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Modelling and forecasting volatility for the Chinese equity market

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ABSTRACT: The analysis of the stock market volatility has generated broad interest of many scholars and financial industry participants. This research conducts a series of GARCH models to examine the volatility of the Chinese equity market over January 2005 to June 2015. There has been empirical evidence of volatility clustering leptokurtic distribution, skewness and asymmetric volatility response. Through the comparison of the parameters estimation, diagnosis tests and out-of-sample forecasting, the results also suggest that the EGARCH (1, 1) fit the data better of both stock markets than the other models by several different methods applied to measure the forecast accuracy. It is worth emphasizing that Shanghai stock market reflects the stronger leverage effects than Shenzhen stock market. In view of the acceleration in the Chinese stock market reform process, the relevant departments could employ this model to supervise the development of Chinese equity market.

Keywords: stock volatility; GARCH models; Chinese equity market

1 CHINESE EQUITY MARKET OVERVIEW

At the end of the twentieth century, the price limited settlement system began to be carried out in Shanghai and Shenzhen exchanges simultaneously. This price limits settlement system means that the transaction price rise and drop a day not more than 10% of the price. The Chinese securities regulatory authorities expected that this system could arrest the speculative behaviour and keep the stock market healthier.

Before participating WTO, the Chinese government established many strict restrictions on the foreign capital investment to domestic stock market (Sun and Yan, 2015) [13]. This closed-door policy had been changed after 2001 when China came to be the member of WTO. The opening of equity market makes the Chinese stock market more and more active, producing the high volatility directly. The Chinese equity market has become the new favourite of the world capital investors. However, the speed of improving and perfecting the relevant policies falls behind the development needs of the equity market.

Figure 1 and Figure 2 show the changes of Shanghai Composite Index and Shenzhen Component Index over the past ten years. As it can be seen from the above two figures, the Chinese equity market entered into the bull market from 2006, and the point reached the peak in the middle of 2007. Afterwards, the two stock indices continued to decrease to the point level in 2006 approximately. From the beginning of 2009, the Shanghai and Shenzhen exchanges display the high volatility until now.

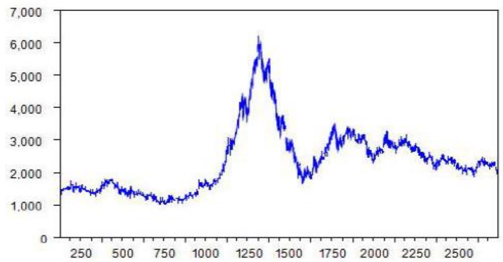

Figure 1. The performance of Shanghai Composite Index

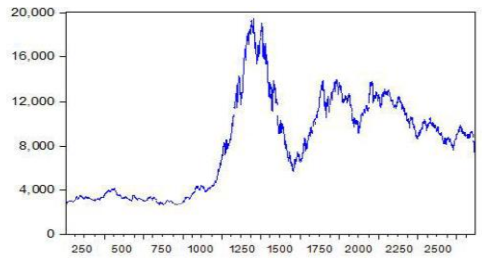

Figure 2. The performance of Shenzhen Component Index

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Generally speaking, the Chinese stock market is still in the emerging stage with a high proportion of irrational investors, high volatility and imperfect policies. Nevertheless, as one of the largest emerging markets, Chinese equity market attracts the high attention from many people. Hence, more and more investors and researchers want to figure out the movements' tendency of Chinese stock market volatility.

2 DATA DESCRIPTION

This research collects the daily closing price and range observation based on the two main stock markets in the mainland of China. The data contain 2641 daily observations from January 2, 2005 to June 28, 2015 for the following considerations.

The data range is separated into two parts. The first part called the estimation procedure uses around 10 years of data from January 2005 to February 2015, which covers 2563 observations as the training data set. The remaining 78 observations are employed for out-of-sample forecasting. These series are taken from China Stock Market and Accounting Research Database (CSMAR database). EViews 6.0 was used to obtain the results of the empirical analysis. In order to remove the influence between the two time points, the daily returns are computed as the first-order difference in the logarithm of the two consecutive trading day closing price P_t: $R_t = \ln(P_t) - \ln(P_{t-1})$. Let the R_t be the continuously compounded return series of the stock prices.

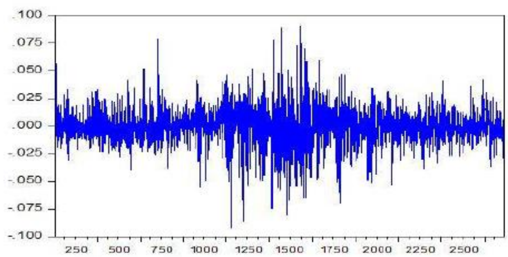

Figure 3. Time series of daily returns for Shanghai Composite Index

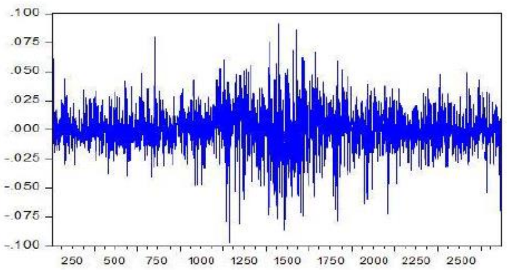

Figure 4. Time series of daily returns for Shenzhen Component Index

As it can be seen from Figure 3 and Figure 4, the stock daily returns of both indices mainly concentrate within the range of 10%. Additionally, the volatility of Shenzhen Component Index daily return is bigger than Shanghai Composite Index. Additionally, the time series of two indices appear several abnormal peaks, indicating that the volatilities exhibit the characteristics of financial time series data such as time-varying and sudden changes in variance. What is more, these abnormal volatilities perform the obvious volatility clustering appearance. Furthermore, the variance is not the constant and the volatility clustering is a type of heteroskedasticity, hinting the sensible use of GARCH family models. The descriptive statistical analysis results of the new time series composited by the daily return R_t are also shown in Table 1:

Table 1. Descriptive statistics for daily return series of Shanghai Composite Index and Shenzhen Component Index

Statistics	Shanghai	Shenzhen
	Daily return distribution	Daily return distribution
Observation	2540	2540
Mean	0.000159	0.000414
Median	0.000546	0.000499
Maximum	0.090345	0.091615
Minimum	-0.092561	-0.097501
Standard Deviation	0.016708	0.018675
Skewness	-0.248101	-0.272173
Kurtosis	6.461005	5.623042
Jarque-Bera	1293.7890	759.5303
Probability	0.000000	0.000000

It can be seen from Table 1 that the two series have asymmetric distributions skewed to the left, and the values of the kurtosis are significantly higher than that of the normal distribution. Hence, the two series have obvious high kurtosis and fat tails distributions. The statistics of Jarque-Bera test and the p-value equal to zero also further implicate that the null hypothesis of normal distribution is rejected.

Figure 5 and Figure 6 plot the daily return frequency diagrams for the two stock markets. The skewness and kurtosis take the measurements of the asymmetry and leptokurtosis of the daily returns distribution. Under the condition of normal distribution, the two values should be 0 and 3 respectively.

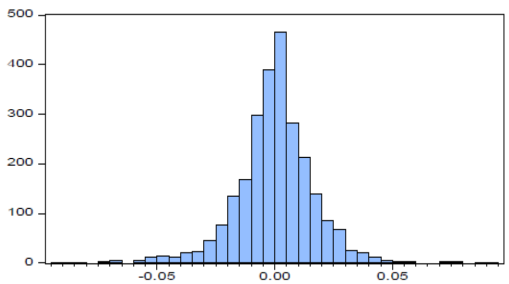

Figure 5. Histogram of Shanghai Composite Index daily returns

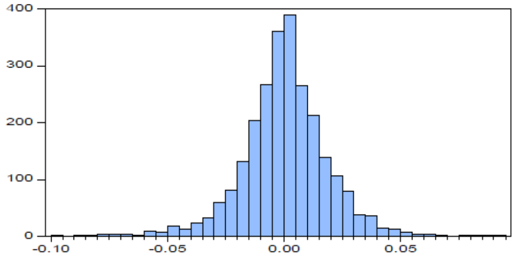

Figure 6. Histogram of Shenzhen Component Index daily returns

3 EMPIRICAL RESULTS AND ANALYSIS

3.1 *Statistical analysis for the daily return series*

3.1.1 *Testing for stationary*

It is essential to research the stationary of the daily return series by using the ADF unit root test at first (Dicky and Fuller, 1979) [3]. And the regression model is,

$$\Delta R_t = \alpha + \theta R_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta R_{t-1} + \varepsilon_t$$

Under the null hypothesis $\theta = 0$ (unit root) against the alternative $\theta < 0$, the results are presented in Table 2 and Table 3.

Table 2. ADF test for daily return series of Shanghai Composite Index

Augmented Dickey-Fuller test statistic	T-Statistic	Prob.
Test critical values	-50.24947	0.0001
1% level	-3.432732	
5% level	-2.862478	
10% level	-2.567315	

Table 3. ADF test for daily return series of Shenzhen Component Index

Augmented Dickey-Fuller test statistic	T-Statistic	Prob.
Test critical values	-48.56465	0.0001
1% level	-3.432732	
5% level	-2.862478	
10% level	-2.567315	

At 1% of the significance level, the ADF test statistics of the two stock markets are -50.24947 and -48.56465, with both less than the critical value. The null hypothesis (having the unit root) is rejected, which indicates that the daily return series of Shanghai Composite Index and Shenzhen Component Index are stationary. Pagan (1996) [10] and Enders (2010) [4] point out that the prices of financial assets are usually random walk (non-stationary) while the daily return series are stable.

3.1.2 *Testing for autocorrelation*

Apply Ljung-Box Q statistics to test the serial correlation and the null hypothesis of the Q-statistic with p lag orders is that there is no autocorrelation in the series. The expression of Q-statistic for:

$$Q_{LB} = T(T+2) \sum_{j=1}^{p} \frac{r_j^2}{T-j}$$

Let *rj*, *T* and *p* be a response to the *j* order autocorrelation coefficient respectively in the residual series, the number of observations and the lag orders.

Table 4. Ljung-Box test for autocorrelation in daily returns

	Q (5)	Prob.	Q (10)	Prob.
Shanghai Composite Index	12.053	0.034	21.401	0.018
Shenzhen Component Index	15.721	0.008	26.391	0.003

The p-values are all less than 0.05, indicating that the null hypothesis (no autocorrelation) could be rejected at 5% significance level. The conclusion is that there is serial correlation in the daily return series of both Shanghai and Shenzhen stock markets.

3.1.3 *Testing for ARCH effect*

Table 5. Ljung-Box test for ARCH effect in daily returns

	Q (5)	Prob.	Q (10)	Prob.
Shanghai Composite Index	212.15	0.000	428.64	0.000
Shenzhen Component Index	190.87	0.000	422.93	0.000

Table 5 provides the relevant statistics of Shanghai and Shenzhen daily stock returns for Q (10). Accordingly, Q statistics show that the high significance with p-value equivalent to zero is less than the 5% significance level, indicating that the null hypothesis should be rejected and the daily return series of the two indices have strong autoregressive conditional heteroskedasticity (ARCH effect).

3.2 *Estimation of GARCH models*

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the two daily stock returns series would be used to determine the orders of the AR and MA procedure in the mean equation. All the models fit the two exchanges with the mean equation of ARMA (4, 0) for the Shanghai Composite Index and ARMA (4, 4) for Shenzhen Component Index.

Table 6 and 7 show the relevant variance parameter estimates for the different GARCH models of Shanghai and Shenzhen exchanges from January 2005 to February 2015.

Table 6. Maximum likelihood estimates of ARMA (4, 0) -GARCH (1, 1), ARMA (4, 0)-GARCH-M (1, 1), ARMA (4, 0)-TGARCH and ARMA (4, 0)-EGARCH models for Shanghai Composite Index

Models	Variance equation			
	α_0	α_1	β_1	γ
GARCH (1, 1)	2.47E-06 *** 5.74E-07	0.054064 *** 0.005934	0.937130 *** 0.006716	
GARCH-M (1, 1)	2.52E-06 *** 5.72E-07	0.055040 *** 0.005969	0.936001 *** 0.006743	
TGARCH (1, 1)	2.82E-06 *** 6.22E-07	0.046619 *** 0.007182	0.933584 *** 0.006817	0.01881 ** 0.008288
EGARCH (1, 1)	-0.191434 *** 0.027158	0.133581 *** 0.012555	0.989072 *** 0.002666	-0.015855 *** 0.006066

Note: *, ** and *** denotes significance in 10%, 5% and 1% respectively.

Table 7. Maximum likelihood estimates of ARMA (4, 4)-GARCH (1, 1), ARMA (4, 4)-GARCH-M (1, 1), ARMA (4, 4)-TGARCH and ARMA (4, 4)-EGARCH models for Shenzhen Component Index

Models	Variance equation			
	α_0	α_1	β_1	γ
GARCH (1, 1)	3.36E-06 *** 8.23E-07	0.048931 *** 0.005689	0.941236 *** 0.006826	
GARCH-M (1, 1)	3.51E-06 *** 8.40E-07	0.050183 *** 0.00588	0.939582 *** 0.007037	
TGARCH (1, 1)	3.87E-06 *** 8.91E-07	0.040504 *** 0.006766	0.935895 *** 0.007312	0.020830 ** 0.008531
EGARCH (1, 1)	-0.178658 *** 0.027010	0.120592 *** 0.012447	0.989206 *** 0.002734	-0.012978 ** 0.006089

Note: *, ** and *** denotes significance in 10%, 5% and 1% respectively.

The estimation of GARCH (1, 1) model for the two stock markets both report that the coefficients of variance equation are significant at 1% level, suggesting the feature of volatility clustering in the daily return series. The sum of ARCH item α_1 and GARCH item β_1 are both approximately equal to 0.99 which is smaller than 1 and all the coefficients are of non-negativity, satisfying the constraints on the parameters of GARCH model stability. The ARCH item reflects the influence degree of the external shocks to the stock market. The considerable value of ARCH item suggests that the volatility responds to the market changes quickly and the volatility tends to be more divergent. Meanwhile, the GARCH item reflects the own memory of the volatility. In considering the sums of the ARCH and GARCH terms coefficients are very close to 1, this also proves that the random impact on the conditional variance is not a fleeting but a persistent process (Philip and Dick, 1996[12]; Huang, 2015[8]). However, when the GARCH item $\beta_1 > 1$, suggesting that the system would be magnified by itself. Accordingly, through this feature it is possible to infer the impact on the future and make a prediction. Although the fluctuations decay slowly, the implication of the past volatility would gradually decline to zero in the someday. This phenomenon is common in the high frequency financial data.

The parameters α_1 and β_1 of GARCH-M (1, 1) model are highly significant at 1% level for the two indices, showing that the conditional variance σ_t^2 of the random error term ε_t in the time series $\{r_t\}$ at time t point that depends not only on the square interference of the past, but also the conditional variance of the past. What is more, the coefficient of variation δ estimates for Shanghai Composite Index is 0.000893, which is bigger than zero and significant at 10% level. This reflects the positive relationship between the returns and risks caused the positive risk premium of returns. The result also proves the investment portfolio theory that the high risk should be in high yield that is consistent with the actual situation. Therefore, it is reasonable to employ the GARCH-M model to describe the volatility of the Shanghai Composite Index and Shenzhen Component Index.

In fact, the ARCH terms of the four models are all significant at 1% level. Meanwhile, the beta estimates of the two stock indices by the different models are all significant at 1% level, which indicates that the volatility clustering of the stocks exist in Shanghai and Shenzhen markets.

According to the previous descriptive statistics on the two certain daily stock return series, it shows that the sequence distribution is not symmetric but biased. The first two models are considered as symmetry classes, so the other two models would be considered as asymmetric models such as TGARCH and EGARCH. From the results, the parameters in the mean equation are not significant while those in the variance equation are highly significant. In TGARCH model of two indices, the asymmetry coefficients γ are bigger than zero and significant at 5% level, providing evidence that the leverage effect exists in the daily returns of both Shanghai and Shenzhen stock markets. In other words, negative shocks tend to trigger the larger impact on volatility than the same degree of the positive shocks (Fabozzi, 2008) [5]. When ε_{t-1} is positive or there is good news, the total effects are 0.046619 (Shanghai) and 0.040504 (Shenzhen). On the contrary, when ε_{t-1} is negative or there is bad news, the total effects are 0.065429 (Shanghai), and 0.061334 (Shenzhen).

Similarly, in EGARCH model, the estimated coefficients of mean equation are not significant. Nevertheless, the asymmetry coefficients γ for both indices are less than zero and significant at 1% and 5% level respectively. That is, the daily returns of Shanghai Composite Index and Shenzhen Component Index have the leverage effect. When $\varepsilon_{t-1} > 0$, the total effects are 0.117726 (Shanghai) and 0.107614 (Shenzhen). In contrast, when $\varepsilon_{t-1} < 0$, the total effects are 0.149436 (Shanghai) and 0.13357 (Shenzhen). It clearly exhibits the changes of variance brought about by the negative shocks are greater than the effects caused by the same degree of positive shocks. This is convincing evidence that the responses to the good and bad news are asymmetric of the daily returns in Shanghai Composite Index and Shenzhen Component Index. After the calculation, the results of the two leverage effects strength are 1.03222086 (Shanghai) and 1.0269729 (Shenzhen). Compared with the two values of m, it provides an interesting finding that the Shanghai Composite Index has a stronger leverage effect.

Table 8. Comparison of the models with AIC and SC

Models	Shanghai Composite Index		Shenzhen Component Index	
	AIC	SC	AIC	SC
GARCH (1, 1)	-5.539683	-5.520783	-5.289607	-5.275451
GARCH-M (1, 1)	-5.539788	-5.518525	-5.289337	-5.272822
TGARCH (1, 1)	-5.540136	-5.518873	-5.290420	-5.273904
EGARCH (1, 1)	-5.542376	-5.521113	-5.292636	-5.276120

In addition to the parameter estimates, the values of AIC and SC could be used to compare the four models. As AIC considers the two factors of model estimation accuracy and concise parameters, the smaller value indicate the superior of fit. After comparison, the EGARCH (1, 1) of both Shanghai and Shenzhen stock markets have the smallest value of AIC and SC as shown in Table 8, suggesting the EGARCH (1, 1) could fit the data best. However, the values of each model are very close so that the statistics are hard to provide an obvious favourite. Maybe more model selection criteria could be employed to fully prove this inference further.

3.3 *Diagnosis Tests*

The acceptability of the fit need to be assessed by applying some statistical diagnostics after the GARCH-type models have been built for the daily stock returns. The standardized residuals have been acquired by estimation of the GARCH model in the previous section. If the GARCH model is specified accurately, the properties of standardized residuals should show the same character as the classical regression residuals (Zivot, 2009) [14]. More specifically, the residuals are expected to have the normal distribution, no serial correlation and no remaining ARCH effects. The Table 9 and Table 10 summarize the Jarque-Bera test for normality and the Ljung-Box test for autocorrelation and heteroskedasticity. In considering the complexity of more than one market with several models, the procedure of diagnosis would be classified to introduce by different stock indices.

Table 9. Diagnosis tests for Shanghai Composite Index

Models		Standardized Residuals		Squared Residuals	
	Jarque-Bera	Q (5)	Prob.	Q (5)	Prob.
GARCH (1, 1)	304.9636 ***	2.2227	0.136	1.3483	0.246
GARCH-M (1, 1)	318.5606 ***	2.6945	0.101	1.3040	0.253
TGARCH (1, 1)	294.7402 ***	2.2695	0.132	1.4758	0.224
EGARC (1, 1)	268.5703	2.3382	0.126	1.3012	0.935

Note: *, ** and *** denotes significance in 10%, 5% and 1% respectively.

Table 9 contains the above three informative diagnosis tests for Shanghai Composite Index. The values of Jarque-Bera across the first three GARCH models are significant at marginal 1% significance level except the EGARCH model. Whereas, compared to the Jarque-Bera statistic of daily return series in Table 1, the values of the GARCH-type models those are significant have reduced substantially. Of course, the EGARCH (1, 1) should be the most appropriate than the other models for the lower Jarque-Bera value and accept the null hypothesis normality. Overall, GARCH (1, 1), GARCH-M (1, 1), TGARCH (1, 1) and EGARCH (1, 1) have been able to capture the feature of high kurtosis and fat tails in the Shanghai daily stock return series.

Afterwards, the results of serial correlation test on standardized residuals by Ljung-Box reports that all Q (5) with the p-values bigger than 0.05, reflecting that the Q-statistic of standardized residuals are not significant at 5% level. In other words, the null hypothesis (no autocorrelation) could be accepted. Simultaneously, the p-values of Ljung-Box Q statistics of all the models on squared residuals are exceeding the significance level, which means the null hypothesis could not be rejected. Hence, the residual series of the two indices do not show significant ARCH effect any more.

The same diagnosis process with Shanghai Composite Index, Table 10 reports the results of diagnosis tests for Shenzhen Component Index in order. Although, the Jarque-Bera statistics are significant at 1% except EGARCH (1, 1), which the values decline dramatically than the initial value 759.5303 in Table 1 in any event. Additionally, the statistic in the last row of EGARCH (1, 1) shows the smallest Jarque-Bera value and accepts the null hypothesis of normality, which means EGARCH (1, 1) model outperforms than the other simulated models. The Ljung-Box test on standardized residuals and squared residuals indicate there are no more serial correlation and remaining ARCH effects.

Table 10. Diagnosis tests for Shenzhen Component Index

Models		Standardized Residuals		Squared Residuals	
	Jarque-Bera	Q (5)	Prob.	Q (5)	Prob.
GARCH (1, 1)	238.0057 ***	5.2525	0.154	4.0294	0.258
GARCH-M (1, 1)	207.9274 ***	5.4004	0.145	4.3007	0.231
TGARCH (1, 1)	207.3768 ***	5.0292	0.170	3.6716	0.299
EGARCH (1, 1)	184.6310	4.8452	0.183	4.5200	0.211

Note: *, ** and *** denotes significance in 10%, 5% and 1% respectively.

3.4 *Out-of-sample Forecasting*

Using the four simulated models to forecast performance of Shanghai Composite Index and Shenzhen Component Index, this is an efficient way to choose a better model to fit the volatility of Chinese stock market.

This section compares volatility forecasts from some representative measures, which are RMSE, MAE and MAPE described clearly in the previous section. The out-of-sample forecasting is carried out for the period from March 2015 to June 2015 including 78 observations.

The forecast function of the model could be evaluated by comparing the actual and predicted values and the forecast error refer to the deviation of the predicted and the actual results. In fact, no matter what type of forecast models are applied, the forecast error statistics might always exist (Hamadu and Ibiwoye, 2010[7]).

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(\hat{y}_t - y_t)^2}$$

$$MAE = \frac{1}{m}\sum_{t=1}^{m}\left|\hat{y}_t - y_t\right|$$

$$MAPE = \frac{1}{M}\sum_{t=1}^{m}\left|(\hat{y}_t - y_t)/y\right|$$

Where $\hat{y}_t$ is denoted as the forecast volatility and y_t denoting the actual volatility. The number of the forecast is m observations. The smaller the forecast error is, the better forecast performance of model should be considered.

The forecast of returns of four models display the horizontal at zero because there is just constant term in the mean equation. Meanwhile, the forecast of variance figures show the rising trend with a steep slope obviously and reach the peak at the end of the out-of-sample period in June 2015, suggesting that the daily stock returns series tend to be more variable result from the increasing variation of the daily returns in the future.

Table 11. Error statistics from forecasting daily volatility for Shanghai Composite Index

Error statistic \ Models		GARCH (1, 1)	GARCH-M (1, 1)	TGARCH (1, 1)	EGARCH (1, 1)
RMSE	Actual	0.012922	0.012961	0.012904	0.012891
	Relative	99.70%	100.00%	99.56%	99.46%
MAE	Actual	0.008724	0.008759	0.008706	0.008698
	Relative	99.60%	100.00%	99.39%	99.30%
MAPE	Actual	100.7121	105.1335	99.01360	99.09152
	Relative	95.79%	100.00%	94.18%	94.25%

Table 12. Error statistics from forecasting daily volatility for Shenzhen Component Index

Error statistic \ Models		GARCH (1, 1)	GARCH-M (1, 1)	TGARCH (1, 1)	EGARCH (1, 1)
RMSE	Actual	0.016513	0.016568	0.016489	0.016480
	Relative	99.67%	100.00%	99.52%	99.47%
MAE	Actual	0.011161	0.011195	0.011147	0.011143
	Relative	99.70%	100.00%	99.57%	99.54%
MAPE	Actual	104.5804	109.5808	103.0456	102.4471
	Relative	95.44%	100.00%	94.04%	93.49%

Table 11 and Table 12 show the real and relative forecast error statistics comparison of each method through various GARCH models in Shanghai and Shenzhen exchanges respectively. The relative forecast error refers to the actual forecast error divided by the maximum forecast error among all the forecast models, producing the model with a maximum error would be selected as a benchmark model.

The principle points out that most forecast accuracy model should possess the smallest value by calculating the mean square error. Under this principle, the RMSE statistics show that the EGARCH (1, 1) model supplies the most accurate forecasting for Shanghai Composite Index. Likewise, the EGARCH (1, 1) is the best forecast model for Shenzhen Component Index. More specifically, for Shanghai stock market, the EGARCH (1, 1) is more accurate than the benchmark model (GARCH-M (1, 1)) by 0.54% and the second ranked model is TGARCH (1, 1) with 0.44% more accuracy. For Shenzhen stock market, the RMSE of GARCH-M (1, 1) is 0.53%, 0.48% and 0.30%, which is less accurate than EGARCH (1, 1), TGARCH (1, 1) and GARCH (1, 1).

Like the results of RMSE, Table 12 also reveals that the EGARCH (1, 1) proves to be superior to other candidate models by using MAE and MAPE forecast evaluation criteria of Shenzhen Component Index. There is no exception for these methods that the next ranking model is TGARCH (1, 1), and the worst is GARCH-M (1, 1). Hence, from the forecast accuracy of the sense, EGARCH (1, 1) model has better simulating and forecasting effect on the volatility of Shenzhen Component Index.

Nevertheless, the results of several forecast error statistics might not point to the same model. As revealed by Table 11, although the result of MAE is consistent with that of RMSE, the MAPE statistic suggests the TGARCH (1, 1) model is more competitive than EGARCH (1, 1) to forecast the volatility of Shanghai Composite Index. This is followed by EGARCH (1, 1) and GARCH (1, 1) and the benchmark model is still GARCH-M (1, 1).

As a consequence, the EGARCH (1, 1) model could reflect the leverage effect in the stock market. What is more, the outcome of the prediction accuracy of this model for Shenzhen Component Index volatility is the best by comparison to other competing models under the three forecast evaluation criteria. As regards Shanghai Composite Index, apart from the MAPE statistic, the RMSE statistic and MAE present the same results that the EGARCH (1, 1) outperforms other models.

4 DISCUSSION

After the investigation, many researchers found that the volatility of Shanghai or Shenzhen stock index is asymmetric. More specifically, the bad news would engender more volatility than that caused by good news. Many researches (e.g., Sun and Yan 2015[13]; Gan 2015[6]) argued that the daily returns exist in the leverage effect of the two markets which indicates that the volatility caused by negative news shock is greater than that produced by the positive news with the same degree. This phenomenon resembles the feature of mature stock market. Although the leverage effect was confirmed existence in the Shanghai and Shenzhen stock market, the results also shows that the leverage effect in Shanghai Composite Index is stronger than Shenzhen Component Index. Similar findings were reported from other studies. Whereas, the results from research conducted by Huang (2014) [8] and Liu and Zhang (2011) [9] produced a very different set of consequences. For instance, Huang (2014) [8] came up with that there is no significant leverage effect in Shenzhen stock market. This researcher also pointed out that having no short selling mechanism in Chinese stock market might be the main reason. Although investors anticipate the stock price would fall further when the stock market is shocked by the bad news, only the investors hold the shares would react to this. However, the rest of the investors are not able to respond by selling stock so that there is no remarkable leverage effect as mature stock market. And Liu and Zhang (2011) [9] explored that Shenzhen stock market has a more significant leverage effect and volatility than that of Shanghai stock market.

This paper draws the inference that the EGARCH model fits both Shanghai and Shenzhen exchanges well with consideration of the following two aspects. One is the model selection criteria AIC and SC, and the other is the forecast performance based on the forecast evaluation statistics. Taking the above factors into consideration could guarantee accurate results. However, some researchers just take one aspect to analyse. Pei and Xu (2012) [11] just compare the fitting results by some criteria such as R square, AIC and SC and then make the conclusion, which is similar with Huang (2014) [8]. However, being only in the view of the model selection criteria is not enough to choose the best fitted model. It is essential to evaluate the forecast performance of each candidate models as the reliable reference by comparing the forecast evaluation statistics such as MAE, RMSE and MAPE. Also, it's noteworthy that the fundamentals of these two classification methods are different so that it might lead to the distinct results. Fortunately, the empirical results all point to the same model EGARCH (1, 1) as the best fitted with the two exchanges. There is possibility that the statistics suggest the dissimilar results, it is mainly caused by different principles of the methodology while the results are all sensible. Alexander and Lazar (2009) [1]also comments that the one with the most accurate forecast performance is the most appropriate model to fit the stock market among the competing models. In other words, the latter aspect is more essential than the former one to some extent.

5 CONCLUSION

This research examined the volatility behaviour of Chinese stock markets by some variations of the heteroscedastic conditional volatility models. The within-sample assessment exhibited that the four models researched were reasonable. Nonetheless, the results show that the EGARCH (1, 1) outperform other traditional models in modelling and forecasting the volatility of Chinese stock market. AIC, SC, RMSE, MAE and MAPE model selection criteria give proof of the above judgement.

In detail, when the daily returns are shocked and then perform the abnormal volatility, the impacts would not eliminate in the short term. Hence, the overall risk of Chinese stock market is high to some extent. More importantly, there exist significant leverage effects in the daily returns series of both indices. That is, the volatility in the diminishing market tends to be higher than in the booming market. It indicates that investment consciousness of most Chinese investors is relatively weak so that the investment behaviour is easily affected by all kinds of news. Also noteworthily, the leverage effect in Shanghai Composite Index is greater than that in Shenzhen Component Index, indicating that the speculation of Shanghai stock market is greater than Shenzhen stock market. Provided that the investors could recognize these features of the volatility in Chinese stock market, this may help them to avoid risk instead of noise trading, as well as provide a policy basis for decision-making departments of government to supervise the securities exchanges.

Despite the fact that the above results are comparatively comprehensible and consistent with the other studies on the emerging capital markets, it should be noted that this study has been primarily concerned with the univariate GARCH models, which contain almost all the popular models. However, big GARCH family models are divided into two main parts. Except for the univariate GARCH models, another classification is multivariate GARCH models such as constant conditional correlation (CCC) model, dynamic conditional correlation (DCC) model and generalized dynamic covariance (GDC) model (Enders, 2010)[4]. In addition, the four months period for evaluating forecast performance is a bit short relative to about ten years post estimation period over 2000 observations. Notwithstanding these limitations, this study does suggest the further investigations could overcome the above weaknesses on this subject. Around 10% to 25% of the total sample observations as the out-of-sample are more appropriate. What is more, the further studies could try to conduct the multivariate GARCH models to analyse the volatility of the stock markets. In order to make the research inferences more abundant, there are many other interesting subjects could be investigated. For example, the interaction effects between the Shanghai and Shenzhen exchanges or empirical research of the industry index.

On the whole, the research shows that the implementation of transaction policy has played an important role among Chinese stock market in recent years. The phenomenon of sudden slump or rise in the prices of stocks has been brought down in a certain extent. Furthermore, the risk conduction mechanism is gradually developed. But there still exists many problems in Chinese stock market. For instance, the stock market organization structure of Shanghai and Shenzhen could not effectively manage and deal with the occasional events, which caused strong impacts on the stock markets (Carroll and Kearney, 2012)[2]. Regulators should take more stringent measures in order to reduce the number of vicious speculation and control the volatility. Listing corporation should continuously improve the adequacy and the authenticity of information's disclosure. Understanding volatility in emerging capital markets is essential for determining the cost of capital and evaluating direct investment and asset allocation decisions. Finally, it would be of benefit for investors to identify risks and increase the awareness of risk investment.

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