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A Comparative Analysis of Stock Return for Amazon and Alibaba Based on Time Series Model and Control Chart

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Abstract: *E-commerce giants Amazon and Alibaba significantly impact the global economy, but their stock return volatility presents challenges for investors and analysts. Traditional volatility models often fail to capture sudden fluctuations, necessitating systematic monitoring through control charts. This study aims to (1) evaluate the performance of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in representing stock returns, (2) detect stock return volatility using residual-based control charts (RBCC), (3) compare the fluctuation patterns of stock returns of Amazon and Alibaba. Using daily opening prices from August 1, 2023, to July 31, 2024, stock returns are analyzed with a GARCH (1,1) model to estimate volatility. Residuals are then examined with Exponential Weighted Moving Average (EWMA) and Cumulative Sum (CUSUM) control charts to detect anomalies. By linking these anomalies to economic events, key drivers of stock return fluctuations are identified. Findings indicate that residual-based control charts effectively detect unusual stock return behaviors, highlighting their potential in financial market analysis. This study offers investors a systematic approach to monitoring stock volatility and contributes to financial research by demonstrating the effectiveness of RBCC in detecting structural market shifts and inefficiencies.*
Keywords: *GARCH model, stock return, control chart, Amazon, Alibaba*

INTRODUCTION

Amazon was founded in 1994 and is headquartered in Seattle, USA. As of 2024, its market value is about $1.6 trillion. Amazon's main businesses include e-commerce, cloud computing, digital content and streaming, artificial intelligence and smart devices, and logistics and supply chain. [1]. Alibaba Group, based in Hangzhou, China, was founded in 1999 by Jack Ma. As of 2024, its market value is about $196.5 billion. Alibaba started as a B2B e-commerce platform and has since grown into a global technology giant covering e-commerce, fintech, cloud computing, digital media, logistics and artificial intelligence [2].As a leader in the field of e-commerce, numerous scholars have conducted research on the stock performance of Amazon and Alibaba. Zheng [3] compared their annual reports, Varadharajan et al. [4] used Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) to forecast Amazon's daily closing prices, Lyn [5] applied linear regression and LSTM to predict stock returns for both firms, and Moiseev [6] examined pandemic-induced market capitalization shocks on open innovation strategies using fuzzy decision-making methods. The main research objective of these scholars is to use models to predict the stock price data of companies, analyze the characteristics of stocks, and compare the predictive capabilities of the models, rather than monitoring abnormal fluctuations in stock prices. There is a need for a more systematic and responsive method to monitor and detect anomalies in stock return behavior, which can help identify underlying market inefficiencies or external economic triggers.

This study aims to evaluate the performance of the GARCH model in representing stock returns; detect stock return volatility using RBCC; compare the fluctuation patterns of stock returns of Amazon and Alibaba. Using daily opening prices from 08/01/2023 to 07/31/2024, stock returns are analyzed with a GARCH (1,1) model to estimate volatility. Residuals are then examined with EWMA and CUSUM control charts to detect anomalies. This study provides investors with a systematic approach to monitoring stock return volatility and contributes to financial research by demonstrating the effectiveness of residual-based control charts in detecting structural market shifts and potential inefficiencies.

LITERATURE REVIEW

Stock returns refer to the returns of investors during the period of holding or trading stocks, which are characterized by random fluctuations, high-frequency trading and sharp price fluctuations. They are influenced by factors such as the macroeconomy, industry and company development. Stock market fluctuations refer to the changes in stock prices at different time periods, used to measure market uncertainty and risk levels. They manifest as short-term sharp fluctuations, long-term trends and unpredictability, and are driven by factors such as macroeconomic data, company financial conditions, market liquidity and unexpected events.

Many researchers have studied different stock returns in different countries or regions. For examples, there were research conducted in Indonesian Stock Exchange [7] [8], Canada [10], African [11], and European & American markets [9] [12]. On the other hand, some research also explored the impact of various initiatives by using stock index statistical output. For example, Hafidiz and Komaria [13] investigated the impact of corporate social responsibility (CSR) and return on assets (ROA) of Indonesian listed companies on the return on equity during the pandemic of the new museum. Kilić et al. [14] explored the influence of the MSCI's ESG (environment, society, and governance) global index on stock market returns. The findings were important because they can reveal the operating mechanism of the stock market, investor behavior, and the influence of policies or major events on the market.

Many researchers use different models to analyze stock returns. The existing research is summarized in Table 1. These studies show that while the ARIMA model is robust for data with fluctuating returns, GARCH models better describe data volatility.

Table 1. Summary of stock return analysis in existing research

Model	Scope	Reference
Autoregressive fractional integral moving average (ARFIMA) Fractional integral GARCH (FIGARCH)	Study the long-term memory characteristics of stock returns and volatility in the Indian stock market.	[15]
ARMA-GARCH model	Examine predictive ability of GARCH family models by using the daily stock return data from Guaranty Trust Bank.	[16]
Generalized dynamic factor model Vector autoregressive (VAR)	Analyze the relationship between stock returns and West Texas Intermediate oil price returns.	[17]
GARCH family of models	Select the most appropriate and effective model for the data of different cryptocurrency returns.	[18]
ARIMA model GARCH model	Forecast the stock returns for China's four major commercial banks and compare the predictive performance of two models.	[19]
GARCH model	Analyze the spillover effects and volatility characteristics of Japanese stocks during the COVID-19 pandemic.	[20]
ARIMA model	Predict the returns of five major international stock indices and compare model performance for each index.	[21]

With the continuous development of statistical process control technology, many scholars try to monitor stock market data changes through quality control charting. The existing research is summarized in Table 2. The aforementioned article indicates that control charts can be utilized to monitor stock market fluctuations. EWMA control charts and CUSUM control charts are commonly employed methods.

Table 2. Summary of control chart analysis in existing research

Control Chart	Scope	Reference
EWMA control chart	Combine EWMA CC with GARCH model and compare different control schemes in different simulation studies.	[22]
CUSUM control chart	Monitor the estimated default rate via a sliding window using various CUSUM CC and compare their results.	[23]
Shewhart control chart EWMA control chart	Analyze the opening prices from the Malaysian Stock Exchange and compare the robustness of control charts.	[24]
Individual control chart EWMA control chart	Analyze the effect of COVID-19 on stock trading decisions by using a control chart	[25]
EWMA control chart	Investigate the volatility prediction performance of small and mid-cap stocks using the EWMA and GARCH.	[26]
Volume-weighted moving average control chart	Use Genting Malaysia Berhad stock transaction data and explore whether the CC can identify stock events.	[27]
CUSUM control chart	Use data from the S&P 500 Index, the Korea Composite Stock Price Index confirms that the CUSUM combined with a time series plot can monitor volatility changes.	[28]

DATA AND METHODOLOGY

To monitor Amazon and Alibaba's stock returns, the study obtains the daily opening prices of Amazon and Alibaba stocks from Yahoo Finance from 08/1/2023 to 07/31/2024 and computes the logarithmic stock returns for both companies.

The opening price reflects the market's reaction to new information from the end of the previous trading day to the current opening, as well as non-trading-hour fluctuations. The main models and control charts mainly used in the research are presented in Table 3.

Table 3. Analysis model and control chart type in this research

Model/Chart	Purpose	Formula & Variable used
ARIMA model	Select an appropriate mean equation for the GARCH model.	$Y_t = \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$
GARCH model	Fit an appropriate model to the fluctuating data.	$Y_t = X_t \beta + \varepsilon_t, \varepsilon \sim N(0,1)$ $h_t = \omega + \lim_{x\to\infty} \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$
GARCH-GED model	Fit an appropriate model to the fluctuating data.	$Y_t = X_t \beta + \varepsilon_t, \varepsilon \sim GED$ $h_t = \omega + \lim_{x\to\infty} \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$
CUSUM control chart	Detect the fluctuation of stock price returns.	$C_n^+ = \max(0, C_{n-1}^n + (X_n - \mu_0 - k))$ $C_n^- = \max(0, C_{n-1}^- + (\mu_0 - X_n - k))$
EWMA control chart	Detect the fluctuation of stock price returns.	$Z_t = \lambda X_t + (1-\lambda) Z_{t-1}$ $UCL_t = \mu + L\sigma\sqrt{\frac{\lambda}{2-\lambda}(1-(1-\lambda)^{2t})}$ $LCL_t = \mu - L\sigma\sqrt{\frac{\lambda}{2-\lambda}(1-(1-\lambda)^{2t})}$

The data fitting of the model is carried out using Eviews software. After conducting the stationarity test, an appropriate ARIMA model is fitted with the stationary data as the form of the mean equation of the GARCH model. Then, the GARCH (1, 1) model is fitted, and the residuals of the model are tested to determine whether they are suitable for drawing control charts. Finally, EWMA and CUSUM control charts are constructed using the residuals.

RESULT AND DISCUSSION

Analysis output of GARCH Model

The model-fitting results of Amazon's stock returns are presented in Table 4. Amazon's stock returns fit the GARCH (1, 1) model. The mean value equation of the GARCH model is as follows: $Y_t = 0.001124 - 0.097573 Y_{t-1} - 0.111512 \varepsilon_{t-1} + \varepsilon_t$. The variance equation can be expressed as: $h_t = 0.00015 + 0.031276 \varepsilon_{t-1}^2 + 0.432693 h_{t-1}^2$. The GARCH term is significant, meaning volatility clustering exists. The ARCH term is not significant, implying that past return shocks have a limited immediate impact on volatility.

Table 4. The GARCH (1, 1) results of Amazon's stock returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001124	0.000903	1.244326	0.2134
AR (1)	-0.097573	0.071118	-1.371999	0.1701
AR (2)	-0.111512	0.062515	-1.783756	0.0745
C	0.000151	5.67E-05	2.664456	0.0077
ARCH (-1)	0.031276	0.051196	0.610896	0.5413
GARCH (-1)	0.432693	0.208167	2.078588	0.0377

Alibaba's stock returns fit the GARCH-GED (1, 1) model. The results of the model are presented in Table 5. Alibaba's stock returns fit GARCH-GED (1, 1) model. The mean value equation of GARCH-GED model is $Y_t = -0.000435 + 0.960382 Y_{t-1} - 0.999986 \varepsilon_{t-1} + \varepsilon_t$. The variance equation can be expressed as: $h_t = 0.000115 + 0.107101 \varepsilon_{t-1}^2 + 0.618496 h_{t-1}^2$. The significant GARCH (1) term means past volatility carries over, leading to volatility clustering. The significant GED parameter confirms that Alibaba's return distribution has heavier tails than a normal distribution, meaning extreme price movements are more common.

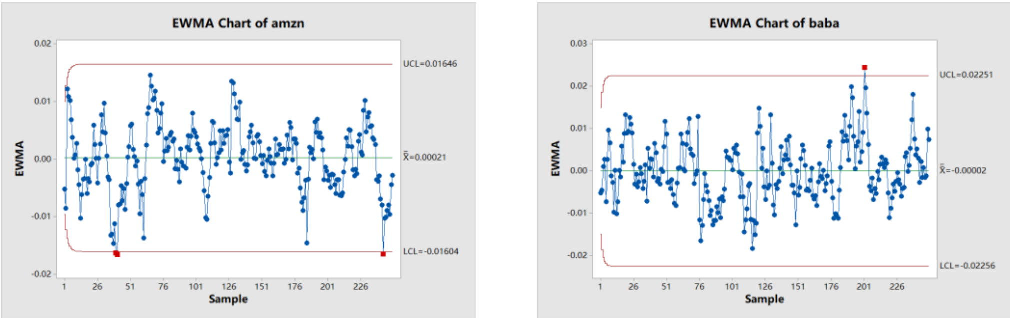
Table 5. The GARCH-GED (1, 1) results of Amazon's stock returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000435	0.000350	-1.240992	0.2146
AR (1)	0.960382	0.016312	58.87489	0.0000
AR (1)	0.999986	3.85E-05	-25982.16	0.0000
C	0.000115	0.000115	0.998468	0.3181
ARCH (-1)	0.107101	0.067296	1.591486	0.1115
GARCH (-1)	0.618496	0.291321	2.123075	0.0337

GED	1.432777	0.192808	7.431103	0.0000

Output of EWMA Control Chart

Figures 1(a) and 1(b) are the results of the EWMA control chart. There are two outliers in Amazon's EWMA control chart and one in Alibaba's. Most values remain within the control range.



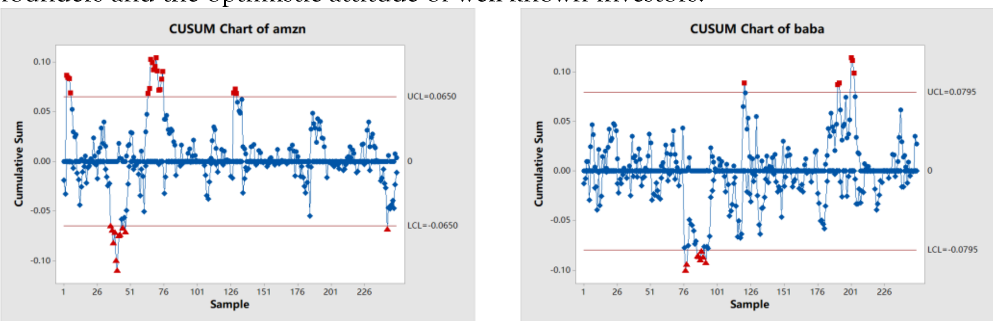
(a) (b)

Figure 1 (a) The EWMA control chart of Amazon, **(b)** The EWMA control chart of Alibaba.

Compared with the standard Shewhart control chart, the EWMA control chart is more sensitive to minor changes in the mean. The exponential weighting emphasizes the most recent values while retaining the information in the past data, reducing noise in stock return monitoring. Moreover, the EWMA control chart detects early outliers and subtle deviations before major stock market changes but lags in identifying market crashes and yield shocks.

Output of CUSUM Control Chart

Figure 2 (a) and (b) are the results of CUSUM control chart. The control charts show that Alibaba has more abnormal points, indicating that its market fluctuations are more intense. Overall, the stock returns of both companies are affected by both natural market fluctuations and special events. Amazon's earnings growth is attributed to its strong financial performance and the favorable economic environment in the USA, while its decline is related to monopoly lawsuits, employee strikes and other events. Alibaba's earnings decline is due to poor financial performance, anti-monopoly pressure and unfavorable economic and trade environment, while its growth is attributed to the increase in the holdings of its founders and the optimistic attitude of well-known investors.



(a) (b)

Figure 2 (a): The CUSUM control chart of Amazon, **(b)**: The CUSUM control chart of Alibaba

Compared with other traditional control charts, the CUSUM control chart is more sensitive to the gradual changes in stock returns and provides a visual representation of whether the deviation accumulates over time, which can help investors detect long-term market changes. The clustering of outliers in the two charts indicates that the CUSUM control chart can precisely locate the key events where stock returns undergo significant changes.

DISCUSSION AND CONCLUSION

In order to monitor the stock returns of Amazon and Alibaba, this study selected the opening stock prices of the two companies from 08/01/2023 to 07/31/2024, calculated the corresponding stock returns, and fitted the GARCH (1, 1) model. Using the model residuals, EWMA and CUSUM control charts were established and analyzed. Through the research, it was found that the EWMA control chart is more suitable for continuous monitoring, while the CUSUM control chart is more suitable for analyzing trend changes. The combination of the two control charts considers both short-term fluctuations and long-term trends, providing a more comprehensive market analysis, improving signal reliability, and enhancing market interpretability. Compared to traditional Shewhart control charts, the EWMA and CUSUM charts provide a more robust framework for financial time series analysis. EWMA charts place greater emphasis on recent data, making them effective for identifying subtle shifts in volatility as they occur. CUSUM charts accumulate small deviations over time, which helps detect systematic drifts or gradual market shifts that may not be evident through other charting methods. In conclusion, the integration of EWMA and CUSUM control charts in residual analysis not only enhances the sensitivity and reliability of anomaly detection in stock return behavior but also provides deeper insights into the underlying market dynamics. This combination is conducive to making wiser investment decisions and enables a clearer understanding of the structural market changes. However, the choice of control chart parameters λ , k and h depend on experience, and it is difficult to find the optimal values in all scenarios. The GARCH-GED model cannot capture the common asymmetric effects in the market. In future, it is possible to consider combining machine learning methods, optimizing parameter selection. And other control charts can be tried in future research, such as HWMA control chart to analyze stock price fluctuations.

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Data Availability: The data that support the findings of this study are available from https://finance.yahoo.com/.

Conflict of interest: The authors declare that there is no conflict of interest.

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