Comparative Analysis of Global Stock Market Volatility in the Post-epidemic Era

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Abstract: With the global economy entering the post-epidemic era, the volatility of the stock market has become an important focus of investors, policymakers and scholars. By using the GARCH model, the volatility of the global stock market is studied in depth, and its dynamic characteristics and main influencing factors are revealed. Studies have shown that macroeconomic environment, policy factors and market psychology factors all have an important impact on stock market volatility. The rapid recovery of the economy, the adjustment of monetary policy, the government's response measures, as well as investors' expectations, risk acceptance, group behavior and mood swings may all cause large fluctuations in the stock market. This research helps to improve the understanding of stock market volatility and provides valuable reference for investors and policy makers.

Keywords: post-epidemic era, global stock market, volatility model

1. Characteristics of the global stock market in the post-pandemic era

In the post-epidemic era, the global stock market presents the following characteristics: First, the global stock market has experienced a period of instability and volatility. The pace of economic recovery around the world has also been out of sync. And various policy support, measures to stimulate the economy and their exit strategies will also have a major impact on the market . Second, technology stocks and innovation stocks will continue to lead the market. During the epidemic, emerging industries such as remote work, online education, e-commerce, and cloud computing have developed rapidly, and technology stocks have therefore been favored by investors. After the epidemic, these industries will continue to expand their scale and market share. Third, green and sustainable investing has become more important. Globally, concerns about climate change and sustainable development have gradually transformed into an emphasis on environmental, social and governance (ESG) investments . This will have profound implications for the structure and dynamics of global stock markets. Fourth, in the context of economic globalization, emerging markets are more closely related to developed markets, and the impact of their economic performance on global stock markets cannot be ignored. According to the forecast of the International Monetary Fund (IMF), emerging markets play an important role in the global economic recovery.

2. Establishment of a global stock market volatility model in the post-pandemic era

2.1 Selection of volatility model

This study chooses to use the GARCH model to study and predict the volatility of the stock market. The GARCH model is called the generalized autoregressive conditional heteroscedastic model. An important feature of this model is that it can capture the “agglomeration effect” of stock market volatility, that is, large fluctuations follow large fluctuations, and small fluctuations follow small fluctuations. This phenomenon is very common in financial markets . The general form of a GARCH model can be expressed as:

$$\sigma^2(t) = \omega + \alpha\varepsilon^2(t-1) + \beta\sigma^2(t-1)$$

Among them, $\sigma^2(t)$ represents the volatility at period t, ε(t-1) denotes the residual error at period t-1, and $\sigma^2(t-1)$ represents the volatility at period t-1. The parameters ω, α, and β are estimated values. Specifically, α measures the impact of past volatility on current volatility, while β measures the impact of past residual errors on current volatility. When the sum of α and β (α + β) approaches 1, it indicates a high persistence of volatility. This implies that past volatility significantly influences volatility over an extended future period.

2.2 Data collection and preprocessing

This study uses the Shanghai Composite Index of a stock market as the research object, and the data comes from the historical transaction data publicly released by a financial futures exchange. The data sample includes daily closing prices from January 1, 2021 to December 31, 2022. The data covers a time span of about two years, which should help better capture the longer-term volatility characteristic of stocks.

The steps of data preprocessing are as follows:

Data cleaning: First, remove null and duplicate values in the data to ensure the integrity and accuracy of the data.

Data transformation: Since the GARCH model needs the return data of the stock market, it is necessary to convert the daily closing price data into return data. The rate of return is calculated as the ratio of the closing price of the current day to the closing price of the previous day minus one , that is, r(t)=P(t) / P(t-1)-1

Data stationarity test: Since the applicability of the GARCH model requires time series data to be stationary, it is necessary to perform a stationarity test on the rate of return series. If the data is not stationary, differencing or other transformation operations may be required.

Heteroscedasticity test: The yield sequence needs to have heteroscedasticity, that is, the variance of the sequence may be different at different time points. This can be checked using the ARCH test or the Ljung -Box Q test.

In this way, the preprocessed data can be used for subsequent construction and analysis of the GARCH model. In the model building stage, the maximum likelihood estimation method will be used to estimate the parameters of the model, and the best model will be selected through indicators such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

3. Analysis of empirical results

Based on the preprocessed data, the GARCH(1,1) model was used for fitting. The parameters of the model were estimated by the maximum likelihood estimation method , and the calculation was performed using R software. The fitting results of the model are as follows:

The formula for the GARCH(1,1) model is: $\sigma^{\wedge}2(t)=\omega+\alpha[r(t-1)-\mu]^{\wedge}2+\beta\sigma^{\wedge}2(t-1)$

Among them, σ^2(t) represents the variance at time t, ω represents the long-term variance, α and β are the parameters of ARCH and GARCH respectively, r(t-1) represents the rate of return at time t-1, and μ represents the mean , σ^2(t-1) represents the variance at time t-1.

The estimated results of the model parameters are:

ω = 0.00003

α = 0.06

β = 0.92

The fitting results of the model show that the coefficient β of the GARCH term is relatively large, reaching 0.92, indicating that the fluctuations in the previous period have a greater impact on the fluctuations in the current period, reflecting the persistence of fluctuations. The coefficient α of the ARCH term is relatively small, 0.06, indicating that the square term of the previous period's rate of return has a relatively small impact on the current period's volatility, which means that the immediate impact of information shocks is weak. Overall, the volatility of the Shanghai Composite Index has a significant GARCH effect and exhibits a high volatility aggregation characteristic.

In the testing part of the model, this study uses Ljung -Box Q test and ARCH-LM test. The p value of the Ljung -Box Q test of the model residuals is greater than 0.05, indicating that there is no autocorrelation in the model residual series, and the model fits well. The p-value of the ARCH-LM test is also greater than 0.05, indicating that the model has captured the heteroscedasticity of the data well, and there is no remaining heteroscedasticity effect.

4. Major Factors Affecting Global Stock Market Volatility

4.1 Macroeconomic factors

Macroeconomic factors significantly impact global stock market volatility in the post-epidemic era. Countries' economic recoveries vary, with faster recoveries leading to positive stock market fluctuations. Conversely, weaker recoveries result in greater stock market volatility. Central banks implemented expansive monetary policies in response to the pandemic's impact. The withdrawal and adjustment of these policies may trigger interest rate changes, impacting stock market volatility. Consumer confidence, heavily influenced by the epidemic, affects consumer demand, thereby impacting company profitability and stock market volatility. The global supply chain adjustments caused by the pandemic impact industry profitability and stock market volatility.

4.2 Policy factors

Policy environment shapes global stock market volatility. Central banks' monetary policies directly impact stocks. Post-epidemic policy withdrawal poses challenges, causing uncertainty and market fluctuations. Government fiscal stimulus during the pandemic and its withdrawal affect stock markets. Trade policy choices reshape global supply chains, impacting market volatility. Vaccination and health policy implementation affect economic recovery speed and stock market stability.

4.3 Market psychology factors

Market psychology plays a pivotal role in stock market volatility. In the post-epidemic era, investor expectations of economic recovery influence their investment decisions. Optimistic expectations lead to higher risk tolerance and stock investments, while pessimism reduces stock market participation and raises volatility. Uncertainty affects investors' risk appetite, potentially increasing market instability. Herd behavior among investors magnifies volatility. Investor sentiment, whether panicked or greedy, can trigger significant market fluctuations.

Epilogue

In the post-epidemic era, multiple factors impact stock market volatility. The GARCH model analyzes these factors. Macroeconomic factors, policy changes, and global trade impact volatility. Monetary and fiscal policies, government responses, and market psychology influence stock market expectations. Future research should focus on emerging markets with unique challenges.

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