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Volatility Asymmetry of Scale Indexes - Taking China as an Example

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ABSTRACT

This study focused on the volatility asymmetry of scale indexes in China's stock market. A total of 12 indexes in four categories were studied during the study period, which lasted from January 1, 2012 to September 30, 2018. The study results showed that large-scale volatility asymmetry almost never occurred but small-scale volatility asymmetry was very significant, which could result from the status of information reception in China. It was easier for large companies to receive information than small companies; therefore, compared with small companies, information asymmetry rarely happened to large companies, leading to the situation where small companies were more likely to have fiercer negative responses to information. However, this study did not divide the study period into bull markets and bear markets, and the addition and subtraction of these two periods could dilute the causes of the disappearance of large-scale volatility asymmetry.

Keywords: Volatility Asymmetry, Scale Indexes, EGARCH
JEL Classification: G2

1. INTRODUCTION

In the past, the studies on asset prices and risks usually used returns to explain risks, however risks have become the factor to explain returns since Fama (1971) indicated the relationship between risks and returns. Risk is a variable that cannot be directly quantified by the market; hence, it is necessary to find a suitable risk proxy variable. The traditional financial literature mostly supports the viewpoint of using volatility as a risk proxy variable. According to the capital asset pricing model (CAPM) proposed by Sharpe (1964), Lintner (1965) and Mossin (1966), it is more certain that system risks are an important factor in explaining returns on assets. Since then, the arbitrage pricing theory (APT) proposed by Ross (1976), the three-factor model (market, scale, and book-to-market ratio) proposed by Fama and French (1992, 1993), and the four factors (market, scale, book-to-market ratio, and momentum effect) proposed by Carhart (1997) have been used to predict returns. The volatility of these factors is the main explanatory variable, therefore studies on volatility have been a major field of financial commodity prices. Additionally, with the development of measuring instruments, volatility has been extended from static estimations to dynamic models for prediction. Therefore, this study proposed using dynamic models to investigate the changes in risk (volatility) of real estate in Taiwan.

Volatility asymmetry attracted considerable attention in academic circles in the past. For example, studies conducted by Chelley-Steeley and Steeley (1996), Laopodis (1997), Hung (1997), Yang (2000), and other scholars showed the phenomenon of volatility asymmetry. The so-called phenomenon of volatility asymmetry refers to new information causing price volatility. If the new information is positive, the future price volatility will be reduced.

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On the contrary, if the new information is negative, the future price volatility will rise. The phenomenon of volatility asymmetry first appeared in studies on stick markets, such as when Black (1976) verified the negative relationship between the current returns and future volatility of the stock market. Christie (1982), Schwert (1990), and Koutmos and Saidi (1991) also found the same results. From the above studies, it can be deduced that companies' financial leverage ratios will rise when new information causes stock prices to fall; in other words, the risks of holding stocks will increase (the volatility of future returns is high). On the contrary, when new information causes stock prices to rise, the companies' financial leverage ratios will fall and the volatility of future returns will be low. This phenomenon is called the leverage effect. Nevertheless, Lo and MacKinlay (1988) believed that this phenomenon originates from nonsynchronous trading. Sentana and Wadhwani (1992) deduced that the phenomenon of volatility asymmetry is caused by traders' herding behavior. Shih-Yung et al. (2012) found that government policies also have significant effects on risk changes in asset investment. Hence, no unanimous conclusion has been reached on whether the volatility asymmetry of stock returns is caused by the leverage effect.

On the other hand, prices and trading volumes in the stock market can be considered high-frequency financial time series data. Brooks (2002) believed that the phenomena related to financial time series, such as leptokurtosis and volatility clustering, cannot be processed by using linear models, therefore it is necessary to consider using non-linear models. On finance, the two series of models most commonly used are ARCH (Autoregressive Conditional Heteroskedasticity) models and switching models. Among them, ARCH models are the most widely used. The ARCH models were proposed by Engle (1982) and were extended to GARCH models (Generalized ARCH) by Bollerslev (1986) to describe the volatility clustering of returns. Studies on volatility mainly focus on volatility asymmetry and the long-term and short-term effects of volatility. GARCH models cannot differentiate the different effects of positive and negative information on the degree of volatility (volatility asymmetry), therefore Nelson (1991) developed the exponential GARCH model (EGARCH) for differentiation, while Campbell and Hentschel (1992) created the Quadratic GARCH model (QGARCH) to fit the phenomenon of volatility asymmetry. However, through a comparison of both series of models, Engle et al., (1993) found that the fitness of the EGARCH model was better. Hafner et al., (1998) also used empirical data to verify the advantages of the EGARCH model in fitting the volatility of high-frequency data.

About the volatility asymmetry of scale indexes, Cheung and Ng (1992) first proposed that the volatility asymmetry of company scale indexes will change over time. Duffee (1995), in a study of the NYSE and AMEX, found that the volatility of small-scale indexes is higher than that of large-scale indexes. Shih-yung et al. (2014) studied Taiwan and found that the volatility asymmetry of small-scale indexes is less likely to exist and that the volatility asymmetry of large-scale indexes was reduced significantly after the financial tsunami. So far, it has been developed for 30 years since the pilot project was started in 1989, and the compilation of these indexes, such as industry indexes and scale indexes, has matured. Hence, this study explored the volatility asymmetry of the scale indexes based on scale indexes in China.

This study consists of four sections. Section 1 is the introduction, which introduces the literature on volatility asymmetry. Section 2 shows the research method and further introduces the methods used in this study. Section 3 shows the data and empirical analysis, including brief descriptions of the data used in the study and analysis of the volatility asymmetry of 12 major scale indexes in China. The last section is the conclusion, which summarizes the analysis results and provides suggestions.

2. RESEARCH METHODOLOGY

This study explored the effects of volatility in different company scales. EGARCH was adopted in this paper to discuss volatility asymmetry. According to the suggestions of Bollerslev et al. (1992), models should be designed according to the principle of simplicity. This study used the EGARCH (1,1) models developed by Nelson (1991) for analysis, and the models are described below.

$$R_t \left| I_{t-1} \sim f\left(\mu_t, \sigma_t^{\,2}\right)\right. \tag{1}$$

$$R_t = \beta_0 + \sum_{i=1}^{p} \beta_i R_{t-1} + \varepsilon_t \tag{2}$$

$$\ln\left(h_t\right) = \alpha_0 + \alpha_1\left(\left|z_{t-1}\right| - E\left[\left|z_{t-1}\right|\right] + \delta \cdot z_{t-1}\right) + \varphi \ln\left(h_{t-1}\right) \tag{3}$$

In the above models, Eq. (1) represents that, based on the information set (I_{t-1}) in the Period t-1, the return (R_t) in period t is subject to a distribution in which both the expected values and variances change with time. Eq. (2) describes the auto-correlated behavior of a return, namely, the mean equation. In Eq. (3), the variance equation is the key formula of the EGARCH models. It shows that the variance is also exponentially auto-correlated and that the residual will affect the future variance, where, $z_t \equiv \varepsilon_t / h_t$ is the value gained after the residual is standardized by the conditional variance. In Eq. (3), the effects of the standardized residual in the previous period on the current variance can be seen from the coefficient α_1 in ($\left|z_{t-1}\right| - E\left[\left|z_{t-1}\right|\right] + \delta \cdot z_{t-1}$). If the value of α_1 is positive, it indicates that the new information will increase the future volatility. however, positive or negative information will cause different increases in volatility. If z_{t-1} of the positive information is positive and z_{t-1} of the negative information is negative, when the coefficient δ is negative, the increase in future volatility caused by negative information will be greater than that caused by positive information; when the coefficient δ is positive, the increase in future volatility caused by positive information will be greater than that caused by negative information, which is volatility asymmetry.

3. DATA AND EMPIRICAL ANALYSIS

3.1. Research Data

The purpose of this study was to investigate the effects of scale on volatility asymmetry. Hence, large-cap, mid-cap and small-cap indexes were selected from all the indexes in China's stock market for comparison with the composite indexes selected. After that, whether there was volatility asymmetry of all the indexes during the sample period was investigated. A total of 12 indexes in four categories were selected, as shown in Table 1, and the study period was from January 1, 2012 to September 30, 2018. The data were sourced from the Shanghai Stock Exchange, the Shenzhen Stock Exchange, and China Securities Index Co., Ltd.

As shown in Table 1, this study divided the indexes into composite, large-cap, mid-cap, and small-cap indexes. The composite indexes included the SSE composite index and the SZSE composite index; the large-cap indexes included the mega-cap index, the SSE 50 index, the CSI 100 index, and the SZSE 100 index; the mid-cap indexes included the SSE mid-cap index, the CSI 200 index, and the SZSE 200 index; and the small-cap indexes included the SSE small-cap index, the CSI 500 index, and the SZSE 700 index. The scale index division and index abbreviations of this study are shown in Table 2.

The trend charts of all indexes are shown in Figures 1-12, which indicate that all the peaks of the stock indexes were concentrated in June 2015 as well as from 2012 to 2014, and that the stocks entered a consolidation phase after 2016.

Table 1: Introduction to indexes (1)

Abbreviation	Index category	Introduction to indexes and sample range	Base period	Basis point	Release date
SI	SSE composite index	All the listed stocks, including A shares and B shares, which overall reflect the price changes in the stocks listed on the Shanghai Stock Exchange. Indexes are weighted by the total issued capital stocks.	1990/12/19	100	1991/7/15
ZI	SZSE composite index	All the listed stocks, including A shares and B shares, which overall reflect the price changes in the stocks listed on the Shenzhen Stock Exchange and are weighted by the total issued capital stocks. SZSE code: 399106	1991/4/3	100	1991/4/4
SI50	SSE 50 index	The 50 most representative stocks with large market scale and good liquidity selected from the SSE 180 index components so as to comprehensively reflect the overall situation of a number of leading enterprises with the most market influence in the shanghai stock exchange. Indexes are weighted by their adjusted capital stocks	2003/12/31	1000	2004/1/2
SSEMG	Mega-cap index	The mega-cap index consists of 20 mega-cap companies with a certain scale and liquidity listed on the shanghai stock exchange, which comprehensively reflect the overall performance of the mega-cap listed companies in the shanghai stock exchange	2008/12/31	1000	2009/4/23
SSEM	SSE mid-cap index	The SSE mid-cap index is compiled by removing the SSE 50 index components from the SSE 180 index components to comprehensively reflect the overall situation of mid-cap companies in Shanghai	2003/12/31	1000	2009/7/3
Introduction to indexes (2)					
SSES	SSE small-cap index	The SSE small-cap index is comprised of the 320 stocks that are comprehensively top-ranked based on total values and trading volumes after the 180 SSE 180 index components are removed, which comprehensively reflect the overall situation of small-cap companies in Shanghai	2003/12/31	1000	2009/7/3
CSI100	CSI 100 index	The CSI 100 index is comprised of the 100 largest stocks selected from the Shanghai and Shenzhen 300 index sample stocks, which comprehensively reflect the overall situation of a number of large-cap companies with the most market influence in the Shanghai and Shenzhen stock markets	2004/12/31	1000	2006/5/29
CSI200	CSI 200 index	Components include 200 component companies with indexes other than the CSI 100 in Shanghai and the Shenzhen 300 index components. The CSI 200 index comprehensively reflects the overall situation of mid-cap companies in the shanghai and Shenzhen stock markets	2004/12/31	1000	2006/5/29
CSI500	CSI 500 index	The stocks in the sample space consist of the top 500 stocks by total market value, after the Shanghai and Shenzhen 300 index components, which are the top 300 stocks by total market value, are removed from all A shares, and which comprehensively reflect the stock price performance of a number of mid-cap and small-cap companies in China's A-share market. The CSI small-cap 500 index	2004/12/31	1000	2006/5/29
Introduction to indexes (3)					
ZI100	SZSE 100 index	A shares of the 100 companies listed on the Shenzhen Stock Exchange are the components, which are weighted by actually outstanding shares	2002/12/31	1000	2003/1/2
ZI200	SZSE 200 index	As the mid-cap index in the SZSE scale index, the SZSE 200 index consists of the remaining 200 stocks after the SZSE 100 index components in the current period are removed from the SZSE 300 index, with the aim of reflecting the overall situation of mid-cap enterprises in the Shenzhen market. SZSE code: 399009	2004/12/31	1000	2011/9/1
ZI700	SZSE 700 index	As the small-cap index in the scale index, the SZSE 700 index consists of the remaining 700 stocks after the SZSE 300 index components in the current period are removed from the SZSE 1000 index, which reflect the overall situation of small-cap enterprises in the Shenzhen market. SZSE code: 399010	2004/12/31	1000	2011/9/1

Table 2: Indicators of scale indexes

Index category	Index name	Index category	Index name
Composite index	SSE composite index	Mid-cap index	SSE mid-cap index
	SZSE composite index		CSI 200 index
large-cap index	Mega-cap index		SZSE 200 index
	SSE 50 index	Small-cap index	SSE small-cap index
	CSI 100 index		CSI 500 index
	SZSE 100 index		SZSE700 index

3.2. Descriptive Statistics

Firstly, the basic statistics (including sample sizes, means, standard deviations, skewness coefficients, and kurtosis coefficients in all periods), the Jarque-Bera statistics, and the ADF and PP unit root test statistics of the return sequences of the four major categories of indexes were observed, and the data were collected and recorded as shown in Tables 3-5.

According to Engle and Clive, (1987), the stationary variable series in the system is required to be verified before co-integration test of the multivariables, and the variable series must be corrected through difference. Therefore, the stationary distribution of the

Figure 1: SSE composite index

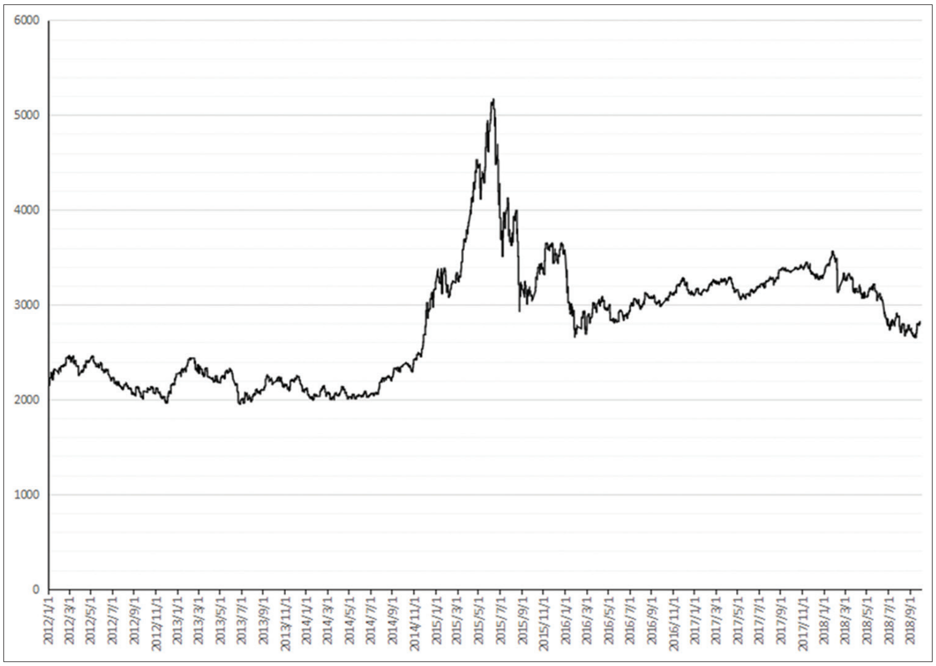


Figure 2: SZSE composite index

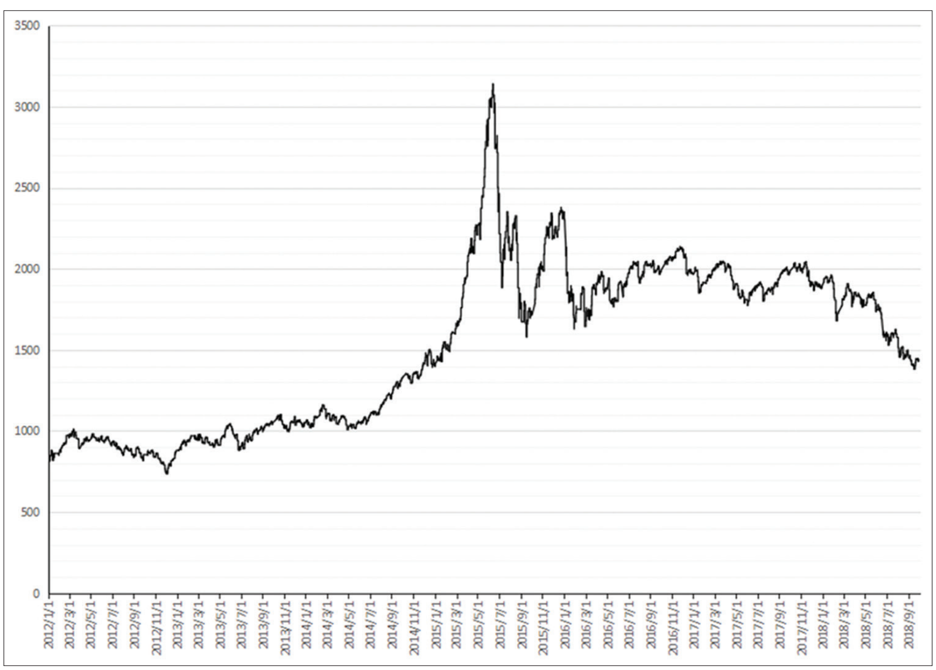


Figure 3: Mega-cap index

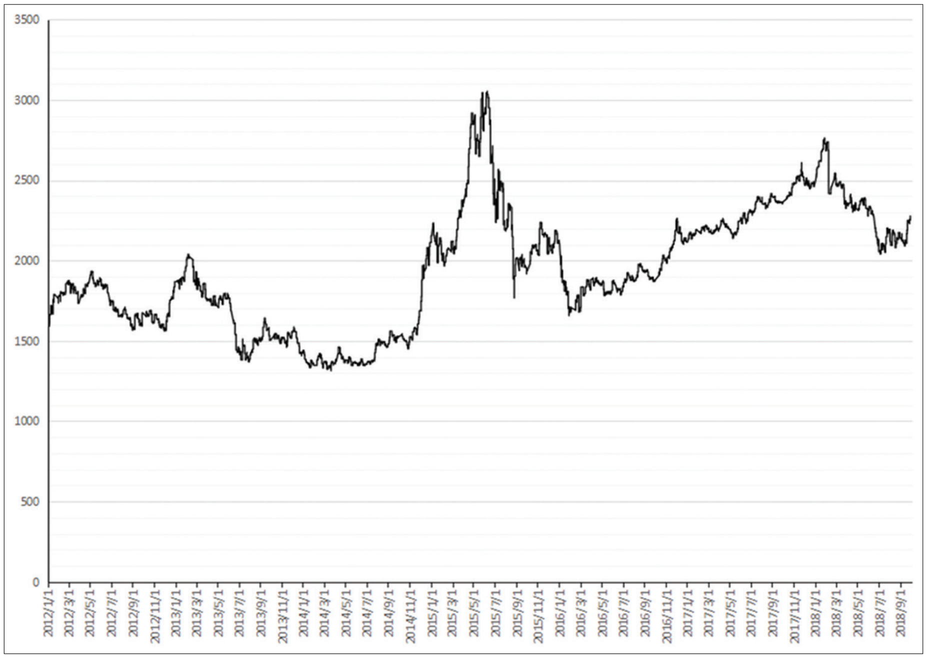


Figure 4: SSE 50 index

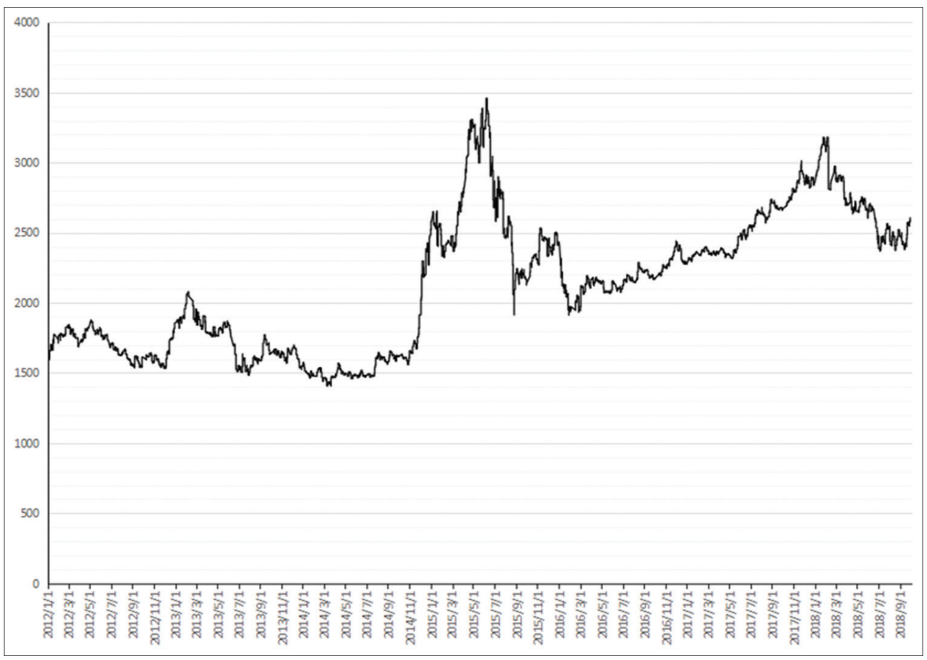


Table 3: Descriptive statistics

Index	Obs.	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB-test	
SI	1641	0.0250	0.0607	5.7635	−8.4909	1.3930	−0.9176	9.5781	3189	0.0000
ZI	1641	0.0448	0.1368	6.5244	−8.2414	1.6546	−0.8084	6.5223	1027	0.0000
SSEMG	1641	0.0320	0.0149	7.9097	−9.2035	1.5001	−0.4432	8.8186	2369	0.0000
SI50	1641	0.0408	0.0063	7.8392	−9.3824	1.5292	−0.3166	8.8844	2395	0.0000
SSEM	1641	0.0336	0.0664	6.7688	−8.6884	1.5644	−0.8305	8.8530	2531	0.0000
SSES	1641	0.0345	0.1456	7.7150	−8.4463	1.7337	−0.8755	7.6504	1688	0.0000
CSI100	1641	0.0406	0.0262	6.9281	−8.9418	1.4797	−0.4517	8.6715	2255	0.0000
CSI200	1641	0.0249	0.0857	7.0738	−8.9375	1.6468	−0.7517	7.8886	1789	0.0000
CSI500	1641	0.0384	0.1409	6.6013	−8.5395	1.7196	−0.9055	7.0408	1341	0.0000
ZI100	1641	0.0273	0.0584	6.6127	−8.1668	1.6112	−0.6032	6.8473	1112	0.0000
ZI200	1641	0.0350	0.1162	6.5711	−8.5155	1.7235	−0.8183	6.7443	1142	0.0000
ZI700	1641	0.0454	0.1197	6.2548	−8.6461	1.7594	−0.8706	6.2796	943	0.0000

Figure 5: CSI 100 index

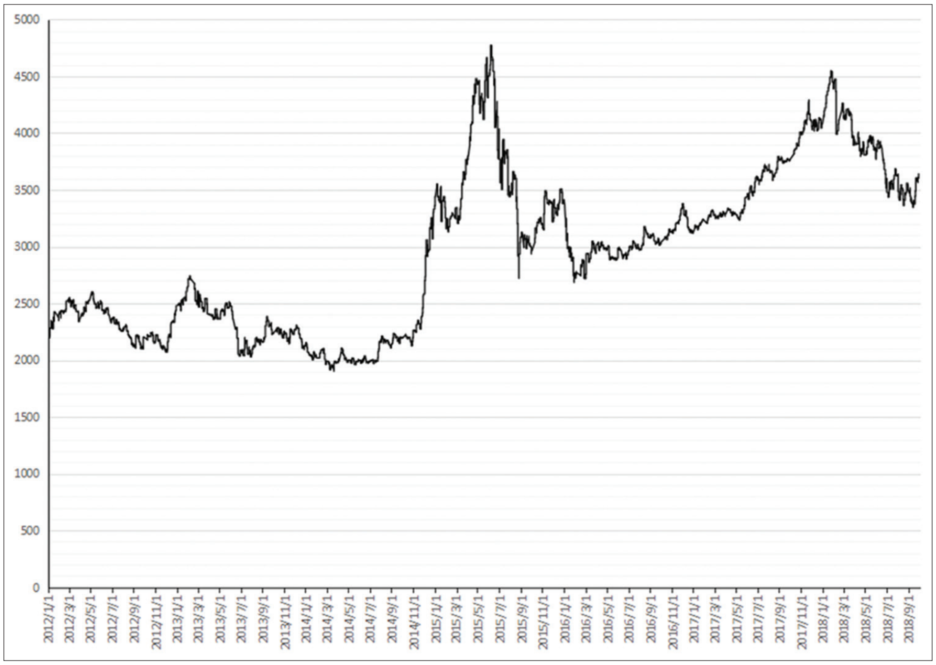


Figure 6: SZSE 100 index

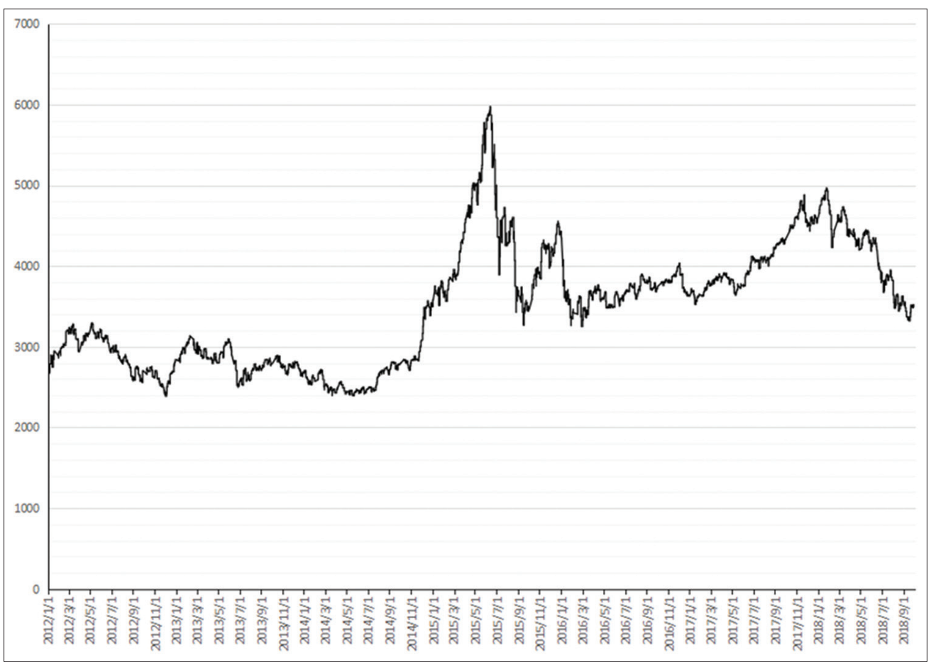


Table 4: Unit root test

Index		ADF			PP	
SI	−38.3823	(0.0000)	***	−38.3471	(0.0000)	***
ZI	−37.4969	(0.0000)	***	−37.6487	(0.0000)	***
SSEMG	−39.0353	(0.0000)	***	−39.0154	(0.0000)	***
SI50	−39.2557	(0.0000)	***	−39.2399	(0.0000)	***
SSEM	−38.1214	(0.0000)	***	−38.0898	(0.0000)	***
SSES	−37.2759	(0.0000)	***	−37.3399	(0.0000)	***
CSI100	−39.0125	(0.0000)	***	−38.9889	(0.0000)	***
CSI200	−38.2508	(0.0000)	***	−38.2196	(0.0000)	***
CSI500	−37.6204	(0.0000)	***	−37.7088	(0.0000)	***
ZI100	−38.9522	(0.0000)	***	−38.9326	(0.0000)	***
ZI200	−37.3119	(0.0000)	***	−37.4295	(0.0000)	***
ZI700	−36.7153	(0.0000)	***	−36.9626	(0.0000)	***

Figure 7: SSE mid-cap index

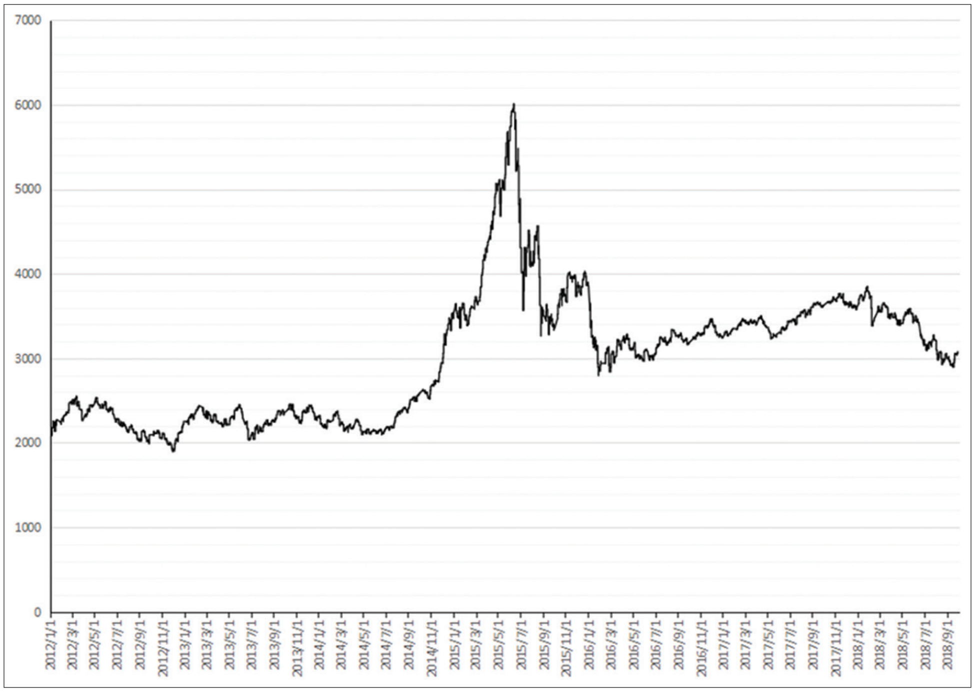
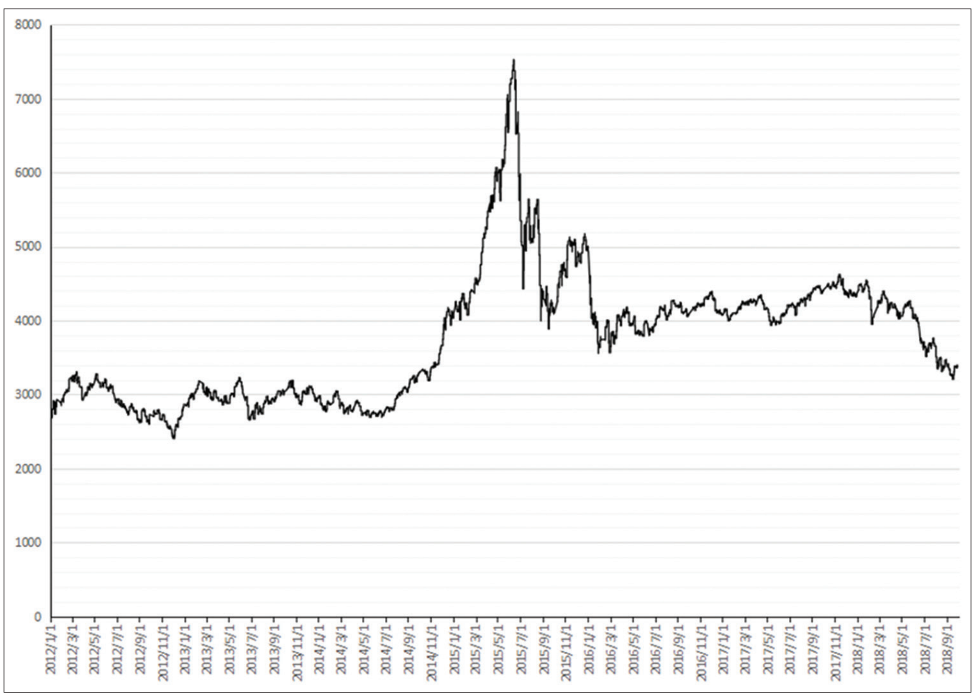


Figure 8: CSI 200 index



time series must be identified through the single root test. Also, the order of integration of the time series can be identified through unit root test.

According to the time-series literature by Pagan and Wickens (1989), it can be found that the unit root test includes Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP). ADF is stronger and more stable than DF. ADF and PP can solve white noise problem caused by the moving average term. The Engle and Clive (1987) pointed out that ADF is better than PP. Thus, ADF is used to test stability of the time series in this paper.

In ADF, the regression analysis is conducted for the series lagging one period and the first-order differential lag term after the first-order difference of the non-stationary data series. First, the time tendency is not considered, and the regression equation is applied:

$$\Delta Y_t = \beta + \beta_1 Y_{t-1} + \sum_{k=1}^{n} \gamma_k \Delta T_{t-k} + \varepsilon_t \tag{4}$$

Figure 9: SZSE 200 index

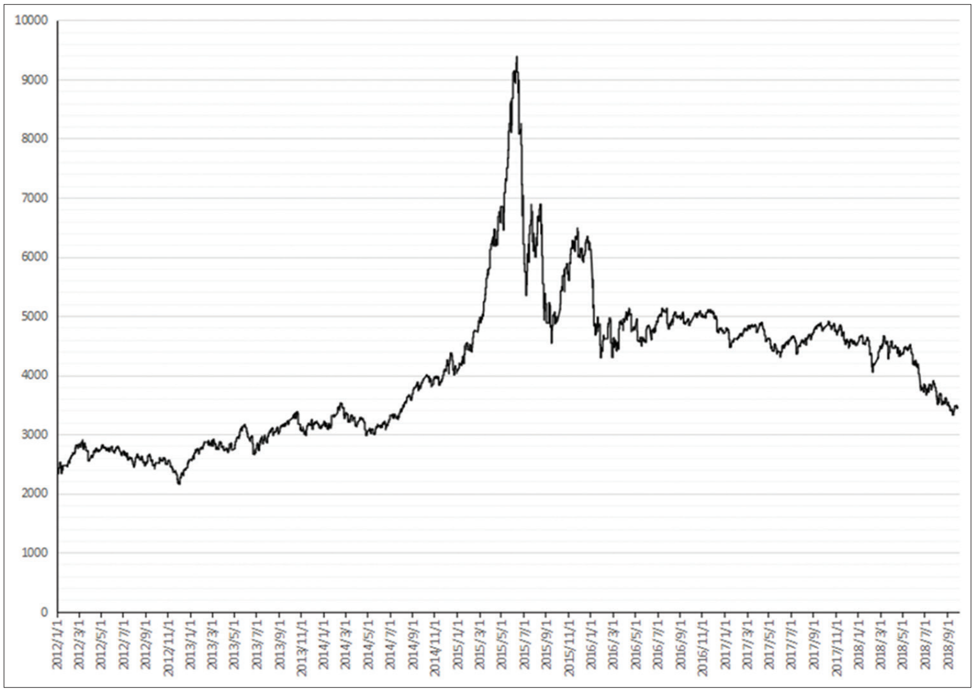
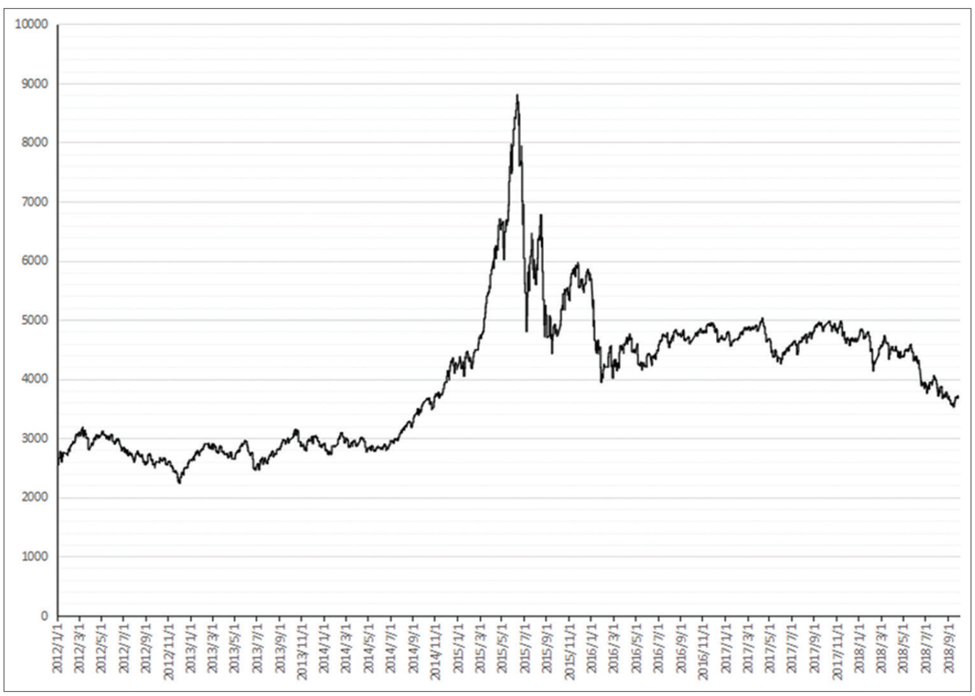


Figure 10: SSE small-cap index



In Eq.(5), ε_t is white noise process, and the appropriate lag period n is selected to make white noise uncorrelated between error terms. From Eq. (4), $\beta_1 = 0$ if Y_t is not stationary, and $\beta_1 \neq 0$ if Y_t is stationary. Thus, the statistical test is assumed to be.

H_0: $\beta_1 = 0$ (when Y_t data series has unit root, it is non-stationary time series).

H_1: $\beta_1 \neq 0$ (when Y_t data series has no unit root, it is stationary time series).

If the time series Y_t cannot reject null hypothesis H_0 after ADF, the data series needs further difference and then is substituted into the ADF model to test whether it is stationary time series. The equation is as follows:

$$\Delta dY_t = \beta + \beta_1 Y_{t-1} + \sum_{k=1}^{n} \gamma_k \Delta dT_{t-k} + \varepsilon_t \tag{5}$$

If the time series Y_t rejects the null hypothesis, the data of the time series are stationary and conform to ARMA. (Y_t) is I(1) data series, and most of economic variables often show properties of I (1). I (d) shows the stationary state after d-order difference of the data.

Figure 11: CSI 500 index

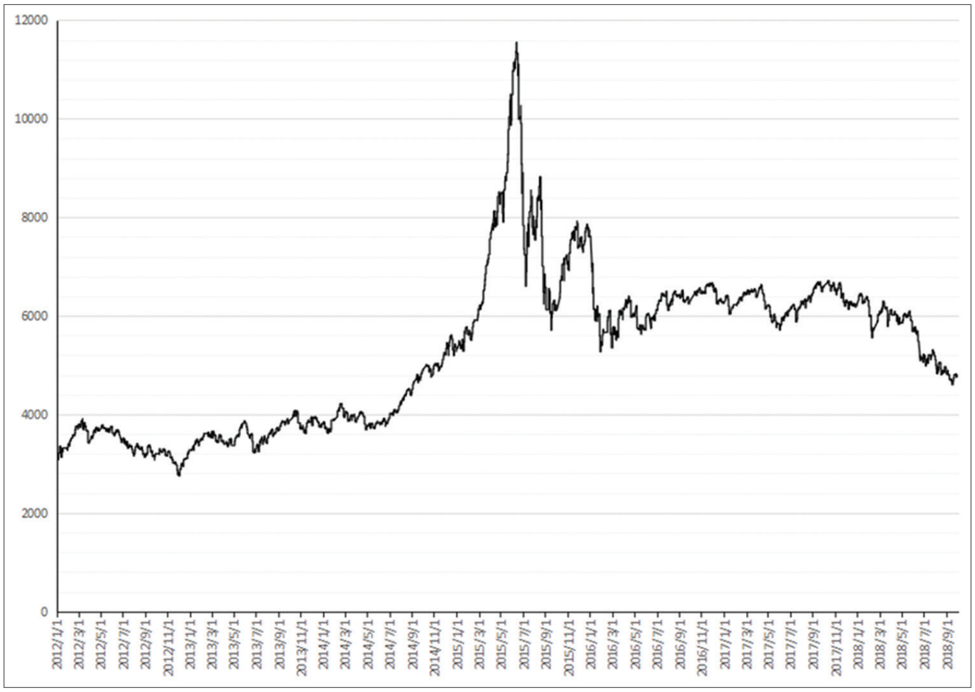


Figure 12: SZSE700 index

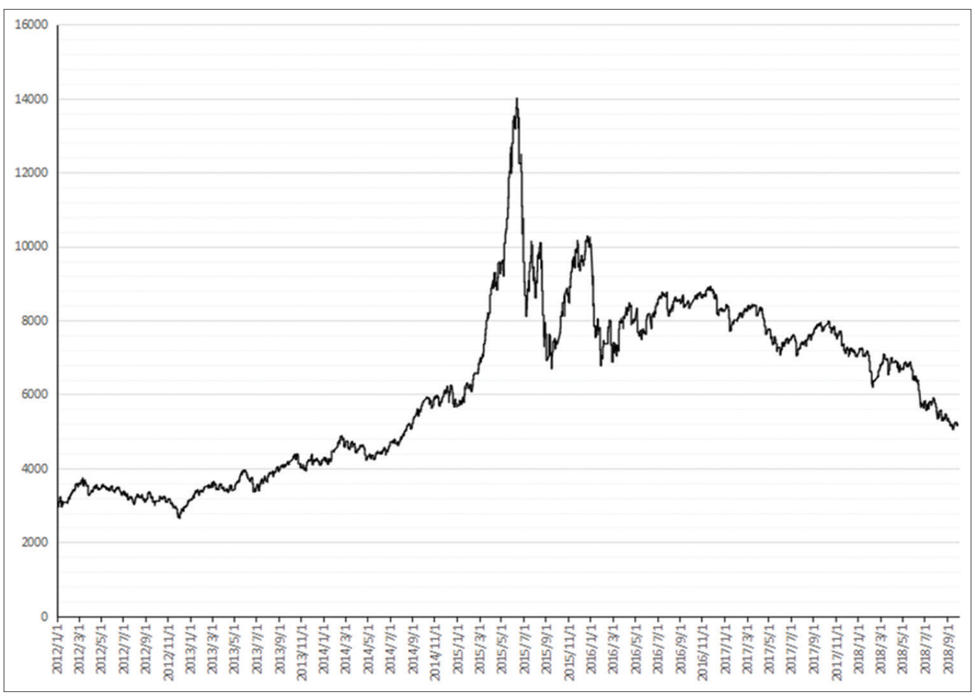


Table 4 shows that the samples in this study were not unit roots after the first order difference.

This study investigated the GARCH models. Bollerslev (1986) indicated that ARCH/ GARCH has a leptokurtic distribution and conditional variance heterogeneity. It could be known from Table 3 that the sample size of this study showed a leptokurtic distribution, therefore it was necessary to consider conditional variance heterogeneity.

In order to understand whether the data in this study had ARCH effects, this study used the Q statistics of the Ljung-Box test for observation. The Q statistics were tested as shown in Table 5 (only LB(2) ^{2}~LB(5)^2) and LB(2)^2~LB(12)^2 are listed), and most of them were significant and under the 1% significance level, which indicated that the squared residuals of all series may have autocorrelations. Therefore, they all had the phenomenon of conditional heteroscedasticity (CH). The mean equation of the GARCH models can process autocorrelations of a series and the

Table 5: Conditional hetrocedesticity test

Index	$LB(2)^2$		$LB(3)^2$		$LB(4)^2$		$LB(5)^2$	
SI	227.8400		354.2700		450.1500		520.7200	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
ZI	238.3100		371.7400		464.2900		557.0600	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
SSEMG	163.7600		291.1400		364.7200		388.8500	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
SI50	173.6900		273.4500		328.2300		362.7600	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
SSEM	372.7500		550.8700		730.8600		864.6400	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
SSES	397.5500		586.5700		791.6800		928.6000	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
CSI100	180.5200		287.3700		349.6600		388.1500	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
CSI20	338.2100		505.1600		642.1900		734.1100	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
CSI500	284.8600		429.3800		567.7400		671.6000	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
ZI100	228.8300		347.8900		418.4500		485.3000	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
ZI200	284.6200		422.6700		535.9500		631.6400	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***
ZI700	225.5600		357.8700		442.2200		543.9700	
	(0.0000)	***	(0.0000)	***	(0.0000)	***	(0.0000)	***

allowable variances of the variance equation are determined by the previous variances and distractions, therefore conditional variance heterogeneity can be acceptable. Hence, the GARCH models were the appropriate choice because all the series in this study showed conditional variance heterogeneity and the samples in this study were suitable for GARCH model analysis.

In order to establish the GARCH models that would be applicable to the correlation study on the return volatility of the stock price index for all stocks, the optimal lag period in the model formulas mentioned in the above paragraphs needed to be determined; that is, the optimal lag period of the mean equation and the variance equation needed to be determined. On the lag period of the variance equation, Brooks (2002) believed that, generally, GARCH (1,1) models can capture the volatility clustering effects in data by taking the conditional variances and the squared residuals of the first lag period. Based on the purpose of parsimonious parameters, in this study, GARCH (1,1) models were first established for empirical analysis. Moreover, after parameter estimation, a test was conducted on the standardized residuals and their square to verify the existence of the autocorrelation effect and determine the applicability of the GARCH (1,1) models.

In addition, regarding the optimal lag period of the mean equation, generally speaking, AIC (Akaike's Information Criterion) is the most suitable for small samples (<100), HQC (the Hannan-Quinn Criterion) is the most suitable for medium samples (100~600), and the smallest model of SBC (the Schwartz Bayesian Criterion) is the most suitable for large samples (>600). With 1,641 samples in this study, the SBC values of all indexes in all periods were adopted, as shown in Table 6. In this study, the optimal mean equation adopted for all indexes was the data in the first lag period, as shown below.

Table 6: SBC value

Index	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)
SI	**3.5064**	3.5094	3.5144	3.5109	3.5138	3.5143
ZI	**3.8465**	3.8483	3.8525	3.8542	3.8562	3.8613
SSEMG	**3.6561**	3.6603	3.6649	3.6613	3.6629	3.6608
SI50	**3.6949**	3.6988	3.7038	3.7018	3.7037	3.7008
SSEM	**3.7369**	3.7383	3.7431	3.7407	3.7424	3.7437
SSES	**3.9394**	3.9402	3.9451	3.9450	3.9469	3.9518
CSI100	**3.6284**	3.6311	3.6361	3.6340	3.6364	3.6337
CSI200	**3.8397**	3.8413	3.8464	3.8470	3.8485	3.8525
CSI500	**3.9246**	3.9254	3.9296	3.9304	3.9321	3.9372
ZI100	**3.7978**	3.7996	3.8047	3.8066	3.8080	3.8115
ZI200	**3.9274**	3.9280	3.9320	3.9336	3.9357	3.9409
ZI700	**3.9659**	3.9662	3.9701	3.9712	3.9735	3.9785

Note: The bold number is the minimum value

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t$$

3.3. Empirical Analysis

The purpose of this study was to explore the effects of scale on volatility asymmetry, and EGARCH was used to discuss the scale indexes and investigate the changes in return volatility. Therefore, the study focused on a comparison of the absolute values of the coefficient δ.

This study first selected large-cap, mid-cap, and small-cap indexes from all the indexes in China's stock market for comparison with the selected composite indexes, and then investigated whether there was volatility asymmetry in all the indexes during the sample period. The above-mentioned EGARCH models were mainly adopted to analyze the phenomenon of volatility asymmetry, with the results as shown in Table 7. By observing whether the value of δ had any significant difference during the two sub-periods, the degree of

Table 7: Estimation of the EGARCH model

Index	Mean equation		EGARCH(1,1)			
	C	AR(1)	α_0	α_1	δ	ψ
SI	0.0412	0.0106	−0.0993	0.1335	−0.0074	0.9938
	(0.0550) *	(0.6803)	(0.0000) ***	(0.0000) ***	(0.4172)	(0.0000) ***
ZI	0.0692	0.0352	−0.0827	0.1153	−0.0299	0.9902
	(0.0346) **	(0.1609)	(0.0000) ***	(0.0000) ***	(0.0046) ***	(0.0000) ***
SSEMG	0.0371	0.0163	−0.1135	0.1557	−0.0057	0.9908
	(0.1443)	(0.5193)	(0.0000) ***	(0.0000) ***	(0.5900)	(0.0000) ***
SI50	0.0313	0.0067	−0.1054	0.1451	−0.0004	0.9908
	(0.2240)	(0.7934)	(0.0000) ***	(0.0000) ***	(0.9682)	(0.0000) ***
SSEM	0.0423	0.0128	−0.1029	0.1390	−0.0189	0.9908
	(0.0898) *	(0.6113)	(0.0000) ***	(0.0000) ***	(0.0774) *	(0.0000) ***
SSES	0.0679	0.0278	−0.0985	0.1390	−0.0349	0.9871
	(0.0354) **	(0.2788)	(0.0000) ***	(0.0000) ***	(0.0030) ***	(0.0000) ***
CSI100	0.0397	0.0143	−0.1040	0.1419	−0.0016	0.9929
	(0.1168)	(0.5797)	(0.0000) ***	(0.0000) ***	(0.8727)	(0.0000) ***
CSI20	0.0421	0.0062	−0.0959	0.1314	−0.0285	0.9915
	(0.1356)	(0.8064)	(0.0000) ***	(0.0000) ***	(0.0070) ***	(0.0000) ***
CSI500	0.0685	0.0290	−0.0891	0.1255	−0.0327	0.9887
	(0.0390) **	(0.2522)	(0.0000) ***	(0.0000) ***	(0.0022) ***	(0.0000) ***
ZI100	0.0490	−0.0005	−0.0932	0.1331	−0.0295	0.9870
	(0.1032)	(0.9833)	(0.0000) ***	(0.0000) ***	(0.0088) ***	(0.0000) ***
ZI200	0.0548	0.0392	−0.0891	0.1238	−0.0325	0.9904
	(0.0989) *	(0.1225)	(0.0000) ***	(0.0000) ***	(0.0027) ***	(0.0000) ***
ZI700	0.0770	0.0492	−0.0770	0.1102	−0.0226	0.9898
	(0.0336) **	(0.0488) **	(0.0000) ***	(0.0000) ***	(0.0262) **	(0.0000) ***

volatility asymmetry in the two sub-periods before and after the luxury tax was analyzed for comparison.

Based on the significant conditions of the Jarque-Bera test shown in Table 3, this study was suitable for generalized error distribution models. Hence, the results of the AR(1)-EGARCH(1,1) models of the SZSE composite index were estimated as below:

$$R_t = 0.0692 + 0.0352 + \varepsilon_t$$

$$\ln\left(\sigma_t^{\,2}\right) = -0.0827 + 0.12253\left(\left|z_{t-1}\right| - E\left[\left|z_{t-1}\right|\right] - 0.0299 z_{t-1}\right)$$
$$+0.9902\ln\left(\sigma_{t-1}^{\,2}\right)$$

As previously mentioned, the so-called phenomenon of volatility asymmetry refers to positive or negative information that causes different increases in volatility. When the coefficient δ is negative, the increase in future volatility caused by negative information will be greater than that caused by positive information; when the coefficient δ is positive, the increase in future volatility caused by positive information will be greater than that caused by negative information.

As can be seen from Table 7, the coefficients δ of the indexes in this study were all negative, revealing that the major composite scale indexes in China showed that the increase in future volatility caused by negative information would be greater than that caused by positive information. However, only eight indexes had significant conditions, including the SZSE composite index (−0.0299, 0.0046, ***), the SSE mid-cap index (−0.0189, 0.0774, *), the SSE small-cap index (−0.00349, 0.0030, ***), the CSI 200 index (−0.0285, 0.0070, ***), the CSI 500 index (−0.0327, 0.0022, ***), the SZSE 100 index (−0.0295, 0.0088, ***), the SZSE 200 index (−0.0325, 0.0027, ***) and the SZSE 700 index (−0.0226, 0.0262, **). The other four indexes had no significant conditions and could not demonstrate that the increase in future volatility caused by negative information would be greater than that caused by positive information.

4. CONCLUSION AND RECOMMENDATIONS

This study focused on the long-term (January 1, 2012 to September 30, 2018) volatility asymmetry of the major composite scale indexes of China (12 in total). The study results showed that long-term volatility asymmetry may not occur.

However, the study results also showed that volatility asymmetry is more likely to happen to small-scale indexes than to large-scale indexes. The results indicated that situations in which the increase in future volatility caused by negative information will be greater than that caused by positive information are more likely to happen to small-scale indexes. The results differed from previous studies which showed that volatility asymmetry is more likely to happen to large-scale indexes. The difference in results may be related to the different shareholder structure in China.

In China's stock market, volatility asymmetry is less likely to happen to large-scale indexes, which may indicate that shareholders in large companies are better informed than those in small companies. Hence, the factors (positive and negative information, and financial leverage ratio) leading to volatility asymmetry of large-scale indexes have relatively small effects.

Generally speaking, volatility asymmetry is more likely to happen in a bear market (Shih-yung et al. (2014). This study covered bull markets, bear markets, and consolidation periods, and the study data may have diluted the results. Further studies conducted in different periods of time may produce more specific results.

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