Research on Impact of Shenzhen-Hong Kong Stock Connect Mechanism on the Volatility of Stock Markets

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Abstract: The implementation of the Shenzhen-Hong Kong Stock Connect (SHSC) mechanism has realized the largest two-way opening of China's capital market, but also increased the transmission of risks. In order to analyze the impact of SHSC on the volatility of single market in Shenzhen or Hong Kong, this paper establishes the volatility models of stock markets in Shenzhen and Hong Kong based on the GARCH-type models with different perturbation terms. The pre-applicable test is made and the result shows that the return rate series of Shenzhen and Hong Kong stock markets are stable and heteroscedastic, and they meet the conditions of establishing the GARCH-type models. Then, the GARCH model and EGARCH model are established to analyze the volatility of stock markets in Shenzhen and Hong Kong respectively. The results show that the opening of SHSC has increased the short-term volatility of the stock markets in Shenzhen and Hong Kong and improved the efficiency of information transmission between these two stock markets. Moreover, influenced by SHSC, the leverage effect of Shenzhen stock market is increasing, while that of Hong Kong stock market is decreasing.

Keywords: Applied statistics; Economic time series analysis; SHSC mechanism; Volatility; GARCH model; EGARCH model

1. Introduction

The Shenzhen-Hong Kong Stock Connect (SHSC) mechanism is an abbreviation of trading interconnection mechanism for the Shenzhen-Hong Kong stock markets. It refers to the technical connection between the Shenzhen Stock Exchange and the Stock Exchange of Hong Kong Ltd., which enables investors in mainland China and Hong Kong to buy and sell stocks listed on each other's exchanges within the prescribed scope through local securities firms or brokers. The SHSC mechanism was officially launched on December 5, 2016, which has been in operation for three years. This mechanism not only optimized the allocation of resources in the mainland of China, but also enhanced the two-way liquidity of funds in the Hong Kong and mainland China markets [1]. Interconnection mechanisms such as SHSC have a certain impact on market sentiment, investor structure and trading behavior of the two stock markets in Shenzhen and Hong Kong [2-5]. The mainland China market is dominated by retail investors, while the Hong Kong market is dominated by institutional investors. With the help of Hong Kong, an international capital market, as a transit point, the participation of the Hong Kong market has been expanded, the investment structure of mainland retail investors has been improved, the source of funds has been stabilized, and the resistance to international capital shocks has been strengthened. The connectivity provides a bridge for two-way capital flows between Hong Kong and the mainland, and meets the needs of international asset allocation for mainland residents, enterprises and institutions.

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In recent years, the implementation of the reforms in China makes the rapid development of capital market, and the degree of marketization and internationalization of capital transaction is increasing. The opening of SHSC undoubtedly brings long-term investment opportunities for China's capital market, facilitates the transformation and upgrading of China's economy, and lays a foundation for the globalization of China's capital market, which is of milestone significance for China's capital market. However, the implementation of the SHSC mechanism will bring information shock to the stock markets of Shenzhen and Hong Kong and will cause local market fluctuations. Based on this research background, this paper will establish the relevant econometric models to study the impact of SHSC on the volatility of single market in Shenzhen and Hong Kong, so as to provide some investment reference for investors, as well as the decision-making basis for relevant departments to promote the orderly opening of capital market and formulate and improve the policy of China's financial system.

Changes in volatility will affect the expected return rate over a relatively short time interval. Therefore, the study of stock market volatility has become one of the key research directions in the financial field for the scholars. For example, in 1982, Engle et al. [6-8] presented the Auto Regressive Conditional Heteroscedasticity (ARCH) model, which was used to analyze the volatility of financial time series. In order to avoid the problems that the ARCH model cannot determine the order of the time-delay and the parameters are negative, and then Abdalla, Omolo, et al. [9-10] proposed the model of Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model, which makes up some shortcomings of the ARCH model, and enhances its applicability, and provides an effective analytical method in the later processing of a large number of financial time series. Dai et al. [11] established a simple linear autoregressive model to capture predictive relationships between stock market implied volatility and stock volatility, and the results showed there exists very significant Granger causality from stock market implied volatility to stock volatility. Zhang et al. [12] found that the variation tendency of Sina Weibo Index is highly correlated with stock market volatility by using Granger causality tests and time-delay detrended cross-correlation analysis. Baklaci et al. [13] detected the volatility linkages among various currencies during operating and non-operating hours of three major stock markets (Tokyo, London and New York) by employing bivariate VAR-BEKK-GARCH model in selected currency pairs, and the result was that rather than major currencies, some minor and exotic currencies play a leading role in volatility transmission during trading hours of major stock markets.

However, the above symmetric models assume that positive and negative fluctuations have the same impact on volatility, but ignore the asymmetric effect when stock price changes are negatively correlated with volatility. In order to overcome the limitations of symmetric models, various GARCH-type models emerged. Kawakatsu, Glosten and Zakoian et al. [14-16] proposed the models of Exponential GARCH, GJR-GARCH, and TGARCH, respectively. Different from the previous study, Baillie et al. [17] introduced the method of Fractional integral GARCH (FIGARCH) with long-term memory, which not only reflects the characteristics of heteroscedasticity but also captures the changes in the long-term memory of financial assets.

In recent years, scholars have conducted a lot of researches on the error term distribution hypothesis and model optimization for the volatility of return rate on financial assets. Bollerslev and Nelson et al. [18-19] were the first to propose that the student t-distribution and the generalized error distribution can be used to replace the normal distribution obeyed by the error term, as well as Beta distribution, Logistic distribution and the mixed distribution that can reflect the "asymmetry" of the return rate.
Based on existing studies, Fornari [20] proposed a more general Volatility Switching model, which can detect whether the asymmetry can be reversed. Later, Laopodis [21] constructed the MVMA-EGARCH model by combined with the time series model to study whether the long-term interest rate fluctuations of different countries in the world would affect each other. The results showed that the long-term interest rate fluctuations of all countries have a strong correlation. On the basis of above studies, Hung [22] considered that volatility transfer is time-varying and asymmetric, so he established an Intelligent Threshold GARCH (ITGARCH) model to modify the threshold value, and used GA genetic algorithm and fuzzy theory to describe the time-varying and asymmetric volatility. The results showed that volatility transfer is time-varying, nonlinear and asymmetric. In the latest research results, Yu [23] et al. used the GARCH-MIDAS model to evaluate the impact of global economic policy uncertainty on the volatility of Chinese stock market, and the results showed that the error of the prediction result generated by GARCH-MIDAS model is smaller than the Realized Volatility (RV) model.

In addition to studying the features of stock market volatility in foreign countries, domestic scholars in China have gradually begun to deeply study the volatility of return rate in stock markets. Zhou and Huang [24] used Granger causality test, information absorption model and binary VAR-EGARCH model to study the volatility of the Shanghai and Shenzhen stock markets and the relationship between these two markets. The results showed that the information transfer between the two markets is fast and there is two-way fluctuation overflow. In the same year, Jiang [25] also studied the fluctuation of Shanghai and Shenzhen stock markets, and concluded that with the development of the stock market, the reversal of asymmetric effect between the markets gradually became significant. Subsequently, Guo [26] integrated Markov mechanism transformation into GARCH model and constructed RS-GARCH model to study the Shanghai composite index. The results showed that RS-GARCH model significantly improved the phenomenon of "pseudo-continuity" compared with GARCH model. Based on previous studies, Wang and Wang [27] used EGARCH model and extreme value theory to conduct quantitative research on conditional value at risk by considering the two characteristics of volatility and thick-tailed distribution of stock returns, and concluded that the volatility of return rate has a certain durability. Different from the above, Zheng et al. [28] took the jumping and fluctuating characteristics of SSE 50ETF as the object, introduced Levy-GARCH non-gaussian conditional heteroskedasticity model with jump, and performed analysis with Fourier value maximum likelihood estimation and backtracking test. The results showed that the SSE 50ETF market also has significant conditional heteroskedasticity effect and random jumping behavior, but the volatility does not have significant leverage effect. Moreover, Kim and Won [29] proposed a new hybrid long short-term memory (LSTM) model to forecast stock price volatility that combines the LSTM model with various generalized autoregressive conditional heteroscedasticity (GARCH)-type models. Wang et al. [30] introduced a combination of asymmetry and extreme volatility effects and established a superior extension of the GARCH-MIDAS model for modeling and forecasting the stock volatility, and the results showed that the asymmetry and extreme volatility effects in our GARCH-MIDAS model frameworks have significant impacts on the stock price volatility.

From the literature above, the scholars mainly study the volatility or model effectiveness of different stock or securities markets. Due to the opening of SHSC in recent years, the amount of data is small and unstable, and there are relatively few research literatures on SHSC. Therefore, the impact of SHSC on the volatility of Shenzhen-Hong Kong stock market needs to be further studied. Based on this background, this paper
selected the Shenzhen component index and Hang Seng index as the proxy variables to measure the volatility characteristics of stock markets in Shenzhen and Hong Kong, and studied the impact of SHSC on the volatility of stock markets in Shenzhen and Hong Kong, and drew some valuable conclusions about the impact.

The rest of the paper is organized as follows. Section 2 gives the volatility analysis of the stock markets. Section 3 gives the quantitative analysis on the impact of SHSC on the volatility of stock markets in Shenzhen and Hong Kong by establishing the GARCH model and EGARCH model. Section 4 concludes the paper.

2. Volatility Analysis of the Stock Markets

Market volatility is directly related to uncertainty and risk. When market uncertainty dominates, the study on stock market volatility is of great importance. On the one hand, significant changes in the volatility of financial market returns may have a significant negative impact on risk-averse investors. On the other hand, these changes may also affect consumption patterns, corporate capital investment decisions and macroeconomic variables. Therefore, volatility is one of the effective indexes that comprehensively reflect the price behavior of stock market and measure the market quality.

After the reform of non-tradable shares in 2006, the stock market experienced many abnormal fluctuations from 2006 to 2018, which affected the development trend of economy. Among them, at the beginning of 2008, due to the "herd effect", investors threw the Olympic market plate one after another. In the same year, affected by the financial crisis in the United States, the stock market of Shanghai, Shenzhen and Hong Kong was on a downward trend, and the Shanghai composite index closed at 1834 points at the end of the year, with a decline of 187%. From 2014 to 2015, affected by the "Internet +" development concept, emerging industries and other macroeconomic aspects, the stock market experienced a cliff-edge decline after two booms. The stock market disaster reduced the market value of Shanghai and Shenzhen stock markets by nearly 33 trillion yuan, and a large range of listed companies appeared the "stop trading tide", and at the same time, 50% of a-share listed companies announced to suspend trading. Then, in the last Hong Kong stock trading day in 2018, the Hang Seng Index rose 1.34%, but fell 13.6% for the whole year (36% in 2017 which leads the global stock market), which is the biggest annual decline after 2011. According to statistics data from CSDC company, the value of the A-share market decreased by 14.39 trillion yuan in 2018, and the number of end-stage investors was 145 million. Therefore, the average loss of A-share investors was 99,200 yuan. According to the above analysis, China's stock market volatility has the characteristics of high frequency and large range, which will bring great investment risk to investors and may cause a wide range of economic losses [31-34]. Therefore, it is of great significance to study stock market volatility for promoting macroeconomic stability and regulating the economic functions of financial market.

Stock market volatility is the result of the interaction of multiple factors, such as policy, economy, market, investor's psychological expectation and other influencing factors [35-40]. The research on the influencing factors of volatility has become the focus of securities management departments and investors. Good market volatility will be of great benefit to the entire financial market and its participants. The factors affecting stock market volatility are generally divided into three categories, i.e., national policies, economic fundamentals and market factors. Each category plays a different role in the impact on the stock market. The factors cross each other and thus affect the volatility of the stock market.
3. Analysis on the Impact of SHSC on the Volatility of Stock Markets in Shenzhen and Hong Kong

We choose the closing price of stock markets in Shenzhen and Hong Kong before and after the opening of SHSC as the research object, and establish specific GARCH-type models to measure the volatility change of stock markets in Shenzhen and Hong Kong. In this section, the return rate of stock index by logarithmic difference method are obtained, and its related statistical characteristics are described firstly. Secondly, the stability, correlation and ARCH effect of return rate of stock index are tested. Finally, the GARCH and EGARCH models with different disturbance terms are established to respectively estimate the volatility parameters.

3.1 Data collection and preprocessing of stock markets in Shenzhen and Hong Kong

3.1.1 Data source and stage division

In this paper, we select the closing price of Shenzhen Stock Exchange (399001) and Hong Kong Hang Seng Index (HIS) from December 4, 2014 to December 5, 2018 as the representative sample data. Due to the differences in the regulations of holidays in Hong Kong and Mainland China, the trading dates of stock market in Hong Kong, Shanghai and Shenzhen have certain discrepancies. Thus, we exclude the data in inconsistent trading days of Shenzhen and Hong Kong. After data cleansing, we obtained 950 trading data in total. The daily closing data of Shenzhen Component Index and Hong Kong Hang Seng Index are from the website Investing.com.

In this paper, we select the logarithmic return rate of stock index with stable characteristics to characterize the volatility of different stock markets, i.e., \( R_t = \ln y_t - \ln y_{t-1} \), where \( \ln y_t \) is the daily closing price of each stock index on the \( t \)-th day. The purpose is to reduce the calculation error, and when the daily price of the stock index changes little in the market, \( R_t \) approximately represents the overall daily return rate of the market in which the stock index is located. Here, we take the logarithm operation for the daily closing price of Shenzhen Stock Exchange and Hang Seng Index respectively, where RZ refers to the daily logarithmic return rate of Shenzhen Component Index and RK refers to the daily logarithmic return rate of Hang Seng Index. In this paper, EVIEWS 8.0 software is used for preliminary data preprocessing.

Considering the SHSC was officially opened on December 5, 2016, thus we take the opening time of SHSC as the dividing node, and divide the data into two stages, i.e., the period before the opening of SHSC and the period after the opening of SHSC, that is, the first stage is from December 4, 2014 to December 12, 2014, and the second stage is from December 5, 2016 to December 5, 2018. Thus we study the changes in the volatility characteristics of Shenzhen and Hong Kong before and after the opening of SHSC. The symbol explanations in this section are shown in Table 1.

Please insert Table 1 about here

The basic statistical characteristics of stock markets in Shenzhen and Hong Kong were analyzed in different stages, and the results of descriptive statistical analysis of the return rate were shown in the following Table 2.

Please insert Table 2 about here
It can be seen from Table 2 that the skewness of logarithmic return rate series in Shenzhen and Hong Kong stock market is not 0, which indicates that the series does not obey the normal distribution with the mean value 0. The kurtosis of Shenzhen and Hong Kong stock markets in different stages is all higher than the kurtosis value 3 of the normal distribution, which indicates that the series has the characteristic of leptokurtosis and fat-tail. Moreover, the logarithmic return rate series passes the J-B statistical test, and the p values are all 0, which indicates that the logarithmic return rate of stock markets in Shenzhen and Hong Kong does not conform to the normal distribution under the significance level of 5%.

According to the QQ graph in Figure 1 and Figure 2, we can draw the conclusion that the logarithmic return rate of stock markets in Shenzhen and Hong Kong does not obey the normal distribution and has the characteristic of leptokurtosis and fat-tail.

3.1.2 Stationarity and correlation test

Before making the statistical analysis for financial time series, the stationarity should be tested first, and the next step statistical analysis can be made only when the series is stable. In this paper, follow the principle of AIC and BIC minimum, the Augmented Dickey-Fuller test (ADF test) is used to judge the stability of the stock market sequences in Shenzhen and Hong Kong.

As shown in Table 3, ADF statistics of R sequences of stock markets in Shenzhen and Hong Kong are all less than the critical values of 1%, 5% and 10%, and it can be seen from the p value in the output results that the null hypothesis that the sequences have unit root is rejected at the significance level of 5%. Therefore, it can be considered that the logarithmic return sequences of stock markets in Shenzhen and Hong Kong are stable.

Table 4 shows the autocorrelation test results of the R_t sequences. From the corresponding p values, we can see that none of the full sample sequence and the four sequences in two stages, i.e., before and after the opening of SHSC, can reject the null hypothesis, which means that there does not exist autocorrelation sequence, is the white noise sequence, and it also shows that the mean model does not need to introduce the autocorrelation part, and the mean equation consists of a constant term plus a random perturbation term. In order to fit the GARCH model, so we need to discuss the autocorrelation of the square value of the return rate sequence. According to the results in Table 4, R_t^2 rejects the null hypothesis when the delay order is n, which indicates that the square value of the return rate sequence is autocorrelated and the GARCH model can be used.

3.1.3 ARCH effect test

For the return rate sequences data of the stock markets in Shenzhen and Hong Kong in the two stages before and after the opening of SHSC, we use the maximum likelihood estimation method to estimate the parameters, and extract the residual sequence for the
ARCH-Lagrange Multiplier (ARCH-LM) test. Then we can determine whether the sequences have the ARCH effect and whether the GARCH model is needed to describe the volatility clustering phenomenon. The ARCH effect test results for each sequence are shown in Table 5.

LM test statistics are calculated by an auxiliary test regression. The null hypothesis is that there is no heteroscedasticity in the residual sequence up to order \( p \). Regression was performed as follows.

\[
u_t^2 = \beta_0 + \left( \sum_{i=1}^{p} \beta_i u_{t-i}^2 \right) + \varepsilon_t, \tag{1}\]

where \( u_t \) is the residual error. This is a regression of the constants and the delay squared residuals up to order \( p \). The null hypothesis of the test is that the ARCH effect does not exist in the residual sequence up to order \( p \).

If the sequence passes the ARCH-LM test, indicating that there is no ARCH effect among the sequences, then there is no need to introduce GARCH-type models to eliminate heteroscedasticity, and the residual sequence can be extracted directly. At the same time, for white noise sequences without autocorrelation, the original sequence is directly used for testing. The results are shown in Table 5. At a significance level of 5%, the \( p \) values of all the sequences are less than 0.05, which indicates that all the return rate sequences reject the null hypothesis that there is no heteroscedasticity. Therefore, it can be judged that there is ARCH effect in the return rate sequences in the two stages before and after the opening of SHSC, which meets the conditions for the establishment of GARCH model.

Please insert Table 5 about here

From the concept of volatility in Section 2 and the existing literature [41-42], we know that the volatility has the characteristics of volatility clustering, leptokurtosis and fat-tail and leverage effect. Therefore, we will establish a GARCH(1,1) model [43] and an EGARCH(1,1) model [44-45] to study the volatility change of Shenzhen stock market and Hong Kong stock market respectively, and discuss that whether there is leverage effect in different stages, so as to analyze the impact of the opening of SHSC on the volatility change of Shenzhen stock market and Hong Kong stock market.

3.2 Volatility analysis of Shenzhen stock market before and after the opening of SHSC

3.2.1 Volatility modeling of Shenzhen stock market based on GARCH(1,1) model

The GARCH(1,1) model [43] which describes the volatility of Shenzhen stock market can be expressed by

\[
y_i = \mathbf{x}_i' \gamma + u_i, \quad i = 1, 2, \ldots, T, \tag{2}\]

\[
u_i = \sqrt{\sigma_i} \varepsilon_i, \tag{3}\]

\[
\sigma_i^2 = \omega + \alpha u_{i-1}^2 + \beta \sigma_{i-1}^2, \tag{4}\]

where \( \mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{ik})' \) is return rate sequence of Shenzhen stock market, \( \gamma = (\gamma_1, \gamma_2, \ldots, \gamma_k)' \) is the coefficient vector of the mean value equation, \( u_i \) is the residual and satisfies \( u_i \sim N(0, \sigma_i) \), and \( \sigma_i \) is the conditional heteroscedasticity.

Firstly, the GARCH(1,1) models under different perturbation term distributions are established to the return rates of the full sample stage, the stages before and after the
opening of SHSC, and the parameters of the GARCH(1,1) model are estimated. According to AIC and BIC information criteria, we obtain that the return rate models of Shenzhen stock market under partial \( t \) distribution all have a good fitting effect, and the results are listed in Table 6.

**Please insert Table 6 about here**

From the calculation results in Table 6, we can conclude the following conclusions.

1. In the parameter estimation of full sample stage in Shenzhen stock market, the \( \mu \) and \( \omega_1 \) term is not significant. In the two stages before and after the opening of SHSC in Shenzhen stock market, except the parameter \( \mu \) and parameter \( \omega_1 \) are not significant, the estimation of other parameters of the model is significant.

2. The variance equations of the GARCH(1,1) models in the full sample stage and the two stages before and after the opening of SHSC are shown in Table 7. Since the sum of the coefficients of the ARCH term and the GARCH term is very close to 1, and all the coefficients in the equation are significant except the constant term, which indicates that the return rate model of stock index in different stages can well explain the conditional variance of the return rate. At the same time, it shows that the volatility of stock return rate is persistent with a phenomenon of volatility cluster, and it will return to unconditional variance in a long time.

**Please insert Table 7 about here**

### 3.2.2 Leverage test of Shenzhen stock market based on EGARCH(1,1) model

In a symmetric model, conditional variance depends only on the value of \( \varepsilon_t \), but in an asymmetric model, positive or negative shocks of the same size have different effects on future volatility.

Many researchers have found asymmetric examples of stock price behavior, i.e., the negative shocks seem to increase volatility more easily than the positive shocks. In order to reflect the asymmetry of volatility in financial market, Nelson [19] proposed the index GARCH model, namely the EGARCH model [8]. The conditional variance equation in the EGARCH(1,1) model can be expressed as

\[
\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_t^{2e}) + \alpha \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}, \quad t = 1, 2, \ldots, T
\]

The advantage of the model (5) is that the calculated result of \( \sigma_t^2 \) will be positive because of the logarithmic conditional variance, and there is no need to impose artificial non-negative constraints on the model parameters.

In order to determine whether the leverage effect exists in Shenzhen stock market, this paper establishes an asymmetric EGARCH(1,1) model for the return rate of stock index in Shenzhen stock market according to different disturbance term distributions. According to the AIC and BIC information criterion, the fitting effect of return rate in Shenzhen stock market under \( t \) distribution is good, and the parameter estimation results are listed in Table 8.

**Please insert Table 8 about here**

According to the analysis of the results in Table 8, we can conclude the following conclusions.
The leverage factors in the Shenzhen stock market during the stage of full sample are all significant, which is consistent with the results of a large number of existing studies: the leverage effect is universal in the global stock market. The variance equation of Shenzhen stock market is as follows:
\[
\ln(\sigma_r^2) = -0.1867 + 0.1484 \frac{u_{t-1}}{\sigma_{t-1}} - 0.0663 \frac{u_{t-1}}{\sigma_{t-1}} + 0.9909 \ln(\sigma_{t-1}^2).
\]

During the full sample stage of Shenzhen stock market, when "good news" appears, this information impact has 0.1484+(-0.0663)=0.0821 times impact on the logarithm of conditional variance. In the case of "bad news", the impact will be 0.1484+(-0.0663)=0.2147 times.

(2) In the first stage before the opening of SHSC, the leverage factor \( \gamma_1 \) of RZ1 in Shenzhen stock market was not significant in the model, and the other parameters were significant, which indicates that the asymmetric response of Shenzhen stock market to information impact was not obvious in this stage.

(3) In the second stage after the opening of SHSC, asymmetry was detected in RZ2 of Shenzhen stock market, and its variance equation can be expressed as
\[
\ln(\sigma_r^2) = -0.6306 + 0.0440 \frac{u_{t-1}}{\sigma_{t-1}} - 0.2292 \frac{u_{t-1}}{\sigma_{t-1}} + 0.9346 \ln(\sigma_{t-1}^2).
\]

According to the specific analysis, the estimated value of the asymmetric item is -0.2292, which indicates that the stock price fluctuation in the second stage has a "leverage effect", that is, "bad news" can generate more fluctuations than an equivalent amount of "good news". When "good news" appears, \( u_{t-1} > 0 \), the information shock has 0.0440+(-0.2292)=-0.1852 times impact on the logarithm of conditional variance. In the case of "bad news", \( u_{t-1} < 0 \), the impact will be 0.1891+(-0.1101)*(-1)=0.2732 times.

From above analysis, there are leverage effect and asymmetric fluctuations in the full sample stage (RZ) and the second stage (RZ2) of Shenzhen stock market. Therefore, we can draw the corresponding information impact curve to understand Shenzhen stock market intuitively. We set
\[
f(u_{t-1}) = \alpha \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}, \quad (6)
\]
and \( z_r = \frac{u_r}{\sigma_r} \), then we have
\[
f(z_r) = \alpha \left| z_r \right| + \gamma z_r. \quad (7)
\]

The function \( f(\cdot) \) is called an information impact curve, that is, \( f(\cdot) \) is a curve that plots volatility \( \sigma_r^2 \) under the impact \( u_r/\sigma_r \), which links the correction of conditional volatility (given by \( \ln(\sigma_r^2) \)) to "shock information".

The function of information impact curve of Shenzhen stock market during the full sample stage (RZ) is
\[
f(\cdot) = 0.1484\left| z_{t-1} \right| - 0.0663z_{t-1}.
\]

The function of information impact curve of Shenzhen stock market during the second stage (RZ2) is
\[
f(\cdot) = 0.0440\left| z_{t-1} \right| - 0.2292z_{t-1}.
\]

Information impact curves in different stages can be drawn by the above four
information impact curve functions, as shown in Figure 3 and Figure 4.

Please insert Figure 3 about here

Please insert Figure 4 about here

Finally, the ARCH effect is tested for the residual sequence of EGARCH model in Shenzhen stock market, and the results are shown in Table 9. From the results, we can see that the heteroscedasticity of stock index data is effectively eliminated.

Please insert Table 9 about here

3.3 Volatility analysis of Hong Kong stock market before and after the opening of SHSC

3.3.1 Volatility modeling of Hong Kong stock market based on GARCH(1,1) model

Similar to Section 3.2.1, the GARCH(1,1) models under different perturbation term distributions are established to the return rates of the full sample stage, the stages before and after the opening of SHSC, and the parameters of the GARCH(1,1) model are estimated, and the estimated results are listed in Table 10.

Please insert Table 10 about here

From the calculation results in Table 10, we can conclude the following conclusions.

(1) In the parameter estimation of full sample stage in Hong Kong stock market, except the parameter $\omega_1$ is not significant, the estimation of other parameters of the model is significant. In the first stage, except the parameters $\mu$, $\omega_1$ and $\xi$, the estimation of other parameters of the model is significant. But in the second stage, only the estimation of $\omega_1$ is not significant.

(2) The variance equations of GARCH(1,1) model of Hong Kong stock market at different stages are shown in Table 11.

Please insert Table 11 about here

In the variance equation of Hong Kong stock market, the value of $\alpha_1 + \beta_1$ is less than 1 and is very close to 1, which satisfies the constraint conditions of parameters in the conditional variance equation of GARCH model. The skewness coefficients of the return rate of Hong Kong stock market are all not 0 in all stages, which indicates that the fitting effect of partial student $t$ distribution is the best.

3.3.2 Leverage test of Hong Kong stock market based on EGARCH(1,1) model

According to the AIC and BIC information criterion, the fitting effect of return rate in Hong Kong stock market under $t$ distribution is good, and the parameter estimation results are listed in Table 12.
According to the results in Table 12, we can conclude the following conclusions.

1) The variance equation of the Hong Kong stock market can be expressed by
\[ \ln(\sigma_t^2) = -0.34 + 0.0995 \frac{u_{t-1}}{\sigma_{t-1}} - 0.0737 \frac{u_{t-1}}{\sigma_{t-1}} + 0.9707 \ln(\sigma_{t-1}^2). \]

During the full sample stage of Hong Kong stock market, when "good news" appears, this information impact has 0.0995+(-0.0737)=0.0258 times impact on the logarithm of conditional variance. In the case of "bad news", the impact will be 0.0995-(0.0737)=-0.1732 times.

2) In the first stage (RK1) of Hong Kong stock market, all the parameters except parameter \( \mu \) are significant in the EGARCH model. And the variance equation of the EGARCH(1,1) model in the first stage (RK1) can be expressed by
\[ \ln(\sigma_t^2) = -1.0458 + 0.1891 \frac{u_{t-1}}{\sigma_{t-1}} - 0.1101 \frac{u_{t-1}}{\sigma_{t-1}} + 0.8973 \ln(\sigma_{t-1}^2), \]
where the estimated value of asymmetric term \( \gamma_1 \) is -0.1101, which indicates that the stock price fluctuation in the first stage has a "leverage effect", that is, "bad news" can generate more fluctuations than an equivalent amount of "good news". When "good news" appears, \( u_{t-1} > 0 \), the information impact has 0.1891+(-0.1101)=0.079 times impact on the logarithm of conditional variance. In the case of "bad news", \( u_{t-1} < 0 \), the impact will be 0.1891+(-0.1101)*(-1)=0.2992 times.

3) In the second stage (RK2) of Hong Kong stock market, the parameters \( \omega_1, \alpha_1 \) and leverage factor \( \gamma_1 \) are not significant, which indicates that the asymmetric response of the Hong Kong stock market to information impact is not obvious in the second stage.

From above analysis, we can obtain the information impact curve function of Hong Kong stock market. Specifically, the function of information impact curve during the full sample stage (RK) is
\[ f(\cdot) = 0.0995[z_{t-1}] - 0.0737z_{t-1}, \]
and the function of information impact curve during the first stage (RZ1) is
\[ f(\cdot) = 0.1891[z_{t-1}] - 0.1101z_{t-1}. \]

Information impact curves in different stages can be drawn by the above functions of information impact curve, as shown in Figure 5 and Figure 6.

Please insert Figure 5 about here

Please insert Figure 6 about here

Finally, the ARCH effect is tested for the residual sequence of EGARCH model in Hong Kong stock market, and the results are shown in Table 13. From the results, we can see that the ARCH effect The ARCH effect of different stages in Hong Kong stock market is effectively eliminated.

Please insert Table 13 about here

3.4 Impact analysis of SHSC on the volatility of stock marks in Shenzhen and Hong Kong
From the analysis in Section 3.2 and Section 3.3, by comparing the volatility changes of return rate series of stock index in stock markets of Shenzhen and Hong Kong before and after the opening of the SHSC, we can draw some conclusions about the impact of SHSC on the volatility of Shenzhen and Hong Kong stock markets as follows.

(1) The information transfer rate of Shenzhen and Hong Kong stock markets can be analyzed through the parameter changes corresponding to the models. The parameter estimation results are shown in Table 14.

Please insert Table 14 about here

From above Table 14, we can see that the ARCH term coefficients $\alpha_i$ all decreased after the opening of SHSC, which indicates that the volatility persistence and long-term memory of the Shenzhen and Hong Kong stock markets weakened, but the short-term volatility increased. At the same time, the GARCH coefficient $\beta_i$ represents the information transmission speed of the market, and their increases indicate that the opening of SHSC improves the information transmission speed of the Shenzhen and Hong Kong stock market and improves the efficiency of market information transmission. The values of $\alpha_i + \beta_i$ are all close to 1, which indicates that the impact on the conditional variance of the stock market is not a short-term process, but it will continue to occur.

(2) According to the parameter estimation results of GARCH model listed in Table 6 and Table 10, the return rate of stock index in Shenzhen and Hong Kong has conditional heteroscedasticity. The coefficients of ARCH term and GARCH term are both significant, which confirms that the volatility series have the feature of clustering. Meanwhile, the conditional variance fitted by the model can approximate simulate the square of stock index return rate. When the stock market volatility is large, the conditional variance is also, and the variance is small when the stock market is stable.

The opening of SHSC has enhanced the risk absorption and tolerance of Shenzhen and Hong Kong stock markets. Although Shenzhen and Hong Kong stock markets have certain fluctuations affected by the downward pressure of macro-economy in 2018, they are not as violent as the stock market crash in 2014. This is also because the opening of SHSC enhances the efficiency of market information transmission, and investors can timely digest bad news and play a positive role in stabilizing the stock market.

(3) Before and after the opening of SHSC, the leverage effect of Shenzhen and Hong Kong stock markets has changed, but the overall fluctuation for the return rate of stock index had obvious negative leverage effect. The specific leverage factors of Shenzhen and Hong Kong stock markets are shown in Table 15.

Please insert Table 15 about here

From Table 15, we can see that the significant leverage factor $\gamma_i < 0$, which indicates that the negative impact brought by negative news is negatively correlated with volatility, and positive news can produce greater impact than negative news. The SHSC mechanism on Chinese stock market is good news, which can stimulate the volatility of stock markets. For the Shenzhen stock market, China's stock market was in a deleveraging cycle opening of SHS mechanism, and the leverage effect was not significant. However, after the opening of SHS mechanism, the openness degree of Shenzhen stock market was increased, and the leverage effect of asset price fluctuations was also improved. For the Hong Kong stock market, the leverage effect in the early stage is obvious. The possible reason is that the mechanism of Shanghai-Hong Kong Stock Connect has been opened. So the good news
brought by this mechanism were fully digested. But with the opening of the SHSC mechanism in 2016, the expectation difference of Hong Kong stock market indirectly damped the market sentiment and reduced the "leverage effect" of Hong Kong stock market.

4. Conclusion

In order to measure the impact of the opening of SHSC on the stock markets in Shenzhen and Hong Kong, this paper uses Shenzhen component index and Hang Seng index as the proxy variables to study the volatility changes of the stock markets in Shenzhen and Hong Kong based on the GARCH-type models. Concretely, the data preprocessing of stock index sequences of Shenzhen and Hong Kong stock markets is firstly made. Then, the volatility models based on GARCH and EGARCH are established to analyze the impact of SHSC on the volatility of the stock markets in Shenzhen and Hong Kong. According to AIC criteria, the optimal model is selected to analyze the impact of the SHSC on the volatility of the stock markets, the main conclusions are drew that the SHSC mechanism improves the efficiency of information transmission between the two stock markets of Shenzhen and Hong Kong, and increases the short-term volatility of these two stock markets. In addition, the SHSC mechanism increases the openness degree of Shenzhen and Hong Kong, which makes them more capable of absorbing stock market risks and influences the leverage effect of stock markets in Shenzhen and Hong Kong in different degrees and directions.

The main contribution of this paper is as follows. We take the SHSC mechanism as the research background and establish the volatility models of stock market based on GARCH and EGARCH to comprehensively analyze the impact of SHSC on the volatility of the stock markets in Shenzhen and Hong Kong. By comparing the distributions of different disturbance terms in these two models of GARCH and EGARCH, we obtain that the GARCH-skewt model is more suitable for modeling the marginal distribution of daily return rate data of stock markets in Shenzhen and Hong Kong.

The Shanghai–Hong Kong Stock Connect mechanism has also been launched. We should further simultaneously consider the impact of SHSC mechanism and Shanghai–Hong Kong Stock Connect mechanism on the volatility of stock markets in Shenzhen and Hong Kong. This is a challenging problem and just a limitation of our work in this paper. In the future, we will take a closer look at this challenging problem, and further study the multi-asset portfolio risk assessment methods and different optimized portfolio models in the stock markets of Shenzhen and Hong Kong on the basis of the research result in this paper, which can provide decision-making reference for rational investment of investors.

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Table 1. The symbol explanations of the used variables

| Variables | Paraphrase |
|-----------|------------|
| SZ        | Closing price of Shenzhen |
| HK        | Closing price of Hong Kong |
| RZ        | Daily logarithmic return rate of full sample in Shenzhen |
| RK        | Daily logarithmic return rate of full sample in Hong Kong |
| RZ1       | Daily logarithmic return rate of the first stage in Shenzhen |
| RK1       | Daily logarithmic return rate of the first stage in Hong Kong |
| RZ2       | Daily logarithmic return rate of the second stage in Shenzhen |
| RK2       | Daily logarithmic return rate of the second stage in Hong Kong |
| \( \mu \) | Constant term coefficient of the mean value equation |
| \( \omega_1 \) | Constant term coefficient of variance equation |
| \( \alpha \) | The ARCH coefficient |
| \( \beta \) | The GARCH coefficient |
| \( \gamma \) | Coefficient of asymmetric term (leverage factor) |
| \( \upsilon \) | Shape parameter |
| \( \xi \) | The coefficient of skewness |

Table 2. Basic data characteristics of exponential logarithmic return rate of Shenzhen and Hong Kong stock markets

| Stage          | Full sample | The first stage | The second stage |
|----------------|-------------|-----------------|------------------|
|                | RZ          | RK              | RZ1             | RK1             | RZ2  | RK2  |
| Mean value     | -0.0002     | 0.0001          | 0.0002          | -0.0001         | -0.0006 | 0.0004 |
| Median         | 0.0006      | 0.0008          | 0.0015          | -0.0002         | 0.0001  | 0.0011 |
| Maximum value  | 0.0625      | 0.0699          | 0.0625          | 0.0699          | 0.0477  | 0.0413 |
| Minimum value  | -0.1038     | -0.0602         | -0.1038         | -0.0602         | -0.0627  | -0.0588 |
| Standard       | 0.0190      | 0.0117          | 0.0238          | 0.0129          | 0.0126  | 0.0104 |
| skewness       | -1.0091     | -0.2941         | -0.9871         | -0.0023         | -0.5789  | -0.7948 |
| Kurtosis       | 7.3846      | 6.7320          | 5.6364          | 6.3129          | 5.9549  | 6.8201 |
| J-B statistics | 921.2474    | 564.4087        | 213.3556        | 215.8502        | 199.7580 | 339.5424 |

Table 3. ADF test for logarithmic return rate of stock markets in Shenzhen and Hong Kong

| Stage division | Full sample | The first stage | The second stage |
|----------------|-------------|-----------------|------------------|
|                | RZ          | RK              | RZ1             | RK1             | RZ2  | RK2  |
| ADF test       | -29.2450    | -30.2830        | -20.2528        | -21.0731        | -22.0300 | -21.8309 |
| Conclusion     | Stable      | Stable          | Stable          | Stable          | Stable | Stable |

Table 4. Autocorrelation checklist of \( R_t \) sequence

| Stage division | \( n \) | \( Q(n) \) | \( p \) value | The square value of the return rate sequence | \( n \) | \( Q(n) \) | \( p \) value |
|----------------|--------|------------|--------------|---------------------------------------------|--------|------------|--------------|
| Full sample    | RZ     | 1          | 2.4160       | 0.1200                                       | RZ\(^2\) | 1          | 52.4840      | 0.0000 |
|                | RK     | 1          | 0.2040       | 0.6510                                       | RK\(^2\) | 1          | 6.6550       | 0.0100 |
| The first stage| RZ1    | 1          | 2.1570       | 0.1420                                       | RZ1\(^2\) | 1          | 20.8480      | 0.0000 |
|                | RK1    | 1          | 0.3550       | 0.5520                                       | RK1\(^2\) | 1          | 4.9590       | 0.0260 |
| The second stage| RZ2    | 1          | 0.1010       | 0.7510                                       | RZ2\(^2\) | 3          | 20.6460      | 0.0000 |
|                | RK2    | 1          | 0.0180       | 0.8950                                       | RK2\(^2\) | 3          | 31.5840      | 0.0000 |
Table 5. ARCH effect test of the return rate sequence

| Stages | Full sample | The first stage | The second stage |
|--------|-------------|----------------|-----------------|
| RZ     | 55.2612     | 21.6075        | 6.3207          |
| RK     | 6.5635      | 5.0106         | 8.0122          |
| RZ1    | 52.3217     | 20.7439        | 4.9787          |
| RK1    | (0.0000)    | 4.0527         | (0.0005)        |
| RZ2    | (0.0000)    | 18.3806        | 23.0597         |
| RK2    | (0.0000)    | (0.0004)       | (0.0000)        |

(Note: the value of \( p \) corresponding to the statistic is in brackets)

Table 6. GARCH(1,1)-skewt model for the daily logarithmic return rate of Shenzhen stock market

| Stages | \( \mu \) | \( \omega \) | \( \alpha \) | \( \beta \) | \( \nu \) | \( \xi \) | AIC | BIC |
|--------|------------|------------|------------|---------|--------|--------|-----|-----|
| RZ     | 2.5375×10^{-4} | 7.4774×10^{-9} | 0.0563**   | 0.9430** | 5.2096** | -0.1639** | -5.6374 | -5.5762 |
| RZ1    | 8.0000×10^{-4} | 4.2000×10^{-7} | 0.0676**   | 0.9313** | 4.3114** | -0.1449*  | -5.0694 | -5.0346 |
| RZ2    | 1.0240×10^{-3} | -3.5500×10^{-7} | 0.0362*    | 0.9617*  | 6.0497** | -0.1542** | -6.1044 | -6.0694 |

Note: * and ** indicate that it is significant at the level of 10% and 5% respectively.

Table 7. Variance equations of the GARCH(1,1) models in different stages of Shenzhen stock market

| Stages | Variance equations |
|--------|--------------------|
| RZ     | \( \hat{\sigma}_t^2 = 0.0570\hat{\epsilon}_{t-1}^2 + 0.9430\hat{\sigma}_{t-1}^2 \) |
| RZ1    | \( \hat{\sigma}_t^2 = 0.0676\hat{\epsilon}_{t-1}^2 + 0.9313\hat{\sigma}_{t-1}^2 \) |
| RZ2    | \( \hat{\sigma}_t^2 = 0.0362\hat{\epsilon}_{t-1}^2 + 0.9617\hat{\sigma}_{t-1}^2 \) |

Table 8. EGARCH(1,1)-t model for the daily logarithmic return rate of Shenzhen stock market

| Stages | \( \mu \) | \( \omega \) | \( \alpha \) | \( \beta \) | \( \mu \) | \( \nu \) | AIC | BIC |
|--------|------------|------------|------------|---------|--------|--------|-----|-----|
| RZ     | 0.0006     | -0.1867**  | 0.1484**   | -0.0669** | 0.9909** | 4.1281** | -5.5981 | -5.5674 |
| RZ1    | 0.0013**   | -0.1824**  | 0.1948**   | -0.0450  | 0.9945** | 3.5061** | -5.0659 | -5.0130 |
| RZ2    | -1.0500×10^{-5} | -0.6306** | 0.0440*    | -0.2292** | 5.8658** | -6.1437 | -6.0912 |

Note: * and ** indicate that it is significant at the level of 10% and 5% respectively.

Table 9. The ARCH effect test for the residual sequence of EGARCH model

| Stages | F statistic | Sample R² |
|--------|-------------|-----------|
| RZ     | 1.8710(p=0.1717) | 1.8712(p=0.1713) |
| RZ2    | 2.4830(p=0.1158) | 2.4804(p=0.1153) |

Table 10. GARCH(1,1)-skewt model for the daily logarithmic return rate of Hong Kong stock market

| Stages | \( \mu \) | \( \omega \) | \( \alpha \) |
|--------|------------|------------|------------|
| RK     | 5.6881×10^{10}** | 8.2100×10^{-4} | 8.0000×10^{10}** |
| RK1    | 1.5469×10^{10}** | 1.5900×10^{-5} | -3.5500×10^{-7} |
| RK2    | 0.0500**   | 0.1258*    | 0.0271**   |
Table 11. Variance equations of the GARCH(1,1) models in different stages of Hong Kong stock market

| Stages | The variance equations |
|--------|------------------------|
| RK     | \( \hat{\sigma}^2_t = 0.0500\hat{\epsilon}_{t-1}^2 + 0.9373\hat{\sigma}^2_{t-1} \) |
| RK1    | \( \hat{\sigma}^2_t = 0.1258\hat{\epsilon}_{t-1}^2 + 0.7565\hat{\sigma}^2_{t-1} \) |
| RK2    | \( \hat{\sigma}^2_t = 0.0271\hat{\epsilon}_{t-1}^2 + 0.9709\hat{\sigma}^2_{t-1} \) |

Table 12. EGARCH(1,1)-\( t \) model for the daily logarithmic return rate of Hong Kong stock market

| Stages | \( \mu \) | \( \alpha \) | \( \beta \) | \( \gamma \) | AIC | SC |
|--------|--------|--------|--------|--------|-----|----|
| RK     | 0.0005* | -0.3400*** | 0.0995** | -0.0737** | 5.4584*** | 6.2370 |
| RK1    | 0.0005* | -0.3400*** | 0.0995** | -0.0737** | 5.4584*** | 6.2370 |
| RK2    | 0.0005* | -0.3400*** | 0.0995** | -0.0737** | 5.4584*** | 6.2370 |

Table 13. The ARCH effect test for the residual sequence of EGARCH model

| Stages | F statistic | Sample R^2 |
|--------|-------------|------------|
| RK     | 0.1715(p=0.6788) | 0.1719(p=0.6784) |
| RK1    | 0.0074(0.9314) | 0.0075(0.9312) |

Table 14. Parameter estimation results of GARCH(1,1) model

| Parameters     | Before the opening of the SHSC (2014.12.4-2016.12.4) | After the opening of the SHSC (2016.12.5-2018.12.5) |
|----------------|--------------------------------------------------------|--------------------------------------------------------|
|                | RZ1          | RK1          | RZ2          | RK2          |
| \( \alpha \)  | 0.0676       | 0.1258       | 0.0362       | 0.0271       |
| \( \beta \)   | 0.9313       | 0.7565       | 0.9617       | 0.9709       |
| \( \gamma \)  | 0.9989       | 0.8823       | 0.9979       | 0.9980       |

Table 15. Leverage factor coefficients of stock index sequences in Shenzhen and Hong Kong stock markets

| Leverage factor | RZ1 | RK1 | RZ2 | RK1 | RK2 |
|-----------------|-----|-----|-----|-----|-----|
| \( \gamma \)   | -0.0663** | -0.0737** | -0.0450 | -0.2292** | -0.1101** | -0.0337 |

Note: * and ** indicate that it is significant at the level of 10% and 5% respectively.
Figure 1. Normal distribution QQ graph for stage logarithmic return rate of full sample in Shenzhen and Hong Kong.

Figure 2. Normal distribution QQ graph for logarithmic return rate of different stages in Shenzhen and Hong Kong.
Figure 3. Information impact curve graph of Shenzhen stock market during the full sample stage (RZ)

Figure 4. Information impact curve graph of Shenzhen stock market during the second stage (RZ2)

Figure 5. Information impact curve graph of Hong Kong stock market during the full sample stage (RZ)

Figure 6. Information impact curve graph of Hong Kong stock market during the first stage (RZ1)
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