Volatility Spillovers between the US and the China Stock Market: Structural Break Test with Symmetric and Asymmetric GARCH Approach

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Abstract

The paper examines the short-run spillover effect of daily stock returns and volatilities between the S&P 500 in the U.S. and Shanghai SSE composite in China. First, we find that a structural break happened in the SSE stock return mean in December 2005. Second, analyzing modified GARCH (1,1)-M models, we find evidence of a symmetric and asymmetric volatility spillover effect from the U.S. to the China stock market in the post-break period. Third, the symmetric volatility spillover effect from China to the U.S. is also observed in the post-break period.

JEL Classification: C22; F30; N20

Keywords: Volatility Spillover; China Stock Market; Structural Break; CARCH Model

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Abstract

The paper examines the short-run spillover effect of daily stock returns and volatilities between the S&P 500 in the U.S. and Shanghai SSE composite in China. First, we find that a structural break happened in the SSE stock return mean in December 2005. Second, analyzing modified GARCH (1,1)-M models, we find evidence of a symmetric and asymmetric volatility spillover effect from the U.S. to the China stock market in the post-break period. Third, the symmetric volatility spillover effect from China to the U.S. is also observed in the post-break period.

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1. Introduction

International stock market transmission among developed markets has been widely documented. For example, Eun and Shim (1989), Hamao, Masulis, and Ng (1990), and Barclay, Litzenberger, and Warner (1990) suggest that major stock market returns and volatilities are interdependent and there are information spillover effects from the U.S. to other developed markets. Over the past decades, emerging markets have been getting more and more attention in the integrating globalized stock market. As the interest in emerging stock markets is growing, there has been rising literature of the international transmission and spillover of stock returns and volatilities between developed and emerging markets. Chou, Lin, and Wu (1999) find conventional evidence that stock volatility spillovers from the US, a major developed country, to Taiwan, a relatively small emerging market. Miyakoshi (2003) investigates how the Asian stock markets are influenced by the main regional market – Japan stock market as well as the main global market – the US stock market. He finds that there are return spillovers from the US to the Asian emerging markets and volatility spillover from Japan to Asian markets. Chan, Lien and Weng (2008) examine the interactions between Hong Kong and the US financial markets for the periods of the pre and post Asian financial crisis.

Recently, China's stock market becomes playing a more important role in the emerging markets because of its large economic scale and impressive economic growth. However, there is little literature regarding spillover effect between China and developed counties. There are few exceptions. For example, Johansson and Ljungwall (2009) use multivariate general autoregressive conditional heteroscedasticity (GARCH) model to explore the linkages and spillover effects among China, Hong Kong and Taiwan. However, their focus is only on closely related Greater China region. Li (2007) use multivariate GARCH model to examine the linkages among the China and the US stock markets. He finds that there is no direct spillover between the US and China stock markets. However, he uses the data from January 2000 to August 2005, which misses the structural reform in China stock exchanges happened in the end of 2005. Therefore, Li (2007)'s sample fails to cover the post-2005 period, which is less restricted, more transparent, dynamic, and more representative for modern China stock market. Using dynamic conditional correlation (DCC) model, Lin, Menkveld, and Yang (2009) study the correlation between the China and the world stock markets. They find no evidence of an increasing trend of correlation from 1993 to 2006.

In this paper, we use the GARCH models to test the information spillover effect of stock market returns and volatilities between the U.S. Standard & Poor's (S&P) 500 stock index and China Shanghai Stock index (SSE) from January 1999 through June 2007. The more important contribution of the paper is that we extend the methodology to test for parameter stability and use structural break test to endogenously find the breakdate and choose the appropriate subsample. Using the structural break test, we identify the breakdate happened in December 2005 in China SSE stock market. This step is particularly important given the fact that in our sample the phenomenal change of stock returns are observed in SSE market while we are not certain the exact time of the structural change. This is an improvement over the ad-hoc methods employed in the earlier studies.

In addition to the conventional method, which only investigates the symmetric spillover effects on mean and volatility, we modify the GJR-GARCH model from the domestic to the cross-border leverage/asymmetric spillover perspective. This study finds that the unexpected volatility in the US S&P 500 stock return has no significant spillover effect on the volatility of China's SSE composite returns during the pre-break period. Our finding is consistent with Li (2007), which covers the similar period. During the post-break period, however, S&P 500 stock return has both significant symmetric and asymmetric spillover effects on the volatility of China's SSE composite returns. More importantly, we find that the spillover effect has unconventional opposite effect in terms of the sign of volatility shock. In other words, the unexpected rising volatilities from the US will reduce the volatilities in China stock market during the post-break period. To explain this abnormity, we use the modified GJR-GARCH model and find that bad news from the U.S. would increase China's stock return volatilities while good news from the U.S. would reduce China's stock return volatilities. Furthermore, this study finds that there is also a significant symmetric volatility spillover effect from China's SSE to the U.S.'s S&P500 returns in the post-break period.

The rest of the paper is organized as follows: Section 2 discusses the data and conducts the structural break test. Section 3 explains the models employed. Section 4 presents the empirical results. Section 5 concludes.

2. Data

2.1. Data Description

We examine daily stock returns series over the eight-year period from January 5, 1999 through June 12, 2007, with a total of 1,527 observations. The data used are from *Global Financial Data*. We use daily closing prices (close-to-close returns) from the stock market indices to compute daily rate of returns in two countries: the U.S. and China. For the U.S. (New York) stock market, we adopt the Standard & Poor's 500 Composite Index. The S&P 500 is a market value weighted index, which is widely accepted as an ideal proxy for the total U.S. market. For the China's stock market, we adopt Shanghai Stock Exchange (SSE) composite index. The SSE composite index is a market value weighted index, which includes all the listed stocks in SSE.[3] The market capitalization of Shanghai Stock Exchange has been growing significantly over the past two years. For example, its market value has raised from $402 billion on December 30, 2005, $1,362 billion on December 29, 2006, to $2,324 billion on May 31, 2007.[4]

The New York stock market opens at 9:30 and closes at 16:00 in Eastern Standard Time (EST). Shanghai stock market opens at 20:30 EST, and closes at 2:00 EST next day with a lunch break between 22:30 and 24:00 EST. Therefore, trading activities in these markets are not concurrent. This provides us the reason to use univariate GARCH model (in the following section) to treat the counterpart market as exogenous variables in both mean and variance equations. The advantage of univariate GARCH rather than multivariate GARCH model in this paper provides us more flexible setting to see the asymmetric effect. Figure 1 shows these stock indices in the whole sample period. The second columns of Table 1 and Table 2 display the

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[3] In SSE, stocks are divided into A Shares and B Shares, with A Shares limited to domestic investors while B Shares available to both domestic and foreign investors. However, since November 5, 2002, qualified foreign institutions have been allowed to invest and trade A Shares via special accounts opened at designated custodian banks. As of October 14, 2004, a total of 25 foreign institutions have received Qualified Foreign Institutional Investor (QFII) licenses with quotas ranging from $50 million to $800 million. By the end of 2006, there are 832 A Shares and 54 B Shares.

[4] The data is from *Global Financial Data*.

summary statistics, including the mean, standard deviation, skewness, and excess kurtosis of S&P 500 and SSE stock returns over the whole sample period, respectively. SSE return series has higher return mean (0.0007) than the S&P 500 (0.0002). SSE also has higher volatility and excess kurtosis, which means it has heavier tails and sharper peaks at the center compared to the S&P500. Figure 2 presents the stock returns. China's stock market has risen substantially since 2006. Therefore, it is necessary to conduct a structural break test on return means to check the sample stability before we move to advanced model estimations.

2.2. Structural Break Test

It is well known that the parameter stability condition of the model should be satisfied in order to avoid a spurious inference and to get stable forecasts. For example, Stock and Watson (1996) find that there is substantial instability in a significant fraction of macroeconomic time series models. Also, some studies, such as Hamao et al. (1990), Lin, Engle, and Ito (1994), and Lee and Rui (2002) presume that the 1987 stock market crash is a breakdate and use it as the model subsample point. Quandt (1960) provides a method to detect the unknown single structural breakdate. The *sup* statistic is simply the maximum of the individual Chow *F*-statistics,

$$\sup F = \max_{\tau_1 \le \tau \le \tau_2} (F(\tau)) \tag{1}$$

where the Chow F statistic is $((\tilde{u}'\tilde{u} - (u_1'u_1 + u_2'u_2))/(u_1'u_1 + u_2'u_2) \times (T - 2k)/k$; $\tilde{u}'\tilde{u}$ is the restricted sum of squared residuals; $u_i'u_i$ is the sum of squared residuals from subsample i; T is the total number of observations; and k is the number of parameters in the equation. Because the breakdate is an unknown prior, the chi-square critical values are inappropriate. The problem was solved by Andrews (1993), Andrews and Ploberger (1994),[5] and Hansen (1997). Andrews and Ploberger provide tables of critical values and Hansen provides a method to calculate *p*-values. Because the distribution of these statistics becomes degenerate as τ_1 and τ_2 approaches the beginning or the end of the sample, it is generally suggested to exclude both ends of the sample. We therefore trim the first and last 15% of the observations, which is conventional setting for the structural break test.

The structural break test for S&P 500 and SSE stock returns is as follows,

$$\begin{aligned} & r_t = \mu_0 + \mu_1 D_t + \varepsilon_t \qquad \varepsilon_t \sim i.i.d(0, \sigma_t^2) \\ & D_t = 0 \quad for\ t < \tau; \quad D_t = 1 \quad for\ t \geq \tau \end{aligned} \tag{2}$$

where τ is the structural breakdate. Before the breakdate, the return mean is μ_0 while after the breakdate, the return mean is $\mu_0 + \mu_1$. Table 4 presents the breakdate test result. On S&P 500 returns, for all three of summary statistic measures fail to reject the null hypothesis of no structural breaks within the sample. On SSE return, however, for all the summary statistics, they all reject the null hypothesis of no structural breaks within the sample. The maximum statistic is on December 2, 2005. Figure 3 illustrates the series of *F*-statistic and the Andrews 5% critical value, which is 11.79 when the parameter of the model is one. We can see that no *F*-statistic exceeds the Andrews critical value for the S&P 500, while for SSE returns, the maximum *F*-statistic (15.6298) easily exceeds the Andrews critical value. That said, the SSE stock return series has a mean structural break and it is on December 2, 2005.

We offer two potential explanations for the break in the China stock market. The first one could be a series of non-tradable share reforms since 2005. On April 29,

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[5]Andrews and Ploberger (1994) suggest that we could improve the power by taking exponential and averages of the Chow test series.

2005, China Securities Regulatory Commission (CSRC) issued *the Circular on Relevant Issues Concerning the Pilot Reform of Non-tradable Shares of Listed Companies*, which began the reform of state-owned non-tradable shares. The reform was implemented from then until December 12, 2005, when SSE indices were set to reshuffle on the first day in 2006. In other words, the estimated structural break of SSE on December 2, 2005 appeared amid a series of China's share structural reforms. The result is consistent with the conventional prediction that emerging stock market liberalization may reduce the cost of equity capital by allowing for risk sharing between domestic and foreign agents (Henry 2000).

Second, on July 21, 2005, the Chinese currency (Renminbi) exchange rate was revalued to 8.11 per U.S. dollar after a decade of fixed-exchange rate regime pegged to 8.28 Renminbi per dollar. Since December, 2005, the Renminbi has been appreciated against dollar slowly and gradually under the intervention of People's Bank of China (Chinese central bank). As Roubini (2007) suggests, the policy of partially sterilized intervention creates excessive liquidity credit and asset bubbles. The managed intervention of slowing down the speed of Renminbi's appreciation creates an expectation and attracts the capital inflow. This speculation funds the stock market indirectly (Xu, 2008).

2.3. Autocorrelations and Cross-correlations of Returns

The sample autocorrelations for S&P 500 index returns and squared returns are presented in Table 1. By and large, most results of autocorrelations for squared returns are different from zero. Lag 1 of full sample and pre-break sample has negative serial correlations at the 10% significant level. Lag 3 and lag 4 of all samples show negative serial correlations at least at 10% significant level. Most sample autocorrelations of squared returns reject the null hypothesis of no autocorrelations at the 1% significant level in the whole sample period and pre-break period.

Table 2 shows the autocorrelations for SSE composite index returns and squared returns. The strong negative autocorrelations of returns appear at lag 4 for the full and pre-break samples, and at lag 1 of post-break sample. The significant autocorrelations for lag 1 could be explained by momentum effect. Our following model setting will consider this effect. The significant autocorrelations for lag 4 could be explained by the day-of-the-week effect (Cai, Li, and Qi, 2006). Although it is significant, it is not the main focus of this study and it will not affect our model setting as well as spillover effect results. Similar to the S&P 500, we also get consistent serial correlations for squared returns in the full sample and pre-break period. The existence of autocorrelation coefficients for the squared returns would be the evidence of volatility dependence in both S&P 500 returns and SSE composite returns. The autoregressive conditional heteroskedastic (ARCH) models developed by Engle (1982) and generalized ARCH (GARCH) developed by Bollerslev (1986) could approximate these second-order nonlinear processes by allowing the first and second moments of the returns to depend on its past values. This paper employs such models to catch the characteristics of returns generating processes.

Table 3 shows the average daily cross-correlations between S&P 500 returns and SSE composite returns for up to six leads and lags for the three sample periods. Negative lags ($k < 0$) indicate cross-correlations between past SSE composite index returns and current S&P 500 index returns. Positive lags ($k > 0$) indicate cross-correlations between past S&P 500 index returns and current SSE composite index returns. Most of the cross-correlations coefficients are not zero. Negative lags 3 and 4 of full and pre-break samples show the lead from S&P 500 index returns to SSE composite index returns. However, the SSE composite index returns lead the S&P 500 index returns at positive lag 1 of the post-break sample.

The cross-correlation coefficients for the squared returns are also computed and displayed in Table 3. These results represent an approximate measure of intermarket association of volatility. Most cross-correlations are greater than zero. In particular, the strong lead from SSE composite index squared returns to S&P 500 index squared returns appears at positive lags of post-break sample. Basically, these preliminary results suggest that the lead and lag relationship tend to exist in volatilities of S&P 500 index and SSE composite index. That said, stock return volatility is predictable. Therefore we could employ GARCH family models to investigate their first and second moment relations.

3. Methodology

Because of the summary statistics in Section 2, including non-zero skewness, excess kurtosis, autocorrelations and cross-correlations, it is reasonable to employ GARCH family models following Bollerslev (1986). They can catch both the time variation in the volatility of S&P 500 returns, SSE composite returns and the intermarket dependence of the returns and return volatilities between S&P 500 and SSE composite index. In this paper, we estimate three models from the rich GARCH family.

3.1. GARCH-M Model

First, we use the univariate GARCH(1,1)-M model[6] developed by Engle, Lilien, and Robins (1987) as a benchmark model,

$$r_t = \alpha + \beta h_t + \varepsilon_t \qquad \text{where } \varepsilon_t \mid \Phi_{t-1} \sim N(0, h_t)$$

$$h_t = a + b h_{t-1} + c\varepsilon_{t-1}^2 \tag{3}$$

where r_t is the daily return and h_t is the conditional variance. In the mean equation, the return is dependent on the conditional variance because of the existence of risk premium. Using GARCH(1,1)-M model, for example, French, Schwert, and Stambaugh (1987) find the stock return is related to its stock return volatility. In the volatility equation, the conditional variance is a function of its last period's variance and last period's squared errors. The sum of the coefficients of the lagged errors (GARCH term) and lagged conditional variances (ARCH term) should be less than one to confirm the stability of the volatility process.

3.2. Symmetric Spillover GARCH-M Model

Second, to assess the symmetric spillover effect between the S&P 500 index returns and SSE composite index returns, we expanded the benchmark model to univariate AR(1)-GARCH(1,1)-M by introducing two exogenous variables into the model as follows

$$r_{i,t} = \alpha + \beta h_{i,t} + \delta r_{i,t-1} + \gamma Y_{j,t-1} + \varepsilon_{i,t} \qquad \text{where } \varepsilon_{i,t} \mid \Phi_{t-1} \sim N(0, h_{i,t})$$

$$h_{i,t} = a + b h_{i,t-1} + c\varepsilon_{i,t-1}^2 + dX_{j,t-1} \tag{4}$$

[6] It denotes GARCH in mean model. We find GARCH(1,1)-M is superior to other specifications of lags for GARCH(*p*, *q*) model in term of log-likelihood value.

where $r_{i,t}$ is the domestic daily return and exogenous variable ($Y_{j,t}$) is the previous (lagged) daily return of the counterpart stock market. $Y_{j,t}$ in the mean equation would therefore catch the mean spillover effect between two countries' stock markets. Following the summary statistics in Table 1 and 2, the mean equation models the return as an AR(1) process.[7] It is well known that the nonsynchronous trading, bid-ask spreads, and limited price changes can cause serial correlation in stock returns. Therefore, it would increase the log-likelihood value for the model specification by introducing AR(1) in the mean equation.

We use a two-stage procedure in the volatility equation. In the first stage, we estimate the unexpected volatility ($X_{j,t}$), which is the most recent squared residual from the counterpart stock market based on the benchmark model in equation (3). In the second stage, we use $X_{j,t}$ as an exogenous volatility surprise to investigate the interdependence of volatilities between the US and China market. Consequently, the exogenous variable X_t in the volatility equation will catch the potential volatility spillover effect from one country to another. In sum, if coefficients (γ and d) of both exogenous variables are significant, the spillover effects between two markets exist.

3.3. Asymmetric Spillover GJR-GARCH-M model

Third, to understand if one stock market has a different response of return to the bad news and good news from another stock market, we extend the AR(1)-GARCH(1,1)-M model to the AR(1)-GJR-GARCH(1,1)-M model, introduced by

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[7] Chan, Chan, and Karolyi (1991) use AR(1) in the mean equation as well while Bollerslev (1987) and French, Schwert, and Stambaugh (1987) use MA(1) in their mean equations for the same reason.

Glosten, Jagannathan, and Runkle (1993) to catch the asymmetric spillover effects. The GJR-GARCH model is also called threshold GARCH model, which is popular and practical in volatility models. For example, Poon and Granger (2003) suggest that asymmetric models perform better than the GARCH model. Engle and Ng (1993) argue that the GJR model is a better parametric model than another popular asymmetric GARCH model – Exponential GARCH (EGARCH) introduced by Nelson (1991). It is worth noting that our model is partially different from the GJR model, in which their asymmetric effect is from the domestic market per se while the asymmetric source in our modified model is from the foreign market. Our model is

$$r_{i,t} = \alpha + \beta h_{i,t} + \delta r_{i,t-1} + \gamma Y_{j,t-1} + \varepsilon_{i,t} \qquad \text{where } \varepsilon_{i,t} \mid \Phi_{t-1} \sim N(0, h_{i,t})$$

$$h_{i,t} = a + b h_{i,t-1} + c\varepsilon_{i,t-1}^2 + dX_{j,t-1} + kS_{j,t-1}X_{j,t-1} \tag{5}$$

where the dummy variable S_t keeps track of whether the lagged residual error of the counterpart market is positive or negative. When the residual error is negative, which means bad news abroad, S_t =1. Otherwise, S_t is zero. If the coefficient (k) is significant, it implies that there is asymmetric information spillover effect from one market to the other market. Compared to good news, bad news happening in one market increases the volatility of the other market.

We used the nonlinear optimization techniques to get the maximum-likelihood estimates of both AR(1)-GARCH(1,1)-M model and AR(1)-GJR-GARCH(1,1)-M model, based on the Berndt-Hall-Hall-Hausman algorithm (Berndt et al. 1974). The Ljung-Box (LB) statistic is used as a primary model specification test with the null hypothesis of no serial correlation of model normalized residuals and squared residuals. Tests of Skewness and Kurtosis coefficients for the normalized residuals are provided as well. The likelihood ratio (LR) statistic, which follows chi-square distribution is employed as a robustness check of model specification.

4. Empirical Results

4.1. GARCH-M Model

Table 5 and Table 6 show the results of the estimation of the benchmark GARCH(1,1)-M model for S&P 500 and SSE composite daily returns, respectively. The likelihood ratio [LR(3)] statistic tests the null hypothesis that the returns are normally distributed against the alternative that they are generated by a GARCH(1,1)-M model. Test statistics are significant at 1% level in both markets. The null hypothesis is rejected. The model is well specified. For instance, none of the Ljung-Box values for the first 12 normalized residuals or squared residuals is significant except the statistic for normalized residuals of the post-break of S&P 500 returns. And most coefficients of skewness and kurtosis of normalized residuals are not considerably different from standard levels. The sum of coefficient of the lagged error (GARCH-term) and coefficient of the lagged conditional variances (ARCH-term) is less than 1 giving the stability of the volatility process. Finally, we can see that the conditional variance has a significant effect on the conditional mean for S&P 500 in the whole sample ($\beta = 17.603$) while this risk premium effect on mean equation is not significant in China's SSE composite returns during the whole sample period.

4.2. Symmetric Spillover GARCH-M Model

In Table 7 and 8, we consider the possibility of an information spillover effect between S&P 500 and SSE composite returns by using AR(1)-GARCH(1,1)-M model, which has two exogenous variables in both conditional mean equation and variance equation. The likelihood ratio [LR(6)] statistics are significant at the 1 percent level in all samples. Ljung-Box values of whole tests, including the first 12 normalized residuals or squared residuals are not significant at conventional levels except one (normalized residuals in post-break period in Table 8). That said, the model is well specified. From Table 7, we cannot find significant information spillover effect from S&P 500 returns to SSE composite returns, based on the coefficients (γ = 0.0339, 0.0349, 0.1162) in the mean equation for all three sample periods. We do find the information spillover effect from the US to China according to the coefficients [*d* = -0.0071 (*t*-stat: -1.79), -0.1895 (*t*-stat: -6.83)] from the variance equation through full sample and post-break sample at 10% and 1% significant levels, respectively. However, it is surprising and puzzling to see the coefficient of significant volatility spillover effect is negative. In other words, the unexpected volatility in the U.S. would reduce the China's stock return volatilities. This counterintuitive sign has rarely been discussed in the previous literature. We will discuss it in the following model. It is noteworthy that although we find the negative volatility spillover effect from the U.S. to China in the whole sample period, it is mainly from the post-break period. There is no significant volatility spillover effect from the U.S. to China in the pre-break period.

Table 8 shows the information spillover effect from SSE composite returns to S&P 500 returns. The evidence does not indicate any information spillover effect from SSE to S&P 500 at the conditional mean equation through all three sample periods. Although there is no informational spillover effect in the variance equation from the SSE to the S&P 500 in the whole sample period, we do find the volatility spillover effect from the SSE to the S&P 500 with the 5% significant coefficient (*d* =

0.0129) of the post-break period. In other words, in the post-break period, China's stock market plays a more important role and has more informational influence on the U.S. stock market. But we cannot exclude the possibility that this volatility spillover effect is partially caused from Japan or other Asian stock markets.

4.3. Asymmetric Spillover GJR-GARCH-M Model

The asymmetric information spillover effects between two observed stock markets are estimated by AR(1)-GJR-GARCH(1,1)-M model and the result are shown in Table 9 and 10. The likelihood ratio [LR(7)] statistics support the model specification in all sample periods. In addition, most Ljung-Box values of the first 12 normalized residuals or residuals squared are not statistically significant at conventional levels. In Table 9, first, we find the significant information spillover effect from S&P 500 to SSE at the full sample [*d* = -0.0093 (*t*-stat: -2.12)], pre-break sample (*d* = 0.0003 (*t*-stat: 1.95)], and post-break sample [*d* = -0.2350 (*t*-stat: -2.64)] of the conditional variance equation at 5%, 10%, and 1% significant level, respectively. This result is mostly consistent with our previous model in which there is weaker evidence of positive volatility spillover effect in the pre-break period from the U.S. to China stock market. But we confirm again the puzzling significantly negative volatility spillover effect in the whole sample and post-break period from the U.S. to China.

Second, in spite of the small values of coefficient *k*, we can find the statistically significant asymmetric spillover effect from S&P 500 to SSE in the variance equation in the full sample period (*t*-stat: 194.52) and post-break period (*t*-stat: 10.23) at the 1% significant level. That said, at the full sample and post-break sample, the bad news happening in the U.S. stock market rather than good news has bigger and positive influence on the China stock market through the volatility channel. The result suggests that there is a cross-border leverage effect from the U.S. to the China stock market. Combined with the estimates of *d* and *k*, we could interpret that only good news from the U.S. has a significant negative effect on the China's stock return volatilities. That said, the unexpected positive volatility in the U.S. reduces China's stock volatilities while the negative volatility shock in the U.S. increases China's stock volatilities. It is hard to explain this dichotomy between good news and bad news. One of the possible reasons is that bad news from the U.S., which is a global factor, would increase China's stock volatilities, as the saying goes," U.S. sneezes; world catches cold." God news from the U.S., on the contrary, attracts the global capital and therefore crowds out the fund in China's stock market, which reduces its stock return volatility.

In Table 10, we investigate the symmetric and asymmetric spillover effects from SSE to S&P 500. Though there is no significant volatility spillover symmetric effect from China to the U.S. in the full sample period, we find a significant volatility spillover effect in the post-break period. This is consistent with our second model's result, shown in Table 8. The coefficient (d = 0.0128) in the conditional variance equation during the post-break period is significant at 5% level. It implies that China's stock market has more information influence on the international stock market transmission since December 2005 as its stock exchanges became more liquid, open and influential. For the asymmetric spillover effects from the SSE to the S&P 500 index returns, we find it is not significant in the full sample period and post-break period. Although it is still hard to explain why there is a significant asymmetric spillover effect in the pre-break period with a counterintuitive sign (*t*-stat: -4.09), the magnitude of the cross-border (from China to the U.S.) leverage effect is much less than that from the U.S. to China in the post-break period (*t*-stat: 10.23).

5. Conclusion

This paper finds the evidence of a structural break on the SSE composite daily return mean from January 5, 1999 through June 12, 2007 in the China stock market. Using Andrews (1993) method, the breakdate is estimated on December 2, 2005. Stock returns mean in the post-break period is much higher than those in the pre-break period. This structural break might explain by two events in China. The first one is the structural reform, particularly on state-owned non-tradable shares, completed by China Securities Regulatory Commission in December 2005. The second one might be the sterilization policy and capital inflows attracted from the regime change of Chinese exchange rate, which has been gradually appreciated against the U.S. dollar since December, 2005 under expectation.

Using the symmetric and asymmetric spillover GARCH models, we find the unexpected volatility in the S&P 500 stock return has both symmetric and asymmetric spillover effects on the volatility of China's SSE composite returns only for the post-break period. More importantly, we find that the spillover effect has unconventional opposite effect in terms of the sign of volatility shock – the unexpected rising volatilities from the US will reduce the volatilities in China stock market during the post-break period. Breaking down the unexpected volatility as good news (positive volatility) and bad news (negative volatility), we argue that bad news from the U.S. will increase China's stock return volatilities, which is consistent with conventional expectation. However, good news from the U.S. will reduce China's stock return volatilities. We argue that good news from the U.S attracts the global capital and therefore crowds out the fund in China's stock market, which reduces its stock return volatility. As the first and second largest economy in terms of purchasing power in the world, the US and China's integration and competition in global capital market will be important in global portfolio management, hedging and trading. Additionally, this study finds that there is also a significant symmetric volatility spillover effect from China's SSE to the U.S.'s S&P500 returns in the post-break period. It implies that China's stock market has more information influence on the international stock market transmission since December 2005 as its stock exchanges became more liquid, open and influential. We suggest that the little spillover effect and correlation between the China and global stock markets from previous findings, such as Li (2007) and Lin, Menkveld, and Yang (2009), will change its nature and magnitude as we have larger post-2005 breakdate sample.

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Table 1

Summary Statistics of the S&P 500 Index Stock Daily Return in the U.S.

Statistic	Total Period 1999.1.5-2007.6.12	Pre-Structural break 1999.1.5-2005.12.1	Post-Structural break 2005.12.2-2007.6.12
Sample Size	1527	1258	269
Mean	0.0002	0.0001	0.0008
Std. Dev.	0.0113	0.0120	0.0067
Skewness	0.2550	0.2918	-0.4224
Excess Kurtosis	5.43	4.9816	6.2638
$\rho(r_t, r_{t-k})$			
1	-0.036*	-0.040*	0.033
2	-0.003	-0.000	-0.061
3	-0.052**	-0.046*	-0.148***
4	-0.052**	-0.045*	-0.169***
5	0.010	0.012	-0.041
6	-0.005	-0.004	-0.038
$\rho(r_t^2, r_{t-k}^2)$			
1	0.124***	0.111***	-0.030
2	0.271***	0.262***	0.003
3	0.189***	0.174***	0.122***
4	0.186***	0.173***	0.038
5	0.166***	0.154***	-0.010
6	0.168***	0.156***	-0.022

Note: The kurtosis coefficient is computed in excess of 3. Autocorrelation coefficients $\rho(r_t, r_{t-k})$, for up to k lags are calculated based on daily returns and autocorrelation coefficients $\rho(r_t^2, r_{t-k}^2)$ are calculated on daily squared returns. Asymptotic standard errors for the autocorrelation coefficients can be approximated as the squared root of the reciprocal of the number of observations under the null hypothesis of no autocorrelations. *, **, and *** represent the coefficients are at least 1.282, 1.645, and 2.325 standard errors from zero, respectively, which approximate 10%, 5%, and 1% significance level, respectively.

Table 2

Summary Statistics of the SSE Composite Index Daily Stock Returns in China

Statistic	Total Period 1999.1.5-2007.6.12	Pre-Structural Break 1999.1.5-2005.12.1	Post-Structural Break 2005.12.2-2007.6.12
Sample Size	1527	1258	269
Mean	0.0007	0.0004	0.0021
Std. Dev.	0.0142	0.0138	0.0160
Skewness	0.2612	0.8180	-1.4818
Excess Kurtosis	8.45	8.5447	8.5461
$\rho(r_t, r_{t-k})$			
1	-0.022	0.002	-0.112***
2	-0.015	-0.032	0.034
3	-0.022	-0.003	-0.098*
4	-0.075***	-0.085***	-0.045
5	-0.012	-0.018	-0.001
6	0.012	0.014	0.001
$\rho(r_t^2, r_{t-k}^2)$			
1	0.091***	0.087***	0.092*
2	0.105***	0.112***	0.078*
3	0.076***	0.061***	0.111***
4	0.043***	0.040***	0.043
5	0.080***	0.108***	-0.009
6	0.042***	0.033	0.060

Note: See Table 1.

Table 3

Cross Correlation Between the S&P 500 Returns and the SSE Composite Returns

Statistic	Total Period 1999.1.5-2007.6.12	Pre-Structural Break 1999.1.5-2005.12.1	Post-Structural Break 2005.12.2-2007.6.12
$\rho(r_{i,t}, r_{j,t-k})$			
-6	0.0143	0.0292	-0.0982*
-5	-0.0279	-0.0244	-0.0583
-4	0.0560**	0.0612**	0.0274
-3	0.0516**	0.0700***	-0.0717
-2	-0.0245	-0.0255	-0.0327
-1	-0.0235	-0.0264	-0.0189
0	0.0210	0.0227	0.0046
1	-0.0114	-0.0341	0.1422***
2	0.0160	0.0072	0.0716
3	-0.0279	-0.0330	0.0051
4	-0.0592***	-0.0435*	-0.2073
5	-0.0111	-0.0041	-0.0586
6	0.0098	0.0186	-0.0698
$\rho(r_{i,t}^2, r_{j,t-k}^2)$			
-6	-0.0201	-0.0137	-0.0293
-5	-0.0327*	-0.0275	-0.0459
-4	-0.0466**	-0.0420	-0.0642
-3	-0.0235	-0.0205	-0.0004
-2	-0.0296*	-0.0292	0.0194
-1	-0.0101	-0.0033	-0.0084
0	-0.0256	-0.0290	0.0677
1	0.0202	-0.0159	0.4972***
2	-0.0339*	-0.0264	-0.0688
3	-0.0290	-0.0377*	0.1082***
4	0.0051	-0.0046	0.1672***
5	-0.0367*	-0.0349*	-0.0398
6	-0.0276	-0.0356	0.0812*

Note: Negative lags (or leads) (*k*) denote cross-correlations between past SSE returns and current S&P 500 returns. Positive lags denote cross correlations between future SSE returns and current S&P 500 returns. *, **, and *** represent 10%, 5%, and 1% significance level, respectively.

Table 4

Structural Break Test of the SSE Composite Index Return

		Value	*P*-Value
	U.S. S&P 500 Returns		
Sup F-Statistic	(No Breakdate)	4.3213	0.2875
Exp F-Statistic		0.5942	0.3739
Ave F-Statistic		0.934	0.3665
	China SSE Returns		
Sup F-Statistic	(Breakdate: Dec 2 , 2005)	15.6298	0.0002
Exp F-Statistic		6.7469	0.0000
Ave F-Statistic		4.0650	0.0179

Note: The Sup F-Stat takes the form $\max_{\tau_1 \le \tau \le \tau_2} (F(\tau))$

The Exp F-Stat takes the form $\ln(\frac{1}{k}\sum_{\tau=\tau_1}^{\tau_2} \exp(\frac{1}{2}F(\tau)))$

The Ave F-State takes the form $\frac{1}{k}\sum_{\tau=\tau_1}^{\tau_2} F(\tau)$

The above test statistics are from Andrews (1993) and Andrews and Ploberger (1994).

The probabilities computed using Hansen’s (1997) method.

Table 5

Estimation of GARCH(1,1)-M Model for S&P 500 Stock Index

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	-0.0010	-1.97**	-0.0003	-0.52	-0.0019	-0.72
β	17.6028	3.71***	6.0586	1.52	62.4899	1.04
a	0.0000	0.97	0.0000	1.45	0.0000	0.89
b	0.9181	51.15***	0.9565	65.83***	0.8765	6.85***
c	0.0659	4.48***	0.0674	4.09***	0.0319	1.06
LR (3) for: $H_0: \beta = b = c = 0$	14501.66***		37189.85***		298.38***	
Coefficient of skewness for normalized residuals	-0.19		-0.06		-0.63	
Coefficient of kurtosis for normalized residuals	4.19		3.75		6.91	
Ljung-Box (12) for normalized residuals	12.54		7.07		26.50**	
Ljung-Box (12) for normalized squared residuals	12.04		13.75		10.07	
Log-likelihood	4859.63		3904.77		967.03	

$$r_t = \alpha + \beta h_t + \varepsilon_t$$

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2$$

where r_t denotes S&P 500 return, h_t denotes conditional variance of r_t. *** and ** indicate significance at the 1% and the 5% levels.

Table 6

Estimation of GARCH(1,1)-M Model for SSE Composite Index

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	0.0002	0.29	-0.0001	-0.18	0.0024	2.12*
β	4.2248	1.35	5.9903	1.77*	-3.1468	-0.61
a	5.05E-06	3.46***	8.19E-06	4.04***	0.0000	1.23
b	0.8658	33.55***	0.8182	25.78***	0.9127	24.45***
c	0.1197	4.52***	0.1508	4.22***	0.0920	2.43**
LR (3) for: $H_0: \beta = b = c = 0$	6484.90***		3868.87***		2782.09***	
Coefficient of skewness for normalized	0.24		0.59		-0.88	
Coefficient of kurtosis for normalized residuals	6.02		6.00		5.18	
Ljung-Box (12) for normalized residuals	11.74		14.05		14.83	
Ljung-Box (12) for normalized squared	10.10		9.09		5.87	
Log-likelihood	4451.38		3699.91		758.12	

$$r_t = \alpha + \beta h_t + \varepsilon_t$$

$$h_t = a + b h_{t-1} + c\varepsilon_{t-1}^2$$

where r_t denotes Shanghai Stock Exchange composite return; h_t denotes conditional variance of r_t. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7

AR(1)-GARCH(1,1)-M Model: Symmetric Spillover from S&P 500 Returns to SSE Composite Returns

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	0.0000	0.05	-0.0002	-0.33	0.0024	1.88*
β	4.8129	1.53	6.3431	1.91*	-1.5401	-0.26
δ	-0.0468	-1.38	-0.0337	-0.84	-0.1518	-2.72***
γ	0.0339	1.51	0.0349	1.5	0.1162	0.99
a	7.07E-06	3.12***	7.69E-06	3.47***	6.50E-06	177.66***
b	0.8576	31.38***	0.8262	25.66***	1.0318	56.13***
c	0.1217	4.53***	0.1447	4.17***	-0.0206	-0.98
d	-0.0071	-1.79*	0.0001	0.82	-0.1895	-6.83***
LR (6) for: $H_0 : \beta = \delta = \gamma = b = c = d = 0$	5489.26***		3747.83***		129321.6***	
Coefficient of skewness for normalized residuals	0.21		0.57		-2.56	
Coefficient of kurtosis for normalized residuals	5.84		5.90		18.45	
Ljung-Box (12) for normalized residuals	12.84		15.76		14.62	
Ljung-Box (12) for normalized squared residuals	11.58		8.99		6.05	
Log-likelihood	4450.84		3698.73		770.26	

$$SSE_t = \alpha + \beta h_t + \delta SSE_{t-1} + \gamma SP500_{t-1} + \varepsilon_t$$

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2 + dX_{t-1}$$

where SSE_t denotes Shanghai Stock Exchange composite index return at time t; $SP500_{t-1}$ denotes S&P 500 index return at t-1, X_{t-1} denotes the most recent squared residual derived from an AR(1)-GARCH(1,1)-M model applied to the S&P 500 index return, and h_t denotes the conditional variance of SSE_t. *** and * indicate significance at the 1% and 10% levels.

Table 8

AR(1)-GARCH(1,1)-M Model: Symmetric Spillover from SSE Composite Returns to S&P 500 Returns

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	0.0003	0.89	-0.0003	-0.64	0.0018	2.01**
β	2.7016	0.74	6.3060	1.62	-27.0526	-1.18
δ	-0.0465	-1.82*	-0.0545	-1.94*	-0.0069	-0.13
γ	0.0109	0.59	-0.0130	-0.66	0.0344	1.21
a	0.0000	0.38	1.09E-06	2.12**	0.0000	0.95
b	0.9300	67.19***	0.9240	61.01***	0.8678	13.30***
c	0.0630	4.43***	0.0694	4.08***	-0.0128	-0.55
d	0.0036	1.25	-0.0003	-0.23	0.0129	2.42**
LR (6) for: $H_0 : \beta = \delta = \gamma = b = c = d = 0$	9028.92***		8423.47***		88.81***	
Coefficient of skewness for normalized residuals	-0.09		-0.08		0.22	
Coefficient of kurtosis for normalized residuals	3.97		3.76		3.73	
Ljung-Box (12) for normalized residuals	10.39		4.64		22.47**	
Ljung-Box (12) for normalized squared residuals	12.76		13.33		9.63	
Log-likelihood	4868.89		3900.77		978.21	

$$SP500_t = \alpha + \beta h_t + \delta SP500_{t-1} + \gamma SSE_{t-1} + \varepsilon_t$$

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2 + dX_{t-1}$$

where $SP500_t$ denotes S&P 500 index return at time t; SSE_{t-1} denotes Shanghai Stock Exchange composite index return at time t-1; X_t denotes the most recent squared residual derived from an AR(1)-GARCH(1,1)-M model applied to the SSE composite index return, and h_t denotes conditional variance of $SP500_t$. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Table 9

AR(1)-GJR-GARCH(1,1)-M Model: Asymmetric Spillover from S&P 500 Returns to SSE Composite Returns

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	0.0043	8.44**	-0.0002	-0.34	0.0014	0.85
β	-16.3431	-4.60***	6.3857	1.95*	3.9134	0.45
δ	-0.0387	-1.20	-0.0357	-0.89	-0.1178	-1.99**
γ	0.0157	0.65	0.0343	1.49	0.1149	0.8851
a	-8.35E-06	-12.36***	0.0000	0.70	1.55E-06	2.17**
b	0.7783	51.70***	0.8063	25.28***	1.0203	41.35***
c	0.1365	6.02***	0.1586	4.43***	0.0067	0.85
d	-0.0093	-2.12**	0.0003	1.95*	-0.2350	-2.64***
k	5.51E-05	194.52***	1.14E-05	1.01	9.57E-07	10.23***
LR (7) for H_0: $\beta=\delta=\gamma=b=c=d=k=0$	9998.89***		495.95***		29466.95***	
Coefficient of skewness for normalized	0.43		0.57		-0.85	
Coefficient of kurtosis for normalized residuals	6.18		5.81		5.74	
Ljung-Box (12) for normalized residuals	10.58		15.61		14.34	
Ljung-Box (12) for normalized squared	13.37		9.22		7.79	
Log-likelihood	4468.13		3699.54		769.41	

$$SSE_t = \alpha + \beta h_t + \delta SSE_{t-1} + \gamma SP500_{t-1} + \varepsilon_t$$

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2 + dX_{t-1} + kS_{t-1}X_{t-1}$$

where SSE_t denotes Shanghai Stock Exchange composite index return at time t; $SP500_{t-1}$ denotes S&P 500 index return at t-1, X_{t-1} denotes the most recent squared residual derived from an AR(1)-GARCH(1,1)-M model applied to the S&P 500 index return, h_t denotes the conditional variance of SSE_t, and S_t = 1 if $\varepsilon_t < 0$ from the S&P500, S_t = 0 otherwise.

***, ** and * indicate significance at the 1%, 5%, and 10% levels.

Table 10

AR(1)-GJR-GARCH(1,1)-M Model: Asymmetric Spillover from SSE Composite Returns to S&P 500 Returns

	Total Period		Pre-Break		Post-Break	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	0.0003	0.88	-0.0003	-0.67	0.0018	2.07**
β	2.7158	0.74	6.4370	1.64	-27.1439	-1.20
δ	-0.0467	-1.82*	-0.0558	-1.98**	-0.0059	-0.11
γ	0.0108	0.59	-0.0133	-0.67	0.0355	1.25
a	0.0000	0.80	2.69E-06	4.92***	0.0000	1.20
b	0.9302	67.94***	0.9226	59.09***	0.8650	12.89***
c	0.0631	4.45***	0.0692	4.15***	-0.0110	-0.47
d	0.0036	1.17	-0.0002	-0.12	0.0128	2.28**
k	-2.73E-07	-0.35	-2.65E-06	-4.09***	-1.61E-06	-0.45
LR (7) for H_0 : $\beta = \delta = \gamma = b = c = d = k = 0$	8637.02***		5468.83***		79.41***	
Coefficient of skewness for normalized	-0.09		-0.07		0.22	
Coefficient of kurtosis for normalized residuals	3.96		3.72		3.70	
Ljung-Box (12) for normalized residuals	10.33		4.69		22.50**	
Ljung-Box (12) for normalized squared	12.67		13.04		9.84	
Log-likelihood	4868.90		3901.20		978.30	

$$SP500_t = \alpha + \beta h_t + \delta SP500_{t-1} + \gamma SSE_{t-1} + \varepsilon_t$$

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2 + dX_{t-1} + kS_{t-1}X_{t-1}$$

where $SP500_t$ denotes S&P 500 index return at time t; SSE_{t-1} denotes Shanghai Stock Exchange composite index return at term t-1; X_t denotes the most recent squared residual derived from an AR(1)-GARCH(1,1)-M model applied to the SSE composite index return; h_t denotes the conditional variance of SSE_t, and S_t = 1 if $\varepsilon_t < 0$ from the SSE, S_t = 0 otherwise. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Figure 1

The Price Trends of the S&P 500 Index and the SSE Composite Index

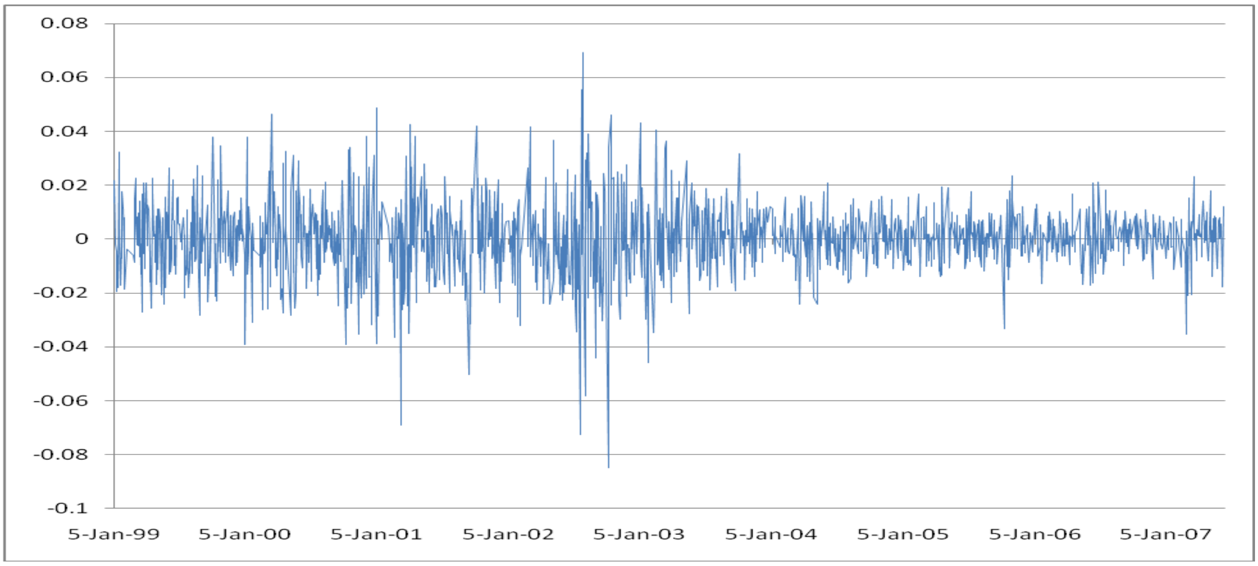

Figure 2. A

The S&P 500 Stock Returns Time Series

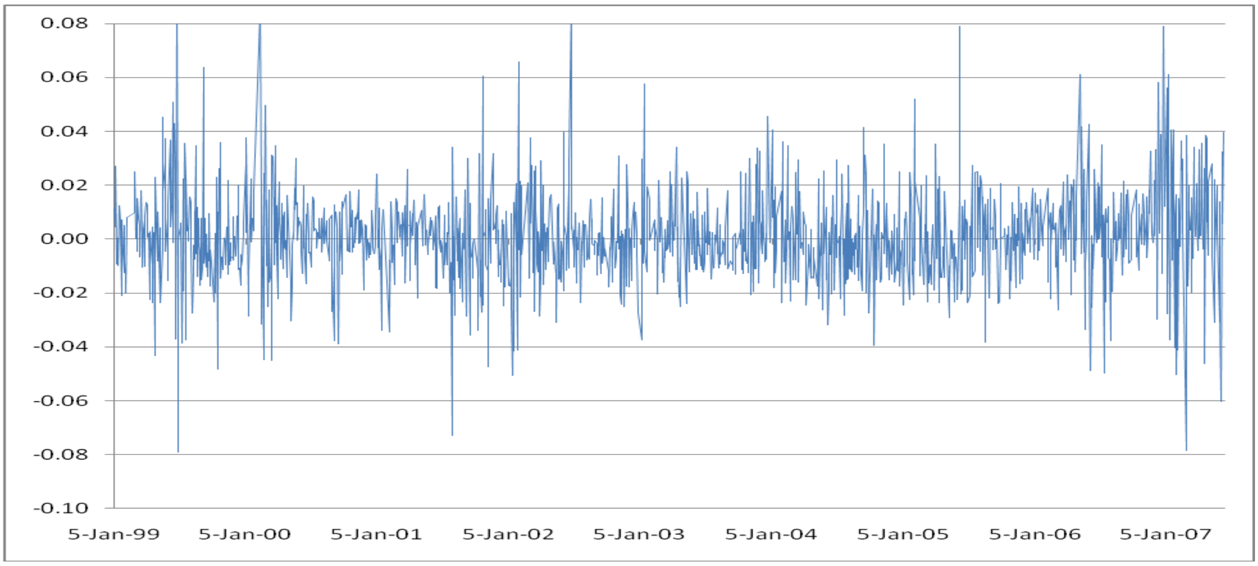

Figure 2. B

The SSE Composite Index Stock Returns Time Series

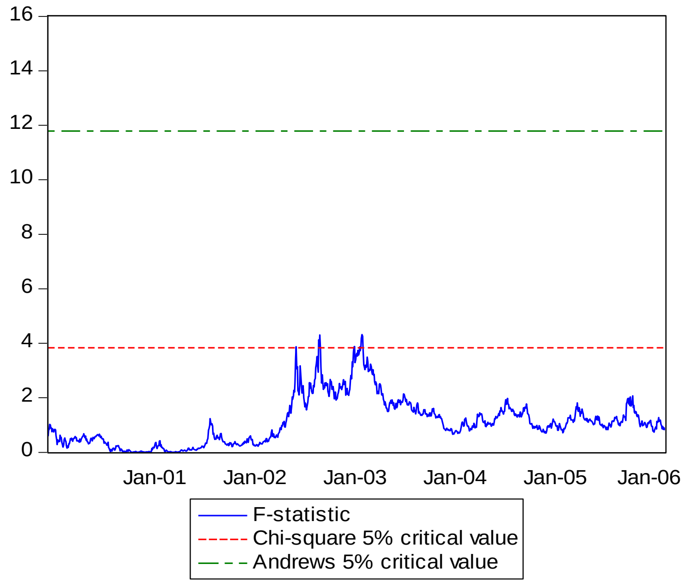

Figure 3. A

Structural Break for the S&P 500 Returns: Quant-Andrews Test

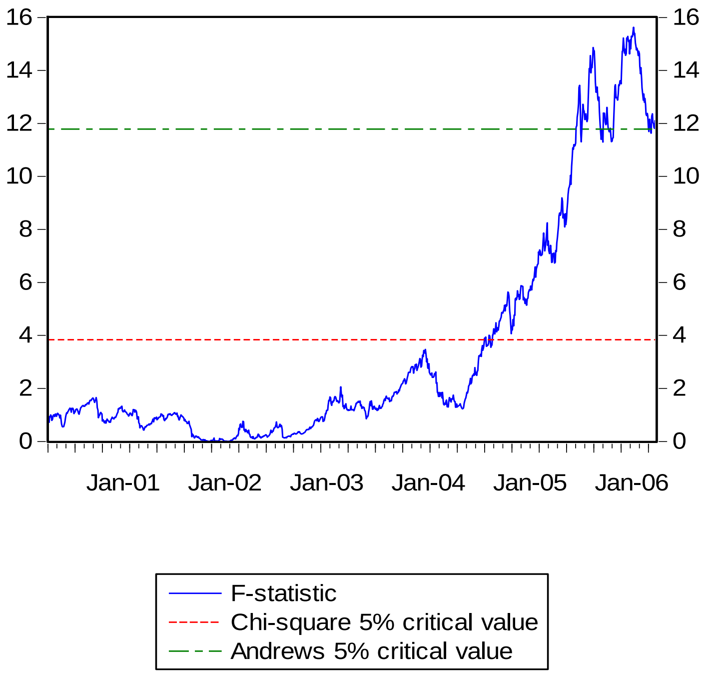

Figure 3. B

Structural Break for the SSE Composite Returns: Quant-Andrews Test