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Analysis of Volatilities and Correlations for Chinese Stock Markets

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Abstract. *In this paper, GARCH, EGARCH and GJR models are used to fit the volatilities of stock returns for two markets in China, namely, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) in both the developing and the developed stages. We also compare the performance of the volatilities and the leverage effects both across and within the two markets. Furthermore, we use VAR model to detect the correlation between the targeted markets based on impulse response and variance decomposition analyses. The experimental results indicate that the markets are less volatile and positively skewed in the developing phase while these are more volatile and negatively skewed in the developed phase. Another finding is that one standard-deviation innovation impulses die out after 7 days in the targeted markets and the impact of the SSE on the SZSE is stronger than that of the SZSE on the SSE.*
Keywords: Return volatility; Stock return; GARCH, EGARCH; GJR Model; VAR Model.

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1. **Introduction.** Investors, brokers and even regulators are concerned for the volatile equity market in recent years. The volatilities of stock returns may not only hold back economic progress through consumers?spending but also influence the investment outcomes of enterprises. Moreover, the original financial system that functions smoothly may be destroyed, bringing about changes in structure or regulation. An appropriate quantitative model is needed for the new development of financial econometrics, in which way investors' attitudes towards returns, risks, and volatility can be explained. Therefore, any involved party in the market ought to understand the importance of risk management with regard

to volatility, under which situation effective models are needed [15]. Due to the possibility of unexpected events, price (or return) uncertainties and the discrete financial market variances, financial analysts began to set models and to offer explanations about the performance of returns and the volatilities for stock markets through econometric models. Autorgressive Conditional Heteroskedasticity (ARCH) together with Generalized ARCH (GARCH) models established by Engle [7] and further developed by Bollerslev [3] can be taken as the most significant tools to observe the variances. The GARCH family models can grasp the two significant characteristics concerning financial time series, i.e. fat tails and volatilities that may cluster or pool ([1] and [15]). Clustered volatility can be regarded as the clustered variance with respect to the residual term. Specifically speaking, the variance of error with regression this time is closely related to the decreasing trend of variance next time. The error which shows the time-varying heteroskedasticity can be reflected by the clustered volatility, on the basis of non-constant unconditional deviations of standard.

There are some studies on volatilities of world stock markets (except for Chinese markets) in the literature. Horng and Lee [11] find evidence of asymmetric volatility in the German stock market and pay attention to the relationship among USA, U.K and German stock markets using threshold-GRACH(1, 1) model. Horng and Huang [12] find empirical evidence against the above hypothesis of asymmetric volatilities in Malaysia and Singapore stock markets using bivariate GARCH(1, 1) model. Celik and Ergin [4] discuss about volatility calculation using traditional GARCH models. Mohamed, et al. [13] and William [18] used Vector Autoregressive (VAR) models to examine volatilities for GCC countries. Nevertheless, there are very few studies on the topic for the Chinese markets. Qi and Chen [19] examine and forecast the out of sample volatility using GARCH models. Pan [15] analyzed the volatilities of Chinese stock markets based on GARCH family models and find evidence of stationarity and strong ARCH effect in the return series.

The exploration of patterns of volatility for stock returns of a stock market is quite intriguing at different phases of its development. In this paper, we attempt to focus on the volatilities of stock returns for the two stock markets in China - the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), at two stages. We also investigate the correlation between the two stock markets. The whole data set of index for the SSE includes data from Dec. 19, 1990 to Dec. 31, 2015, and that for the SZSE includes from Dec. 19, 1995 to Dec. 31, 2015 (the composite index of SZSE started only on Dec. 19, 1995). Each data set is divided into two parts. The first part is the stock return series of the first ten years, which marks the developing phase of the stock market (developing phase). In the first phase the market has transformed from purely closed to open market to a certain extent. The second part consists of the data for the rest of years (developed phase).

The main contribution of this paper includes: (1) to calculate and to compare the statistical characteristics of stock return series in the developing and the developed phases of the two Chinese markets; (2) to fit and to compare the volatilities and leverage effects of the stock markets by using GARCH(1,1) model as well as EGARCH and GJR models at different phases of the two stock markets; and (3) to detect the correlation between the two stock markets based on impulse response and variance decomposition analyses using VAR models.

The rest of the paper is organized as follows. The methodology of the ARCH, GARCH, EARCH and GJR models is introduced in Section 2. The data sets used in the empirical studies are described in Section 3, and the econometric models and estimation results are also presented in the same section. The VAR model is run to detect the correlation between the two stock markets in Section 4. The conclusions are summarized in Section 5.

2. **Methodology.** With the conditional models of heteroskedasticity as a primary tool for evaluating and predicting the volatile asset returns, there have been several models proposed over time.

2.1. **ARCH Model.** For the purpose of understanding the conditional dynamics of variances, Engle [7] put forward ARCH model which models variances of the series and makes it possible for variances of the error term vary with the use of disturbance in the past:

$$y_t = \theta_0 + \sum_{i=1}^{p}(\theta_i y_{t-i}) + \epsilon_t, \tag{1}$$

and

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2, \tag{2}$$

where $\epsilon_t = \delta_t z_t$ and z_t are i.i.d standard normal random. Therefore, under certain conditions the variances δ_t^2 of error term relies on the squared error previous values. This is known as an ARCH(p) model.

An ARCH model provides a framework to analyze and to develop volatility series. On the other hand, there are some drawbacks for ARCH models: There is no fixed method to settle q which is the lag number concerning the squared residual within the model. One solution is to use a ratio test of likelihood, but there is no such thing as the best approach. The value of q, the number of lags of the squared error term required to capture all of the dependence in the conditional variance, might be very large. Non-negativity constraints might be violated.

2.2. **GARCH Model.** A natural extension of the ARCH model, which overcomes some of these problems is the GARCH model. One of the disadvantages of an ARCH model is that it often needs lots of parameters as well as a q with high order for the purpose of grasping the process of volatility. To remedy this, Bollerslev [3] proposed the process of the ARCH by granting the conditional variance with a function of squared errors in prior periods and its conditional variances in the past ([5], [2] and [17]). Therefore, owing to the GARCH model in the basis of a limitless specification of ARCH, we are able to decrease in number with regard to evaluated parameters through the use of nonlinear restrictions. Since it is possible for the stock index conditional variance to rely on previous lags based on the GARCH, its (p,q) model is given by:

$$y_t = \theta_0 + \sum_{i=1}^{p}(\theta_i y_{t-i}) + \epsilon_t, \tag{3}$$

and

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{q} \beta_k \delta_{t-k}^2, \tag{4}$$

where p is the GARCH order, q is the order of the ARCH process,ϵ_t is the error term considered to be normally distributed with mean zero and conditional variance δ_t^2.

Although the GARCH model seems to be superior to the ARCH model to some extent, the former still has certain limitations. Firstly, its response to both good and bad news is the same just like the ARCH model. Secondly, even with student t-innovations that are standardized, the GARCH model may bring about short tail behavior on the basis of the

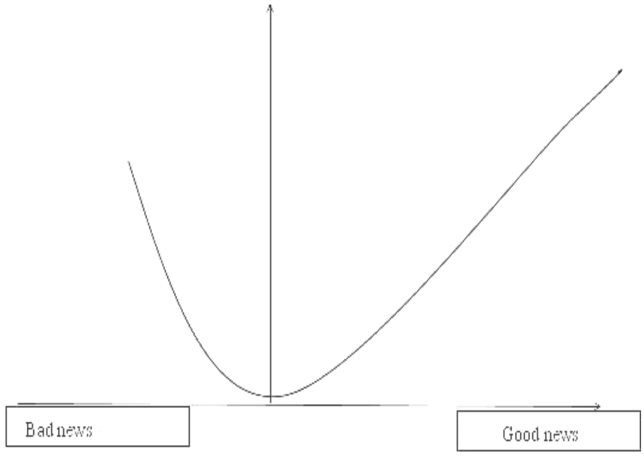

FIGURE 1. Leverage Effect-Reaction of good and bad news.

data with high frequency [6]. Neither the ARCH model nor the GARCH model takes the asymmetry into account.

In a GARCH model, both the squared error and conditional variance can include any lags number. The GARCH (p,q) model has lags of p on the term of conditional variance and lags of q on the term of squared error. Generally speaking, however, a GARCH (1,1) model suffices.

2.3. **GARCH Models of Asymmetry.** GARCH models of asymmetry are required owing to the effect of leverage based on the prices of asset, under which situation a positive shock exerts a smaller effect on conditional variance than a shock of negativity. Symmetric GARCH model does not succeed in controlling the effect of leverage, and therefore, a GARCH model that can take care of asymmetry is needed, The leverage effect, as discovered by Black, indicates that stock market volatility increases with bad news and decreases with good news. The leverage effect is illustrated in Figure 1.

2.3.1. *GJR Model.* One possible way of incorporating this asymmetry into GARCH model is the use of a dummy variable, which was put forward by Glosten, Jangathann and Runkle [10]. They proved that the adjustment of asymmetry was a significant consideration based on asset prices. It is a simple extension of the GARCH model when an extra term is added to explain possible asymmetries. The model is of the form:

$$\delta_t^2 = \alpha_0 + \alpha\epsilon_{t-1}^2 + \beta\delta_{t-1}^2 + \gamma\epsilon_{t-i}^2 d_{t-1}, \tag{5}$$

where d_{t-1} is a dummy variable that takes the value of 1 when the shock(ϵ_{t-1}) is less than 0 (negative) and 0 otherwise, α_0 is constant.The last term is important to decide whether there should be an adjustment of asymmetry on using the t-statistic.

2.3.2. *EGARCH Model.* The alternative to the above model is the use of Exponential GARCH model (EGARCH) by Nelson [14], which is blessed with a lot of advantages compared with the fundamental GARCH model, as the constraint of non-negativity does not require to be utilized and the asymmetries are also possible in this model. It takes the form:

$$ln(\delta_t^2) = \omega + \beta ln(\delta_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\delta_{t-1}} + \alpha\left[\left|\frac{\epsilon_{t-1}}{\delta_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right], \tag{6}$$

where ω is a constant. This model has several advantages over the simple GARCH specification ([7], [8] and [9]). Since we consider the logarithm of δ_t^2, it will be positive even if the parameters turn out to be negative. Thus, constraints of non-negativity may not be needed. Moreover, asymmetries between positive and negative shocks are possible in this model, because if the relationship is negative between the volatility and the return, then γ will be negative.

3. **Fitting and Comparing Stock Return Volatilities Using GARCH Type Models at Different Phases.** Consider a time series of asset returns. It can be shown below:

$$var(y_t|y_{t-1}, y_{t-2}, \ldots) = var(\epsilon_t|\epsilon_{t-1}, \epsilon_{t-2}, \ldots).$$

So the conditional values of y_t, given its previous values, is the same as the conditional values of ϵ_t, given its previous values. In other words, modeling δ_t^2 will offer models and predicts for the variance of as well. Thus, if the dependent variable in a regression is an asset return series, predictions of δ_t^2 will be that of the future variance of y_t. As a result, the primary usage of GARCH models is in the volatility prediction.

3.1. **Daily Returns as Stock Time Series.** Daily returns are defined as the differences in the natural logarithm of the closing index value for the two consecutive trading days, i.e., $r_t = lnp_t - lnp_{t-1}$ where r_t is the daily return of the logarithm at time t, p_t and p_{t-1} are the daily closing prices of an asset during the two days $t-1$ and t, respectively. For the purpose of analyzing the time series, transformation of original series is required depending upon the type of series when the data is in the level form, i.e. the raw data. In this paper, the return series is transformed by using natural logarithm of the series. Some scholars (e.g. [3]) have pointed out two advantages of this type of series transformation. Firstly, it eliminates the possible dependence of changes in stock price index on the price level of the index. Secondly, the change in the log of the stock price index yields continuously compounded series.

3.2. **Data.** The data used in our study consists of daily closing prices for the two indices, SSE and SZSE. The daily return prices of each of the stock markets are being analyzed in two phases for each of the stock markets. The first part (developing phase) involves the analysis of first ten years of the closing prices i.e. from December 1990 to December 2000 for the Shanghai stock market and from Dec. 1995 to Dec. 2005 for the Shenzhen stock market and the second part (developed phase) of the analysis deals with the data of the rest of the years i.e up to December 2015 for both the Shanghai and the Shenzhen stock market.

3.3. **Descriptive Statistics.** Some summary statistics of the returns of the two indices are shown in Table 1, where numbers with * are those whose probabilities of J-B tests are smaller than 5%. The mean of the returns r_t is positive implying the fact that two price series have increased over the period. Also, the means are close to zero, which indicates that they are mean-reverting.

TABLE 1. Summary of statistics of returns r_t

Index		Mean	Std Dev.	Skewness	Kurtosis	Jarque-Bera*
SSE	Part 1	.000528	.013773	5.562223	117.7232	1376991.*
	Part 2	6.39E-05	.007221	-.305390	7.209037	2737.475*
SZSE	Part 1	.000154	.007940	-.257553	8.380316	2952.961*
	Part2	.000037	.008618	-.702905	5.273105	722.9622*

The statistics show that returns are positively skewed in the first part while negatively skewed in the second part of SSE and the two parts of SZSE index series. These implies that the returns of the shares traded in the markets have higher probability of earning negative in the second half of SSE and two parts of SZSE while returns in the first half might probably be positive in SSE. The value of the kurtosis is greater than 3 in all series, and the probability of J-B test is smaller than 5%, this implies that they have sharp peak and fat tail (leptokurtosis). These results strongly illustrate that the stock returns are much more impulsive than the major macroeconomic variables.

3.4. **Volatility Clustering.** Figures 2 and 3 depict the return series of the SSE index part 1 (Dec. 1990 to Dec. 2000) and part 2 (Jan. 2001 to Dec. 2015) of the whole dataset, respectively. While Figures 4 and 5 depict the return series of the SZSE index that again divided into two parts. From these figures, it appears that there are stretches of time where the volatility is relatively high and stretches of time where the volatility is relatively low which suggests an apparent volatility clustering in some periods. Statistically, volatility clustering implies a strong autocorrelation in squared returns; so, a simple method for detecting volatility clustering is to calculate the first-order autocorrelation coefficient in squared returns.

One may be curious to know about the reasons for this volatility clustering. Researchers provide two possible explanations about this phenomenon: first, if information arrives in clusters, returns may exhibit clustering. Nominal interest rate, dividend yield, money supply, oil price, margin requirement, business cycles, and information patterns are the sources of volatility clustering; second, if participants have different prior beliefs and if they take time to digest the information shocks and resolve their expectation differences, market dynamics can lead to volatility clustering.

3.5. **ADF Test.** We use ADF test method to test the stability of the daily returns data of SSE and SZSE, the testing results are displayed in Table 2.

TABLE 2. ADF test results of returns γ_t

Index		ADF test statistics	1% level	5% level	10% level	Prob.
SSE	Part 1	-47.02250	-3.432780	-2.862500	-2.567326	.00001
	Part 2	-58.51186	-3.431964	-2.862139	-2.567326	.00001
SZSE	Part 1	-25.55385	-3.432854	-2.862532	-2.567344	.00000
	Part2	-44.90412	-3.432849	-2.862530	-2.567342	.00001

The ADF statistics are all smaller than the test critical values of 1%, 2% and 5% level, and the probabilities are also smaller than corresponding critical value. Therefore, it is concluded that the data of SSE and SZSE are stationary.

3.6. **ARCH-LM test.** From the above, we note that the data of SSE and SZSE are stationary through ADF test, we now investigate the heteroscedasticity of the data using ARCH-LM test, and the result is listed in Table 3.

From the ARCH-LM testing result, excluding the heteroskedasticity of part1 of SSE is not so critical, the other three parts i.e., the part 1 of SSE and both parts of SZSE, are very critical. So it is appropriate to use a GARCH model to fit the variances of return series.

3.7. **GARCH(1,1) Model.** Once volatility clustering and heteroskedasticity of the return series are confirmed, we focus on determining the fitted GARCH model applicable to the return series. The parameters α_0, α_1 and β were fitted for the GARCH (1,1) model. The GARCH(1,1) fitting results are listed in Tables 4-7.

(1) Fitting Results

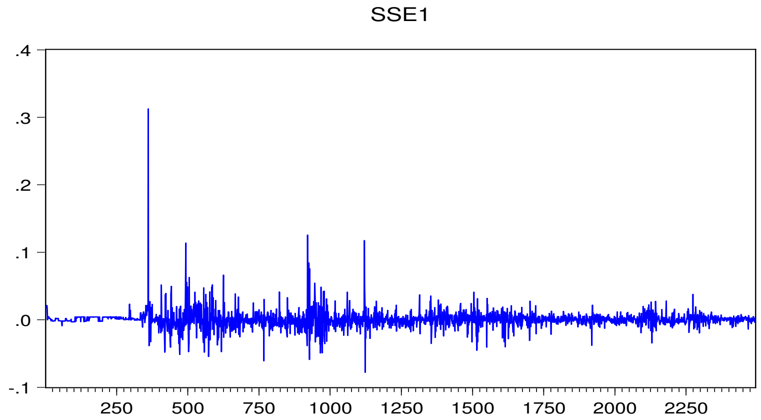

FIGURE 2. SSE Returns Part 1

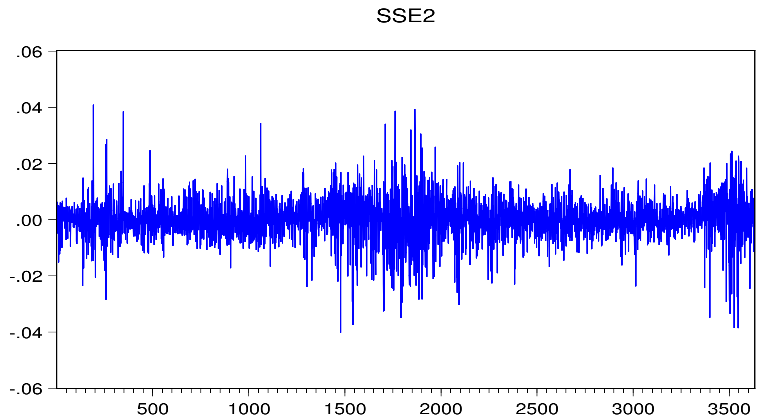

FIGURE 3. SSE Returns Part 2

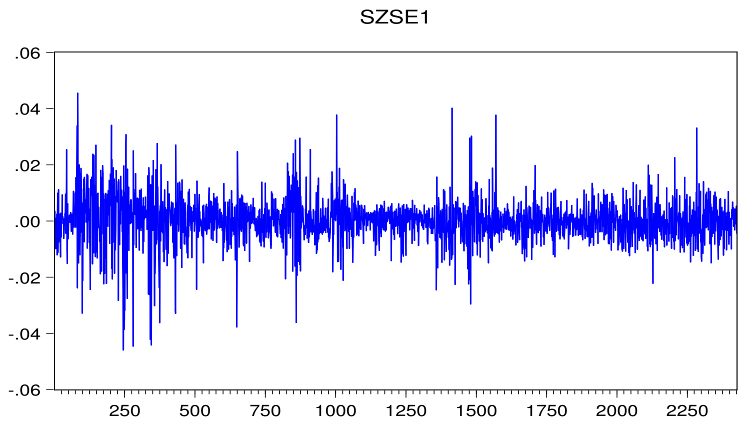

FIGURE 4. SZSE Returns Part 1

While running the GARCH(1,1) process, we get the following fit conditional variance equations:

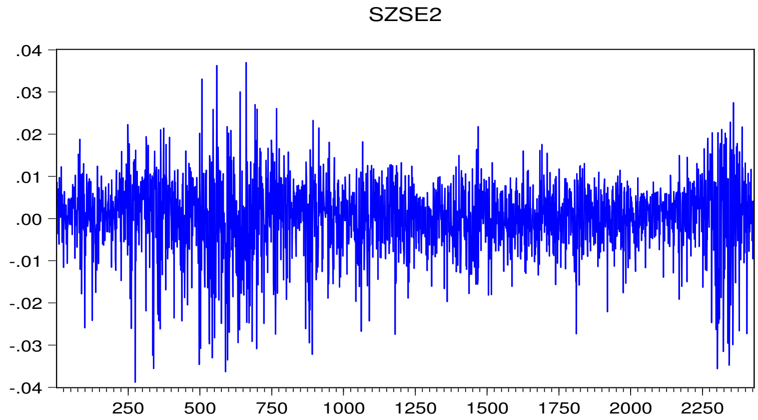

FIGURE 5. SZSE Returns Part 2

TABLE 3. Heteroskedasticity Test using ARCH-LM

SSE	Part 1	F-statistics:2.742170 Obs*R-squared: 10.94243	Prob.F(4,2483): 0.0271 Prob.Chi-square(1): 0.0272
	Part 2	F-statsitics: 109.2702 Obs*R-squared: 106.1339	Prob.F(1,3628): 0.0000 Prob.Chi-square(1): 0.0000
SZSE	Part 1	F-statistics:259.1698 Obs*R-squared: 234.3017	Prob.F(1,2421): 0.0000 Prob.Chi-square(1): 0.0000
	Part 2	F-statistics:118.8764 Obs*R-squared:113.4126	Prob.F(1,2421): 0.0000 Prob.Chi-square(1): 0.0000

TABLE 4. Estimation results of Part 1 for the SSE index

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Variance Equation				
α_0	1.43E-06	9.94E-08	14.34142	0.0000
α_1	0.494878	0.008693	56.93144	0.0000
β_1	0.706702	0.004102	172.3026	0.0000

TABLE 5. Estimation results of the Part 2 for the SSE index

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Variance Equation				
α_0	5.91E-07	8.85E-08	6.681987	0.0000
α_1	0.074472	0.005067	14.69886	0.0000
β_1	0.915833	0.005271	173.7504	0.0000

$$\delta_t^2 = 0.000143 + 0.494878\epsilon_t^2 + 0.706702\delta_{t-1}^2, \tag{7}$$

for the first part of the return series of SSE index;

$$\delta_t^2 = 0.0000591 + 0.074472\epsilon_t^2 + 0.915833\delta_{t-1}^2, \tag{8}$$

for the second part of the return series of SSE index;

Table 6. Estimation results of the Part 1 for the SZSE index

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Variance Equation				
α_0	1.21E-06	1.49E-07	8.136956	0.0000
α_1	0.132756	0.006882	19.28888	0.0000
β_1	0.855067	0.003839	222.7126	0.0000

Table 7. Estimation results of the Part 2 for the SZSE index

Variable	Coefficient	Std. Error	z-Statistics	Prob.
Variance Equation				
α_0	7.86E-07	1.78E-07	4.418928	0.0000
α_1	0.061527	0.006747	9.119102	0.0000
β_1	0.928114	0.007212	128.6985	0.0000

$$\delta_t^2 = 0.000121 + 0.1327566\epsilon_t^2 + 0.855067\delta_{t-1}^2, \tag{9}$$

for the first part of the return series of SZSE index; and

$$\delta_t^2 = 0.0000786 + 0.061527\epsilon_t^2 + 0.928114\delta_{t-1}^2, \tag{10}$$

for the Second part of the return series of SZSE index.

From the above results we observe the following. The coefficients of the variance equations are highly significant. The fits of β_1 are always markedly greater than those of α_1 and the sum $\alpha_1 + \beta_1$ is very close to but smaller than unity except for the SSE index part one. The sum of $\alpha_1 + \beta_1$ indicates the persistence of the shock effects on volatility of error term ϵ_t. It is observed that $\alpha_1 + \beta_1$ is equal to 1.201 and 0.990 for SSE index Parts 1 and 2, respectively. While for the SZSE index it is 0.988 and 0.989, respectively. This is less than unity indicating error term ϵ_t process is stationary with the exception of Part 1 of the SSE index, which maybe the result from nonstandard and small scale stock exchange in the first two years from 1992 to 1993 in SSE. So we cannot investigate further on part 1 of SSE index series on the same guidelines since it violates one of the basic assumptions of GARCH model. The sum of $\alpha_1 + \beta_1$ of Shanghai stock market is higher than that of Shenzhen stock market in the second part, this indicates a longer persistence of shocks in volatility in SSE. The lag coefficient of conditional variance β_1 is higher than the error coefficient α_1. This implies that volatility is not spiky in both stock markets. It also indicates that the volatility does not decay speedily and tends to die out slowly.

(2) Conditional Variance Figures 6-9 show the time series plot for these fit series of conditional variances. It is clear that the volatility behavior in the Figures is qualitatively like the apparent volatility variation in the returns of Figures 2-5, respectively. We can notice that the fit volatility is high for some periods and low for other periods. We may recall that β_1 is close to one, α_0 and α_1 are small for both indices.

Since $\delta_t^2 = \alpha_1 + \alpha_0\epsilon_{t-1}^2 + \beta_1\delta_{t-1}^2$, we see that δ_t^2 tends to δ_{t-1}^2. Both big and small values of δ_t^2 gather together. Also, a big value of lag coefficient β_1 demonstrates that it may take a long time for conditional variance shock to disappear, which results in the persistence of volatility. As to the comparatively small value of error coefficient α_1, it infers that big market shock can influence the comparatively small change about the volatility in the future. Thus, in both figures, we find strong evidence of time-varying volatility. We also find that periods of high and low volatilities tend to cluster. Moreover, volatility shows high persistence and is predictable.

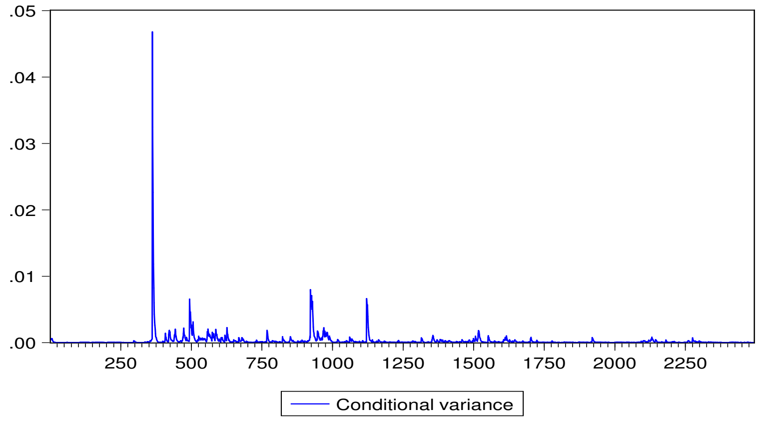

FIGURE 6. Conditional variance of the SSE Index Part 1

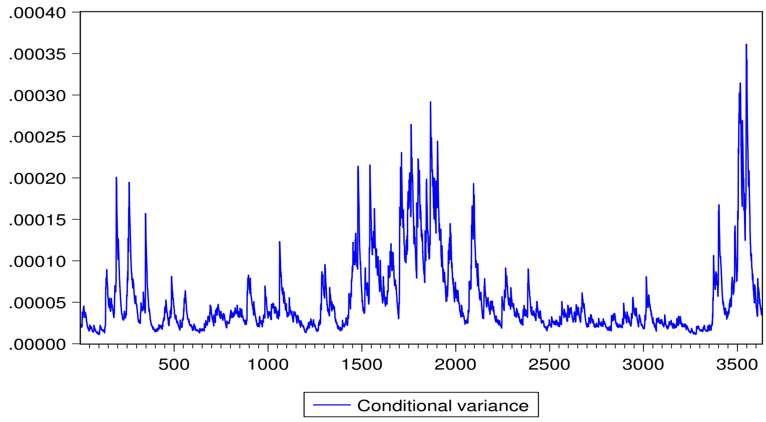

FIGURE 7. Conditional variance of the SSE Index Part 2

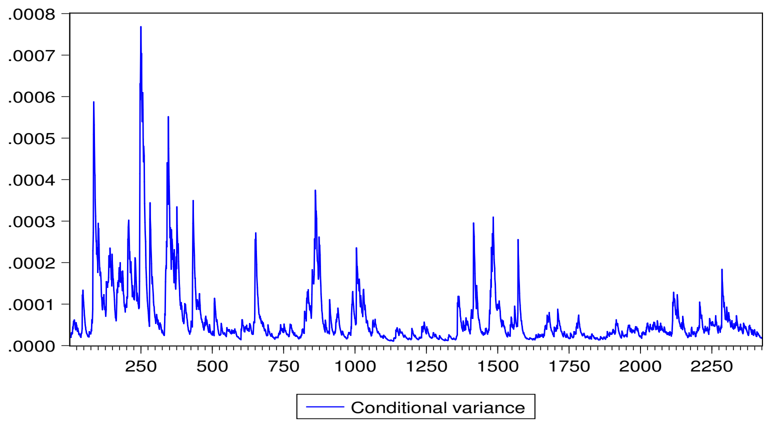

FIGURE 8. Conditional variance of the SZSE Index Part1

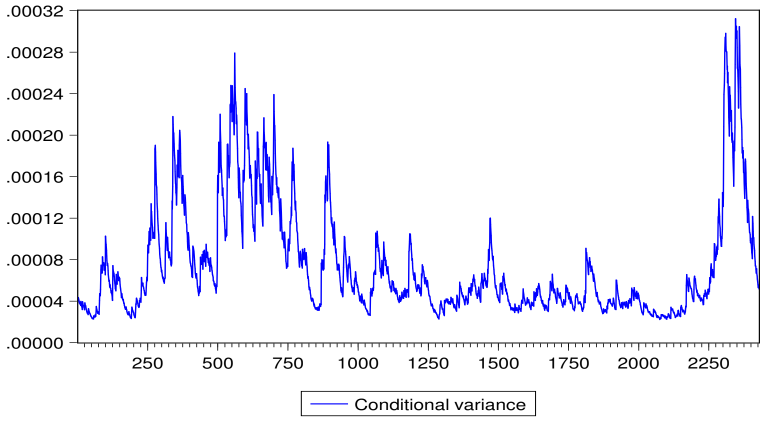

FIGURE 9. Conditional variance of the SZSE Index Part 2

3.8. **GJR model and EGARCH Model.** The above fitting results of GARCH(1,1) models indicate the autocorrelation of conditional variances of error term ϵ_t and describe the relationship between them and their lag terms. However, the leverage effects could not been detected by GARCH model. We use asymmetric econometric models, such as GJR model and EGARCH model to detect the leverage effects in SSE and SZSE in different parts of them (except part 1 of SSE).

The results are displayed in Tables 8-9, it can be observed that the coefficient γ in the EGARCH model is negative for both indices, which indicates that there are leverage effects in different parts of SSE and SZSE, This also states that a negative shock has a greater impact than a positive shock. Similarly, in the GJR model, the coefficient γ of the dummy variable is significantly different from zero, which again indicates that a negative shock has a greater impact than a positive shock. Thus, we find evidence of leverage effects, and they are considerably significant.

TABLE 8. The Results of GJR model in SZSE and SSE

Index	α_0(constant)	$\alpha_1(\epsilon_{t-1}^2)$	$\beta(\delta_{t-1}^2)$	$\gamma(\epsilon_{t-1}^2 * d_{t-1})$
SSE Part 2	6.34E-07	0.060505	0.914342	0.028537
SZSE Part 1	1.09E-06	0.106464	0.860487	0.045424
SZSE Part 2	8.39E-07	0.057873	0.926913	0.007522

TABLE 9. The Results of EGARCH model in SZSE and SSE

Index	ω(constant)	$\alpha(\lvert\epsilon_{t-1}/\delta_{t-1}\rvert)$	$\beta(\delta_{t-1}^2)$	$\gamma(\epsilon_{t-1}/\delta_{t-1})$
SSE Part 2	-0.271503	0.166365	0.985304	-0.024467
SZSE Part 1	-0.449794	0.254575	0.974059	-0.022397
SZSE Part 2	-0.242538	0.140949	0.986092	-0.014676

4. **Correlation Detection Between SSE and SZSE Based on VAR Model.** We have analyzed different parts of SSE and SZSE and have found different characteristics in the developing and developed parts of each stock market. The interaction relationship between SSE and SZSE in the past 20 years can be explored by the VAR model, In particular, we use impulse response analysis and variance decomposition to detect the

correlation between SSE and SZSE during the period from Dec. 19, 1995 to Dec. 31, 2015.

A VAR model allows all the variables to be endogenous. We run a VAR model for detecting the correlation. We fit the extent to which unpredictable changes or innovations are determined with respect to these two stock markets. In general, a VAR model is of the form:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + BX_t + \epsilon_t, \tag{11}$$

where $Y_t = m \times 1$ is a vector of endogenous variables, $X_t = q \times 1$ is a vector of deterministic and exogenous variables,A_i and B are $m \times m$ and $q \times q$ coefficient matrices, respectively. The following function presents a VAR(5) model for the indices of SSE and SZSE during the period from Dec. 19, 1995 to Dec. 31, 2015. In the VAR specification we end up with five lags in the estimations based on the lag order selection. The VAR test result is displayed in Table 10, the results indicate the model is appropriate.

$$\begin{aligned}\begin{bmatrix} SSE \\ SZSE \end{bmatrix}_t &= \begin{bmatrix} 0.0002 \\ 0.0003 \end{bmatrix} + \begin{bmatrix} 0.0714 & -0.0508 \\ -0.0251 & 0.08 \end{bmatrix} \begin{bmatrix} SSE \\ SZSE \end{bmatrix}_{t-1} \\ &+ \begin{bmatrix} 0.0222 & -0.045 \\ -0.0299 & -0.0419 \end{bmatrix} \begin{bmatrix} SSE \\ SZSE \end{bmatrix}_{t-2} + \begin{bmatrix} 0.0896 & -0.0423 \\ -0.0434 & 0.0237 \end{bmatrix} \begin{bmatrix} SSE \\ SZSE \end{bmatrix}_{t-3} \\ &+ \begin{bmatrix} 0.001 & 0.0393 \\ 0.0678 & -0.016 \end{bmatrix} \begin{bmatrix} SSE \\ SZSE \end{bmatrix}_{t-4} + \begin{bmatrix} 0.04588 & -0.0385 \\ 0.1664 & -0.1259 \end{bmatrix} \begin{bmatrix} SSE \\ SZSE \end{bmatrix}_{t-5} + \begin{bmatrix} \hat{\varepsilon_1} \\ \hat{\varepsilon_2} \end{bmatrix}.\end{aligned}$$

The model diagnostics is shown in Figure 10 and the residual correlation matrix is shown in Table 11. The unit root test result shows that VAR model is stationary and high correlation between SSE and SZSE, which is 0.901655. However, we only find a few significant variables in the VAR estimations, and the R^2s is not high. To analyze the interaction between the two stock markets, we ran an impulse response analysis and variance decomposition analysis. In an impulse response analysis one tries to

TABLE 10. VAR Test Statistics

	SSE	SZSE
R-squared	0.007578	0.015534
Adj. R-squared	0.005527	0.013500
Sum sq. resids	0.274629	0.327925
F-statistics	3.695070	7.635484
Log Likelihood	16832.39	16402.28
Akaike AIC	-6.936655	-6.759290
Schwarz SC	-6.921943	-6.744578

determine the impact of an unexpected change (shock) in one variable on the variable itself and on the rest of the variables in the VAR model over time. Variance decomposition measures how much of the variance of the variable in question is based on different shocks and it thus helps to analyze the exogeneity of the variables.

Figures 11-12 show the generalized impulse responses and the accumulated impulse response functions between SSE and SZSE. The point impulse responses are all not statistically significant and die out to zero after 7 days. However, the accumulated impulse responses are statistically significant, and tend to non-zero constants. We have a stable process and the VAR model is applicable. That is, the cumulative between SSE and SZSE

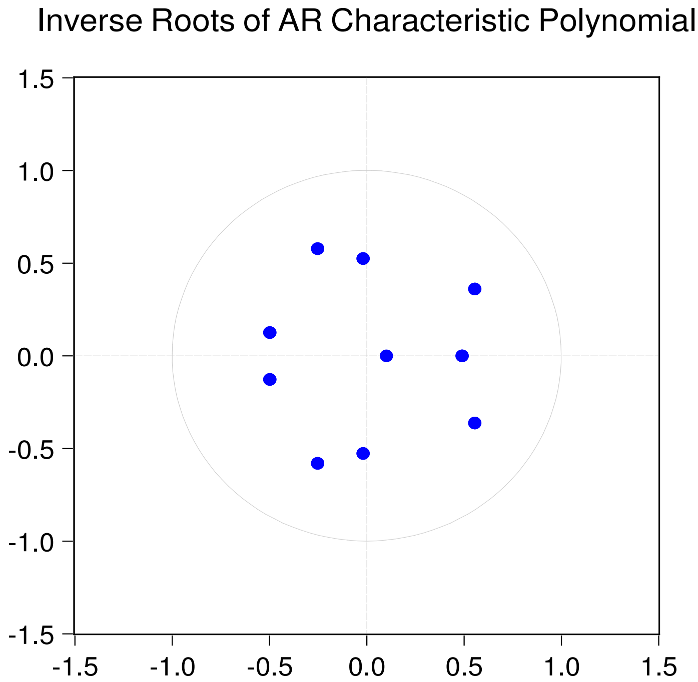

FIGURE 10. The Unit Root Test result of VAR(5) model.

TABLE 11. Residual Correlations of VAR

	SSE	SZSE
SSE	1.0000	0.901655
SZSE	0.901655	1.0000

are finite and measurable, except the cumulative effects of SSE to SZSE are negative, they are all positive.

The variance decomposition result is displayed in Table 12. It shows the shares of information that each variable contributes to the others. Variance decomposition reveals two interesting results. First, the results show, in line with the impulse responses, a rather stable process. The decomposition of the variances stabilizes after 7 periods: that is, there is no statistically significant difference from period 7 to period 10 in variance decompositions. Second, we observe that SZSE has relatively small contributes to SSE, but SSE has strong effect on SZSE.

5. **Conclusion.** In this paper, we calculate and compare the descriptive statistics for the volatilities of the returns for the two Chines stock markets at different phases. We fit the volatilities at different phases for SSE and SZSE using GARCH, EGARCH, GJR. We also investigate the correlation between the two markets by impulse response and variance decomposition analyses using VAR models. As it can be seen from the results that volatilities of the stock markets have increased as the markets become more and more globalizing. Means of the return series of both stock markets are positive. However the mean return at developing phase is significantly larger than the developed phase at each stock market. This phenomenon signifies the higher scope of growth in the developing phases. Similarly, the markets are positively skewed in the developing phase whereas

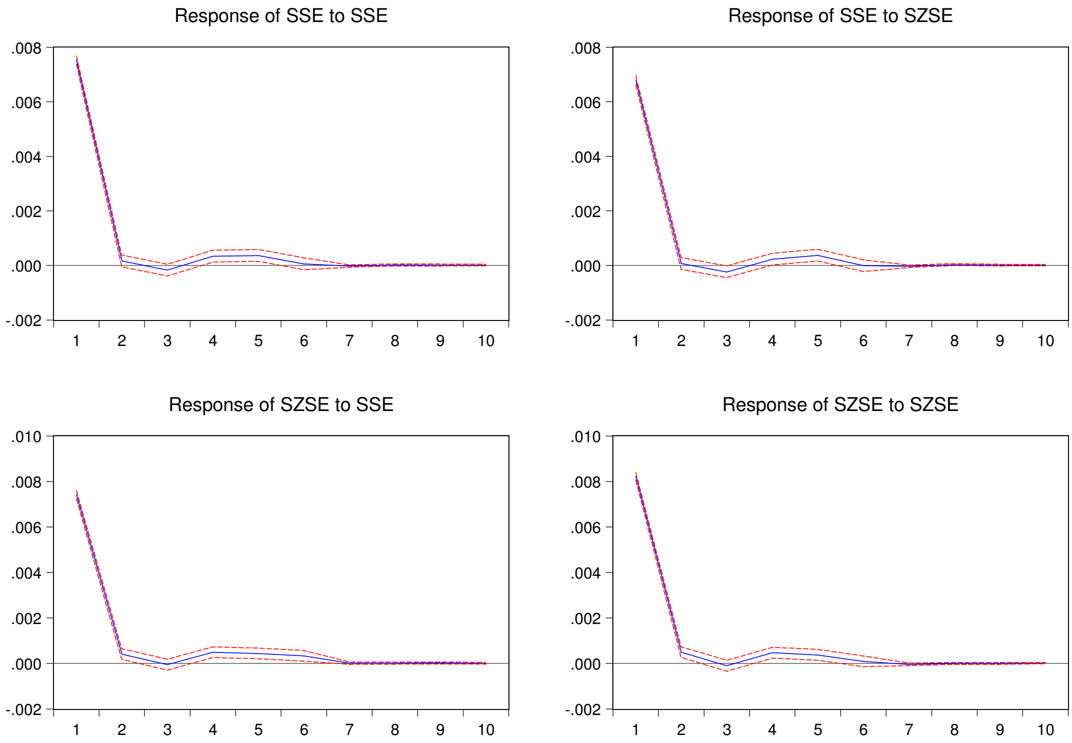

FIGURE 11. Responses of generalized one standard-deviation innovations and confidence intervals.

TABLE 12. Variance decomposition Result

Variance decomposition of SSE				Variance decomposition of SZSE		
Period	S.E.	SSE	SZSE	S.E.	SSE	SZSE
1	0.00753	100.000	0.000	0.00823	81.298	18.702
2	0.00757	99.942	0.058	0.00825	81.246	18.754
3	0.00754	99.880	0.120	0.00825	81.230	18.770
4	0.00755	99.827	0.173	0.00826	81.291	18.709
5	0.00756	99.812	0.188	0.00828	81.340	18.660
6	0.00756	99.779	0.221	0.00830	81.085	18.915
7	0.00756	99.778	0.222	0.00830	81.070	18.930
8	0.00756	99.776	0.224	0.00830	81.070	18.930
9	0.00756	99.776	0.224	0.00830	81.070	18.930
10	0.00756	99.776	0.224	0.00830	81.070	18.930

negatively skewed in the developed phase again signifying the effect of growth of the market in the returns.

Once the volatility clustering is confirmed, the GARCH(1,1) model and its extensions are used to fit both indices. Our results show that the sum of the coefficients in the GARCH(1,1) model is close to one in almost all cases. That implies persistence of the conditional variance. A large sum of the coefficients in the conditional variance equations implies that a large positive or a large negative return will lead to future forecasts of the variance to be high. Finally, the fits of the persistence in the long run component are significant, indicating that the long run component converges very slowly to the steady

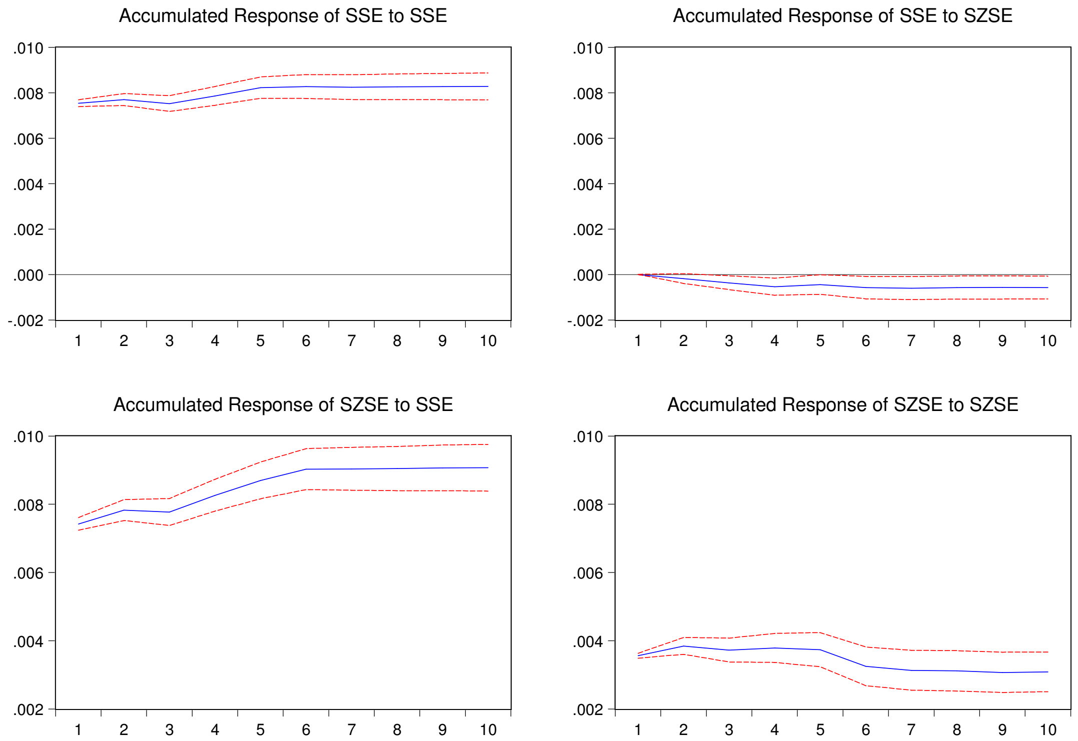

FIGURE 12. Accumulated responses of generalized onetandard-deviation innovations.

state. In both markets, volatilities tend to die out slowly. Our results suggest that the volatility is a little more persistent in the Shanghai stock market than the Shenzhen stock market.

The results obtained using impulse response analysis and variance decomposition analysis based on VAR(5) model show that the one standard-deviation innovation impulse die out after 7 days in the two markets. The results also show that the impact of the SSE on the SZSE is stronger than that of the SZSE on the SSE.

These findings provide useful recommendations to financial managers and modelers dealing with the Chinese stock markets. Future research should examine the performance of multivariate time series models using daily returns of international mature and emerging markets.

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