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Application of EGARCH Model to Estimate Financial Volatility of Daily Returns:

The empirical case of China

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Abstract

The financial crisis generates a practical case to measure the variation of return volatility in high fluctuating stock markets that may exhibit different characteristics from the relatively stable stock market. Hence, the main purpose of this paper is to analyze whether the long term volatility is more extensive during the crisis period than before the crisis, and compare the movements of the return volatility of Chinese stock market to the other stock markets before and throughout the crisis period. We apply the daily data from January 2000 to April 2010 and split the time series into two parts: before the crisis and during the crisis period. The analysis is based on employing both GARCH and EGARCH models. The empirical results suggest that EGARCH model fits the sample data better than GARCH model in modeling the volatility of Chinese stock returns. The result also shows that long term volatility is more volatile during the crisis period. Bad news produces stronger effect than good news for the Chinese stock market during the crisis.

Key words: EGARCH models, Long term volatility estimation, Chinese stock markets

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1 Introduction

The investigation of modeling the temporal behavior of stock market volatility has been considered by various researchers, a large part of which focuses on the estimation of the stock return volatility and the persistence of shocks to volatility, see Choudhry (1996). Early research, for example Chou (1988) and Baillie and De Gennaro (1990) examined the volatility in US and found that the 1987 crash led support to the hypothesis that lower than average returns induce more speculative activity and therefore increased market volatility. A recent study, Alexander and Lazar (2004) estimated the volatility of stock return in key mature markets, while Drakos *et al.* (2010) measured the financial volatility of the Athens Stock Exchange from 1998 to 2008.

Although there are a number of empirical approaches and finding, research so far primarily relies on the developed markets, such as US and Europe. It is necessary to exhibit more international evidence on the volatility measurement. This paper investigates the emerging markets and China in particular and perhaps is the one of most updated studies for evaluating the volatility variation in Chinese Stock Exchange in the period of the financial crisis 2007-2010.

The main objective of the paper is to describe the behavior of risk in the Chinese stock markets and examine the predictability of the stock market returns by analyzing the long term volatility. It also explores the influence caused by the 2007-2010 financial crisis on the volatility of stock market returns in China.

I adopt Alexander's (2009) approach to compare GARCH(1,1) and EGARCH(1,1) models with alternative probability density function for the error term in order to estimate the time varying volatility of the daily stock returns for the Chinese Stock Exchange. Specifically, I carry out my analysis with alternative distributions, namely normal distribution and Student- t distribution.

The results of analysis display that higher stock market returns are associated with larger risk exposure in Chinese stock markets. The variance of stock market returns are better characterized by a non-normal distribution such as the Student-t distribution. The empirical results also suggest that EGARCH model fits the sample data better than GARCH model in modeling the volatility of Chinese stock returns. Moreover, the large volatility increasing connects to abnormal events in the stock market.

Details are organized as follow. The second Section briefly introduces the background of Chinese stock markets. The Sections 3 reviews the previous study including Chinese stock market feature and the volatility modeling. Section 4 describes the empirical specification used in this paper. The data and analysis results are presented in Section 5 and 6. The final part provides a summary of the paper.

2 Background

2.1 Chinese stock markets overview

In mainland china, there are dual classes of shares traded in both Shanghai Stock Exchange and Shenzhen Stock Exchange, called, A- and B-shares. Shanghai Stock Exchange established on December 19, 1990 while Shenzhen Stock Exchange built on July 2, 1991, see Gao and Tse (2001).

After 19 years operation, the basic statistics report of stock markets produced by China Securities Regulatory Commission (CSRC) indicated that approximately 1918 companies listed in A- and B-shares markets at December 2009. Meanwhile, the total market capitalization had reached around 243939 billion Chinese Yuan (more or less 243939 billion Swedish Krona). The market capitalization and liquidity of B-shares is relatively low contrast to A-shares, see Bohl *et al.* (2009).

Additional categories of shares are Hang Seng and H-shares which are traded in Hong Kong Stock Exchange. Hang Seng index started on 1969 is the key indicator of the

overall market performance in Hong Kong. It is one of the oldest and important indices in the Asian markets. H-shares is well known as Hang Seng China Enterprises Index. It represents the shares of companies that operate or have headquarters in mainland China whereas are listed and traded on the Hong Kong Stock Exchange. Many of these companies issue not only on H-shares but also on A- or B-shares. By doing this way, international investors can purchase mainland Chinese securities more freely from Hong Kong Exchange which is more open and rigorous in terms of listing requirements and information exposure than the mainland equity market, see Wang and Jiang (2004)

Both A-shares in Shanghai and Shenzhen Stock Exchange employ Chinese Yuan as the currency, whereas Shanghai B-shares exercises US dollar and Shenzhen B-shares allows Hong Kong dollar to trade. No doubt, Hang Seng and H shares denominate in Hong Kong dollar, see Wang (2004).

2.2 Special Regulation of Chinese stock markets

Like many developing countries, in order to sustain the domestic control of local companies, Chinese government had set up the strict restriction on the foreign investment to the domestic equity market. Even around the year of 2000, the Chinese regulation of its securities markets was still very restrictive, not only by comparison to countries that were member of the Organization for Economic Cooperation and Development (OECD) comprised by advanced market economies, but also to its Asian non-OECD neighbors, see Wang (2004). However, since China had been permitted to become the member of World Trade Organization (WTO), the government gradually released the restriction for both domestic and international investors according to the requirement of WTO, see Wang (2004).

For instance, until early 2001, B-shares market was off-limits to individual an

institutional investors with Chinese citizen. The policy was removed by a government policy in February 2001, which allowed domestic investors to buy and trade B-shares (Wang, 2004), i.e. if domestic investors had foreign currencies which were US dollars for Shanghai B-shares and Hong Kong dollars for Shenzhen B-shares, respectively, they were granted access to trade B-shares as well, see Wang and Jiang (2004).

Another notable effort was the variety of new rules access to foreign firms to invest in the domestic shares markets, which was completely reserved only for domestic investors in the past. At present, the Qualified Foreign Institutional Investors (QFII) has already received authorization to trade on A-shares (Algren *et al.*, 2010 and Bohl *et al.*, 2009).

Wang (2004) investigated the policy of Chinese stock markets and pointed out that the A-shares market was being opened to foreign investors under some limitations and many Chinese companies was going abroad to raise foreign capital. Thereby he forecasted that the future development of Chinese capital market probably was merging the A-shares and B-shares, and eliminating class distinctions among different types of stock.

3 Literature Review

3.1 Chinese Stock Market

A number of publications study the characteristic of Chinese stock market. The paper written by Kim and Shin (2000) suggested that A-and B-shares markets appeared to follow independent price dynamics. Information and capital flow did not frequently occur in A-and B-shares market. Yet, A-and B-shares started to integrate gradually after loose constraint from 2001. Ahlgren *et al.* (2010) investigated whether it had the significant premium and cointegration between A-and B-shares. Their finding hinted that the relaxation of the investment restrictions declined the segmentation in mainland Chinese stock markets. Besides, Chelly-Steeley and Qian (2005) estimated

if volatility changes took place at the same time in the A- and B- shares. Their analysis inferred that there were integration between the two A-shares markets, but not between the A-and B-shares.

This paper focuses on some different analysis related to the previous study. I modeled the dynamic movement of risk of the volatility in Chinese stock markets and tried to characterize the time series properties before and during the year 2007-2010. Most of the earlier papers did not measure the effect caused by financial crisis and most of the studies that investigated the return dynamics of stock exchange during crash time concentrated on the mature markets, such as US and Europe. What's more, I extended the analysis of Chinese stock indices by including stock indices from other countries that contributed to a better understanding of the effect of the economic globalization.

3.2 Volatility Modeling

The original work of Engle (1982) and Bollerslev (1986) introduced that generalized autoregressive conditional heteroskedastic (GARCH) models were handy if we model the time-varying volatility of the financial assets. Therefore it became the bedrock of the dynamic volatility models, see Alexander and Lazar (2006).The advantage of these models was that they were practically easy to estimate in addition to allow us to perform diagnostic tests, see Drakos *et al.* (2010). However, GARCH (1, 1) only captured some of the skewness and leptokurtosis (fat tails relative to the normal distribution) in the financial data. Alexakis and Xanthakis (1995). Bollerslev(1987), Baillie and Bollerslev (1989), Nelson *et al.*(1996) also found that if the observed conditional densities was non-normal, it was higher than that could be forecasted by normal GARCH(1,1). Therefore, more researchers explored alternative distributional functions for the error term in order to supply a better explanation of data. Consequently, numerous non-normal conditional densities had been introduced in the GARCH framework. In particular, Bollerslev (1987) presented the Student

t-GARCH that had also been captured by GARCH models (Alexander and Lazar, 2006). These developments in GARCH models were obviously crucial for modeling volatility variation. If the conditional variance did not follow the normal distribution, the normal GARCH model could not explain the entire leptokurtosis in the sample data and it was better to apply the non-normal distributions, such as Student t, normal-lognormal distribution or the exponential GARCH model to capture higher conditional moments, see Alexander and Lazar (2006).

On the other hand, many authors (Christie, 1982; and Nelson, 1991) had pointed out the evidence of asymmetric responses, suggesting the *leverage effect*¹ and differential financial risk depending on the direction of price change movements. In response to the weakness of symmetric assumption, Nelson (1991) brought out exponential GARCH (EGARCH) models with a conditional variance formulation that successfully captured asymmetric response in the conditional variance. EGARCH models had been demonstrated to be superior compare to other competing asymmetric conditional variance in many studies, see Alexander (2009).

4 Methodology Framework

With the aim of have further understanding EGARCH model, I started to introduce GARCH (1, 1) model and then extended it into EGARCH (1, 1) model. I specified an empirical model which captured the asymmetric effect of the variation in stock market returns and explored the conditional moments. In particular, I built a baseline EGARCH (1, 1) model which expressed daily stock market returns as a function to explain the variation of the conditional mean. Then, I combined the baseline model with two types of error distributions in the conditional variance process to check the predictability of stock market returns in China.

¹ *Leverage effect*-the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude. (Brooks, 2008)

4.1 Symmetric GARCH model

The standard GARCH model allows the conditional variance to be dependent upon previous own lags. The basic structure of the symmetric normal GARCH model is GARCH (1, 1) given by Chris Brooks (2008)

$$y_t = \mu + \varepsilon_t \quad (1)$$

$$\varepsilon_t = v_t \sigma_t \quad v_t \sim N(0,1) \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3)$$

where σ_t^2 denotes the conditional variance since it is a one-period ahead estimate for the variance calculated on any past information thought relevant.

As the above shown, it is apparently to perceive that there are some limitation in GARCH (1, 1) model. The non-negativity conditions may be violated by the estimated method, since the coefficients of model probably are negative. GARCH model also cannot account for leverage effects, along with GARCH model does not allow for any direct feedback between the conditional variance and the conditional mean.

For those reasons I pursued practical asymmetric GARCH model called EGARCH model created by Nelson (1991) to measure the volatility of stock return in this case. The GARCH (1, 1) model used by Su and Fleisher (1999) inspired me to construct the appropriate EGARCH model instead of the symmetric normal GARCH (1, 1) model.

4.2 Extensions to the EGARCH model

Let $r_{j,t}$ represents the return on a market index at time t, where subscript $j \in \{\text{Shanghai A-shares, Shanghai B-shares, Shenzhen A-shares, Shenzhen B-shares, Hang Seng, H- shares}\}$:

$$r_{j,t} = \delta_j' I_{j,t-1} + \xi_{j,t} \quad (4)$$

$$\xi_{j,t} = \sigma_{j,t} z_{j,t} \quad (5)$$

$$z_{j,t} | \Omega_{t-1} \sim \psi(0,1,\nu) \quad (6)$$

$$\ln \sigma_{j,t}^2 = \omega_j + \beta_j \ln(\sigma_{j,t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (7)$$

where $\sigma_{j,t}^2$ is known as the conditional variance since it is a one period ahead estimate for the variance calculate on any past information thought relevant. $z_{j,t}$ is the standardized residual. $\psi(\cdot)$ marks a conditional density function and ν denotes a vector of parameters needed to specify the probability distribution. Because equation (4) defines a variance, $\omega, \alpha, \beta, \gamma$ are parameters to be estimated. Since the $\ln \sigma_t^2$ is modeled, then the significant advantage of EGARCH models is that even if the parameters are negative, σ_t^2 will be positive.

The α parameter represents a magnitude effect or the symmetric effect of the model, the ‘‘GARCH’’ effect. β measures the persistence in conditional volatility irrespective of anything happening in the market. When β is relatively large, then volatility takes a long time to die out following a crisis in the market, see Alexander (2009).

The γ parameter measures the asymmetry or the leverage effect, the parameter of importance so that the EGARCH model allows for testing of asymmetries.

If $\gamma = 0$, then the model is symmetric. When $\gamma < 0$, then positive shocks (good news) generate less volatility than negative shocks (bad news). When $\gamma > 0$, it

implies that positive innovations are more destabilizing than negative innovations.

Our EGARCH (1, 1) model got a distinctive feature, i.e., conditional variance was modeled to capture the leverage effect of volatility.

4.3 Specification of Conditional Variance

The strict form of the error distribution plays an important role in estimating the EGARCH (1, 1) formulation. I conducted two different functional forms of the conditional density $\psi(\cdot)$, the Gaussian normal distribution and the standardized Student t-distribution.

4.3.1 Normal Distribution

Under a Gaussian standard normality assumption, equation (3) becomes:

$$z_{j,t} | \Omega_{t-1} \sim N(0,1) \quad (8)$$

The Gaussian EGARCH model consider volatility clustering, but it is not sufficient to account for all the leptokurtosis that appears in the Chinese data. The number of very high and very low returns observed suggests that a fatter-tailed distribution might better characterize the error process for Chinese stock market returns.

4.3.2 Student t-distribution

The student t-EGARCH model assumes the conditional distribution of market shocks is t distributed. The conditional density function for $z_{j,t}$, under the Student t-distribution with mean 0, variance 1 and degrees of freedom ν , can be written as:

$$\rho(z_{j,t} | \Omega_{t-1}) = \Gamma\left(\frac{\nu+1}{2}\right) \Gamma\left(\frac{\nu}{2}\right)^{-1} ((\nu-2)\pi)^{-1/2} \times \left(1 + z_{j,t}^2 (\nu-2)^{-1}\right)^{-(\nu+1)/2}, \quad \nu > 2 \quad (9)$$

As we known, the parameter ν can be explained as the degree of leptokurtosis. The interpretation by Su and Fleisher (1999) is that large values of ν are associated with the absence of leptokurtosis whereas small values are associated with some degree of

leptokurtosis. If $\frac{1}{\nu}$ approaches 0, the Student t-distribution approaches to a standard normal distribution, but when $\frac{1}{\nu} > 0$, the t-distribution has fatter tails than the corresponding normal distribution.

The normal EGARCH models (8) do not tend to fit financial returns in which the market shocks have a non-normal conditional distribution. As above revealed, if measured at the daily or higher frequency, market returns typically have skewed and leptokurtic conditional (and unconditional) distributions, see Wang and Fawson, (2001). The student-t EGARCH model, introduced by Bollerslev (1987), assumes the conditional distribution of market shocks is t distributed. The degrees of freedom in this distribution become an additional parameter that is estimated along with the parameters in the conditional variance equation. The Student-t EGARCH model has also been extended to skewed Student-t distributions by Lambert and Laurent (2001).

4.3 Long Term Volatility

According to Alexander (2009), without the market shocks the EGARCH variance will ultimately settle down to a steady state value. This is the value $\bar{\sigma}^2$ such that $\sigma_t^2 = \bar{\sigma}^2$ for all t. We call $\bar{\sigma}^2$ the unconditional variance of the EGARCH model. The unconditional variance is the variance of the unconditional returns distribution, which is assumed constant over the entire data period. It corresponds to a long term average value of the conditional variance. The theoretical value of the EGARCH long term or unconditional variance is not the same as the unconditional variance in a moving average volatility model. The theoretical value of the unconditional variance in an EGARCH model differs depending on the GARCH model. The long term or unconditional variance is formatted by substituting $\sigma_t^2 = \sigma_{t-1}^2 = \bar{\sigma}^2$ into the EGARCH conditional variance equation. For example, for the EGARCH we use the fact that $E(\varepsilon_{t-1}^2) = \sigma_{t-1}^2$ and then put $\sigma_t^2 = \sigma_{t-1}^2 = \bar{\sigma}^2$ into (8) to obtain

$$\bar{\sigma}^{-2} = \exp\left(\frac{\omega}{1-\beta}\right) \quad (10)$$

The unconditional volatility (also called long term volatility) of the EGARCH (1, 1) model is the annualized square root of (10). If unconditional volatility is relatively large then long term volatility in the market is relatively high.

First, I measured the GARCH (1, 1) model and EGARCH (1, 1) under two alternative formulations of the error-generation process. Then, I computed two tests, the likelihood ratio test statistic and log likelihood comparison to choose the best-fitted model. Finally, I utilized the parameter estimation under the best-fitted model. Consecutively, I applied the best-fitted model to calculate the impact of long term volatility.

5 Data and Preliminary Results

5.1 Data Characteristic

The analysis in this paper was based on the Hang Seng, H-shares, A- and B-shares data from 31 December 1999 until 8 April 2010. I initially estimated stock market volatility and returns to investors using data of daily Chinese stock market indices. These series were taken from DataStream and each consist of $T=2215$ observations in the last decade. In order to have a benchmark for the results, the study related trading in these shares to daily market indices representing more mature stock markets, including indices of the Tokyo Stock Exchange (Nikkei 225), the New York Stock Exchange (NYSE) and S&P Stock Exchange (SP 500 index).

The sample data was split into the periods before and during the period of financial crisis of 2007-2010. The first subsample covered all trading days between 2000 and 2006. The day trading (4 January 2007) during the financial crisis was the start of the financial crisis subsample.

Let $P_t = \log(P_t) - \log(P_{t-1})$ stood for the daily return of the index P_t . Table 1 presents some sample distributional statistics for the stock market indices included in this paper. Statistics consist of the daily sample mean returns, standard deviation, minimum returns and maximum returns. I characterize the stock market return and volatility pattern as follows: (1) Mean returns for A- and B- shares on Shanghai and Shenzhen securities exchanges as well as H-shares are positive and apparently higher than the Hang Seng, Nikkei 225, NYSE and SP500 indices, but the standard deviations of these returns (or the volatility of returns) are also higher. This output is meaningful, because China got rapid growth in the past ten years and it boosted the Chinese stock exchange flourishing compared to the other countries. (2) Mean returns on A-shares are lower than those on B-shares for both exchanges, nevertheless the volatility of returns are also smaller. (3) Hang Seng index generates different mean

return along with standard deviation from the other five Chinese indices. It has negative mean return which is more close to other countries' results. The reason probably is that Hong Kong financial market is more mature and open so that it is more easily to be pressured by the global financial environment.

	Hang Seng	H-shares	Shanghai A-shares	Shanghai B-shares	Shenzhen A-shares	Shenzhen B-shares	Nikkei 225	NYSE.	SP500.
Daily mean return	-0.02%	0.03%	0.03%	0.08%	0.04%	0.08%	-0.04%	-0.01%	-0.03%
Std. deviation	1.70%	2.25%	1.74%	2.33%	1.86%	2.18%	1.65%	1.35%	1.37%
Minimum	-13.58%	-15.09%	-9.26%	-10.29%	-8.93%	-9.58%	-12.11%	-10.23%	-9.47%
Maximum	13.41%	15.61%	9.40%	9.45%	9.24%	9.40%	13.23%	9.83%	10.25%

Table 1 Distributional Characteristic of Chinese Stock Markets and Other World Market Index returns

Summing up that higher average returns are connected with larger risk exposure in Chinese stock markets, which coincides with traditional asset pricing theory and previous findings for Su and Fleisher (1998).

5.2 Tests of the normality of sample data

I practiced two methods to test the normality of sample data. In the beginning I could get quantiles of normal distribution plot by STATA. Figure 1 presents a normal distribution plot. If the sample is perfectly normally distributed the points should all fall on the 45 degree line. The more the points diverge from this line, the less data will be approximate to a normal distribution. Apparently, all six Chinese indices do not follow normal distribution in the long run. There are more points fall on the 45 degree lines in Hong Kong and H-shares, implying that they are perhaps more close to normal distributions whereas error term in B-shares shows low probability to be normal distribution.

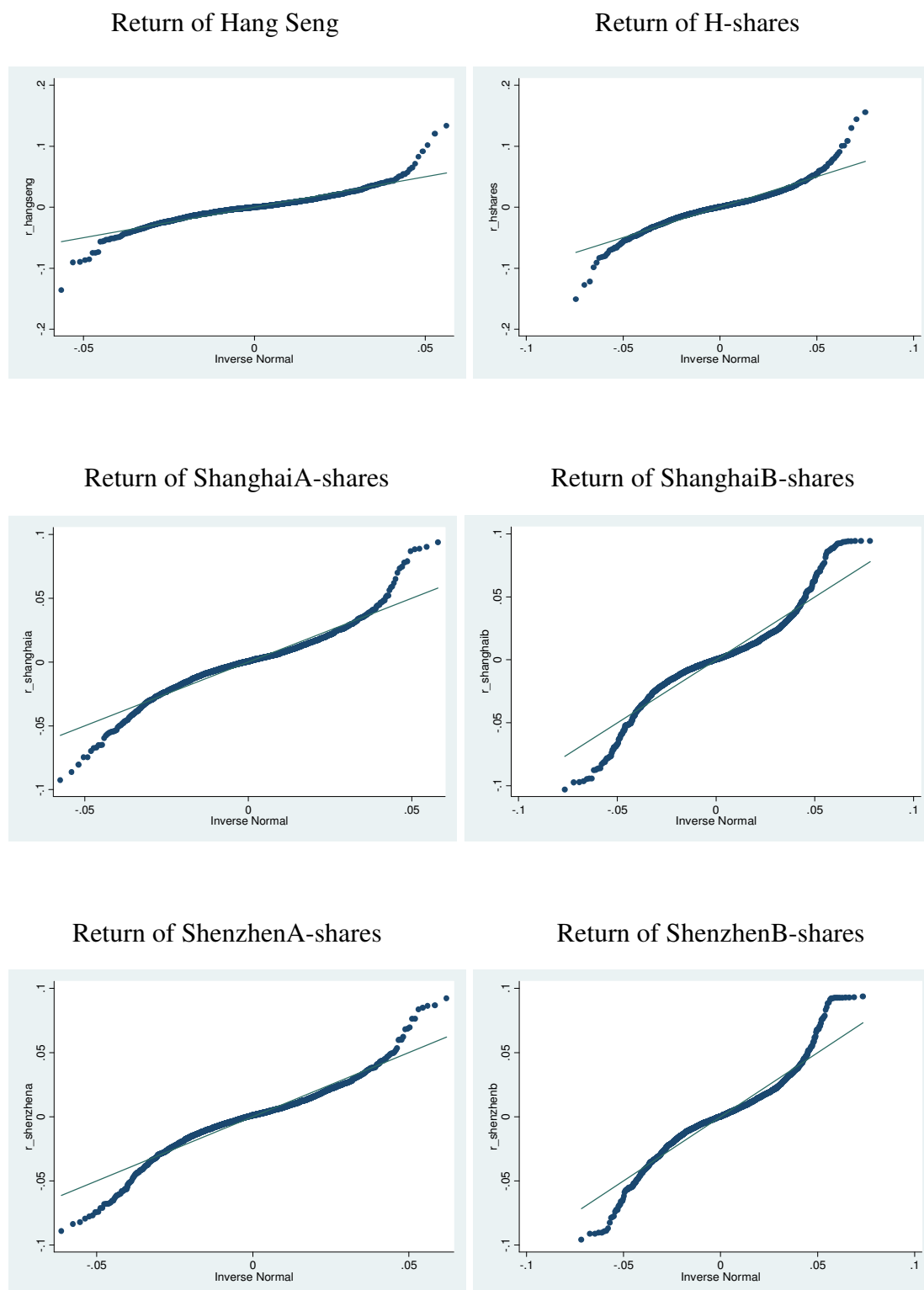


Figure 1 The quantiles of normal distribution plot

Next the skewness and kurtosis tests were utilized and the coefficients of skewness and kurtosis were jointly estimated with the mean and variance. The null and

alternative hypothesis was that:

H_0 = The sample data are normally distributed

$H_1 = H_0$ is not true

The result is presented Table 2. We reject the null hypothesis that the sample is normally distributed at 5% significant level. The skewness parameters are highly significant, indicating that the stock market returns were not symmetrically distributed. Coefficients of kurtosis are all significant in Chinese equity markets, referring that stock market return volatility exist in all exchanges.

	Hang Seng	H-shares	Shanghai A-shares	Shanghai B-shares	Shenzhen A-shares	Shenzhen B-shares
Skewness	0.6428**	0.3373**	0.3897**	0.9401**	0**	0.0802**
Kurtosis	0**	0**	0**	0**	0**	0**

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

Table 2 The skewness and kurtosis estimates

Then I inspected the returns series to examine how they evolved during the same period. In Figure 2, the plot exposes that at most of the time there are large swings in returns. B- Shares achieves more volatility than A-shares. Hang Seng and H shares look more stable than A- and B- shares from 2000 to 2010. The period from the middle of 2007 until 2010 presents strongly fluctuation compared with the other years, particularly for Hang Seng and H-shares. It may show that the volatility of stock return fluctuated more intensely during financial crisis than before crisis. This figure also performs the coincidence with the finding by Chelly-Steeley and Qian (2005). They investigated whether volatility changed occur at the same time in A- and B-shares. They found evidence of integration between two A-shares and B-shares, but not between A-and B-shares.

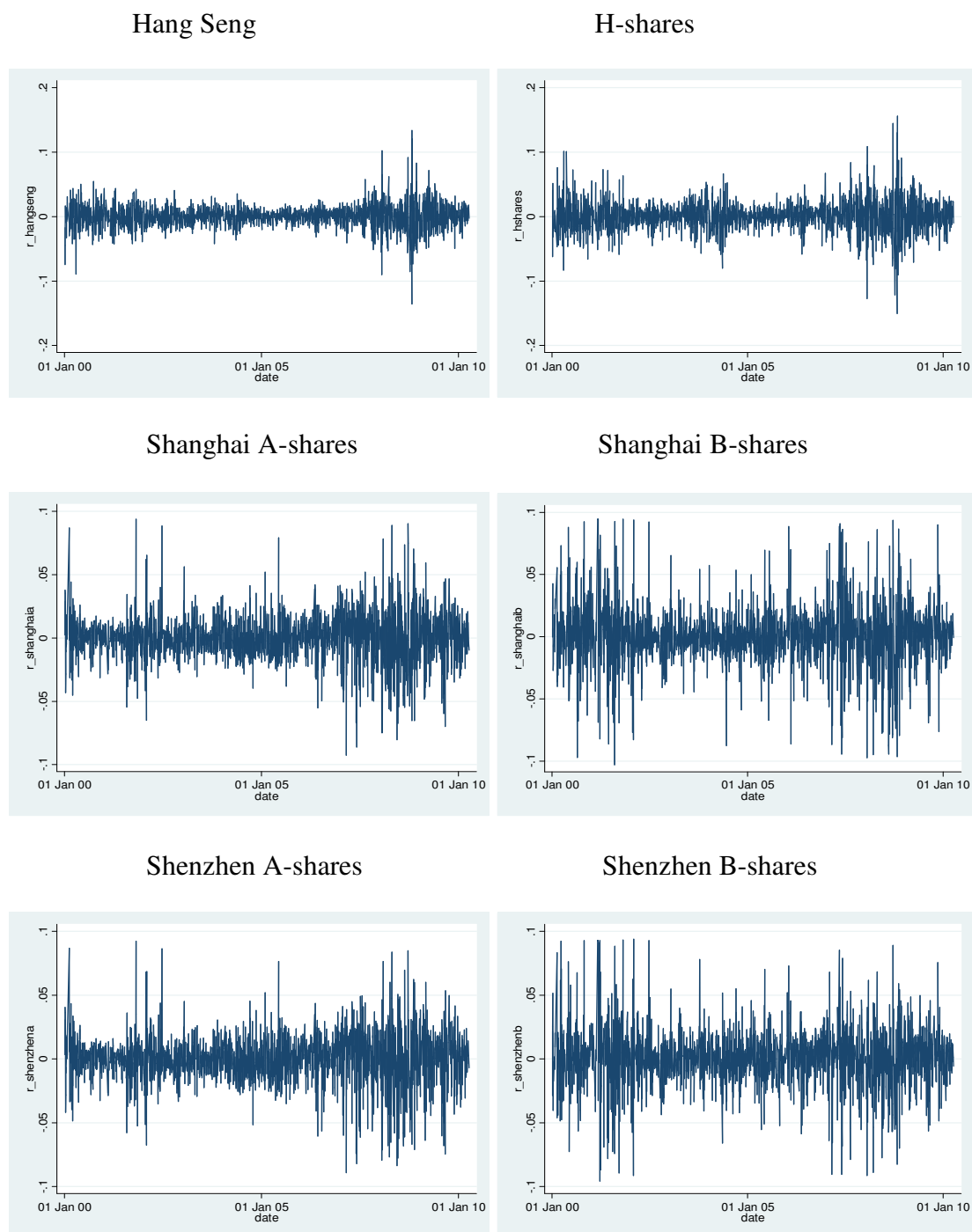


Figure 2 Stock Returns volatility on the Chinese Market

Figure 3 illustrates the development of six Chinese stock indices and Nikkei 225, NYSE and SP 500 as benchmark. We could see from the graph that there were larger fluctuations in the all indices during 2007 until now compared with the period between 2000 and 2006. From 2000 until 2006, the indices followed each other quite

well, except for B-shares which displayed obviously higher volatility. From the middle of 2007 until the beginning of 2006, Hang Seng, H-shares and other developed markets indices stayed on the same level, while the A-and B-shares indices reached their peak. After that, the Chinese indices really screwed up and declined towards the bottom, which almost back to the starting value around 100 in the graph. After that they started to go up again, hence there were big fluctuations among six Chinese indices in the end. It was may led by the economic stimulus from Chinese government after the worst time of financial crisis. The stock market reflected the Chinese financial market gradually recover again, however it was hard to say the stock prices will reach the maximum point before the finance crisis.

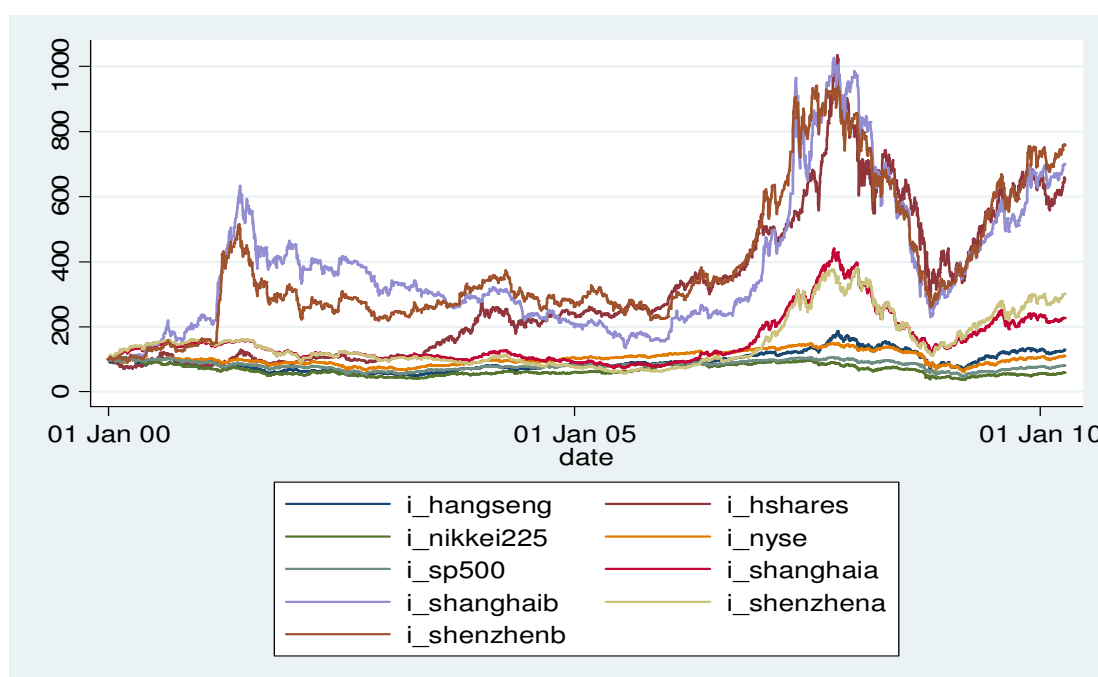


Figure 3 The movements of Chinese and other countries' stock indices

Table 3 reports the pair wise correlation coefficient estimations of stock returns for period from December 31, 1999 to April 8, 2010. Considering the time difference and leading effect of the global financial market, I applied the SP 500 index to analyze its correlation with Chinese indices. It is clear to see from the table that the coefficients of A-and B- shares in mainland China are insignificant related to SP500, which means they have much lower correlations with SP500 compared to Hang Seng and H-shares.

But there is strong evidence of highly positive correlation between Shanghai and Shenzhen A-and B-shares. This indicates that the stock markets in mainland China are still a relatively separated market with other markets in the world during this period. Hang Seng and H-shares get positive correlation with SP 500 index, although the correlation between Hang Seng and SP 500 is higher than the correlation between H-shares and SP 500. In view of the acceleration of openness for China's capital markets in recent years and financial crisis probably brought out specific effects, we also presented the estimation results for the correlation coefficient from Jan.1, 2007 to Apr. 8, 2010.

	ShanghaiA	ShanghaiB	ShenzhenA	ShenzhenB	HangSeng	H-shares	SP500
ShanghaiA	1.0000						
ShanghaiB	0.7323**	1.0000					
ShenzhenA	0.9431**	0.7463**	1.0000				
ShenzhenB	0.7237**	0.8527**	0.7256**	1.0000			
HangSeng	0.3313**	0.2839**	0.2835**	0.3213**	1.0000		
H-shares	0.3757**	0.3115**	0.3196**	0.3367**	0.7864**	1.0000	
SP500	0.0186	0.0109	0.0075	0.0226	0.1845**	0.1455**	1.0000

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level.

Table 3 Correlations between Different Markets for period 2000-2010

Table 4 displays the correlations between different markets for period 2007-2010. It is interesting to see from the table that all coefficients between Chinese stock markets are significant whereas only stock indices from Hong Kong have correlation with SP500. It have a remarkable growing for the correlation between Hang Seng, H-shares and SP 500 indices, inferring that the correlation of the global financial infrastructure is steadily increasing. The correlation between Hang Seng and two mainland stock markets is almost doubled, which means that Hong Kong stock market become more integrated with the two mainland stock markets in recent years, and we believe the trend should continue in the future, considering the closer and closer economic relations between these market.

	ShanghaiA	ShanghaiB	ShenzhenA	ShenzhenB	HangSeng	H-shares	SP500
ShanghaiA	1.0000						
ShanghaiB	0.8131**	1.0000					
ShenzhenA	0.9266**	0.8353**	1.0000				
shenzhenB	0.8263**	0.8942**	0.8279**	1.0000			
HangSeng	0.4823**	0.4192**	0.4050**	0.4931**	1.0000		
H-shares	0.5299**	0.4591**	0.4391**	0.5347**	0.9584**	1.0000	
SP500	0.0523	0.0451	0.0348	0.0535	0.2643**	0.2440**	1.0000

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level.

Table 4 Correlations between Different Markets for period 2007-2010

6 Empirical Results

6.1 Model Comparison

I conducted comparative tests of the models against conventional models presented in this section. The criteria used to determine the performance include the log likelihood value comparison and likelihood ratio test according to Alexander (2009).

Since the prevailing concern about traditional GARCH models of stock index returns was their unsatisfactory accommodation of the leverage effect, volatility persistence, fat tails and skewness, I proposed an EGARCH model to accommodate these characteristics. The skewness and kurtosis test in the last section in the standardized residuals indicated the inappropriateness of the assumption of conditional normality in the error distribution.

This model structure was tested against GARCH models using Gaussian and student-t distribution assumptions. In all, four models were estimated: Gaussian GARCH and Gaussian EGARCH, student-t GARCH and student-t EGARCH.

I chose among the alternative error-distribution formulations for the best fit by first comparing the log likelihood Value and likelihood ratio statistics would be applied for

six Chinese stock indices.

Table 5 reports the log-likelihood (LLH) values for each model estimated. Models based on the Student-t distribution generally produce the largest LLH value, whereas the LLH value for models that assume the Gaussian distribution are consistently much worse than those associated with either student-t distributions. This informs that the common convention of adopting a Gaussian assumption is significantly worse than the alternative leptokurtic alternatives, and the more leptokurtic Student-t assumption is generally better than the competing Gaussian distribution. A log likelihood ranking of alternative estimated models suggest the following ranking from most descriptive to least: Student-t EGARCH, Student-t GARCH, Gaussian EGARCH, Gaussian GARCH. Of the models evaluated, the EGARCH model with student-t distributions is the best fit, i.e., Student-t EGARCH is the most likely to be consistent with the data generating process for Chinese stock index returns.

Model	GARCH		EGARCH	
Distribution	Gaussian	Student-t	Gaussian	Student-t
Hang Seng	6087.267	6199.823	6087.224	6203.406
H-shares	5426.916	5526.919	5432.825	5534.057
ShanghaiA.	5925.641	6084.943	5924.272	6086.568
ShanghaiB.	5311.51	5537.541	5317.026	5541.209
ShenzhenA.	5792.708	5936.286	5795.926	5939.4
ShenzhenB.	5430.584	5611.558	5429.623	5612.428

Table 5 The Log-Likelihood Value for each Estimated Model from 2000 to 2010

The second phase of residual diagnosis was to determine whether the results under the assumption of the t-distributions were statistically different from those obtained under the normal distribution. To do this, I calculated likelihood ratio statistics. The definition of likelihood ratio (LR) test is given by Brooks (2008):

$$LR = -2(L_r - L_u) \sim \chi^2(1)$$

L_u denotes the a given maximized log likelihood value of the Gaussian model while

L_r comes from the student-t model. Basically LR test statistic follows a Chi-square distribution.

Likelihood ratio test between EGARCH models and their conventional Gaussian counterparts is reported in Table 6. It demonstrates that an EGARCH model specification is more fit in the sample data than GARCH model under student-t distribution except Shenzhen B-shares index. But the Shenzhen B-shares case is not necessarily disturbing to the other Chinese stock indices.

Distribution Statistics	Student-t LR^{EGARCH}
HangSeng	7.166***
H-shares	14.276***
ShanghaiA	3.25*
ShanghaiB	7.336***
ShenzhenA	6.228**
ShenzhenB	1.740

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

Table 6 The Likelihood ratio test of EGARCH verse GARCH models under student-t distribution assumption

Therefore, both our tests indicate that the GARCH model with conditional normal errors does not fully capture the leptokurtosis and the serial correlation of the standardized residuals. The EGARCH model with Student-t distributions is the best fit in this case.

6.2 Analysis by Student-t EGARCH model

I moved to estimate the volatility variation in Chinese stock exchange along with evaluating the effects of financial crisis of 2007-2010 based on student-t EGARCH (1, 1) model. As we discussed in the above section, the time-series was divided into two periods, i.e., Dec.31, 1999 to Dec. 29, 2006 and Jan.1, 2007 to Apr.8, 2010 signifying before the financial crisis period and during the financial crisis period, respectively.

The parameter estimation for the EGARCH (1, 1) model is presented in Table 7. According to the results we can find that the leverage effects γ are almost negative that significant at 5% significant level which means that good news generates less volatility than bad news for Chinese stock market despite of financial crisis². It is interesting to observe that the coefficient of Shenzhen B-shares before financial crisis is positive as the exception. The possible reason is that because B-shares market is quite young financial market, it have special characteristic and does not follow any track of movement. Nevertheless, by developing several years later, the leverage effect of Shenzhen B-shares exhibits the similar output as the other Chinese stock markets. Furthermore, during the financial crisis γ is larger than it compares with the period before the crisis and also there are more γ are significant during the crisis period. Thus we might be able to say that investors of Chinese stock market preferred to hear good news than bad news when they suffer the bad time. Basically in the crisis, shareholders feel scarier for bad news, because bad investment will go bankrupt. It is reliable to declare that stock market is more sensitive for bad news.

To all indices during financial crisis, the symmetric effect α which is a little bit different than it in the previous period in EGARCH model, however it is relatively large than 0.1 too, so it means that the volatility is sensitive to market events in the whole period. On the other hand, during the crisis α is the largest, implying that volatility was very sensitive in the bad time.

The parameter β measures the persistence in conditional volatility irrespective of anything happening in the market. Besides the parameter of A-shares before the crisis, β are all positive and relatively large, e.g. above 0.9, then volatility takes long time to

² See page 8.

die out following a crisis in the Chinese stock market.

Also, according to the relative scale of the coefficients, the leverage effect or the symmetric effects dominated. In order to find the long term volatility, we first have to find the long term variance in the EGARCH model.

6. Empirical Results

	Hang Seng	H-shares	ShanghaiA	ShanghaiB	ShenzhenA	ShenzhenB
2000-2010						
ω	1.764**	1.280**	2.003**	0.268	1.495	0.506
β	1.221**	1.175**	1.249**	1.033**	1.189**	1.067**
α	0.356**	0.385**	0.315**	0.486**	0.371**	0.436**
γ	-0.080**	-0.083**	-0.057**	-0.085**	-0.044	-0.028
2000-2006						
ω	3.886**	1.120	-14.212**	0.985	-14.266**	1.105
β	1.449**	1.143**	-0.689**	1.126**	-0.716**	1.143**
α	0.159**	0.317**	0.073	0.394**	0.088	0.453**
γ	-0.059**	-0.090**	-0.031	-0.058	-0.041	0.002
2007-2010						
ω	1.335	1.695	1.549	-0.23710	0.816	-1.739
β	1.188**	1.250**	1.211**	0.968**	1.116**	0.773**
α	0.396**	0.355**	0.154	0.565**	0.231**	0.282**
γ	-0.107**	-0.084**	-0.091	-0.135**	-0.094	-0.176**

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

Table 7 Parameters Estimates of Chinese Stock Return

6.3 Long Term Volatility Calculation

It makes sense to try several scenarios for long term volatility. In this section, I estimated the period before the financial crisis of 2000-2006 and during the financial crisis of 2007-2010, separately and then compared the results with the whole period result.

Table 8 shows the long term volatility calculating result based on student-t EGARCH (1,1) models. Clearly the estimation of long term volatility during the financial crisis are larger than those before the crisis in all Chinese stock returns on yearly based. This prove the above comments that is investors are more sensitive to the bad financial information, i.e. bad news produces stronger effect than good news for Chinese stock market during the financial crisis period. Although I measure the long term volatility in the whole period, the outputs are different compared to those in crisis period. We can declare that financial collapse throughout the world hit the investors' confidence to the flourishing market. Even in China, it still takes quite long time for financial market to recover.

Year	Hang Seng	H-shares	ShanghaiA	ShanghaiB	ShenzhenA	ShenzhenB
2000-2010	29.22%	40.80%	28.33%	27.26%	30.29%	36.23%
2000-2006	20.87%	31.49%	23.54%	31.73%	24.76%	33.19%
2007-2010	45.39%	53.30%	40.26%	40.39%	46.93%	34.31%

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

Table 8 Long term volatility of Chinese Stock Return

7 Summary and Conclusion

This article has considered the modeling of the stock returns volatility in the Chinese Stock Exchange during the last decade. Particularly, there are dual stock markets in mainland china while Hong Kong stock market is more mature and should be included. Therefore, six Chinese stock indices returns have been estimated respectively and some correlations with their volatility have been found. The financial

crisis attracts us to evaluate its effect to Chinese stock market so that we can use daily data for the periods before and during financial crisis.

Stock index return data for Chinese stock market have been examined to compare the performance of GARCH and EGARCH models under two distributional assumptions: Gaussian, student-t distributions. There are enough evidences to reject the assumptions of conditional normality in a broad cross-section of Chinese stock index data series: this reflected in the form of skewness and kurtosis. Although traditional GARCH modeling with a leptokurtic distribution have been found which is useful to account for the conditional heteroscedasticity and leptokurtosis, it cannot easily accommodate other commonly observed stylized characteristics in our sample data, such as skewness.

In addition, the evidences of leverage effect and volatility persistence are well documented in the literature for Chinese stock market estimations. The results indicate that it is important to specify the EGARCH model which is sufficiently flexible to accommodate these data characteristics because estimation procedures that fail to explicitly account for data characteristics are likely to lead to spurious results. As expected before, I have found that the most empirical evidence favors EGARCH models which allow for the increased flexibility provided by the student-t specification. Empirical evidences suggest that the EGARCH model provides a better description and more parsimonious representation than the traditional GARCH model.

Since the EGARCH model with student-t distribution outperform better than normal GARCH model, I apply it to estimate the parameters together with three time periods, i.e, the whole period, before the financial crisis and during the crisis. The finding is that Chinese stock market is dramatically beat by the financial crisis and it takes a long time for investors to recover their confidence to market. On the other hand, the result also shows that the stimulus policies by Chinese government lead the price of

stock increase again. It is a good sign for Chinese financial market to boom in the future.

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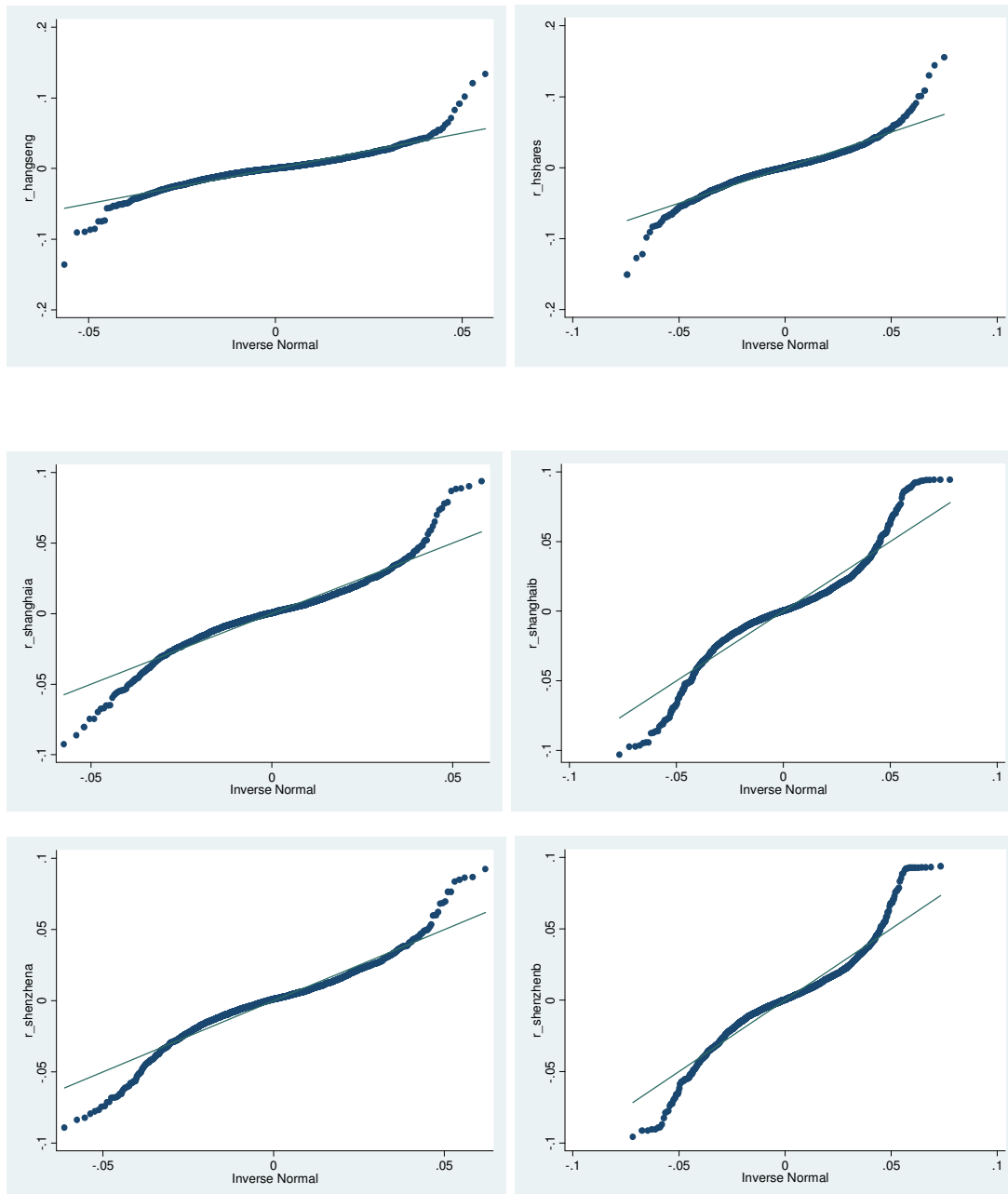
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Appendices

Appendice I Figure 4 The quantiles of normal distribution plot



Appendice II Figure 5 Stock Returns on the Chinese Market

