INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 15, Issue 2, (2025) E-ISSN: 2222-6990

Volatility of the Chinese Stock Market: Evidence from the GARCH Model

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To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v15-i2/24754 DOI:10.6007/IJARBSS/v15-i2/24754

Published Date: 26 February 2025

Abstract
This study conducts an empirical analysis of the volatility characteristics of SSE, SZSE and CNI using GARCH model, aiming to investigate the dynamic volatility patterns of the Chinese stock market and its response to external shocks. The findings reveal that the volatility of the Chinese stock market exhibits significant persistence, asymmetry, and sensitivity to external disturbances. Among the three indices, SSE, which primarily consists of large capitalization enterprises, demonstrates the lowest volatility, whereas CNI, which includes a greater proportion of small and medium sized oriented firms, exhibits the highest level of volatility. Furthermore, major financial and economic disruptions, such as 2015 stock market crash, 2018 trade conflict between China and the US, and 2020 outbreak of the COVID-19 pandemic, significantly increased market volatility, with CNI being the most affected and SSE remaining relatively stable. Based on these findings, this study suggests enhancing market risk monitoring systems by leveraging financial technology to improve early warning mechanisms and implementing appropriate regulatory measures in extreme market conditions. Additionally, it advocates for optimizing financial policies and promoting long term investments by encouraging greater participation from institutional investors. Furthermore, a differentiated regulatory approach should be adopted, requiring stricter disclosure and governance standards for highly volatile market segments. Lastly, strengthening international cooperation is essential to reduce uncertainties arising from external economic disturbances and ensure overall market stability. This study provides valuable insights for investors and regulators, contributing to improved risk management and the resilience of financial markets.
Keywords: Chinese Stock Market, GARCH Model, Risk Measurement

Introduction

The measurement of stock market volatility is one of the core topics in financial research. It plays a crucial role in risk assessment, asset pricing, portfolio management, and financial stability analysis. Volatility not only reflects the risk level of the market but also influences investor sentiment, asset returns, and financial regulatory policies. Therefore, accurately measuring stock market volatility is of great significance for academic research, investment practices, and policy formulation (Lang et al., 2021; Bollerslev et al., 2018).

In the context of China, the necessity of studying stock market volatility is particularly pronounced. In recent years, the Chinese stock market has experienced rapid development, becoming an integral part of the global capital market. With increasing financial liberalization, market internationalization, and foreign capital inflows, the volatility of the Chinese stock market has attracted growing attention from global investors and policymakers. However, the volatility characteristics of the Chinese market differ from those of mature markets. Its market structure, investor behavior, and policy environment interact in a complex manner, resulting in highly dynamic volatility patterns (Carpenter et al., 2021; Leippold et al., 2022). Therefore, a deeper investigation into the volatility of the Chinese stock market is essential for understanding its risk characteristics, improving risk management strategies, and providing a scientific basis for regulatory authorities.

Moreover, the volatility of the Chinese stock market not only affects domestic investors' decision-making but also contributes to spillover effects on global capital markets. In recent years, the interconnectedness of international financial markets has intensified, making the transmission of volatility between China and global markets increasingly evident. For instance, fluctuations in global commodity prices, adjustments in the U.S. Federal Reserve's monetary policy, and geopolitical risks all have a significant impact on the volatility of the Chinese stock market. Conversely, China's market volatility can also influence emerging markets and even the global financial system (Pan & Mishra, 2018; Li & Wei, 2018). Therefore, studying the measurement of Chinese stock market volatility is essential for understanding both its internal risk structure and its role in the global financial landscape.

Existing research on the Chinese stock market remains relatively limited. Most studies have primarily focused on the Shanghai Stock Exchange Composite Index, while giving less attention to the Shenzhen Stock Exchange Composite Index and the ChiNext Index. As a result, a systematic analysis of the overall volatility of the Chinese stock market is lacking. The contribution of this study lies in its simultaneous examination of these three indices, providing a more comprehensive perspective on market volatility. By analyzing the distinct volatility characteristics of different market segments and their interactions, this study aims to address the existing research gap.

The primary objective of this study is to measure the volatility of the Chinese stock market. By applying the GARCH model, this study seeks to reveal the dynamic characteristics of stock market volatility and provide a scientific risk assessment framework for investors, risk managers, and policymakers. The Shanghai Stock Exchange Composite Index, the Shenzhen Stock Exchange Composite Index, and the ChiNext Index are selected as research subjects due to their representativeness and structural differences within the Chinese equity market. The Shanghai Stock Exchange Composite Index primarily consists of large and mid sized enterprises listed on the Shanghai Stock Exchange, representing the main board market in China. Its volatility is significantly influenced by macroeconomic trends, policy adjustments, and foreign capital flows (Lin, 2018). In contrast, the Shenzhen Stock Exchange Composite Index reflects the performance of small and medium sized enterprises listed on the Shenzhen Stock Exchange. Compared to the Shanghai Stock Exchange Composite Index, it exhibits a higher degree of market orientation and stronger industry concentration, particularly in the fields of technology, consumer goods, and pharmaceuticals. As a result, its volatility characteristics may differ significantly from those of the Shanghai Stock Exchange Composite Index (Peng et al., 2024).

The ChiNext Index, on the other hand, represents high growth enterprises, particularly firms focused on technology and innovation. Its market volatility tends to be more pronounced, as it is more sensitive to industry cycles, investor sentiment, and risk preferences (Zeng et al., 2024). By simultaneously analyzing the Shanghai Stock Exchange Composite Index, the Shenzhen Stock Exchange Composite Index, and the ChiNext Index, this study offers a holistic perspective on stock market volatility. The comparative assessment of different market segments enhances the understanding of volatility levels, cross market interactions, and risk transmission mechanisms, thereby providing valuable insights for risk assessment and investment decision making.

Empirical Methodology

Data

This study focuses on the Chinese stock market and selects the Shanghai Stock Exchange Composite Index, Shenzhen Stock Exchange Composite Index, and ChiNext Index as the primary research subjects. The empirical analysis is based on the daily closing prices of these indices over the period from January 1, 2014, to December 31, 2023. To more accurately capture market volatility, this study calculates and employs the daily logarithmic returns of the indices as the research variable. The formula for logarithmic return is expressed as follows:

$$R_t = 100\ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

R_t represents the logarithmic return. P_t denotes the closing price on the current trading day. P_{t-1} refers to the closing price on the previous trading day.

Empirical Model

GARCH Model

In financial market time series analysis, traditional models struggle to effectively capture the volatility characteristics of asset returns, particularly volatility clustering and conditional heteroscedasticity. Moreover, conventional models can only estimate static volatility, lacking the ability to model dynamic volatility (Ardia et al., 2019; Caporale & Zekokh, 2019).

To more accurately describe these features, Bollerslev (1986) proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which incorporates lagged conditional variance terms into the volatility equation. This enhancement enables the model to effectively estimate dynamic volatility. The GARCH model has been widely applied in stock market volatility estimation and risk management, providing valuable insights into understanding and predicting market fluctuations.

The standard GARCH model consists of the following two equations:

$$r_t = \mu + \varepsilon_t \qquad (2)$$

r_t represents the logarithmic daily return. μ denotes the conditional mean of returns. ε_t refers to the error term.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

σ_t^2 represents the conditional variance of the residuals. α_0 denotes the constant term. ε_{t-1}^2 refers to the lagged stochastic error term. σ_{t-1}^2 represents the lagged forecast variance. α_1 and β_1 are the coefficients of the model (Fakhfekh & Jeribi, 2020).

EGARCH Model

The GARCH model assumes that positive and negative shocks have an identical impact on stock price volatility. However, in financial markets, positive and negative shocks often lead to asymmetric volatility responses. The Exponential GARCH (EGARCH) model was introduced to better explain this leverage effect (Harvey & Lange, 2018; Xu & Lien, 2022).

The EGARCH model is formulated as follows:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln\left(\sigma_{t-1}^2\right) \tag{4}$$

The coefficient γ is used to test for the leverage effect. If γ is statistically significant and not equal to zero, it indicates the presence of a leverage effect.

Results and Analysis

Descriptive Analysis

Table 1 and Figure 1 present the characteristics of returns for SSE, SZSE, and CNI. The mean values for all three markets are close to zero, indicating that long-term returns remain relatively stable. Additionally, the median values are also near zero, suggesting that the return distributions do not exhibit significant skewness.

The standard deviation, which reflects return volatility, varies across indices. The CNI exhibits the highest standard deviation of 0.0189, whereas the SSE has the lowest standard deviation of 0.0130, indicating that the CNI experiences the greatest short-term fluctuations. Moreover, the skewness values for the three indices are -1.1096, -0.8130, and -0.4730 for the SSE, SZSE, and CNI, respectively. Since all skewness values are negative, the return distributions exhibit longer left tails, indicating a greater risk of market downturns.

Furthermore, the kurtosis values for all three indices exceed 3, confirming that their return distributions exhibit high peaked ness and fat tails, which suggests an increased probability of extreme market fluctuations. Finally, the results of the Jarque-Bera test are statistically significant for all indices, indicating that the return distributions deviate significantly from a normal distribution.

Table 1
Descriptive Statistics of Returns

	Minimum	Maximum	Mean	Median	Stdev	Skewness	Kurtosis	JB Test
SSE	-8.8729	5.6036	0.0141	0.0506	0.0130	-1.1096	7.8744	6800.1226***
SZSE	-8.8245	6.2542	0.0066	0.0345	0.0157	-0.8130	4.3778	2216.6588***
CNI	-9.3319	6.9145	0.0144	0.0049	0.0189	-0.4730	3.5351	744.7051***

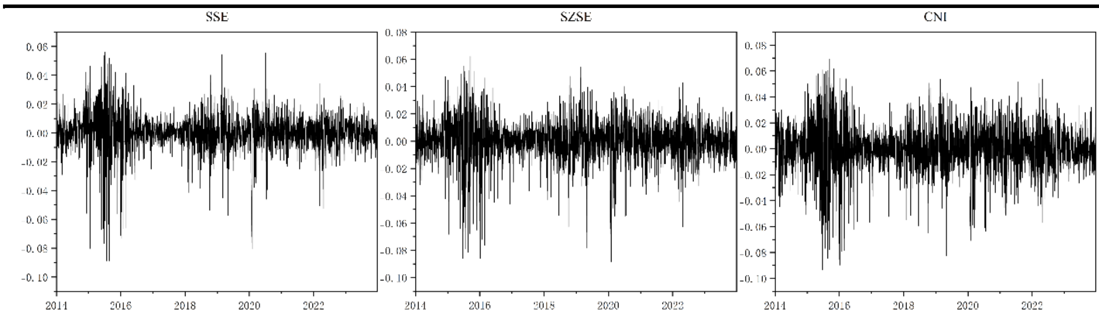

Figure 1. Trends of Returns

The results in Table 2 indicate that the ADF test statistics for SSE, SZSE, and CNI are -13.7094, -13.1251, and -12.5170, respectively, with corresponding p-values of 0.0000. This implies that the null hypothesis is rejected at the 1 percent, 5 percent, and 10 percent significance levels, confirming that the return series of all three indices are stationary.

Similarly, the Phillips-Perron (PP) test yields test statistics of -2315.9080, -2359.5990, and -2339.5340 for SSE, SZSE, and CNI, respectively, with corresponding p-values of 0.0000. These results further validate the stationarity of the return data. The findings of the unit root tests confirm that the return series exhibit no long-term trends or non-stationarity, indicating their suitability for modeling within the GARCH framework.

Table 2
Results of ADF and PP Tests

	ADF Statistics	p-value	PP Statistics	p-value
SSE	-13.7094	0.0000	-2315.9080	0.0000
SZSE	-13.1251	0.0000	-2359.5990	0.0000
CNI	-12.5170	0.0000	-2339.5340	0.0000

The Ljung-Box test and ARCH test are employed to examine the autocorrelation and conditional heteroscedasticity of the return series. Table 3 presents the results of the Ljung-Box test, where the test statistics for SSE, SZSE, and CNI are 36.4775, 26.4464, and 20.5353, respectively. These results indicate that the return series of all three indices exhibit significant autocorrelation at conventional significance levels.

The ARCH test results further reveal that the test statistics for SSE, SZSE, and CNI are 351.0939, 345.7483, and 385.3110, respectively, with p-values of 0.0000. This confirms the presence of significant conditional heteroscedasticity in the return series of all three indices. These findings provide a strong rationale for employing the GARCH model or other heteroscedasticity-based models in subsequent analyses.

Table 3
Results of Ljung-Box and ARCH Tests

	LB Statistics	p-value	ARCH Statistics	p-value
SSE	36.4775	0.0000	351.0939	0.0000
SZSE	26.4464	0.0031	345.7483	0.0000
CNI	20.5353	0.0245	385.3110	0.0000

Stock Market Characteristics Analysis

Table 4 presents the estimated key parameters of the GARCH model. These estimates and their statistical significance provide insights into the volatility behavior of the Chinese stock market and its response to external shocks. The GARCH coefficient β measures the extent to which past volatility influences current volatility. The estimated β values for SSE, SZSE, and CNI are 0.9893, 0.9857, and 0.9888, respectively, all of which are statistically significant at the 1 percent level. This indicates that all three markets exhibit a strong persistence in volatility, meaning that past volatility has a prolonged impact on future volatility. Such persistence suggests the presence of a memory effect, where market participants may adjust their trading strategies based on past volatility patterns, further reinforcing the persistence of fluctuations. The asymmetry term γ captures the market's symmetric response to external shocks.

These parameter estimates carry significant empirical and policy implications. First, the persistence and asymmetry of volatility serve as an essential reference for risk management by both investors and regulators. In the event of extreme market fluctuations, regulators may implement temporary trading restrictions or early warning mechanisms to mitigate panic-driven market reactions. Additionally, investors should consider the long-term persistence of volatility when optimizing their risk exposure and asset allocation strategies.

Table 4
Results of the EGARCH Model

	μ	θ	ω	α	β	γ
SSE	0.0001	0.0281	-0.0844***	-0.0068*	0.9893***	0.1910***
SZSE	0.0000	0.0190	-0.1143***	-0.0165*	0.9857***	0.1572***
CNI	-0.0002	0.0311	-0.0868***	-0.0215*	0.9888***	0.1330***

Subsequently, as shown in Table 5, the results of the ARCH effect test indicate that at lag orders of 3, 5, and 7, the p-values are all significantly greater than 0.1. This suggests that the EGARCH model successfully eliminates the ARCH effect in the original return series, confirming that the EGARCH model effectively captures the conditional volatility of the three stock indices.

Table 5
Results of the ARCH Effect Test

	ARCH (3)	ARCH (5)	ARCH (7)
SSE	0.6201	0.2138	0.3341
SZSE	0.2744	0.1103	0.2324
CNI	0.4424	0.6306	0.7474

Stock Market Volatility Analysis

As shown in Table 6, the results of the volatility analysis indicate that the ChiNext Index exhibits the highest level of volatility, whereas the Shanghai Stock Exchange Composite Index demonstrates the lowest volatility. This discrepancy is likely attributable to differences in the composition of the indices. The Shanghai Stock Exchange Composite Index consists primarily of large-cap enterprises, which generally possess strong market stability and robust profitability. As a result, this index exhibits lower volatility. In contrast, the ChiNext Index includes a higher proportion of small and medium-sized enterprises, growth-oriented firms, and emerging industry stocks. These companies tend to experience greater fluctuations in market valuation, as they are more susceptible to changes in government policies, industry cycles, and investor sentiment, leading to higher volatility levels.

Table 6
Descriptive Statistics of the EGARCH Model Results

	Minimum	Maximum	Mean	Median
SSE	0.0039	0.0439	0.0117	0.0100
SZSE	0.0068	0.0432	0.0146	0.0131
CNI	0.0089	0.0483	0.0177	0.0167

Figure 2 illustrates the volatility trends of SSE, SZSE, and CNI from 2014 to 2022. These trends reflect market sentiment and external shocks affecting the Chinese stock market at different stages. Notably, the volatility levels exhibit significant increases in specific years, which are closely associated with major economic and financial events.

In 2015, the Chinese stock market experienced a severe market crash, during which the Shanghai Stock Exchange Composite Index plummeted sharply within a few months, triggering widespread market panic. This event led to a sharp surge in volatility across all indices, with ChiNext Index and Shenzhen Stock Exchange Composite Index being the most affected. These indices include a larger proportion of growth-oriented and small to mid-sized stocks, which are more vulnerable to liquidity constraints and shifts in investor sentiment. In contrast, the Shanghai Stock Exchange Composite Index, with its more stable constituents, exhibited a relatively moderate increase in volatility.

In 2018, the escalation of the trade conflict between China and the US heightened market uncertainty, causing further market turbulence. During this period, ChiNext Index exhibited another sharp increase in volatility, highlighting the greater sensitivity of small and medium enterprises to changes in the international trade environment.

In 2020, the outbreak of the COVID-19 pandemic triggered extreme market turbulence on a global scale. In the early stages of the crisis, widespread supply chain disruptions, corporate shutdowns, and deteriorating economic growth expectations led to panic-driven sell-offs, causing a significant rise in volatility across all indices. However, as the government implemented monetary easing policies and fiscal stimulus measures, the market gradually stabilized, and volatility levels declined. The volatility of the ChiNext Index exhibited drastic fluctuations during this period, while the Shanghai Stock Exchange Composite Index remained relatively stable, as large-cap firms demonstrated stronger resilience to external shocks.

These findings indicate that during periods of global crises, different market segments exhibit significantly different responses. Large-cap firms provide greater stability, whereas growth-oriented and small to mid-sized enterprises are more susceptible to heightened volatility.

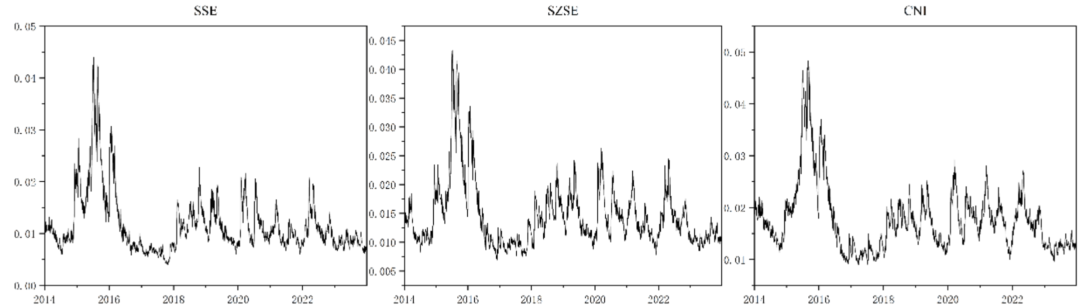

Figure 2. Conditional Volatility of the Chinese Stock Market

Conclusion and Policy Recommendations

This study conducts an empirical analysis of the volatility characteristics of SSE, SZSE, and CNI using the GARCH model. Additionally, it examines how the Chinese stock market responds to external shocks. The findings indicate that market volatility in China exhibits significant persistence, asymmetry, and sensitivity to external disturbances. These volatility characteristics have important implications for understanding risk transmission mechanisms, developing investment strategies, and optimizing regulatory policies.

The results demonstrate notable differences in volatility among the three indices. The ChiNext Index exhibits the highest volatility, while the Shanghai Stock Exchange Composite Index experiences the lowest, primarily due to differences in index composition. The Shanghai Stock Exchange Composite Index consists mainly of large-cap enterprises, which contribute to greater market stability and lower volatility. In contrast, the ChiNext Index comprises growth-oriented and small to medium-sized firms, which are more susceptible to investor sentiment and policy changes, leading to higher volatility.

A historical event analysis further highlights the impact of major financial shocks. The 2015 Chinese stock market crash, the 2018 trade conflict between China and the United States, and the 2020 COVID-19 pandemic all significantly increased market volatility. During the 2015 stock market crash, volatility surged across all indices, with ChiNext Index and Shenzhen Stock Exchange Composite Index being the most affected, as small-cap stocks are more sensitive to shifts in market sentiment. The 2018 trade conflict heightened market uncertainty, causing another increase in ChiNext Index volatility, reflecting the vulnerability of growth firms to changes in global trade conditions. The 2020 COVID-19 crisis triggered severe market turbulence, with volatility rising across all indices. However, due to their inherent stability, large-cap firms in the Shanghai Stock Exchange Composite Index exhibited relatively moderate volatility fluctuations. As fiscal and monetary policy interventions were implemented, market conditions gradually stabilized, and volatility declined.

Based on these findings, this study proposes several policy recommendations to enhance market stability and optimize risk management. First, regulatory authorities should strengthen market risk monitoring systems by leveraging big data and machine learning technologies to establish more precise early warning mechanisms. Particularly in extreme market conditions, timely interventions such as raising margin requirements or imposing short-term trading restrictions can help mitigate market panic. Second, financial policies should be optimized to stabilize market expectations. During trade conflicts or global financial crises, governments should implement fiscal stimulus, interest rate reductions, or liquidity support measures to reduce uncertainty and support economic stability. Additionally, long-term investment should be encouraged to reduce market speculation. Policies aimed at increasing the participation of pension funds and insurance funds and providing tax incentives for long-term stockholders can help curb short-term speculative activities and reduce excessive market volatility.

Finally, a differentiated regulatory approach should be adopted based on market structure. Given that the ChiNext Index exhibits the highest volatility, regulators should enhance disclosure requirements, refine listing standards, and promote corporate governance improvements to mitigate excessive speculation. At the international level, governments should strengthen trade negotiations and global cooperation to minimize the adverse effects of external shocks. Measures such as multilateral trade agreements and tariff reductions can help mitigate market uncertainty and enhance the stability of domestic capital markets. Overall, the persistence of volatility and its sensitivity to external shocks underscore the need for both policymakers and investors to closely monitor volatility risks and implement effective strategies to reduce market instability and enhance financial market resilience.

The Chinese stock market, due to its unique market structure, policy influences, and investor behavior characteristics, exhibits volatility patterns that are significantly different from those of Western developed markets. Research on the volatility of the Shanghai Composite Index, the ChiNext Index, and the Shenzhen Composite Index not only helps to uncover the underlying mechanisms behind the volatility of the Chinese stock market, but also provides theoretical support for evaluating the market's efficiency and maturity. Furthermore, this research offers a fresh perspective for portfolio risk management and asset allocation strategies, especially within the context of the Chinese stock market, exploring how to optimize investment decisions by leveraging the volatility characteristics of these indices and contributing to the development of modern portfolio theory. Additionally, through a differentiated analysis of volatility across different market segments, this study provides valuable insights into the market efficiency of the Chinese stock market, particularly with regard to the functioning of information transmission, price discovery, and market adjustment mechanisms. This research not only aids the academic understanding of the market efficiency of the Chinese stock market, but also provides theoretical foundations and practical guidance for the development of market monitoring and forecasting models in real-world applications.

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