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Effect of the Shenzhen-Hong Kong stock connect mechanism on stock market volatility

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Abstract. The Shenzhen-Hong Kong Stock Connect (SHSC) mechanism has created the largest two-way opening of the China capital market, but it has also increased risk transmission. To analyze the impact of SHSC on the volatility of a single market in Shenzhen or Hong Kong, this paper establishes the volatility models of stock markets in Shenzhen and Hong Kong based on the Generalized Auto-Regressive Conditional Heteroscedasticity (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. Furthermore, the leverage effect of the Shenzhen stock market is expanding under the effect of SHSC, but the leverage effect of the Hong Kong stock market is decreasing.

1. Introduction

The Shenzhen-Hong Kong Stock Connect (SHSC) mechanism is an abbreviation of a 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 mainland Chinese and Hong Kong investors to buy and sell stocks listed on each other exchanges within the prescribed scope through local securities firms or brokers. The SHSC mechanism, which has been in operation for three years, was officially launched on December 5, 2016. 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. 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 with the help of Hong Kong, an international capital

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market that was considered a transit point. 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.

In recent years, China reforms have accelerated the growth of the capital market, and the degree of marketization and globalization of capital transactions has risen. 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 capital market. The SHSC mechanism, however, will produce information shock and local market fluctuations in the stock markets of Shenzhen and Hong Kong. Based on the literature, this paper will develop relevant econometric models to investigate the impact of SHSC on the volatility of the single market in Shenzhen and Hong Kong, to provide some investment reference for investors and a decision-making basis for relevant departments to promote the orderly opening of the capital market and formulate and improve China financial system policy.

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 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 this regard, there are some problems; for example, the ARCH model cannot determine the order of the time delay and the parameters are negative. Therefore, Abdalla [9] and Omolo [10] proposed the model of Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model, which rectifies some of the ARCH model shortcomings, improves its applicability, and provides an effective analytical method for the later processing of a large number of financial time series. Dai et al. [11] developed a simple linear autoregressive model to capture predictive correlations between stock market implied volatility and stock volatility, and the findings revealed that there is very significant Granger causality between the two. Zhang et al. [12] found that the variation tendency of the 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 minor and exotic currencies, rather than major 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. To overcome the limitations of symmetric models, various GARCH-type models emerged. Kawakatsu [14], Glosten et al. [15], and Zakoian [16] proposed the models of exponential GARCH, the GARCH model of Glosten, Jagannathan, and Runkle (GJR-GARCH), and Threshold GARCH (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 [18] and Nelson [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 previous research, Fornari and Mele [20] proposed a more general volatility switching model, which can detect whether the asymmetry can be reversed. Later, Laopodis [21] integrated the Multivariate Vector Moving Average Exponential GARCH (MVMA-EGARCH) model with the time series model to investigate if long-term interest rate fluctuations in different countries affected each other. The results showed that all countries long-term interest rate fluctuations are highly correlated. Based on the previous research, Hung [22] hypothesized that volatility transfer is time-varying and asymmetric, so he devised an Intelligent Threshold GARCH (ITGARCH) model to modify the threshold value, and used the GA genetic algorithm and fuzzy theory to describe time-varying and asymmetric volatility. The results showed that volatility transfer is time-varying, nonlinear and asymmetric. Yu et al. [23] employed the GARCH-Mixed Data Sampling (GARCH-MIDAS) model to assess the effect of global economic policy uncertainty on Chinese stock market volatility, and the results revealed that the error of the prediction result obtained by the GARCH-MIDAS model is smaller than the Realized Volatility (RV) model.

In addition to studying the features of stock market volatility in foreign countries, Chinese scholars have gradually begun to delve deeper into the volatility of stock market return rates. Zhou and

Huang [24] used the 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 the 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 the GARCH model and constructed the RS-GARCH model to study the Shanghai composite index. The results showed that the RS-GARCH model significantly improved the phenomenon of "pseudo-continuity" compared with the GARCH model. Based on previous studies, Wang and Wang [27] used the 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 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 the jump, and performed the analysis with Fourier value maximum likelihood estimation and backtracking test. The results showed that the SSE 50ETF market also has a significant conditional heteroscedasticity effect and random jumping behavior, but the volatility does not have a significant leverage effect. Furthermore, Kim and Won [29] introduced a new hybrid Long Short-Term Memory (LSTM) model that combines the LSTM model with various Generalized Autoregressive Conditional Heteroscedasticity (GARCH)-type models to forecast stock price volatility. 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 the GARCH-MIDAS model frameworks have significant impacts on the stock price volatility.

According to the literature, scholars are primarily interested in the volatility of model efficacy 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 works of literature on SHSC. As a result, more research into the impact of SHSC on the volatility of the Shenzhen-Hong Kong stock market is required. 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 the 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 the 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 number of listed companies joined the "stop trading tide", with 50 percent of A-share listed companies announcing that trading would be suspended at the same time. 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, 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 the financial market.

Stock market volatility is the result of the interaction of multiple factors, such as policy, economy, market, investor psychological expectation, and other influencing factors [35–40]. The study of the elements that affect volatility has become a priority for 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. The impact on the stock market is different for each group. 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. The return rate of a stock index is calculated using the logarithmic difference method in this section, and its statistical properties are first described. Secondly, the stability, correlation, and ARCH effect of the return rate of the 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 the Shenzhen Stock Exchange (399001) and Hong Kong Hang Seng Index (HSI) 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 the 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 cleaning the data, we obtained 950 trading data in total. Investing.com provided the daily closing data relating to the Shenzhen Component Index and Hong Kong Hang Seng Index. In this paper, we select the logarithmic return rate of the 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 y_t is the daily closing price of each stock index on the tth day. 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.

Because the SHSC officially opened on December 5, 2016, we use that date as the dividing node and divide the data into two stages, namely, the period before the SHSC opened and the period after the SHSC opened, 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. Table 1 shows the symbol explanations in this section.

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

It can be seen from Table 2 that the skewness of the logarithmic return rate series in the 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 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 Figures 1 and 2, we can conclude 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

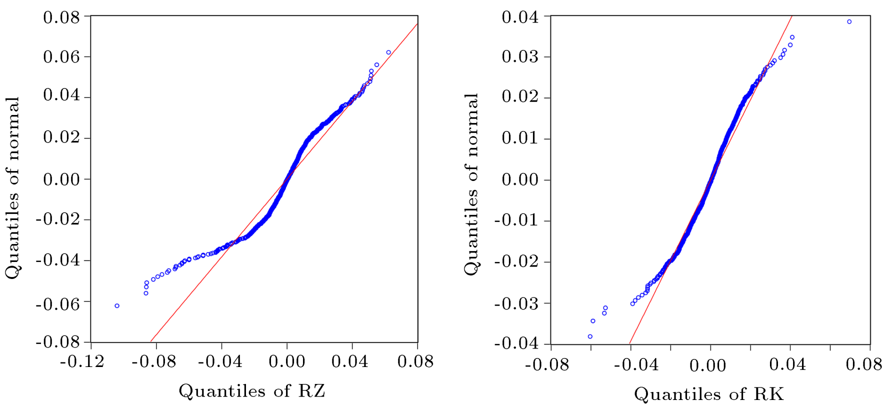
Before performing a statistical analysis on a financial time series, the series stationarity should be tested first, and only then can the following stage statistical analysis be performed. The Augmented Dickey-Fuller test is utilized in this research to judge the stability of stock market sequences in Shenzhen and Hong Kong, using the AIC and BIC minimum principles. 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 the null hypothesis that the sequences have unit root is rejected at the significance level of 5%, as shown by the p-value

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
μ	Constant term coefficient of the mean value equation
ω_1	Constant term coefficient of variance equation
α_1	The ARCH coefficient
β_1	The GARCH coefficient
γ_1	Coefficient of asymmetric term (leverage factor)
υ	Shape parameter
ξ	The coefficient of skewness

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

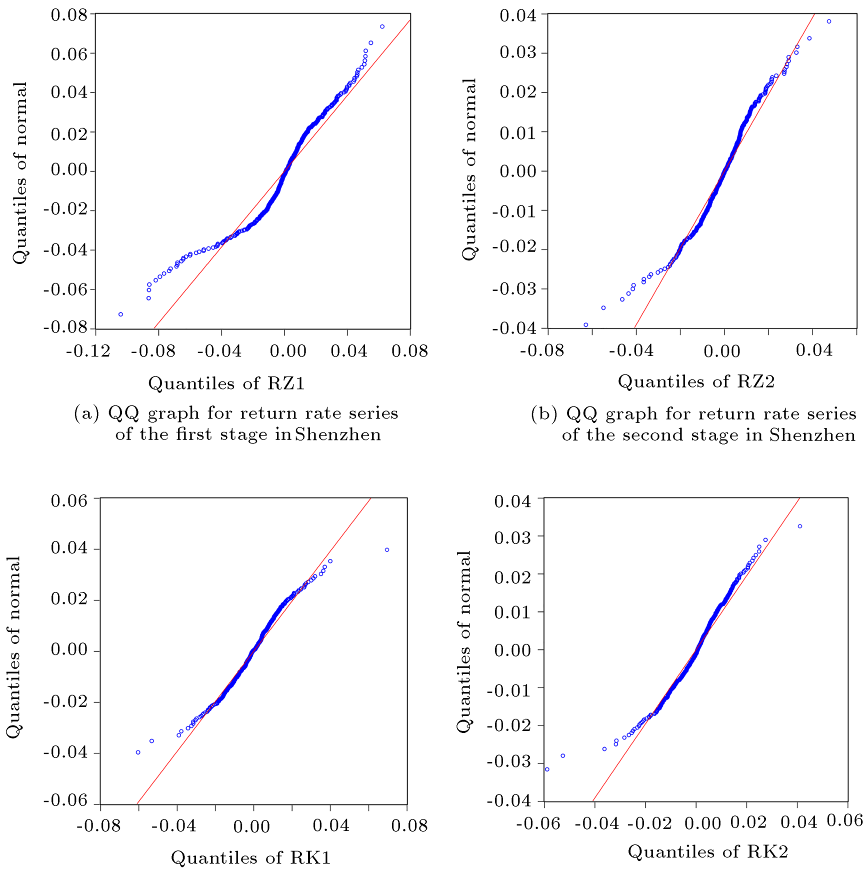
Stage	Full sample		The first stage		The second stage	
	RZ	**RK**	**RZ1**	**RK1**	**RZ2**	**RK2**
Mean value	–0.0002	0.0001	0.0002	–0.0001	–0.0006	0.0004
median	0.0006	0.0008	0.0015	–0.0002	0.0001	0.0011
Maximum value	0.0625	0.0699	0.0625	0.0699	0.0477	0.0413
Minimum value	–0.1038	-0.0602	–0.1038	–0.0602	–0.0627	–0.0588
Standard deviation	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 (0.0000)	564.4087 (0.0000)	213.3556 (0.0000)	215.8502 (0.0000)	199.7580 (0.0000)	339.5424 (0.0000)



(a) QQ graph for stage return rate series of full sample in Shenzhen

(b) QQ graph for stage return rate series of full sample in Hong Kong

Figure 1. Normal distribution QQ graph for stage logarithmic return rate of full sample in Shenzhen and Hong Kong.



(a) QQ graph for return rate series of the first stage in Shenzhen
(b) QQ graph for return rate series of the second stage in Shenzhen
(c) QQ graph for return rate series of the first stage in Hong Kong
(d) QQ graph for return rate series of the second stage in Hong Kong

Figure 2. Normal distribution QQ graph for logarithmic return rate of different stages in Shenzhen and Hong Kong.

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**	
Variables	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

in the output results. As a result, the logarithmic return sequences of the stock markets in Shenzhen and Hong Kong can be considered stable.

Table 4 shows the autocorrelation test results of the R_t sequences. We can see from the corresponding p values 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, implying that there is no autocorrelation sequence, (ADF) is the white noise sequence, and it also demonstrates that the mean model does not require the autocorrelation part, and the mean equation consists of a constant term plus a random perturbation term. We must explain the autocorrelation of the square value of the return rate sequence to fit the GARCH model. 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

We apply the maximum likelihood estimation method to estimate the parameters 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, 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.

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	RZ2	1	52.4840	0.0000
	RK	1	0.2040	0.6510	RK2	1	6.6550	0.0100
The first stage	RZ1	1	2.1570	0.1420	RZ12	1	20.8480	0.0000
	RK1	1	0.3550	0.5520	RK12	1	4.9590	0.0260
The second stage	RZ2	1	0.1010	0.7510	RZ22	3	20.6460	0.0000
	RK2	1	0.0180	0.8950	RK22	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	**RK**	**RZ1**	**RK1**	**RZ2**	**RK2**
F statistic	55.2612 (0.0000)	6.5635 (0.0106)	21.6075 (0.0000)	5.0106 (0.0257)	6.3207 (0.0003)	8.0122 (0.0000)
Sample R^2	52.3217 (0.0000)	6.5321 (0.0106)	20.7439 (0.0000)	4.9787 (0.0257)	18.3806 (0.0004)	23.0597 (0.0000)

Note: The value of p corresponding to the statistic is in brackets.

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 an ARCH effect among the sequences, no GARCH-type models are required 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 an 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 the GARCH model.

From the concept of volatility in Section 2 and the existing literature [41,42], we know that 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 the Shenzhen stock market and Hong Kong stock market respectively, and discuss whether there is a leverage effect in different stages, 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 the 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:

$$\mathbf{y}_t = \mathbf{x}_{t'}\gamma + u_t, \quad t = 1, 2, \cdots, T, \tag{2}$$

$$u_t = \sqrt{\sigma_t}\varepsilon_t, \tag{3}$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{4}$$

where $\mathbf{x}_t = (x_{1t}, x_{2t}, \cdots, x_{kt})'$ is the return rate sequence of Shenzhen stock market, $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \cdots, \gamma_k)'$ is the coefficient vector of the mean value equation, u_t

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

Stages	RZ	RZ1	RZ2
μ	2.5375×10^{-4}	8.0000×10^{-4}	1.0240×10^{-3}
ω_1	7.4774×10^{-9}	4.2000×10^{-7}	-3.5500×10^{-7}
α_1	0.0563^{**}	0.0676^{**}	0.0362^{*}
β_1	0.9430^{**}	0.9313^{**}	0.9617^{**}
ν	5.2096^{**}	4.3114^{**}	6.0497^{**}
ξ	-0.1639^{**}	-0.1449^{*}	-0.1542^{**}
AIC	–5.6374	–5.0694	–6.1044
BIC	–5.5762	–5.0346	–6.0694

Note: * and ** indicate that they are 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.

Different stages of Shenzhen stock market	Variance equations
RZ	$\hat{\sigma}_t^2 = 0.0570\hat{\varepsilon}_{t-1}^2 + 0.9430\hat{\sigma}_{t-1}^2$
RZ1	$\hat{\sigma}_t^2 = 0.0676\hat{\varepsilon}_{t-1}^2 + 0.9313\hat{\sigma}_{t-1}^2$
RZ2	$\hat{\sigma}_t^2 = 0.0362\hat{\varepsilon}_{t-1}^2 + 0.9617\hat{\sigma}_{t-1}^2$

is residual and satisfies $u_t \sim N(0, \sigma_t)$, and σ_t 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 the Shenzhen stock market under partial t distribution all have a good fitting effect, and the results are listed in Table 6.

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

1. In the parameter estimation of the full sample stage in the Shenzhen stock market, the μ and ω_1 terms are not significant. In the two stages before and after the opening of SHSC in the Shenzhen stock market, except the parameter μ and parameter ω_1 which 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 for the constant term, the return rate model of the stock index at different stages can well explain the conditional variance of the return rate. At the same time, it shows that stock return rate volatility persists due to a phenomenon known as volatility cluster and that it will eventually return to unconditional variance.

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

In asymmetric model, conditional variance depends only on the value of ε_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. To reflect the asymmetry of volatility in the 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 follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}},$$

$$t = 1, 2, \cdots, T. \tag{5}$$

The advantage of Model (5) is that the calculated result of σ_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.

To determine whether the leverage effect exists in the Shenzhen stock market, this paper establishes an asymmetric EGARCH(1,1) model for the return rate of stock index in the 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.

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

Stages	RZ	RZ1	RZ2
μ	0.0006	0.0013**	-1.0500×10^{-4}
ω_1	−0.1867**	−0.1824**	−0.6306**
α_1	0.1484**	0.1948**	0.0440*
β_1	−0.0663**	−0.0450	−0.2292**
ν	0.9909**	0.9945**	0.9346**
μ	4.1281**	3.5061**	5.8658**
AIC	−5.5981	−5.0659	−6.1437
SC	−5.5674	−5.0130	−6.0912

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

According to the analysis of the results in Table 8, we can conclude the following:

1. The leverage factors in the Shenzhen stock market during the stage of the 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 the Shenzhen stock market is as follows:

$$\ln(\sigma_t^2) = -0.1867 + 0.1484\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| - 0.0663\frac{u_{t-1}}{\sigma_{t-1}} + 0.9909\ln(\sigma_{t-1}^2).$$

   During the full sample stage of the 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 γ_1 of RZ1 in the 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 the Shenzhen stock market, and its variance equation can be expressed as follows:

$$\ln(\sigma_t^2) = -0.6306 + 0.0440\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| - 0.2292\frac{u_{t-1}}{\sigma_{t-1}} + 0.9346\ln(\sigma_{t-1}^2).$$

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, that is $u_{t-1} > 0$, the information shock has $0.0440 + (-0.2292) = -0.1852$ times impact on the logarithm of conditional variance. In the case of "bad news", that is $u_{t-1} < 0$, the impact will be $0.1891+(-0.1101)^*(-1) = 0.2732$ times.

From the above analysis, there are leverage effects and asymmetric fluctuations in the full sample stage (RZ) and the second stage (RZ2) of the Shenzhen stock market. Therefore, we can draw the corresponding information impact curve to understand the Shenzhen stock market intuitively. We set:

$$f\left(\frac{u_{t-1}}{\sigma_{t-1}}\right) = \alpha\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{u_{t-1}}{\sigma_{t-1}}, \tag{6}$$

and $z_t = \frac{u_t}{\sigma_t}$, then we have:

$$f(z_t) = \alpha\,|z_{t-1}| + \gamma z_{t-1}. \tag{7}$$

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

The function of the information impact curve of Shenzhen stock market during the full sample stage (RZ) is:

$$f(\cdot) = 0.1484\,|z_{t-1}| - 0.0663 z_{t-1}.$$

The function of the information impact curve of the Shenzhen stock market during the second stage (RZ2) is:

$$f(\cdot) = 0.0440\,|z_{t-1}| - 0.2292 z_{t-1}.$$

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

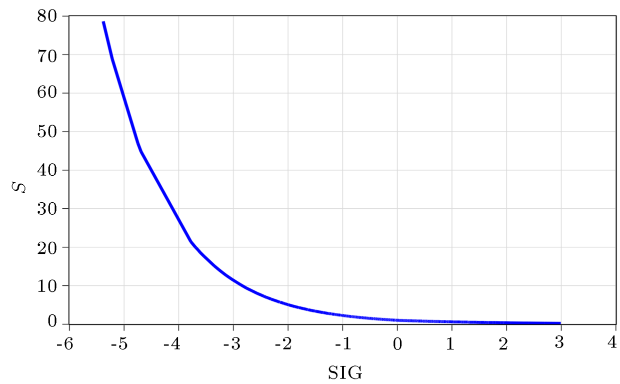


Figure 3. Information impact curve graph of Shenzhen stock market during the full sample stage (RZ).

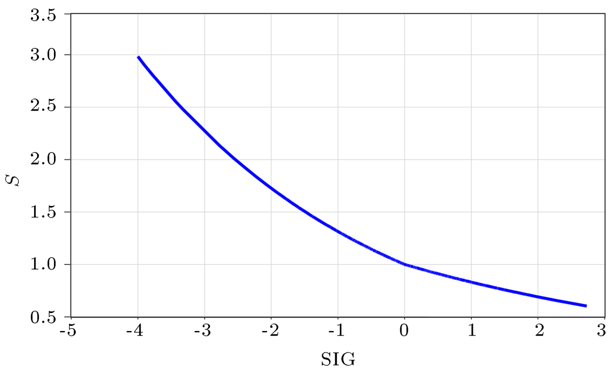


Figure 4. Information impact curve graph of Shenzhen stock market during the second stage (RZ2).

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

Stages	F statistic	Sample R^2
RZ	1.8710 ($p = 0.1717$)	1.8712 ($p = 0.1713$)
RZ2	2.4830 ($p = 0.1158$)	2.4804 ($p = 0.1153$)

Finally, the ARCH effect is tested for the residual sequence of the EGARCH model in the 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.

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

Table 11. Variance equations of the GARCH(1,1) models in different stages of Hong Kong stock market.

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

1. In the parameter estimation of the full sample stage in the Hong Kong stock market, except the parameter ω_1 which is not significant, the estimation of other parameters of the model is significant. In the first stage, except for the parameters μ, ω_1, and ξ, the estimation of other parameters of the model is significant. But in the second stage, only the estimation of ω_1 is not significant;
2. The variance equations of the GARCH(1,1) model of Hong Kong stock market at different stages are shown in Table 11.

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

1. The variance equation of the Hong Kong stock market can be expressed by:

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

Stages	RK	RK1	RK2
μ	$5.6881 \times 10^{-4*}$	8.2100×10^{-4}	$8.0000 \times 10^{-4*}$
ω_1	1.5469×10^{-6}	1.5900×10^{-5}	-3.5500×10^{-7}
α_1	0.0500^{**}	0.1258^{*}	0.0271^{**}
ν	5.8034^{**}	5.1823^{**}	6.9505^{**}
β_1	0.9373^{**}	0.7565^{**}	0.9709^{**}
ξ	-0.0802^{**}	-0.0784^{*}	-0.1093^{**}
AIC	–6.3587	–5.9883	–6.4873
BIC	–6.3248	–5.9564	–6.4668

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

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

Stages	RK	RK1	RK2
μ	0.0005*	0.0005*	0.0005*
ω_1	–0.3400**	–0.3400**	–0.3400**
α_1	0.0995**	0.0995**	0.0995**
γ_1	–0.0737**	–0.0737**	–0.0737**
β_1	0.9707**	0.9707**	0.9707**
ν	5.4584**	5.4584**	5.4584**
AIC	–6.2370	–6.2370	–6.2370
SC	–6.2063	–6.2063	–6.2063

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

$$\ln(\sigma_t^2) = -0.34 + 0.0995\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| - 0.0737\frac{u_{t-1}}{\sigma_{t-1}} +0.9707\ln(\sigma_{t-1}^2).$$

During the full sample stage of the 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 the Hong Kong stock market, all the parameters except parameters μ 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:

$$\ln(\sigma_t^2) = -1.0458 + 0.1891\left|\frac{u_{t-1}}{\sigma_{t-1}}\right| - 0.1101\frac{u_{t-1}}{\sigma_{t-1}} +0.8973\ln(\sigma_{t-1}^2),$$

where the estimated value of the asymmetric term γ_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, that is $u_{t-1} > 0$, the information impact has $0.1891 + (-0.1101) = 0.079$ times impact on the logarithm of conditional variance. In the case of "bad news", that is $u_{t-1} < 0$, the impact will be $0.1891 + (-0.1101)^*(-1) = 0.2992$ times.

3. In the second stage (RK2) of the Hong Kong stock market, the parameters ω_1, α_1, and leverage factor γ_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.

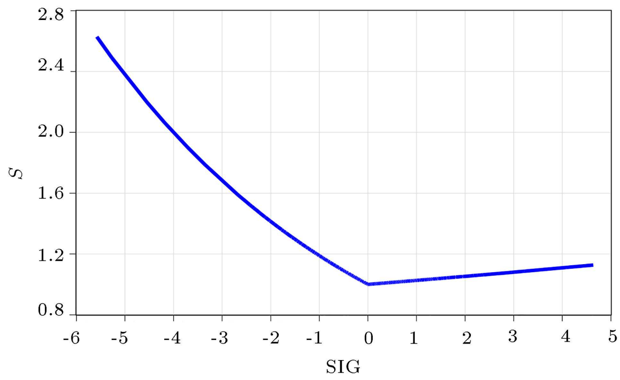


Figure 5. Information impact curve graph of Hong Kong stock market during the full sample stage (RZ).

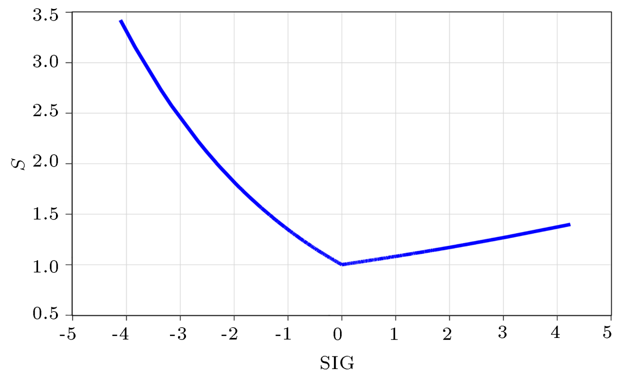


Figure 6. Information impact curve graph of Hong Kong stock market during the first stage (RZ1).

From the above analysis, we can obtain the information impact curve function of the Hong Kong stock market. Specifically, the function of the information impact curve during the full sample stage (RK) is:

$$f(\cdot) = 0.0995\,|z_{t-1}| - 0.0737 z_{t-1},$$

and the function of the information impact curve during the first stage (RZ1) is:

$$f(\cdot) = 0.1891\,|z_{t-1}| - 0.1101 z_{t-1}.$$

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

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

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)

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.

   From Table 14, we can see that the ARCH term coefficients α_1 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 β_1 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 the market information transmission. The values $\alpha_1+\beta_1$ 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 the GARCH model listed in Tables 6 and 10, the return rate of the stock index in Shenzhen and Hong Kong has conditional heteroscedasticity. The coefficients of the 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 approximately simulate the square of stock index return rate. When the stock market volatility is large, the conditional variance is large, 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 the 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 the stock index had an obvious negative leverage effect. The specific leverage factors of Shenzhen and Hong Kong stock markets are shown in Table 15.

   Table 15 shows the significant leverage factor $\gamma_1 < 0$, implying that the negative impact of negative news is negatively correlated with volatility and that positive news has a greater impact than negative news. China stock market was in a deleveraging cycle when the SHS mechanism was opened in Shenzhen, and the leverage effect was not significant. However, after the opening of SHS mechanism, the openness degree of the 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

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
α_1	0.0676	0.1258	0.0362	0.0271
β_1	0.9313	0.7565	0.9617	0.9709
$\alpha_1+\beta_1$	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	RZ	RK	RZ1	RZ2	RK1	RK2
γ_1	-0.0663^{**}	-0.0737^{**}	-0.0450	-0.2292^{**}	-0.1101^{**}	-0.0337

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

brought by this mechanism was fully digested. But with the opening of the SHSC mechanism in 2016, the expectation difference of the Hong Kong stock market indirectly damped the market sentiment and reduced the "leverage effect" of the Hong Kong stock market.

4. Conclusion

To measure the impact of the opening of SHSC on the stock markets in Shenzhen and Hong Kong, this paper used the 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 first 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 SHSC mechanism improves the effectiveness of information transmission between the two stock markets of Shenzhen and Hong Kong and increases the short-term volatility of these two stock markets based on the provided information. Furthermore, the SHSC mechanism increases Shenzhen and Hong Kong openness making them more capable of absorbing stock market risks and affecting the leverage effect of stock markets in different degrees and directions in Shenzhen and Hong Kong.

The main contribution of this paper is as follows:

- We took the SHSC mechanism as the research background and establish the volatility models of the 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 found that the Skew-t GARCH 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 the 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. Based on the findings of this paper, we will take a closer look at this challenging problem in the future and investigate multi-asset portfolio risk assessment methods and different optimized portfolio models in the stock markets of Shenzhen and Hong Kong, which can serve as a decision-making reference for investors.

Acknowledgments

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