Chinese Stock Index Futures' Effects on the A Share Market — A Study Based on the Improved TGARCH Model

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Abstract

The paper improves the TGARCH model, and then builds three state transition models for the population sample of Hushen (Shanghai and Shenzhen) 300 Index. The paper selects the samples in the two years before and after the launch of stock index futures, and then uses the improved TGARCH model for market modelling, and makes a comparison with the original TGARCH model. The paper finds that after the launch of stock index futures, the A share market's volatility ratio decreased greatly and volatility asymmetry weakened significantly, but still existed. The paper finally analyses the causes why stock index futures can stabilize A share market volatility and comes to a conclusion.

Keywords: stock index futures, GARCH model, TGARCH model, A share market, Hushen 300 Index

1 Introduction

The secondary stock market is one of the most active financial markets, so the study on the laws of volatility of its return rate not only has positive significance for equity pricing, investment portfolio optimization, risk level management, and even market supervision, but also provides some recommendations on investors' decisions.

A lot of research on the volatility has been done by many scholars, but the study on the volatility of asset price is still in the ascendant. Engle[1] proposed the ARCH (autoregressive conditional heteroskedasticity) model in his study on inflation in 1982, getting a good imitative effect by describing the variation of variance using the auto regression. Based on the model, in 1986, Bollerslev [2] made a direct linear expansion to the expression form of heteroscadacity and proposed the GARCH model, solving the higher-order lag problem of ARCH model. Then, on this basis, a lot of GARCH-class models were proposed, such as the IGARCH model, the GARCH-M model and the EGARCH model, making the GARCH model the most extensive model. Compared with the traditional linear model, the GARCH model, to some extent, solves financial data's problems, such as the high peak, fat tail, weak and long-term memory process, and volatility clustering, showing a good in—sample data fitting effect. However, the GARCH-class models, due to the limitations of themselves, present a strong persistency of single impact which causes unsatisfactory prediction outcomes of model. Diebold [3] believed that if the conditional volatility had structural changes, the persistency would be fake. However, economic development shows a run cycle of prosperity — recession — depression — recovery, and the financial market, especially the stock market, is closely related to the macroeconomic operation, so we have reasons to believe that volatility state is not changeless in financial time series. Considering the changes of volatility state, Hamilton [4] introduced the Markov-switching model (MS model) and built the MS-ARCH model by combining it with the ARCH model, to study the volatility, but the new model had a higher-order lag problem. This method provided new ideas for the study on the asymmetric reaction of volatility. The models built later in the paper are also state transition models.

The volatility asymmetry of stock market means that good news and bad news have different effects on market volatility, which was first proposed by Black in 1976. Most empirical studies show that in the mature western market, the bad news has greater effects on market volatility compared with the good news of the same degree. However, Chinese securities market is known as a news-dependent market and a policy-dependent market, with distinctive Chinese characteristics. Langnan Chen, Jiekun Huang [5], Rong Lu and Longbing Xu [6] studied Shenzhen component indexes and Shanghai composite indexes respectively, but they all drew a conclusion opposite to that in the context of western market. Their study results showed that the good news has more effects on market volatility than the bad news in Chinese stock market. Then, they explained the phenomenon from market system, government policy and investor psychology. Wei Zhang, Xiaotao Zhang, et. al. found the same law in the empirical study using the VS-GARCH model, and believed that it was connected with the system and investor psychology.

However, their research was limited to the model itself and implied that volatility asymmetry didn't change over time. However, in fact, the bull market alternates with the

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bear market in China with a distinct periodicity, so there is every reason to believe that volatility asymmetry changes over time. Given this, Jun Wan [7], Hua Zhao [8], Junjun Zhu [9], et. al. established state transition models later, and further studied the volatility asymmetry in Chinese stock market. The models established by Jun Wan and Hua Zhao are both similar to the Gray [10] simplified model (simplifying the state transition model proposed by Hamilton to make h_t only depend on the state of previous period, to solve with the maximum likelihood method), but the parameter estimation of the model couldn't determine whether parameters had converged to the local maximum. Junjun Zhu built a MS-TGARCH and made parameter estimations using the Gibbs-sampling-based MCMC method steadier than the maximum likelihood method. The model's two states both had a significant volatility asymmetry, and the high volatility state showed obvious characteristics of bull market, while the low volatility state showed obvious characteristics of bear market.

However, his model had a long sample period and studied the volatility using weekly return rate, but the volatility of stock market is changing constantly, and the period of daily data is kind of long for studying the effects of news on the short-term volatility of market, not to mention the weekly data. Therefore, the paper believes that his empirical study might reflect the effects of some long-term good news, such as the sustainable growth of macro-economy, on stock market volatility, but the applicability of his study to the asymmetry of short-term volatility remains to be proven. In addition, because the stock index futures have just been launched for a short time, his model can't show what the effects of the launch of stock index futures are on the market. Now, the stock index futures have been introduced, which equals to the introduction of selling-short mechanism, and securities-loan short is also available. In addition, the restriction on securities loan has been relaxed in 2012, so we can say A share market will soon enter into an overall-selling-short age. In this case, whether Chinese stock market will react to the good news more greatly than to the bad news just like before is the focus of the paper.

Besides, currently, there are the following views on the effects of stock index futures on the volatility of stock market:

One view is that stock index futures reduce the volatility of spot market. Robinson (1994) selected the data of 1980-1993 based on FE—SEl00 indexes to study the effects of stock index futures' launch on the volatility of stock index, and found that stock index volatility fell by 17% after the listing of stock index futures.

Another view is that there are many speculators in the futures market, which may increase market instability. People with the view mainly have the following explanations: first, risk preference, believing the risk preference of stock index futures traders decides the volatility relationship between futures and spots; second, information dissemination, believing the launch of stock index reduces information dissemination cost and improves the efficiency of information flow, so it's easier for the stock price to reflect market changes, thus increasing price fluctuation.

Some other scholars believe that the launch of stock index futures can increase market volatility in the short term, but in the long run, the effect doesn't exist.

As to which situation Chinese market is in, because stock index futures have just been launched in China, and current Chinese literatures all discuss the topic based on Hushen 300 Index emulation trade data or foreign stock markets, no final conclusion has yet been reached on it.

As to the comparison of GARCH-class models, Engle and Ng had made related studies as early as 1993. They found that the GJR(TGARCH)model could better reflect the volatility asymmetry. To explore the effects of trading volume on volatility and improve the accuracy of model estimation, the paper improves the TGARCH model slightly and builds a state transition model of the overall market. As to parameter estimates, the paper refers to the research of Junjun Zhu et. al. (2011), and uses the steadier MCMC method. The improved model can also be applied to other fields, only if replacing the trading volume with corresponding explanatory variable. The paper's estimation of information asymmetry coefficient in TGARCH model is more accurate and reasonable, thus improving the estimation accuracy of the whole model. The study on stock index futures also uses the improved model.

Paper structure: the second section introduces different models, such as the MS-TGARCH model, and the parameter sampling methods of the models, and calculates the probability density of parameters; the third section first builds three state transition models for the overall sample of Hushen 300 Index, which all show that the trading volume has great influence on stock market volatility and Chinese stock market currently has the same volatility asymmetry responses as those of mature western markets, greatly different from previous studies; then, the section selects samples of two years before and after the launch of stock index, and uses them respectively to the improved TGARCH model for market modeling, and makes a comparison with the original TGARCH model, and finally analyzes the effects of stock index futures on Chinese stock market volatility and finds that the volatility declined significantly after the launch of stock index futures and volatility asymmetry declined significantly, but still existed; the fourth section analyzes why the stock index futures can stabilize the volatility. The final part gives the conclusion.

2 MS Model with a Time-Varying Probability and MCMC Estimation Method

This section first introduces GARCH-class models briefly.

The regression model considering random variable Y_t～explanatory variable X_t (if the explanatory variable is $Y_{t-1},\ldots Y_{t-I}$, it is an autoregressive progress ; the model is often built in financial time series):

$$Y_t = f\left(X_{1,t},\ldots,X_{p,t}\right) + \delta_t$$

If residual δ_t satisfies the following formula, the model is a standard GARCH (p, q) model:

$$\delta_t \middle| \Delta_{t-1} \sim N(0, h_t)$$

$$h_t = \eta_0 + \sum_{i=1}^{q} \alpha_i \delta_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2$$

The model used to handle financial time series can solve the fat tail and volatility clustering of data properly. Therefore, the GARCH model is widely used in financial field. The GARCH-class models derived from this model, such as M—GARCH, N—GARCH (asymmetrical nonlinear GARCH) and TGARCH, won't be introduced here.

2.1 MODEL AND HYPOTHESIS

In this part, two models are used to study market volatility to reveal more laws of trading volume's effects on volatility.

2.1.1 Assume that A share market has two volatility states from the endogenous division of model.

We can certainly assume more volatility states, but the sample period chosen in the paper is not very long which only contains one bull-bear period with volatility state changes not very frequent; besides, volatility states are nothing more than the high volatility state and the low volatility state, so it makes little sense to divide into more states. And, the estimation difficulty of model increases greatly with the increase in the number of state. To better reveal the asymmetry of stock market volatility, the paper uses the GJR model and introduces the positive impact and the negative impact to reflect volatility asymmetry. See the following formula for the concrete model:

$$y_t = \mu_{s_t} + \delta_t, \qquad \frac{\delta_t}{\sqrt{h_t}} \sim N(0,1) \tag{1}$$

$$h_t = \eta_{s_t} + \alpha_{s_t} \cdot \delta_{+,t-1}^2 + \beta_{s_t} \cdot \delta_{-,t-1}^2 + \gamma_{s_t} . h_{t-1} \tag{2}$$

where μ_{st} reflects the return rate of market, h_t is the variance of residual δ_t, η_{st} is the constant term of variance, α and β are information coefficients representing the degrees of effects of good and bad news on market respectively, γ is the persistency coefficient representing the degree of persistency of current volatility state; $\delta_{+t} = \delta_t \cdot I$ ($\delta_t > 0, I$ is an indicative function)represents the effects of good news on volatility e.g., the positive impact; $\delta_{-t} = \delta_t \cdot I(\delta_t < 0)$ represents the effects of bad news on stock market volatility, e.g. the negative impact. To ensure that the conditional variance is positive, parameters must meet the following limiting conditions: $\eta > 0, \alpha \geq 0, \beta \geq 0, \gamma \geq 0$, and $(\alpha+\beta)/2+\gamma<1$, which are necessary and sufficient conditions for the wide sense stationary of the model. In addition, the sample size studied in the paper is large and there is no substantial difference whether residual δ_t follows t- distribution or normal distribution, so the paper assumes for a moment that it follows the normal distribution.

The model has two volatility states $S_t = \{1, 2\} (t = 1, 2. \ldots . T)$,

and state transition follows the Markov chain. Let π_{ik} be the probability of switching from state i to state k, recorded as $\pi = \{\pi_{ij}\} (i, j = 1, 2)$. The transition probability should be essentially related to macroeconomic operation closely, because in different development stages, investor expectation and market sentiment are different, which may affect market volatility state. The indexes reflecting macroeconomic operation, such as GDP, are all on the level of year, so, clearly the transition models with a constant transition probability and a fixed probability are almost the same with little sense. Therefore, the paper doesn't consider in this way, but selects vol, the trading volume reflecting market sentiment, as the explanatory variable of transition probability, and considers π_{ik} as the logistic function representing the variable of trading volume z.

$$\pi_{t,11} = \frac{\exp(\theta_1 + \phi_1 z_t)}{1+\exp(\theta_1 + \phi_1 z_t)}^2, \pi_{t,22} = \frac{\exp(\theta_2 + \phi_2 z_t)}{1+\exp(\theta_2 + \phi_2 z_t)} \tag{3}$$

2.1.2 Also in a state transition model, assume that A share market has two volatility states, but the transition probability is not time varying.

In the securities market, when the trading volume enlarges, the impact strength of good and bad news on the market increase significantly; when the trading volume shrinks, the impact strength declines significantly. Based on the fact, the paper introduces trading volume into formula 2 as an explanatory variable, equivalent to weighing the original impact coefficient. The concrete model (referred to as MS-GTGAGCH model in the paper) is as follows:

$$\mathrm{y}_t = \mu_{s_t} + \delta_t, \qquad \frac{\delta_t}{\sqrt{h_t}} \sim N(0,1) \tag{4}$$

$$h_t = \eta_{s_t} + \alpha_{s_t} . z_{t-1} \cdot \delta_{+,t-1}^2 + \beta_{s_t} \cdot z_{t-1} . \delta_{-,t-1}^2 + \gamma_{s_t} \cdot h_{t-1} \tag{5}$$

Where z_{t-1} is a random variable representing the trading volume in period t-1 with the expectation of 1, and other variables and parameters have the same meanings as those mentioned above. Because transition probability π is closely related to trading volume, and trading volume is related to the time factor, π is not assumed to be time varying.

Then, how to analyze the asymmetric behaviors of conditional volatility using the GTGARCH model? The paper adopts the news impact curve proposed by Engle and Ng [11] (1993) for description. The model built here is a MS model with two volatility states, so the news curves should be defined respectively. According to the definition, the news curve equations of TGARCH model are:

$$h_t = C + \alpha\delta_{t-1}^2 \quad (\delta_{t-1} > 0) \tag{6}$$

$$h_t = C + \beta\delta_{t-1}^2 \quad (\delta_{t-1} < 0) \tag{7}$$

where $C \equiv \eta + \gamma\sigma_1^2$, and σ_1^2 is the unconditional variance of unexpected residual (δ_t). Analyzing parameters α and β in formulas (6) and (7), it's found that the model can compare the asymmetry of volatility. In the case that α is significantly greater than β, the good news has more effects on the market than the bad news; otherwise, the bad news has more effects.

Compared with the traditional GARCH model, this model has obvious advantages when describing the stock market. The traditional GARCH model makes a linear modeling to financial time series, but the stock market presents bull-bear cycles with macroeconomic development and may show completely different properties in rising period and falling period, so if we ignore these facts blindly, we may also ignore many meaningful things. For Chinese stock market, Junjun Zhu (2011) has proved many different things appearing in the rising period and the falling period. The Markov model makes state estimation endogenous and allows different states in different periods, capturing the nonlinearity better. Besides, according to the latest research results, the model can improve investment portfolio income greatly and find more laws of volatility.

2.2 GIBBS SAMPLING OF PARAMETERS IN MODELS

In the times with backward computing facilities, the maximum likelihood method was the best choice. Nowadays, computer technologies develop fast and computer processing capacity has increased greatly, in which case using the MCMC method for statistical inference has no technological difficulty. The method solves the probability model by experiment rather than computation, which is fundamentally different from the maximum likelihood method. For instance, there is an inference with a parameter of θ and the data of X to be made, and $\theta \in \Theta$. To estimate θ, distribution $P(\theta \mid X)$ should be understood. Therefore, we first make a Markov chain simulation, building a Markov process with a stationary transition distribution $P(\theta \mid X)$ on Θ. We can prove that when running for a time long enough, the Markov chain will reach a stationary state, in which case the value of chain is equivalent to the sampling from distribution $P(\theta \mid X)$ and can be estimated using the ergodic theorem. The method obtaining distribution $P(\theta \mid X)$ through a Markov chain simulation is called MCMC. The most common sampling method of MCMC is Gibbs sampling. Because of the particularity of the model in the paper, Gibbs sampling can't be used to some parameters directly, for which we sue Griddy-Gibbs sampling.

The model contains three kinds of parameters: $\Lambda = \{\mu_k, \eta_k, \alpha_k, \beta_k, \gamma_k\}$, the principal parameter; $\Delta = \{\theta_k, \varphi_k\}$(k=1,2), the function parameter of transition probability π (in the second model, the parameter is transition probability π); $S= \{S_t\}$, the implied state sequence of model.

As to the principal parameter $\{\mu_k, \eta_k, \alpha_k, \beta_k, \gamma_k\}$, the paper assumes its prior distribution is a constant without any information content, and then the posterior probability density is

$$p(\Lambda|y,S) \sim \prod_{t=1}^{T}\left[(h_t)^{-0.5} \cdot \exp\left(-\frac{(y_t - \mu_{S_t})^2}{2h_t}\right)\right] \tag{8}$$

It can be seen from the formula that the probability of principal parameter is related to state sequence S_t, and the posteriori probability density can be determined with a given state sequence $\{S_t\}$ combined with $\{h_t\}$ and the variance. But, in this formula, it's hard to separate parameters from Λ, so we can't use Gibbs sampling directly but only use Griddy-Gibbs sampling.

Take μ_1 as an example to explain the following processing simply. Choose m grid points from the definitional domain of μ_1, and arrange them from small to large as $\omega_1 \le \omega_2 \le \cdots \le \omega_m$. Work out $p(w_i|y,S,\Lambda_{-\mu_1})$ with formula (8).

Let $f_j = \frac{\sum_{i=1}^{j} p(\omega_i \mid y, S, \Lambda_{-i})}{\sum_{i=1}^{i=m} p(\omega_i \mid y, S, \Lambda_{-i})}$ be the estimation value of μ_1's inverse cumulative distribution function in ω_j.

The paper mainly uses Matlab to make sampling estimation to the model. Machine precision is limited, but data sequence is long, so the likelihood value after log processing is a four-digit minus, which is very small after reduction and exceeds the numerical computation range of Matlab. Fortunately, in grid sampling, p, the probability density kernel in the estimation numerator and denominator of inverse cumulative function distribution is homogeneous, so the paper processes probability dentistry kernels as follows:

$$\log\left(p\left(\omega_i \middle| y, S, \Lambda_{-\mu_1}\right)\right)$$
$$= \exp\left(\log p\left(\omega_i \middle| y, S, \Lambda_{-\mu_1}\right) - \max\log\left(p\left(\omega_j \middle| y, S, \Lambda_{-\mu_1}\right)\right)\right)$$

Just because the parameter sampling of MS-TGARCH model is difficult, and the problem of the model's full estimation has just been solved by scholars in recent years, the model is rarely used for stock market study. Bauwens(2007)[12] used the method for the estimation of MS-GARCH model and fitted the return rate of S&P500, showing good effects. Junjun Zhu et. al. (2011) also introduced the sampling method in details in literatures. The method has a good convergence property, so the paper won't make a simulation experiment to the sampling method.

For θ and φ, the impact factors of transition probability π in the first model, their probability densities are:

$$\begin{aligned}&\log\left(p\left(\theta,\phi|z,S\right)\right)\\ &\sim\sum_{t=2}^{T}\left[\theta_1+z_{t-1}\phi_1-\log\left(1+\exp\left(\theta_1+z_{t-1}\phi_1\right)\right)\right]\cdot I_{(S_{t-1}=1,S_t=1)}\\ &+\sum_{t=2}^{T}\left[-\log\left(1+\exp\left(\theta_1+z_{t-1}\phi_1\right)\right)\right]\cdot I_{(S_{t-1}=1,S_t=2)}\\ &+\sum_{t=2}^{T}\left[-\log\left(1+\exp\left(\theta_2+z_{t-1}\phi_2\right)\right)\right]\cdot I_{(S_{t-1}=2,S_t=1)}\\ &+\sum_{t=2}^{T}\left[\theta_2+z_{t-1}\phi_2-\log\left(1+\exp\left(\theta_2+z_{t-1}\phi_2\right)\right)\right]\cdot I_{(S_{t-1}=2,S_t=2)}\end{aligned} \tag{9}$$

In the formula, $I_{(S_{t-1}=i,S_t=j)}$ is equal to 1 in the case the state is i at the time of t-1 and the state is j at the time of t, otherwise it is equal to 0. Formula (9) shows that the probability density kernels of determined state sequences S and z can be obtained, and then the sampling can be made using the Griddy-Gibbs method similar to that for the principal parameter. Specific operational procedure is similar to that mentioned above.

For the second model, the transition probability in MS-TGARCH model is fixed, so it's easy to get:

$$p\left(\pi|S,y,\Lambda\right)\sim a\left(\pi\right)\cdot\prod_{t=1}^{T-1}\pi_{S_t,S_{t+1}}$$

where $a(\pi)$ is the prior distribution. We can assume the prior distributions of (π_{11},π_{12}) and (π_{21},π_{22}) follow independent beta (1, 1) distribution, respectively. So, π_{11} 's posteriori probability density is as follows:

$$p\left(\pi_{11}|S,y,\Lambda\right)\sim\pi_{11}^{n_{11}}\cdot\left(1-\pi_{11}\right)^{n_{12}} \tag{10}$$

where n_{1i} means the number of transition from state 1 to state i.

At last, about the probability distribution of implied state sequence S, it's easy to determine its joint distribution with y:

$$\begin{aligned}&p\left(y,S|\Lambda,\pi\right)\\ &\sim\prod_{t=1}^{T}\left[\left(h_t\right)^{-0.5}\cdot\exp\left(-\frac{\left(y_t-\mu_{S_t}\right)^2}{2h_t}\right)\cdot\pi_{S_{t-1}S_t}\right]\end{aligned} \tag{11}$$

In the model, S_t not only is related to the likelihood of current period but also affects the likelihoods of all periods after period t through the conditional variance depending on the path. Therefore, its conditional probability distribution is:

$$\begin{aligned}&p\left(s_t\,|\,S_{-t},\Lambda,\pi\right)\\ &\sim\pi_{s_{t-1},1}^{2-s_t}\pi_{s_{t-1},2}^{s_t-1}\pi_{s_t,1}^{2-s_{t+1}}\pi_{s_t,2}^{s_{t+1}-1}\cdot\\ &\prod_{i=t}^{T}\left[\left(h_t\right)^{-0.5}\cdot\exp\left(-\frac{\left(y_i-\mu_{s_j}\right)^2}{2h_t}\right)\right]\end{aligned} \tag{12}$$

Or

$$\begin{aligned}&p\left(s_t=i\,|\,S_{-t},\Lambda,\pi\right)\\ &=\frac{\pi_{s_{t-1},i}\,\pi_{i,s_{t+1}}\prod_{i=t}^{T}\left[\left(h_t\right)^{-0.5}\cdot\exp\left(-\frac{\left(y_i-\mu_{s_j}\right)^2}{2h_t}\right)\right]}{\sum_{j=1}^{2}\pi_{s_{t-1}j}\,\pi_{j,s_{t+1}}\prod_{i=t}^{T}\left[\left(h_t\right)^{-0.5}\cdot\exp\left(-\frac{\left(y_i-\mu_{s_j}\right)^2}{2h_t}\right)\right]}\end{aligned} \tag{13}$$

where S_{-t} represents the sequence obtained by removing the value of period t from state sequence S. The estimation becomes complicated due to the path dependence of probability distribution, but it is essentially the same as the sate sampling of MS model. For instance, in each sampling, we first work out p_t , the probability of $s_t=1$, though formula (9), and then get u_t by sampling the uniform distribution U(0,1); in the case $u_t>p_t$, let $s_t=2$; otherwise, let $s_t=1$.

After determining parameters' posteriori probabilities and sampling methods, the next section introduces the MCMC estimation steps of model 1 simply.

(1) To set the original values of parameters Λ^o, Δ^o and s^o, respectively;
(2) To sample $\mu_1^i,\mu_2^i,\eta_1^i,\eta_2^i,\alpha_1^i,\alpha_2^i,\beta_1^i,\beta_2^i,\gamma_1^i,\gamma_2^i,\theta_1^i,\theta_2^i,\phi_1^i,\phi_2^i$ and S_t^i respectively according to formulas (8), (9) and (13).
(3) To repeat step (2) until the number of sampling reaches the preset value.

In model 2, the sampling of parameter estimation transition probability π shall follow formula (7), but other samplings are the same as those of model 1.

3 FluctuationsEmpirical Study on Chinese Securities Market

3.1 DATA SELECTION

After proposing a reform plan of non-tradable shares, China began to implement it substantially since August, 2005. As of June, 2006, Chinese companies have entered into the reform procedure with few exceptions. Later, after unlocking the non-tradable shares, shares of shareholders could circulate in the secondary market, and Chinese markets have entered into a full circulation stage with a trading volume obviously different from that in previous stage. In addition, securities market volatility is closely linked to market development, in which case factors, such as listed companies' governing capacity, market financing level and investors' expectation, will affect market volatility, more or less. The reform has improved Chinese markets in many aspects, so we have every reason to believe that volatility state would have qualitative changes. Some researches show that [13] the share reform has stabilized volatility effectively. Therefore,to avoid the effects of the obvious difference of prior distribution on models, the paper selects data from Hushen 300 Index in the period of 01/1/2006—14/12/2012, including the daily closing price and the daily trading volume, from the source of Galaxy Securities Neptune V2.2 Client's export of real-time quotes. The paper chooses Hushen 300 Index for the following reasons.

The Hushen 300 Index covers all the data after 2005, meeting research needs. Its companies are all high-quality blue chips and its trend basically reflects the trend of Shanghai Stock Exchange, very representative. Using the data we can avoid the impact from initially public offered shares on the index.

As an emerging market, the Chinese market has been expanding fast. Due to market formation, Shanghai securities composite index's changes are not always caused by market volatility [14], but are partly affected by the initially public offer of shares. There are totally 1659 data of daily return rate. Then, to study the effects of the launch of stock index futures on market volatility, we partition the data and build a model. That is, we build a model according to the data of a period about more than 2 years (two time sections: 18/10/2007-21/4/2010, and 22/4/2010-01/11/2012) around April 21st, 2010 (the date of the launch of stock index). For each time section, there are 614 data, respectively.

Let's explain some points about why choosing the two time sections as study phases. Factors affecting market volatility are very complicated. Spot market's volatility level mainly depends on the development phase of the whole market, resulting from the joint effects of macroeconomic factor, market structure and investor behavior in a particular period. To study the effects of the launch of stock index futures, an exogenous variable, on market volatility, we must control major factors, otherwise empirical studies for different sample periods may get completely opposite results. Chinese stock index futures came to market at a proper time, and the two time sections are exactly the decline periods of market. The rise from 2009 to 2010 (although index has nearly doubled in this period of time) is a rebound at best, compared to the decline from the end of 2007 to the end of 2008. The plunge of market after the launch of stock index in 2010 made the rebound come to an end, and stock index entered into a fast decline phase. Therefore, the market in the two periods is very comparable.

3.2 DATA PREPROCESSING AND ANALYSIS

To make the observation easier, the monthly logarithm return rate is chosen:

$$r_t = \left[\ln\left(p_t\right) - \ln\left(p_{t-1}\right)\right] \cdot 30$$

As to the processing of trading volume, volt, it is divided by the mean:

$$z_t = \frac{vol}{mean(vol_t)}$$

Analyzing return rate, r (daily return rate), with the Eviews[15] software, we get FIGURE 1 which shows r's histogram and statistics such as mean and standard deviation (Std. Dev). The JB statistics test shows that the sequence clearly doesn't follow a normal distribution.

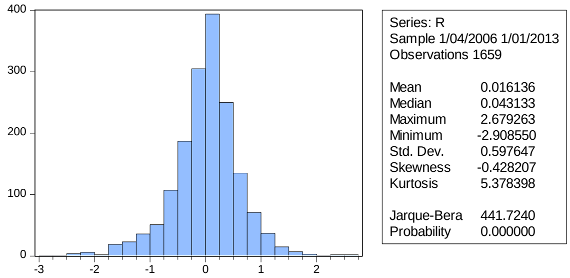

FIGURE 1 Preliminary Statistical Analysis on Daily Return Rate r

Many research show that using GRACH-class models to study Chinese securities market can get good results. The paper first builds a GARCH model.

TABLE 1 Parameter estimation of garch Model

Parameter	μ	η	α	β	γ	AIC
GARCH (1,1)	0.01395	0.00258	0.04848	0.0475	0.9446	1.6212
TGARCH (1,1,1)	0.01507	0.00257	0.04890	0.0479	0.9447	1.6224

The TGARCH model generated with software Eviews shows that α and β have little difference, possibly because the software fails to estimate r effectively with the model due to large samples. Actually, the significance tests of parameter β also fail.

3.3 ESTABLISHMENT AND ESTIMATION OF MS-GARCH MODEL

3.3.1 Estimation of Overall Model

First, determine the initial values of parameters and grid intervals [16-17].The initial values of principal parameters are chosen with the general GARCH model built above. The initial values with implied state sequence S are determined according to return rate sequence r_t. Volatility state and return rate are closely related, so we determine S_t^o in this way: if $|r_t| < mean(|r_t|)$, then S_t^o =1; otherwise, S_t^o =2.

As to the parameters of trading volume z in model 1, we first build the logistic function [18] of transition probability π with determined state sequence S_t^o, and then consider the estimate results obtained through regression as the initial values of parameters of Δ. In model 2, the initial value of transition probability π is assigned as [0.9, 0.1, 0.1, 0.9].

As to the determination of grid intervals of principal parameters, the paper first determines a large interval according to the analysis above to ensure truth values lie within the interval, and then chooses the interval containing more than 99% samples according to sampling results, and uses the new interval for estimation again. In this way, the size of interval shrinks continuously through multiple samplings, until its accuracy reaches a certain degree.

Finally, as to the determination of M, the number of grids in an interval, M should not be too small or too big. If it is too small, parameter estimation's accuracy is too low; if it is too big, running speed becomes slow and there will be more requirements on the number of sampling. Bauwens (2007) and some literatures suggested 30 grid points should be enough, and Junjun Zhu (2011) ever selected 100 grid points to improve the accuracy. In this paper, the model built doesn't have big parameters, so 50 grid points are chosen.

TABLE 2 Determination of grid intervals of principal parameters

Parameter	Grid Interval	Mean	Standard Deviation
μ1	[-0.14,0.18]	0.0125	0.0025
μ2	[-0.13,0.16]	0.0147	0.0029
η1	[0.0001,0.045]	0.0338	3.518e-04
η2	[0.0001,0.06]	0.0356	3.269e-04
α1	[0.001,0.3]	0.1462	0.0145
α2	[0.001,0.4]	0.1886	0.0279
β1	[0.01,0.4]	0.2191	0.0208
β2	[0.01,0.3]	0.2479	0.0292
γ1	[0.7,0.95]	0.6991	0.0226
γ2	[0.7,0.95]	0.6297	0.0270
θ1	[-0.3,1.7]	0.9197	0.6476
θ2	[-1.5,0.6]	-0.2789	0.6787
φ1	[-1,0.1]	-0.1853	0.1753
φ2	[-0.1,1]	0.5198	0.1826

Because the data are large, the paper decides to make 50000 samplings to parameters (Matlab runs for about 20 hours for computation), dropping the 20000 data in the front and making parameter estimation based on the rest of data. The results obtained with Matlab[19] are as follows (parameter intervals are determined after screening).

All parameters are converged well, which will not be described in details due to the limited length of the paper. After estimating the density function of effective samples using the kernel estimation method with Matlab, the paper finds that the maximum and mean of estimated probability density are close (FIGURE 2 and FIGURE 3 are the probability density estimation maps of parameter μ_1 and parameter μ_2 in MS-TGARCH model, respectively), so considering the mean as the estimate of parameter is a good processing way.

The figures show that in two volatility states, some principal parameters don't have significant difference, so in the period from 2006 to 2012 (including a complete bull-bear cycle), parameters μ_1 and μ_2 , which represent average return rate, in two volatility states had no significant difference, and it isn't like Junjun Zhu (2011) said the average return rate in high volatility state was significantly positive and the return rate in low volatility state was negative or significantly smaller than that in high volatility state. Analyses in the ensuing paragraphs are all based on the estimation results of MS-GTGARCH model. (The superiority of the model over the MS-TGARCH model shall be mentioned later in the part about time-interval model, and shall not be described here).

TABLE 3 Grid Intervals, Means and Standard Deviations of the MS-TGARCH Model and the MS-GTGARCH Model

	Grid Interval	MS-TGARCH		MS-GTGARCH	
		Mean	Standard Deviation	Mean	Standard Deviation
μ1	[-0.14,0.18]	0.0203	0.0042	0.0186	0.0038
μ2	[-0.13,0.16]	0.0178	0.0039	0.0158	0.0043
η1	[0.0001,0.09]	0.0329	0.0006	0.0335	0.0005
η2	[0.0001,0.09]	0.0316	0.0006	0.0345	0.0006
α1	[0.001,0.5]	0.1592	0.0158	0.1342	0.0174
α2	[0.001,0.7]	0.2007	0.0350	0.1983	0.0419
β1	[0.01,0.6]	0.2095	0.0218	0.2034	0.0216
β2	[0.01,0.7]	0.2284	0.0320	0.2411	0.0354
γ1	[0.3,0.95]	0.7241	0.0301	0.7307	0.0288
γ2	[0.3,0.95]	0.7300	0.0311	0.7157	0.0329
π11		0.6930	0.1255	0.7224	0.1210
π12		0.3070	0.1255	0.2776	0.1210
π21		0.3076	0.1268	0.3309	0.1288
π22		0.6924	0.1268	0.6691	0.1288

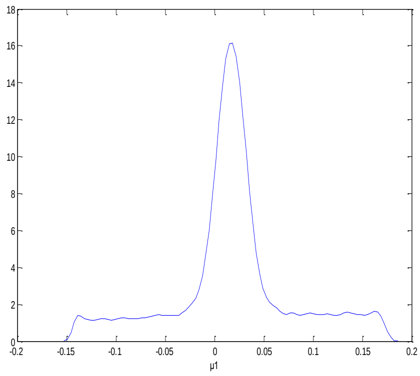

FIGURE 2 Probability Density Estimation of Parameter Parameter μ_1 in the MS-TGARCH Model

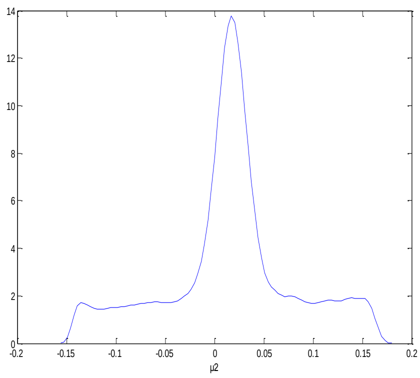

FIGURE3 Probability Density Estimation of μ_2 in the MS-TGARCH Model

3.3.2 Estimation Results of Time-interval Model

After the partition, two time sections are not very long, and the state transition model built don't have good effects, so the paper restores the state transition models stated in the second section into non-state-transition models—the TGARCH model and the GTGARCH model (a model introducing an explanatory variable z into conditional variance h), respectively, and then uses them to make modeling to two time sections. The paper still uses MCMC estimation method for parameter estimation, making 25000 samplings for both models and abandoning the 10000 data in the front, and obtains 15000 effective samples for estimation. Grid intervals are obtained through many experiments, and the estimation results are as follows (TABLE 5).

To study the superiority of improved model, the paper computes the AIC (Akaike's Information Criterion) value and BIC (Schwartz Bayesian Information Criterion) value of the two models above, and makes a comparison (the smaller the value is, the better the fitting result is). Results show that both AIC value and BIC value are bigger in the TGARCH model than those in the model introducing trading volume, so the improved model has obvious advantages.

TABLE 4 Comparison of AIC Value and BIC value in improved model before and after the launch of stock index futures

	Number of Parameter	AIC	BIC
TGARCH(Before launch)	5	0.558329	0.578791
GTGARCH（Before launch）	5	0.558236	0.578695
TGARCH（After launch）	5	0.179044	0.185606
GTGARCH(After launch)	5	0.179035	0.185597

3.3.3 Model Analysis

Model results show a series of interesting characteristics of Chinese securities market. The paper builds a time-varying MS model and a stationary state transition model for the whole period of time. The state transition model with a time varying probability reveals the laws of trading volume's effects on volatility, but doesn't find the significant difference of return rates in two volatility states described in Junjun Zhu's paper (2011). However, the estimation results above show that the volatility in the second state is higher than that in the first state. Take the MS-GTGACH model as an example, the unconditional volatilities in the first state and the second state are 0.3333 and 0.5341,respectively,ofwhich the latter is 1.6 times of the former and the positive & negative impact coefficients in the latter are both bigger than those in the former. It shows that in Chinese securities market, the level of reaction to information in the high volatility state is bigger than that in the low volatility state, and in each state, the negative impact coefficient is bigger than positive impact coefficient. Therefore, in this period, the negative impact has bigger effects on the market.

Substitute time-varying model's parameters θ_1, θ_2, φ_1 and φ_2 into formula(3), then,

$$\pi_{t,11} = \frac{\exp(0.5708 - 0.4302 z_t)}{1 + \exp(0.5708 - 0.4302 z_t)}$$

$$\pi_{t,22} = \frac{\exp(0.5845 - 0.4296 z_t)}{1 + \exp(-0.5845 - 0.4296 z_t)}$$

It can be seen that in the low volatility state, the trading volume has a negative correlation with the pause probability; while in the high volatility state, the situation is the opposite. The result is similar to the traditional understanding that the low volatility is generally accompanied with a low trading volume, and the continuous shrinkage of trading volume will prolong the state; the high volatility is generally accompanied with a high trading volume, and the continuous enlargement of trading volume helps the continuity of high volatility state.

The estimation results of two time sections show that the parameter μ is always negative before and after the launch of stock index, which indicates the average return rate in the market at that time was negative, consistent with the characteristics of bear market. The unconditional volatility rate was 0.5586 before the launch of stock index futures and declined greatly to 0.1762 after the launch, and γ representing persistency coefficient also declined greatly. The characteristic shows that the volatility is different before and after the launch of stock index futures. After the launch, volatility of the market was smaller, but the persistency also declined correspondingly, indicating the acceleration of return rate regression to the mean. The results are similar to the study of Dan Zhang [20] on the effects of India's launch of stock index futures on Indian market.

The positive impact coefficient α is always significantly smaller than the negative impact coefficient β. See the following two figures of curve graph in the two time sections to understand the characteristic visually.

The figures show that two markets both have the volatility asymmetry, and the bad news has more effects on the market than the good news. Combining the fact that the market was in a bear state in the period, it's clearly that the market was extremely sensitive to any

TABLE 5 Model parameter estimation and comparison before and after the launch of stock index futures

Before the Launch of Stock Index Futures	TGARCH			GTGARCH		
	Grid Interval	Mean	Standard Deviation	Grid Interval	Mean	Standard Deviation
μ	[-0.14,0.1]	-0.0172	7e-4	[-0.15,0.1]	-0.0311	8e-4
η	[0.01,0.1]	0.0399	1e-4	[0.02,0.13]	0.0637	4e-4
α	[0,0.16]	0.0326	5e-4	[0.001,0.12]	0.0206	2e-4
β	[0.05,0.45]	0.1947	1.9e-3	[0.04,0.6]	0.1751	2.3e-3
γ	[0.65,0.92]	0.8158	1.1e-3	[0.55,0.9]	0.7881	1.8e-3
μ	[-0.1,0.06]	-0.022	3e-4	[-0.1,0.05]	-0.0212	3e-4
η	[0.05,0.1]	0.0494	3e-4	[0.01,0.1]	0.0526	3e-4
α	[0,0.19]	0.0252	5e-4	[0.001,0.12]	0.0149	2e-4
β	[0,0.3]	0.0511	1.1e-3	[0.001,0.2]	0.0312	5e-4
γ	[0.4,0.9]	0.6866	0.0104	[0.4,0.9]	0.6785	9.3e-3

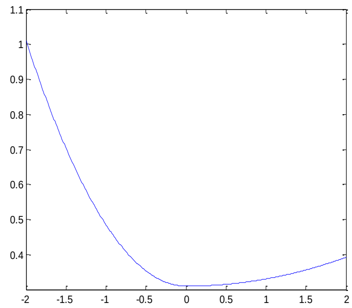

FIGURE 4 Information Curve Graph before the Launch of Stock Index Futures

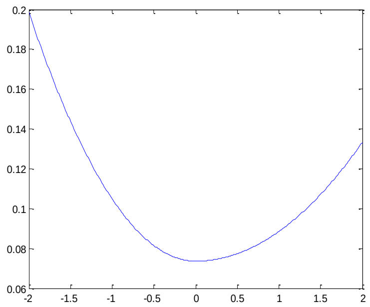

FIGURE 5 Information Curve Graph after the Launch of Stock Index Futures

sign of bad news and would be blind to the good news. It is very similar to the mature markets in the Europe and America, where the market still rises with the bad news in a bull period, but won't change its trend even with the good news in a bear period.

It should be noticed that β was more than eight times of α before the launch of stock index futures(GTGARCH), but after the launch, β was only about two times of α. From the figures, it also can be found that the curve in FIGURE 5 is more close to a quadratic function, but the curve in FIGURE 4 shows distinct sections. It means volatility asymmetry was weakening. The significant decline of negative impact coefficient also indicates the effects of bad news on the market were decreasing. The reason might be the introduction of sell-short mechanism, in which case informed traders' reaction cost for mispriced stocks decreased, futures trades improved the depth of stock market, and leverage effect decreased. Comparing the two figures, it's also found that the curve in FIGURE 4 as a whole is much steeper than the curve in FIGURE 4 (may be not very obvious in the figures due to the difference in ordinate scales). It shows after the launch of stock index futures, the market has less range of reaction to information and more rational judgment on information.

3.3.4 Difference from Existing Literatures

Reviewing existing domestic research literatures, a characteristic of Chinese securities market different from the mature market in the west can be found, which is the good news can improve market volatility more easily (Langnan Chen, 2002, Rong Lu, 2004). However, the paper draws an opposite conclusion through the empirical study for the period of 2006-2012. As to the reason, the paper believes that Chinese securities market has entered into a full-circulation age after 20 years of development and improvement, especially the reform of non-tradable shares. Now Chinese market is in keep with the mature market in the west, and has stepped into an age when fully selling short is available after the launches of stock index futures and securities margin trading, which is very different from the policy-dependent market and the information-dependent market in the past.

The state transition model built in the paper includes two states with the characteristics of low volatility and high volatility, respectively, but the paper doesn't find the phenomenon as Junjun Zhu(2011)said, the high volatility state has the characteristics of bull market and the low volatility state corresponding to bear market. It may largely because of the data selected in the paper. In addition, Zhuzhu Jun(2011)established a TGARCH model without taking the effects of trading volume on model estimation results into consideration, and selected weekly data, but the effects of information on market volatility are generally on the level of day or even a shorter period, so it is not very persuasive to study volatility with weekly data.

As to the study on the effects of stock index futures' launch on market volatility, Dan Zhang (2009) studied Indian stock market and found that information dissemination efficiency improved after the introduction of stock index futures, so the information could be reflected in the changes of stock price rapidly and could aggravate market volatility more easily after the launch of stock index futures, especially the bad news. The reason was in the past there was no selling-short mechanism, so even if there was the bad news, some investors could not bear to sell out at a loss. However, the study on Chinese securities market in the paper gets opposite results which are the special characteristics of Chinese market.

Hushen 300 Index only selects blue-chip stocks, and it has many institutional investors flocking together with more chips. It's hard for the investors to change investment orientations due to some bad news in the market (they are not very incentive to sell short because they can't make money for that). However, in the futures market, there are some people who may sell short (since they can make money by selling short, they have a strong incentive for that), so when the bad news is clear in the market, the people selling short previously may choose to close out, offsetting the selling partly. That is, many times, the futures market reacts to the stock market in advance.

4 Analysis on the Reason Why Stock Index Futures' Launch Affects Volatility

In the sample period chosen in the paper, the launch of stock index futures restrained volatility to some extent, weakened the speculative atmosphere in the market and improved information dissemination efficiency, which is similar to the research results in some domestic literatures. As quantitative investment develops rapidly in China, more and more hedge funds and private placements get access to the market of stock index futures. For the purpose of hedging, they make bidirectional operations in the stock market and the futures market, partly stabilizing the markets and reducing market volatilities. In addition, the stock index futures weaken volatility asymmetry effectively and reduce information asymmetry in the stock market, which is consistent with foreign research. There is an interesting phenomenon that the launch of stock index futures is the equivalent of the introduction of selling-short mechanism, in which case, the bad news in the market may accelerate market decline due to the existence of futures, so the bad news should have more effects on the volatility; or to say, in this case, market information dissemination has a higher efficiency, and the index may react to good news in one step, so the information should has more impacts on the market. However, the empirical study on Hushen 300 Index in this paper has opposite results. The paper believes that the futures market and the spot market have difference in information reaction due to the frictions in trading time and information dissemination, and the price in one market lags behind that in the other market. The futures market contains more information, and its traders grasp more sufficient index information (market information), so when the traders in the spot market sense the bad news and indexes falls, some bears in the futures market begin to close out and take profits, which restrains the further falling of indexes. In other words, the futures market digests some bad news in the stock market in advance, thus weakening the effects of bad news on market volatility. The futures market won't form a vicious circle with the spot market to increase spot market volatility infinitely and cause a stock market crash unless some extremely big bad news appears.

5 Conclusion

(1) In the sample period chosen by the paper, Chinese stock market has a volatility asymmetry in both the high volatility state and the low volatility state, that is, the bad news has bigger impact on the market than the good news of the same degree. In addition, the trading volume has significant and continuous influence on volatility state. In the low volatility state, the shrinkage of trading volume is good for the persistency of state, while in the high volatility state, the situation is just the opposite. The characteristics show that Chinese securities market is becoming mature, affirming the market development in recent years. They also scientifically show that trading volume has significant effects on volatility state. If the market is soaring/plummeting with a large trading volume, the success rate for investors to make buying/selling decisions is bigger; in the case that the market is in a consolidation state, if the trading volume shrinks continuously, it can be considered that the consolidation state will continues; if the trading volume increases suddenly, it's a good time for investors to take actions.

(2) After the launch of stock index futures, market volatility structure has great changes. The volatility, information coefficient and persistence coefficient all declined significantly and the volatility weakened. In addition, the futures market sometimes can react to the stock market in advance. The decline of volatility in the stock market shows that it can stabilize the market, which affirms the management's launch of stock index futures and also proves that selling short won't raise market volatility or increase the speculative atmosphere, which is the basis to expand securities margin trading scope. Therefore, the management should expand securities margin trading scope firmly, and investors should learn how to make reasonable investment decisions for the stock market by using the futures market.

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