecasting of volatility, the probability of shifting or regimes has not been affected to any great extent. The simple MSARCH can provide as good a regime estimation as the more complicated MSGARCH models. Thus, the MSARCH model is used to identify regime switching properties in the present paper.

The properties of volatility of the stock returns in SSE will be investigated using the two approaches mentioned above. As an emerging market with less than 20 years of history , SSE is still developing. It experienced high volatility in its opening stages, like other stock markets, but the volatility reduced significantly thereafter. This reduction of volatility is necessary to build up and maintain the smooth operation of the capital market. If we can detect volatility switching and date the transition accurately, then we can identify what factors or policy changes may influence the level of volatility, which can provide useful information to the policy makers and provide further implications for the other new developing stock markets.

This paper has three main objectives: the first is to detect and date volatility switching in SSE; the second is to show whether the existence of outliers can affect the estimation significantly and find a result which is outlier robust; and the third objective is to investigate the reason that volatility changes over time. The organization of this paper is as follows: Section 2 briefly reviews the methods used in this study. Section 3 discusses the data and presents the empirical results. We then discuss improving the regulations in SSE so as to identify possible reasons for volatility switching. The last section provides some concluding comments.

2 Methods to detect volatility switching

2.1 CUSUM type tests

2.1.1 Inclan and Tiao (1994) CUSUM test and the ICSS Algorithm

Inclan and Tiao (1994)'s method (IT test hereafter) is one of the earliest attempts to deal with changes in volatility. They start with an investigation of changes in the variance of a sequence of independent observations. Their test statistic is the centered cumulative sums of squares. Consider a sequence of independent random variables of $\{\nu_t\}, t = 0, ..., T$ with zero mean and time varying variance σ_t^2. The statistics (called the DK statistics) are written as:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, k = 1, ..., T \tag{1}$$

Where $C_k = \sum_{t=1}^{k} \nu_t^2$ is the cumulative sums of squares. For a series with homogeneous variance, Inclan and Tiao prove that the adjusted DK statistics: $\sqrt{T/2} \cdot DK$ are distributed asymptotically as a Brownian bridge. To investigate whether there is a shift in variance, we need to look at the significance of the maximum of the adjusted DK statistics where the position of the maximum value of the statistics identifies the timing of the shift in volatility.

In case of a single shift in variance, the DK statistics provide a very simple solution. However, if there is more than one shift, especially when the shifts are in different directions, the result is affected by the "masking effects" and is not reliable. In order to deal with this problem, Inclan and Tiao proposed an iterative procedure called the ICSS (iterated cumulative sums of squares) algorithm. This is a three step procedure. The principle of this algorithm is very simple: the maximum of DK statistics are successively applied to sub-samples identified by break points previously identified. By isolating those breaking points, we can reduce the "masking effects" and detect the true timing of shifts.

2.1.2 Testing for breaks in the ARCH(∞) process

Inclan and Tiao (1994) consider only variance change in a sequence of independent observations. It may be necessary to look at more general cases. Kokoszka and Leipus (1998) and Kokoszka and Leipus (2000) modified the simple CUSUM test to detect volatility switching in the return process which follows the ARCH(∞)(KL test hereafter). Suppose a series of return $\{r_t\}$ follows the ARCH(∞) process, let $S_k = \sum_{t=1}^{k} r_t^2$ as the cumulative sums of squares similar to the C_k in Equation 1, the statistic (we call it AK) is written as:

$$A_k = \left(\frac{S_k}{\sqrt{T}} - \frac{k \cdot S_T}{T \cdot \sqrt{T}} \right), k = 1, ..., T \tag{2}$$

Kokoszka and Leipus (1998) show that the adjusted AK statistic AK/σ, where σ is the standard error, converges asymptotically to a Brownian bridge, which has a similar property to the Inclan and Tiao (1994) adjusted DK statistics. For the estimation of standard error σ, Andreou and Ghysels (2002) suggest using the den Haan and Levin (1997) Heteroscedasticity and Autocorrelation Consistent (HAC) estimator. They also claim that the Kokoszka and Leipus (1998) AK test can be used for more general processes. In case of multiple breaks, the ICSS algorithm can be applied.

2.1.3 Testing for breaks in the GARCH(1,1) model

Although AK statistics can be used to deal with more general series than DK statistics, they share the same approach, that both of them test the series rather than any underlying model. A test of shifts of parameters in a model such as GARCH may be more revealing.

Lee et al. (2003) investigate the problem of testing parameter shifts in a GARCH(1,1) model using the principle of CUSUM tests (the LTM test hereafter). Their test statistics are mainly modifications of Inclan and Tiao's DK statistics and are based on Kim et al. (2000). The difference is that the test is applied to the standardized residuals $\{\epsilon_t\}$ of a GARCH(1,1) model. Let τ represent the standard deviation of squared residuals, $S_k = \sum_{t=1}^{k} \epsilon_t^2$ again the cumulative sums of squares, then the test statistic (called the TK statistic) is given by a similar form to the AK statistic discussed previously. The adjusted statistic: TK/τ then converges to a Brownian bridge. However, as Lee et al. (2003) point out, the statistic is not reliable in small samples.

To extend the same principle, we apply the Inclan and Tiao (1994) technique to the standardized residuals for a GARCH(1,1) model. Under the null hypothesis, if the parameter of a GARCH model is constant, then the distribution of standardized residuals is a white noise process, thus complying with the assumption of Inclan and Tiao. Simulation results[1] show that the extended DK test statistic applied to the standardized residuals for a GARCH(1,1) model perform better than the LTM statistics although still affected by the small sample problem.

2.1.4 Outlier detection procedure

An additional concern of the CUSUM tests is that it is necessary to distinguish true parameter shifts from outliers. The existence of outliers can cause significant "masking effects" which influence the test results. Therefore, it is important to test and remove outliers from the series before performing tests. In the present paper, we focus on looking for shifts in GARCH models, and pay particular attention to detect outliers in such models. Some recent work by Franses and van Dijk (1999) and Doornik and Ooms (2005) consider how to perform such a procedure. In this paper, we use a method proposed by Franses and van Dijk (1999), and first briefly explain the procedure used to detect and remove additive outliers in the GARCH model. This is mainly based on earlier work

[1]The results are available upon request from the author.

by Chen and Liu (1993). The method is simply to consider all observations as possible outliers, and to test them iteratively.

Consider a simple GARCH(1,1) model with an outlier:

$$y_t = \mu + \epsilon_t + \gamma I_t[t = \tau], \ \epsilon_t = z_t \cdot \sqrt{h_t} \tag{3}$$

$$h_t = \omega_t + \alpha\epsilon_t^2 + \beta \cdot h_{t-1} \tag{4}$$

Here $I[\cdot]$ as an indicator function means that if $t = \tau$, then $I[\cdot] = 1$ and zero otherwise. z_t is an $i.i.d.$ process with zero mean and unit variance.

According to Bollerslev (1986), write $\eta_t = \epsilon_t^2 - h_t$, and the conditional variance function (Equation 4) can be written in the form of an ARMA(1,1) model:

$$\epsilon_t^2 = \omega + (\alpha + \beta)\epsilon_{t-1}^2 + \eta_t - \beta\eta_{t-1} \tag{5}$$

Define a lag polynomial $\pi(L) = 1 - \pi_1 L - \pi_2 L^2 - ...$ with $\pi_j = \alpha\beta^{j-1}$ for $j = 1, 2, ...$, this allows equation (5) to be written as:

$$\eta_t = \pi(L)\epsilon_t^2 - \frac{\alpha}{1-\beta} \tag{6}$$

The conditional variance h_t is not observed but can be estimated as:

$$h_t^e = \omega + \alpha y_t^2 + \beta h_{t-1}^e \tag{7}$$

Equation (7) can be written as:

$$h_t^e = h_t \quad for \quad t \leq \tau \tag{8}$$

$$h_{\tau+j}^e = h_{\tau+j} + \pi_j(\gamma^2 + 2\gamma\epsilon_\tau) \quad for \quad j = 1, 2, ... \tag{9}$$

Let $\nu_t = y_t^2 - h_t^e$, then we have a regression model:

$$\nu_t = \xi x_t + \eta_t \tag{10}$$

with:

$$x_t = 0 \quad for \quad t < \tau$$

$$x_t = 1 \quad for \quad t = \tau$$

$$x_{\tau+k} = -\pi_k \quad for \quad k = 1, 2, ...$$

The parameter $\xi \equiv f(\gamma) = -\gamma^2 + 2\gamma y_\tau$ is a function of the magnitude of the outlier, which can be estimated by the least square in Equation (10). This can then can be converted to the estimator of the coefficient on outliers $\hat{\gamma}(\tau)$.

Following Chen and Liu (1993), Franses and van Dijk (1999) construct a t-statistic to test the existence of outliers, which is given by Equation (11) with σ_η as the standard deviation of η.

$$t(\hat{\gamma}) = \frac{2y_\tau \hat{\gamma(\tau)}}{\sigma_\eta \left(\Sigma_{t=\tau}^n x_t^2\right)^{-1/2}} \tag{11}$$

Since the location of the outlier is unknown, Franses and van Dijk (1999) suggest using the maximum of the t-statistics of all possible outliers, that is:

$$t_{max}(\hat{\gamma}) = \max_{1<\tau<n} |t_{\hat{\gamma(\tau)}}| \tag{12}$$

The statistic is non-standard, but we can use the critical value provided by Franses and van Dijk (1999, Table1). Once an outlier is found to be significant, it can be removed from the original series, and then we return to a new search of the dataset without the outlier. The process is finished when no more significant test statistics are found.

2.2 Markov-switching ARCH model

Combining Markov-switching with ARCH models is an excellent way of modelling volatility switching. Although it provides no exact timing of when the shifts occur, MSARCH models are able to find the probabilities of staying in each regime and also to estimate the model for each regime simultaneously.

Among all the MSARCH models mentioned in Section 1, Hamilton and Susmel (1994) develop a model which allows the parameters of an ARCH process to be different in several different regimes. The transitions in these regimes will follow a first order Markov process, which suggests that the probability in the current state will depend only on the most recent state.

$$prob(s_t) = j|s_{t-1} = i, s_{t-2} = k, ...) = prob(s_t = j|s_{t-1} = i) = p_{ij} \tag{13}$$

For the case with n states, the transition probabilities can be expressed in a matrix, or transition matrix:

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{21} & \cdots & p_{n1} \\ p_{12} & p_{22} & & p_{n2} \\ \vdots & & \ddots & \vdots \\ p_{1n} & p_{2n} & \cdots & p_{nn} \end{pmatrix} \tag{14}$$

The summation of any column equals unity, for example $p_{11} + p_{12} + ... + p_{1n} = 1$.

Hamilton and Susmel estimate the model as follows:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} +, ..., +\alpha_p y_{t-p} + u_t & (15) \\ u_t &= \sqrt{g_{s_t}} \cdot \tilde{u}_t & (16) \\ \tilde{u}_t &= h_t \cdot \varepsilon_t,\ \varepsilon_t \sim Gaussian\ or\ t - distribution & (17) \\ h_t^2 &= \beta_0 + \beta_1 \tilde{u}_{t-1}^2 +, ..., +\beta_q \tilde{u}_{t-q}^2 + \xi \cdot I(\tilde{u}_{t-1} \leq 0) \cdot \tilde{u}_{t-1}^2 & (18) \end{aligned}$$

where $I(\cdot)$ is the indicator function which equals 1 if the statement is true and zero otherwise. The last term here represents the leverage effects which have been generally considered in most of the ARCH models. The difference between each state in this model is captured by the scale factor g_{s_t}. To analyze the stock return, we mainly use a two states model with one low volatility and low persistency state and the alternative a high volatility and high persistency state.

3 Data description and empirical results

3.1 Data description

In this empirical investigation, we use the returns of the composite index of SSEcollected from DATASTREAM. The full sample is in weekly frequency covers from Sep. 12, 1994 to Sep. 06, 2004 (plotted in Figure 1). This gives us 522 observations in total. According to the simulation results of Andreou and Ghysels (2002), the CUSUM type tests have relatively good power with this sample size. Using weekly data can avoid some other problems, for example, day of the week effect, missing observations etc.

Figure 1 shows high volatility in the earlier stage of our sample and some significant reduction towards the end of the sample. Viewing the graph of this time series suggests that outliers may exist. Like most of the financial series, we can observe volatility clustering. Table 1 gives some basic descriptive statistics for the return (the series are in percentage points). The Kurtosis is 16.9 for the full sample, which is normally considered to indicate ARCH effects. Additionally, the Engle LM test for ARCH effects (LM(1)=40.5) is highly significant. The standard deviation of the full sample is 4.956. However, if we split our sample in half, the statistic turns out to be 6.274 for the first half and 3.135 for the second half, evidence of a significant reduction in volatility.

A rolling windows estimation is also applied to obtain a better view of the time path of volatility. The windows size is chosen to be one third of the total observation (n=174). The rolling standard deviation is plotted in Figure 2 and shows a clear downward trend, which suggests that volatility has been reduced in SSE. Another interesting finding from Figure 2 is that volatility does not fall smoothly, but contains at least one clear structural shift. For example, there is a significant drop from the window started at May 22, 1995 to the window started at May 29, 1995. Such a significant drop in volatility suggests that in our observation there may be some outliers or indeed structural breaks. Furthermore, the rolling standard deviation measures from early 1997 onwards are smaller than those before this date.

3.2 Empirical results

3.2.1 Results of the CUSUM type tests

In this section, we show the results of the CUSUM type tests mentioned above, including IT, KL, LTM and IT on GARCH residuals. The Franses and van Dijk (1999) outlier detection procedure is also used to produce an outlier robust estimation. The main results are shown in Tables 2 and 3. The absolute value of the DK, AK and TK statistics are plotted against all possible breaks over the whole time period. They are shown in Figures 3, 4 and 5, note that the DK statistics are for the IT test on GARCH residuals.

The graphical analysis of the return series show that they are very likely to be affected by outliers. The Franses and van Dijk (1999) techniques are applied to detect outliers, and then the outlier robust tests can be performed. The iterative procedure has identified only one significant outlier. The t_{max} statistic is 58.72[2], and it is located on May 22, 1995 or the 37th observation. According to Franses and van Dijk (1999), the size of this outlier is calculated as 36.46. The function value for the GARCH estimation before the outlier is removed is -1509.29, whereas it is -1472.08 afterwards. This indicates how significantly the outlier can affect the estimation.

After removing the outlier, we apply the CUSUM type tests again to obtain the

[2] 5% critical value is 14.82. The critical value is sensitive to the size of the parameters; thus it is necessary to mention here that we use the method described Franses and van Dijk (1999, page 9) to calculate the critical value.

outlier robust test results, which are shown in Table 3. Since we examine the impact of the outliers for the GARCH model, only the IT and LTM test on the GARCH residuals are performed here. Comparing the results with those in Table 2, there are significant difference. First of all, without outlier correction, these tests are not consistent with each other. The break dates are different for different methods. Secondly, without outlier correction, the break date tends to be biased towards the early part of the time period, in other words, biased towards the outlier. After correcting for outliers, both the IT and LTM test consistently find a main break point at the 148th observation, which is July 07, 1997.

Further evidence on outliers and the benefit of outlier correction can be seen from the figures which plot the absolute value of DK, AK and TK statistics against all possible break points. From Figures 3 and 5, we can see the plots being skewed towards the outlier and having more volatility. After correcting for outliers, the plots of the DK and TK statistics are smoother and converge on the same break point.

3.2.2 Sub-sample estimation

The next step is to investigate sub-sample properties according to the results found above. With outlier correction, there is only a single break under the IT test on the GARCH residuals, whereas we find two breaks for the LTM test. Two break points will be used to identify the sub-samples.

The break points occur in observations 148 and 407, and this divides the full sample into three sub-samples: the first (Sample I) starts from Sep. 12, 1994 and goes on to Jul. 07, 1997 with 148 observations; the second (Sample II) starts from Jul. 14, 1997 and finishes on Jun. 24, 2002 with 259 observations and the last (Sample III) starts from Jul. 1, 2002 and goes on to the end of the data. This sub-sample division is also consistent with the analysis from the rolling windows estimation. Table 4 presents the estimation results. Here the model estimated is GARCH(1,1) with t-distributed errors. μ is the constant parameter of the GARCH mean equation (Equation 3); ω, α, β are the parameters of the variance equation (Equation 4), where ψ is the degree of freedom of the t-distribution estimated in the model.

The estimation of sub-samples can be summarized as follows. First, the estimation of standard deviation shows a similar picture to the rolling windows estimation: volatility falls, but in several stages. The magnitude of reduction from Sample I to Sample II is quite remarkable, at almost 50% . Secondly, for the GARCH estimation, the results for the model using the full sample are not accurate. They ignore some critical features of the underlying data, so that the forecasts using the model will be significantly biased. Thirdly, the coefficients of ARCH and GARCH terms in the full sample sum to 0.95, which indicates a highly persistent process and one very close to an Integrated GARCH. However, as mentioned in the introduction, this may be due to structural shifts and is consistent with the interpretation of the sub-sample estimation. Although the level of persistence in each sub-sample is different, we note that the values are generally lower than the full sample estimation.

3.2.3 MSARCH estimation

In this sub-section, we perform an MSARCH estimation for returns on the SSE composite index using Hamilton and Susmel (1994) settings. The result of a two-state model is given in Table 5, together with a three-state model for comparison. The optimal lag order of the ARCH process is decided via information criteria. These criteria can also be applied to determine other key options such as the form of the mean equation in the ARCH estimation and the optimal number of states. Again the error term is assumed to have a t-distribution with a degree of freedom determined by the data. Since the return of a financial series often responds to shocks asymmetrically, we also include a factor which measures this leverage effect.

The parameters in Table 5 are defined as the following: μ is the constant in the mean equation; ω is the constant in the variance equation; αs is the coefficient of the ARCH term, since in both cases there is only one lag included and we have only one α

coefficient; g_1 and g_2 are scale factors, where g_2 applies only to the three-state model; ψ represents the degree of freedom in the t-distribution, where the parameter is rounded up to the nearest integer; ℓ is the coefficient of the leverage effect. The regime switching transition probabilities are defined as $p_{ij} = Pr(s_{t+1} = j|s_t = i)$, which gives a probability of switching from regime i to regime j.

We show the filtered and smoothed probabilities of an MSARCH estimation in Figure 6 for a two-state model. The graph gives a straightforward view of the probability of being in each regime for each observation. This provides an indication of when regime switching might happen.

From the diagrams, we can see that in the early part of the time period the SSE is dominated by high volatility and the high persistence of State 2, whereas after mid-1997, State 1 dominates. This is consistent with our previous regime switching analysis using CUSUM type tests. However, the state after mid-1997 is not solely State 1, since there is switching also in 1999 and around 2002. The first case was not identified from previous analysis and it lasts for a fairly short period, whereas the second one is consistent with the CUSUM test and corresponds to the second break point. This finding is very important, since it suggests that the second break point found by the CUSUM test may only be a short-lived phenomenon, or temporary shock.

4 Volatility switching and Regulation improvement in SSE

The empirical analysis has discovered some very interesting results for the volatility modelling of the returns of the SSE composite index. Volatility is reduced and is characterized by some structural changes. The existence of outliers can affect the tests significantly. Almost all the methods consistently identify a major break point in the middle of 1997. There are two other short-run high volatility regimes after 1997. For the sub-sample GARCH estimation, α coefficient is reducing, whereas the β coefficient increases from

Sample I to Sample III. Considering all these features of our analysis, one of the key questions is what causes such shifts.

For most literatures on the subject of volatility switching in the Asian stock markets, such as Chaudhuri and Klaassen (2001), the financial crisis in 1997 across most of the Asian markets is the focus, where most of the markets experienced huge increases in volatility and falls in value. However, the volatility in SSE is not shown in the same way; on the contrary, there is no evidence to suggest any relationship between changes of volatility of stock returns in SSE and the crisis.

The driving force for the major volatility switching in May 1997 may have been complicated. It may be better to look at the history of SSE from its very beginning. SSE is one of the two stock exchanges in China and was founded on Nov. 26, 1990. It started full operations in December of the same year. Some key statistics showing the features of SSE are given in Table 6.

For a new stock market, it is normally to have high volatility. There are not enough regulations available, the liquidity is low, investors and even market regulators are inexperienced. Meanwhile, there is a great deal of noise in the market, speculative trading is normally frequent and big players such as banks and insurance companies can easily control the market. All these added together create huge uncertainty and thus volatility. This can be observed not only in the SSE but also in the history of many other stock markets. But as the market develops, more stocks are listed and the market size increases, especially with proper regulation, volatility can be reduced. In this paper, we found not only a general reduction of volatility, but also a significant shift in 1997. Thus, in order to draw any conclusion about the relationship between volatility and regulation improvement, it is necessary to refer to the situation in and around 1997.

There were almost no formal laws on the security market until Nov. 15 1997, where the first ever securities regulation guides– "Provisional Measures on Administration of Securities and Investment funds" was implemented. Other regulation measures were also limited. In 1997, however, a significant number of regulation improvements and changes were implemented; see Table 7 for a list of the major ones.

Among these changes, a critical one was the direct regulation and supervision of SSE by an independent regulatory body, the China Securities Regulation Commission (CSRC). CSRC was established in 1992 as the executive branch of the State Council Securities Commission (SCSC), responsible for supervising and regulating the securities markets in accordance with the law. In August 1997, the State Council decided to put the securities markets in Shanghai and Shenzhen under the supervision of the CSRC. This kind of regulation agency can be observed in many other countries and regions, for example, the Financial Services Authority (FSA) in the UK, the Hong Kong Securities and Futures Commission, the U.S. Securities and Exchange Commission, etc. These independent regulation agencies are designed to help maintain financial stability and provide better regulation. The experiences in these developed markets show that this is a very important and successful solution.

In the year 1997, apart from the above two major changes in the implementation and regulation of the law, several other measures regarding trade restrictions on institutions, banks, and other state-owned corporate were also promulgated. Moreover, many more acts of regulation have been performed by the CSRC and the states since then. By the end of 2003, there were over 300 sets of regulations, rules, guidelines and codes in force. These regulations further help the SSE to build up a healthy environment, reduce speculative trading and uncertainty and maintain financial stability, thus reduce volatility in stock market.

Through the overall discussion above, it is quite clear and can be confidently argued that regulation improvement is the main reason for the volatility switching in the SSE. It may of course also be argued that there are other reasons for the volatility to switch, the effect of which we do not deny, for example, an increase of market size or liquidity (represented as turnovers) in the market. In a relatively small market, negative shocks are more likely to generate large price movements; markets are more easily maneuvered by big players and thus high volatility ensues. The historical statistics about market size and turnover show a large increase of both for 1997 over those of 1996.

The annual turnover of SSE for 1995 was only 310.346 billion RMB, but increased to 911.481 billion RMB in 1996 and 1376.317 billion RMB in 1997. Market capitalization (excluding B share) increased significantly from 531.613 billion RMB in 1996 to 903.245 billion RMB in 1997. This increase may helped the stock market to absorb shocks and avoid large shifts. Furthermore, the annual turnover reduced from 3137.386 billion RMB in 2000 to 2270.938 billion RMB in 2001 and further reduced to 1695.909 billion RMB in 2002, which can be an explanation for the finding of a high volatility period around 2001 and 2002 in the MSARCH estimation.

5 Conclusion

We investigated volatility switching in the SSE in this paper. Through several recently developed techniques, the objectives mentioned in the first section were successfully undertaken. First of all, the empirical results show that there was volatility switching in the SSE via CUSUM-type tests as well as the MSARCH model. Secondly, outliers in the series were shown to significantly affect the results of our estimation. Using the procedure proposed by Franses and van Dijk (1999), we successfully identified an outlier. After removing the outlier from the data, there was a consistent estimation of break points. Regarding the major break point in May 1997, which was found by almost all the methods, we argue that regulation improvements are the main cause. Looking back at the history of the SSE, several key changes in regulation were implemented in 1997, which would have worked in favour of a reduction in volatility. Among those changes, the appearance of a formal law regarding securities and investment and CSRC direct supervision is considered to be critical. We further argue that other factors, such as increased market size and liquidity were additional driving force for the low volatility regime in the SSE.

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Table 1: Descriptive statistics

Mean	0.065
Median	0.000
Maximum	43.299
Minimum	-23.343
Std. Dev.	4.956
Skewness	1.226
Kurtosis	16.888
Jarque-Bera	4325.980
Observations	522
ARCH(1) LM	40.487
ARCH(4) LM	42.476

Table 2: CUSUM-type tests on Volatility Switching

Panel I:	***IT test on series***		
Type of break	Test statistics	Break point	Break date
Single break	6.2053	149	Jul. 14, 1997
Multiple breaks	2.4277	38	May 29, 1995
	3.0726	149	Jul. 14, 1997
	2.0683	407	Jun. 24, 2002
Panel II:	***IT test on GARCH residuals***		
Type of break	Test statistics	Break point	Break date
Single break	2.0431	38	May 29, 1995
Multiple breaks	2.2390	36	May 15, 1995
	1.4377	120	Dec. 23, 1996
Panel III:	***KL test on series***		
Type of break	Test statistics	Break point	Break date
Single break	1.6809	149	Jul. 14, 1997
Multiple breaks	1.6809	149	Jul. 14, 1997
Panel IV:	***LTM test on GARCH residuals***		
Type of break	Test statistics	Break point	Break date
Single break	2.9221	38	May 29, 1995
Multiple breaks	5.2351	36	May 15, 1995
	2.0042	120	Dec. 23,1996

Note: We use 5% asymptotic critical value of 1.358 to select break points. ICSS algorithm is applied in all cases of multiple breaks. A GAUSS procedure is available upon request.

Table 3: Outlier robust tests on Volatility Switching

Panel I:	***IT test on series***		
Type of break	Test statistics	Break point	Break date
Single break	1.9830	148	Jul. 07, 1997
Panel IV:	***LTM test on GARCH residuals***		
Type of break	Test statistics	Break point	Break date
Single break	2.8070	148	Jul. 07, 1997
Multiple breaks	2.8962	148	Jul. 07, 1997
	1.6566	407	Jun. 24, 2002

Table 4: Sub-sample estimation

Sample	Full Sample	I	II	III
Observation	522	148	259	115
Standard deviation	4.97	7.61	3.75	2.40
μ	-0.0580	0.1736	0.1193	-0.3305
	(-0.4221)	(0.3808)	(0.6388)	(-1.3406)
ω	1.5429	19.1875	2.1200	0.6595
	(2.3329)	(1.2917)	(1.5803)	(0.2013)
α	0.2198	0.2941	0.2179	0.0207
	(3.1517)	(1.2239)	(1.9286)	(0.2713)
β	0.7282	0.3707	0.6656	0.8715
	(10.7360)	(0.9480)	(4.5584)	(1.4839)
ψ	4.1828	4.3402	4.3541	9.8359
	(6.6161)	(3.7731)	(3.3381)	(0.7252)

Note: the t-statistics are given in brackets.

Table 5: MSARCH estimation

Parameters	Two states MSARCH	Three states MSARCH
μ	-0.0593	-0.0612
	(0.1381)	(0.1368)
ω	6.5299	5.8127
	(1.5096)	(1.4947)
α	0.1479	0.1340
	(0.0810)	(0.0989)
g_1	4.7944	4.0650
	(0.9869)	(2.7961)
g_2		5.8141
		(1.7694)
ℓ	0.1453	0.1305
	(0.1590)	(0.1603)
ψ	5	5
$p_{11}/p_{21}/p_{31}$	0.9882/0.0118	0.9762/0.0213/0.0025
$p_{22}/p_{12}/p_{32}$	0.9841/0.0159	0.9221/0.0779/0.0000
$p_{33}/p_{13}/p_{23}$		0.9968/0.0000/0.0032
Function value	-1430.1714	-1428.1546
AIC	5.5528	5.5643
BIC	5.6184	5.6710

Note: the standard errors of estimation are given in brackets.

Table 6: Historical statistics of the SSE

Year	Number of stock	Annual turnover	Capitalization I	Capitalization II
1994	203	573.507	259.013	248.354
1995	220	310.346	252.566	243.371
1996	329	911.481	547.801	531.613
1997	422	1376.317	921.806	903.245
1998	477	1238.611	1062.591	1052.538
1999	525	1696.579	1458.047	1444.072
2000	614	3137.386	2693.086	2659.632
2001	690	2270.938	2759.056	2693.451
2002	759	1695.909	2536.372	–
2003	824	2082.414	2980.492	–

Data source: http://www.sse.com.cn/, Capitalization I includes B share and Capitalization II excludes B share.

Units: billions of RMB (excludes number of stocks).

Table 7: Major regulation improvements of the SSE in 1997

Date	Regulation Items
Mar. 17	New modified Criminal Law of P.R.C. appear publicly including securities criminal clause, which will be implemented at Oct. 01, 1997.
Mar. 25	State Council Security Committee promulgate 'Provisional Measures on Administration of Convertible Corporate Bonds'
May. 22	State Council Security Committee, People's Bank of China, Economics and Trade Committee announced State owned companies and listing companies are prohibited from stock trading.
Jun. 06	People's Bank of China announces that all commercial banks stop securities Repo and trade on securities.
Aug. 15	The China State Council decide SSE under direct administration of CSRC (China Securities Regulation Commission)
Nov. 15	'Provisional Measures on Administration of Securities and Investment Funds' implemented, this is the first ever securities regulation guides
Dec. 31	State Council Security Committee promulgates 'Provisional Measures on Administration of Securities and Futures Investment Consultation'.

Data source: http://www.sse.com.cn/.

Figure 1: Returns of the SSE Composite Index

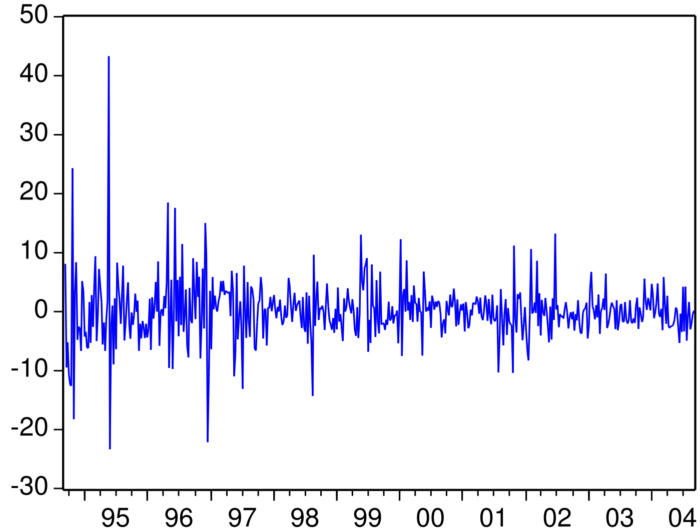

Figure 2: Rolling Windows Estimation of the Standard Deviation of the SSE Composite Index Return

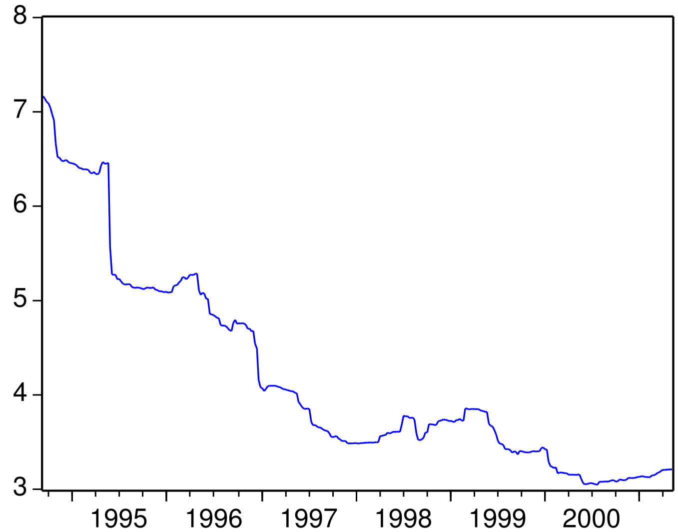

Figure 3: Graphs of Absolute value of the DK statistics

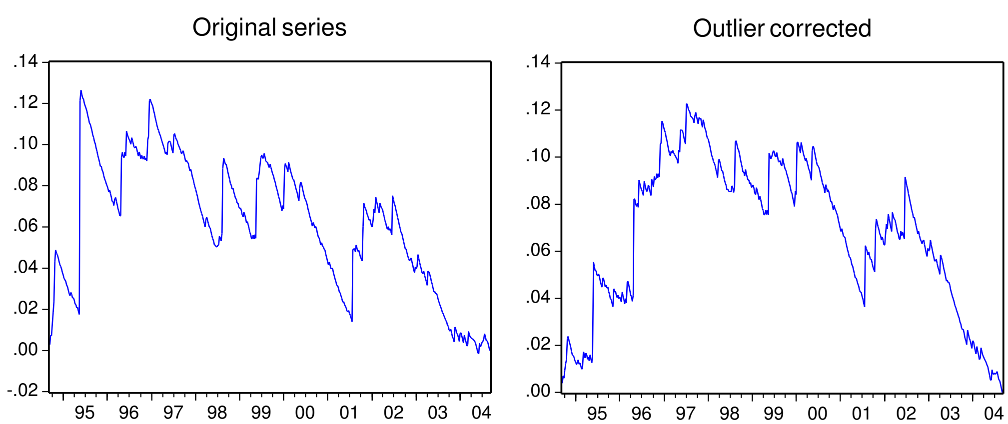

Figure 4: Graphs of Absolute value of the KL statistics

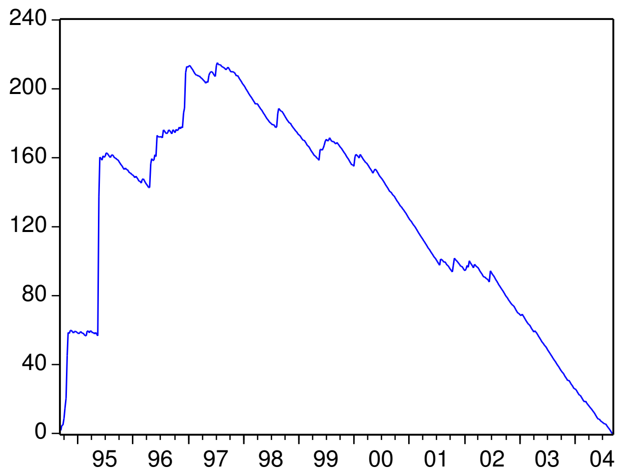

Figure 5: Graphs of Absolute value of the TK statistics

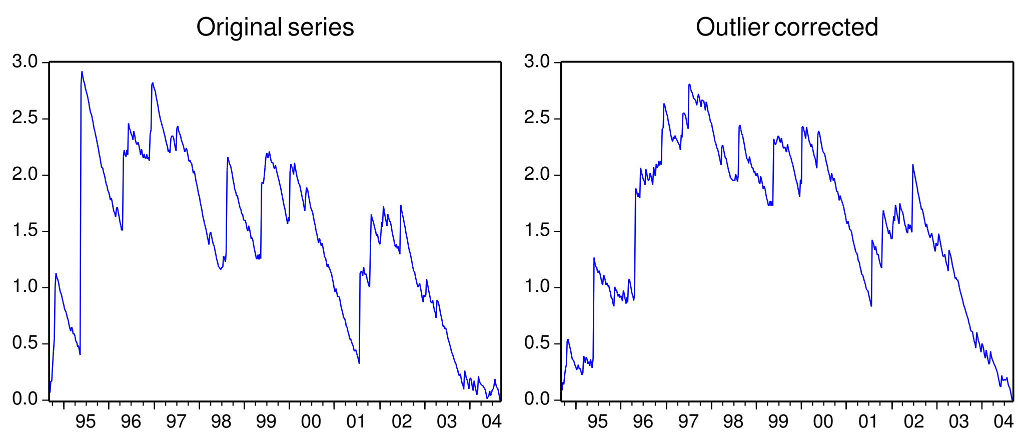

Figure 6: Filtered and smoothed probabilities for a Two-State MSARCH model