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Original Paper

Research on Return Volatility of Shenzhen Stock Exchange Component Index Based on GARCH Model

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Abstract

Volatility has been an interesting and important topic in finance filed, especially for the financial time series research. In recent years, stock market volatility has been a prominent research area due to its critical role in financial decision-making and risk management. In the context of China's rapidly evolving financial markets, the Shenzhen Stock Exchange Composite Index (SZSE Component Index) is a key benchmark reflecting the performance of the country's emerging and high-growth enterprises. This paper use GARCH model, TGARCH and EGARCH to test the volatility of Shenzhen Stock Exchange Component Index. The research conclude that leverage effect and asymmetric effect exist, implying that investors react differently to positive and negative news. Finally, based on the results, it is recommended that government and related institutions should keep strong supervision on the market, improve information transparency by asking for more information disclosure from corporations.

Keywords

Shenzhen Component Index, GARCH, Volatility

1. Introduction

The financial market serves as a critical pillar of modern economies, facilitating capital allocation, risk management, and economic growth. Among the myriad indicators that provide insights into market behavior, returns play a particularly vital role. Returns, representing the gain or loss from an investment over a specific period, are fundamental to assessing market performance and form the basis for evaluating investment strategies, portfolio management, and market efficiency.

In recent years, stock market volatility has been a prominent research area due to its critical role in financial decision-making and risk management. Stock price volatility is a common feature of financial markets, even in developed economies like America. In emerging markets such as China, where the financial system is still evolving, volatility is even more pronounced (Wang & Wu, 2023; Hong et al., 2021). Understanding volatility is vital for investors to manage risk effectively. Regulators and institutional investors also need to address volatility. Regulators must factor it into investor protection policies, while institutions must consider its impact on returns and risk management (Pan & Mishra, 2018). The study of stock price volatility has gained further importance due to the increased frequency and magnitude of market shocks, including global events such as the COVID-19 pandemic and trade tensions. These events have amplified fluctuations in emerging markets like China, making it crucial to analyze up-to-date data for accurate volatility assessment (Gao et al., 2022.)

In the context of China's rapidly evolving financial markets, the Shenzhen Stock Exchange Composite Index (SZSE Component Index) is a key benchmark reflecting the performance of the country's emerging and high-growth enterprises. Its role in capturing the dynamics of China's innovation-driven sectors makes it a focal point for investors, policymakers, and researchers alike. However, returns in this index are inherently volatile, influenced by factors including macroeconomic policies, investor sentiment, and global financial trends.

SZSI was released on 23 January 1995, SZSE Composite Index was released on 4 April 1991. Even though these two indices have different sample selection, calculation method, they are still useful indices in the market. The SZSE Composite Index and SZSI reflect significant market coverage and exhibit a high degree of correlation. Their movements move closely, with minimal daily differences in volatility and a strong tendency to converge. In this paper, author uses Shenzhen Component Index (SZSI) as research target as this index has been less investigated while this index is representative in the market. This is also the main reason why this paper starts to research.

Understanding the volatility of returns is essential, as it serves as a proxy for market risk and provides critical insights for financial risk management. High volatility often signals uncertainty and heightened risk, impacting investment decisions and portfolio strategies. Conversely, low volatility can imply stability but may also mask underlying structural issues. For investors and regulators, a nuanced understanding of return volatility is crucial for navigating market complexities and implementing effective risk mitigation strategies. Analyzing recent data will not only enhance the accuracy of volatility forecasts but also offer deeper insights into the impact of contemporary economic and policy shifts

The rest of this paper is structured as follows: Section 2 reviews relevant literature on volatility modeling and GARCH applications. Section 3 details the data and methodology, section 4 presents the empirical findings, and section 5 concludes with a summary and suggestions for future research.

2. Literature Review

Stock market volatility can be reflected as the deviation in expected asset values, indicating price uncertainty, which is often measured by variance or standard deviation. Academically, this is explained by two theories: the leverage effect, where bad news lowers stock prices and raises volatility, and the volatility feedback hypothesis, where unpredictable volatility increases future risk (Bhowmik & Wang, 2020). Stock market volatility is a very complex issue and is influenced by many factors. Scholars have conducted extensive research on stock market volatility and have proposed many theories and models to explain and predict stock market volatility (Shanthi & Thamilselvan, 2019).

It is found that generalized autoregressive conditional heteroskedasticity model (GARCH)-type models are still popular among financial volatility research in recent 30 years and still experiencing fast development (Bhowmik & Wang, 2020). Nelson (1991) proposed an exponential GARCH model, the EGARCH model, by logarithmizing the conditional variance. This model better captures the leverage effect of volatility by comparing the absolute values of the perturbation and disturbance terms of the mean equation as well as the ratio of the standard deviations of the perturbation terms. Using GARCH and TARCH to analyze the Hong Kong stock index and estimate the Hong Kong Hang Seng Index, respectively, Sabiruzzaman (2010) discovered that the TGARCH model was more precise. Pati et al. (2018) investigated the in-sample information content in three Asia-Pacific stock market by using an implied volatility index incorporated GARCH model. Khan et al. (2023) used GARCH models to test COVID-19 financial market volatility and suggested that EGARCH provided the best performance.

Besides, researchers have also studied the impact of macroeconomic factors, policy changes and investor sentiment on stock market volatility (Liu et al., 2021; Raza, et al., 2023; Yu et al., 2021). Scholars also extended the models for deeper researches. Previous literatures can be categorized into two groups of studies. One focused on GARCH and its variations, while the other focused on bivariate and multivariate GARCH models (Bhowmik & Wang, 2020). Sen et al., (2021) conducted research on testing Indian stock market volatility using GARCH models. Fang et al. (2023) used GARCH-MIDAS model to investigate the effect of global economic policy on crude oil futures volatility. In addition, GARCH models can be applied in discussing the relationship between geopolitical risk and stock market volatility in emerging markets (Salisu et al., 2022). In terms of literatures in China, researches follow similar patterns. Wang et al. (2022) applied GARCH-type models in the research and concluded that the Chinese stock market is highly volatile, GARCH-type models are effective for analyzing this volatility, and these insights have significant implications for investors and policymakers. Xie et al. (2023) employed MIDAS-GARCH model to explore the impact of investor sentiment on stock volatility in China A-shares stock market.

3. Method/Model

Time series models are a class of statistical models used to analyze time series data. Common time series models include these following models.

3.1 ARIMA Models

AR models (autoregressive models): this model assumes a linear relationship between the current value and the values of a number of past periods. MA models (moving average models): this model assumes a linear relationship between the current value and the error term over a number of periods. ARMA model (autoregressive moving average model): This model combines the AR and MA models and assumes that the current value is related to both the value of a number of past periods and the error term of a number of past periods. ARIMA model (differential autoregressive moving average model): This model is an extension of the ARMA model and is used to deal with non-stationary time series data.

3.2 ARCH and GARCH Models

ARCH/GARCH models (autoregressive conditional heteroskedasticity/generalized autoregressive conditional heteroskedasticity models): These models are used to establish the relationship between volatility and time series data. These are just some of the common time series models, and there are actually many other types of time series models available.

A time series model called the GARCH is used to examine volatility aggregation. It is founded on the 'generalized ARCH model' or 'generalized autoregressive conditional heteroskedasticity model,' which is a generalization of the ARCH model. It assumes that the conditional variance of the current period is a linear combination of the conditional variance of the previous N periods and the square of the series, which is the result of the conditional variance of the current period and white noise. It can be a crucial decision-making tool for investors and is especially well-suited for volatility analysis and forecasting.

A group of models called the GARCH family of models is employed to determine the link between volatility and time series data. The EGARCH (Exponential GARCH) model enhances the GARCH model by allowing asymmetric effects of positive and negative asset returns on volatility. The TGARCH (Threshold GARCH) model also permits asymmetric effects on volatility from both positive and negative asset returns. The introduction of TGARCH and EGARCH allow researchers to capture the leverage and asymmetric effect within the data and provide more useful insights for policymakers. This paper will employ GARCH to test volatility, TGARCH and EGARCH to test leverage effect and asymmetric effect.

4. Discussion

4.1 Data Source

The sample interval is from January 2, 2018 to May 12, 2023. The data source is Wind Financial Terminal and data analysis was performed using Eviews 10.0 software. In this paper, we use SZ variable to represent the closing price of SZSI for data processing.

4.2 Stationarity Test

The closing price series is tested for stationarity and the results are shown in table 1:

Table 1. SZ Result

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.357462	0.6043

*MacKinnon (1996) one-sided p-values.

Based on the results from Table 1, the original hypothesis is accepted, indicating that the series does not adhere to the requirement of smoothness, as shown by the ADF test results, which show that the p-values of the sz series are currently significantly greater than 0.05 and that the corresponding value of its T-statistic is greater than the T-value at 5% significance level. Therefore, the original series must be logarithmically and first-order differentially processed to create the dlnsz series, and the ADF test must be repeated in order to confirm the smoothness of the financial time series.

Table 2. DLNSZ Result

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-35.61445	0.0000

*MacKinnon (1996) one-sided p-values.

According to Table 2, the P-value of the dlnsz series is significantly less than 0.05 at this time, and the corresponding value of its T-statistic is less than the T-value at the 5% significance level, showing that the series complies with the requirement of smoothness, preventing the emergence of pseudo-regression phenomenon, and can be analyzed further, according to the results of the ADF test.

4.3 Data Description

Based on Figure 1, it can be initially judged that the series is smooth and does not show a basic trend up or trend down. According to Figure 2, descriptive statistical analysis, it can be seen that the mean value of dlnsz return series is -0.000012, the median is 0.0000427, the skewness is = 0.499944, which is less than 0; the kurtosis is 5.755224, which is greater than 3, indicating that the sample is left skewed and the distribution is spiky and thick tailed. Meanwhile, the variable J-B statistic is accompanied by a significant probability of 0. The series does not obey the normal distribution, and this pattern is consistent with the characteristics of most financial time return series.

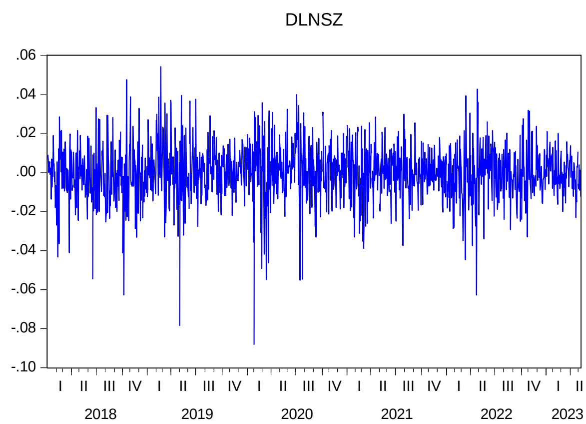

Figure 1. DLNSZ Diagram

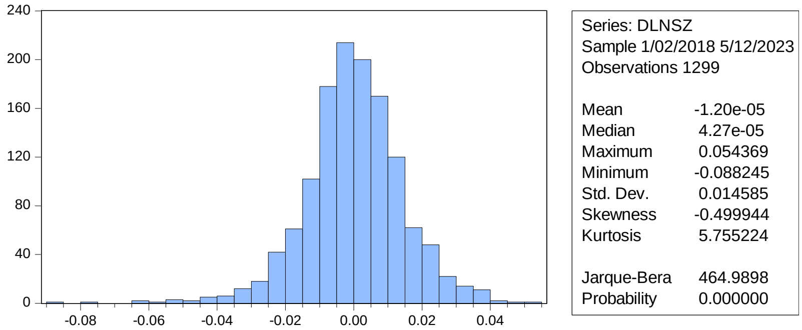

Figure 2. DLNSZ Descriptivce Statistics

4.4 Autocorrelation and Partial Autocorrelation Tests

Based on the results from Figure 3, p-values are significantly greater than 0.05. Accepting the original hypothesis, results indicates that there is no autocorrelation in the return series. Therefore, it is unnecessary to build an ARMA model or ARIMA model to eliminate autocorrelation. And, the ARCH effect test can be conducted afterwards.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.1473	0.701
		2	-0.002	-0.002	0.1515	0.927
		3	0.018	0.018	0.5609	0.905
		4	-0.037	-0.037	2.3547	0.671
		5	-0.003	-0.002	2.3640	0.797
		6	-0.034	-0.034	3.8592	0.696
		7	0.028	0.030	4.8638	0.677
		8	-0.005	-0.007	4.8947	0.769
		9	-0.009	-0.007	4.9960	0.835
		10	0.043	0.039	7.3907	0.688

Figure 3. Autocorrelation and Partial Autocorrelation Tests Results

4.5 ARCH Effect Test

The results of the serial ARCH-LM test demonstrate that the model has a significant ARCH effect, and this result reflects the riskiness of the variables' return changes. Referring to table 3, the lagged residual squared terms are jointly significant, the probability of Obs*R-squared is also 0, and the probabilities of the model F-statistics are significantly less than 0.05. As a result, building a GARCH model to describe the return variability is suitable.

Table 3. Heteroskedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	6.397390	Prob. F(1,1296)	0.0115
Obs*R-squared	6.375790	Prob. Chi-Square(1)	0.0116

4.6 Empirical Analysis

4.6.1 GARCH Model

To further characterize the volatility cumulative and time-varying nature of the series returns, a GARCH(1,1) model is constructed in this paper based on the above equation, and the estimation results are shown below. According to the descriptive statistical analysis above, it is known that the series does not obey the normal distribution, so the T-distribution is adopted in all the choices of error distribution, and the results are as follows.

Table 4. GARCH Result

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000319	0.000351	0.908343	0.3637
	Variance Equation			
C	6.94E-06	2.63E-06	2.641498	0.0083
RESID(-1)^2	0.064778	0.016422	3.944491	0.0001
GARCH(-1)	0.903160	0.023758	38.01524	0.0000
T-DIST. DOF	6.966599	1.230193	5.663011	0.0000

The equation for the variance equation is as follows:

$$\sigma_t^2 = 6.94E - 06 + 0.064778a_t^2 + 0.903160\sigma_{t-1}^2$$

Table 4 illustrates the results from GARCH model. Since the whole series pass the test at the 5% level of significance, it is plausible to believe that the model lag terms are jointly significant overall based on the aforementioned table. The model's ARCH term coefficients and GARCH term coefficients also satisfy the requirements for the GARCH family of model parameters, passing the test at the 1% significance level and being positive. Additionally, the model's ARCH and GARCH coefficient total is less than or very close to 1, which satisfies the parameters' constraint limits and shows that price swings are persistent and that the most recent information is crucial for projecting future risk.

Further, the residuals of the GARCH model were tested for ARCH effects and the results are shown in Table 5.

Table 5. Heteroskedasticity Test of GARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.806712	Prob. F(1,1296)	0.3693
Obs*R-squared	0.807454	Prob. Chi-Square(1)	0.3689

According to Table 5, when the fitted GARCH model is tested for residual ARCH effect, probability is greater than 0.05. This indicates that there is no residual ARCH effect and the established GARCH model has successfully extracted useful information, making it suitable for use in subsequent prediction analysis.

4.6.2 TGARCH Model

Table 6. TGARCH Model Result

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000194	0.000353	0.551446	0.5813
	Variance Equation			
C	1.02E-05	3.34E-06	3.038374	0.0024
RESID(-1)^2	0.038114	0.018009	2.116391	0.0343
RESID(-1)^2*(RESID(-1)<0)	0.069410	0.026460	2.623154	0.0087
GARCH(-1)	0.877792	0.028267	31.05361	0.0000
T-DIST. DOF	7.069714	1.351510	5.230974	0.0000

The equation for the variance equation is as follows:

$$\sigma_t^2 = 1.02E - 05 + 0.038114a_t^2 + 0.069410a_{t-1}^2 d_{t-1} + 0.877792\sigma_{t-1}^2$$

Based on the results from Table 6, the model results show that the series as a whole all reach significance at the 5% level of significance and the model lagged terms can be considered as jointly significant overall. Noticeably, the coefficient estimates of the leverage term are significant, proving that there is a significant leverage effect in the series. That is, the impact on the volatility of the variables caused by positive and negative news in the market is different. A coefficient of 0.069410 demonstrates that the impact of negative news is larger than the impact of positive news.

Table 7. Heteroskedasticity Test of TGARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.242207	Prob. F(1,1296)	0.6227
Obs*R-squared	0.242535	Prob. Chi-Square(1)	0.6224

Table 7 shows the results of Heteroskedasticity Test of TGARCH. When the fitted GARCH model is tested for residual ARCH effect, probability is greater than 0.05. The results show that there is no ARCH effect on the residuals and useful information has been extracted by the established TGARCH model, and the model is established appropriately for subsequent analysis.

4.6.3 EGARCH Model

Table 8. EGARCH Model Result

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000162	0.000348	0.465011	0.6419
	Variance Equation			
C(2)	-0.694082	0.185684	-3.737970	0.0002
C(3)	0.180577	0.039771	4.540428	0.0000
C(4)	-0.070665	0.021444	-3.295385	0.0010
C(5)	0.934904	0.019981	46.78863	0.0000
T-DIST. DOF	7.296276	1.464570	4.981855	0.0000

The equation for the variance equation is as follows:

$$ln\sigma_t^2 = -0.694082 + 0.180577\frac{|\mu_{t-1}|}{\sigma_{t-1}} - 0.070665\frac{\mu_{t-1}}{\sigma_{t-1}} + 0.934904ln\sigma_{t-1}^2$$

According to EGARCH model results from table 8, the EGARCH model shows that the asymmetric term also rejects the original hypothesis at the 5% significance level. And a coefficient of -0.070665 indicates that the asymmetric term is significant, impact of negative news is greater than the impact of positive news. EGARCH's results are consistent with results from TGARCH models, convincing that the model possesses strong robustness.

Table 9. Heteroskedasticity Test of EGARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.133377	Prob. F(1,1296)	0.7150
Obs*R-squared	0.133569	Prob. Chi-Square(1)	0.7148

Table 9 shows the results of Heteroskedasticity Test of EGARCH. When the fitted GARCH model is tested for residual ARCH effect, probability is greater than 0.05. The results from above table indicate that there is no ARCH effect on the residuals, and the useful information has been extracted by the established EGARCH model, and the model is established appropriately.

5. Conclusion

Stock volatility refers to the magnitude of changes in stock prices over time. It is an important research topic in the field of finance, and scholars have conducted a large number of theoretical and empirical studies on it. Early research focused on the statistical characteristics that describe stock volatility. For example, scholars have found that stock return series are usually characterized by thick tails, volatility aggregation and leverage effects. To explain these phenomena, scholars have proposed a number of theoretical models, the most famous of which are the ARCH and GARCH models. These models were able to describe the volatility of stock returns very well and laid the foundation for later studies. In this paper, we found that asymmetric effect and leverage effect exist in SZSI, implying there is existence of observable volatility. The observed volatility can be largely caused by market information and fake information can even increase stock volatility. Therefore, regulation on information disclosure is essential to financial market’s stability. Moreover, government and related institutions should keep strong supervision on the market in order to eliminate illegal behavior in financial market. The implementation of major policies often triggers fluctuations in the stock market, impacting investment behavior and occasionally fostering activities like insider trading and speculation. China's stock market is still less developed. This underdevelopment highlights the need for regulatory oversight and policy guidance. Nonetheless, as the market evolves and matures, the government's role should shift toward fostering self-regulation within the market while gradually reducing direct intervention. Lastly, individual investors should improve their own literacy in financial investment and make rational decisions. Government agencies and financial institutions should promote investment knowledge and risk awareness. By guiding individual investors to develop a deeper understanding of financial management and its associated risks, they can avoid impulsive investments driven by cognitive biases. This approach plays a crucial role in mitigating stock market volatility.

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